# TO LEAVE OR NOT TO LEAVE: A POPULATION STUDY INVESTIGATING HOW COMPENSATION AND AUXILIARY SPENDING INFLUENCE TEACHER TURNOVER IN THE COMMONWEALTH OF PENNSYLVANIA

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by
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## ABSTRACT

Teacher turnover is a well-studied phenomenon, particularly in highly urbanized locales, but not well researched in a state as geographically and demographically diverse as Pennsylvania, which is a composition of two major metropolitan areas combined with smaller urban centers and expansive rural regions. Those retention studies that do exist have been mainly exclusive to the Philadelphia region, with limited research devoted to the remainder of the state. This lack of a comprehensive empirical approach that compares turnover in three distinct settings limits a nuanced understanding of the issue and, in turn, can lead to incomplete policy considerations. This study utilizes Pennsylvania Department of Education data from 2012-2017, which describes the entire public-school workforce in all local education agencies (LEAs), to study how compensation and auxiliary spending (per student spending *sans* instructional costs) influence teacher turnover using multiple, parallel Cox Proportional Hazards survival models. Findings suggest that despite a "one size fits all" approach to public school funding policy popular amongst politicians on both sides of the political aisle, the effects of a monetary increase in reducing the likelihood of turnover varies considerably when accounting for the region, Title I status, experience and subject matter. The study highlights how the lack of monetary investment can lead teachers to seek employment elsewhere since low pay functions as a strong demotivator. Additionally, the results suggest that while a pay raise may arrest turnover risk, it is a poor long-term motivator or cause of job satisfaction. The study concludes by offering state and LEA leaders with policy recommendations that may improve both retention and job satisfaction. To date, this is the only study in the current literature that explores teacher turnover extensively in the nation's fifth most populous state.

"In a completely rational society, the best of us would be teachers
and the rest of us would have to settle for something less."

Lee Iacocca, Former *President, Chairman, and CEO of Chrysler Corporation*
and Allentown, Pennsylvania's Native Son

This study is dedicated to teachers within and outside the Commonwealth of Pennsylvania, who dedicate themselves every day to one of the noblest pursuits of humankind, and without whom the advancement of society would not be possible.

## ACKNOWLEDGMENT

"No man is an island, entire of itself; every man
is a piece of the continent, a part of the main."

John Donne, *Devotions upon Emergent Occasions*, Meditation 17

This study began as a reflection of my own experiences as a high school science teacher – first in an urban, charter school and later at a suburban, independent school – in the Greater Philadelphia region. These reflections evolved into opportunities for growth and research that were nurtured by my supervisors in the General Education program and the faculty within and outside the College of Education. Consequently, I would like first to acknowledge my colleagues and instructors, past and present, who encouraged me to explore the world through a multitude of perspectives. Second, I would like to acknowledge my Examining Committee for helping this study come to fruition. Specifically, I want to thank Will Jordan and Christopher McGinley, whose wisdom I value, experiences I honor, and careers I aspire to emulate. Throughout my graduate career, they have simultaneously viewed me as a student, colleague, and friend.

I also want to acknowledge my colleagues at the American Federation of Teachers/Pennsylvania and the Temple University Graduate Students Association (TUGSA AFT Local #6290), without whom I would not have developed a deep appreciation for the complexities associated with organizational leadership. Perhaps, most importantly, I want to acknowledge my mother and husband, Drs. Stacey Ake and Shaun Ake-Little. Both not only serve as my support system but also are my better angels since neither hesitates to speak truth to power while providing unconditional love. Both came into my life during a critical period and are living testaments that Divine Providence is the real author of our lives.

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# INTRODUCTION

"No one will doubt that the legislator should direct his attention above all to the education of youth; for the neglect of education does harm to the constitution [of the polis]"

– Aristotle, *Politics*

When Aristotle penned these words in 350 B.C.E., he put forth the argument that a life committed to public service was superior to that of a private, since the former required attending to the needs of a community, whereas the latter was limited only to the needs of the household. In the intervening centuries since *Politics*, the polis has evolved beyond the Athenian city-state of Aristotle's time to encompass larger political entities, and with the advent of new democratic institutions, giving rise to bureaucratic structures that distance the community from its legislators. However, underpinning the health of any state is the paramountcy of education, especially during a time when solutions to society's most pressing issues require comprehensive solutions predicated on community unity. In this study, I explore one facet of the education system—public school funding, and specifically, whether financial investments help retain teachers, those who actively engage in the education of youth—as well as the power of legislators to influence such investment.

## Impetus for the Study

The study of teacher retention is not new, and aphorisms about the influence of a good teacher can be found dating to the Old Testament. Debating the value of teachers, and what they are due, evokes strong emotion from all of those connected with schooling such as politicians, community members, parents, administrators, students, and, of course, teachers themselves. (Throughout this study, I refer to all these individuals collectively as "stakeholders"). Equally important is the effect teachers have on all these stakeholders; parents are thankful for those who support their child's academic or social growth, administrators trust those who share their vision for teaching and learning, community members admire those who serve as a role model, and students remember those with whom they formed an emotional bond. What is new, and why the issue of teacher retention warrants scrutiny, are recent extraordinary events in American public education, which are themselves a manifestation of subtler political and socioeconomic shifts.

### ***The Age of Mass Teachers' Strikes***

Perhaps the most salient of these events has been the endless cavalcade of teacher strikes in the past year, starting with a statewide walkout in West Virginia, which left classrooms empty for nearly two weeks in late February 2018. The West Virginia action launched a wave of similar actions in Arizona, Colorado, and Oklahoma—all within a subsequent three-month period. More recently, urban schools have entered the fray, with teachers at 15 Acero Schools in Chicago striking this past fall in the nation's first teacher strike against a charter operator, followed by a strike at Chicago International Charter Schools, another charter operator that manages 14 schools. These actions were complemented by striking teachers in the Los Angeles Unified School District, who went to the picket line for the first time in nearly 30 years. All had a similar motif—low pay, increasing workloads, proposed changes to benefits, and the need for more classroom support. Moreover, these actions did result in varying wins, from an impressive 20 percent increase in pay for teachers in Arizona to the restoration of school funding to pre-2009 levels in Colorado. The success of each work stoppage has inspired others to follow suit, with more likely to come throughout 2019 and beyond.

While the collective action and organizing of these teachers are commendable, the causes leading to their predicament are not. More recent data from the National Education Association (2018) reveals that West Virginia, the progenitor of these strikes, has an average teacher salary that ranks 48th in the country at a time when Governor Jim Justice (R) reported a $186 million budget surplus in the second half of 2018 his State of the State address this year. The same data reveals Arizona as 42$^{nd}$ in teacher pay; Hunting (2017) found that Arizona has the highest teacher turnover rate in the nation with overall attrition at 24 percent and 42 percent of teachers leaving the profession in the first three years *statewide*. In addition to expressing longstanding grievances about teacher pay, the strikes have also exposed severe structural problems in state funding. North Carolina, where the average teacher salary ranks slightly higher at 39$^{th}$, faces such a gaping budget deficit that *The Washington Post* reported a proposed bill in the state's General Assembly that would eliminate state healthcare subsidies for teachers hired after January 1, 2021—a move that is expected to cost these new hires up to $10,000 per year in out-of-pocket premium payments (Strauss, 2018). Perhaps the gravest of these financial problems are unfunded pension obligations, which according to the Pew Charitable Trusts (2016), nationally amount to $1.4 trillion. In many states, this means increased pension contributions by districts and their teachers do not go to save for these employees' retirement, but rather to make payments on *current* retirement obligations, amounting to a government-sponsored Ponzi scheme.

### ***The Rapidly Changing Labor Landscape***

Inextricably linked to the debate over teacher compensation is the issue of teacher workload; one which has attracted detractors and apologies across the political spectrum. Critics on the right, such as the Heritage Foundation and the Cato Institute, contend that teachers enjoy a shorter work week and year compared to other professions, in addition to unheard of union protections such as tenure—all at the expense of students and taxpayers. Supporters of teachers on the left, such as the Urban Institute and the Economic Policy Institute, argue that this calculation is an oversimplification, as teachers work many undocumented hours throughout the academic year and are expected to engage in professional development over the summer with a salary that only compensates them for ten months. Moreover, they uphold the concept of tenure by maintaining that it allows teachers to advocate on behalf of students without the fear of reprisal. Predictably, this debate has spilled into the policy arena with implications for teachers' workplaces.

Arguably, the most impactful of these policy decisions is the *Janus v. AFSCME* (2017) Supreme Court case, which decided against the "fair share" provision of membership dues payments sanctioned in *Abood v. Detroit Board of Education* (1977). The provision stated that unions could collect a certain percentage of membership dues from non-members since the latter benefited from the fruits of collective bargaining ("fair share"). In the wake of the *Janus* decision, unions can no longer automatically collect dues without the express written consent of the represented individual, which pro-labor groups view as an attempt to starve unions of their financial lifeline. Like the 2018-19 teacher strikes, the *Janus* decision is a culmination of several anti-labor policies enacted since the Reagan administration, collectively referred to as "Right-to-Work" (RtW) legislation.

Deceptively termed, RtW does not provide a guarantee of employment, and perhaps unknown to the affected employee, excludes non-members from participating in union-related activities that have a substantial effect on their workplace conditions, such as a strike authorization or voting to ratify a collective bargaining agreement (CBA). Gould and Shierholz (2011) found that in RtW states, the average worker made $1,500 less annually and paid 2.6 percentage points more in healthcare premium contributions, compared to the same worker in a state that had no such laws. These oft-overlooked implications have led Josh Bivens (2018) of the Economic Policy Institute to comment that "the *Janus* decision is a far scarier portent about the 'future of work' than any article you've read about advances in AI or robotics or the rise of the gig economy."

Emboldened by the *Janus* decision, RtW advocates have attempted to further their agenda within the realm of public education. In Pennsylvania, such activists have lobbied for the state legislature to repeal laws that permit teachers to strike legally or to curb certain due process rights associated with tenure. Others have taken a less direct approach, seeking to infuse the spirit of RtW into public education via charter school legislation. Whereas many of these measures have failed, others have become riders to education funding bills resulting in a "tit-for-tat" tradeoff. In 2014, Republicans in the state's General Assembly offered to raise the state's cigarette tax to fund the School District of Philadelphia (SDP), but only if the district permitted issuance of new charters. The Pennsylvania Department of the Auditor General (PDAG) denounced this move, stating that payments made to charters would dilute any gains made by the tax hike (PDAG, 2016). In 2017, as a condition of approving Governor Tom Wolf's (D) budget proposal, Republicans again attached a rider, yet this time as an amendment to the Public School Code of 1949. To date, the

Pennsylvania Department of Education (PDE) treats each charter school as an independent organization, regardless of its parent charter network. The rider amendment paves the way for the formation of a Multiple Charter School Organization (MCSO), a move that allows for the creation of a "charter school district" (a singularly recognized entity) from the merger of multiple charter schools under the management of a single school board.

### *The Flood of New School Funding Lawsuits*

Like conservatives, liberals have also attempted to use the levers of government but to promote progressive school funding initiatives. At the national level, several attempts to remedy funding disparities have found their way to the U.S. Supreme Court with *San Antonio Independent School District v. Rodriguez* (1973) perhaps the most famous of these cases. Although the Court did acknowledge that inequities did exist in Texas's approach to school funding, it declined to intervene because it ruled education is not a "fundamental interest" per the Enumerated Powers clause of the U.S. Constitution.

Many groups, having failed to achieve more equitable funding at the federal level, have turned to state courts to pursue their cause. In Pennsylvania, a group of parents, school districts, and statewide organizations came together in 2014 to file suit against the state, arguing it had failed to meet its obligations of, "the maintenance and support of a thorough and efficient system of public education," as outlined in Article 3, Section 14 of the state's constitution. The case—*William Penn School District, et al. v. Pennsylvania Dept. of Education, et al.*—will formally proceed to trial in 2020, with either outcome foreboding implications for state funding policy.

Perhaps, the most well-established of these funding lawsuits are the Abbott cases in New Jersey, with the initial *Abbott v. Burke* (known as Abbott I) case decision dating back to 1985, when the New Jersey Supreme Court ruled that the state's school funding system led to significant expenditure disparities between poorer and wealthier school districts. In adopting such a skewed system, the state was derelict in its obligation to provide students with equal access that, in turn, resulted in inadequate educational provisions. In the 30+ years since Abbott I, a series of subsequent cases have pressured Trenton legislators to correct for funding disparities that limit access to high-quality education. For instance, in 1998 (Abbott V), 2000 (Abbott VI & Abbott VII), and in 2002 (Abbott VIII), the Court required more funds by the state for school building improvements as well as for the implementation of a preschool program. In 2008 (Abbott XX), the Court required the implementation of a weighted student funding formula in favor of low-income districts with certain demographic disproportionalities.

In the past five years alone, there has been an uptick in the number of such lawsuits all embodying the spirit of *Abbott*. Plaintiffs in *McCleary v. State of Washington* (2012) asserted that the state failed to meet its constitutional obligations resulting in a state Supreme Court ruling in their favor. Although Olympia legislators did pass school funding reforms, in 2017, the Court found that these were insufficient to remedy the violations. The following year, the legislature passed a supplementary budget that significantly raised school funding, believing that this change would satisfy the Constitution's requirements. Plaintiffs in Arizona filed *Glendale Elementary School District v. State* (2017) in Arizona Supreme Court, alleging that the state failed to meet its constitutional obligations toward public education as the consequence of an empty school facilities fund that languished under the state's agenda of continuous tax cuts for a decade. In Kansas, which faces a similar situation thanks to what former Governor Sam Brownback (R) described as "red state experiment" in extreme tax cuts, the Kansas Supreme Court has ordered the Topeka legislature to raise the revenue need to fund a $2 billion increase in school funding just to meet student performance targets. The legislature is currently facing an April deadline set by the Court to satisfy this order.

### *A Declining Interest in Teaching*

Teaching is a profession that has historically commanded a high degree of respect in any society. According to The Varkey Foundation (2018), which administers the $1 million Global Education Prize, in its latest survey of 35,000 respondents across 35 countries, 63 percent trust teachers to deliver a high-quality education to their children, with parents in China, India, and Ghana most encouraging towards their children to pursue the profession. At home, the picture is far less rosy. An annual poll conducted by Phi Delta Kappa and Gallup found that although an overwhelming 73 percent say they would support teachers in their community if they went on strike, 54 percent of these Americans would not want their child to become a teacher, a majority for the first time in the poll's 50-year history (PDK & Gallup, 2018). Many respondents cited low pay, a perennial concern that has assumed more importance at a time when the average graduating senior has now accrued almost $30,000 in student debt.

The data appears to bear out this disinterest; the National Center for Education Statistics (2017) reported that in the years following the passage of the No Child Left Behind (NCLB) Act of 2001, the number of graduates with Masters-level degrees in Education grew by almost 45 percent. This percentage peaked in AY2010-11 when the labor market began to show signs of recovery following the Great Recession of 2009. However, in the subsequent five years ending in AY2015-16, there was a 23 percent decline in the number of graduates from teacher-preparation programs, with the sharpest in alternative programs such as Teach for America (32 percent). Closer to home, 2017 Higher Education Title II data shows that the number of education graduates in Pennsylvania colleges has dropped 55 percent since 1996, with the number of new teaching certificates issued plummeting by 71 percent between AY2009-10 and AY2016-17 (OPE, 2018). This drop has been even more precipitous in STEM subjects, where the Commonwealth has experienced a decline in Biology (52 percent), Mathematics (63 percent), Chemistry (74 percent), and Physics (78 percent) certifications in the period between 2013 and 2016.

Several policy pundits have attributed this decline to a highly robust labor market, noting Bureau of Labor Statistics (2018) data that the unemployment rate hit a 49-year low of just 3.7 percent in late 2018, but the implication is that teaching is a “fallback profession,” one that provides a safe harbor in economically turbulent times and is worth abandoning when better opportunities arise. Consequently, many states have embraced some innovative measures to encourage a longer-term commitment from teachers. In 2017, *The San Francisco Chronicle* reported that the city had allocated $44 million just in rental subsidies for teachers to teach within the city (Tucker, 2017). The following year, Pennsylvania followed suit with *The Philadelphia Inquirer* reporting that the state sought to invest $2 million in teacher residency programs in addition to partnering with the Woodrow Wilson National Fellowship Foundation to offer STEM preparation fellowships to teachers committed to at least three years of urban teaching in the state (Graham, 2018).

## Background of the Study

This section discusses the state of school funding policy in Pennsylvania, but because of the diverse nature of this state, it is worth examining how the interplay between geography, politics, economics, and demographics has led to some of the most apparent funding disparities nationally.

### *The Commonwealth of Pennsylvania: A State of Contrasts*

Pennsylvania has several unique characteristics that set it apart from other states in the union. It is one of the oldest states, second only to neighboring Delaware, to ratify the U.S. Constitution as well as simultaneously large (ranking fifth in population) and small (placing 33rd in the nation in terms of area). It is home to the fifth-largest city in the country (Philadelphia) and the largest city in the Ohio River Valley as well as the Appalachian region (Pittsburgh), earning it the unofficial nickname of the "Paris of Appalachia" by *Pittsburgh Post-Gazette* columnist Brian O'Neill (2011) because of its status as an economic hub in that region. Geographically, it also lies at a crossroads; the eastern portions of the state have traditionally been influenced by East Coast developments, with Philadelphia firmly ensconced in the "Bos-Wash" region, a megalopolis home to nearly 50 million Americans and 20 percent of the nation's Gross Domestic Product (GDP). The Western portion of the state identifies economically and culturally with the Midwestern Rust Belt, and the state's southern boundary served as the historic Mason-Dixon Line, the once literal and now figurative political and social border between the North and the South.

#### *Geographic, Political, and Educational Character of the State.*

Geographic Organization. Aside from its (pejorative) characterization as "Pennsyltucky," the Commonwealth does have formal demarcations defined by the U.S. Office of Management and Budget. The OMB organizes regions into Combined Statistical

Areas (CSAs), Metropolitan Statistical Areas (MSAs), and Micro Statistical Areas (μSAs) based on shared economic and social activity. According to the U.S. Census Bureau (2018), Pennsylvania is home to two of top 25 CSAs in the country–the Philadelphia region, which is formally defined as the Philadelphia-Reading-Camden PA-NJ-DE CSA region (and referred to throughout this study as “Greater Philadelphia” or the “PHL” region) and the Pittsburgh region, formally defined as the Pittsburgh-New Castle-Weirton PA-OH-WV CSA (and referred to throughout this study as “Greater Pittsburgh” or the “PGH” region). The PHL and PGH regions are ranked eighth and 21$^{st}$ in the nation, respectively, concerning population. Dispersed clusters of small cities, towns, and even villages, which are a combination of MSAs and μSAs (and referred to throughout this study as “Central Pennsylvania” or the “CPA” regions), constitute the remainder of the state. Table 1.1 provides a classification of all 67 Pennsylvania counties organized into one of these three regions and provides information relating to their population. Each region consists of one or more urban hubs, with Philadelphia and Pittsburgh being of prime importance in their respective regions. The six counties of the PHL region are home to 35 percent of the state’s estimated 12.8 million residents with the nine counties of the PGH region accounting for 20 percent of the state’s population. The remaining 52 counties account for the remaining 45 percent of the populace, and because of its expanse, this study separates the region into urbanized (regional cities and surrounding suburbs) and rural regions.

Political Constitution. Politically, the state has been reliably “blue” (Democratic) since the election of Bill Clinton in 1992 but was “red” (Republican) in 2016, with the election of Donald Trump; in almost all these elections, the vote was decided with a small margin of error earning it “battleground” status.

**Table 1.1 • Population Change and Cost of Living Index (CoLI) by Pennsylvania Counties**

| Name of Region/ U.S. Census Bureau Statistical Area Definition | Corresponding PA County | Major Urban Centers | County Population (2010)[1] | County Population (2017)[2] | Population Change | Percent Change (Since 2010) | Cost of Living (CoLI) Adjustment[3] |
|---|---|---|---|---|---|---|---|
| ***Greater Philadelphia Region*** | Philadelphia County | Philadelphia | 1,526,006 | 1,567,442 | 41,436 | 2.72% | 109.7 |
| Philadelphia-Reading-Camden (NJ) Combined Statistical Area | Montgomery County | | 799,874 | 819,264 | 19,390 | 2.42% | 125.0 |
| | Bucks County | | 625,249 | 627,367 | 2,118 | 0.34% | 132.0 |
| | Delaware County | | 558,979 | 563,894 | 4,915 | 0.88% | 114.6 |
| | Chester County | | 498,886 | 515,939 | 17,053 | 3.42% | 132.3 |
| | Berks County | | 411,442 | 415,271 | 3,829 | 0.93% | 101.1 |
| *Subtotal* | *(6 Counties)* | | *4,420,436* | *4,509,177* | *88,741* | *2.01%* | |
| ***Greater Pittsburgh Region*** | Allegheny County | Pittsburgh | 1,223,348 | 1,230,459 | 7,111 | 0.58% | 96.9 |
| Pittsburgh-New Castle-Weirton (WV) Combined Statistical Area | Westmoreland County | | 365,169 | 357,841 | -7,328 | -2.01% | 88.6 |
| | Washington County | | 207,820 | 208,261 | 441 | 0.21% | 94.8 |
| | Butler County | | 183,862 | 186,818 | 2,956 | 1.61% | 105.3 |
| | Beaver County | | 170,539 | 168,871 | -1,668 | -0.98% | 96.7 |
| | Fayette County | | 136,606 | 133,628 | -2,978 | -2.18% | 81.2 |
| | Lawrence County | | 91,108 | 88,082 | -3,026 | -3.32% | 78.9 |
| | Indiana County | | 88,880 | 86,966 | -1,914 | -2.15% | 84.8 |
| | Armstrong County | | 68,941 | 67,052 | -1,889 | -2.74% | 88.7 |
| *Subtotal* | *(9 Counties)* | | *2,536,273* | *2,527,978* | *-8,295* | *-0.33%* | |
| ***Central Pennsylvania Region - Regional Cities & Suburban Regions*** | | | | | | | |
| Harrisburg–York–Lebanon Combined Statistical Area | York County | York | 434,972 | 442,867 | 7,895 | 1.82% | 103.9 |
| | Dauphin County | Harrisburg | 268,100 | 272,983 | 4,883 | 1.82% | 96.0 |
| | Cumberland County | | 235,406 | 246,338 | 10,932 | 4.64% | 102.1 |
| | Lebanon County | Lebanon | 133,568 | 137,067 | 3,499 | 2.62% | 97.1 |
| | Adams County | | 101,407 | 102,295 | 888 | 0.88% | 103.6 |
| | Perry County | | 45,969 | 45,685 | -284 | -0.62% | 99.0 |
| Allentown-Bethlehem-Easton Metropolitan Statistical Area | Northampton County | Bethlehem, Easton | 297,735 | 300,813 | 3,078 | 1.03% | 105.6 |
| | Lehigh County | Allentown | 349,497 | 360,685 | 11,188 | 3.20% | 105.4 |
| | Carbon County | | 65,249 | 63,960 | -1,289 | -1.98% | 99.5 |
| Scranton-Wilkes Barre-Hazelton Metropolitan Statistical Area | Luzerne County | Wilkes Barre, Hazelton | 320,918 | 318,449 | -2,469 | -0.77% | 84.8 |
| | Lackawanna County | Scranton | 214,437 | 211,917 | -2,520 | -1.18% | 88.9 |
| | Wyoming County | | 28,276 | 27,800 | -476 | -1.68% | 95.0 |
| Lancaster Metropolitan Statistical Area | Lancaster County | Lancaster | 519,445 | 536,624 | 17,179 | 3.31% | 105.4 |
| Erie-Meadville Combined Statistical Area | Erie County | Erie | 280,566 | 278,045 | -2,521 | -0.90% | 86.2 |
| | Crawford County | Meadville | 88,765 | 86,484 | -2,281 | -2.57% | 80.8 |
| Subtotal | (15 Counties) | | 3,384,310 | 3,432,012 | 47,702 | 1.41% | |
| ***Central Pennsylvania Region - Rural Regions*** | | | | | | | |
| | Monroe County | | 169,842 | 166,397 | -3,445 | -2.03% | 96.8 |
| | Centre County | | 153,990 | 160,580 | 6,590 | 4.28% | 102.0 |
| | Franklin County | | 149,618 | 153,638 | 4,020 | 2.69% | 97.4 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | Schuylkill County | 148,289 | 144,590 | -3,699 | -2.49% | 80.8 |
| | Cambria County | 143,679 | 136,441 | -7,238 | -5.04% | 79.9 |
| | Blair County | 127,089 | 125,593 | -1,496 | -1.18% | 84.4 |
| | Mercer County | 116,638 | 114,234 | -2,404 | -2.06% | 82.1 |
| | Lycoming County | 116,111 | 116,048 | -63 | -0.05% | 92.0 |
| | Northumberland County | 94,528 | 93,246 | -1,282 | -1.36% | 81.0 |
| | Clearfield County | 81,642 | 80,994 | -648 | -0.79% | 78.0 |
| | Somerset County | 77,742 | 75,522 | -2,220 | -2.86% | 80.6 |
| | Columbia County | 67,295 | 66,672 | -623 | -0.93% | 87.9 |
| | Bradford County | 62,622 | 61,281 | -1,341 | -2.14% | 88.9 |
| | Pike County | 57,369 | 55,949 | -1,420 | -2.48% | 113.1 |
| | Venango County | 54,984 | 53,119 | -1,865 | -3.39% | 77.4 |
| | Wayne County | 52,822 | 51,198 | -1,624 | -3.07% | 94.5 |
| | Bedford County | 49,762 | 48,586 | -1,176 | -2.36% | 88.1 |
| | Mifflin County | 46,682 | 46,500 | -182 | -0.39% | 82.7 |
| | Huntingdon County | 45,913 | 45,668 | -245 | -0.53% | 86.6 |
| | Jefferson County | 45,200 | 44,430 | -770 | -1.70% | 80.2 |
| | Union County | 44,947 | 44,954 | 7 | 0.02% | 91.6 |
| | McKean County | 43,450 | 42,412 | -1,038 | -2.39% | 75.5 |
| | Susquehanna County | 43,356 | 41,666 | -1,690 | -3.90% | 91.1 |
| | Tioga County | 41,981 | 41,877 | -104 | -0.25% | 86.8 |
| | Warren County | 41,815 | 40,396 | -1,419 | -3.39% | 79.3 |
| | Clarion County | 39,988 | 39,498 | -490 | -1.23% | 83.0 |
| | Snyder County | 39,702 | 40,444 | 742 | 1.87% | 93.2 |
| | Clinton County | 39,238 | 39,441 | 203 | 0.52% | 89.1 |
| | Greene County | 38,686 | 37,519 | -1,167 | -3.02% | 81.8 |
| | Elk County | 31,946 | 30,872 | -1,074 | -3.36% | 75.2 |
| | Juniata County | 24,636 | 24,737 | 101 | 0.41% | 91.1 |
| | Montour County | 18,267 | 18,557 | 290 | 1.59% | 86.5 |
| | Potter County | 17,457 | 17,093 | -364 | -2.09% | 79.4 |
| | Fulton County | 14,845 | 14,629 | -216 | -1.46% | 97.7 |
| | Forest County | 7,716 | 7,410 | -306 | -3.97% | 78.5 |
| | Sullivan County | 6,428 | 6,328 | -100 | -1.56% | 93.0 |
| | Cameron County | 5,085 | 4,732 | -353 | -6.94% | 75.0 |
| Subtotal | (37 Counties) | 2,361,360 | 2,333,251 | -28,109 | -1.19% | |
| *Central Pennsylvania Total* | *(52 Counties)* | *5,745,670* | *5,765,263* | *19,593* | 0.22% | |
| Grand Totals | (67 Counties) | 12,702,379 | 12,802,418 | 100,039 | 0.79% | |

[1]Numbers based on 2010 U.S. Census results.

[2]Numbers based on 2017 U.S. Census estimates.

[3]Cost of Living Index (CoLI) for all counties is based on 2017 Council for Community and Economic Research data using 100 as the baseline for the Commonwealth.

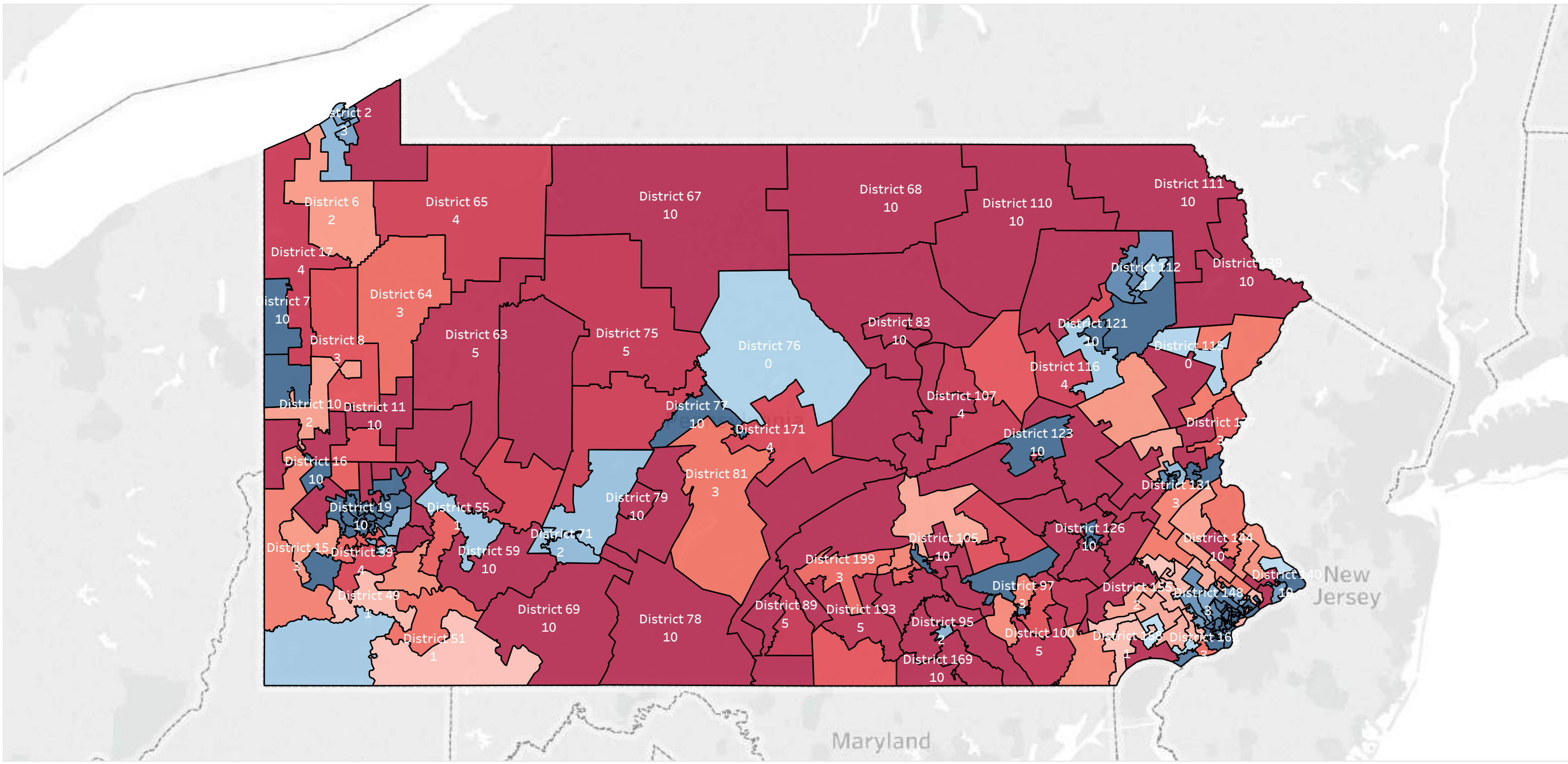
The Pennsylvania Department of State (2016), which oversees elections in the state, reports that the registered number of Democrats is higher than the number of registered Republicans by 900,000; still, this aggregate measure masks significant differences by region. The most substantial support for Democrats has been in the PHL region, with 65 percent of ballots cast in the 2016 election in favor of the Democratic candidate Hillary Clinton, followed by 47 percent in the PGH region, and trailing by 38 percent in the CPA region. Conversely, Republicans have enjoyed considerable support, especially in the CPA region, followed by the PGH and PHL regions.

These state's General Assembly reflects these disparities, with a highly partisan bias toward Republicans. Although it has roughly a third of the population of California, the largest state in the country, the Commonwealth has more than twice as many state legislators (CA: 120 vs. PA: 253), making the General Assembly the second largest state legislature in the country behind the New Hampshire General Court. Figure 1.1 shows a map of all 203 House of Representative seats rated for partisanship on a scale of 0 (lowest) to 10 (highest) calculated using 2016 state election returns. A score of 10 indicates that the district was one in which the incumbent faced no challenger whereas a score of 0 indicates that the candidate won with <10 percent of the vote. In the House alone, where Republicans dominate with 121 seats, 50 of these seats had a score of 10 compared to Democrats who hold the remaining 82 seats and had 48 such safe seats, indicating that nearly half of the lower is substantially partisan. Figure 1.2 shows the same calculations for the Senate, where, of the total 50 seats, Republicans hold 12 safe seats of their 34-seat majority compared to Democrats who possess ten safe seats of the remaining 16, again resulting in a highly partisan upper house. This highly partisan approach to government has had an echoing effect on education policy legislation from school funding to accountability.

Educational Organization. Furthermore, the state's educational hierarchy mirrors these regional and political divisions. The Commonwealth ranks in the top ten nationally for its total number of Local Education Agencies (LEAs), which are independent school organizations ranging from traditional school districts to career and technical schools. Of the 800+ LEAs in operation, their sizes span considerably from the largest being the SDP, which serves over 130,000 students to the smallest being Youth Forestry Camp #2, a State Juvenile Correctional Institution that educates only 14 students (PDE, 2018). Most LEAs are traditional school districts (500), of which all save one are in operation. (Bryn Athyn School District does not contain any schools, since 90 percent of their student population attends schools operated by the Academy of the New Church, with the remaining 10 percent serviced by the Lower Moreland School District). Even as the number of school districts has stayed relatively constant over the years, the number of charter schools has not. Under Pennsylvania charter law, charters are legally under the jurisdiction of their parent school district, which oversees their dispersion of funds, charter issuance, and renewal process among others. Consequently, this number fluctuates annually, depending on the number of charters opened and closed.

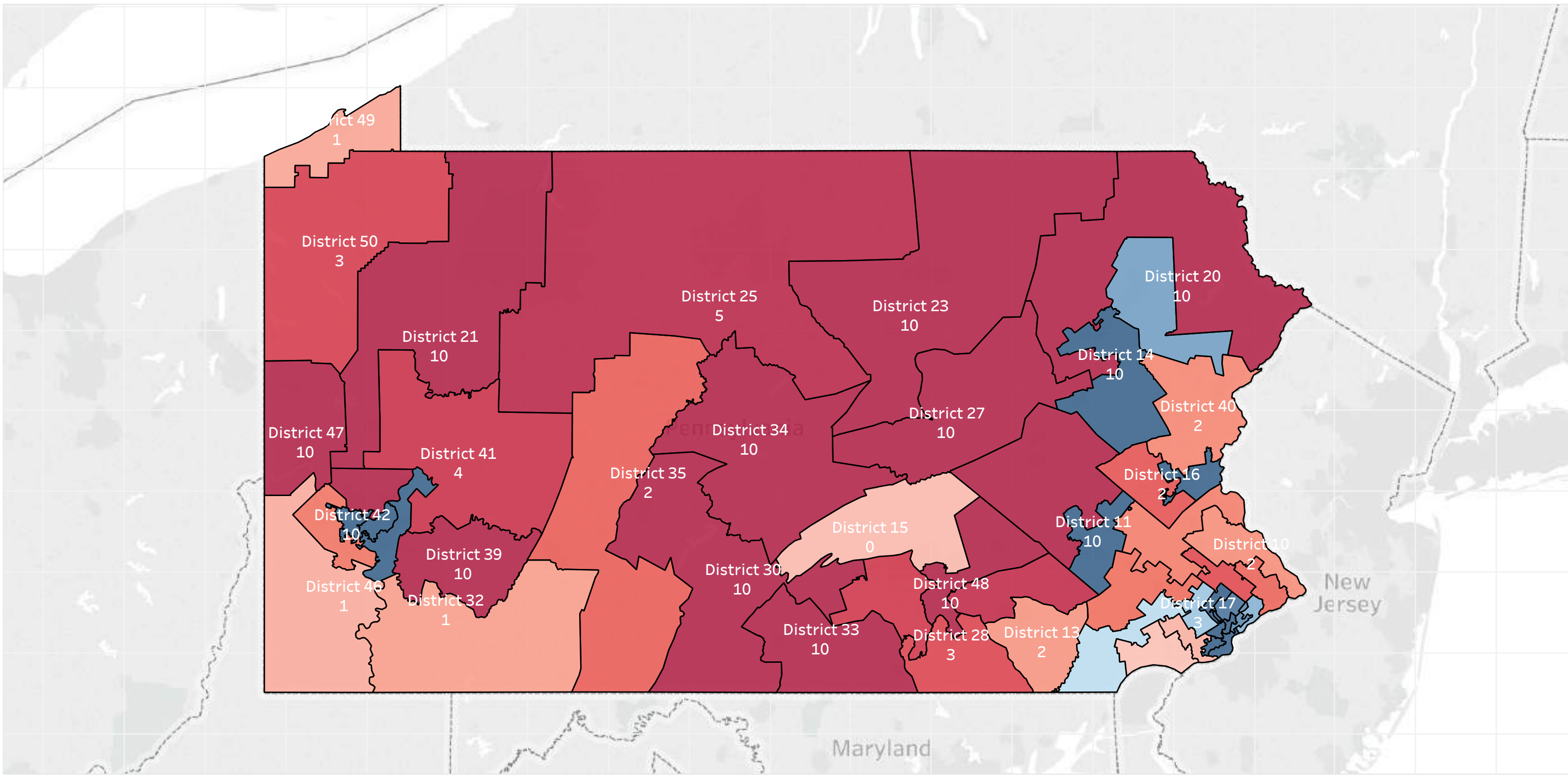
On a more macro level, districts and charters are served by another type of LEA known as Intermediate Units, which, as their name implies, serve as intermediate liaisons between federal/state agencies and districts/charter LEAs, in addition to providing services in curriculum and instruction, professional development, technological support, among others.

Figure 1.1: Pennsylvania General Assembly House of Representatives Political Composition (2016)




Legend of Pennsylvania House Districts
(Note: Darker colors indicate safer districts, ligher colors indicate more borderline districts.)
Democratic Party (82 seats)
Republican Party (121 seats)

Figure 1.2: Pennsylvania General Assembly Senate Political Composition (2016)




Legend of Pennsylvania Senate Districts
(Note: Darker colors indicate safer districts, ligher colors indicate more borderline districts.)
Democratic Party (16 seats)
Republican Party (34 seats)

There are 29 IUs in the state, and as illustrated in Figure 1.3, their service regions can cover multiple counties with the only exceptions being IU2 and IU26, which cater exclusively to Pittsburgh Public Schools (PPS) and the SDP, respectively. Because IUs do not have the power to tax, they are supported by their constituent districts, limiting the effectiveness of IU2 and IU26, which are supported and managed by the same LEA. At the apex of this structure is the PDE itself, which oversees, among other things, the K-12 public education system in the state and is the central data collection agency for all public education-related matters, which it shares with other branches of state government and the United States Department of Education (USDoE).

Finally, the complexity of the Commonwealth's education system, coupled with its varied geography, necessitated organizing these LEAs by shared commonalities to answer the research questions posed at the end of this chapter. In this study, LEAs are first organized geographically by region (PHL, PGH, and CPA), and within each region, by type: (a) the Major Urban District(s), (b) Suburban Title I Districts, (c) Suburban Non-Title I Districts, (d) Charter Schools, and (e) Career & Technical Schools (CTEs). The CPA region has an additional two LEA types, Rural Title I Districts and Rural Non-Title I Districts. Major Urban District(s) are those districts that serve the population hub in that region. For the PHL and PGH regions, this is the SDP and PPS, respectively. For the CPA region, this is a collection of 12 cities (Allentown, Bethlehem, Easton, Erie, Harrisburg, Hazelton, Lancaster, Lebanon, Meadville, Scranton, Wilkes-Barre, and York), collectively termed Regional City Districts (RCDs).

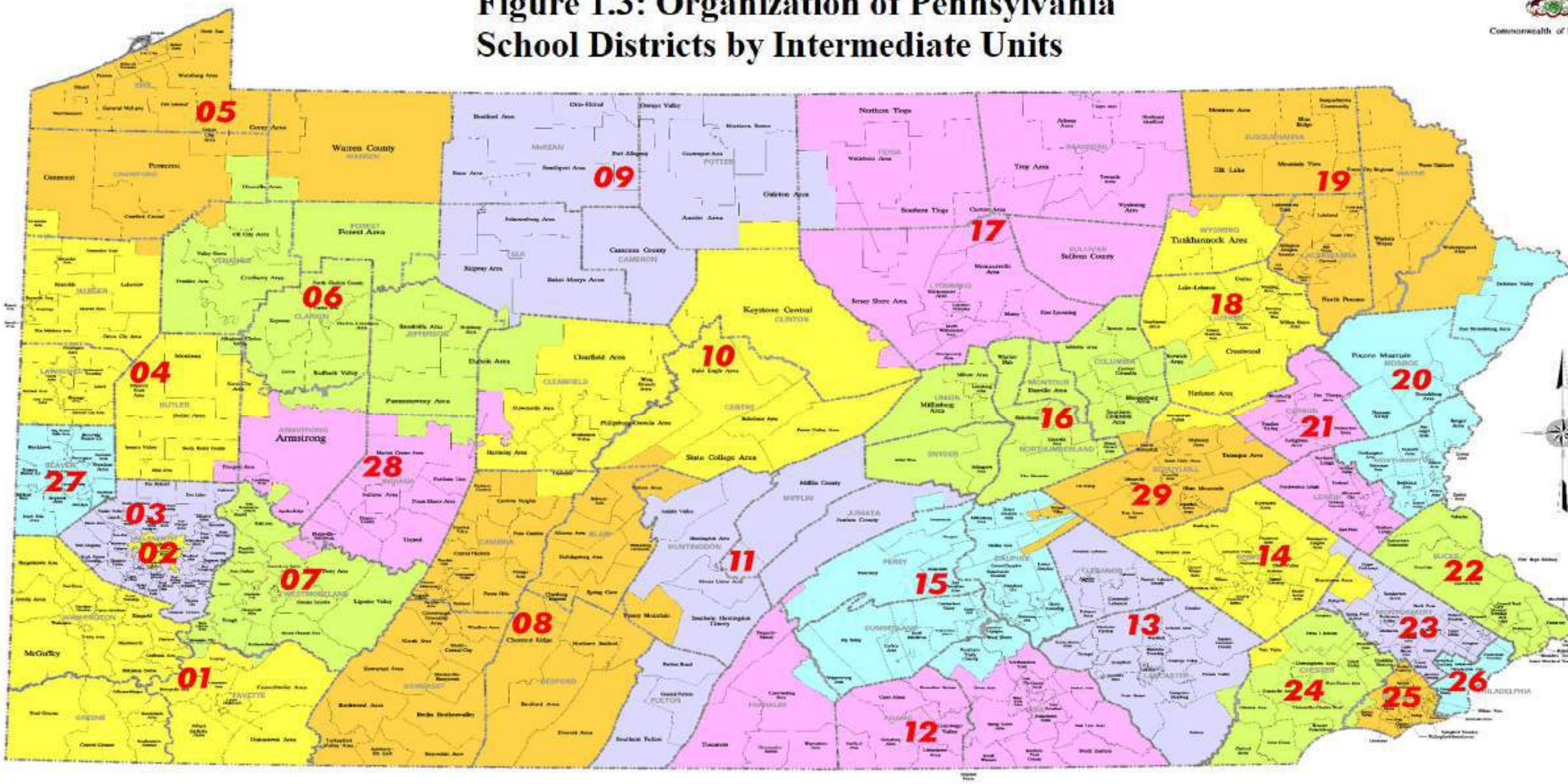
The terms "Title I" and "Non-Title I" are consistent with USDoE (2018) guidelines, which state that any school with at least a 2 percent low-income student population can qualify for Title I funds, provided that these funds go directly to supporting this student population. In schools with at least 40 percent of qualifying students, the school may use Title I funds to operate school-wide programs that serve all students enrolled, with the intended goal of improving academic achievement for the entire school. Because this study examines teachers in LEAs, a "Title I LEA" is one in which ≥40 percent of the entire LEA population qualifies for these funds, whereas a "Non-Title I LEA" is one that has less than this minimum threshold. Figure 1.4 illustrates this classification scheme.

***Economic and Demographic Diversity.***

Economic Profile. Economically, Pennsylvania has historically enjoyed a reputation for being one of the star manufacturing economies in the country, with images of steel plants, coal mines, and railroads ingrained in both the Pennsylvanian and the American psyche. However, this romanticized image is in sharp contrast to economic reality. Table 1.2 shows the economic productivity (GDP) for all Pennsylvania counties, both in aggregate terms and three main sectors: government-related activity, private goods production (e.g., manufacturing and agriculture), and in private services production (e.g., healthcare, education, financial services). Recall that the PHL region is home to 35 percent of the state's population, but accounts for an outsized 44 percent of the Commonwealth's total GDP of $710 billion. The PGH's share of economic activity (20 percent) is roughly on par with its population share, but it is the CPA region, long known for its manufacturing prowess, which is underperforming, with only 35 percent of state's share of GDP. Equally important is the breakdown by sector, with the CPA region dependent on government-related activity and the production of private goods for its economic sustenance, compared to the PHL region where private services production is 10 to 15 percentage points higher than other sectors. Remarkably, all 37 rural counties collectively account for 12 percent of the state's GDP.

# Figure 1.3: Organization of Pennsylvania School Districts by Intermediate Units

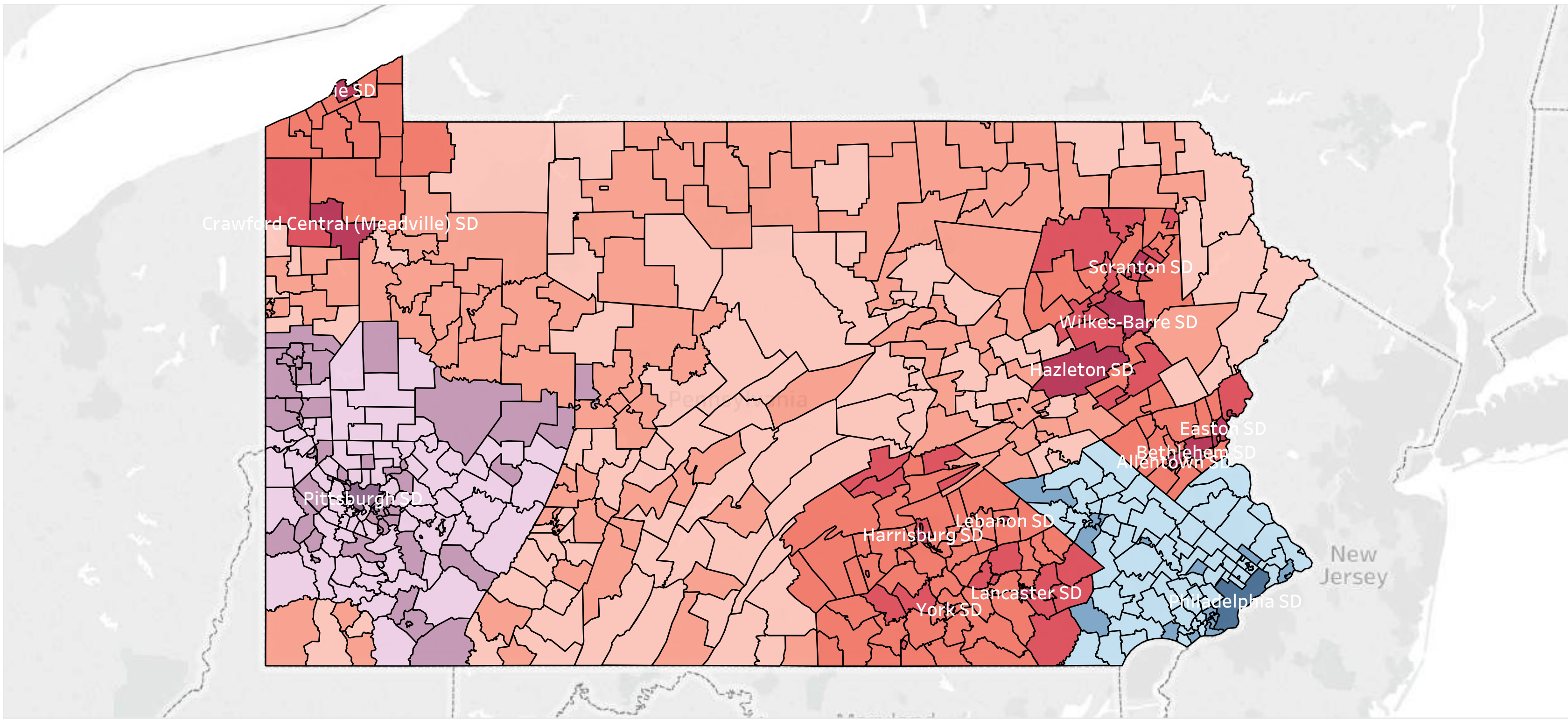
Commonwealth of Pennsylvania




## PENNSYLVANIA'S INTERMEDIATE UNITS

| Key – IU Name | Key – IU Name | Key – IU Name | Key – IU Name |
|---|---|---|---|
| 01 – Intermediate Unit 1 | 09 – Seneca Highlands IU 9 | 17 – Blast IU 17 | 25 – Delaware County IU 25 |
| 02 – Pittsburgh – Mt. Oliver IU 2 | 10 – Central IU 10 | 18 – Luzerne IU 18 | 26 – Philadelphia IU 26 |
| 03 – Allegheny IU 3 | 11 – Tuscarora IU 11 | 19 – Northeastern Educational IU 19 | 27 – Beaver Valley IU 27 |
| 04 – Midwestern IU 4 | 12 – Lincoln IU 12 | 20 – Colonial IU 20 | 28 – ARIN IU 28 |
| 05 – Northwest Tri – County IU 5 | 13 – Lancaster – Lebanon IU 13 | 21 – Carbon – Lehigh IU 21 | 29 – Schuylkill IU 29 |
| 06 – Riverview IU 6 | 14 – Berks County IU 14 | 22 – Bucks County IU 22 | County Boundary Line |
| 07 – Westmoreland IU 7 | 15 – Capital Area IU 15 | 23 – Montgomery County IU 23 | |
| 08 – Appalachia IU 8 | 16 – Central Susquehanna IU 16 | 24 – Chester County IU 24 | |

Figure 1.4: Organization of Pennsylvania School Districts by U.S. Census Bureau Statistical Area Designation




**Legend of Pennsylvania Statistical Regions & LEA Types**
**(Note: Major Regional Urban School Districts have been labeled.)**

- Central Pennsylvania MSAs & µSAs, Rural Non Title I District
- Central Pennsylvania MSAs & µSAs, Rural Title I District
- Central Pennsylvania MSAs & µSAs, Suburban Non Title I Di..
- Central Pennsylvania MSAs & µSAs, Suburban Title I District
- Central Pennsylvania MSAs & µSAs, Urban District
- Greater Philadelphia CSA, Suburban Non Title I District
- Greater Philadelphia CSA, Suburban Title I District
- Greater Philadelphia CSA, Urban District
- Greater Pittsburgh CSA, Suburban Non Title I District
- Greater Pittsburgh CSA, Suburban Title I District
- Greater Pittsburgh CSA, Urban District

**Table 1.2 • Gross Domestic Product (GDP) of Pennsylvania Counties by Production Sector**

| Name of Region/ U.S. Census Bureau Statistical Area Definition | Corresponding PA County | County Gross Domestic Product[4] ($ Millions) | Percent of GDP: State Total | Percent of GDP: Government Related | Percent of GDP: Private Goods Production | Percent of GDP: Private Services Production |
|---|---|---|---|---|---|---|
| ***Greater Philadelphia Region*** | Philadelphia County | 110.339 | 15.54% | 18.01% | 5.01% | 17.90% |
| Philadelphia-Reading-Camden (NJ) Combined Statistical Area | Montgomery County | 81.404 | 11.46% | 5.23% | 9.21% | 12.91% |
| | Bucks County | 30.862 | 4.35% | 3.41% | 5.34% | 4.22% |
| | Delaware County | 28.938 | 4.08% | 3.51% | 4.41% | 4.07% |
| | Chester County | 42.968 | 6.05% | 3.44% | 4.78% | 6.74% |
| | Berks County | 18.630 | 2.62% | 2.65% | 4.29% | 2.19% |
| *Subtotal* | *(6 Counties)* | *313.141* | *44.10%* | *36.25%* | *33.03%* | *48.03%* |
| ***Greater Pittsburgh Region*** | Allegheny County | 89.048 | 12.54% | 9.84% | 8.11% | 14.05% |
| Pittsburgh-New Castle-Weirton (WV) Combined Statistical Area | Westmoreland County | 13.208 | 1.86% | 1.91% | 2.36% | 1.73% |
| | Washington County | 14.381 | 2.03% | 1.18% | 3.34% | 1.81% |
| | Butler County | 9.417 | 1.33% | 1.50% | 2.24% | 1.07% |
| | Beaver County | 6.531 | 0.92% | 0.89% | 1.23% | 0.85% |
| | Fayette County | 3.596 | 0.51% | 0.79% | 0.67% | 0.43% |
| | Lawrence County | 2.733 | 0.38% | 0.43% | 0.55% | 0.34% |
| | Indiana County | 4.358 | 0.61% | 0.87% | 0.84% | 0.52% |
| | Armstrong County | 2.492 | 0.35% | 0.32% | 0.71% | 0.26% |
| *Subtotal* | *(9 Counties)* | *145.764* | *20.53%* | *17.71%* | *20.03%* | *21.05%* |
| ***Central Pennsylvania Region - Regional Cities & Suburban Regions*** | | | | | | |
| Harrisburg–York–Lebanon Combined Statistical Area | York County | 19.109 | 2.69% | 2.79% | 4.04% | 2.33% |
| | Dauphin County | 22.549 | 3.18% | 5.51% | 2.08% | 3.13% |
| | Cumberland County | 13.837 | 1.95% | 2.91% | 1.35% | 1.97% |
| | Lebanon County | 4.909 | 0.69% | 1.10% | 1.09% | 0.53% |
| | Adams County | 3.274 | 0.46% | 0.55% | 0.84% | 0.35% |
| | Perry County | 0.677 | 0.10% | 0.21% | 0.13% | 0.07% |
| Allentown-Bethlehem-Easton Metropolitan Statistical Area | Northampton County | 11.697 | 1.65% | 1.83% | 2.02% | 1.53% |
| | Lehigh County | 24.320 | 3.43% | 2.12% | 3.41% | 3.61% |
| | Carbon County | 1.685 | 0.24% | 0.30% | 0.21% | 0.24% |
| Scranton-Wilkes Barre-Hazelton Metropolitan Statistical Area | Luzerne County | 15.898 | 2.24% | 2.36% | 1.89% | 2.31% |
| | Lackawanna County | 8.725 | 1.23% | 1.37% | 0.97% | 1.27% |
| | Wyoming County | 1.457 | 0.21% | 0.13% | 0.59% | 0.12% |
| Lancaster Metropolitan Statistical Area | Lancaster County | 26.275 | 3.70% | 2.52% | 6.09% | 3.25% |
| Erie-Meadville Combined Statistical Area | Erie County | 10.755 | 1.51% | 2.04% | 2.23% | 1.26% |
| | Crawford County | 2.466 | 0.35% | 0.48% | 0.77% | 0.22% |
| Urbanized Regions Subtotal | (15 Counties) | 167.633 | 23.61% | 26.23% | 27.71% | 22.19% |
| ***Central Pennsylvania Region - Rural Regions*** | | | | | | |
| | Monroe County | 5.374 | 0.76% | 1.58% | 1.25% | 0.52% |

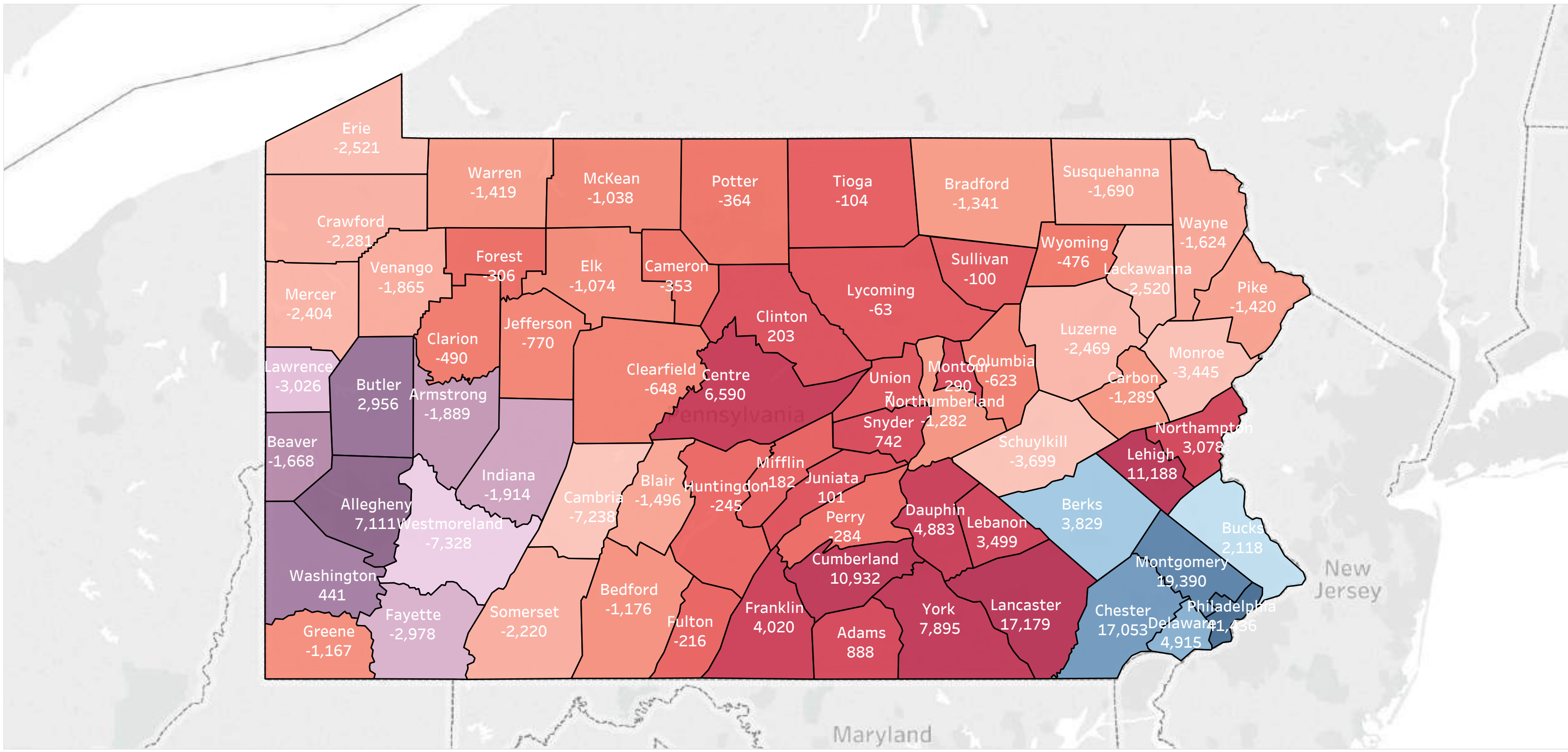
| | | | | | | |
|---|---|---|---|---|---|---|
| | Centre County | 8.402 | 1.18% | 4.62% | 0.87% | 0.79% |
| | Franklin County | 5.164 | 0.73% | 1.06% | 1.05% | 0.60% |
| | Schuylkill County | 4.374 | 0.62% | 0.91% | 1.18% | 0.43% |
| | Cambria County | 4.289 | 0.60% | 0.91% | 0.46% | 0.60% |
| | Blair County | 5.123 | 0.72% | 0.96% | 0.87% | 0.65% |
| | Mercer County | 3.996 | 0.56% | 0.61% | 0.95% | 0.46% |
| | Lycoming County | 5.494 | 0.77% | 1.01% | 1.52% | 0.55% |
| | Northumberland County | 2.695 | 0.38% | 0.49% | 0.81% | 0.26% |
| | Clearfield County | 2.435 | 0.34% | 0.54% | 0.36% | 0.31% |
| | Somerset County | 2.382 | 0.34% | 0.52% | 0.52% | 0.26% |
| | Columbia County | 2.213 | 0.31% | 0.54% | 0.50% | 0.23% |
| | Bradford County | 2.965 | 0.42% | 0.35% | 0.79% | 0.33% |
| | Pike County | 1.020 | 0.14% | 0.32% | 0.07% | 0.14% |
| | Venango County | 1.648 | 0.23% | 0.38% | 0.45% | 0.16% |
| | Wayne County | 1.313 | 0.18% | 0.41% | 0.17% | 0.16% |
| | Bedford County | 1.342 | 0.19% | 0.24% | 0.29% | 0.16% |
| | Mifflin County | 1.307 | 0.18% | 0.20% | 0.42% | 0.12% |
| | Huntingdon County | 1.026 | 0.14% | 0.37% | 0.19% | 0.10% |
| | Jefferson County | 1.531 | 0.22% | 0.21% | 0.54% | 0.13% |
| | Union County | 1.510 | 0.21% | 0.48% | 0.22% | 0.17% |
| | McKean County | 1.843 | 0.26% | 0.29% | 0.80% | 0.12% |
| | Susquehanna County | 1.181 | 0.17% | 0.21% | 0.42% | 0.09% |
| | Tioga County | 1.451 | 0.20% | 0.30% | 0.38% | 0.15% |
| | Warren County | 1.618 | 0.23% | 0.24% | 0.60% | 0.13% |
| | Clarion County | 1.128 | 0.16% | 0.35% | 0.23% | 0.11% |
| | Snyder County | 1.168 | 0.16% | 0.26% | 0.29% | 0.12% |
| | Clinton County | 1.486 | 0.21% | 0.34% | 0.48% | 0.12% |
| | Greene County | 2.730 | 0.38% | 0.32% | 1.28% | 0.16% |
| | Elk County | 1.252 | 0.18% | 0.14% | 0.52% | 0.09% |
| | Juniata County | 0.563 | 0.08% | 0.08% | 0.21% | 0.05% |
| | Montour County | 1.875 | 0.26% | 0.17% | 0.07% | 0.33% |
| | Potter County | 0.597 | 0.08% | 0.11% | 0.08% | 0.08% |
| | Fulton County | 0.455 | 0.06% | 0.08% | 0.22% | 0.02% |
| | Forest County | 0.244 | 0.03% | 0.14% | 0.07% | 0.01% |
| | Sullivan County | 0.144 | 0.02% | 0.04% | 0.03% | 0.02% |
| | Cameron County | 0.164 | 0.02% | 0.04% | 0.07% | 0.01% |
| Rural Regions Subtotal | (37 Counties) | 83.502 | 11.76% | 19.81% | 19.23% | 8.73% |
| *Central Pennsylvania Total* | *(52 Counties)* | *251.135* | *35.37%* | *46.04%* | *46.94%* | *30.92%* |
| *Grand Totals* | (67 Counties) | 710.040 | | | | |

[4]Numbers based on 2015 Bureau of Economic Analysis data.

Demographic & Racial Profile. Expectedly, the Commonwealth's geography and politics are influenced by and reinforce historical economic and demographic boundaries. Table 1.1 also presents the population changes between the 2010 Census and 2017 projected estimates made with data from the annual American Community Survey (2018). Overall, the state is projected to have increased by a little over 100,000 individuals, but this growth has primarily been in the PHL region (88 percent). Though the remainder of that growth can is in the CPA region, it is mostly in urbanized centers, with rural regions experiencing a loss of over 28,000 individuals. Moreover, the PGH region has experienced almost no change in population, with growth in Allegheny County washed away by losses in neighboring Westmoreland County. Figure 1.5 provides a comprehensive visual for population loss of all 67 counties in the state. It is easy to see that the General Assembly skews toward Republican control despite the demographic shifts in favor of Democratic regions.

This discussion of demography and economics would not be complete with an understanding of historical and current racial/ethnic trends, since Harrisburg's approach to policy has, whether intended or not, led to some notable discriminatory overtones. According to data from the Pennsylvania State Data Center (2018), the PHL region has historically had a high African-American population, with the City of Philadelphia alone accounting for 48 percent of the state's black population. This disproportionate distribution has its roots in the Great Migration, which between 1910 and 1970 saw a mass exodus of African-Americans from their historic localities in the South to the Northern urban centers in search of more significant economic opportunities at a time of great industrial expansion.

Figure 1.5: Population Change by Pennsylvania County (2010-2017)




Legend of Pennsylvania Statistical Regions & Counties
(Note: Darker colors indicate population gain, ligher colors indicate population loss.)
Greater Philadelphia CSA Counties
Greater Pittsburgh CSA Counties
Central Pennsylvania MSA and µSA Counties

Unfortunately, the subsequent decades of deindustrialization saw European-Americans, many of whom had moved into the middle-class during this period, flee cities and leaving the black population stranded in urban cores in what became a familiar pattern throughout the country. Pittsburgh, like its Midwestern compatriots, has had a historically low African-American population, with the 1970 U.S. Census Bureau reporting that only 20 percent of that city's population identified as black (U.S. Census Bureau, 2012). The loss of so many middle-class jobs in Pennsylvania's urban centers in the decades since 1970 has resulted in mostly poor and isolated "islands" of poverty littered within metropolitan areas and throughout the state, leading Sharkey (2013) to claim that this economic and social stagnation has led to many urban minority communities being "stuck in place."

African-American and European-American population trends have been well-documented in urban locales. More recently, demographers have started to pay attention to the rapid increase in Latino-Americans (Hispanics) and Asian-Americans, which, the same ACS data estimates, are the two fastest-growing minority groups in the country. National figures put these two groups at 18 percent and 7 percent, respectively and Pennsylvania has a smaller, but growing, share at 7 percent and 3.3 percent, both of whom are concentrated mainly in urban regions, but for different reasons. Growth in blue-collar jobs associated with agriculture, dining, and hospitality has attracted large numbers of Mexican-Americans to the PHL and CPA regions with Norristown (Montgomery County), Reading (Berks County), Allentown (Lehigh County), and Lancaster (Lancaster County); all of which report a Latino population that constitutes at least a quarter of their overall populace boosted by Mexican-American immigration (PSDC, 2017). The issue of immigration and education has hobbled the social mobility of Hispanics, who, on average in Pennsylvania, earned only $23,000 in 2017–about half the average income of $59,195 (ACS, 2018).

Historically, Pennsylvania has had a high percentage of Puerto Ricans, who are the second largest Hispanic ethnicity in the United States after Mexican-Americans. Much of Pennsylvania's share is in the City of Philadelphia, which has the second biggest Puerto Rican community outside of the Commonwealth of Puerto Rico and superseded only by New York City (ACS, 2018). Migration between Pennsylvania and Puerto Rico has traditionally been robust since the island became a U.S. possession in 1898 and Puerto Ricans were granted U.S. citizenship in 1917. The ebb and flow of Puerto Rican migration have mirrored employment trends for predominantly blue-collar workers in both regions. However, recent economic turmoil in Puerto Rico has accelerated this migration towards the mainland; as of August 2017, Puerto Rico had an outstanding bond debt over $70 billion accompanied by a 12.4% unemployment rate and a poverty rate of 45% (Bases, 2017). Undoubtedly, the collapse of the island's economy in the wake of Hurricane Maria has only accelerated migration from Puerto Rico to urban centers such as Philadelphia.

Conversely, PSDC (2017) data indicates the growth in white-collar service jobs has attracted large numbers of Asian-Americans, especially in Philadelphia and Pittsburgh, due to the resurgence of education, healthcare, and financial industries and in RCDs that have a substantial amount of these services. Nationally, Asian-Americans have a much higher average income of $80,720 and higher educational attainment, with 51 percent holding at least a four-year degree. Nevertheless, these numbers disguise some of the most severe inequities present in any racial group. For instance, ACS (2018) data reveals that Burmese-Americans have an average household income of $35,016, with <20 percent holding at least a four-year degree compared to Indian-Americans, who have an average household income of $122,026, with >70 percent holding at least a four-year degree.

### ***Policy Context I: School Funding Sources***

As is the case with finances, the allocation of funds is hardly ever an impartial endeavor, but rather one—in the case of a public entity—that is engendered with political and demographic bias. Unfortunately, all public programs can fall prey to partisanship and ideology, and the deleterious effects of this politicking have, arguably, the most significant effect on public education, which impacts the lives of everyday Americans more so than any other public program. It is little wonder then that Americans think education should be the third highest priority for the new 2019 Congress – outranking terrorism, immigration, and drug abuse which have received ample media coverage (Pew Research Center, 2019).

***Federal Lines of Support.*** Because education is not an enumerated power under Article I, Section 8 and the Tenth Amendment of the U.S. Constitution, the federal government plays a limited role in supporting schools directly, apart from assisting low-income schools housed in Title I LEAs. Federal funding can come in many forms because of direct aid to schools or broader legislation. For instance, the American Reinvestment and Recovery Act (ARRA) of 2009 (USDoE, 2009) set aside a total $100 billion, the majority of which—$53.6 billion—was provided to local school districts to prevent layoffs and cutbacks. Moreover, an additional $13 billion was earmarked to supplement Title I funds, $12.2 billion for special education services, and $4.1 billion for child support programs such as Head Start and childcare. The School District of Philadelphia received $588 million of these funds for two academic years (AY2009-10 and AY2010-11). Another federal source has been the Affordable Care Act (ACA), from which the Medicaid Expansion provision has allowed states to use these funds for special education student services. Both pieces of federal legislation have repeatedly come came under attack on Capitol Hill for their respective price tags. This Keynesian approach to economic recovery did prevent the country from sliding into depression, but the effects of the ARRA on schools was only temporary, with districts seeing a return to red ink once ARRA money evaporated. Likewise, the Tax Cuts & Jobs Act of 2017 curtailed many additional funding provisions linked with the ACA.

The USDoE also directly supports school funding, albeit with some caveats, under the Title I provisions specified by the Elementary and Secondary Education Act (ESEA) of 1965 and its subsequent amendments. Title I funds are, by far, the most popular, serving over 17 million students nationally across the entire PreK-12 spectrum. Dynarski and Kainz (2015) have calculated that the average \$500-\$600 provided per Title I students, which amounts to a significant source of funding for large urban districts like the SDP and the PPS, goes to feed budgetary deficits rather than developing academic programs. Generally overlooked are smaller Title II and Title III funds, which, among others, provide for professional development programs and language instruction programs for English Language Learners (ELLs). Under the Obama administration, Secretary of Education Arne Duncan offered states an additional \$4.35 billion in "Race-to-the-Top" Grants designed to spur states to adopt more innovative school reforms, though some researchers have criticized the program as a backdoor attempt to promote charter schools (Onosko, 2011; Tanner, 2013). As was the case with the ARRA and ACA, these programs were also subject to Congressional budgetary politics, priorities, and compromises.

***The State's Regressive Funding Formula.*** In Pennsylvania, a budget analysis by the Education Law Center (2012) revealed that for AY2011-12, federal funding accounted for only \$12 of every \$100 spent on education statewide, with the bulk coming from either state (\$35) or local property taxes (\$43). While the state share dwarfs federal support, the

General Assembly has increasingly shifted its educational funding responsibilities from Harrisburg to local municipalities over the past 40+ years, leading Ushomirsky and Williams (2015) to label Pennsylvania as the fourth most regressive state in terms of school funding. In 1965, the General Assembly passed the “50 Percent Minimum Rule,” which required the state to pay at least 50 percent of the total cost of public education, resulting in a peak contribution of 55 percent in 1974. In 1983, the General Assembly, seeking a less stringent requirement, adopted the Equalized Subsidy for Basic Education (ESBE) method, which has come to be known as the “hold harmless” provision, in which the state guaranteed LEAs the same state funding as the previous budgetary appropriation. While this approach appears to provide some sense of security at face value, in effect, it benefited those (majority white, Republican) areas experiencing a population decline because of reduced economic opportunity and conversely sanctioned (racially diverse, Democratic) areas experiencing population growth because of increased economic opportunity.

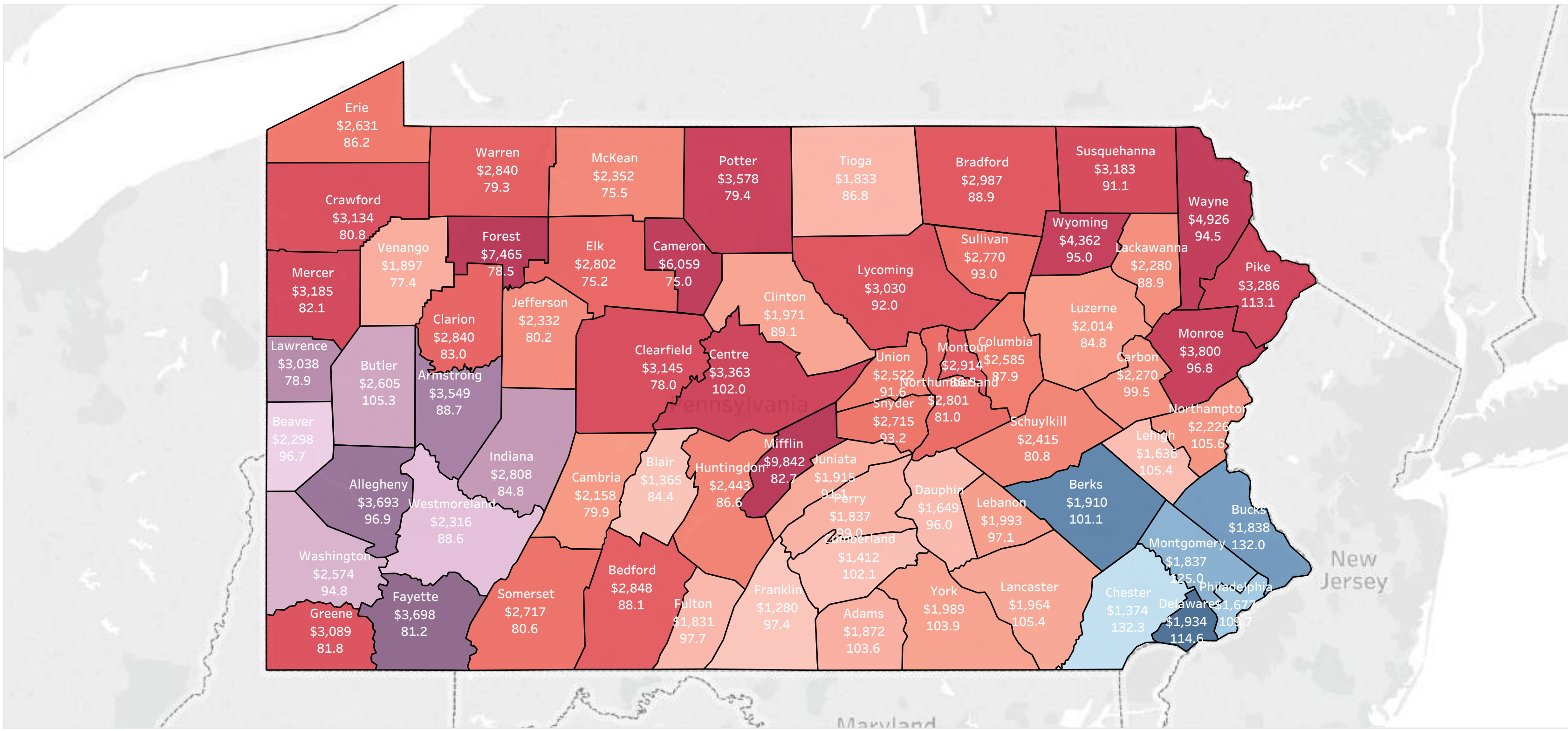
Further complicating this situation was fixed state appropriations between 1992 and 2012, resulting in a “held hostage” situation, which left the PGH and CPA region with increasing per-student spending in contrast to the PHL region, which continually fell behind because of a booming population in that region during the intervening 20 years. Figure 1.6 illustrates this disparity in per-student funding comparing only the five years of this study. If extrapolated over time, it is easy to see why the state’s funding formula has received much ire from progressive school funding advocates.

***The Weight of Local Taxes.*** As Harrisburg embarked on an ambitious program to divest itself of state funding responsibilities, local municipalities were left scrambling to fill the ensuing gap. What followed in the years since 1992 was a chaotic approach by cities and towns to find any possible sources of revenue. For most of the districts, this meant an exponential rise in taxes, either property or commercial. This love affair with property taxes came to a screeching halt with the passage of Act I of 2006, which limited property tax increases to a statewide index that accounted for average increases statewide in several areas apart from special education and pension-related costs. Moreover, the Act I Index is variable and has historically floated around 2.5 percent (PASBO, 2018).

However, the Commonwealth's two major urban districts—the PPS and SDP—are a contrast study in fiscal policy. The City and County of Philadelphia are coterminous compared to the City of Pittsburgh, in which the city is in Allegheny County surrounded by wealthy suburbs. Such an arrangement results in a financial subsidy of sorts for PPS, which benefits from countywide taxes (in addition to the hold harmless provision), with no such relief for the SDP. Consequently, Philadelphia has resorted to aggressive tax policy, predicated on a host of sin taxes, merely to support its schools, with adverse effects for a city in which nearly a quarter of residents live below the poverty line.

Such taxes include a higher sales tax (8 percent, compared to 7 percent in Pittsburgh and 6 percent statewide), a higher alcohol tax (10 percent, compared to 7 percent in Pittsburgh and none in the rest of the state), and, of course, the newly-issued beverage tax, which does not exist elsewhere in the state (U.S. Census Bureau, 2014). Several economists (Haile, 2009; O'Donoghue & Rabin, 2003, 2006) have argued that even though the primary goal of sin taxes is to influence public behavior (generally, with an eye toward improved physical or mental health), too many states have indulged in this kind of revenue generation, which, if the tax is successful, will diminish revenue over time.

Figure 1.6: Per Student Funding Change by Pennsylvania County (2012-2017)




Legend of Pennsylvania Statistical Regions & Counties

[Note: Darker colors indicate greater per student funding gain, ligher colors indicate less per student funding gain. Funding figures (above) are adjusted according to county cost of living index (below).]

Greater Philadelphia CSA Counties

Greater Pittsburgh CSA Counties

Central Pennsylvania MSA and µSA Counties

Furthermore, the SDP has no independent taxing authority compared to other districts in the state, and instead must rely on the grace of City Council to deliver its local share of funding. City government and the SDP do not always share the same fiscal priorities; the former is more interested in providing rewards for businesses to relocate to Philadelphia, while the latter continually seeks to reduce its perennial budget deficit. Such corporate benefits have included property tax abatements, selling public land for cents on the dollar to attract investment, and allocating generous subsidies. (The national courtship for a second Amazon headquarters in the past year is yet another extreme example of this approach.) Furthermore, issuing these benefits may not provide the immediate revenue needed to offset the SDP's deficit. The City has attempted to justify this approach with a higher wage tax (3.9 percent, compared to 1.5 percent in Pittsburgh and 1 percent statewide) to offset losses, but given the fact that nearly a quarter of the city's residents lives under the poverty line, it is hard to imagine that this is an equal calculation.

Lastly, during this study's observation period, the SDP did not have a traditional nine-member Board of Education but rather a five-member panel termed the School Reform Commission (SRC), which was composed of three members appointed by the Governor of Pennsylvania and two members appointed by the Mayor of Philadelphia. When the General Assembly imposed this governance structure on the SDP, the legislature justified its intervention as a means of state inclusion in the management of an academically and financially distressed district. However, in the 17-year history of the SRC, this purpose did not fully materialize, and this quasi-public board quickly became an instrument of exclusion. Repeatedly, the district's budget became a perennial source of political angst between Harrisburg legislators and the Philadelphia community, with the latter engaged in a perpetual cycle of begging and wrangling for more school funding.

### *Policy Context II: Per-Student Spending Management*

This second policy section continues examining the issue of school funding policy, yet this time at the LEA level, specifically concerning those factors that influence the allotment of per-student spending. It is important to clarify in this discussion that per-student spending is a crude quotient of an LEA's total budget, divided by the number of pupils served. Researchers often use per-student spending to compare districts within or between states; still, this type of analysis can be fraught with inaccurate assumptions. On the surface, per-student spending does not provide any insight about how LEAs allocate costs, nor does it provide any detail on what expenditures constitute this aggregate number. Writing for the BBC, Andreas Schleicher (2017), Director of Education for the Organization for Economic Cooperation and Development (OECD), asserts that aggregated per-student spending was so misleading that the OECD found, at best, a tenuous relationship between spending and outcome. While it is true that comparing per-student spending between two LEAs that are close to one another can provide some insight into the financial health of each LEA, again, these aggregate values fail to provide any details regarding the allocation of this funding.

***Components of Per-Student Spending.*** Contrary to widespread assumption, districts do not receive state and federal appropriations in a lump sum at the start of the fiscal year

(July 1st). Instead, these funds are dispersed daily, based on school attendance (i.e., enrollment on any given day). Consequently, schools with the highest daily attendance rates receive almost their entire share of per-student funding, whereas those with lower daily attendance rates may experience periodic budget shortfalls. Such a funding approach is especially problematic for urban schools, which suffer from chronic absenteeism and rely on these funds heavily to continue essential services. Accordingly, at the end of the fiscal year (June 30th), the PDE requires LEAs to submit reconciliation reports. These annual expenditures are reported by the following categories, as summarized by the Pennsylvania School Boards Association (PSBA, 2018):

(1) Instructional Costs: This category is by far the largest share of per-student spending (57.2 percent) and mostly includes all costs related to the direct instruction of students, which is assumed to mean compensation packages for teachers (e.g., salaries, healthcare premium subsidies, employer pension obligations),

(2) Student Support Costs: This is the second largest category (26.4 percent) and includes compensation costs for all employees not directly involved with student instruction (e.g., school administrators, counselors, nurses, librarians),

(3) Non-instructional Costs: These are costs associated with extracurricular activities (e.g., after-school activities, food services, transportation services, security personnel) and generally constitutes a small sliver of spending (1.7 percent),

(4) Facilities Costs: These are costs associated with the maintenance and upkeep of buildings as well as campus grounds (e.g., custodian, building maintenance, HVAC, electric, gas), *and*

(5) Financing Costs: These are generally debt service payments (e.g., loan obligations, interest associated with issuing bonds). Financing and facilities costs together account for 14.7 percent.

Because LEAs have broad discretion to set their budgets, the ratios of these five components can vary immensely, with real effects for both teachers and students. For instance, the SDP, like many other urban districts, has historically had an outsized portion of its overall budget devoted to instructional costs to merely attract and retain teachers. Such a budgetary limitation does come at the price of other expenditures such as fewer librarians, security personnel, or building improvements, which have become a higher priority as the district is forced to close schools on exceptionally hot or cold days, resulting in a loss of valuable instructional time.

***Collective Bargaining and Per-Student Spending.*** Though LEAs do possess the authority to set their budgets, apart from charter schools, most LEAs must plan with collective bargaining agreements (CBAs) in mind. CBAs, which are legally binding contracts, can span anywhere from one to two-year extensions of a previous CBA to five or more years, though the latter is rare and generally used to backdate an agreement if the collective bargaining process stalled during that period. Therefore, LEA administrators must manage their school budgets for the current fiscal year and multiple years into the future at a time when political and economic uncertainty can result in abrupt short-term policy changes. Furthermore, while stakeholders often associate collective bargaining with teachers and their unions, a district could have one or more unions representing a wide array of constituents, from educators to bus drives. Therefore, collective bargaining places control on a significant portion of per-student funding allocation.

Furthermore, within the SDP, building administrators and their peers are organized into a local, separate from that of the teachers' union (and the only such arrangement in the Commonwealth). Aside from real compensatory costs, CBAs impose certain limitations that can also influence how LEA administrators allocate resources. Many CBAs have provisions for class size, seniority rules that give more experienced teachers preferential treatment in specific hiring and placement decisions and have Reduction-in-Force clauses (commonly referred to in "Last In, First Out"), all of which influence administrator decision making from assigning teacher workload to filling potential vacancies.

Although critics of labor unions dismiss CBAs as hindrances to growth and executive management, the spirit of collective bargaining is as relevant now as it has ever been. A recent flood of media reports, from gender pay inequities to forced arbitration clauses, highlights that many of the same injustices encountered by Margaret Haley, when, in 1916, she founded the first chapter of the American Federation of Teachers, are thriving today. Then, as now, the teaching labor force is predominantly female, with 2012 figures placing the figure at 76 percent (NCES, 2016). As recently as late 2018, the Bureau of Labor Statics (2019) estimates that, nationally, women earn 82 cents on the dollar compared to men**.** In Pennsylvania, teachers' unions, have attempted to remedy these disparities by negotiating salary schedules that: (a) do not differentiate by gender, race/ethnicity, and other related demographics; (b) do not account for subject matter taught since specific fields, such as mathematics and science, have disproportionately low numbers of females and minorities; and (c) are uniformly applied throughout the district. Therefore, the only two measures that define salary schedules in Pennsylvania are experience and educational attainment, both of which, are intimately related.

***Major Stressors on Per-Student Spending.*** Lastly, administrators must balance certain expenditures that have rapidly increased over the years because of market conditions and policies well outside their control. Three major stressors—pensions, special education costs, and healthcare—have predominantly been the result of Harrisburg's agenda to divest in public education.

Soaring Pension Obligations. Perhaps the greatest of these expenses and one that has addled many states is pension obligations, which directly factor into instruction and student support services costs—the two largest allotments of per-student spending. Pension liabilities have played a prominent role in abetting municipal bankruptcies, with Jefferson County (AL), Stockton (CA), San Bernardino (CA), and Detroit (MI) among the more famous jurisdictions that have filed for Chapter IX in the past decade alone. Pennsylvania's pension problems are no sunnier; PSBA (2018) estimates that district pension obligations have skyrocketed by a whopping 3500 percent during the 15 years between 2002 and 2017, in part, because of a sharp blow to revenue due to the 2008 subprime mortgage crisis, coupled with more Baby Boomers seeking retirement annually. As discussed in the previous policy section, Harrisburg's hold harmless school funding provision, coupled with a state-funding freeze for 20 years, led districts to enact austere tax hikes in the hope of meeting their obligations.

The structure of Pennsylvania's Public School Employees' Retirement System (PSERS) has also resulted in some unsavory side effects in terms of LEA budgets, hiring, and retirement. First, PSERS has progressively placed more onus for pension contributions on LEAs. Thus, even small increases in teacher salaries, vis-à-vis salary schedules, can result in geometric growth in the LEA's pension obligations. Second, districts with a more experienced faculty and lower turnover rate will find themselves paying a high cost for this retention, both in terms of salary and pension contributions, since ultimate more teachers will climb towards the top of the salary schedule in approaching years. Third, to keep PSERS solvent, Harrisburg legislators have extended the superannuation period from 30 years of service to 35 (the total number of years needed to receive a full pension), which has incentivized more senior teachers to stay longer in the profession. Extenuating this superannuation period has the double effect of increasing employer contributions and hindering the hiring of new teachers since vacancies may not be readily available. As expected, LEAs have attempted to minimize these obligations by offering these teachers early retirement, in which the LEA, at a reduced price, purchases the remainder of the contract by providing a one-time payment to the outgoing employee. The National Conference of State Legislators (2010) has criticized these practices as "ill-conceived," as they may save money in the short-term, yet cost much more in the long-term, as retirees are living much longer than the previous generation. Ultimately, even Pennsylvania, which has a Democratic governor who enjoys the support of the teachers' union, has succumbed to the realities of unbearable pension obligations with the passage of Act 5 of 2017, which creates a two-tiered system for new hires after July 1, 2019. These employees will have the option of either enrolling in a defined contribution account or a hybrid defined contribution/defined benefit account.

Rising Special Education Costs. The second significant stressor of per-student funding is the rise of special education costs. Hartman (2016) estimates that in 2002, the Commonwealth and LEAs shared the cost of special education funding roughly equally, but as of 2017, the state's share has plummeted to 23 percent, with LEAs absorbing 71.5 percent and the remainder funded by the federal government. As is the case with pension obligations, districts have little recourse except to increase taxes, particularly property taxes, since they yield the most revenue per unit increase, to fill the void. Interestingly, Suburban Non-Title I Districts are drowning in special education expenses more so than any other LEA type. Of the top 10 districts that assume the most significant local share of special education funding, all are in Bucks, Montgomery, or Chester counties, with Lower Merion School District leading the group with a remarkable 90 percent (Education Law Center & PA Schools Work, 2018). As Table 1.1 describes, this sharp increase in cost is the result of an increase in population across the PHL region as well as higher numbers of identified students.

Mounting Healthcare Costs. Lastly, rising healthcare costs continues to vex employers nationally; 2017 data from the Centers for Medicare and Medicaid Services (2018) states that per capita healthcare costs have increased by 89 percent in the 15 years between 2002 and 2017. This sharp increase has forced LEAs to spend more in healthcare subsidies, which in turn, drive increases in instructional and student support services costs, shift more of the premium cost onto employees, or both. The drain on LEA budgets has led some districts to attempt innovative approaches, such as the Bucks and Montgomery County Schools Health Care Consortium, which is designed to pool school district employees in both counties into one insurance group, thereby lowering the overall risk exposure to health insurance companies, and, in turn, the premiums billed to these districts.

## Purpose of the Study

Researchers have studied the issue of K-12 educator retention from several angles, such as teachers and principals, and on various levels ranging from urban districts such as Chicago or New York City to even international analyses (Pitsoe, 2013; Sharma, 2013; Weinstein, 2009). Curiously, Pennsylvania has largely eluded this scrutiny, a puzzling circumstance given the geographic, economic, and demographic diversity discussed above. What research regarding teacher turnover that does exist in Pennsylvania is mostly exclusive to the SDP (Neild & Balfanz, 2007; Pugh, 2003; Useem & Neild, 2001). More studies about the SDP have come into the limelight since 2014, with the creation of the Philadelphia Education Research Consortium (PERC), as a collaboration between the SDP, the city's charter school sector, the city's three R1 universities—University of

Pennsylvania, Temple University, and Drexel University—as well as the Philadelphia-based nonprofit research organization Research for Action. Since then, the SDP has made district data available to researchers on par with other major urban centers such as Chicago, New York City, Baltimore, and Los Angeles. Some studies do explore turnover in rural Pennsylvania (Lamkin, 2006; Monk, 2007), somewhat surprisingly, virtually none has studied the phenomena in Pittsburgh Public Schools.

This lack of a comprehensive body of research in the state with the sixth largest pupil population can be problematic in several respects. As noted in the previous section, while many stakeholders agree that the Commonwealth employs an ineffective funding formula, there appears to be less consensus about what a viable alternative should be. With the opening arguments in the William Penn trial set for next year, it is worth scrutinizing the plaintiff's argument that the current funding approach deprives affected students of a high-quality learning environment complete with better-paid teachers and more support services. This study tests and dissects this argument by region and various district types to see where monetary increases, if any, have the most acute effect on retaining teachers.

In addition to the possible policy implications for this study, educational leaders, who are in the unenviable position of delivering academic results at a time of public divestment, may also find value in this study. This study examines two specific teacher populations in mind—new/experienced teachers and high need subject area teachers. To the first point, new educators in the Commonwealth are subject to the same teacher evaluation framework as their more experienced peers. Act 82 of 2012 outlines teacher evaluation criteria with nearly two-thirds (65 percent) of the evaluation score derived from both observation data (via the Danielson framework) and valued added student performance data (term Pennsylvania Valued Added Assessment System or PVAAS). However, neither differentiates by experience level and, so it stands to reason, new teachers are likely to struggle more compared to experienced teachers when vying for the same performance rating, leading to increased chances of burnout.

Similarly, mathematics and science teachers are expected to deliver achievement gains in two subject areas that have traditionally experienced lower student performance gains compared to English/Language Arts (ELA). Moreover, while special education and English as a Second Language (ESL) teachers may not be subject area teachers *per se*, they support some of the most challenging students, whose performance on standardized testing is given more weight since they constitute separate subgroups. Thus, these high need subject teachers also face more pressure to deliver student growth (again, increases chances of burnout), which, in turn, is reflected on their PVAAS scores and evaluation ratings. An educational leader charged with resource allocation at the LEA level may find some value in this study's goal of retaining these crucial teachers vis-à-vis financial investments.

## Research Questions

This study examines the variable effects of salary and auxiliary spending increases on teacher turnover. To that end, it seeks to answer the following two parallel research questions for each of the three regions in the population data:

RQ1: Comparison of New Teachers (w/Bachelor's Degrees) and Experienced Teachers (w/Master's Degrees)

(a) Do turnover rates decrease for either group when accounting for a 10 percent or 20 percent salary increase?

(b) Do turnover rates further decrease for either group when accounting for a 10 percent or 20 percent increase in auxiliary spending?

RQ2: Comparison of High Need Content Teachers (Math and Science) and High Need Support Teachers (Special Education and ESL)

(a) Do turnover rates decrease for either group when accounting for a 10 percent or 20 percent salary increase?

(b) Do turnover rates further decrease for either group when accounting for a 10 percent or 20 percent increase in auxiliary spending?

Additionally, the term turnover encompasses internal and external behavior; internal turnover refers to a change in placement within a system, whereas external turnover refers to a change in placement between the system and its surroundings. In this study, the Commonwealth's public-school system is the system and therefore internal turnover is taken to mean movement between LEAs, while external turnover is taken to mean moving out of the public school system entirely. The outcome does *not* make this distinction, since, at the LEA level, where central office administrators make per-student funding and compensation decisions, it makes no difference if the teacher disassociates from the organization or the public-school system because, in either case, the teacher no longer is a part of the LEA. However, to facilitate analysis, "movers" are internal turnover candidates whereas "leavers" are external turnover candidates.

## Operational Definitions

This study introduces some original terminology as well as more familiar terms that inject nuance into the analysis and findings.

***Clarifying Educator Experience Terminology***. The turnover literature makes an explicit distinction between a "New Educator," who has had at most five years of teaching experience (≤5yrs.), compared to an "Experienced Educator," who has more than five years of teaching experience (>5yrs.) (Liston, Whitcomb, and Borko, 2006; Papay & Kraft, 2015). Note that to qualify for administrative credentials, educators must have at least five years of teaching experience, thereby automatically identifying these individuals as Experienced Educator(s).

Additionally**,** the first research question pairs New Teachers with a Bachelor's Degree, whereas Experienced Teachers pair with a Master's Degree. New teachers must hold at least a bachelor's degree and either an Emergency, Intern or Instructional I certification, which expires after 1, 3, or 6 years of service, respectively, to teach in the Commonwealth. Furthermore, to convert these certificates to permanent Instructional II certification, which is valid for 99 years of service, a new teacher holding an Instructional I must complete at least 24 post-baccalaureate credits by the sixth year of service, by which point the teacher is considered an experienced teacher. Since 30 post-baccalaureate credits are generally required to obtain a master's degree, most experienced teachers opt to pursue a full master's degree, since districts will either support tuition payments, increase compensation for this credential or require the credential as a condition of employment.

***Clarifying Monetary Investment Terminology.*** This study makes a distinction between the terms "salary" and "compensation," with the former referring to the wage or remuneration as stated in the employee's paycheck (pre-tax) whereas the latter refers to the entire package offered by the employer (e.g., salary, healthcare benefits, pension contributions). Note that this study only examines the effect of the former on turnover. Also, the term "auxiliary spending" is defined as all per-student spending components combined, absent instructional costs (i.e., pupil support services and non-instructional support, in addition to finance and facilities, spending).

***Clarifying Subject Area Terminology***. The term "high-need subject" applies to teachers who hold positions in mathematics; (natural) sciences; special, remedial, and alternative education; and ESL. This designation is consistent with critical shortage areas reported by the PDE to the USDoE as evidenced by 2017 Title II (Higher Education) data. This study further divides "high-need subject" into "high-need content" areas (math and science) and "high-need support" areas (special education and ESL). Inversely, the term "low-need subject area" refers to teachers who hold positions in elementary education; ELA; social studies/sciences; foreign languages; health, driver, and physical education; visual and performing arts; and vocational or technical education. Also, the term "administrative support" refers to any educator who has at least *one* year of service in school administration, instructional and building support, or different building staff (e.g., clerical, janitorial, security).

## Significance of the Study

Two innovative characteristics of this study set it apart from comparable studies: the novelty of the data and the application of a methodology never used to study turnover on such a scale. To the first point, this is the *only* study that has attempted to examine teacher turnover throughout an entire state using population data because, as discussed in the next chapter, the bulk of teacher retention studies to date have experienced sampling limitations. For instance, those who have attempted a longitudinal approach towards studying turnover are constricted by their sample size, choosing their subjects either via some sampling mechanism or focusing on a subcategory of teachers (Achinstein et al. 2010; Hancock & Scherff, 2010; Patterson, Roehrig, and Luft, 2003). Others who attempted a cross-sectional approach are hampered by the availability of time series data, with most studies spanning only one to at most a three-year observation periods (Luekens, Lyter, and Fox, 2004; Rinke, 2014; Zheng & Zeller, 2016). These studies rely upon intermittent secondary data collected at the national level, such as the popular Schools and Staffing Survey (SASS) or the High School Longitudinal Study (HSLS). For instance, there were only seven offerings of the SASS between 1987 through 2011 and only three years of HSLS data between 2009 and 2016—a setup that complicates assumptions and inferences made from resulting analyses. In either case, the tradeoff between size and time panel have limited the generalizability of these results, posing hurdles when attempting more complicated changes to policy and practice. The second feature follows from the first. Traditional approaches to quantitative turnover studies use some form of logistic regression to uncover odds ratios, which are the basis of analysis. Using ordinary (binomial or multinomial) logistic regression assumes that each observation (event) is independent of the others, which is flawed when using longitudinal data, since, for the same person, a previous event likely influences the next. For instance, if we compare a person's odds of whether he/she will purchase a specific allergy medication over a year for a year-round allergy, it is safe to assume that the first few experiences with this medication are likely to influence future choices for the remaining months.

Finally, keep in mind that despite the potential of this study, no model can indeed account for all (or possibly even most) of the variance in the outcome. I hope that this study makes a valuable contribution to not only policymakers and practitioners, but also the academy, by wedding theory, methodology, and concepts found across a wide range of disciplines. As the need for high-quality teachers becomes critical, the teacher labor market becomes more fluid, and a new generation of workers seeks to enter employment in the field, there is a pressing case for a more holistic approach to studying teacher retention as the profession undergoes a seismic change. As famed economist Robert Schiller, winner of the 2013 Nobel Memorial Prize in Economic Sciences, commented, “In the long run and for wide-reaching issues, more creative solutions tend to come from imaginative interdisciplinary collaboration” (Nemko, 2016).

# CHAPTER 2

# THEORETICAL FRAMEWORK AND LITERATURE REVIEW

Teacher turnover is an issue that has historically received much attention in the extant literature. Concerns regarding teacher retention have their roots in the Sputnik era when 40 percent of school board presidents listed teacher turnover as a significant problem at a time when the "Three Rs" of reading, writing, and arithmetic, were becoming issues of national interest (McQuinn, 1957). This apprehension has only intensified in the last quarter century since the landmark *A Nation at Risk* study (National Commission on Excellence in Education, 1983) issued a scathing indictment of public schooling and apocalyptically predicted that the pending retirement of an aging teaching force combined with increasing student enrollment would lead to dramatic teacher shortages. Since then, there has been a flurry of studies that seek to explain teacher turnover at all levels of the educational hierarchy, diverse in their methodological approach and their theoretical frameworks. In this chapter, I investigate much of this research by first examining these distinct, yet interrelated approaches to understanding both the context and executive calculus associated with the decision to leave, followed by a survey of the existing literature. Note that throughout this chapter, I use the terms "turnover" and "retention" reciprocally and the terms "turnover" and "burnout" are used interchangeably since the latter is known to have a sharp correlation with the former.

Before undertaking this enterprise, it bears mentioning that qualitative and quantitative researchers have both studied teacher turnover, with each approach making unique contributions to the discipline concerning what motivates teachers to engage in a field with an ever-growing range of responsibilities. From a qualitative perspective, teacher retention studies tend to be constructivist and utilize case studies to ascertain the rationale for why a group of teachers (or even a single teacher) leaves an educational setting. These case studies analyze the decision-making process either at the time of turnover or longitudinally, following said teacher or group over a period and comparing the characteristics of those who remained with those who departed (Forbes, 2004; Guin, 2004).

In either case, these studies offer valuable insight into the decision-making process since they contextualize the habitus of these individuals within the organizational culture of schools. Conversely, quantitative studies employ a (post) positivist approach which uses numerical data to dissect the reasons for turnover. As is the case with qualitative studies, these studies can be cross-sectional or longitudinal and can incorporate sophisticated modeling techniques designed to understand the turnover environment**.** In turn, depending on the scope of the dataset, the most salient variable(s) are interpreted as functions of some broader psychological, social, or economic theory. It is this interplay between both distinct yet complementary traditions that have helped to shape this body of literature.

## Theoretical Framework

Just as the approaches to studying turnover are diverse, so too are its explanations. Since teaching is a profession that requires enormous emotional investment, has considerable social implications considering the various racial and socioeconomic bands served, and is subject to many of the same principles that govern labor markets, psychologists, sociologists, and economists have examined the issue from multiple perspectives respective to their fields. This study deals primarily with monetary investment, yet it is essential to recognize that money is by no means the single lens through which teachers make turnover decisions. The first half of this chapter explores the reasons why teachers teach, the side effects associated with their departure, and how theories of job satisfaction can be used to help explain some of these behaviors.

### *Teachers and Teaching*

Many individuals within and outside the profession have described teaching as a calling rather than a vocation – a characterization which carries overtones ranging from a divine influence or even a fatalistic pull towards the profession. This portrayal does evoke a sense of nobility, but it can lead to cavalier assumptions about why teachers teach and, perhaps more importantly, what they are justly expected to do.

***Motivations to Teach.*** A wealth of research has sought to embed teacher satisfaction into the broader construct of job satisfaction. Quantitatively, a series of researchers (Kim & Loadman, 1994; Klecker & Loadman, 1997; Newman, 1979; Ulriksen, 1996) have identified some critical correlates of teacher job satisfaction, including intrinsic (e.g., professional autonomy, interactions with students and colleagues) and extrinsic (e.g., salary, opportunities for advancement) rewards. More recently, Nieto (2003) has suggested that these intrinsic and extrinsic rewards combine to form a network of interrelated conditions and values that motivate teachers to stay in a given school environment. These conditions create an unseen fabric that binds all actors in a school. In a large-scale study of job satisfaction, Perie & Baker (1997) found that only 26 percent of public high-school teachers characterized themselves as highly satisfied in their position, with this percentage declining with experience. They noted that 36 percent of teachers with three years of experience or less rated themselves as highly satisfied with just under 23 percent of teachers with 20 years of experience rating themselves the same.

Qualitatively, several researchers have used an anthropological (emic) approach known as life history studies, in which researchers use extensive interviews to frame teacher experiences and beliefs (Ball & Goodson, 1985; Goodson, 1992; Goodson & Hargreaves, 1996; Knowles & Holt-Reynolds, 1994; Sikes, Measor, & Woods, 1985). Perhaps the best known of these studies is by Huberman (1993) who, through his interviews of nearly 160 Swiss teachers, made a case for identifying the professional life cycles of secondary teachers, suggesting that the later phases of teaching (ages 40-60) as periods of serenity and disengagement and, on occasion, bitterness and conservatism.

***Comparing Teachers with Other Professionals.*** As in any sector, some turnover is unavoidable. Teachers, like any other professional, are subject to the complications of life, which can range from changes to their family structure (e.g., the addition of children or divorce) or changes to a significant other's employment that require movement intra- or extra-state and even internationally. Others may seek to retire at the time of eligibility with others choosing to continue employment and a rare few even experiencing death during employment. Consequently, aspiring to achieve a virtually nonexistent rate of turnover is fantastical. There is a broad consensus amongst researchers that some turnover is unavoidable and therefore expected yet attempting to determine what is an "acceptable" rate has proven to more elusive since such a determination cannot be divorced from the researcher's beliefs regarding the state of the profession. Consequently, many comparisons between teachers and other professionals as well as teachers in other regions have made their way into the literature.

One popular approach has been to compare teacher turnover to other similar professions. Ingersoll & Perda (2008) compared entry and exit numbers of various professions between 1997 and 2003 and noticed that teachers experience an attrition rate of 30 percent, which is 11 percentage points higher than the loss for either nurses or lawyers and roughly double that of pharmacists. Comparisons to other professional service-based occupations such as medicine and law are tempting but using the latter to benchmark teaching can be misleading. For instance, the three professions not only deal primarily with three different age groups but also teaching is performed in a group setting (e.g., a classroom) with multiple "clients" as opposed to medicine and law, in which "clients" are generally seen on a one-to-one basis in a clinical setting.

Nor are geographic comparisons altogether too attractive. As the recent wave of teacher strikes suggest, state to state comparison of turnover can be fraught with complications since states have adopted highly variable policies ranging from school funding to general policy. According to the U.S. Census Bureau (2016), Florida and Nevada have virtually the same per-student spending and the same source of educational funding revenue (i.e., games of chance). However, Alaska and Vermont, which also have the same per-student spending, depend on very different revenue streams to fund public education, with the former reliant on oil and the latter reliant on property taxes. Even two states that appear to have similar approaches to education funding may have different policies. For instance, Minnesota and Nebraska also have nearly the same per-student funding, yet the former is home to the nation's first charter school, and the latter has none.

Some researchers have attempted to go beyond the United States when comparing turnover rates to inform policy at home. A well-cited study by Carver-Thomas & Darling-

Hammond (2017) maintains that the United States has roughly double the teacher turnover rate in comparison to the highest performing countries on the Programme for International Student Assessment (PISA), a triennial exam administered worldwide to 15-year old students by the OECD and designed to evaluate performance in mathematics, science, and reading. Hanushek (2010), goes as far to insinuate that high rates of turnover could help the United States achieve results on par with Canada, a regular top 10 PISA performer (OECD, 2016). He asserts that eliminating the bottom 10 percent of the nation's three million teachers (in terms of student achievement), coupled with replacement by a "strong teacher," which he defines as one standard deviation above the average in terms of student achievement, would eliminate the achievement gap in four years. Hanushek is correct that schools with high poor and minority populations have a higher than average share of inexperienced and uncertified teachers. Still, it is highly impracticable to assume that at a time when many states are reporting teacher shortages, somewhere there is a "waiting list" of over 300,000 prospective teachers who are ready to be seated at the teacher's desk.

Interestingly, both researchers make virtually polar arguments concerning the role of turnover, but their appeal to the same PISA rankings is misleading. For instance, many European countries that rank highly on the PISA exam have populations and GDPs on par with American states rather than the United States wholly; California and France have a comparable GDP of $2.5 trillion as does Texas and the four Scandinavian countries combined with a GDP of $1.6 trillion (IMF, 2019). Maybe a better economic comparison to the United States is China, but the latter has a population about four times that of the former. Additionally, China does not entirely participate in the PISA exam with Hong Kong and Macau as separate entries and only students in Beijing, Shanghai, Jiangsu, and

Guangdong – three of which are China's wealthiest provinces – participating on the exam. Moreover, the United States has an unparalleled amount of racial and ethnic diversity further complicating comparisons. Perhaps a more accurate comparison would be between the United States and the European Union, which have similar GDPs (US: $20.9 trillion vs. EU: $19.1 trillion), similar population size (US: 327 million vs. EU: 512 million), and high degrees of racial and ethnic diversity. However, the most recent PISA figures do not provide combined results for the EU.

### *The Burdens of High Teacher Turnover*

Recall from the previous chapter that turnover has an internal and external component and this study treats movers as those who change LEAs and leavers as those who exit the state's public school system either. Additionally, comparison across LEAs rather than schools is preferable since, apart from charters, LEAs under the influence of CBAs do not have an intra-LEA salary differential by subject area, grade level taught (except for special education), or any demographic identification. Estimates by Sutcher, Darling-Hammond and Carver-Thomas (2016) note that internal and external turnover occurs at roughly equal rates with each accounting for eight percent in the teacher labor market from year to year (for a total of 16 percent turnover). Despite that finding, these aggregate numbers mask considerable disparities by region and LEA type. Nonetheless, across all LEA types, researchers and practitioners alike are acutely aware of the challenges that students, peers, and the workplace experience when teachers depart.

***Detriment to Student Learning.*** Perhaps the most critical consequence of teacher loss is the immediate and long-term effects on students' academic performance. Ronfeldt, Loeb, and Wyckoff (2013) reasoned that the literature discusses the negative impact of turnover on student achievement in two parallel terms – “compositional” and “disruptive” – with the former comparing the efficacy of the incoming vs. outgoing teacher whereas the latter focuses on the impact made on the culture of teaching and learning. Several studies have attempted to capture the “compositional” effect with Rowan, Correnti, and Miller (2002) and Rivkin, Hanushek, and Kain (2005) speaking to the importance of retaining high-quality teachers, particularly those classified above average ($>50^{th}$ percentile) in terms of student achievement. They contend that these teachers can help reduce the achievement gap and cover more curriculum in one year compared to a below average ($<50^{th}$ percentile) teacher. However, when a below average teacher swaps an above average teacher because of turnover, student gains disappear when comparing cohorts. In the “disruptive” approach, teachers have some social and human capital because of their experience that is part of the academic milieu of the school. This nontransferable capital is vital to student engagement, and so when a teacher leaves, this investment is also lost, resulting in a noticeable decline in student achievement (Bryk & Schneider, 2002).

***Impact on Workplace Morale.*** High rates of teacher turnover also have the potential to disrupt workplace cohesion. Ingersoll & Smith (2003) state that effective teaching relies on interactions with students, parents, and staff that culminate in a fruitful relationship over time. A teacher’s long-term commitment to the school creates a stable and productive environment in which all stakeholders can better understand one another’s strengths and needs. For every teacher who leaves that environment, the school community loses either a connection or opportunity to gain wisdom. Turnover also hinders the formation of trust between remaining colleagues and supervisors, leading to a climate of mutual suspicion and distrust (Bryk & Schneider, 2002; Guin 2004; Hanselman et al., 2016).

In terms of educational leadership, a stable school characterized by low turnover and generally more experienced staff provides fertile soil for growth when attempting improvements in curriculum and instruction as well as whole child development – all of which require patience, resilience, and long-term commitment (Sarason, 1990). Smylie & Wenzel (2003) go as far as to say that implementing an agenda of education reform in a poorly performing school can take anywhere between 5-10 years. Moreover, Shields et al. (2001) found a relationship between the number of new, inexperienced teachers and the amount of time, energy, and resources spent by administrators on inducting these recruits into both the school culture and the profession. Unsurprisingly, administrators who lead in environments marked by continuous turnover experience a "battery drain" of sorts with little power remaining to address any severe structural problems in their organizations.

***Financial Costs.*** Perhaps the easiest way to express the detrimental impact of teacher turnover is in monetary terms. As any human resources officer will attest to, the process of recruiting, hiring, and training new teachers is expensive and time-consuming. Depending on the quality of this process, rapid turnover can increase costs exponentially. Quartz et al. (2008) calculated that in 2001, Texas alone wasted anywhere from $329 million to $2.1 billion annually on turnover, depending on the conservative nature of the estimates. Barnes, Crowe, and Schaefer (2007) ventured to determine costs more acutely by comparing turnover costs in various LEAs. In small rural districts (Jemez Valley, NM), the cost per teacher leaver was $4,366 compared to small urban districts (Milwaukee, MN) where the cost per teacher leaver was $15,325. In a typical middle-income county (Granville County, NC), the average cost per teacher leaver was just under $10,000 whereas, in large urban districts (Chicago, IL), the average cost per teacher leaver was $17,872. Summating these values across Pennsylvania, it is easy to see that teacher turnover costs can run into the tens of millions of dollars in a state is composite of rural, suburban and urban districts. Critics of these studies contend that these studies fail to consider the savings experienced from losing an experienced teacher and hiring a newly minted replacement. If turnover rates are indeed higher among new teachers than more experienced ones, there is little gain from the salary difference and more to lose since the costs associated with replacement are likely to offset any gains made (Boe, et al., 1997; Marvel et al., 2007).

### *Theories of Turnover*

This section provides an overview of three distinct theoretical constructs, which are then reconciled into a single framework aligned with Maslow's Hierarchy of Needs but modified to explain why teachers choose to stay or leave a teaching assignment via the lens of job satisfaction. Maslow (1943) posited that all individuals in a given social environment seek to obtain five basic needs, which in descending order of need are survival, safety, belonging, esteem, and self-actualization. The first theory, Human Capital Theory, examines teachers' need for survival, not in a physiological sense *per se* as originally conceptualized by Maslow, rather in an economic sense, in which wages fulfill a teacher's basic living and lifestyle needs. The second theory, Motivation-Hygiene, incorporates the concept of safety by differentiating between motivators and demotivators. Lastly, Person-Environment Fit Theory provides insight into how the remaining three layers of Maslow's framework – a sense of belonging, esteem, and self-actualization – can be interpreted as a function of high fit between the employer and the employee.

***Human Capital Theory.*** Arguably, the birth of modern job satisfaction theories lies in the work of Simon (1979**)**, who adopted the classical laws of supply and demand to formulate a theory of organizational equilibrium, arguing that organizations continually seek to balance employee contributions and inducements throughout the former’s lifespan. The reasoning here is simple – employees are economically rational creatures who, if provided with enough inducements, will be motivated to participate with and produce for the organization. The existence of the organization then depends on its ability to maintain a balance between motivating employees and meeting production requirements. Moreover, both actors engage in arithmetic that weights the pros and cons of either retaining the employer (for the employee) or the employee (for the employer).

Furthermore, the ability of the employee to continue employment with an employer depends on (a) the perceived desirability of movement and (b) the perceived ease of movement. Therefore, in keeping with the rational approach, if the investment made by the employee is less than the expected returns, there is an increased chance of a turnover. Ehrenberg & Smith (2003) revised this formula to expand the definition of investment as both classical opportunity costs (e.g. the amount of time, energy, and money spent looking for a new job) and all the knowledge and skills accumulated over time that are idiosyncratic to the position and the field, broadly termed human capital. Likewise, they interpret payoff not only in monetary terms, but also intangible rewards such as career advancement, improvements in the work environment, and opportunities for growth.

Since teaching is associated with a steep learning curve in which a new teacher generally needs five years of experience before being considered an experienced one (Killion & Harrison, 2017; Trotter, 1986), the professional development of teachers becomes an investment and return for both the employee and the organization. In the case of teachers, Becker (1993) categories teacher professional development in two camps –

general and specific. General professional development is applicable across a range of organizations (e.g. differentiated instructional practices, detailed lesson planning, developing better aligned formative and summative assessments), compared to specific professional development, which is only applicable to the organization itself (e.g. supervising certain extracurricular activities, teaching niche electives, communication protocol with stakeholders, etc.). General professional development is a more significant investment on the part of the school compared to its returns since teachers need these skills to perform the job in the first place. Furthermore, this investment makes the teacher a more attractive candidate in the labor market since a previous employer (school) has already made this initial investment, saving resources for future ones. Specific professional development is much more desirable from the perspective of the employer since those skills increase productivity for that school and do not have much value elsewhere.

Though an employee can engage in an internal estimation between investment and returns, no employee exists independent of the broader labor market. At any given time, the job market provides a set of alternatives, which can moderate this estimation and the decision to leave (Muchinsky & Morrow, 1980). Mobley et al. (1979) have suggested that *perception* is equally as important as *reality* since the employee's decision to leave is the product of his risk assessment. For instance, a social studies teacher specializing in civics and government who *perceives* a need by schools to offer civics education during these politically charged times, may factor that into his risk assessment and decide to leave his current employment. However, if the job market has no vacancies available for such a teacher, then leaving a position may not net any returns.

Human capital theory can lead to the false assumption that employees are merely avaricious, and an ever-increasing amount of pay is necessary to placate them. Berry (1997) disputes the common misconception that pay is the most critical factor in job satisfaction. Instead, she suggests that employees are most satisfied when they enjoy the environment in which they work (see Person-Environment Fit Theory). Bivens et al. (2014) conceptually reinforce this finding by noting that compared to productivity, which has increased on average 77 percent between 1973-2017, average wages have only increased 12.4 percent resulting in a six-fold increase in the former compared to the latter. Consequently, because teachers generally feel overworked and underpaid, increasing salary is seen more as a corrective action rather than a motivating tool.

***Motivation-Hygiene Theory.*** While survival and adequate compensation link to one another, since a low amount of it *requires* the employee to seek supplemental or alternative employment, safety and job security also link with each other. Job security does not necessarily imply tenure since LEAs such as charter schools do not offer it, but more broadly to mean the ability of a hired employee to perform his job. The inability to meet the expectations of the job are not exclusively the fault of the employee; an employer can fail to provide the proper training, time, support of materials necessary to perform the job in the first place. Regrettably, many urban schools fall victim to an ability to offer (economic) survival or (job) security – both of which are necessary for teachers to even commit, let alone thrive, in these demanding settings. The beginning of this chapter discussed how teachers see themselves less as mechanical cogs in some bureaucratic machine and more as professionals who have a desire to influence the development and lives of students. The first two of Maslow's needs are termed demotivators since their absence results in employees expressing demotivating behaviors (e.g., boredom and disengagement). Conversely, motivating behaviors do increase the chances of obtaining the remaining three of Maslow's needs – belonging, esteem, and self-actualization – as well as the expression of motivating behaviors (e.g., volunteerism and leadership), both of which are directly related to reducing employee turnover (Bernstein & Nash, 2008).

Herzberg (1966) articulates this reasoning in what is now known as Herzberg's Motivation-Hygiene Theory, which identifies two distinct categories of factors related to job satisfaction – motivators (e.g. responsibility, achievement, recognition, promotion/advancement, etc.), which lead to job satisfaction, and hygiene (e.g. company policies, salary, work conditions, and relationships with coworkers and supervisors), without whom leads employees to job dissatisfaction. Intuitively, hygiene is the more important of the two since, while these factors do not lead to job satisfaction, their absence puts an organization's viability at risk (Herzberg, Mausner, and Snyderman, 1959). Integrating Maslow's framework, Herzberg asserts that motivating factors lead to job satisfaction because they address a psychological need for belonging and even enhance an employee's perception of self-worth. Conversely, he cautions that improvements in hygiene factors may produce a short-term change in job satisfaction and even boost immediate performance, but these gains will quickly evaporate because hygiene factors are always viewed as prerequisites for employee attendance and likely fail to inspire any long-term behavioral changes. By extension, Motivation-Hygiene Theory has led to a popular misconception that motivation and motivators are static (i.e., once a motivator has been introduced and sparks motivation, it need not be applied again) (Syptak et al., 1999). Even though this may be true in the period immediately following application of the motivator, Bassett (1994) observed that over time, the novelty effects of the motivator fade, productivity reverts to pre-motivator levels, and a new motivator is needed to boost output.

***Person-Environment Fit Theory.*** Several researchers have built upon the Motivator-Hygiene Theory by studying the alignment between employee needs and character compared to organizational logistics and culture, termed Person-Environment (P-E) fit (French, Caplan, & Harrison, 1982; Muchinsky & Monahan, 1987). This matching can occur on several levels such as Person-Organization (P-O) fit, Person-Job (P-J) fit, Person-Group (P-G) fit, and Person-Person (P-P) fit. Though all are undoubtedly related, this study only explores (P-O) and (P-J) fittings.

Kristof (1996) defines P-O fit as either "needs-supplies" or "demands-abilities" where the former deals with the *organization's* ability to meet the employee's needs and the latter deals with the *employee*'s ability to meet organizational demands. Unlike blue-collar workers who often seek P-O alignment in terms of "demands-abilities," white-collar professionals, such as teachers, generally engage in "needs-supplies" job search behaviors.

Moreover, if there a high correlation between employee and employer in terms of shared values, then the P-O fit is highly congruent, leading to increased levels of trust and shared responsibility between both parties. This close association between employee and employer in education is critical to the development of any school community and, in turn, results in reduced risk of turnover (Andrews et al., 201; Boon & Hartog, 2011). Such a strong association is particularly crucial to more experienced teachers who are likely to seek a community where their skills, abilities, and perspectives are valued and nourished, all needs that are associated with the highest levels of Maslow's hierarchy.

Complimentarily, employees can achieve these higher levels of needs through the right P-J fit, which is the compatibility between a person's characteristics and those of a specific job (Kristof-Brown & Guay, 2011). Ployhart, Schneider, and Schmitt (2005) suggest that employers consider skills as well as the perspectives and personality of prospective employees when finding the "right" candidate for a job. While the P-J fit approach can explain several positions in public education, one interesting application is school leadership. LEAs require administrators to have first served as teachers and completed educational administration coursework (i.e., certification) before even being deemed eligible for school leadership positions. In doing so, hiring managers use certification as means to winnow the prospective pool of applicants to only those candidates who have a high chance of achieving P-J fit, since pursuing administrative credentialing requires investment by the prospective employee with no guarantee of return.

Lastly, Schneider, Smith, and Goldstein (2000) combined elements of P-O and P-J fit models to explain how the attraction, selection, and attrition (ASA) of employees is used to promote high fit in an organization, thereby reducing turnover to comparatively low levels. For instance, applicants will seek and apply to organizations that they feel represent their values and goals. Bretz and Judge (1994) found that individuals who scored high on team orientation measures were likely to pick an organization that had good work-family policies. Boon & Hartog (2011) also observed that job applicants would look for job characteristics such as opportunities to participate in decision making, offer increased autonomy, and the expectant roles associated with the job, all of which are also highly prized by teachers. Finally, if there is a mismatch in the hiring process or after, those who no longer have an excellent P-O or P-J fit will likely leave (voluntarily or otherwise), resulting in more organizational homogeneity.

***Towards a Synthetic Maslowian Framework.*** Each of these three theories not only describes some aspect of job satisfaction and job dissatisfaction but also build upon one another's ideas. Human capital theory, which posits that humans are rational economic creatures, provides the most fundamental reason why employees seek a change in position – compensation, which, of course, is essential to survival. However, compensation is not enough to diminish turnover. Motivation-Hygiene Theory postulates that employees must have the adequate supports necessary to perform their job; without them, employees are likely to experience loss of employment (voluntarily or otherwise) because of decline in performance, stress and anxiety, or burnout. The risk of turnover reduces considerably once an organization meets an employee's survival and security needs. Consequently, the employee can commit to the organization's mission and goals while employers can improve productivity using one or more motivators.

The remaining three stages in Maslow's Hierarchy of Needs are dependent on the degree of P-E Fit. If there is a highly congruent fit, employees will exhibit a high degree of motivating behaviors such as leadership, creativity, initiative and so on, leading to self-actualization (i.e., realization of full employee potential). By extension, less P-E fit corresponds with less "realization" with a moderate fit resulting in a sense of purpose or importance (high engagement but not full leadership) and a marginal fit resulting in a sense of belonging (some engagement but still no leadership behavior). Figure 2.1 illustrates this framework using a pyramidal structure to categorize job satisfaction needs.

Lastly, it is critical to note two significant implications inherent in this framework. First, achieving the next level depends on successfully meeting the requirements associated with those below it. Thus, there can be no “realization” of employee potential if the basic needs of survival (compensation) and security (supportive conditions) are absent. Second, not all employees will achieve self-actualization status. Those who do will assume managerial or administrative roles in the organization, but it is their responsibility as organizational leaders to guide their subordinates and offer as many opportunities for these individuals to achieve some degree of self-actualization. In an interview, University of Pennsylvania Wharton School of Business Professor of Management and Psychology Adam Grant was asked to describe the secret to successful leadership to which he replied, "The most meaningful way to succeed is to help other people succeed." (Schwantes, 2017).

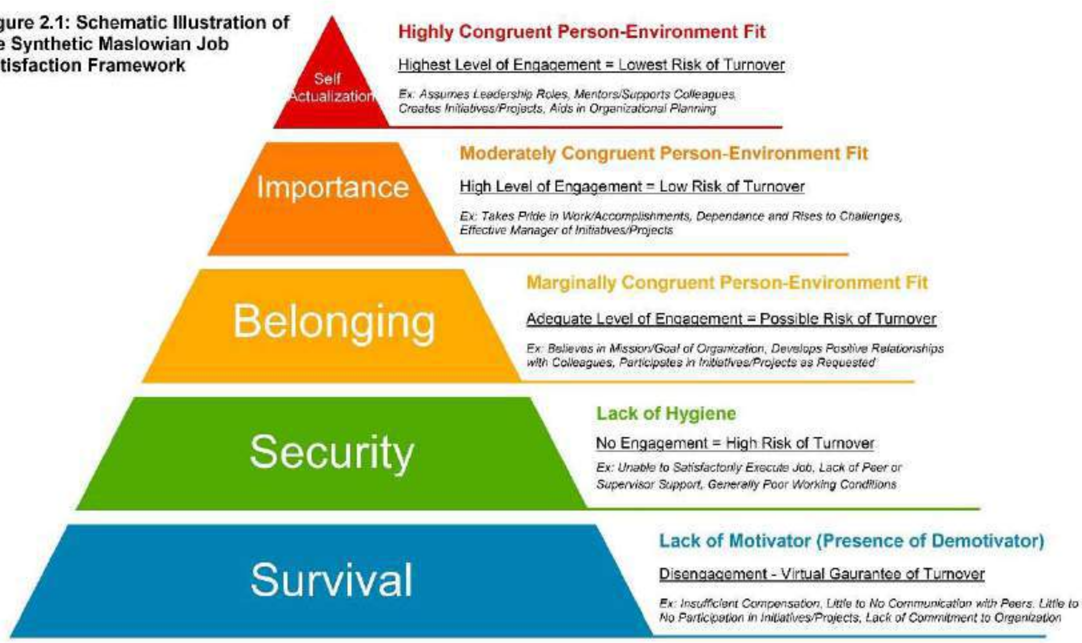



**Figure 2.1: Schematic Illustration of the Synthetic Maslowian Job Satisfaction Framework**

## Literature Review

Having explored various theories of turnover, it worth the effort then to fully explore the various demographic and socioeconomic avenues researchers use to study teacher turnover. As mentioned at the start of this chapter, the current body of literature regarding teacher turnover is expansive and interconnected to other areas such as educational leadership, school reform initiatives as well as finance and education policy. As such, the review invokes these studies as needed to support the main argument.

Seemingly reports of teacher turnover can appear inconsistent with Ingersoll & Smith (2003) reporting turnover at 14 percent and Sutcher, Darling-Hammond, and Carver-Thomas (2016) reporting turnover at 16 percent. However, it is possible to reconcile these values considering macro-level finance and economic policy changes. For instance, Ellerson (2010) notes that the ARRA of 2009 provided many districts with stopgap funding to offset the losses from tax revenue and keep payroll solvent. Follow up data shows that once the funding period ended, districts reverted to their original constraints as the much hoped for tax revenue did not recover to pre-2009 levels. Although the calculation of aggregate national turnover numbers may be the subject of methodological debate in academia, these values conceal an underlying and massive inequity permeated by LEA type and region. Darling-Hammond & Sykes (2003) argue that if school funding continues to be reliant on local sources of revenue, then the labor market for teachers will always produce hiring and retention-related inequities.

### *Teacher Turnover and Compensation*

Perhaps the most well-cited reason for teacher turnover is compensation. At the start of this study, the wave of teacher strikes over the last 18 months have been visual illustrations of both low pay and state investment in public education. Salaries can vary significantly across and within states with Boser & Straus (2014) reporting that in more than 30 states, the average teacher who is the breadwinner for a family of four would qualify for several forms of government assistance. The online hospitality service Airbnb reported that a surprising 10 percent of its hosting population are teachers with the number of such hosts reaching 17 percent in Philadelphia alone, furthering bolstering this argument (Airbnb, 2018). Even by international comparisons, where salaries are in U.S. dollars with a conversation rate often in the dollar’s favor, the OECD (2018) found that salaries on average in the block (absent the United States) are comparable to those of other college graduates whereas American teachers received 30 percent less remuneration on average than other college graduates. Even Hanushek, Piopiunik, and Wiederhold (2014) have gone as far as to say that in OECD countries where teacher pay is above average, student achievement on PISA results show significant improvement vis-à-vis the attraction of teachers with higher cognitive abilities with a 10 percent increase in wages correlating with a higher return in math and science achievement compared to reading.

In the United States, teacher salaries have precipitously declined relative to those of other college-educated workers since 1994, when the disparity between both groups was a mere 1.8 percent. Unfortunately, in the nearly 30 intervening years, the gap has exacerbated to 17 percent, with the most significant drop amongst experienced teachers rather than on entry-level teachers (Allegretto & Mishel, 2016). Their finding does not mean that starting salaries for new teachers have fared much better. As early as the late 1990s, Gritz & Theobald (1996) and Hanushek, Kain, and Rivkin (1999) both noticed that salary differences seem to matter more at the start of the teaching career (within the first five years) more than any other factor in terms of teacher retention. A few years later, Temin (2003) suggested that new teacher salaries were sufficiently low enough to attract a disproportionately higher number of unqualified individuals compared to other professions, thereby increasing the chances of a turnover. The concept of low compensation is often associated with urban schools, although rural schools are also victims of inequitable spending with salaries in some cases even lower than their urban counterparts. Beginning teacher salaries in the ten most rural states were on average $7,000 less than beginning teacher salaries in the ten most urbanized states with the difference only increasing over time (NEA, 2018). Moreover, DeFeo et al. (2017) found that teacher turnover in rural Alaska averaged 25 percent to 30 percent annually costing the state over $20 million annually. In response, the state raised teacher wages to include a premium for rural teachers to stay in remote areas; Alaska today compensates the average teacher ~$10,000 above the median income for all teachers in the country with a noticeable drop in turnover despite persistent shortages.

Critics have often contended that these studies fail to account for the generous benefits, including a state pension, that public school teachers receive – a rarity in the private sector. However, these improved benefits are the result of collective bargaining, rather than some employer munificence. This disparity does decrease when the whole compensation package, including benefits, is considered, but the Allegretto & Mishel study found that even the full package was still 11 percent less than that of comparable workers in 2015. Keefe (2018) reinforces these findings arguing that Pennsylvania public school teachers are significantly under-compensated relative to other full-time workers with similar education and skills by 12 percent, but the effect of better benefits reduced this gap to 6.8 percent because of collective bargaining. Interestingly, critics also fail to acknowledge that in other OECD countries, teacher wages are higher and social programs, such as universal healthcare and state-sponsored pensions, are available to all employees effectively increasing the power of their wages.

### ***Teacher Turnover and the School Environment***

Within and outside the education field, job-related stress has historically been a factor in issues as far ranging as productivity to employee mental and physical health. Some researchers have suggested that the unique nature of teaching, the needs of the population served, and the rapid increase in accountability measures, all contribute to an elevated stress level that is ultimately unsustainable (Garmston, 1998; Moulthrop et al., 2005). However, the provisions associated with collective labor action can reduce stress and, in turn, job dissatisfaction that leads to higher chances of turnover.

***The Connection Between Workplace Stress & Burnout.*** In the school setting, sources of stress can be discrete or interrelated, with poor working conditions, poor relations with staff/administrators, and student behavior all known to contribute to teacher turnover or burnout. Abel & Sewell (1999) observe that both urban and rural teachers experience stress from poor working conditions, but the effects of pupil misbehavior compounded stress for urban teachers whereas time pressures compounded stress for rural teachers. Both the number of assignments and years of experience can also influence teacher stress. Torres (2014) found that in "no excuses" charter schools, nearly a third of teachers who perceived their workload to be "unmanageable" left their school in less than two years of initial hire. Even experienced teachers are not immune to the effects of overloaded schedules. When faced with shortages, administrators often lean on more experienced educators to help shoulder the gap left by a departing teacher with a simple solution being an increase in workload. Butt & Lance (2005) found that increasing number of assignments either in a given school year or over many consecutive school years can lead to burnout since these teachers are forced to adjust to both new work dynamics and develop new lesson plans. Fisher (2011) claims that even without the shifting of assignments, prolonged exposure in a high pressured and short-staffed teaching environment can lead to burnout rather than acclimation and improvement. Previous studies validate this argument; Clotfelter et al. (2009), in their study of North Carolina teachers, found that teachers employed in the bottom quartile of schools academically took more sick days than those employed in the top quartile. In some extreme cases, the lack of an adequate supply of substitute teachers often involved colleagues taking turns covering for the absent teacher's classes – a surefire way to increase burnout and reduce trust among coworkers. Predictably, from an international perspective, the OECD (2014) calculated that the average number of hours a primary and secondary public-school teacher taught annually was 782 and 694, respectively, compared to over 1,000 hours for each in the United States.

***The Role of Support Services.*** Support services include non-instructional school staff such as security personnel, counselors, nurses, psychologists, and so on, who attend to the safety, physical, and mental welfare of students. At times it is easy to overlook their role in schools since they are not in front of the classroom; their background support is nonetheless vital to the functioning of the school. Moreover, even though administrators in this group receive much attention, it is the other support staff coupled with teachers who can translate and administrator's goals or vision into action.

The lack of support services and their resulting impact on teacher stress, burnout, and ultimately retention, have been most studied most often in urban schools because of their underfunded and high-need population. For instance, school counselors, on top of providing one-on-one and small grouping counseling services, also work with various stakeholders to design, implement, and evaluate comprehensive wellness programs within schools (e.g., drug abuse awareness, addressing bullying, promoting tolerance and respect). Gagnon & Mattingly (2016) found that although the American School Counselors Association recommends a student: school counselor ratio of 250:1, rural and school districts were the greatest transgressors with a student: counselor ratios of 380:1 and 499:1, respectively. Hightower (2002) spoke of the power of having both adequately supplied support staff that was strategically applied to complement teaching and learning over three years at the San Diego Unified School District. Coupled with reforms in California's state funding laws, which made even more money available to that district for support services, the district has enjoyed some of the highest student achievement results and lowest turnover rates amongst similarly sized urban districts nationally.

Moreover, a parallel vein of literature has emerged about incorporating support services into the urban school setting called community schooling, which seeks to serve the holistic needs of students and their families with expanded medical services, after-school programming, and even job training, with the goal of lifting the burden of these needs off already overloaded teachers and school staff. (Epstein & Sheldon, 2002; Sheldon, 2003; Sheldon & Van Voorhis, 2004) The SDP, which had eliminated most support services at the start of the AY2012-13 due to severe financial constraints following the ARRA stimulus period, has established 12 such schools since AY2016-17 using revenue from its controversial soda tax to finance this venture.

Like their urban counterparts, rural areas also experience a shortage of support services with the most acute effects felt by special education teachers. Berry (2012) found that, in a study of rural districts across 33 states, those with a limited number of support services found lower rates of job satisfaction and commitment to the position amongst special education teachers. Berry & Gravelle (2013) expounded on this finding by stating that special educators did enjoy working in rural communities, which fostered family-like relationships resulting in in-depth relationships with parents and students but did feel generally overwhelmed by the non-instructional aspects of their role, such as counseling and therapy, which they attributed to role confusion and shortage of services.

Lastly, even in suburban schools, which are generally thought to be well staffed, the exponential rise in youth mental health issues such as the effects of bullying, anxiety, depression, and even suicidal ideation, has resulted in school nurses increasingly assuming more therapy-related services along with counselors and psychologists. Teich, Robinson, and Weist (2008) found in the first national survey of mental health services in public schools, that suburban schools reported that the frequency and severity of mental health problems were increasing as resource levels were either static or decreasing, resulting in overtaxed staff prone to an increased risk of burnout.

***The Tempering Effects of Organized Labor.*** The previous section highlighted the role CBAs play in buoying teacher pay. Equally important is the effect they have on mitigating adverse working conditions. Eberts (1987), in his study of unionized school districts in New York state, found that the reduction in force (i.e., seniority rules) and class size limitation provisions significantly reduced the probability of teacher turnover in these districts compared to those lacking such provisions. Milkman (1997) in his comparison of minority student achievement amongst unionized and nonunionized schools, found that student achievement in unionized schools with large minority populations was significantly higher since teachers were permitted a voice in setting school priorities compared with their peers in nonunionized schools with similar demographics. Both Bubb & Earley (2004) and Day (2008) have linked teacher satisfaction to the ability of CBAs to place limits on workloads, resulting in more work-life balance.

The previous chapter discussed how “Right-to-Work” legislation has sought to weaken the bargaining power of teachers’ unions, resulting in some unsettling side effects. Roth (2017) found that following Wisconsin’s Act 10, which weakened the collective bargaining power of teachers’ unions, specifically teacher tenure, there was a sharp increase in turnover driven almost entirely by the exit of more experienced older (tenured) teachers who were incentivized to seek retirement. Likewise, Cowen & Strunk (2014) found that in Michigan, which passed laws limiting teacher tenure and implemented more accountability measures, teacher turnover had a disparate effect on low incoming, high minority schools compared to wealthier, middle-class ones.

### *Teacher Turnover in Relation to Preparation and Age*

Researchers have also attempted the find a relationship between teacher preparation and turnover through direct and indirect means, with the latter focusing on student achievement as an outcome. These academics reason that teachers who experience difficulties improving student achievement, particularly in high-pressure environments, are likely to be more at risk of leaving than those who meet expectations. More recently, others have approached the issue from a generational perspective, especially between Generation

Millennials and Baby Boomers, the former of which will tie the latter in workplace representation by 2020, resulting in significant implications for leaders (Lynch, 2008).

***Debating the Utility of Teacher Certification.*** Teacher certification across the country consists of three components – an undergraduate degree, completion of a teacher certification program and a certification exam. These requirements are an outgrowth of NCLB's "Highly Qualified Teacher" (HQT) designation, which was (in theory) designed to prepare all teachers well enough to handle the challenges associated with meeting the law's ambitious goal of ensuring 100 percent proficiency for all students on reading, writing, and mathematics standardized tests. Researchers since the law's passage in 2001 have debated if the requirement has had any influence on student achievement or just exacerbated a pre-existing shortage.

Eppley (2009) is a disciple of the latter, believing that the timeline for rural schools to have 100 percent "highly qualified" teachers was so unrealistic given the demographic and geographic challenges present in Pennsylvania's rural schools that those LEAs, even by the end of the decade, were struggling to meet the HQT requirement. Murname & Steele (2007) invoke a similar argument in suggesting that instituting a certification requirement places a restriction on supply and demand and deterring potentially qualified educators from the classroom. Ingvarson (1999) uses the same argument of supply and demand to advocate on behalf of certification, noting that in constricting supply, it also increases wages. Boyd et al. (2007) add to this by proposing that teacher certification serves as quality control designed to keep the least capable candidates and, by extension, those potentially at the highest risk of turnover, out of the profession altogether. This assertion validates research done by Miller, Brownell & Smith (1999), who reported a higher level of external turnover among uncertified special education teachers than certified ones.

Regarding degree attainment, Goldhaber (2002) notes a small association in which the effect of degree attainment depends on the subject matter taught with the effects most pronounced in STEM fields. Curiously, Quartz (2003) found that most of the teachers who left the profession within the first seven years did not major in education, implying that those who intended to pursue education from the onset are more likely to be committed to the field than those who did not consider teaching as a first option. Prospective teacher licensure candidates must also obtain a passing score on the PRAXIS Series Examinations either on the general exam or the subject content knowledge exam. In an extension of the Boyd et al., study, Angrist & Guryan (2008) suggest that the PRAXIS requirement serves more as an exclusionary measure rather than an indicator of teacher effectiveness with African-American and Hispanics candidates having markedly low licensure scores compared to other groups. Curiously, the effect of standardized test scores on attracting and retaining teachers appears to begin before the PRAXIS series exams. Stinebrickner (2002) observed that those teachers who left the profession and did not major in education on average received higher SAT math scores than those who majored in education and stayed. The same finding was found to be true in a similar comparison of ACT scores (Podgursky, Monroe, and Watson, 2004). Hanushek (2003) adds that despite increases in teacher educational attainment and teacher standardized testing (PRAXIS or otherwise), both factors were statistically insignificant in predicting student achievement. Rockoff et al. (2011) confirm this finding by suggesting that that traditional indicators of teacher quality, particularly education, have limited correlation with student achievement as opposed to non-traditional indicators such as personality traits, self-efficacy, beliefs/values have much better predictive power; these latter characteristics are also known to have a negative correlation with turnover.

Perhaps the fiercest debate amongst researchers has been about the efficacy of teacher preparation programs in training graduates for a long-term career in the profession. Linda Darling-Hammond of Stanford University has published several studies that speak to the potential of teacher preparation programs to be highly effective in setting teachers on the path to success well after their initial years in the profession. She and her colleagues note that those programs which diminish the gap between theory and practice, provide extensive experience in schools, and immerse preservice teachers in the school climate, report teachers who have a high degree of confidence and resilience during the critical first few years of teaching (Darling-Hammond, Wise, and Klein, 1999; Darling-Hammond, Chung, and Frelow, 2002; Darling Hammond & Youngs, 2002). Others have had a less favorable view of these programs. Greenberg, McKee, and Walsh (2013) labeled teacher preparation programs as “an industry of mediocrity” contending that 75 percent of teacher training programs do not train potential educators in how to teaching reading based on the latest research. Furthermore, only 10 percent of primary training programs and 33 percent of secondary training programs prepare students to teach Common Core Standards, and only 7 percent of teacher training programs ensure students are partnered with an experienced and competent teacher with most placed *ad hoc* with any teacher willing to host them regardless of quality or experience.

These findings have been used to support alternative teacher preparation programs such as Teach for America (TfA) as well as The New Teacher Project (TNTP) and New York City (NYC) Teaching Fellows programs, which are designed to place teachers in high need environments within only a few weeks of preparation. Clark et al. (2013) in their analysis of data across eight states, found that students taught by TfA and TNTP Teaching Fellow teachers learned on average 2.6 more months of secondary math compared to students taught by traditionally certified teachers. Critics of that study are quick to draw attention to the fact that, in this same study, these initial gains faded over time; by the fourth and fifth year, student achievement from the alternative certified cohort and the traditionally certified cohort was indistinguishable. Others such as Kane, Rockoff, and Staiger (2008) charge that instead of helping to reduce turnover, programs like TfA and NYC Teaching Fellows worsen it with 50 percent of NYC Teaching Fellows and 80 percent of TfA graduates leaving their respective teaching positions after four years into the profession compared to only 37 percent of traditionally prepared teachers.

***The Generational Divide in the Teacher Workforce***. When approaching the study of turnover from a generational perspective, several researchers have maintained that high rates of teacher turnover compound what is an aging labor workforce coupled with low supply. Ingersoll & Merrill (2010) observed that the teacher labor market bifurcates into two categories rather than existing as a continuum between Baby Boomers and Millennials. The former is nearing retirement whereas there is a diminishing number of the latter seeking to go into teaching, especially in high needs subjects such as STEM, special education and ESL. Grissmer & Kirby (1997) showed that the incidence of teacher turnover followed a U-shaped distribution, with the highest attrition occurring early and later in teachers' careers. Moreover, they stated what though pay and working conditions are known to influences of teacher turnover earlier in one’s career, retirement influences turnover at the opposite end of the age spectrum. The exodus of Baby Boomers because of retirement has sounded alarms all over the country regarding the financial solvency of state pension systems, particularly in Pennsylvania, where the U.S. Census Bureau (2010) estimates that the Commonwealth is seventh in the country in terms of the aging population with almost 18 percent of the state over the age of 65.

Anticipating financial costs associated with this generational shift, many social scientists have implored organizations to embrace changes in their management approach to this much younger demographic as older Baby Boomers find themselves leading and managing younger Millennials. Hershatter & Epstein (2010) explored ways that Millennials approached the world of work and suggested that this generation actively sought to integrate technology into their lives and expect accommodations by organizations based upon their experiences, needs, and desires. Myers & Sadaghiani (2010) discussed Millennials workplace expectations, communication styles, and relationships with team and organizational members. Both researchers suggested that Millennials work well in team settings, are motivated by meaningful tasks, prefer open and frequent communication, and are adept at communication technologies, which will require reconfigurations of workplace logistics. In their empirical study of the effect of generation on work attitudes, Kowske, Rasch, and Wiley (2010) found that Millennials have higher levels of overall company satisfaction, sense of with job security, and chances for career advancement than Baby Boomers and Ng, Schweitzer, and Lyons (2010) discovered that Millennials place a high premium on skill development as well as a work-life balance. These findings have consequences for current school leaders, many of them who are for an older generation, for how to lead and motivate a younger generation of teachers.

### ***Teacher Turnover by High Need Subject Area***

There is a well-established stock of turnover literature that highlights issues associated with attracting and retaining high need teachers, especially those teaching in the areas of mathematics, science, special education, and ESL. In some cases, this need is the result of supply and demand, where there is either not enough graduates to teach in a given subject area or need because of rapid student population growth in specific demographics is faster than capacity. In addition to supply and demand, the nature of these positions adds a layer of stress unbeknownst to their low need counterparts.

***Math and Science Teachers.*** The concern over math and science teacher shortages is nothing new with a series of commission reports trumpeting the need for an increase (National Commission on Teaching and America's Future, 1996, 1997, 2003) well after the *A Nation at Risk* report. What is new is the additional thrust this concern has received in the last two decades in the name of more STEM education, with arguments ranging from the economic to the political as the American labor force faces increasing competition from rising Asian economies (The Glenn Commission, 2000; National Research Council, 2002). Consequently, federal and state agencies have unleashed a host of STEM-related grants and initiatives that have received bipartisan Congressional support in recent budget proposals. Supply, both raw and because of excessive turnover in STEM, continues to be a vital issue in attracting and retaining qualified STEM teachers.

Ingersoll & May (2012) have attempted to separate discussion of math and science teacher need by arguing that shortages in both subjects are not the result of the same cause. The suggest that shortages in the latter are more likely the result of retention, with nearly two-thirds of departing science teachers citing better opportunities in pay and working conditions. However, they note that math teachers are at lower risk of turnover since they are far less likely to be laid off than science teachers, given the importance of mathematics in standardized test accountability. Likewise, Sutcher, Darling-Hammond, and Carver-Thomas (2016) have argued that turnover of STEM teachers in urban environments reaches 70 percent because these individuals are often in high demand both within and outside the public education system. Schwartzbeck et al. (2003) note a parallel between the challenges urban and rural schools have in attracting math and science teachers in the wake of the NCLB's HQT provision. Rural schools have attempted to reconcile limitations in supply, size, and retention by seeking multi-certificated teachers who can teach many subjects within the same school. Moreover, this approach has had some success in non-high subjects such as English and Social Studies but finding a singularly certified math or science educator alone is a challenge.

A further complicating factor is that secondary mathematics certifications encompass all levels of mathematics from Pre-Algebra/Algebra I to Calculus compared to secondary science certifications, which are parsed by subject matter (e.g., biology, chemistry, and physics), a distinction that has a noticeable impact on curriculum and instruction. Kelly & Sheppard (2008) found that nearly 50 percent of NYC high schools do not offer physics, a subject that is critical to career advancement in many post-secondary STEM programs and one that the figures from Bureau of Labor Statistics consistently show is the most challenging position to fill in secondary schools. One reason cited for the elimination of physics was the NYC Department of Education's (DoE) inability to fill the position due to prolonged vacancies and excessive turnover. Without a viable supply of candidates, districts like the NYC DoE have reworked their curriculums and academic programming to exclude such subjects. Perhaps even more concerning is the dire shortage of qualified computer science teachers with 2017 Higher Education Title II data reporting a mere 75 computer science teachers graduates from teacher preparation programs that year – a sharp contrast to The College Board's report of 72,187 students who took the new AP Computer Science Principles Exam when administered for the second time in May 2018 (College Board, 2018).

***Special Education and ESL Teachers.*** Although special educators may not always serve as teachers of record, several studies have claimed that these supporting teachers experience higher levels of stress due to more challenging student behaviors and "role workload" (i.e., the presumption that special needs students are the sole responsibility of the assigned special education teacher) (Adera & Bullock, 2010; Hastings & Brown, 2002; Skaalvik & Skaalvik, 2007). While the issue of discrepancy (fit) is not exclusive to supporting teachers, Wasburn-Moses (2009) maintains that while pre-service special educators' expectations of the classroom are relatively accurate, they considerably overestimate the amount of support they will receive from administrators and peers. Vannest & Hagan-Burke (2010) provide evidence for this discrepancy by noting that special educators believe they spend an inordinate amount of their schedule performing administrative type work such as IEP meetings, paperwork, communications with parents and lawyers, and so on, rather than supporting either teachers or students. Billingsley (2004) has suggested that turnover rates for special education teachers are likely higher since many special educators, disillusioned by their work, often transition to the general education classroom with no intention of returning.

While ESL teachers support students in much the same way special educators do, they generally work with a student population demarcated by race or ethnicity. According to the National Center for Education Statistics (2016), an overwhelming 77 percent of Spanish speaking students comprise the English Language Learner (ELL) population trailed by Arabic, Chinese, and Vietnamese speakers. With respect to all ESL teachers, Durgunoglu & Hughes (2010) confirm the same discrepancy related finding as Wasburn-Moses noting that pre-service teachers were confident in their preparedness to teach ESL (as evidenced by performance on the knowledge test), yet struggled to teach ELLs in the classroom, notably absent any guidance from their mentoring teachers. Katz (1999) highlights how an incongruence between the perceptions of a predominantly European-American ESL teachers and their majority Central-American ELL students can lead to disengagement for both parties. Using a case study of a Northern California school, she observed that Latino students often felt discriminated against by their teachers, leading to disengagement and ultimately drop out. However, their teachers felt they were always struggling to give these students due attention because their school administration pressured them to focus on those students who had the highest chance of improvement on state standardized testing. Because of this pressure and feeling of impotence, the school ultimately suffered from long-term difficulties in retaining qualified ESL teachers. Several researchers (Cummins, 2003; Hargreaves, 2003; Miller, 2011) have confirmed this relationship between ESL teacher burnout and the outsized role of standardized testing in the name of educational reform. These academics reason that ELL students require intensive one-on-one interaction with their teachers, who ultimately come to develop a nuanced understanding of these students' languages, families, sociocultural traditions, and community. However, this socioemotional investment becomes tricky in a culture of scapegoating, where district administrators, politicians, and the public expect an immediate turnaround in schools with high minority populations, which puts additional pressures on teachers to deliver results.

### ***Teacher Turnover by Geography and LEA Type***

Because teaching is a highly social field, Boyd et al. (2005) have claimed that teachers have an affinity to take jobs close to the neighborhood of their youth, and if they do indeed choose to leave, teach in districts that are similar demographically to their hometown. Because teaching is considered a middle-class profession, there is often a surplus of teachers interested in teaching in popular locales with few seeking to go actively into urban or rural teaching, both of which can have a high concentration of low-income students. Such reasoning does not exclude a preference for urban teaching. Engel (2013) found that Chicago Public Schools principals reported being encouraged to advertise positions only within the school district’s eBulletin and most principals reported networking only within the district to find prospective teachers. In a continuation study, Engel, Jacob, and Curran (2014) found that prospective teachers in Chicago were likely to apply for positions in schools that had similar demographics to their current neighborhood.

***Unique Properties of Urban LEAs.*** In perhaps the most famous of all teacher turnover studies, Ingersoll (2001) found that nearly half of urban teachers leave the teaching profession within the first five years of teaching citing low pay and poor administrative support as the top two reasons for leaving. Moreover, he suggests that teacher turnover also has a disproportionate impact on disadvantaged students (low income, minority) since urban schools are chronically understaffed, thereby leading to a host of interrelated problems from poor school climate to subpar student achievement. Even among more experienced teachers, Loeb & Page (2000) note that turnover between schools appears to be influenced more by “nonpecuniary factors” like working conditions as well as opportunities for growth and leadership. Steinberg et al. (2018) found that in the School District of Philadelphia, an average of 27 percent of teachers either undergo internal or external turnover at the end of a school year with serious implications for school leadership. Guin (2004) contends that teacher turnover is a barometer for urban elementary school health as it hinders the implementation of a coherent and uniform instruction and can lead to highly variable quality of teaching and learning *within the same school*. Guin’s argument is validated by Harris (2002), who found that teachers in high-minority, low-income schools who reported significantly fewer amenities including poorer facilities, less availability of textbooks and supplies, larger class sizes, and were most acutely affected, were the likeliest to search for alternative teaching assignments either outside the school or the district. Moreover, as the Guin study implies, certain types of educational leadership in urban schools can accentuate the risk of turnover with many educational leaders engaging in “top-down” reform with the side effect of negating teacher professionalism. Bogler (2001) reported that the more teachers who perceived their occupation as a profession and the more they perceived their principals to embody shared leadership, the higher the number of teachers who reported job satisfaction.

***Unique Properties of Rural LEAs.*** Rural teacher turnover, while often underreported, has striking similarities compared to its urban counterpart. For instance, while urban researchers discuss the achievement in racial terms with African-American and Hispanic students academically lagging when compared to their European/Asian-American peers, low-income rural students also struggle to make progress on par with their wealthier suburban counterparts (Allensworth, Ponisciak, and Mazzeo, 2009). Unique to rural schools is the issue of size and its relation to recruitment. Because rural LEAs tend to be expansive in size, attracting and retaining teachers presents additional geographic hurdles. Strauss et al. (2000) found that school superintendents in Pennsylvania often prioritized recruiting teachers from local rural and small-town settings even if their qualifications did not meet position requirements in the hopes that these teachers were more rooted in the community and therefore less likely to leave. Ingersoll & Rossi (1995) found that smaller schools (≤300 students enrolled) experienced higher turnover rates than larger schools (≥1,000 students enrolled). These findings together complement research that suggests that the retention rate for rural teachers is often on par with urban districts, with some areas reaching a high of 30 percent compared to the natural average of eight percent cited at the beginning of this half of the chapter (Davis, 2002).

***Unique Properties of Suburban LEAs.*** Researchers have historically paid less attention to suburban teacher turnover believing these schools to be the beneficiaries of urban and rural turnover. This assumption is only correct for wealthy suburban schools since they receive multiple applications for a given vacancy that, in turn, permits more rigorous hiring practices such as requiring prior years of experience or post-baccalaureate credentials as only requirements for the position. With the rise of income equality coupled with substance abuse issues, some middle- and working-class suburbs are quickly become “islands” of poverty with students in these residents quickly falling behind their upper-middle-class peers (Kneebone & Garr, 2010). Moreover, while these pockets of suburban poverty may have more resources than their urban counterparts, they equally suffer from a supply of capable and qualified candidates including school leaders. In a research study of four South Florida school districts, Watlington et al. (2004) assessed the relationship between teacher retention and demographics in four districts with varied demographic profiles from the urban Broward County School District (BCSD), which served over 270,000 students to the suburban Okeechobee County School District (OCSD), which served 7,000 students and had a high minority and ESL population. After the three-year study period, it was not the BCSD which had the lowest retention but the OCSD, which failed to implement a teacher induction and principal leadership program with any fidelity, thereby pushing the onus of adapting to rapidly changing demographics on teachers. Although findings revealed that all four districts collectively retained 96 percent, 79 percent, and 72 percent of the sample population after the first, second, and third years, respectively, the OCSD had significantly lower retention rates compared to this overall average, suggesting that an inadequate approach to both instructional leadership and teacher induction had a role in abetting teacher turnover.

# CHAPTER 3

# DATA & METHODS

In the previous chapter, I discussed how researchers had approached the issue of teacher retention from multiple dimensions, with each facet examining an aspect of the teaching environment. In this chapter, I explore the data and methodological approach used in this study, both of which lie at the heart of its novelty. As I mentioned at the start of this study, the use of the data spans the entire population as well across multiple years warrants a sophisticated methodology that can both accommodate nuance and minimize assumptions. In a sense, both concepts oppose one another, and so I provide reasoning for my methodological instrument of choice – survival modeling – as well as the modifications I made to account for nuance as well as limit assumptions.

## Overview of Data & Variables

The master dataset in this study was built using a total of 17 datasets. The first set of six datasets titled Professional Personnel Individual Staff (PPIS) data came from the PDE for AY2012-13 through AY2017-18. These files contained individual (teacher) data such as qualifications and assignments for all certified staff employed within the Commonwealth for each academic year. The second set of five (5) datasets titled School Performance Profile (SPP) data came from the PDE for AY2012-13 through AY2016-17 – the five-year observation period for this study. These files contained demographic and academic variables for each school operating in the Commonwealth. The last set of five datasets titled Annual Financial Report (AFR) Data for AY2012-13 through AY2016-17 came from the PDE. These files contained all LEA level expenditures – aggregate and per student – for each fiscal year per the spending categories outlined in Chapter 1. The final dataset came from the Council for Community and Economic Research (C2ER) and contained Cost of Living Indices (CoLIs) for each county in the state.

### ***Data Acquisition***

The first 16 datasets are publicly available to any individual within and outside the Commonwealth via the PDE's website. While these datasets do contain identifiable information for all certificated staff in the state, this study is exempt from Institutional Review Board approval since this data is public record. The final dataset is from C2ER, but only for the Commonwealth and for the tax ending in December 2017.

***Data Collection Procedures.*** Given the enormity and complexity of these datasets, the PDE relies on a reporting database called the Pennsylvania Information Management System (PIMS). All LEAs are required annually to submit student, teacher, and school data for a breadth of demographic, academic, and organizational related inquiries. Moreover, this data is reported consistent with USDoE definitions (e.g., Title I, race/ethnicity, IDEA designations) and PDE established guidelines.

***Significance of the Observation Period.*** The SPP datasets span a five-year observation period during which there were critical education policy changes at the federal and state levels. In 2011, the USDoE, under the direction of the Obama administration, permitted states to apply for a waiver from specific provisions, such as the Adequate Yearly Progress (AYP) requirement, of the NCLB Act. As a condition of the waiver, the applicant was required to implement its system of accountability that needed approval from the USDoE. Consequently, Pennsylvania enacted Act 82, which outlines the various components of this new accountability system including a revised standardized testing program aligned to the Common Core State Standards, termed the Pennsylvania System of State Assessments (PSSA) and the Keystone Exams; the adoption of a new teacher evaluation framework (Danielson and PVAAS); and more transparent reporting requirements. SPP data, which was first published in AY2012-13, was an outgrowth of Act 82's transparency reporting requirements in which the PDE was required to publish a composite building score (on a 100-point scale), along with several other demographic and academic metrics (also on a 100-point scale) for each school in the Commonwealth.

These state waivers stayed in effect until Congress approved a new amendment to ESEA titled Every Student Succeeds Act (ESSA) of 2015, which is the federal education policy still in effect today. Since ESSA is a formal replacement to NCLB, several states have opted to either modify or terminate provisions established in their initial NCLB waivers in favor of more flexible criteria. In Pennsylvania, the PDE modified some waiver provisions, especially those relating to the public reporting of school performance and issued the last SPP dataset in AY2016-17. Because the General Assembly has not formally repealed Act 82, the PDE is still required to compile SPP data for internal evaluation purposes although it does make this data public. Instead, the PDE now reports school performance using the Future Ready PA Index, which became public in AY2018-19.

### *Data Preparation*

The data preparation process consisted of several stages designed to simplify, transform, and ultimately merge all 17 independent datasets into one master file. This section provides an overview and, perhaps more importantly, the reasoning associated with the data preparation protocol. For a detailed stepwise strategy, see attached Appendix A.

***Working with Population Data.*** Sample sizes and power have historically vexed quantitative research since many quantitative studies rely on data collection via survey instruments, which can suffer from sampling bias or too few respondents (Hackshaw, 2008). The PDE requires all LEAS to submit institutional data via PIMS, which is essentially a survey instrument in the form of a database, resulting in longitudinal population data which accounts for a dynamic teacher population – one that is entering, leaving or changing assignments, schools or LEAs between academic years. This type of population data can help researchers create both holistic and granular analyses at various levels to identify and compare trends.

The availability and ability to process such extensive data have only recently been possible thanks to advancements in computing. For instance, although the number of certified education professionals in the Commonwealth has been well above 100,000 for well over a decade, PPIS data files until 2010 only reported 65,000 records since they were publicly available as *.xls files, an older Microsoft Excel format that could accommodate only 65,536 entries. Post-2010 files are now available as *.xlsx files, the latest Excel format, which can accommodate over a million entries. Moreover, advances in computing such as the introduction of multi-core/64-bit processors, solid state drives, and several modules of RAM, all have reduced the processing time associated with such vast tracts of data, resulting in expedient calculations in a relatively small period.

***Data Restructuring Procedures.*** Working with population data is not without its challenges and restructuring all 17 datasets required inferring missing data and manipulating variables, such that model results provided meaningful values. Consequently, to simplify what would otherwise have been an overly tedious process, data management occurred in either Microsoft Excel 2016 or IBM SPSS v23.0, the latter of which offered a more straightforward graphic user interface (GUI) menu system as opposed to creating macros in the former to perform the same functions. Data assemblage occurred in the following six stages.

(1) Cleaning, simplifying, and manipulating teacher level PPIS data

(2) Cleaning, refining, and manipulating SPP data,

(3) Interpolating missing data and aggregating all measures into LEA level variables,

(4) Incorporating AFR and COLI data into the newly created LEA level datasets,

(5) Merging teacher level and LEA level datasets first by year and then all years into one master file, *and*

(6) Creating a sophisticated algorithm to link teacher records throughout the dataset and formatting variable names and labels as needed.

***Missing Data Analysis.*** Although PDE requires all LEAs to submit metrics via the PIMS database, some data might become omitted due to some exceptional reason. While there is the possibility of missing data in any of the PDE issued datasets, missing data was limited only to one SPP file. The *de facto* approach to handling missing data is multiple imputations. However, this method presents significant logistical hurdles when working with large datasets. There is general agreement in the research community that multiple imputations are a superior method to data replacement compared to others (e.g., replacement by mean, listwise deletion).

Furthermore, some researchers have asserted that multiple imputations provide the most accurate value ranges when the number of imputations equals the highest percentage of missing data, a supposition that disputes the traditional "rule-of-thumb" of calculating only five imputations (Royston, 2004; Rubin, 2004; Schafer, 1999). Other researchers have attempted to work around this suggestion by first performing the recommended number of imputations but then summating the imputed values into one dataset. This approach may seem practical, but several researchers have noted it is statistically problematic since the variation associated with the imputed values is lost in aggregation (Mittag, 2013; Musil et al., 2000). Regardless, the sheer volume of the data makes the prospect of multiple imputations unpalatable since one SPP file contains over 3,500 entries, and with even five imputations, this would result in a dataset of 17,500 imputations, far too unwieldy to link with hundreds of thousands of PPIS cases, when creating a single master file.

A more straightforward yet potent approach to handling this missing data is to perform a series of interpolations, in which a few data points are used to infer missing data. These interpolations can be linear or polynomial (known as spline interpolations) with the intent of approximating either a line or a curve to best match the available data points to estimate the missing value. Interpolation has received support from researchers in the natural sciences who view it as a viable alternative to the complications associated with multiple imputations when working with large datasets (Junninen et al., 2004; Stuart et al., 2009). In this study, the following SPP variables needed interpolation vis-à-vis their percent missingness:

(1) Building Score (20.0 percent),

(2) PSSA/Keystone ELA/Literature Proficiency Scores (9.98 percent),

(3) PSSA/Keystone Math/Algebra I Proficiency Scores (9.98 percent),

(4) PSSA/Keystone Science/Biology Proficiency Scores (9.98 percent),

(5) ELA/Lit Average Growth Index (AGI) (20.0 percent),

(6) Math/Algebra I Average Growth Index (20.0 percent), *and*

(7) Science/Biology Average Growth Index (20.0 percent)

The pattern in the missing data is no coincidence. In AY2014-15, the year the state applied for an extension to its NCLB waiver, there was delay first in the processing and later in the reporting of standardized test scores by the PDE. However, one of the state's NCLB waiver provisions, as specified in Act 82, required the PDE to nonetheless report the data publicly by a pre-established deadline. Accordingly, that year, SPP data did not include standardized test scores as well as Building and AGI scores derived from those standardized test scores. Furthermore, because this data is Not Missing at Random (NMAR), even attempting multiple imputations would violate this method's underlying concept of shared variance, leaving interpolation as a more realistic option.

The most accurate linear and curvilinear interpolations were the result of the following three steps in SPSS:

(1) The interpolation was performed longitudinally since an LEA's performance from one year to the next is far more likely to consistent than performance between all LEAs in a single year,

(2) The interpolation was performed on each LEA individually so as not to influence or be influenced by the values of other LEAs, *and*

(3) Because of the limited number of points (with a maximum of five years), standardized test scores would first undergo a linear interpolation followed by a curvilinear interpolation for Building and AGI scores.

Unlike standardized test scores, which tend to have some degree of consistency in their calculations and meanings from year to year, building and AGI scores can fluctuate significantly because of their value-added formulas. For the latter variables, using a curvilinear (polynomial) approximation that utilized at least three data points, provided more accurate values compared to linear interpolation alone. Because of this procedure, the three standardized testing variables used in the final models had a post-interpolation missingness value of ≤two percent.

### ***Summary of Variables***

The master dataset contained a total of 737,683 cases each with 55 variables of either nominal, ordinal, or scalar value. Of course, attempting to load so many variables into a single model is both unrealistic and problematic. Some of these variables are complementary (e.g., male/female) and including them in a single model would lead to issues of collinearity. Other variables were in a raw state (e.g., salary) that needed transformation if they were to yield any meaningful results. This study used only 25 of these variables, and a full summary that includes means and standard deviations for them is provided in Table 3.1 by region.

***Defining Dependent and Independent Variables.*** The dependent variable is a simple binary measure used to identify turnover. Because this study examines teacher departure from an LEA, a value of ‘1’ corresponds to any teacher who left an LEA at the *end* of the academic year whereas a value of ‘0’ corresponds to any teacher who remained at the *end* of the academic year in an LEA.

**Table 3.1 • Summary for All Variables by Region (Avg. AY2011-12 through AY2016-17) [*n* (cases)=596,118]**

| | | Greater Philadelphia CSA | | Greater Pittsburgh CSA | | Central Pennsylvania Region | |
|---|---|---|---|---|---|---|---|
| **Variable Name** | **Variable Measure** | **Mean** | **Standard Deviation** | **Mean** | **Standard Deviation** | **Mean** | **Standard Deviation** |
| **yearsexp** | Years Experience | 12.68 | 8.46 | 13.40 | 8.12 | 13.77 | 8.66 |
| **adjsalary** | CoLI Adjusted Salary | $59,381 | $16,199 | $68,651 | $19,584 | $64,127 | $14,715 |
| **expstatus** | New Educators | 22.60% | | 17.53% | | 17.91% | |
| | Experienced Educators | 77.40% | | 82.47% | | 82.09% | |
| **higheduc** | Some College or Less | 0.17% | | 0.18% | | 0.32% | |
| | Bachelor's Degree | 44.64% | | 49.11% | | 43.58% | |
| | Master's Degree | 54.50% | | 50.11% | | 55.73% | |
| | Specialist's or Doctoral Degree | 0.69% | | 0.60% | | 0.36% | |
| **highneed** | Low Need Areas | 63.75% | | 65.77% | | 64.47% | |
| | Mathematics | 7.52% | | 7.42% | | 7.20% | |
| | Natural Sciences | 5.69% | | 6.44% | | 6.61% | |
| | Special, Alternative or Remedial Education | 17.88% | | 18.07% | | 19.38% | |
| | English as a Second Language | 1.77% | | 0.46% | | 1.39% | |
| | Administrators/Building Support | 3.39% | | 1.84% | | 1.49% | |
| **numassign** | Number of Assignments | 1.37 | 0.93 | 1.21 | 0.55 | 1.26 | 0.67 |
| **leaclass** | Urban District(s) | 20.10% | | 8.55% | | 13.67% | |
| | Suburban Title I Districts | 11.85% | | 27.72% | | 10.39% | |
| | Suburban Non-Title I Districts | 54.71% | | 59.12% | | 32.13% | |
| | Rural Title I Districts | 12.97% | | 4.20% | | 18.32% | |
| | Rural Non-Title I Districts | | | | | 22.14% | |
| | Charter Schools | | | | | 2.53% | |
| | Career & Technical Schools | 0.38% | | 0.41% | | 0.82% | |
| **adjauxspend** | CoLI Adjusted Auxiliary Per Student Spending | $5,784 | $1,492 | $7,571 | $1,678 | $6,916 | $1,698 |
| **black** | Percent African-American | 24.89 | 27.25 | 13.55 | 21.06 | 6.93 | 10.21 |
| **hisp** | Percent (Non-White) Hispanic | 12.06 | 16.25 | 1.39 | 0.87 | 10.67 | `5.07 |
| **sped** | Percent Special Education | 15.64 | 3.56 | 14.54 | 3.91 | 15.27 | 3.26 |
| **ell** | English Language Learner | 4.45 | 4.61 | 0.75 | 1.10 | 2.50 | 3.96 |
| **readprof** | Percent PSSA/Keystone ELA/Literature Proficiency | 65.04 | 20.97 | 70.63 | 14.99 | 67.13 | 12.93 |
| **mathprof** | Percent PSSA/Keystone Math/Algebra I Proficiency | 56.68 | 24.04 | 61.81 | 18.86 | 58.71 | 17.37 |
| **sciprof** | Percent PSSA/Keystone Science/Biology Proficiency | 71.39 | 17.41 | 74.49 | 13.88 | 75.98 | 13.04 |

Therefore, each case has either a' 0' or '1' value and any given teacher could conceivably have stayed in the LEA for all five years (all '0's), changed LEAs at the end of every year (all '1's), or have some combination thereof. Since this variable is not native to the PPIS data, I compared each educator's newly created educator ID (see Appendix A) with the following year to determine if that individual was retained or left; for the final year of the study, AY2016-17, I used AY2017-18 data (released on July 31, 2018) to finalize the dataset.

The variables used in this study exist in two groupings: predictors that answered the research questions and covariates designed to control for other influencing effects on the outcome. The two continuous predictors were salary and auxiliary spending, both of which needed to be manipulated to capture their effects on the outcome variable accurately. The four categorical predictors were: experience status, the highest level of education, subject area taught, and LEA type. Experience status is dichotomous, with "New Teacher" defined as those with ≤five years of experience and an "Experienced Teacher" defined as those with >five years of experience. The highest level of education category collapsed into four categories: (a) "Some College or Less," (b) "Bachelor's Degree," (c) "Master's Degree," and (d) "Specialist's or Doctoral Degree." (Note that all teachers *except* vocational teachers are required to have at least an undergraduate degree to teach in the state.) During the observation period, the state employed teachers in 385 areas, which I categorized into 14 categories (Appendix B) and later further reduced into six domains to facilitate analysis in my models: (a) "Non-High Needs", (b) "Mathematics", (c) "Science", (d) "Special Education", (e) "English as a Second Language", and (f) "Others". Lastly, the

PHL and PGH regions have five LEA types compared with seven LEA types in the CPA region based on their shared characteristics. (See Chapter 1 for more details.)

For the covariates, LEA demographic and academic variables were provided by PDE as percentage points (on a 100-point scale), and so I divided their values into five percentage point increments to make a reasonable inference about a unit increase in any of those covariables. Furthermore, those covariates were group centered by LEA, meaning that the variance that remained was exclusively between-group variance, therefore, allowing for the model to better estimate the effect of the predictors on the outcome.

***Recalculating Continuous Variables of Interest.*** The two continuous predictor variables, which are monetary values, needed to be recalculated and transformed before including them in the models. First, the PDE reports teacher salaries and LEA expenditures in $1.00 increments. Consequently, calculating auxiliary spending for all LEAs for each year of the study required dividing the total amount spent in each of the five reporting categories (instructional costs, pupil support service costs, non-instructional costs, facilitates costs, and financing costs) by the LEA's total expenditure and then summating all spending outside instructional costs.

PDE, however, did not provide raw values for either salary or auxiliary spending adjusted for cost of living. Because of the vast differences in the cost of living by county across the Commonwealth as detailed in Table 1.1, without equalizing these monetary values, it would be difficult to make an accurate comparison statewide. To do so required multiplying salary and auxiliary spending by the county CoLI in which the LEA resides. CoLI values can be interpreted as ratios to a baseline of 100 for the whole state, A teacher earning $50,000 in a county with a CoLI of 125 (25 percent above state average) will likely see the power of his earnings lessened compared to a teacher earning the same amount in a county with a CoLI of 80 (20 percent below state average).

Lastly, when researchers study the effect of money on an outcome, they need to contend with the concept of diminishing returns. For instance, the effect on some outcome of a $5,000 pay raise for an individual earning $40,000 is likely to be higher than the same raise given to individual earning $100,000. Economists therefore often opt to use a natural log (ln) transformation which magnifies the effect of lower earnings and diminishes the effect of higher earnings (Klein, 1997). The models, therefore, employ these recalculated CoLI adjusted salaries and CoLI adjusted auxiliary spending in log dollars.

## Modeling Theory: Survival Analysis

Survival models are used by researchers to analyze time to event data. (In fact, the name is derived from medical studies, which examine time to an event such as relapse or death.) Singer & Willett (2003) maintain that data must have the following three characteristics to justify using a survival model:

(1) The dependent variables are (a) the occurrence of a well-defined event (known as failure) and (b) the wait time until the occurrence of a failure event,

(2) There are predictors or explanatory variables whose effect on the wait time can be assessed or control, *and*

(3) The observations are censored, which means that for some individuals, the event (failure) has not occurred at the end of the observation period.

They also argue that the utility of survival models lies in the third criterion since censored observations can provide insight into how predictors exert influence the outcome.

***Understanding the Concept of Hazard***

The crux of understanding survival models lies in the concept of hazard. Because survival models incorporate two outcomes – the event (failure) and time – the concept of survival hinges on the risk that a subject will survive at the next time interval $t$+1 based on the conditions that led to its survival at time $t$. Mathematically, hazard at time $t$ can be expressed using the function h($t$) = f($t$)/S($t$), where h($t$) is the hazard function, f($t$) is the probability that the subject will experience the event (failure) at time $t$, and S($t$) is the probability that the subject will survive past time $t$ (Singer & Willett, 2003). Because survival models span multiple time points ranging from a few periods (as is the case in this study) to much longer lengths of time (days, months, years, etc.) attempting to calculate a hazard rate for each time point would result in a lengthy list of hazard values that would inevitably become far too cumbersome to interpret. Survival models provide a single hazard rate that is calculated using the following equation:

$$h(t) = \lim_{\Delta t \to 0} \frac{\text{observed events in interval}[t, t + \Delta t]/N(t)}{\Delta t} \quad (3.1)$$

where $t_1$ is the initial time, $t+\Delta t$ is the subsequent time and N(t) the number of individuals who start at time $t$. For short observations, as is the case in this study, the hazard rate is merely an average since it is reasonable to assume that the hazard does not fluctuate radically between any of the time points in the time series. However, if there are multiple time points, such an assumption is not valid since the risk of achieving the event (failure) in the distant past is not likely to be the same risk as experiencing it today. Accordingly, the more time points, $\Delta t$ becomes smaller and smaller. Ultimately, because of the Central

Limit Theorem, as $\Delta t \rightarrow 0$, the hazard rate becomes the *instantaneous rate of change* (i.e., the derivate of function h($t$)) (Case et al., 2002)

### *Overview of Cox Proportional Survival Models*

Fitting the appropriate survival model to the data, known as model validity, rests on understanding the relationship between time and the event (failure) subjects experience during the observation period. Neelamkavil (1987) notes that "true validation is a philosophical impossibility and all we can do is either invalidate or fail to invalidate." The goal then becomes developing a model that is sufficiently accurate for the intended application and theoretically defensible (Schlesinger, 1979).

Survival models fall into three basic categories – parametric, non-parametric, and semi-parametric – with selection dependent on the underlying assumption the researcher makes about the outcome and covariates (Rodríguez, 2007). In parametric survival models, the researcher assumes some distribution of the outcome and the covariates (e.g., a group of patients monitored for rabies will undoubtedly achieve the event (death) at some point). However, in some scenarios, the researcher cannot make these assumptions (e.g., a group of patients monitored for the flu may experience recovery, relapse or even death) and must, therefore, use nonparametric survival models. In a semi-parametric model, the researcher does not make assumptions about the distribution of the outcome (as in nonparametric models) but can make assumptions about the distribution of the covariates (as in parametric models). This study fits into the third category since I cannot assume the outcome (turnover); an increase in salary or auxiliary spending may motivate some teachers to leave but have no effect on others since, as I detailed in the theoretical framework, teachers weigh many factors when considering the option leave with money and support as only two.

***Satisfying the Proportional Hazards Assumption.*** The most popular semi-parametric model and the one I used in this study is the Cox Proportional Hazards Model. These models establish a baseline hazard tailored to the time and event profile of the data, in contrast to parametric models where the baseline hazard is specified (Cox, 1972). Cox Proportional Hazard Models take the form of the equation:

$$\mathbf{h(t)} = \mathbf{h_0(t)} \times e^{\beta_1 \mathbf{x_1} + \beta_2 \mathbf{x_2} + \beta_3 \mathbf{x_3} + \ldots + \beta_n \mathbf{x_n}} \qquad (3.2)$$

where h($t$) is the hazard function at time $t$; $h_0(t)$ is the calculated baseline hazard at time $t$; and $\beta_1$, $\beta_2$, $\beta_3$ represent the model coefficient that measures the strength of variables $x_1$, $x_2$, $x_3$, respectively. On top of the three criteria established for survival models, Cox models must also satisfy an additional two fundamental assumption:

(1) The covariates in the model must have some distribution (normal or otherwise), *and*

(2) The hazard rates for all groups in the model are proportional to one another (i.e., all groups consistently show an increase or decrease in the hazard rate in tandem throughout the observation period).

Table 3.1 provides a summary of all covariates, which can be used to infer that these variables have some distribution thereby satisfying the first assumption. However, satisfying the second assumption can be a challenge especially in large datasets. There are two complementary ways to test the proportional hazards assumption in such datasets – statistically or graphically (Schoenfeld, 1982).

Statistically, researchers have traditionally used a chi-square test to test the proportional hazards assumption by testing for a non-significant relationship between covariate residuals and time. This approach can be problematic for researchers working with large datasets since it a chi-square test of these residuals is virtually guaranteed to be statistically significant (Franke, Ho, and Christie, 2012; McHugh, 2013). With the increasing popularity of "big data," this approach appears to have severe limitations. In general, attempting to calibrate global tests like the chi-squared test to large datasets is a well-known problem articulated in the extant literature with some researchers recently going as far as to state that the proportional hazards assumption can never be satisfied in large datasets (Austin, 2018; Xue, et. al., 2018).

Stratification is an alternative statistical approach that can be used to satisfy the proportional hazards assumption. In stratification, baseline hazards are calculated for specific groups (termed strata) in the dataset (Lee et al., 1992). In this study, the stratified variable is LEA type since it is safe to assume that the baseline hazard rates between LEA types likely vary even within the same region. This assumption can be validated graphically by plotting a Kaplan Meier graph or its inverse, a survival curve. If any of the curves cross or drop to zero, then the assumption has been violated. Table 3.2 provides the baseline hazards (and survival rates) for all three regional models as the result of stratification. The proportional hazards assumption is then graphically validated for each region using stratified LEA types in Figures 3.1-3.3.

***The General Estimation Equation Approach.*** Because the study incorporates both teacher and LEA data, a mixed effects equation would likely be the first approach to come to mind since these models calculate both fixed and random effects components. Therneau & Grambsch (2000) note that to engage in multilevel survival models, yet another three conditions need to be satisfied:

(1) There must be a large sample with multiple individuals, each of whom is a group of observations,

(2) Each of these individuals experiences an event several times, *and*

(3) There need to be several time points.

While this dataset easily satisfies the first condition, the remaining two conditions pose a challenge in attempting to use a mixed effects model. Concerning the second criterion, they argue that multiple events per individual (in this study, each teacher) are necessary since experienced events are necessary to calculate the numerator f($t$) of the hazard function h($t$). Logically, the more events that individual experiences, the better the estimation of the random effects. In this dataset, most educators in each region only experience the event (turnover) perhaps no more than one or two times in the study period, which leads to the third point – since there are only five-time points in this study, there are too few opportunities for individuals to experience the event. If the study period extended to 30 or more years, it is likely that not only would a more substantial number of teachers experience the event (turnover), but also many would likely experience it multiple times.

However, in the context of this study, most teachers experience the event either none, one or two times. A mixed effect approach then would create a random effects profile that would be flat and ultimately meaningless. In disqualifying the use of a mixed-effects approach, the remaining alternative is the Generalized Estimating Equation (GEE) approach, which utilizes a more flexible semi-parametric approach to survival modeling. This flexibility of GEEs is the result of several relaxed assumptions. First, the homogeneity of variance assumption does not need to be satisfied. Second, GEEs can support interaction terms as well as covariates that are either normally distributed or have a nonlinear transformation. Third, although there is no random effects component, observations can be clustered such and outcomes in a group are correlated (Zeger, Liang, and Albert, 1988).

**Table 3.2 • Baseline Hazards for Survival Models by Region [*n* (educators)=151,808]**

| | Educator Has Only 1 Year of Service in Study Period | | Educator Has Any 2 Years of Service in Study Period | | Educator Has Any 3 Years of Service in Study Period | | Educator Has Any 4 Years of Service in Study Period | | Educator Has All 5 Years of Service in Study Period | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Hazard Coefficient (β) | Survival Rate ($e^{-\beta}$) | Hazard Coefficient (β) | Survival Rate ($e^{-\beta}$) | Hazard Coefficient (β) | Survival Rate ($e^{-\beta}$) | Hazard Coefficient (β) | Survival Rate ($e^{-\beta}$) | Hazard Coefficient (β) | Survival Rate ($e^{-\beta}$) |
| ***Greater Philadelphia CSA Model*** | | | | | | | | | | |
| School District of Philadelphia | 0.121 | 89% | 0.192 | 83% | 0.252 | 78% | 0.304 | 74% | 0.354 | 70% |
| Suburban Title I Districts | 0.083 | 92% | 0.147 | 86% | 0.198 | 82% | 0.249 | 78% | 0.293 | 75% |
| Suburban Non-Title I Districts | 0.112 | 89% | 0.185 | 83% | 0.241 | 79% | 0.290 | 75% | 0.339 | 71% |
| Charter Schools | 0.235 | 79% | 0.428 | 65% | 0.608 | 54% | 0.755 | 47% | 0.880 | 41% |
| Career & Technical Schools | 0.055 | 95% | 0.109 | 90% | 0.154 | 86% | 0.185 | 83% | 0.223 | 80% |
| ***Greater Pittsburgh CSA Model*** | | | | | | | | | | |
| Pittsburgh Public Schools | 0.066 | 94% | 0.107 | 90% | 0.148 | 86% | 0.171 | 84% | 0.201 | 82% |
| Suburban Title I Districts | 0.080 | 92% | 0.127 | 88% | 0.170 | 84% | 0.202 | 82% | 0.227 | 80% |
| Suburban Non-Title I Districts | 0.087 | 92% | 0.141 | 87% | 0.181 | 83% | 0.214 | 81% | 0.239 | 79% |
| Charter Schools | 0.210 | 81% | 0.375 | 69% | 0.504 | 60% | 0.601 | 55% | 0.670 | 51% |
| Career & Technical Schools | 0.116 | 89% | 0.168 | 85% | 0.209 | 81% | 0.236 | 79% | 0.257 | 77% |
| ***Central Pennsylvania MSAs and µSAs Model*** | | | | | | | | | | |
| Regional City Districts | 0.063 | 94% | 0.110 | 90% | 0.149 | 86% | 0.184 | 83% | 0.213 | 81% |
| Suburban Title I Districts | 0.092 | 91% | 0.148 | 86% | 0.193 | 82% | 0.240 | 79% | 0.277 | 76% |
| Suburban Non-Title I Districts | 0.099 | 91% | 0.162 | 85% | 0.208 | 81% | 0.249 | 78% | 0.284 | 75% |
| Rural Title I Districts | 0.107 | 90% | 0.166 | 85% | 0.210 | 81% | 0.255 | 78% | 0.295 | 74% |
| Rural Non-Title I Districts | 0.125 | 88% | 0.185 | 83% | 0.231 | 79% | 0.282 | 75% | 0.320 | 73% |
| Charter Schools | 0.210 | 81% | 0.373 | 69% | 0.506 | 60% | 0.607 | 54% | 0.705 | 49% |
| Career & Technical Schools | 0.065 | 94% | 0.116 | 89% | 0.159 | 85% | 0.204 | 82% | 0.242 | 78% |

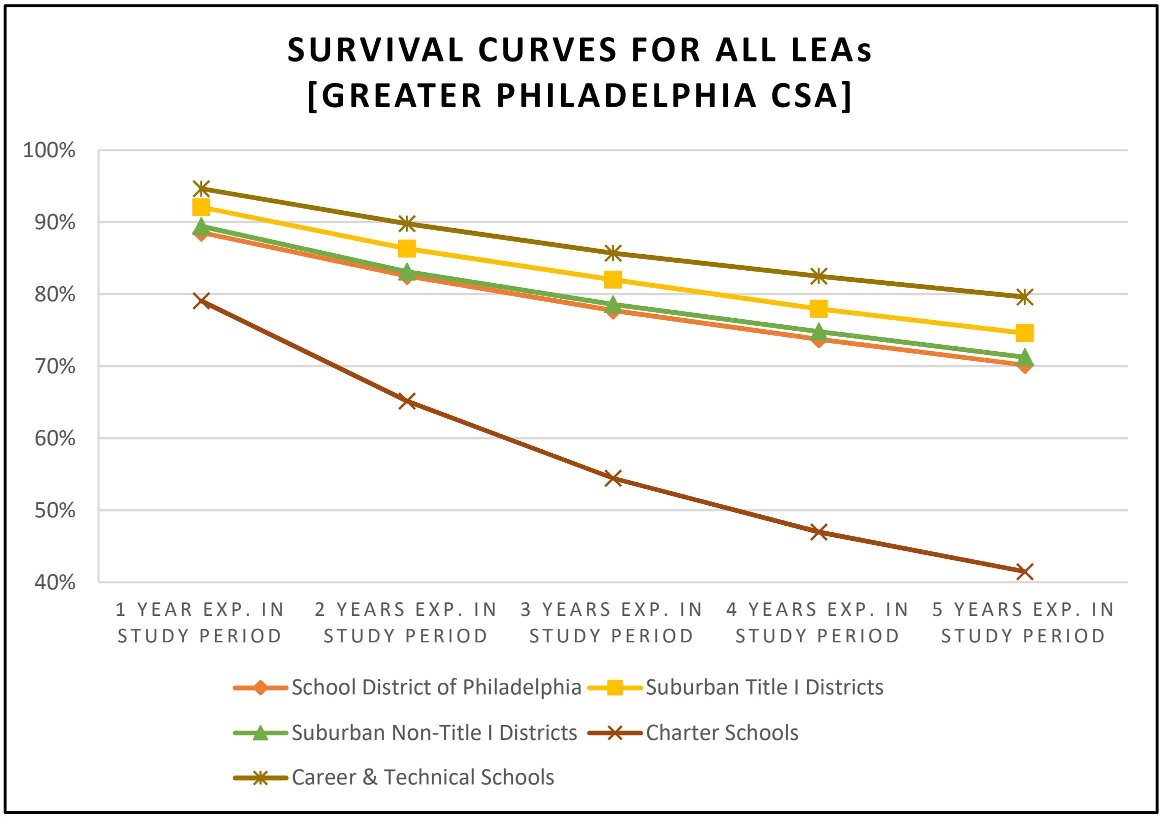



**Figure 3.1** Survival (Reciprocal Kaplan-Meier) Curve for All LEAs in the Greater Philadelphia Region.

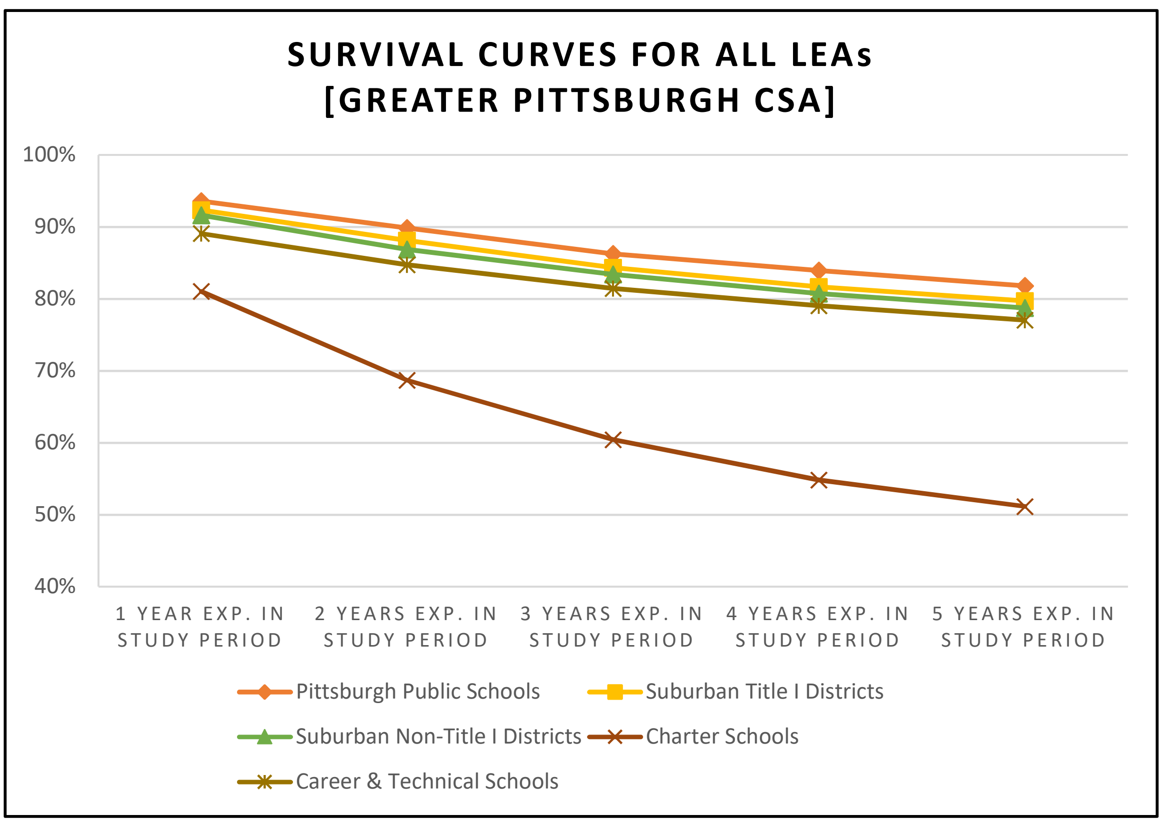



**Figure 3.2** Survival (Reciprocal Kaplan-Meier) Curve for All LEAs in the Greater Pittsburgh Region.

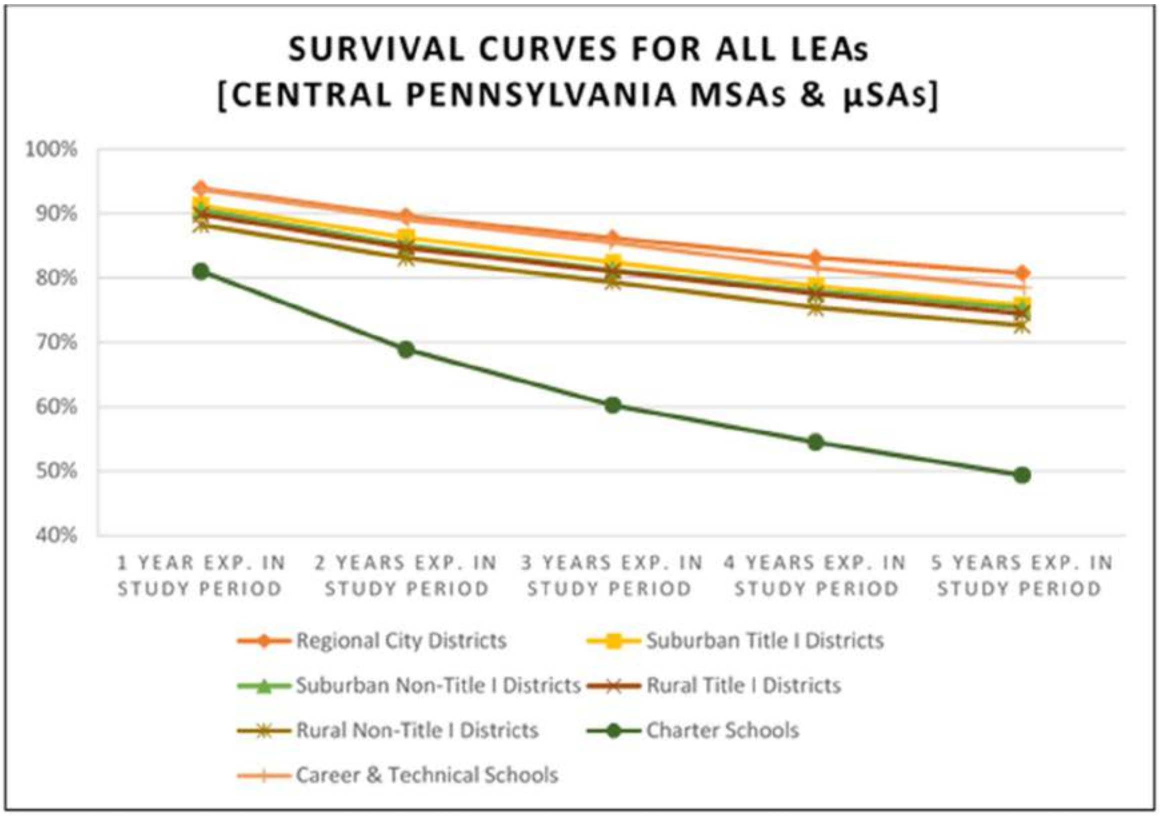



**Figure 3.3** Survival (Reciprocal Kaplan-Meier) Curve for All LEAs in the Central Pennsylvania Region.

## Data Analytic Plan

However, correctly identifying the strengths and limitations of survival models is only half the battle. The data has to be in the form of the person-period format, which is necessary for useful survival analysis. Accordingly, each observation had its own set of dependent, and independent values and observations belonging to the same teacher were linked across years using an artificially produced teacher ID (see Appendix A).

### *Accommodating Discrete Time Points into Cox Models*

It is worth mentioning here that usually in Cox Proportional Hazard Models, time is continuous (e.g., minutes, hours, days) rather than discrete (e.g., months, years, decades). However, these models can be modified to account for discrete time. The benefit of using a Cox Proportional Hazard Model in this study is that the model can accommodate an uneven number of observations per group in a way that standard logistic regression cannot. This imbalance results from the fact that study period covers a dynamic population; many teachers in this dataset were already employed at some point before the start of the observation period while others came into the population during the observation period. In either case, a teacher may have experienced the event one or more times or not at all, thereby surviving past the end of the observation period. Some teachers may have left early in the observation period only to reappear towards the end. It is critical then that this person-period dataset accounts for all types of behavior within the Cox model.

The ideal situation is if all teachers in the dataset had the same number of observations (e.g., all teachers had only four years of service during the study period) resulting in balanced panel data. However, this dataset is quite unbalanced since teachers can range from having anywhere between one to all five years of service in the study period. Creating an *absolute* and *relative* clock with start and stop years that could account for the year of the study period and the year of service performed in the study period, respectively, is one approach to compensate for this unbalance. For instance, a continuously employed teacher for the first three years of the observation period would have an absolute and relative clock that were aligned (e.g., AY2012-13, AY2013-14, and AY2014-15 of study matched the first, second, and third years of service during the observation period). However, a teacher who left the system to emerge later in the observation period would have disjointed clocks (e.g., had three years of service during the study period but in AY2012-13, AY2014-15, and AY2016-17). By incorporating both an absolute and relative clock into the model, the survival model becomes a series of logistic (binomial) regressions and thereby modifying the Cox Proportional Hazard Model to accommodate discrete time points. Table 3.2 and Figures 3.1-3.3 express a modified version of the baseline hazard. In traditional Cox models, the baseline hazard rate accumulates with the progression of an absolute clock. In this study, the baseline hazard rate is still cumulative but with the progress of the relative clock. Therefore, the baseline hazard (and the model results) is predicated not on teacher year of entry, but total teacher years of service in the study period (Therneau & Grambsch, 2000).

### *Building the Model Structure*

With the theoretical and logistical concerns addressed, the only remaining step was to create the models themselves. However, executing multiple models, each with nearly two dozen variables and interaction groupings, in addition to analyzing such a large dataset in three parallel parts, required a computer system that could accommodate this task. The natural choice was to use R, a freeware statistical computing program, that came pre-installed on Amazon Web Services, a cloud computing service that allows users to purchase time on a host of preconfigured supercomputers.

***Coding Technique in R.*** The R packages I used to build the models were the survival, and coxme packages with the latter containing the coxph function used to build Cox Proportional Hazard Models. The coxph function uses a GEE approach that allows for stratification, clustering, the incorporation of time-varying covariates, and interactions. Appendix C outlines the full R code for this study.

In addition to the theoretical underpinnings of the models, each set of research questions required individually tailored equations conditioned on preset reference groups as required by the research questions posed. The first set of research questions attempt to capture the hazard incurred by either a "New Teacher" or an "Experienced Teacher" in each LEA category by region. As such, model coefficients are the product of a three-way interaction:

(1) Log Salary x LEA Type x Experience & Education Level *and*

(2) Log Auxiliary Spending x LEA Type x Experience & Education Level

Including a three-way interaction allows parsing the main effect of Log Salary or Log Auxiliary Spending by obtaining a model coefficient (β) for every possible permutation of the three-way interaction. The main effect then is the value conditioned on reference group tested (e.g., the main effect of Log Salary for a New Teacher in the School District of Philadelphia is Log Salary *x* SDP *x* New Teacher w/Bachelor's Degree). Since the main effect for Log Salary and Log Auxiliary Spending is dependent on the reference category in any given model, the plan necessitated creating a total of 34 parallel models across all three regions [2 (experience/education levels) x 17 LEA Types].

By extension, the same reasoning applies to the models created to address the second set of research questions, which requires capturing the hazard incurred by a "High Needs Subject Area" teacher for each LEA category by region. As such, the model coefficients are also a product of a three-way interaction:

(1) Log Salary x LEA Type x High Need Subject Area *and*

(2) Log Auxiliary Spending x LEA Type x High Need Subject Area

Again, including a three-way interaction allows parsing the main effect of Log Salary or Log Auxiliary Spending by obtaining a model coefficient (β) for every possible permutation of the three-way interaction. Therefore, the main effect is the value conditioned on the reference group tested (e.g., the main effect of Log Salary for a Science Teacher in Pittsburgh Public Schools is Log Salary *x* PPS *x* Science). Since the main effect for Log Salary and Log Auxiliary Spending is dependent on the reference category in any given model, the plan mandated a total of 46 parallel models across all three regions [4 (high need subjects) x 14 LEA Types].

***Excluded Cases.*** Finally, there were many individual cases excluded from the final analysis. First, the analysis excluded any educator who singularly served an administrator or building support staff personnel during the observation period since these individuals are not relevant to the study and their inclusion would unduly skew the model results. However, if an administrator or building support staff member served as a teacher for even one year of service during the observation period, then the individual was included in the study and excluding these administrators and building support staff removed about 15 percent of the population data.

Second, teachers employed by the Intermediate Units (IUs) were not included in the analysis because all IUs, except for IU#2 (Pittsburgh Public Schools) and IU#26 (School District of Philadelphia), do not have defined per student spending or, by extension, per student spending components and they lack any academic or demographic information, rendering them ineligible for analysis. Likewise, teachers that taught in the Commonwealth's eight Juvenile Justice Centers (JJCs) are also not included in the study. Recall from the missing values analysis discussion that 3 percent of LEA academic profile variables were still missing post-interpolation. These missing values belong to IUs and JJCs, who employ certificated staff but are not subject to the same operations as their more traditional LEA counterparts. Accordingly, excluding these teachers removed approximately 2.5 percent of the population data.

Finally, about two percent of the data did not match using the algorithm provided in Appendix A. These cases were also teachers, but because of some exceptional reason could not be identified. These omissions would include complete name changes, change in sex/gender identification, and so on. As a result, the dataset used in the final analysis 596,118 cases across all three regions, accounting for 96.3 percent of the teacher population and 80.8 percent of the entire teacher population in the Commonwealth.

# CHAPTER 4

# RESULTS

In the previous chapter, I detailed the assembly and organization of the master data file followed by an extensive discussion of the modeling approach used to analyze this data. In this chapter, I delve into this data by first presenting the descriptive findings, which are intended to provide a synoptic overview of teachers and their employing LEAs, followed by an exploration of the inferential (modeling) results. Recall that this study focuses on two veins of research questions: (a) the effect of fiscal spending on salary and auxiliary spending on new vs. experienced teachers and (b) the effect of the same monetary increase on high need teacher (content vs. support).

Whereas both questions examine two different teacher populations, they seek to understand the same phenomenon – do monetary increases encourage teachers to retain their placement? In Chapter 2, I outlined the financial, academic, and organizational costs associated with teacher turnover in addition to some theoretical frameworks that describe how teachers (and, by extension, any employee) engage in the calculus to leave an organization. Considering the impetus for this study, LEAs and state agencies have good reason to identify and understand the economic influences on teacher turnover and what policy changes, if any, are possible. In addition to the simplicity of both questions, the use of population data coupled with a rigorous methodological approach provides an opportunity to make a compelling argument that links teacher turnover with financial incentives, teacher motives, and the ramifications of local and state education policy.

## Descriptive Results

Descriptive results, which focus on illustrating summary details of the data, are a powerful tool in recognizing trends that emerge in the dataset. In fact, in large datasets with a comprehensive set of variables, a close examination of descriptive results is necessary first to identify and later explicate these trends with model findings. In the analyses that follow, note that the summary data is an average across all five years of the study and therefore these results are not representative of any one year. Statistically, presenting an average minimizes variation over the study period, mitigating the influence of any outstanding values. Furthermore, the values in all descriptive tables are weighted means using either the number of teachers in a given category or student enrollment.

### *Overview of LEAs*

Recall from Chapter 1 that the Commonwealth contains 500 LEAs, which are all included in the master dataset except Bryn Athyn School District. Moreover, three of the remaining 499 districts serve only a K-8 population; Midland Borough School District, Duquesne City School District, and Saint Clair Area School District do not contain 9-12 schools because of low enrollment coupled with financial constraints.

***Demographic Trends.*** Table 4.1 provides a summary of both the distribution of study cases throughout the three regions and LEA characteristics such as student enrollment, demographics, and academics. The percent of observations, which serve as proxy for the overall teacher population, and the percent of the state's student enrollment, are aligned within each region – PHL (Obs.: 35 percent vs Enroll. 36 percent), PGH (Obs.: 19 percent vs. Enroll.: 19 percent), and CPA (Obs.: 46 percent vs. Enroll.: 45 percent) – suggesting that no one region has a disproportionate number of teachers relative to the other. Nevertheless, the percentages for Historically Underperforming Students (HUS) are more skewed. The PHL region educates the highest portion of African-American students (61 percent) in the Commonwealth on top of the highest share of charter school enrollment (68 percent). Despite the demographic diversity of the PHL region, the CPA region educates the highest percentage of Hispanic students (51 percent) followed by the PHL region (46 percent) with both regions dwarfing the PGH region (4 percent). Curiously though, the highest share of ELLs is in the PHL region (56 percent) with the CPA region (39 percent) and PGH region (5 percent) trailing behind – mirroring statewide demographic changes due to the recent Hispanic population migration patterns presented at the start of this study. The distribution of special education students is much more even throughout the PHL (37 percent), PGH (18 percent), and CPA (45 percent) regions.

There is also a skewness in terms of the academic profile of each region. The PHL region has the lowest PSSA/Keystone ELA/Literature proficiency rate (65 percent) compared to that of the PGH region (71 percent) and slightly lower compared to the CPA region (67 percent). The same is true concerning PSSA/Keystone Mathematics/Algebra I proficiency rates with the PHL region (57 percent) again behind the PGH (62 percent) and CPA (59 percent) regions. Proficiency rates for LEAs with the lowest number of HUS performed similarly to their counterparts in the other regions on all three test measures, confirming long-established findings regarding the racial achievement gap.

***Financial Trends.*** Table 4.2 provides an overview of financial metrics for the 700+ LEAs operating in the Commonwealth during the study period. (Remember from the previous chapter that this analysis does not include teachers employed in correctional institutions or IUs.) Expectedly, the PHL region has the highest CoLI of 116.1 compared to the PGH and CPA regions, which have CoLIs of 93.4 and 90.9, respectively. What may not be clear is how much these CoLI values can alter the buying power of each dollar spent on goods and services by an LEA. For instance, in the PHL region, the value of $1.00 is roughly equivalent to $0.86 whereas, in the PGH and CPA regions, that same dollar would have a purchasing power of $1.07 and $1.10, respectively. Adjusting salaries for CoLIs to equalize value across a region is analogous to invoking the macroeconomic concept of Purchasing Power Parity (PPP) (The Economist, 2019). PPP calculations argue that "true" currency exchange rates between countries should factor the relative cost of the same goods and services (i.e., the purchasing power of wages) rather than the current nominal approach based on the supply and demand for a country's currency in the foreign exchange market. Accordingly, compared to nominal values, values adjusted for CoLI allow for a more authentic comparison between the effect of money on an outcome across regions with high differences in the cost of living. However, this reasoning does not discount the role of nominal values since at the state level, government agencies treat all dollars equally terms of policy. Since the focus of this study is to understand teacher decision-making, the models use CoLI adjusted dollars; nominal dollars will receive attention in the next chapter.

Furthermore, as a product of the state's funding formula, the PHL region has the highest nominal per-student spending ($16,736), except when adjusted for the region's CoLI, has a diminished value ($14,124) compared to the PGH ($17,683) and CPA ($16,344) regions, which benefit from lower CoLIs. This finding is even more remarkable when considering that the PHL region furnishes almost 44 percent of Pennsylvania's nominal GDP as detailed in Table 1.2. Problematically, this disparity increases geometrically over time because of the state funding formula's hold harmless provision.

Not only is the value of the dollar diminished in terms of purchasing power in the PHL region, the steady population increase here means that this diminished dollar must accommodate even more students in the absence of compensatory tax revenue.

**Table 4.1 • Overview of LEAs: Student Population, Historically Underperforming Student Groups, and Standardized Testing Profile (Avg. AY2011-12 through AY2016-17) [*n* (cases)=596,118]**

| | Study Cases & LEA Student Population | | | | Historically Underperfoming Student Groups | | | | Standardized Testing Profile | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | *n* (Study Cases) | *n* (LEAs in 2017) | *n* (Student Enrollment) | Percent of Region (Student Enrollment) | Percent African-American Student Population | Percent Hispanic Student Population | Percent Special Education Student Population | Percent English Language Learner Student Population | PSSA ELA/Keystone Literature Proficiency Rate | PSSA Mathematics/ Keystone Algebra I Proficiency Rate | PSSA Science/ Keystone Biology Proficiency Rate |
| ***Greater Philadelphia CSA*** | | | | | | | | | | | |
| School District of Philadelphia | 41,989 | 1 | 136983 | 21.94% | 52.74% | 15.55% | 13.65% | 9.24% | 40.00% | 31.94% | 52.21% |
| Suburban Title I Districts | 24,749 | 17 | 73,998 | 11.85% | 27.95% | 26.06% | 17.57% | 7.17% | 54.04% | 45.82% | 64.03% |
| Suburban Non-Title I Districts | 114,309 | 62 | 323,238 | 51.78% | 7.55% | 6.68% | 15.71% | 2.30% | 80.84% | 73.26% | 82.43% |
| Charter Schools | 27,096 | 100 | 87,512 | 14.02% | 52.59% | 16.64% | 16.56% | 3.71% | 47.49% | 35.35% | 61.91% |
| Career & Technical Schools | 790 | 7 | 2,518 | 0.40% | 7.79% | 7.95% | 19.94% | 0.78% | 55.80% | 45.71% | 51.55% |
| Greater Philadelphia CSA Totals/Weighted Average (by Student Enrollment) | 208,933 | 187 | 624,249 | | 24.89% | 12.06% | 15.64% | 4.45% | 65.04% | 56.68% | 71.39% |
| ***Greater Pittsburgh CSA*** | | | | | | | | | | | |
| Pittsburgh Public Schools | 9,903 | 1 | 24,713 | 7.50% | 53.72% | 2.48% | 16.47% | 3.07% | 50.78% | 42.85% | 54.88% |
| Suburban Title I Districts | 32,100 | 45 | 88,008 | 26.69% | 17.55% | 1.17% | 16.28% | 0.31% | 63.15% | 54.37% | 70.30% |
| Suburban Non-Title I Districts | 68,474 | 74 | 197,447 | 59.89% | 4.09% | 1.28% | 13.24% | 0.65% | 78.40% | 69.89% | 79.85% |
| Charter Schools | 4,859 | 25 | 18,343 | 5.56% | 39.61% | 2.30% | 16.86% | 0.38% | 53.30% | 38.09% | 68.47% |
| Career & Technical Schools | 478 | 3 | 1,187 | 0.36% | 2.29% | 0.24% | 19.24% | 0.02% | 46.81% | 37.35% | 54.48% |
| Greater Pittsburgh CSA Totals/Weighted Average (by Student Enrollment) | 115,814 | 148 | 329,698 | | 13.55% | 1.39% | 14.54% | 0.75% | 70.63% | 61.81% | 74.49% |
| ***Central Pennsylvania MSAs and µSAs*** | | | | | | | | | | | |
| Regional City Districts | 37,217 | 12 | 110,293 | 14.13% | 19.19% | 38.05% | 16.31% | 10.23% | 48.37% | 39.45% | 62.82% |
| Suburban Title I Districts | 28,142 | 32 | 83,132 | 10.65% | 4.61% | 7.20% | 14.89% | 1.34% | 68.21% | 59.15% | 77.64% |
| Suburban Non-Title I Districts | 87,139 | 83 | 259,045 | 33.18% | 4.46% | 6.83% | 14.18% | 1.62% | 75.07% | 67.23% | 81.82% |
| Rural Title I Districts | 49,699 | 96 | 133,798 | 17.14% | 5.45% | 3.72% | 16.65% | 0.59% | 65.32% | 56.82% | 75.16% |
| Rural Non-Title I Districts | 60,010 | 76 | 165,175 | 21.16% | 3.93% | 4.99% | 15.13% | 0.97% | 70.98% | 63.06% | 76.97% |
| Charter Schools | 6,928 | 45 | 22,044 | 2.82% | 16.92% | 23.41% | 15.53% | 3.97% | 51.18% | 36.45% | 68.90% |
| Career & Technical Schools | 2,236 | 7 | 7,144 | 0.92% | 10.43% | 15.76% | 17.85% | 1.91% | 42.57% | 35.11% | 60.55% |
| Central Pennsylvania Totals/Weighted Average (by Student Enrollment) | 271,371 | 351 | 780,630 | | 6.93% | 10.67% | 15.27% | 2.50% | 67.13% | 58.71% | 75.98% |

**Table 4.2 • Overview of LEAs: Per Student Spending & Spending Components (Avg. AY2011-12 through AY2016-17) [*n* (Total LEAs)=801]**

| | Aggregate Spending | | | | | Per Student Spending Components | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Average CoLI (PA =100) | Raw Per Student Spending | Adjusted Per Student Spending | Adjusted Per Student 5yr. Spending Diff. | Adjusted Auxiliary Spending | Percent Instructional | Percent Student Support Services | Percent Non-Instructional | Percent Facilities & Financing |
| ***Greater Philadelphia CSA*** | | | | | | | | | |
| School District of Philadelphia | 109.7 | $14,027 | $12,951 | $1,677 | $4,545 | 65.14% | 20.51% | 0.50% | 13.85% |
| Suburban Title I Districts | 118.1 | $17,036 | $14,597 | $1,928 | $5,512 | 61.49% | 26.96% | 1.54% | 10.01% |
| Suburban Non-Title I Districts | 120.3 | $18,042 | $14,728 | $1,853 | $6,275 | 56.86% | 28.24% | 1.73% | 13.18% |
| Charter Schools | 112.6 | $14,803 | $12,939 | $1,581 | $5,894 | 53.77% | 39.44% | 2.34% | 4.45% |
| Career & Technical Schools | 121.9 | $19,223 | $14,807 | $1,703 | $5,196 | 63.84% | 32.11% | 0.42% | 3.62% |
| Greater Philadelphia CSA Weighted Average (by LEA size) | 116.1 | $16,736 | $14,124 | | $5,784 | | | | |
| ***Greater Pittsburgh CSA*** | | | | | | | | | |
| Pittsburgh Public Schools | 96.9 | $22,615 | $23,339 | $4,399 | $9,758 | 58.09% | 29.93% | 0.91% | 11.06% |
| Suburban Title I Districts | 91.8 | $16,399 | $17,959 | $3,791 | $7,471 | 58.26% | 29.19% | 2.22% | 10.34% |
| Suburban Non-Title I Districts | 93.8 | $15,741 | $16,671 | $2,772 | $7,281 | 56.12% | 29.59% | 2.36% | 11.93% |
| Charter Schools | 96.5 | $17,772 | $18,388 | $3,535 | $7,814 | 54.95% | 39.18% | 1.28% | 4.59% |
| Career & Technical Schools | 91.8 | $16,539 | $19,801 | $2,655 | $8,045 | 60.81% | 37.38% | 0.55% | 1.26% |
| Greater Pittsburgh CSA Weighted Average (by LEA size) | 93.4 | $16,600 | $17,683 | | $7,571 | | | | |
| ***Central Pennsylvania MSAs and µSAs*** | | | | | | | | | |
| Regional City Districts | 95.4 | $14,510 | $15,088 | $2,158 | $5,649 | 61.97% | 25.96% | 1.46% | 10.61% |
| Suburban Title I Districts | 96.0 | $15,086 | $15,586 | $2,171 | $6,481 | 58.40% | 27.21% | 2.18% | 12.21% |
| Suburban Non-Title I Districts | 98.7 | $15,096 | $15,174 | $2,183 | $6,498 | 56.75% | 28.45% | 2.07% | 12.74% |
| Rural Title I Districts | 83.7 | $15,595 | $18,400 | $2,943 | $7,944 | 56.70% | 29.67% | 2.38% | 11.24% |
| Rural Non-Title I Districts | 86.8 | $15,648 | $17,510 | $2,653 | $7,676 | 56.21% | 29.65% | 2.15% | 11.99% |
| Charter Schools | 96.4 | $15,466 | $16,005 | $2,181 | $6,870 | 56.81% | 36.10% | 2.01% | 5.08% |
| Career & Technical Schools | 89.5 | $15,873 | $16,452 | $2,788 | $6,637 | 59.25% | 34.21% | 0.95% | 5.59% |
| Central Pennsylvania Weighted Average (by LEA size) | 90.9 | $15,244 | $16,344 | | $6,916 | | | | |

Expectedly, when comparing per student spending components, Title I LEAs, which tend to be in areas with higher CoLIs, spend considerably more on instructional costs (teacher compensation packages) and conversely less on student support services, suggesting that remaining competitive in the labor market can be taxing on their finances.

### ***Overview of Teachers by Experience Level***

Before attempting to answer the first research question, which concerns the effect of increases in monetary value for new and experienced teachers on teacher retention, understanding the population data apropos this demographic can provide valuable insight into developing trends that are influenced by monetary investment.

***Distribution of Teachers.*** Table 4.3 provides a summary of the distribution of the on average nearly 120,000 teachers employed during the study period. As stated in Table 4.1, the percentage of teachers employed in the PHL (36 percent), PGH (19 percent), and CPA (45 percent) regions mirrors their respective share of statewide student enrollment. Ideally, the distribution of new and experienced teachers would also follow these values if no one region had more teachers of either type relative to the other. However, this is not the case. It is true that the percentage of new teachers and experienced teachers are the highest in the CPA region (New: 42 percent vs. Exp.: 46 percent), followed by the PHL (New: 41 percent vs. Exp.: 34 percent) and PGH (New: 18 percent vs. Exp.: 20 percent) regions. However, a simple comparison of these values against their equal share of statewide student enrollment suggests that the PHL region has a higher number of new teachers (or a lower number of experienced teachers) compared to its counterparts.

By extension, the ratio of experienced to new teachers is lowest in PHL region (3.4:1) and higher in both the PGH (4.7:1) and CPA (4.6:1) regions. In all three regions, every LEA type save charter schools generally has a higher percentage of experienced teachers compared to new teachers. Conversely, charters employ a disproportionately high number of new teachers with a ratio of experienced to new teachers approaching 1:1 across all three regions.

**Table 4.3 • Overview of Educator Distribution by Experience Level (Avg. AY2011-12 through AY2016-17) [*n* (educators)=119,258]**

| | New Educators | | Experienced Educators | | All Educators | | | |
|---|---|---|---|---|---|---|---|---|
| | *n* (Educators Employed) | Percent of Region | *n* (Educators Employed) | Percent of Region | *n* (Educators Employed) | Percent of Region | Student to Educator Ratio | Percent Diff. From Mean |
| ***Greater Philadelphia CSA*** | | | | | | | | |
| School District of Philadelphia | 1,626 | 17.22% | 6,772 | 20.92% | 8,398 | 20.08% | 16.31 | 9.27% |
| Suburban Title I Districts | 934 | 9.89% | 4,026 | 12.44% | 4,960 | 11.86% | 14.92 | -0.05% |
| Suburban Non-Title I Districts | 4,013 | 42.49% | 18,848 | 58.22% | 22,861 | 54.67% | 14.14 | -5.28% |
| Charter Schools | 2,844 | 30.11% | 2,576 | 7.96% | 5,420 | 12.96% | 16.15 | 8.17% |
| Career & Technical Schools | 27 | 0.29% | 154 | 0.48% | 181 | 0.43% | 13.91 | -6.80% |
| Greater Philadelphia CSA Totals/Weighted Average (by Educator Population) | 9,444 | | 32,376 | | 41,820 | | 14.93 | |
| ***Greater Pittsburgh CSA*** | | | | | | | | |
| Pittsburgh Public Schools | 365 | 8.99% | 1,616 | 8.46% | 1,981 | 8.55% | 12.47 | -12.36% |
| Suburban Title I Districts | 1,066 | 26.25% | 5,354 | 28.03% | 6,420 | 27.72% | 13.71 | -3.69% |
| Suburban Non-Title I Districts | 2,157 | 53.11% | 11,538 | 60.40% | 13,695 | 59.12% | 14.42 | 1.29% |
| Charter Schools | 454 | 11.18% | 518 | 2.71% | 972 | 4.20% | 18.87 | 32.58% |
| Career & Technical Schools | 19 | 0.47% | 76 | 0.40% | 95 | 0.41% | 12.49 | -12.23% |
| Greater Pittsburgh CSA Totals/Weighted Average (by Educator Population) | 4,061 | | 19,102 | | 23,163 | | 14.23 | |
| ***Central Pennsylvania MSAs and µSAs*** | | | | | | | | |
| Regional City Districts | 1,420 | 14.63% | 6,023 | 13.51% | 7,443 | 13.71% | 14.82 | 3.03% |
| Suburban Title I Districts | 933 | 9.62% | 4,696 | 10.54% | 5,629 | 10.37% | 14.77 | 2.68% |
| Suburban Non-Title I Districts | 2,812 | 28.98% | 14,616 | 32.79% | 17,428 | 32.11% | 14.86 | 3.34% |
| Rural Title I Districts | 1,729 | 17.82% | 8,211 | 18.42% | 9,940 | 18.31% | 13.46 | -6.41% |
| Rural Non-Title I Districts | 1,967 | 20.27% | 10,035 | 22.51% | 12,002 | 22.11% | 13.76 | -4.31% |
| Charter Schools | 746 | 7.69% | 640 | 1.44% | 1,386 | 2.55% | 15.90 | 10.58% |
| Career & Technical Schools | 96 | 0.99% | 351 | 0.79% | 447 | 0.82% | 15.98 | 11.11% |
| Central Pennsylvania Region Totals/ Weighted Average (by Educator Population) | 9,703 | | 44,572 | | 54,275 | | 14.38 | |

In the PHL region, charters employ almost a third of the entire new teacher workforce (30 percent) suggesting that these LEAs have become dependent on this readily available supply of new teachers in this region.

***Salary and Turnover Trends.*** Table 4.4 provides a summary of salaries and turnover rates for the same teacher demographics. A cursory examination of these values suggests some correlational relationship between salaries and turnover rates; the PGH region offers the highest regional salary ($68,651) and has the lowest rate of turnover (6 percent) as opposed to the PHL region which offers the lowest regional salary ($59,381) and bears the highest rate of turnover (9 percent). Equally meaningful is how these values compare within and across regions by experience level. New teachers on average are remunerated more equally across all three regions within a smaller range of $5,272 compared to experienced teachers whose average salary spans a broader range of $8,806.

Interestingly, in all three regions, both new and experienced average salaries in the major urban district(s) are higher than their regional averages although the trends amongst these three are not equally consistent. The SDP pays new teachers on average considerably more (15 percent) than new teachers in the PHL region with PPS (1 percent) and RCDs (4 percent) lagging in offering their new teachers above par regionally. Excluding experienced teachers, these trends invert with the SDP (6 percent) and RCDs (1 percent) offering marginally above average salaries as the PPS (15 percent) offers on average the highest pay for this group in the PGH region.

Furthermore, extending the findings in Table 4.3, trends in distribution also have a demonstrable influence on both overall teacher salaries and turnover rates. For instance, the number of new and experienced teachers is roughly the same in charter schools across all three regions.

**Table 4.4 • Educator Salary and Turnover Rates by Experience Level (Avg. AY2011-12 through AY2016-17) [*n* (educators)=119,258]**

| | | New Educators | | | | Experienced Educators | | | | All Educators | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Average CoLI (PA =100) | Raw Salary | Adjusted Salary | Percent Diff. From Mean | Rate of Turnover | Raw Salary | Adjusted Salary | Percent Diff. From Mean | Rate of Turnover | Raw Salary | Adjusted Salary | Percent Diff. From Mean | Rate of Turnover |
| ***Greater Philadelphia CSA*** | | | | | | | | | | | | | |
| School District of Philadelphia | 109.7 | $54,725 | $49,886 | 14.77% | 16.55% | $74,212 | $67,650 | 5.66% | 9.25% | $70,440 | $64,211 | 8.13% | 10.66% |
| Suburban Title I Districts | 118.1 | $49,944 | $43,606 | 0.32% | 12.03% | $71,911 | $61,725 | -3.60% | 6.08% | $67,765 | $58,305 | -1.81% | 7.20% |
| Suburban Non-Title I Districts | 120.3 | $51,454 | $42,119 | -3.10% | 8.86% | $80,291 | $65,354 | 2.07% | 4.78% | $75,229 | $61,275 | 3.19% | 5.50% |
| Charter Schools | 112.6 | $46,700 | $41,631 | -4.22% | 30.52% | $55,580 | $48,301 | -24.56% | 21.04% | $50,920 | $44,801 | -24.55% | 26.01% |
| Career & Technical Schools | 121.9 | $59,098 | $45,731 | 5.21% | 5.97% | $85,348 | $65,661 | 2.55% | 4.27% | $80,896 | $62,281 | 4.88% | 4.56% |
| Greater Philadelphia CSA Weighted Average (by Educator Population) | 116.1 | $50,458 | $43,466 | | 17.01% | $76,030 | $64,027 | | 7.17% | $70,251 | $59,381 | | 9.39% |
| ***Greater Pittsburgh CSA*** | | | | | | | | | | | | | |
| Pittsburgh Public Schools | 96.9 | $47,645 | $49,169 | 0.88% | 12.11% | $81,111 | $83,706 | 14.85% | 5.36% | $74,943 | $77,341 | 12.66% | 6.60% |
| Suburban Title I Districts | 91.8 | $44,157 | $48,426 | -0.64% | 9.40% | $64,330 | $70,765 | -2.91% | 5.01% | $60,981 | $67,057 | -2.32% | 5.74% |
| Suburban Non-Title I Districts | 93.8 | $47,187 | $50,045 | 2.68% | 7.47% | $69,197 | $73,256 | 0.51% | 4.61% | $65,731 | $69,601 | 1.38% | 5.06% |
| Charter Schools | 96.5 | $41,290 | $42,683 | -12.42% | 23.85% | $50,769 | $52,601 | -27.83% | 13.01% | $46,344 | $47,971 | -30.12% | 18.07% |
| Career & Technical Schools | 91.8 | $45,341 | $53,969 | 10.73% | 14.43% | $61,284 | $73,817 | 1.28% | 10.76% | $58,049 | $69,789 | 1.66% | 11.51% |
| Greater Pittsburgh CSA Weighted Average (by Educator Population) | 93.4 | $45,766 | $48,738 | | 10.26% | $68,309 | $72,883 | | 5.04% | $64,357 | $68,651 | | 5.95% |
| ***Central Pennsylvania MSAs and µSAs*** | | | | | | | | | | | | | |
| Regional City Districts | 95.4 | $48,292 | $50,302 | 3.93% | 10.83% | $65,709 | $68,383 | 1.23% | 5.91% | $62,385 | $64,932 | 1.26% | 6.85% |
| Suburban Title I Districts | 96.0 | $45,669 | $46,966 | -2.96% | 8.70% | $63,085 | $65,481 | -3.06% | 5.32% | $60,199 | $62,413 | -2.67% | 5.88% |
| Suburban Non-Title I Districts | 98.7 | $47,926 | $48,270 | -0.27% | 7.95% | $66,356 | $66,501 | -1.55% | 5.44% | $63,382 | $63,560 | -0.88% | 5.85% |
| Rural Title I Districts | 83.7 | $42,523 | $50,524 | 4.39% | 9.39% | $59,780 | $70,448 | 4.29% | 5.71% | $56,779 | $66,983 | 4.45% | 6.35% |
| Rural Non-Title I Districts | 86.8 | $43,560 | $49,550 | 2.37% | 9.17% | $61,593 | $68,622 | 1.59% | 6.32% | $58,638 | $65,497 | 2.14% | 6.78% |
| Charter Schools | 96.4 | $38,161 | $39,601 | -18.18% | 25.75% | $45,182 | $47,098 | -30.28% | 15.25% | $41,404 | $42,774 | -33.30% | 20.90% |
| Career & Technical Schools | 89.5 | $47,917 | $48,868 | 0.96% | 9.60% | $61,244 | $63,485 | -6.02% | 7.74% | $58,389 | $60,353 | -5.89% | 8.14% |
| Central Pennsylvania Region Weighted Average (by Educator Population) | 90.9 | $45,164 | $48,401 | | 10.33% | $63,296 | $67,550 | | 6.07% | $60,055 | $64,127 | | 6.69% |

Likewise, the overall average salaries for new and experienced teachers reflects this distribution, with the former paid $41,631 (4 percent below the regional average for this group) and the latter paid $48,301 (25 percent below the regional average for this group), resulting in an overall average that is a virtual mean of these two groups. Charters in the PGH and CPA regions follow the same trend; new teachers in PGH charters are paid on average $42,683 (12 percent below the regional average) and new teachers in CPA charters are paid on average $39,601(18 percent below the CPA regional average). As with PHL charters, this disparity grows for experienced teachers in PGH charters (28 percent below average) and CPA charters (30 percent below average). However, as was the case with PHL charters, turnover rates for new teachers in these LEAs are significantly higher than their experienced peers, suggesting that there is more that factors into leaving than just salary. Lastly, turnover rates in charter schools are also higher than their regional averages by roughly a factor of 2.8 in the PHL region with higher disparities in the PGH (3.0) and CPA (3.1) regions.

Figures 4.1, 4.2, and 4.3 plot the relationship between salary and turnover rates for new and experienced teacher groups in the PHL, PGH, and CPA regions, respectively. A perusal of these graphs confirms that turnover rates reach their apex when salaries reach their nadir, in the character of charter schools. Equally worthwhile is that turnover rates for experienced teachers reach a level consistent with other LEA types in the region, with the exception being charters and CTE schools.

***Comparing Movers and Leavers.*** Table 4.5 provides an overview of 151,508 unique educators employed during the observation period organized by experience level and mover/leaver status.

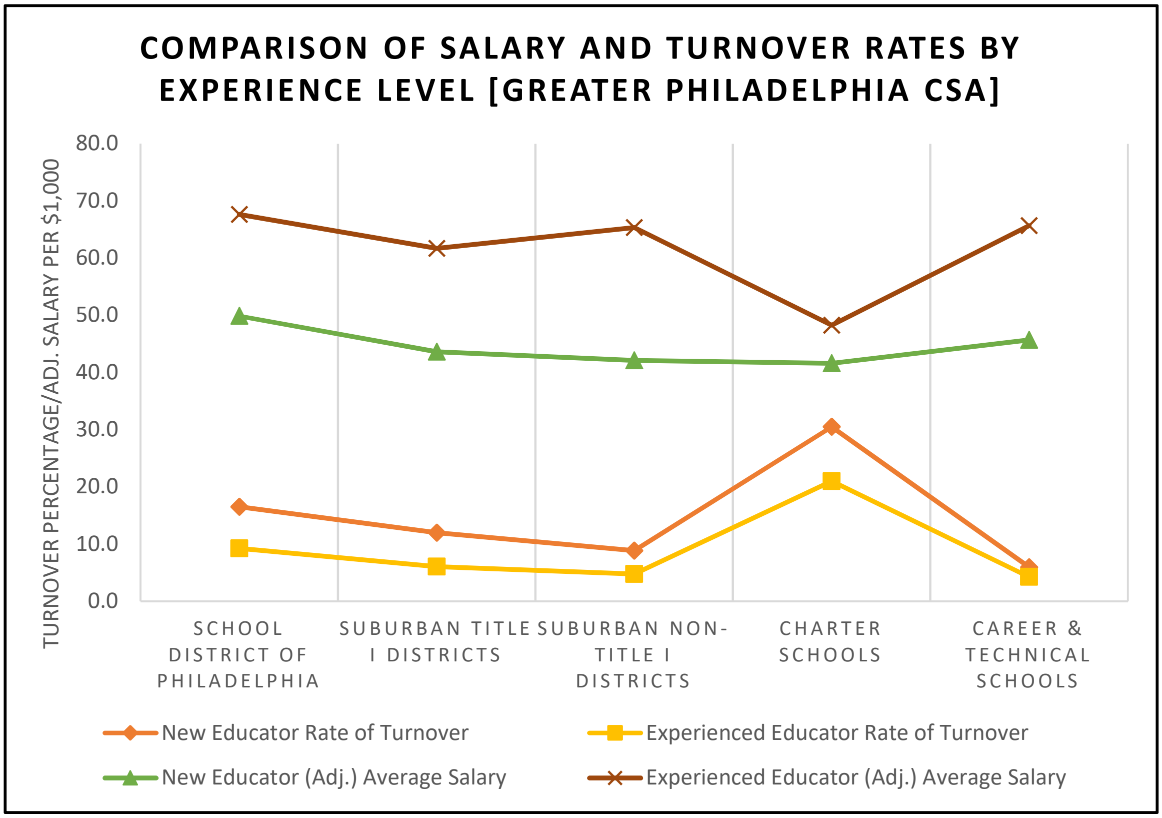



**Figure 4.1** Turnover Rates & Salary for New and Experienced Educators in the Greater Philadelphia

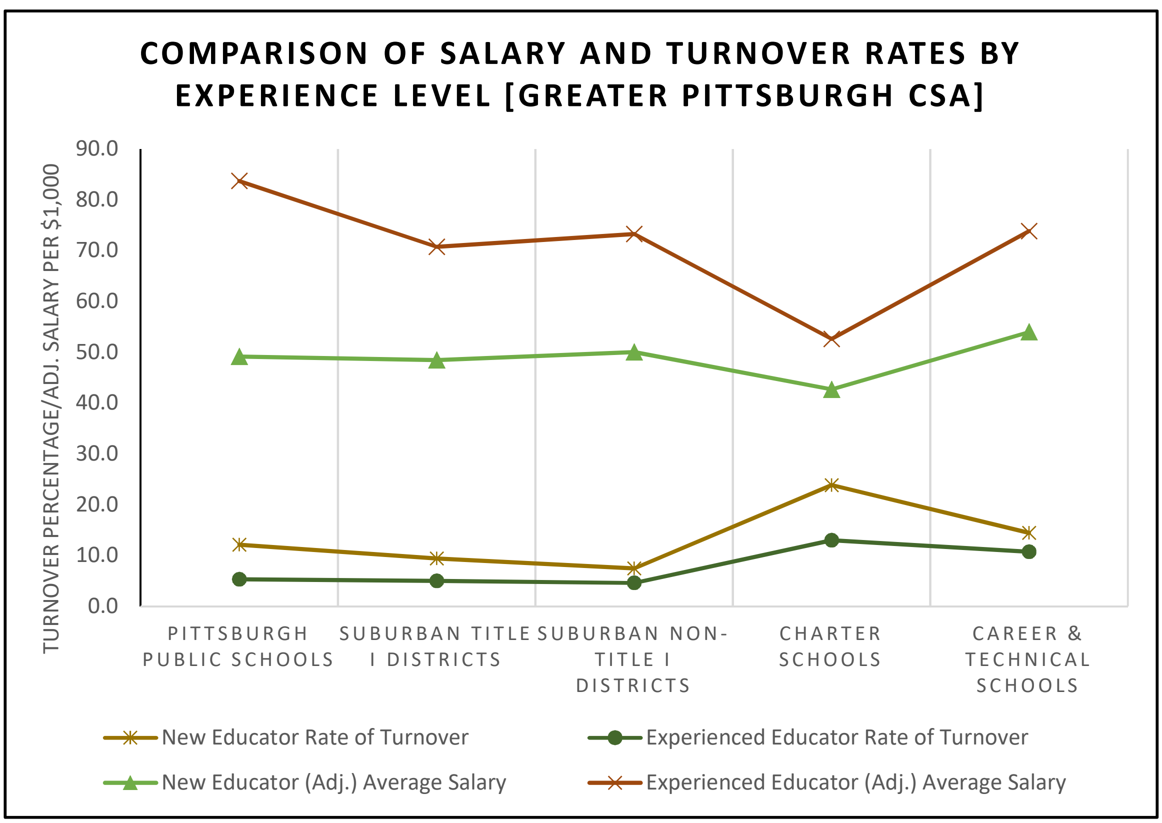



**Figure 4.2** Turnover Rates & Salary for New and Experienced Educators in the Greater Pittsburgh Region.

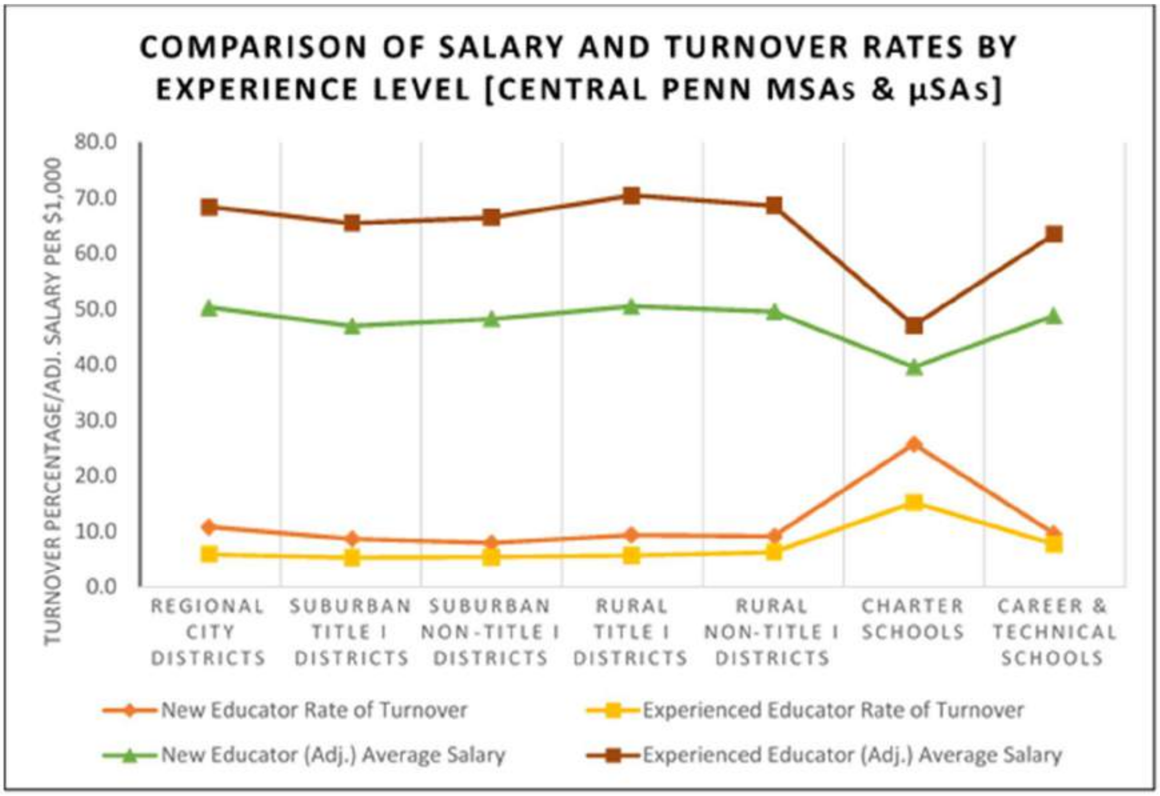



**Figure 4.3** Turnover Rates & Salary for New and Experienced Educators in the Central Pennsylvania Region.

Perhaps the most apparent difference between new and experienced teachers are their comparable rates of transition. For new and experienced teachers, the mover rate in the PHL region in almost three to four times as much compared teachers in the PGH or CPA. Furthermore, new teacher movers in the PHL region have slightly less experience (3.9 years) than their counterparts in the PGH (4.2 years) and CPA (4.3 years) regions with the same trend holding for experienced teachers in the PHL (17.7) region compared to the PGH (19.1) and PGH (18.8) regions. Charters and CTE schools in all three regions have the highest share of movers in all three regions.

However, the values are dramatically different when comparing leaver numbers. Amongst new teachers, the PHL region leads with the most significant percentage of leavers (43.0 percent) with the PGH (35.3 percent) and CPA regions (33.3 percent) not far behind. Across all three regions and all LEA types (apart from CTE schools in the PHL region), new teacher leavers have less than three years of experience, the minimum required to achieve tenure in Pennsylvania (where applicable). These values suggest that new teachers are leaving before making any substantive commitment to the profession either as the result of opportunities outside the profession or merely concluding that the profession is not a good fit. The picture is entirely different for experienced teachers where the PGH and CPA regions lead in the percentage of leavers with 16.9 percent and 19.0 percent, compared with the PHL region’s 13.8 percent. The PGH and CPA regions are also losing teachers with more experience at a corresponding 21.4 and 21.3 years of experience compared to the PHL (17.3 years). Here, these teachers may be experiencing a “mid-career crisis” of sorts since the decision to move or to leave occurs during the 20-year, suggesting that some experienced teachers weight the option of either moving (e.g. to different schools, into administration) or leaving the profession altogether between the 10-year period of investiture and short of the 35-year pension superannuation period.

Finally, Ingersoll (2001) argued that 50 percent of urban teachers leave the profession within the first five years of teaching. Given how well cited this study is both in the literature and the popular understanding of teacher turnover, it is worth confirming its accuracy using this population data. The validity of this claim rests mainly on the definition of “urban” and if it means either: (a) city districts, (b) all city LEAs, or (c) any Title I LEA. Using the first and most restrictive definition, the percentage of new teacher leavers throughout the Commonwealth is 36.1 percent. Though, if the term “urban” means the more inclusive second and third definitions, then the leaver rate for new teachers is precisely 50.0 percent and 43.2 percent, respectively.

**Table 4.5 • Highest Years of Experience and Salary for Movers and Leavers by Experience Level (AY2011-12 through AY2016-17) [*n* (educators)=**

| | New Educator | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | Movers | | | | Leavers | | |
| | Total Number of Educators | Number of Educators | Percent of Movers in LEA Type | Highest Avg. Years Experience | Highest Avg. Salary | Number of Educators | Percent of Leavers in LEA Type | Highest Avg. Years Experience |
| ***Greater Philadelphia CSA*** | | | | | | | | |
| School District of Philadelphia | 2,327 | 93 | 4.00% | 4.38 | $47,598 | 969 | 41.64% | 2.63 |
| Suburban Title I Districts | 1,078 | 64 | 5.94% | 4.08 | $46,803 | 366 | 33.95% | 2.46 |
| Suburban Non-Title I Districts | 4,924 | 281 | 5.71% | 3.74 | $45,707 | 1383 | 28.09% | 2.46 |
| Charter Schools | 5,708 | 553 | 9.69% | 3.82 | $46,837 | 3332 | 58.37% | 2.56 |
| Career & Technical Schools | 34 | 4 | 11.76% | 4.50 | $52,473 | 5 | 14.71% | 3.20 |
| Greater Philadelphia CSA Totals | 14,071 | 995 | 7.07% | 3.87 | $46,609 | 6055 | 43.03% | 2.54 |
| ***Greater Pittsburgh CSA*** | | | | | | | | |
| Pittsburgh Public Schools | 498 | 4 | 0.80% | 5.00 | $56,486 | 153 | 30.72% | 2.29 |
| Suburban Title I Districts | 1,052 | 11 | 1.05% | 4.55 | $49,191 | 377 | 35.84% | 2.50 |
| Suburban Non-Title I Districts | 2,588 | 51 | 1.97% | 4.04 | $55,873 | 733 | 28.32% | 2.58 |
| Charter Schools | 808 | 25 | 3.09% | 4.32 | $51,005 | 481 | 59.53% | 2.70 |
| Career & Technical Schools | 34 | 2 | 5.88% | 4.00 | $56,638 | 13 | 38.24% | 2.92 |
| Greater Pittsburgh CSA Totals | 4,980 | 93 | 1.87% | 4.22 | $53,817 | 1757 | 35.28% | 2.58 |
| ***Central Pennsylvania MSAs and µSAs*** | | | | | | | | |
| Regional City Districts | 1,958 | 12 | 0.61% | 4.42 | $56,673 | 603 | 30.80% | 2.50 |
| Suburban Title I Districts | 983 | 11 | 1.12% | 4.73 | $51,828 | 317 | 32.25% | 2.76 |
| Suburban Non-Title I Districts | 3,609 | 48 | 1.33% | 4.31 | $53,102 | 996 | 27.60% | 2.83 |
| Rural Title I Districts | 1,931 | 24 | 1.24% | 4.54 | $59,485 | 646 | 33.45% | 2.67 |
| Rural Non-Title I Districts | 2,845 | 61 | 2.14% | 4.34 | $56,577 | 850 | 29.88% | 2.83 |
| Charter Schools | 1,471 | 45 | 3.06% | 4.11 | $50,334 | 851 | 57.85% | 2.55 |
| Career & Technical Schools | 129 | 2 | 1.55% | 4.50 | $58,382 | 43 | 33.33% | 2.47 |
| Central Pennsylvania Region Totals | 12,926 | 203 | 1.57% | 4.33 | $54,481 | 4306 | 33.31% | 2.70 |

**151,808]**

| | | Experienced Educator | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Movers | | | | Leavers | | | |
| Highest Avg. Salary | Total Number of Educators | Number of Educators | Percent of Movers in LEA Type | Highest Avg. Years Experience | Highest Avg. Salary | Number of Educators | Percent of Leavers in LEA Type | Highest Avg. Years Experience | Highest Avg. Salary |
| $48,210 | 9,045 | 1555 | 17.19% | 16.92 | $66,770 | 1476 | 16.32% | 19.74 | $68,924 |
| $42,986 | 4,024 | 559 | 13.89% | 18.33 | $63,553 | 491 | 12.20% | 18.56 | $61,753 |
| $39,355 | 23,700 | 2780 | 11.73% | 20.48 | $67,620 | 2041 | 8.61% | 20.52 | $64,876 |
| $42,084 | 4,973 | 1044 | 20.99% | 11.13 | $52,267 | 1769 | 35.57% | 11.03 | $48,382 |
| $43,434 | 154 | 15 | 9.74% | 19.13 | $66,219 | 14 | 9.09% | 23.93 | $68,651 |
| $42,497 | 41,896 | 5953 | 14.21% | 17.71 | $64,320 | 5791 | 13.82% | 17.26 | $60,614 |
| | | | | | | | | | |
| $46,804 | 1,988 | 104 | 5.23% | 19.63 | $89,461 | 350 | 17.61% | 21.68 | $86,151 |
| $40,065 | 5,226 | 196 | 3.75% | 20.52 | $76,432 | 1034 | 19.79% | 22.34 | $76,207 |
| $44,342 | 14,922 | 601 | 4.03% | 19.62 | $78,763 | 2199 | 14.74% | 22.43 | $78,052 |
| $41,678 | 922 | 59 | 6.40% | 9.80 | $56,962 | 298 | 32.32% | 10.05 | $49,019 |
| $53,877 | 102 | 17 | 16.67% | 14.00 | $73,841 | 26 | 25.49% | 17.08 | $77,090 |
| $42,980 | 23,160 | 977 | 4.22% | 19.11 | $78,032 | 3907 | 16.87% | 21.36 | $76,069 |
| | | | | | | | | | |
| $49,266 | 7,288 | 331 | 4.54% | 18.61 | $71,395 | 1363 | 18.70% | 19.39 | $70,251 |
| $43,745 | 4,706 | 196 | 4.16% | 19.66 | $69,264 | 937 | 19.91% | 22.32 | $67,543 |
| $46,567 | 18,666 | 1016 | 5.44% | 19.24 | $68,387 | 3140 | 16.82% | 21.49 | $67,954 |
| $48,016 | 7,446 | 375 | 5.04% | 21.18 | $75,914 | 1607 | 21.58% | 22.78 | $73,217 |
| $47,309 | 15,007 | 795 | 5.30% | 18.17 | $70,659 | 2837 | 18.90% | 22.13 | $72,183 |
| $38,656 | 1,200 | 121 | 10.08% | 11.50 | $53,629 | 436 | 36.33% | 12.13 | $45,049 |
| $46,846 | 459 | 37 | 8.06% | 16.14 | $66,889 | 105 | 22.88% | 19.20 | $66,157 |
| $45,541 | 54,772 | 2871 | 5.24% | 18.79 | $69,765 | 10425 | 19.03% | 21.25 | $69,204 |

Arguably, the second definition, which confirms Ingersoll's famous study, is the one most closely associated with the standard definition of urban schools, particularly since the state has experienced a dramatic proliferation in the number of charter schools since Ingersoll first published the work.

### *Overview of Teachers by High Needs Subject Areas*

The second research question, which is a companion to the first, also attempts to gauge the effect of a monetary increase on teacher retention, but this time for only high need subject area teachers. As noted in Chapter 2, high need content teachers (mathematics and science) have technical knowledge that has a high degree of transferability within and outside the education field whereas high need support teachers (special education and ESL) have skills that have the most utility within the education field.

***Mathematics & Science Teacher Employment Trends.*** The results indicate that the distribution and turnover of these teachers will likely confound the state's renewed commitment to K-12 STEM education. These teachers are distributed equally between regions (i.e., roughly consistent with percent student enrollment), but not within a region. In Table 4.6, the percentage of math teachers approximately matches the percentage of students enrolled in each LEA type, except the distribution is far more distorted for science teachers. This inequality is highest in the SDP, whose local share of student enrollment (22 percent) is more than two-thirds higher than its share of science teacher employment (13 percent). Major urban district(s) in the PGH and CPA regions also experience a (minor) shortage by two percentage points using an analogous comparison. Even Suburban Non-Title I Districts in the PGH and CPA regions experienced a minor shortage by two percentage points when comparing their share of science teacher employment to their respective shares of student enrollment (PGH: 62 percent and CPA: 56 percent).

**Table 4.6 • Overview of Educator Distribution by Need Subject Areas (Avg. AY2011-12 through AY2016-17) [*n* (teachers)=39,629]**

| | Mathematics | | Natural Sciences | | Special, Remedial & Alternate Education | | English as a Second Language | |
|---|---|---|---|---|---|---|---|---|
| | *n* | Percent of Region | *n* | Percent of Region | *n* | Percent of Region | *n* | Percent of Region |
| ***Greater Philadelphia CSA*** | | | | | | | | |
| School District of Philadelphia | 699 | 22.26% | 314 | 13.20% | 749 | 10.03% | 181 | 24.41% |
| Suburban Title I Districts | 326 | 10.39% | 263 | 11.08% | 1,107 | 14.81% | 189 | 25.54% |
| Suburban Non-Title I Districts | 1,636 | 52.09% | 1,446 | 60.79% | 4,713 | 63.07% | 291 | 39.28% |
| Charter Schools | 466 | 14.84% | 343 | 14.42% | 879 | 11.76% | 79 | 10.64% |
| Career & Technical Schools | 13 | 0.41% | 12 | 0.50% | 25 | 0.33% | 1 | 0.13% |
| Greater Philadelphia CSA Totals | 3,141 | 100.00% | 2,378 | 100.00% | 7,473 | 100.00% | 741 | 100.00% |
| ***Greater Pittsburgh CSA*** | | | | | | | | |
| Pittsburgh Public Schools | 138 | 8.03% | 96 | 6.42% | 349 | 8.35% | 31 | 28.94% |
| Suburban Title I Districts | 475 | 27.64% | 393 | 26.34% | 1235 | 29.49% | 12 | 11.32% |
| Suburban Non-Title I Districts | 1014 | 58.98% | 927 | 62.10% | 2408 | 57.51% | 51 | 47.68% |
| Charter Schools | 84 | 4.89% | 71 | 4.74% | 182 | 4.34% | 11 | 10.20% |
| Career & Technical Schools | 8 | 0.47% | 6 | 0.40% | 13 | 0.31% | 2 | 1.86% |
| Greater Pittsburgh CSA Totals | 1,719 | 100.00% | 1,493 | 100.00% | 4,186 | 100.00% | 108 | 100.00% |
| ***Central Pennsylvania MSAs and µSAs*** | | | | | | | | |
| Regional City Districts | 466 | 11.98% | 387 | 11.79% | 1,584 | 15.13% | 362 | 48.10% |
| Suburban Title I Districts | 405 | 10.43% | 339 | 10.33% | 1,077 | 10.28% | 48 | 6.34% |
| Suburban Non-Title I Districts | 1,264 | 32.51% | 1,086 | 33.13% | 3,118 | 29.78% | 178 | 23.68% |
| Rural Title I Districts | 706 | 18.16% | 594 | 18.13% | 2,015 | 19.24% | 51 | 6.74% |
| Rural Non-Title I Districts | 882 | 22.68% | 746 | 22.76% | 2,430 | 23.21% | 86 | 11.36% |
| Charter Schools | 123 | 3.16% | 91 | 2.79% | 188 | 1.80% | 25 | 3.37% |
| Career & Technical Schools | 42 | 1.08% | 35 | 1.07% | 58 | 0.55% | 3 | 0.40% |
| Central Pennsylvania Region Totals | 3,888 | 100.00% | 3,278 | 100.00% | 10,471 | 100.00% | 753 | 100.00% |

Notably, this shortage of science teachers does not appear to afflict other LEA types. Combined regional student enrollment for Suburban Title I, Rural Title I, and Charter LEAs in the PHL (26 percent), PGH (32 percent), and CPA (31 percent) regions is on par with these LEAs' combined share of science teachers (PHL: 26 percent, PGH: 31 percent, and CPA: 31 percent) – an indication that their science teacher needs are on par with their student enrollment. One possible explanation for the "missing science teachers" in major urban district(s) is disparity with Suburban Non-Title I LEAs, especially in the PHL region, where these LEAs have a share of science teacher (61 percent) that is nine percentage points higher compared to its share of student enrollment (52 percent).

Regarding salary, math and science teachers as well as their low-needs counterparts are paid relatively the same. This finding is not surprising since CBAs in the Commonwealth do not discriminate based on subject area taught (apart from special education), and thus differences between high need content and non-high need teachers within each LEA type under the influence of a CBA are likely negligible. For LEAs absent a CBA (i.e., charter schools), there is still no significant difference in remuneration when comparing math and science teachers with other low-need areas. Table 4.7 reports that, for math and science teachers in unionized LEAs, their salaries are roughly on par with the regional average compared to charter schools, who pay these teachers considerably less (~25 percent). Concomitantly, turnover rates between low-need and math teachers in organized LEAs are also less than in charters by a similar 26 to 30 percent margin.

***Special Education & ESL Teacher Employment Trends.*** Several researchers have argued that the motivations for special education and ESL teachers (high need support teachers) could be distinct from content area teachers since these support teachers work primarily with a student subpopulation with an academic or demographic profile that is unrepresentative of the general student population. (See Chapter 2.) In terms of distribution, like their high need content counterparts, Table 4.6 shows the regional percentages of special education teachers – PHL (33 percent), PGH (19 percent), and CPA (47 percent) – are on par with their student enrollment percentages. This finding is not the same for ESL teachers, where the PHL region is short by ten percentage points when compared to its share of ESL enrollment compared to the PGH and CPA regions which have a surplus of these teachers by eight and two percentage points, respectively. Within each region, there is a shortage of both special education and ESL teachers in the major urban district(s) and charter schools, which tend to educate most of both types of students. For instance, in the PHL region, the SDP and charter schools face the most prominent regional disparity between the number of special education students educated (40 percent) versus employment of special education teachers (22 percent). This trend is similar for PPS and its charters in the PGH region, albeit with a smaller difference, where the number of identified students is two percentage points higher than these LEAs' share of special education teachers. In the same vein, major urban district(s) and charter schools in the PHL and CPA regions educate the greatest percentage of their region's ESL student enrollment (PHL: 57 percent and CPA: 62 percent) despite employing proportionately fewer ESL teachers (PHL: 35 percent and CPA: 52 percent).

When analyzing remuneration and turnover for these support teachers in Table 4.7, a noteworthy and even unexpected trend emerges. Although CBAs do have a separate (and higher) salary schedule for special education teachers because LEAs receive supplemental funding for special education students, this increased subsidy does not always appear to manifest itself in special education teacher wages. As summarized in Table 4.7, the average regional salaries of special education teachers are lower than their non-high need counterparts across the PHL and PGH regions even as it practically remains the same in the CPA region. Intra-regionally, there are some stark disparities by LEA type. In the PHL region, SDP special education teachers are paid much more than their low needs counterparts and are, in fact, the highest paid special education teachers in the region (12 percent above the regional average).

On the other hand, this same group has the different experience in charter schools where their salaries are the same as their non-high need peers and, by extension, are the lowest paid in the region (24 percent below average). This inequality also holds for special education teachers employed major urban district(s) and charter schools in the PGH and CPA regions with PPS special education teachers earning well above the regional average (16 percent), though only marginally so for RCDs (1 percent). Predictably then, turnover is dramatically higher for special education teachers in charter schools. In the case of ESL teachers, another critical trend emerges. In the PHL and CPA region, turnover rates for ESL teachers in district LEAs are generally comparable to one another. Curiously, an anomaly emerges in the PGH region – Suburban Title I Districts have a turnover rate that is more than double either its PPS or Suburban Non-Title I counterparts. Figures 4.4-4.6 graphically compare turnover for all four high need subject areas in the PHL, PGH, and CPA regions, respectively. As was the case with Figures 4.-1 4.3, turnover rates in all four subject areas reach their zenith in charter schools.

***Comparing Movers and Leavers.*** Table 4.8 provides an overview of 51,588 unique high need educators observed during this study (34 percent of the population). Across all three regions and all four high need subjects, leavers have fewer years of experience than movers.

**Table 4.7 • Educator Salary and Turnover Rates by High Need Subject Areas (Avg. AY2011-12 through AY2016-17) [*n* (teachers)=39,629]**

| | | Mathematics | | | | Natural Sciences | | |
|---|---|---|---|---|---|---|---|---|
| | Average CoLI (PA=100) | Raw Salary | Adjusted Salary | Percent Diff. From Mean | Rate of Turnover | Raw Salary | Adjusted Salary | Percent Diff. From Mean |
| ***Greater Philadelphia CSA*** | | | | | | | | |
| School District of Philadelphia | 109.7 | $70,233 | $64,023 | 7.55% | 11.81% | $71,183 | $64,889 | 8.36% |
| Suburban Title I Districts | 118.1 | $66,750 | $57,291 | -3.75% | 6.86% | $69,482 | $59,576 | -0.51% |
| Suburban Non-Title I Districts | 120.3 | $76,405 | $62,270 | 4.61% | 4.83% | $77,115 | $62,652 | 4.63% |
| Charter Schools | 112.6 | $50,565 | $44,615 | -25.05% | 31.26% | $49,863 | $43,783 | -26.88% |
| Greater Philadelphia CSA Weighted Average (by Educator Population) | 116.1 | $70,219 | $59,526 | | 10.51% | $71,578 | $59,881 | |
| ***Greater Pittsburgh CSA*** | | | | | | | | |
| Pittsburgh Public Schools | 96.9 | $74,173 | $76,546 | 12.35% | 5.80% | $71,430 | $73,715 | 5.87% |
| Suburban Title I Districts | 91.8 | $60,413 | $66,486 | -2.42% | 5.43% | $62,517 | $68,735 | -1.28% |
| Suburban Non-Title I Districts | 93.8 | $65,454 | $69,448 | 1.93% | 4.42% | $67,390 | $71,296 | 2.40% |
| Charter Schools | 96.5 | $46,306 | $47,977 | -29.58% | 21.19% | $45,549 | $47,219 | -32.18% |
| Greater Pittsburgh CSA Weighted Average (by Educator Population) | 93.4 | $63,771 | $68,131 | | 5.68% | $65,291 | $69,625 | |
| ***Central Pennsylvania MSAs and µSAs*** | | | | | | | | |
| Regional City Districts | 95.4 | $61,341 | $64,030 | -0.06% | 5.71% | $61,900 | $64,628 | -1.49% |
| Suburban Title I Districts | 96.0 | $60,438 | $62,878 | -1.86% | 5.77% | $62,220 | $64,805 | -1.22% |
| Suburban Non-Title I Districts | 98.7 | $63,830 | $64,077 | 0.01% | 5.24% | $65,176 | $65,491 | -0.17% |
| Rural Title I Districts | 83.7 | $56,726 | $67,049 | 4.65% | 5.52% | $57,822 | $68,326 | 4.15% |
| Rural Non-Title I Districts | 86.8 | $58,524 | $65,462 | 2.17% | 5.46% | $60,100 | $67,462 | 2.83% |
| Charter Schools | 96.4 | $42,688 | $44,314 | -30.83% | 21.34% | $42,661 | $44,486 | -32.19% |
| Central Pennsylvania Region Weighted Average (by Educator Population) | 90.9 | $59,887 | $64,070 | | 5.96% | $61,252 | $65,605 | |

| | Special, Remedial, and Alternate Education | | | | English as a Second Language | | | |
|---|---|---|---|---|---|---|---|---|
| Rate of Turnover | Raw Salary | Adjusted Salary | Percent Diff. From Mean | Rate of Turnover | Raw Salary | Adjusted Salary | Percent Diff. From Mean | Rate of Turnover |
| 12.55% | $70,880 | $64,613 | 12.13% | 14.47% | $77,516 | $70,662 | 21.85% | 8.19% |
| 8.05% | $67,342 | $57,937 | 0.54% | 8.76% | $61,962 | $56,437 | -2.68% | 9.94% |
| 4.39% | $72,354 | $58,984 | 2.36% | 7.02% | $67,778 | $54,495 | -6.03% | 7.84% |
| 30.24% | $50,324 | $43,915 | -23.79% | 25.90% | $51,675 | $45,845 | -20.94% | 26.14% |
| 9.59% | $68,892 | $57,624 | | 10.23% | $66,928 | $57,991 | | 10.42% |
| 10.86% | $74,647 | $77,035 | 16.18% | 5.27% | $71,841 | $74,139 | 14.41% | 7.69% |
| 6.26% | $58,666 | $64,557 | -2.64% | 6.64% | $53,342 | $56,602 | -12.65% | 16.39% |
| 4.98% | $63,456 | $67,033 | 1.09% | 6.06% | $61,628 | $64,534 | -0.41% | 6.23% |
| 20.06% | $45,822 | $47,632 | -28.16% | 19.38% | $47,128 | $48,647 | -24.93% | 38.18% |
| 6.43% | $62,196 | $66,306 | | 6.81% | $62,177 | $64,800 | | 11.15% |
| 7.09% | $61,458 | $64,154 | 0.81% | 8.08% | $62,165 | $62,691 | 2.28% | 8.61% |
| 4.55% | $59,109 | $61,537 | -3.30% | 7.26% | $60,189 | $59,728 | -2.55% | 7.53% |
| 4.83% | $62,281 | $62,564 | -1.69% | 7.48% | $61,474 | $60,004 | -2.10% | 6.50% |
| 6.16% | $56,900 | $66,669 | 4.76% | 7.97% | $55,851 | $63,664 | 3.87% | 7.87% |
| 6.33% | $58,025 | $64,739 | 1.73% | 8.28% | $59,449 | $63,118 | 2.98% | 9.58% |
| 19.04% | $41,381 | $43,656 | -31.40% | 26.67% | $44,169 | $43,461 | -29.09% | 34.65% |
| 6.05% | $59,405 | $63,638 | | 8.19% | $60,497 | $61,292 | | 9.00% |

**Table 4.8 • Highest Years of Experience and Salary for Movers and Leavers by High Need Subject Area (AY2011-12 through AY2016-17) [*n* (educators)=51,558]**

| | Mathematics | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Movers | | | | Leavers | | | | |
| | Total Number of Educators | Number of Educators | Percent of LEA Type | Highest Avg. Years Experience | Highest Avg. Salary | Number of Educators | Percent of LEA Type | Highest Avg. Years Experience | Highest Avg. Salary | Total Number of Educators |
| ***Greater Philadelphia CSA*** | | | | | | | | | | |
| School District of Philadelphia | 1,009 | 152 | 15.06% | 15.14 | $66,418 | 212 | 21.01% | 10.74 | $58,482 | 471 |
| Suburban Title I Districts | 314 | 32 | 10.19% | 14.03 | $57,274 | 57 | 18.15% | 9.68 | $52,450 | 251 |
| Suburban Non-Title I Districts | 1,970 | 189 | 9.59% | 17.50 | $64,033 | 216 | 10.96% | 13.48 | $54,637 | 1,743 |
| Charter Schools | 963 | 124 | 12.88% | 8.36 | $50,520 | 548 | 56.91% | 5.55 | $44,305 | 691 |
| Greater Philadelphia CSA Totals | 4,272 | 497 | 11.63% | 14.28 | $60,956 | 1035 | 24.23% | 8.50 | $49,842 | 3,170 |
| ***Greater Pittsburgh CSA*** | | | | | | | | | | |
| Pittsburgh Public Schools | 160 | 4 | 2.50% | 15.22 | $81,889 | 32 | 20.00% | 12.25 | $75,900 | 121 |
| Suburban Title I Districts | 440 | 17 | 3.86% | 18.88 | $75,621 | 93 | 21.14% | 13.83 | $59,094 | 369 |
| Suburban Non-Title I Districts | 1,262 | 36 | 2.85% | 17.78 | $78,076 | 190 | 15.06% | 15.92 | $63,587 | 1,166 |
| Charter Schools | 162 | 9 | 5.56% | 7.89 | $62,216 | 77 | 47.53% | 5.94 | $43,928 | 132 |
| Greater Pittsburgh CSA Totals | 2,037 | 68 | 3.34% | 16.16 | $75,338 | 396 | 19.44% | 13.40 | $59,718 | 1,797 |
| ***Central Pennsylvania MSAs and µSAs*** | | | | | | | | | | |
| Regional City Districts | 542 | 24 | 4.43% | 14.29 | $64,506 | 91 | 16.79% | 9.65 | $58,219 | 461 |
| Suburban Title I Districts | 395 | 19 | 4.81% | 18.26 | $69,359 | 75 | 18.99% | 15.76 | $59,764 | 312 |
| Suburban Non-Title I Districts | 1,572 | 76 | 4.83% | 17.45 | $67,096 | 262 | 16.67% | 16.28 | $62,714 | 1,330 |
| Rural Title I Districts | 634 | 33 | 5.21% | 16.42 | $74,081 | 131 | 20.66% | 14.10 | $60,392 | 527 |
| Rural Non-Title I Districts | 1,261 | 63 | 5.00% | 15.22 | $66,586 | 206 | 16.34% | 16.37 | $64,350 | 1,083 |
| Charter Schools | 235 | 14 | 5.96% | 7.36 | $59,192 | 118 | 50.21% | 7.02 | $41,600 | 168 |
| Central Pennsylvania Region Totals | 4,689 | 233 | 4.97% | 15.77 | $67,273 | 891 | 19.00% | 13.99 | $59,142 | 3,925 |

| Science | | | | | | | | Special, Alternate, and Reme | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Movers | | | | Leavers | | | | | Movers | | | |
| Number of Educators | Percent of LEA Type | Highest Avg. Years Experience | Highest Avg. Salary | Number of Educators | Percent of LEA Type | Highest Avg. Years Experience | Highest Avg. Salary | Total Number of Educators | Number of Educators | Percent of LEA Type | Highest Avg. Years Experience | Highest Avg. Salary |
| 57 | 12.10% | 15.46 | $67,490 | 117 | 24.84% | 12.44 | $62,457 | 1,040 | 140 | 13.46% | 19.27 | $68,110 |
| 26 | 10.36% | 14.85 | $60,721 | 49 | 19.52% | 13.08 | $55,997 | 1,232 | 157 | 12.74% | 16.72 | $60,202 |
| 166 | 9.52% | 18.07 | $65,130 | 171 | 9.81% | 13.78 | $56,879 | 6,286 | 706 | 11.23% | 18.25 | $64,428 |
| 116 | 16.79% | 7.98 | $50,298 | 358 | 51.81% | 5.79 | $44,710 | 1,809 | 246 | 13.60% | 8.74 | $47,321 |
| 367 | 11.58% | 14.22 | $60,491 | 696 | 21.96% | 9.38 | $51,480 | 10,395 | 1251 | 12.03% | 16.28 | $60,926 |
| 5 | 4.13% | 15.40 | $81,069 | 35 | 28.93% | 9.83 | $65,826 | 429 | 19 | 4.43% | 15.53 | $87,820 |
| 18 | 4.88% | 16.78 | $69,997 | 82 | 22.22% | 16.49 | $66,437 | 1,304 | 34 | 2.61% | 19.24 | $73,196 |
| 51 | 4.37% | 14.80 | $70,743 | 193 | 16.55% | 16.08 | $67,153 | 3,167 | 127 | 4.01% | 18.13 | $76,430 |
| 14 | 10.61% | 8.79 | $56,016 | 56 | 42.42% | 5.38 | $44,178 | 348 | 12 | 3.45% | 9.08 | $50,808 |
| 90 | 5.01% | 14.19 | $68,853 | 367 | 20.42% | 13.99 | $63,405 | 5,273 | 194 | 3.68% | 17.41 | $75,320 |
| 17 | 3.69% | 17.47 | $72,506 | 94 | 20.39% | 11.74 | $61,342 | 2,070 | 79 | 3.82% | 17.33 | $70,126 |
| 17 | 5.45% | 14.82 | $63,438 | 50 | 16.03% | 17.78 | $61,360 | 1,161 | 42 | 3.62% | 18.17 | $68,832 |
| 65 | 4.89% | 19.92 | $69,722 | 201 | 15.11% | 15.36 | $60,694 | 4,228 | 201 | 4.75% | 17.23 | $65,763 |
| 23 | 4.36% | 16.96 | $70,036 | 112 | 21.25% | 16.25 | $64,828 | 2,042 | 72 | 3.53% | 23.60 | $76,281 |
| 70 | 6.46% | 18.21 | $70,175 | 203 | 18.74% | 15.62 | $64,955 | 3,826 | 178 | 4.65% | 17.44 | $71,834 |
| 15 | 8.93% | 9.13 | $54,349 | 75 | 44.64% | 6.23 | $44,231 | 399 | 30 | 7.52% | 9.50 | $54,024 |
| 214 | 5.45% | 17.41 | $68,211 | 739 | 18.83% | 14.31 | $60,924 | 13,805 | 608 | 4.40% | 17.75 | $69,021 |

| dial Education | | | | English as a Second Language | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Leavers | | | | | Movers | | | | Leavers | | | |
| Number of Educators | Percent of LEA Type | Highest Avg. Years Experience | Highest Avg. Salary | Total Number of Educators | Number of Educators | Percent of LEA Type | Highest Avg. Years Experience | Highest Avg. Salary | Number of Educators | Percent of LEA Type | Highest Avg. Years Experience | Highest Avg. Salary |
| 356 | 34.23% | 17.43 | $65,232 | 161 | 26 | 16.15% | 15.50 | $69,683 | 46 | 28.57% | 16.22 | $69,044 |
| 266 | 21.59% | 10.10 | $52,245 | 243 | 47 | 19.34% | 14.68 | $58,450 | 33 | 13.58% | 8.58 | $50,811 |
| 999 | 15.89% | 11.69 | $52,926 | 424 | 58 | 13.68% | 16.00 | $57,600 | 65 | 15.33% | 11.51 | $52,067 |
| 843 | 46.60% | 5.56 | $44,505 | 173 | 21 | 12.14% | 8.10 | $51,264 | 81 | 46.82% | 6.49 | $44,249 |
| 2465 | 23.71% | 10.25 | $51,750 | 1,003 | 153 | 15.25% | 14.37 | $58,825 | 225 | 22.43% | 10.24 | $52,539 |
| 65 | 15.15% | 17.38 | $77,551 | 42 | 5 | 11.90% | 22.00 | $95,748 | 7 | 16.67% | 14.86 | $68,399 |
| 335 | 25.69% | 14.74 | $63,937 | 20 | 1 | 5.00% | 31.00 | $92,902 | 8 | 40.00% | 6.63 | $32,606 |
| 622 | 19.64% | 15.12 | $68,128 | 68 | 2 | 2.94% | 12.50 | $64,372 | 14 | 20.59% | 11.64 | $56,235 |
| 162 | 46.55% | 5.43 | $44,494 | 47 | 5 | 10.64% | 12.20 | $62,538 | 17 | 36.17% | 3.47 | $43,380 |
| 1201 | 22.78% | 13.72 | $64,274 | 177 | 13 | 7.34% | 17.46 | $77,929 | 46 | 25.99% | 8.24 | $49,226 |
| 506 | 24.44% | 13.87 | $63,603 | 467 | 25 | 5.35% | 18.40 | $69,644 | 117 | 25.05% | 11.35 | $60,720 |
| 310 | 26.70% | 14.95 | $60,953 | 54 | 5 | 9.26% | 19.40 | $66,214 | 11 | 20.37% | 11.64 | $59,759 |
| 981 | 23.20% | 15.37 | $61,349 | 241 | 10 | 4.15% | 16.00 | $64,928 | 51 | 21.16% | 13.92 | $59,096 |
| 602 | 29.48% | 14.62 | $63,662 | 55 | 1 | 1.82% | 8.00 | $54,200 | 14 | 25.45% | 15.71 | $62,369 |
| 945 | 24.70% | 15.87 | $64,208 | 131 | 9 | 6.87% | 15.78 | $69,675 | 36 | 27.48% | 13.78 | $60,655 |
| 220 | 55.14% | 5.30 | $42,696 | 62 | 4 | 6.45% | 6.25 | $47,412 | 39 | 62.90% | 5.59 | $41,691 |
| 3591 | 26.01% | 14.50 | $61,599 | 1,015 | 54 | 5.32% | 16.52 | $66,525 | 270 | 26.60% | 11.57 | $57,634 |

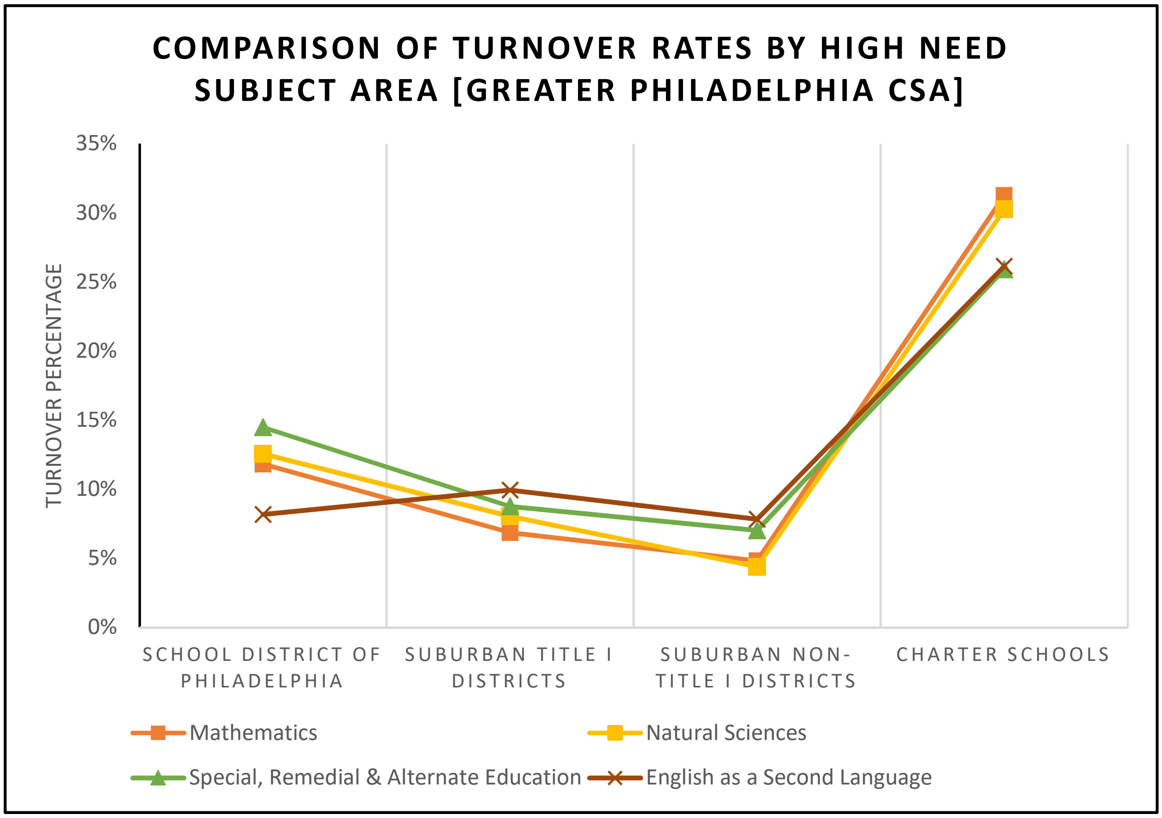



**Figure 4.4** Turnover Rates for HN Educators in All LEA Types (Except CTE Schools) in the Greater Philadelphia Region.

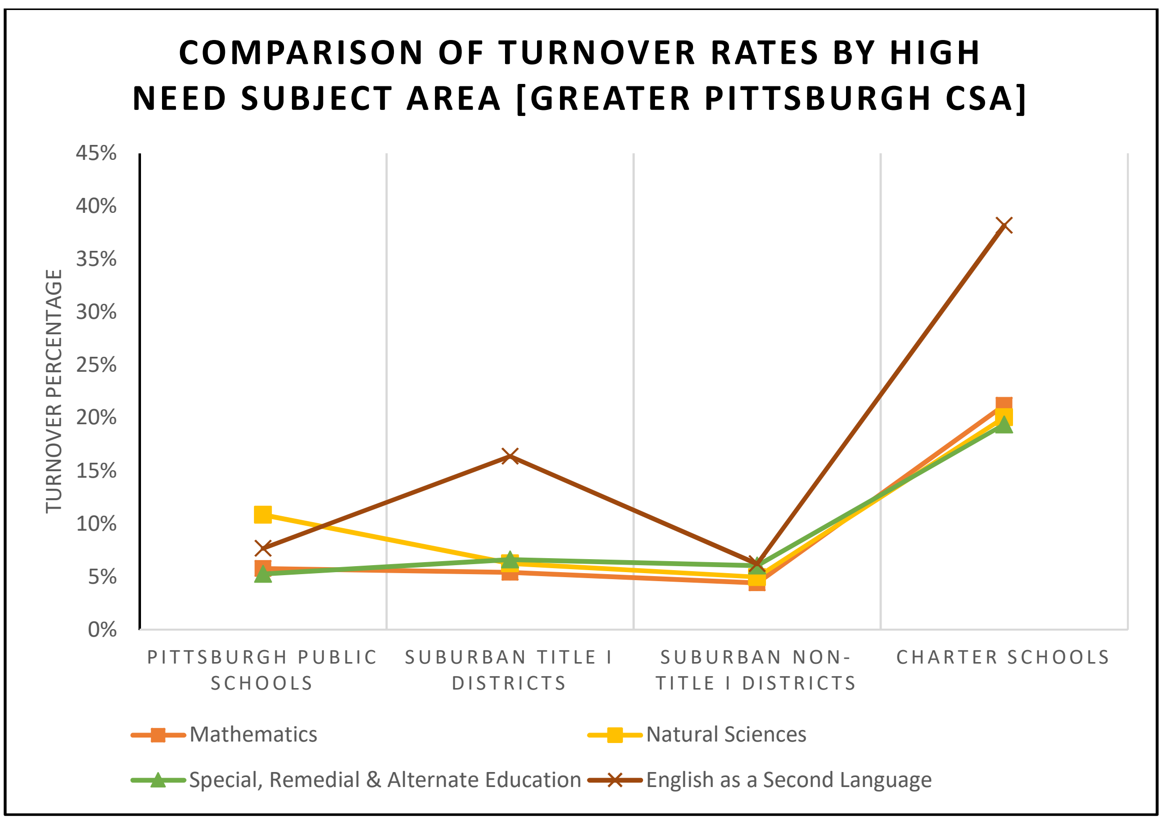



**Figure 4.5** Turnover Rates for HN Educators in All LEA Types (Except CTE Schools) in the Greater Pittsburgh Region.

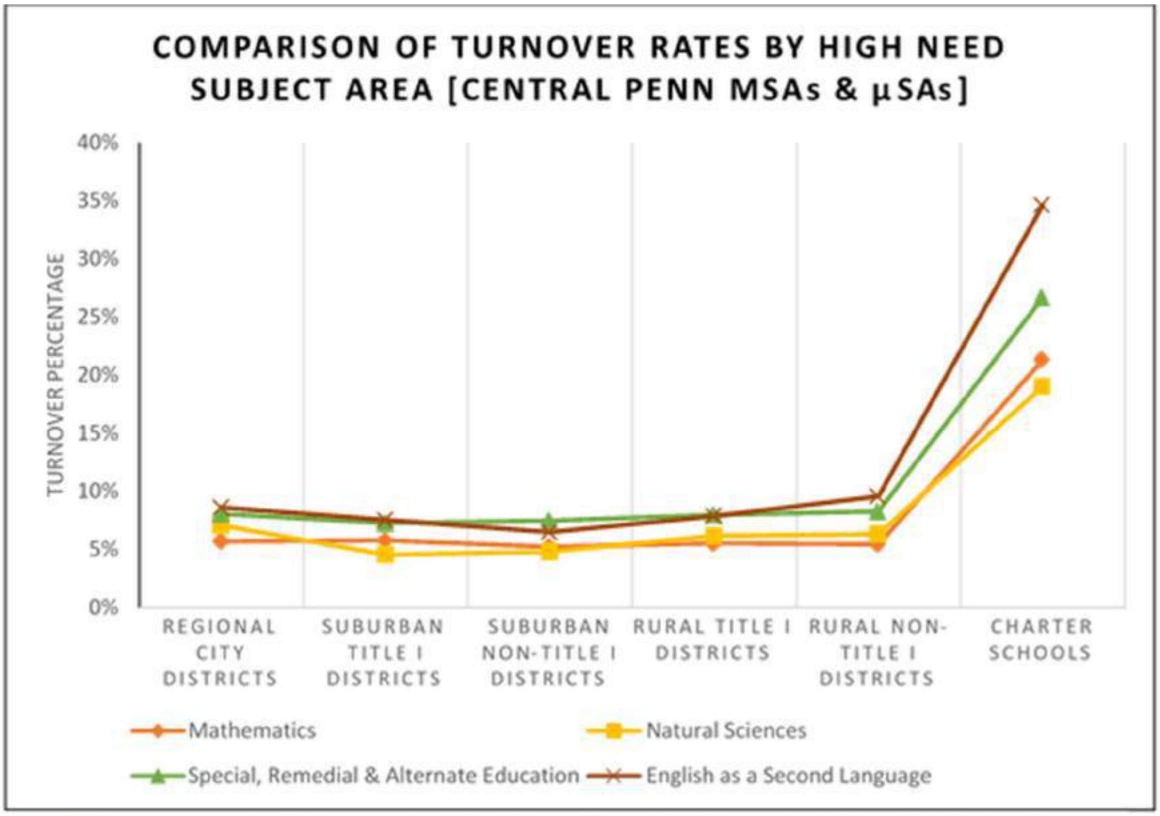



**Figure 4.6** Turnover Rates for HN Educators in All LEA Types (Except CTE Schools) in the Central Pennsylvania Region.

In terms of the high need content subjects, math, and science teachers in the PHL region transition considerably more than their counterparts in the PGH and CPA regions. The transition rate for math teachers in the PHL region is 36 percent compared to the PGH (23 percent) and CPA (24 percent) regions with transition rates for science teachers tracking closely in all three regions – PHL (34 percent), PGH (25 percent), and CPA (24 percent). In terms of experience, math and science teacher movers across all three regions have a highly similar experience profile with only a two to three difference in years of experience. This disparity grows for math and science teacher leavers, where the difference is four to five years of experience.

Comparatively, special education and ESL transition rates are even higher than that of their high need content colleagues across all three regions. These rates, either in special education (PHL: 36 percent; PGH: 36 percent; CPA: 30 percent) or ESL (PHL: 38 percent; PGH: 33 percent; CPA: 32 percent), suggest that either group is more prone to more opportunities, disillusionment, or burnout compared with their content high need peers. A slightly less variant pattern emerges when calculating differences in years of experience between movers and leavers; both special education movers and leavers share a similar experience profile across all three regions of only a two to year gap whereas ESL movers and leavers have a more significant gap of three to four year, respectively.

As with Ingersoll's study, this dataset provides an opportunity to confirm an equally well cited and more recent figure by Carver-Thomas & Darling-Hammond (2017) in which they argue that STEM teacher turnover (internal and external) can reach up to 70 percent in urban schools in some parts of the county. Here, too, the definition of "urban" needs clarification ranging from the least restrictive (only city districts) to the most inclusive (all Title I LEAs). The first definition yields a turnover rate of 30.4 percent amongst math and science teachers combined compared to the second and third definitions which yield turnover rates of 46.2 percent and 38.3 percent. It is important to note that the Carver-Thomas & Darling-Hammond study does cite a critical caveat: states in the Northeast have the lowest turnover rates (10 percent) whereas states in the South have some of the highest rates (16 percent). Accounting for this disparity and utilizing the second definition for urban schools, math and science teacher turnover in Pennsylvania's urban schools would be proportionally equivalent to almost a 74 percent turnover in Southern states for the same subjects in similar urban areas.

***Surrogate Estimates for Shortages in High Need Subjects.*** Although Table 4.6 does provide oversight of high need teacher distribution by subject area, it does not provide a direct measure of a student: teacher ratio as a proxy for teacher shortages by region and

LEA type. Table 4.9 fills this gap through of combination of calculations and comparison idiosyncratic to each of the four high needs areas.

The Commonwealth requires all high school students to take four years of mathematics and three years of science coursework to be eligible for graduation. This study defines mathematics and science teachers as those who possess a secondary (7-12) instructional certification (as detailed in Appendix B) since mathematics and science teachers at the primary level teach math and science under blanket K-6 certifications. Therefore, to calculate a student: teacher ratio for these two subjects, the enrollment for each LEA type as reported in Table 4.1 was multiplied by 6/13 (for Grades 7-12 out of total 13-grade levels) and 5/13 (for Grades 7-11 out of total 13-grade levels). This value was then divided by the average number of math and science teachers reported in Table 4.6 to obtain the student: teacher ratio reported in Table 4.9.

Interpreting this ratio requires knowing that the typical math and science teacher student load is 125 students/year (5 classes with 25 students each). Using that number as a "rule of thumb," the average math teacher in every LEA type teaches below the 125-student threshold although some LEAs (i.e., Suburban Title I Districts in the PHL and RCDs in the CPA region) come within 10 percent of meeting this parameter. The student: teacher ratio for the average science teacher is not as consistent. In the PHL region, SDP science teachers have on average 57 students over the 125-student threshold compared to Suburban Non-Title I Districts, where science teachers teach half that number with an average 93 students, which reflects the uneven distribution of these teachers in the region. Whereas some LEAs (again Suburban Title I Districts in the PHL region and RCDs in the CPA region) come within a 10 percent range of meeting this parameter, only the SDP exceeds this measure and by a substantial margin.

**Table 4.9 • Proxy Need for High Need Subject Areas Using Student:Teacher Ratios (Avg. AY2011-12 through AY2016-17) [*n* (teachers)=39,629]**

| | Mathematics | | | | Natural Sciences | | |
|---|---|---|---|---|---|---|---|
| | *n* (students) | *n* (teachers) | Student-Teacher Ratio | Percent Over/Under Max | *n* (students) | *n* (teachers) | Student-Teacher Ratio |
| ***Greater Philadelphia CSA*** | | | | | | | |
| School District of Philadelphia | 68,492 | 699 | 98 | -22% | 57,076 | 314 | 182 |
| Suburban Title I Districts | 36,999 | 326 | 113 | -9% | 30,832 | 263 | 117 |
| Suburban Non-Title I Districts | 161,619 | 1,636 | 99 | -21% | 134,682 | 1,446 | 93 |
| Charter Schools | 43,756 | 466 | 94 | -25% | 36,463 | 343 | 106 |
| Career & Technical Schools | 1,259 | 13 | 97 | -23% | 1,049 | 12 | 87 |
| Greater Philadelphia CSA Totals | 312,124 | 3,141 | 99 | | 260,104 | 2,378 | 109 |
| ***Greater Pittsburgh CSA*** | | | | | | | |
| Pittsburgh Public Schools | 12,356 | 138 | 90 | -28% | 10,297 | 96 | 107 |
| Suburban Title I Districts | 44,004 | 475 | 93 | -26% | 36,670 | 393 | 93 |
| Suburban Non-Title I Districts | 98,724 | 1014 | 97 | -22% | 82,270 | 927 | 89 |
| Charter Schools | 9,171 | 84 | 109 | -13% | 7,643 | 71 | 108 |
| Career & Technical Schools | 593 | 8 | 74 | -41% | 495 | 6 | 82 |
| Greater Pittsburgh CSA Totals | 164,849 | 1,719 | 96 | | 137,374 | 1,493 | 92 |
| ***Central Pennsylvania MSAs and µSAs*** | | | | | | | |
| Regional City Districts | 55,147 | 466 | 118 | -5% | 45,955 | 387 | 119 |
| Suburban Title I Districts | 41,566 | 405 | 103 | -18% | 34,638 | 339 | 102 |
| Suburban Non-Title I Districts | 129,522 | 1,264 | 102 | -18% | 107,935 | 1,086 | 99 |
| Rural Title I Districts | 66,899 | 706 | 95 | -24% | 55,749 | 594 | 94 |
| Rural Non-Title I Districts | 82,588 | 882 | 94 | -25% | 68,823 | 746 | 92 |
| Charter Schools | 11,022 | 123 | 90 | -28% | 9,185 | 91 | 100 |
| Career & Technical Schools | 3,572 | 42 | 85 | -32% | 2,977 | 35 | 85 |
| Central Pennsylvania Region Totals | 390,315 | 3,888 | 100 | | 325,263 | 3,278 | 99 |

| | Special, Remedial, and Alternate Education | | | | English as a Second Language | | | |
|---|---|---|---|---|---|---|---|---|
| Percent Over/Under Max | *n* (students) | *n* (teachers) | Student-Teacher Ratio | Percent Over/Under Max | *n* (students) | *n* (teachers) | Student-Teacher Ratio | Percent Over/Under Max |
| 45% | 18,694 | 749 | 25 | 108% | 12,659 | 181 | 70 | 100% |
| -6% | 12,999 | 1,107 | 12 | -2% | 5,304 | 189 | 28 | -20% |
| -25% | 50,793 | 4,713 | 11 | -10% | 7,438 | 291 | 26 | -27% |
| -15% | 14,492 | 879 | 16 | 37% | 3,250 | 79 | 41 | 18% |
| -30% | 502 | 25 | 20 | 67% | | | | |
| | 97,655 | 7,473 | 13 | | 27,787 | 741 | 38 | |
| -14% | 4,071 | 349 | 12 | -3% | 759 | 31 | 24 | -31% |
| -25% | 14,325 | 1235 | 12 | -3% | 277 | 12 | 23 | -35% |
| -29% | 26,144 | 2408 | 11 | -10% | 1,284 | 51 | 25 | -29% |
| -14% | 3,093 | 182 | 17 | 42% | 70 | 11 | 6 | -82% |
| -34% | 228 | 13 | 18 | 46% | | | | |
| | 47,924 | 4,186 | 11 | | 2,473 | 108 | 23 | |
| -5% | 17,986 | 1,584 | 11 | -5% | 11,288 | 362 | 31 | -11% |
| -18% | 12,375 | 1,077 | 11 | -4% | 1,114 | 48 | 23 | -33% |
| -20% | 36,741 | 3,118 | 12 | -2% | 4,184 | 178 | 23 | -33% |
| -25% | 22,271 | 2,015 | 11 | -8% | 790 | 51 | 16 | -56% |
| -26% | 24,991 | 2,430 | 10 | -14% | 1,602 | 86 | 19 | -47% |
| -20% | 3,424 | 188 | 18 | 52% | 876 | 25 | 34 | -1% |
| -32% | 1,275 | 58 | 22 | 83% | | | | |
| | 119,227 | 10,471 | 11 | | 19,527 | 753 | 26 | |

Calculating student: teacher ratios for special education students requires both a different approach and interpretation given the legal requirements associated with the Individuals with Disabilities Act (IDEA). The PIMS database requires all LEAs to report the number of special education students in a school using one of three categories:

(1) Full-time support (students who receive services for ≥80 percent of the school day),
(2) Supplemental support (students who receive services for 21 percent to 79 percent of the school day), *and*
(3) Itinerant support (students who receive services for ≤20 percent of the school day).

The PIMS database also includes weights for each category such that the values reported in the SPP are summative full-time equivalent (FTE) percentages of identified students. Obtaining the student: teacher ratio required multiplying student enrollment in each LEA type by their respective special education percentage provided in Table 4.1. Then, this value was divided the product by the number of special education teachers reported in Table 4.6. Under Pennsylvania's IDEA compliance requirements, a single special education teacher can have a maximum caseload of 12 FTE identified students. In the PHL region, the SDP is grossly out of compliance with this regulation with an assignment on average of 25 FTE identified students to a single special education teacher. No other LEA in all three regions, except for charters, is out of compliance, although it is clear from this table that many LEAs are very close to their maximum limits. Charters in all three regions assign on average an additional 4 to 6 FTE identified students above the 12-student limit.

Finally, with respect to ESL, because ESL students are not a protected class (other than for state accountability measures), there is no formal regulation that mandates a maximum student: teacher load and so the PDE has issued a guideline of ≤35 students assigned to an ESL teacher based on their research of best practices in this field. Again, obtaining a student: teacher ratio required multiplying the percent ESL in each LEA type, as provided in Table 4.1, by total student enrollment and then dividing this value by the number of ESL teachers employed in that LEA type. The PHL region's shortage of ESL teachers is most acute in the SDP and charter schools, with both LEA types well over the PDE recommendation by an additional 35 and six students, respectively.

## Modeling Results

The descriptive analyses provide valuable insight into emergent trends in the data but responding to the two sets of research questions requires a more in-depth understanding using inferential results. Given the modifications made to both the variable and the model setup, it is worth first discussing how to interpret the results, test if the model's values are reliable, and, due to the enormity of the sample, establish a practical approach to determining which values are worth an explanation.

### *Deciphering Survival Model Results*

Recall that survival models are grounded in the concept of hazard (risk) in which the researcher seeks to know if a subject survives at time $t$, what are the chances that the same subject will survive at time $t$+1 given how other subjects (with different profiles) fared. The hazard rate h($t$) is, therefore, expressed as the number of individuals who experience the event at time $t$ over the number of individuals who do not experience at time $t$. Although hazard rates are instantaneous rates of change (i.e., a mathematical derivative), because of the short observation period associated with this study, the hazard rate is the hazard averaged across all five-time points.

***Interpreting Hazard Ratios and the Effect of Log Dollars.*** The effectiveness of HRs ($e^{\beta}$) lies in the meaning of the resulting value. As the name implies, it is a ratio of those who experienced the event (in this study, turnover) over those who did not per a given unit of time (in this study, a year). Naturally, this ratio varies by independent variable since it measures the effect of that variable's strength (or lack thereof) to influence the event. Because the function $f(x)=e^{x}$ has a lower asymptotic limit of zero, an HR must always be positive although the hazard associated with an independent variable can be so small that it could practically be considered zero (or nonhazardous). Therefore, a variable with a HR of 1.00 means that there is no increase or decrease in hazard associated with this variable since the hazard rate for the group that did experience the event is virtually the same as the hazard rate for the group that did not experience the event despite a unit increase in the value of the variable. An HR >1.00 means that there is an increasing hazard associated with a unit increase in that variable whereas an HR <1.00 means that there is less hazard associated with the same unit increase. Because the hazard rate is an average over the five-time points of this study, so too is the hazard ratio. Thus, hazard ratios indicate an increase or decrease in the hazard (on average) for any single time point.

Social scientists often use the concept of "log dollars" as a means of compensating for the non-linear effects of money on an outcome (See Chapter 3 for a fuller discussion concerning diminishing returns.) While categorical variables, which are "dummy coded" as '0' or '1' for each category, and continuous variables are easy to interpret in terms of a unit change, the interpretation can be elusive when attempting to interpret the effect of log dollars on the outcome, especially when the outcome is binary. The technical interpretation is for a unit change in the β coefficient for a log dollar variable, such as salary, on the outcome of turnover would be "a 2.718 times increase (the value of *e*) in salary, holding all other variables constant, is associated with an increase or decrease in the hazard (risk of experiencing turnover) by [HR-1] percent." However, the concept of a 2.718 is not only abstract but also impractical as salaries (or any other monetary value for that matter) are generally are not parceled in units of *e.* A more practical way to express log dollars is in terms of percent change using the following equation:

$$\textbf{Percent Change} = -(\mathbf{1} - e^{\mathbf{ln(x)}\beta}) \qquad (4.1)$$

Mathematically, zero percent change in the value of the log dollar variable would be represented by a value of '1' (i.e., 100 percent of the unit is measured) and the percent change on the outcome would, therefore, be 0 percent since ln(1) = 0 as substituted into Equation 4.1. This calculation is conceptually understandable since, without a change in the independent variable, there is no percent change on the outcome. It logically follows then that to calculate a 10 percent change in the outcome, the effect would be the product of ln(1.1) = 0.953*β and the effect for a 20 percent change in the outcome expressed as ln(1.2)=0.182*β and so on depending on the percent increase in change desired. Accordingly, Equation 4.1 can be modified to provide results per the research questions posed as follows:

$$\textbf{10 Percent Change} = -(\mathbf{1} - e^{\mathbf{0.953}\beta}) \qquad (4.2)$$

$$\textbf{20 Percent Change} = -(\mathbf{1} - e^{\mathbf{0.182}\beta}) \qquad (4.3)$$

The inferential result tables created for this study are in two variant forms: Tables 4.10/ 4.12-4.14/ 4.18-4.20 report HRs since this is the standard reporting approach found in medical science literature whereas Tables 4.11/ 4.15-4.17/ 4.21-4.23 provide the effect of a 10 percent or 20 percent increase in monetary investment using Equations 4.2 and 4.3. Each approach has its benefits; providing HRs, as opposed to $\beta$ values, allows the reader to visually gauge if a statistically significant value increases hazard (HR>1.000) or reduces hazard (HR<1.000) whereas providing percent changes removes the hassle of using Equations 4.2 and 4.3. The analysis below focuses on the effects of statistically significant values in terms of percent change, but in keeping with APA standards of reporting regression-based results, also includes the corresponding $\beta$ values with matching t- and p-values.

***Methods of Confirming Model Fit.*** Researchers and reviewers often devote considerable time scrutinizing model fit statistics since any acceptable interpretation of regression-based results are predicated upon the related concepts of validity and fit. The previous chapter already presented a detailed argument for model validity vis-à-vis the theoretical justification and setup of the Cox Proportional Hazards Model (e.g., stratification, clustering, incorporating discrete time) so this chapter discusses measures of model fit as applied to survival models.

Perhaps the most widely understood and used measure of fit is the universal $R^2$ value in linear regression or the similar pseudo-$R^2$ value for logistic regression. This study does have a binary outcome like a logistic regression but attempting to apply a pseudo-$R^2$ test (e.g. Nagelkerke, Tjur, etc.) is problematic because (a) there is clustering of cases into groups (teachers) and (b) the HR ($e^{\beta}$) is not the result of any singular logistic regression since it measures risk experienced throughout the study period. A better fitness value for survival models is the concordance value, which conceptually is a “relaxed” approach to pseudo-$R^2$ in that, instead of determining how much the regression can explain variance in the outcome, concordance values explain how much of the regression explains the pattern of the outcome (i.e., the fraction of changes from '0' to '1' or vice versa) (Austin, & Steyerberg, 2012). For instance, a value of 0.340 indicates that the regression can explain 34 percent of the outcome pattern. Table 4.10 presents the concordance value for all three models created for this study, with values ranging from 0.654 to 0.705, indicating that the models can explain 65 percent to 71 percent of the outcome pattern.

Another traditional determinant of the goodness of fit in linear regression is standard errors. Standard errors represent the average distance that the observed values fall from the regression line (or in the case of a binary outcome, a sigmoidal curve), and as such, smaller standard error values are indicative of a better fit. Typical standard errors rely on an assumption of homoscedasticity, which means the variability of the outcome is the same across all values of the independent variable(s) (Klein, 1997). For instance, if the effects of increased monetary value were consistent across all observations, then it would be appropriate to make a homoscedastic assumption of the two monetary variables. This assumption is, of course, not the case since the use of clustering implies that observations grouped by teacher share some relationship with one another and therefore are likely to have some related influence on the outcome. In effect, clustering limits the "amount of information" that a model can derive from the data since it is bound to consider grouping. For instance, 100 observations on 100 individuals "provide more information" than 100 observations on 10 clustered individuals.

Rejecting an assumption of homoscedasticity means assuming heteroscedasticity, which requires a separate type of standard error calculation known as robust standard errors

(RSEs). Since the coxph function automatically produces RSEs because of clustering, interpreting these values in the context of HRs requires reference to the original β value that resulted in the HR. For instance, if the result for a unit increase in the number of assignment (i.e., each additional subject area assigned to a teacher) is a statistically significant HR ($e^{\beta}$) of 1.436 with an RSE of 0.153, then the β value is ln(1.436) = 0.362. Moreover, the estimate is reliable since the 95 percent confidence interval (i.e., the range between 0.362±0.153) does not cover zero. The result then is interpreted as "Adding an additional assignment to a teacher, holding all other variables constant, will increase turnover by about 44 percent.". Tables 4.10/ 4.12-4.14/ 4.18-20 report RSEs value next to their corresponding HRs. For ease of reference, note that ln(0.002), which is the lowest statistically significant HR, yields a β of -6.215 while ln(10.798), the highest statistically significant HR, yields a β of 2.379.

A third popular measure of fit in more complicated regression-based models is the loglikelihood value, a logarithmic calculated holistic measure of how each independent variable in the model can correctly predict the outcome. Loglikelihood values do not have a universal reference point, such as in $R^2$ measures where a value of 1.00 indicates that all variance in the outcome can be accounted for by the predictors since loglikelihood values are idiosyncratic to a specific model's configuration. Thus, these values are only useful to determine relative fit since the higher loglikelihood value between two or more configuration is indicative of better fit (Klein, 1997). Using the loglikelihood value as a criterion can be problematic in survival models that incorporate clustering since loglikelihoods do not correlate cases within a group. Therefore, a better alternative here is Wald's Test, a chi-squared test ($\chi^2$) for survival models, that tests the relationship between the model variables and the outcome by incorporate clustering. As with any $\chi^2$ test, a non-significant relationship results in accepting the null hypothesis while a statistically significant value results in rejecting the null hypothesis. As was the case with testing for proportional hazard using chi-square test, fitting a global test to a dataset of this magnitude virtually guarantees that this statistic will be statistically significant. However, the statistical significance of this value is less important compared to its magnitude, which measures the strength of the assumption made about clustering the model (Rotnitzky & Jewell, 1990). Table 4.10 provides Wald's Test ($\chi^2$) values for all three regional models – PHL [(24; 55,968 (clusters) = 4,025, $p<0.001$], PGH [(24; 28,141 (clusters) = 2,166, $p<0.001$], and CPA [(24; 67,699 (clusters) = 5,938, $p<0.001$] – well above the critical value of 45.559 associated with 24 degrees of freedom for the $p<0.001$ level.

***Defining a Pragmatic Approach to Results Analysis.*** Since this study uses a total of 84 models, it would be injudicious to explain every value regardless of statistical significance or effect for both variables under study. Accordingly, this study uses a more practical approach that incorporates the following three arguments:

(1) Remember from Chapter 2 how comparing turnover either between fields, nationally, or even internationally, leads to some flawed assumptions. Even a statewide baseline for Pennsylvania is problematic given the diverse demographic and socioeconomic environments in which teachers teach throughout the state.

(2) From a statistical perspective, an inferential analysis of a large dataset will generally produce many statistically significant results since any two variables likely share a substantial amount of variation. Problematically, some of these statistically significant results can lead to committing "Type I-esque" errors in which all statistically significant values give the illusion of a finding, but many have negligible effect sizes.

(3) Form a policy and practice perspective, asking cash-strapped politicians and school administrators to make monetary investments requires providing evidence that the intervention will result in some meaningful (positive) change. Lacking such evidence, these custodians of public funds will eschew propositions that are not cost-effective.

To the first point, this study sets the "baseline" for comparison internally by region rather than appeal to some external standard. Each of Pennsylvania's regions has distinct identities that have led to political tension and a certain degree of dysfunction in Harrisburg. Thus, rather than attempt to a "one size fits all" approach to this study, establishing regional baselines helps account for the geographic, demographic and economic diversity of the state. To the second and third points, this analysis is limited to only those statistically significant variables that result in at least a 10 percent decrease in the risk of achieving turnover because of either a 10 or 20 percent increase in investment. While hazard ratios in this study describe the average increase or decrease in risk of turnover *in any given year*, it is unlikely that either state or local policymakers will be able to invest such a large percentage of funds in a single year since dramatically increasing taxes might result in political suicide. However, policymakers may see reductions in turnover risk as predicted by these models if they choose to invest the 10 to 20 percent over five years (i.e., two to four percent annually) – a far more realistic expectation given recent trends in collective bargaining (Combs, 2018). In brief, both the analysis and discussion are henceforth limited only to hazard ratios that (a) are for LEA types which have a higher turnover than Suburban Non-Title I Districts in each region and (b) result in at least a 10 percent return on investment (ROI).

### ***Interpretation of Main Effects***

As organized in Table 4.10, the main effects are categorized into three parts – teacher qualifications, teacher assignment, and LEA characteristics. The reference category, for this series of regressions in all three regions, is:

> <u>A "New Teacher" with a "Bachelor's Degree" teaching a "Non-High Needs Subject" in a major urban district(s) – either the "School District of Philadelphia" (PHL), "Pittsburgh Public Schools" (PGH), "Regional City Districts" (CPA)…</u>

For the main effects, the discussion below focuses only those statistically significant HRs for non-transformed variables since the two transformed variables receive much attention in the final section. Moreover, interpreting HRs for non-transformed variables is much simpler since "a unit increase in the [variable], holding all other values constant, results in a [HR-1] percent (increase/decrease) of experiencing turnover at any time during the observation period". For the remainder of this study, any interpretation of HRs will assume the condition of "holding all other values constant" and "at any time during the observation period."

With respect to teacher qualifications predictors, in all three regions, there a slightly increase in turnover for new teachers in the reference category for every additional year of experience with those employed in the PPS at the highest risk (9 percent; $\beta = 0.087$, $t(115{,}814) = 38.332$ , $p<0.001$) and those in the SDP with the lowest (5 percent; $\beta = 0.046$, $t(208{,}933) = 35.107$, $p<0.001$). Not surprisingly, the transition to an experienced teacher leads to precipitous drop in the risk of turnover with PPS teachers seeing a much greater chance of survival (76 percent; $\beta = -1.140$, $t(115{,}814) = -29.312$, $p<0.001$) compared to either their SDP (54 percent; β= –0.771, $t$(208,933)= –29.915, $p<0.001$) or RCDs (69 percent; β= –1.169, $t$(271,371)= –39.412, $p<0.001$) counterparts.

With respect to teacher assignment, moving new teachers in the reference group from a low-need subject to a high-need one also increases risk of turnover, especially for those in the SDP who are moved into special education assignments (22 percent; β= 0.195, $t$(208,933)= 10.066, $p<0.001$) and those moved into ESL assignments in PPS (41 percent; β= 0.346, $t$(115,814)= 2.602, $p<0.01$) and RCDs (32 percent; β= 0.211, $t$(271,371)= 11.392, $p<0.001$) teachers. Interestingly, if these same teachers moved from their low need placement into an administrative or support related position, they would experience an increase in survival of 27 percent–29 percent in all three regions.

Lastly, when examining the context of a teacher's employing LEA, a 5-percentage point increase in African–American enrollment also increases turnover in all three LEAs. SDP teachers in the reference category face the highest increased risk of turnover (4 percent; β= 0.400, $t$(208,933)= 14.831, $p<0.001$) followed by their PPS peers (3 percent; β= 0.027, $t$(115,814)= 4.754, $p<0.001$) – an interesting finding given that the SDP and PPS both serve majority African-American students. Another intriguing finding is that a five percentage point increase in the number of special education students does not hurt turnover for the reference group with a nonsignificant result in PPS and an increased chance of survival in the SDP (4 percent; β= –0.041, $t$(208,933)= –3.423, $p<0.001$) and RCDs (6 percent; β= –0.057, $t$(271,371)= –4.108, $p<0.001$) regions. A 5-percentage point increase in PSSA/Keystone ELA/Literature proficiency scores also increases chances of survival considerably in PPS (11 percent; β= –0.114, $t$(115,814)= –4.055, $p<0.001$) and RCDs (8 percent; β= –0.083, $t$(271,371)= –4.055, $p<0.001$) with no statistically significant effect in the SDP.

**Table 4.10a • Main Effects of Survival Models [Hazard Ratios] |**
**[*n* (educators)=151,808, *n* (cases)=596,118; 96.3% of Teacher Workforce; 80.8% of Population]**

| | Outcome: Hazard Ratios ($e^{\beta}$) | | |
|---|---|---|---|
| | Greater Philadelphia CSA (Model w/o Interactions) | Greater Pittsburgh CSA (Model w/o Interactions) | Central Pennsylvania MSAs and µSAs (Model w/o Interactions) |
| *Year of Study* | | | |
| AY2013-14 | 1.291 (0.035)*** | 1.294 (0.079)*** | 1.522 (0.039)*** |
| AY2014-15 | 1.743 (0.033)*** | 1.580 (0.071)*** | 1.978 (0.041)*** |
| AY2015-16 | 1.880 (0.033)*** | 1.803 (0.074)*** | 1.867 (0.042)*** |
| AY2016-17 | 2.010 (0.034)*** | 2.399 (0.074)*** | 2.254 (0.043)*** |
| *Educator Qualification Related Variables* | | | |
| Years of Experience | 1.047 (0.001)*** | 1.091 (0.002)*** | 1.075 (0.001)*** |
| Log Salary | 0.846 (0.009)*** | 0.752 (0.018)*** | 0.828 (0.011)*** |
| Experienced Educator Status | 0.463 (0.026)*** | 0.244 (0.048)*** | 0.311 (0.030)*** |
| Some College or Less (including Vocational Certificate) | 1.237 (0.160) | 1.176 (0.247) | 1.103 (0.127) |
| Master's Degree | 0.907 (0.019)*** | 1.048 (0.026) | 0.939 (0.016)*** |
| Doctoral of Specialist's Degree | 1.143 (0.093) | 1.462 (0.131)** | 1.077 (0.109) |
| *Educator Assignment Related Variables* | | | |
| Mathematics | 1.165 (0.027)*** | 1.024 (0.049) | 0.948 (0.032) |
| Natural Sciences | 1.122 (0.031)*** | 1.134 (0.054)* | 0.954 (0.034) |
| Special, Alternative & Remedial Education | 1.216 (0.019)*** | 1.100 (0.032)** | 1.235 (0.019)*** |
| English as a Second Language | 1.161 (0.053)** | 1.414 (0.133)** | 1.32 (0.057)*** |
| Other Educators (including School Administrators) | 0.706 (0.045)*** | 0.728 (0.103)** | 0.708 (0.077)*** |
| Number of Assignments | 1.009 (0.009) | 1.126 (0.020)*** | 1.028 (0.009)** |
| *LEA Demographic & Academic Variables* | | | |
| Log Auxiliary Funding ł | 1.157 (0.036)*** | 0.973 (0.067) | 1.149 (0.039)*** |
| (5%↑) African-American ł | 1.040 (0.003)*** | 1.028 (0.006)*** | 1.026 (0.004)*** |
| (5%↑) Non-White Hispanic ł | 1.015 (0.005)** | 0.729 (0.091)*** | 0.983 (0.004)*** |
| (5%↑) Special Education ł | 0.960 (0.012)*** | 1.007 (0.021) | 0.945 (0.014)*** |
| (5%↑) English Language Learner ł | 1.026 (0.018) | 1.129 (0.077) | 1.136 (0.017)*** |
| (5%↑) PSSA/Keystone ELA/Literature Proficiency Score ł | 0.988 (0.011) | 0.893 (0.028)*** | 0.92 (0.012)*** |
| (5%↑) PSSA/Keystone Math/Algebra I Proficiency Score ł | 1.014 (0.011) | 1.112 (0.023)*** | 1.041 (0.010)*** |
| (5%↑) PSSA/Keystone Science/Biology Proficiency Score ł | 0.955 (0.006)*** | 0.967 (0.011)** | 0.972 (0.006)*** |
| *Educator Experience Interactions Effects* | Table 4.9 | Table 4.10 | Table 4.11 |
| *High Need Subject Interaction Effects* | Table 4.12 | Table 4.13 | Table 4.14 |
| **Observations** | 208,933 | 115,814 | 271,371 |
| **Number of Clusters (Educators)** | 55,968 | 28,141 | 67,699 |
| **Number of Events** | 19,628 | 6,891 | 18,105 |
| **Concordance** | 0.654 (0.003) | 0.705 (0.004) | 0.665 (0.002) |
| **Wald's Test $\chi^2$** | df(24)=4,025*** | df(24)=2,166*** | df(24)=5,938*** |

ł = z-standardized (LEA centered)
*p≤0.05; **p<0.01; ***p<0.001

**Table 4.11 • Main Effects of Survival Models [Percent Change in Turnover Risk] |**
**[*n* (educators)=151,808, *n* (cases)=596,118; 96.3% of Teacher Workforce; 80.8% of Population]**

| | Outcome: Percent Change in Turnover Risk | | |
|---|---|---|---|
| | Greater Philadelphia CSA (Model w/o Interactions) | Greater Pittsburgh CSA (Model w/o Interactions) | Central Pennsylvania MSAs and µSAs (Model w/o Interactions) |
| *Year of Study* | | | |
| AY2013-14 | 29.10% | 29.40% | 52.20% |
| AY2014-15 | 74.30% | 58.00% | 97.80% |
| AY2015-16 | 88.00% | 80.30% | 86.70% |
| AY2016-17 | 101.00% | 139.90% | 125.40% |
| *Educator Qualifications* | | | |
| Years of Experience | 4.70% | 9.10% | 7.50% |
| Log Salary | -1.58% | -2.68% | -1.78% |
| Experienced Educator Status | -53.70% | -75.60% | -68.90% |
| Some College or Less (including Vocational Certificate) | | | |
| Master's Degree | -9.30% | | -6.10% |
| Doctoral of Specialist's Degree | | 46.20% | |
| *Educator Assignment Related Covariates* | | | |
| Mathematics | 16.50% | | |
| Natural Sciences | 12.20% | 13.40% | |
| Special, Alternative & Remedial Education | 21.60% | 10.00% | 23.50% |
| English as a Second Language | 16.10% | 41.40% | 32.00% |
| Other Educators (including School Administrators) | -29.40% | -27.20% | -29.20% |
| Number of Assignments | | 12.60% | 2.80% |
| *LEA Demographic & Academic Covariates* | | | |
| Log Auxiliary Funding[ł] | 1.40% | | 1.33% |
| (5%↑) African-American[ł] | 4.00% | 2.80% | 2.60% |
| (5%↑) Non-White Hispanic[ł] | 1.50% | -27.10% | -1.70% |
| (5%↑) Special Education[ł] | -4.00% | | -5.50% |
| (5%↑) English Language Learner[ł] | | | 13.60% |
| (5%↑) PSSA/Keystone ELA/Literature Proficiency Score[ł] | | -10.70% | -8.00% |
| (5%↑) PSSA/Keystone Math/Algebra I Proficiency Score[ł] | | 11.20% | 4.10% |
| (5%↑) PSSA/Keystone Science/Biology Proficiency Score[ł] | -4.50% | -3.30% | -2.80% |
| *Educator Experience Interactions Effects* | Table 4.9 | Table 4.10 | Table 4.11 |
| *High Need Subject Interaction Effects* | Table 4.12 | Table 4.13 | Table 4.14 |
| **Observations** | 208,933 | 115,814 | 271,371 |
| **Number of Clusters (Educators)** | 55,968 | 28,141 | 67,699 |
| **Number of Events** | 19,628 | 6,891 | 18,105 |
| **Concordance** | 0.654 (0.003) | 0.705 (0.004) | 0.665 (0.002) |
| **Wald's Test $\chi^2$** | df(24)=4,025*** | df(24)=2,166*** | df(24)=5,938*** |

ł = z-standardized (LEA centered)
*p≤0.05; **p<0.01; ***p<0.001

***Interpretation of Interaction Effects by Experience Level***

Answering the first research question requires analyzing the effect on turnover rates for a 10 percent and 20 percent increase in the variables of interest – salary and auxiliary student spending – by LEA type and region. Additionally, the parallel construction of the 34 models, each a combination of the two experience/education levels for all 17 LEA types but with different reference groups, allows for a generalized comparison of effects across experience, LEA types as well as within and across regions. Consequently, in Tables 4.12-4.14, each Log Salary and Log Auxiliary Spending value is the main effect of that predictor condition on a specific education/experience level as well as LEA type. Also, there is no instructional area variable included in this set of models so that the HR values capture the hazard experienced by new or experienced teachers and not some subset thereof. Therefore, the reference categories are as follows:

A "New Teacher" with a "Bachelor's Degree" who

teaches any subject matter in a [LEA type] *or*

An "Experienced Teacher" with a "Master's Degree" who

teaches any subject matter in a [LEA type]

***New Teachers.*** The effect of a 10 percent or even 20 percent salary increase is highly variable in many LEA types suffering from regionally above average new teacher turnover. A 10 percent salary increase has the most effect in reducing the risk of turnover in the SDP by 11.8 percent ($\beta = -1.318$, $t(208{,}933) = -6.767$, $p<0.001$) followed closely by 11.1 percent in the PPS ($\beta = -1.234$, $t(115{,}814) = -2.705$, $p<0.01$). On the contrary, in the CPA region, the same 10 percent increase results in a minor 1.3 percent decrease in risk of turnover (and, likewise, a 20 percent increase results in a yield of 2.55 percent decrease) for the CPA region. Similarly, neither a 10 percent or 20 percent have any considerable effect (at most

5.9 percent) on reducing the risk of turnover for new teachers either in the PHL's or the PGH's Suburban Title I Districts as well as the PGH's Suburban Non-Title I Districts. Equally, no monetary increase results in any substantive decrease (at most 2.4 percent) in risk or any charters.

***Experienced Teachers.*** For experienced teachers, an increase in salary has either no or minor effects (at most 7.02 percent) on reducing turnover across all three regions save two exceptions. In the SDP, a 20 percent increase in salary leads to a 13 percent reduction in risk of turnover ($\beta = -0.763$, $t(208{,}933) = -9.914$, $p<0.001$) and an even smaller 10 percent increase in pay results in an impressive 24.7 percent decrease ($\beta = -2.984$, $t(115{,}814) = -4.733$, $p<0.001$) in the PGH's CTE schools. To finish, the effect of increased auxiliary spending is either nonsignificant or results in an increase in hazard in every LEA type across all three regions. The next chapter assesses the implications of this finding in depth.

### *Interpretation of Interaction Effects by High Need Subject Area*

Like the first research question, here too the analysis focuses on the effect of a 10 percent and 20 percent increase in the variables of interest – salary and auxiliary student spending – on teacher turnover by region. Again, the parallel construction of the 56 models, each a combination of the four high need subject areas for 14 LEA types (excluding CTE schools) but with different reference groups, also allows for cross-subject, LEA type, and regional comparisons. Correspondingly, in Tables 4.18-4.20, each Log Salary and Log Auxiliary Spending value is the main effect of that predictor conditioned on a specific high need subject area in a corresponding LEA type. There are no education and experience related variables included in this set of models so that the HR values capture the hazard experienced by all teachers who are teaching that subject.

**Table 4.12 • Interaction of Experience Level and (Log) Salary/Auxiliary Spending [Hazard Ratios] | Greater Philadelphia CSA [*n* (educators)=55,968]**

| | New Educator w/Bachelor's Degree | Experienced Educator w/Master's |
|---|---|---|
| Log Salary[J] (School District of Philadelphia) | 0.268 (0.195)*** | 0.466 (0.083)*** |
| Philadelphia) | 0.991 (0.138) | 1.086 (0.206) |
| Log Salary[J] (Suburban Title I) | 0.914 (0.025)*** | 0.816 (0.018)*** |
| Log Auxiliary Spending[J] (Suburban Title I) | 2.593 (0.265)*** | 1.512 (0.198)* |
| Log Salary[J] (Suburban Non-Title I) | 0.770 (0.023)*** | 0.740 (0.026)*** |
| Log Auxiliary Spending[J] (Suburban Non-Title I) | 1.231 (0.105)* | 1.032 (0.068) |
| Log Salary[J] (Charter Schools) | 0.933 (0.018)*** | 0.831 (0.023)*** |
| Log Auxiliary Spending[J] (Charter Schools) | 1.109 (0.062) | 1.254 (0.092)* |
| Log Salary[J] (CTE Schools) | 4.602 (3.333) | 0.369 (1.608) |
| Log Auxiliary Spending[J] (CTE Schools) | 0.571 (3.165) | 0.510 (1.448) |

JHazard ratios are the main effect of Log Salary/Log Auxiliary Spending conditioned on the specified (LEA/Experience Level) reference categories for all education/subject area levels.
*p≤0.05, **p<0.01, *p<0.001

**Table 4.13 • Interaction of Experience Level and (Log) Salary/Auxiliary Spending [Hazard Ratios] | Greater Pittsburgh CSA [*n* (educators)=28,141]**

| | New Educator w/Bachelor's Degree | Experienced Educator w/Master's Degree |
|---|---|---|
| Log Salary[J] (Pittsburgh Public Schools) | 0.291 (0.456)** | 0.509 (0.226)** |
| Log Auxiliary Spending[J] (Pittsburgh Public Schools) | 8.590 (1.850) | 0.002 (2.193)** |
| Log Salary[J] (Suburban Title I) | 0.718 (0.018)*** | 0.820 (0.059)*** |
| Log Auxiliary Spending[J] (Suburban Title I) | 1.219 (0.219) | 0.708 (0.135)** |
| Log Salary[J] (Suburban Non-Title I) | 0.762 (0.021)*** | 0.616 (0.025)*** |
| Log Auxiliary Spending[J] (Suburban Non-Title I) | 0.919 (0.199) | 0.888 (0.108) |
| Log Salary[J] (Charter Schools) | 0.874 (0.057)* | 0.919 (0.039)* |
| Log Auxiliary Spending[J] (Charter Schools) | 1.095 (0.157) | 2.595 (0.209)*** |
| Log Salary[J] (CTE Schools) | 0.647 (1.583) | 0.051 (0.630)*** |
| Log Auxiliary Spending[J] (CTE Schools) | 0.933 (1.178) | 0.95 (0.674) |

JHazard ratios are the main effect of Log Salary/Log Auxiliary Spending conditioned on the specified (LEA/Experience Level) reference categories for all education/subject area levels.
*p≤0.05, **p<0.01, *p<0.001

**Table 4.14 • Interaction of Experience Level and (Log) Salary/Auxiliary Spending [Hazard Ratios] | Central Pennsylvania MSAs & µSAs [*n* (educators)=67,699]**

| | New Educator w/Bachelor's Degree | Experienced Educator w/Master's Degree |
|---|---|---|
| Log Salary[J] (Regional Urban Districts) | 0.868 (0.041)*** | 0.774 (0.019)*** |
| Log Auxiliary Spending[J] (Regional Urban Districts) | 1.468 (0.169)* | 1.796 (0.132)*** |
| Log Salary[J] (Suburban Title I) | 0.776 (0.051)*** | 0.747 (0.024)*** |
| Log Auxiliary Spending[J] (Suburban Title I) | 1.494 (0.247) | 0.988 (0.138) |
| Log Salary[J] (Suburban Non-Title I) | 0.830 (0.020)*** | 0.757 (0.030)*** |
| Log Auxiliary Spending[J] (Suburban Non-Title I) | 1.263 (0.180) | 0.947 (0.095) |
| Log Salary[J] (Rural Title I) | 0.789 (0.037)*** | 0.676 (0.022)*** |
| Log Auxiliary Spending[J] (Rural Title I) | 0.882 (0.165) | 0.969 (0.095) |
| Log Salary[J] (Rural Non-Title I) | 0.787 (0.026)*** | 0.752 (0.024)*** |
| Log Auxiliary Spending[J] (Rural Non-Title I) | 1.830 (0.144)*** | 1.103 (0.087) |
| Log Salary[J] (Charter Schools) | 0.959 (0.024) | 0.932 (0.028)* |
| Log Auxiliary Spending[J] (Charter Schools) | 1.487 (0.142)** | 1.247 (0.183) |
| Log Salary[J] (CTE Schools) | 0.360 (0.354)** | 0.774 (0.019)*** |
| Log Auxiliary Spending[J] (CTE Schools) | 0.238 (1.355) | 1.796 (0.132)*** |

JHazard ratios are the main effect of Log Salary/Log Auxiliary Spending conditioned on the specified (LEA/Experience Level) reference categories for all education/subject area levels.
*p≤0.05, **p<0.01, *p<0.001

**Table 4.15 • Interaction of Experience Level and (Log) Salary/Auxiliary Spending [Percent Change in Turonver Risk] | Greater Philadelphia CSA [n(educators)=55,968]**

| | New Educator w/Bachelor's Degree | | Experienced Educator w/Master's Degree | |
|---|---|---|---|---|
| | 10%↑ | 20%↑ | 10%↑ | 20%↑ |
| Log Salary[J] (School District of Philadelphia) | -11.79% | -21.34% | -7.02% | -13.00% |
| Log Salary[J] (Suburban Title I) | -0.85% | -1.63% | -1.92% | -3.64% |
| Log Auxiliary Spending[J] (Suburban Title I) | 9.51% | 18.97% | 4.02% | 7.83% |
| Log Salary[J] (Suburban Non-Title I) | -2.46% | -4.65% | -2.83% | -5.34% |
| Log Auxiliary Spending[J] (Suburban Non-Title I) | 2.00% | 3.86% | | |
| Log Salary[J] (Charter Schools) | -0.66% | -1.26% | -1.75% | -3.32% |
| Log Auxiliary Spending[J] (Charter Schools) | | | 2.18% | 4.21% |
| Log Salary[J] (CTE Schools) | | | | |
| Log Auxiliary Spending[J] (CTE Schools) | | | | |

JPercent Change is the main effect of Log Salary/Log Auxiliary Spending conditioned on the specified (LEA/Experience Level) reference categories for all education/subject area levels.
Note: Only statistically significant (p<0.05) values are shown.

**Table 4.16 • Interaction of Experience Level and (Log) Salary/Auxiliary Spending [Percent Change in Turonver Risk] | Greater Pittsburgh CSA [n(educators)=28,141]**

| | New Educator w/Bachelor's Degree | | Experienced Educator w/Master's Degree | |
|---|---|---|---|---|
| | 10%↑ | 20%↑ | 10%↑ | 20%↑ |
| Log Salary[J] (Pittsburgh Public Schools) | -11.10% | -20.15% | -6.23% | -11.58% |
| Log Auxiliary Spending[J] (Pittsburgh Public Schools) | | | -44.70% | -67.80% |
| Log Salary[J] (Suburban Title I) | -3.11% | -5.86% | -1.87% | -3.55% |
| Log Auxiliary Spending[J] (Suburban Title I) | | | -3.24% | -6.10% |
| Log Salary[J] (Suburban Non-Title I) | -2.56% | -4.83% | -4.51% | -8.45% |
| Log Auxiliary Spending[J] (Suburban Non-Title I) | | | | |
| Log Salary[J] (Charter Schools) | -1.28% | -2.43% | -0.80% | -1.53% |
| Log Auxiliary Spending[J] (Charter Schools) | | | 9.51% | 18.99% |
| Log Salary[J] (CTE Schools) | | | -24.70% | -41.88% |
| Log Auxiliary Spending[J] (CTE Schools) | | | | |

JPercent Change is the main effect of Log Salary/Log Auxiliary Spending conditioned on the specified (LEA/Experience Level) reference categories for all education/subject area levels.
Note: Only statistically significant (p<0.05) values are shown.

**Table 4.17 • Interaction of Experience Level and (Log) Salary/Auxiliary Spending [Percent Change in Turonver Risk] | Central Pennsylvania MSAs & µSAs [n(educators)=67,699]**

| | New Educator w/Bachelor's Degree | | Experienced Educator w/Master's Degree | |
|---|---|---|---|---|
| | 10%↑ | 20%↑ | 10%↑ | 20%↑ |
| Log Salary[J] (Regional Urban Districts) | -1.34% | -2.55% | -2.41% | -4.56% |
| Log Auxiliary Spending[J] (Regional Urban Districts) | 3.73% | 7.25% | 5.74% | 11.27% |
| Log Salary[J] (Suburban Title I) | -2.39% | -4.52% | -2.74% | -5.18% |
| Log Auxiliary Spending[J] (Suburban Title I) | | | | |
| Log Salary[J] (Suburban Non-Title I) | -1.76% | -3.34% | -2.62% | -4.95% |
| Log Auxiliary Spending[J] (Suburban Non-Title I) | | | | |
| Log Salary[J] (Rural Title I) | -2.23% | -4.23% | -3.66% | -6.89% |
| Log Auxiliary Spending[J] (Rural Title I) | | | | |
| Log Salary[J] (Rural Non-Title I) | -2.26% | -4.27% | -2.68% | -5.06% |
| Log Auxiliary Spending[J] (Rural Non-Title I) | 5.93% | 11.65% | | |
| Log Salary[J] (Charter Schools) | | | -0.67% | -1.28% |
| Log Auxiliary Spending[J] (Charter Schools) | 3.85% | 7.50% | | |
| Log Salary[J] (CTE Schools) | -9.28% | -16.99% | -2.41% | -4.56% |
| Log Auxiliary Spending[J] (CTE Schools) | | | 5.74% | 11.27% |

JPercent Change is the main effect of Log Salary/Log Auxiliary Spending conditioned on the specified (LEA/Experience Level) reference categories for all education/subject area levels.
Note: Only statistically significant (p<0.05) values are shown.

The reference category for these models are:

A teacher of any education or experience level who

teaches [High Need Subject] in a [LEA type]

Lastly, CTEs were not included in this analysis, because as shown in Table 4.6, the number of teachers employed in these subject areas is too small to analyze.

***Mathematics and Science Teachers.*** Table 4.9 presented student: teacher ratios for all four high need subject areas as a way of determining shortages. While this ratio varied markedly between and within regions for all four subject areas, math teachers experienced the least variability where all LEAs had a student: teacher ratio below the 125–student threshold. Many LEA types did not have a turnover rate for math teachers above their regional average with the exception being the SDP and charter schools across all three regions. A 20 percent increase in math teacher salaries does significantly reduce the risk of turnover in the SDP by 11.6 percent ($\beta = -0.672$, $t(208{,}933) = -6.301$, $p<0.001$) whereas there is no effect of a pay increase on charters. A 10 percent raise for math teachers in the PPS does cut the risk of turnover by 14.4 percent ($\beta = -0.856$, $t(115{,}814) = -2.939$, $p<0.01$) as well as a 12.2 percent reduction of risk ($\beta = -1.365$, $t(115{,}814) = -3.197$, $p<0.001$) in PGH's charters. There is also no substantive decrease in turnover risk (at most 3.3 percent) for math teachers in CPA charters.

Table 4.9 also illustrated the extreme shortage of science teachers in the SDP, which was the only LEA in which the student: teacher ratio exceeded the 125–student threshold. Along with the SDP, PPS and Suburban Title I Districts in the PGH region, Rural Schools (Title I/Non-Title I) as well charter schools in all three regions, suffer from higher science teacher turnover compared to their respective regional averages in this subject area. Only in three of those LEAs does any increase in salary result in any meaningful abatement of turnover risk; a 10 percent increase in salary reduces risk in the SDP by 12.7 percent (β= –1.422, $t(208{,}933)= -4.325$, $p<0.001$) and by a remarkable 19.9 percent in PPS (β= –2.336, $t(115{,}814)= -5.985$, $p<0.001$) whereas a 20 percent raise for science teachers leads to a smaller, yet considerable, 13.2 percent reduction for Suburban Title I (β= –0.778, $t(115{,}814)= -6.449$, $p<0.001$). For all remaining LEA types, there is either no or a small (at most 7.15 percent) reduction of risk in science teacher for either a 10 percent or 20 percent increase in either monetary value.

***Special Education and ESL Teachers.*** Also demonstrated in Table 4.9, there is a high need for special education teachers since virtually every LEA was either out of compliance or close to the maximum 12–student regulation imposed by the PDE & IDEA, with the SDP in the greater need compared to all other LEA types. It comes as no surprise then that in addition to the SDP, Suburban Title I Districts in the PHL and PGH regions along with charters in all three regions, all suffer from an abnormally high rate of turnover. Interestingly, no increase in any monetary amount results in a sizeable decrease (at most in the risk of 3.4 percent) of special education teacher turnover except in the SDP, where a 20 percent pay increase does result in a 10 percent reduction in risk (β= –0.576, $t(271{,}371)= -2.587$, $p<0.01$). While students load for urban ESL teachers in the PHL region (specifically the SDP and charters) are well above PDE recommended guidelines, interestingly, it is not the SDP which has a higher than regional average rate of turnover. Multiple LEAs across all three regions – PHL (Suburban Title I Districts), PGH (PPS and Suburban Title I Districts), and CPA (RCDs and Rural Non-Title I schools) as well as charters in each region – and appear to have issues with ESL teacher retention. Again, the effect of a monetary increase is highly variable. A 10 percent increase in salary has the highest effect in reducing ESL teacher turnover for charters in the CPA region by a notable 19.86 percent ($\beta = -2.324$, $t(271{,}371) = -3.542$, $p<0.001$) compared to Suburban Title I Districts in the PGH region who need to offer a 20 percent pay increase to achieve a similar 21.24 percent reduction of risk ($\beta = -1.308$, $t(115{,}814) = -5.817$, $p<0.001$). Charters in the PHL region also require a 20 percent increase in turn by the reduction is somewhat less by 14.5 percent region ($\beta = -0.858$, $t(208{,}933) = -5.515$, $p<0.001$). There is either no or minor effect in all the other LEAs type affected (by at most a 4.65 percent reduction in risk).

**Table 4.18 • Interaction of High Need Subject Area and (Log) Salary/Auxiliary Spending [Hazard Ratios] | Greater Philadelphia CSA [*n* (educators)=18,840]**

| | Mathematics | Natural Sciences | Special, Alternative & Remedial Education | English as Second Language |
|---|---|---|---|---|
| Log Salary[J] (School District of Philadelphia) | 0.510 (0.107)*** | 0.241 (0.329)*** | 0.562 (0.223)** | 0.177 (0.594)** |
| Philadelphia) | 1.129 (0.246) | 0.551 (0.386) | 0.831 (0.255) | 1.38 (0.638) |
| Log Salary[J] (Suburban Title I) | 0.859 (0.056)** | 0.872 (0.061)* | 0.826 (0.024)*** | 0.872 (0.059)* |
| Log Auxiliary Spending[J] (Suburban Title I) | 0.876 (0.693) | 2.098 (0.633) | 2.602 (0.271)*** | 10.798 (0.769)** |
| Log Salary[J] (Suburban Non-Title I) | 0.680 (0.082)*** | 0.744 (0.084)*** | 0.763 (0.030)*** | 0.614 (0.229)* |
| Log Auxiliary Spending[J] (Suburban Non-Title I) | 1.455 (0.227) | 0.921 (0.261) | 0.899 (0.107) | 2.131 (0.400) |
| Log Salary[J] (Charter Schools) | 0.863 (0.081) | 0.944 (0.068) | 0.833 (0.020)*** | 0.424 (0.156)*** |
| Log Auxiliary Spending[J] (Charter Schools) | 1.249 (0.164) | 1.358 (0.199) | 1.225 (0.116) | 0.921 (0.390) |

[J]Hazard ratios are the main effect of Log Salary/Log Auxiliary Spending conditioned on the specified (LEA/High Need Subject) reference categories for all experience/education levels.

Note: There is an insufficent sample of high need educators in Career & Technical Schools in order to execute a viable model. (See Table 4.5)

*p≤0.05, **p<0.01, *p<0.001

**Table 4.19 • Interaction of High Need Subject Area and (Log) Salary/Auxiliary Spending [Hazard Ratios] | Greater Pittsburgh CSA [*n* (educators)=9,284]**

| | Mathematics | Natural Sciences | Special, Alternative & Remedial Education | English as Second Language |
|---|---|---|---|---|
| Log Salary[J] (Pittsburgh Public Schools) | 0.425 (0.291)** | 0.097 (0.390)*** | 0.408 (0.369)* | 0.477 (0.948) |
| Log Auxiliary Spending[J] (Pittsburgh Public Schools) | 0.081 (3.750) | 2.241 (3.285) | 14.870 (2.596) | 337.534 (7.801) |
| Log Salary[J] (Suburban Title I) | 0.642 (0.044)*** | 0.459 (0.121)*** | 0.803 (0.071)** | 0.270 (0.225)*** |
| Log Auxiliary Spending[J] (Suburban Title I) | 1.917 (0.479) | 1.342 (0.508) | 0.963 (0.244) | 0.584 (1.615) |
| Log Salary[J] (Suburban Non-Title I) | 0.687 (0.057)*** | 0.524 (0.069)*** | 0.759 (0.042)*** | 0.675 (0.057)*** |
| Log Auxiliary Spending[J] (Suburban Non-Title I) | 0.282 (0.394)*** | 0.452 (0.409) | 1.106 (0.196) | 1.129 (1.905) |
| Log Salary[J] (Charter Schools) | 0.255 (0.427)*** | 0.964 (0.099) | 0.929 (0.020)*** | 1.319 (0.661) |
| Log Auxiliary Spending[J] (Charter Schools) | 2.057 (0.359)* | 1.421 (0.366) | 0.829 (0.273) | 0.728 (0.723) |

[J]Hazard ratios are the main effect of Log Salary/Log Auxiliary Spending conditioned on the specified (LEA/High Need Subject) reference categories for all experience/education levels.

Note: There is an insufficent sample of high need educators in Career & Technical Schools in order to execute a viable model. (See Table 4.6)

*p≤0.05, **p<0.01, *p<0.001

**Table 4.20 • Interaction of High Need Subject Area and (Log) Salary/Auxiliary Spending [Hazard Ratios] | Central Pennsylvania MSAs & µSAs [*n* (educators)=23,434]**

| | Mathematics | Natural Sciences | Special, Alternative & Remedial Education | English as Second Language |
|---|---|---|---|---|
| Log Salary[J] (Regional Urban Districts) | 0.598 (0.126)*** | 0.760 (0.071)*** | 0.799 (0.037)*** | 0.770 (0.091)** |
| Log Auxiliary Spending[J] (Regional Urban Districts) | 2.393 (0.418)* | 1.211 (0.438) | 2.848 (0.184)*** | 1.143 (0.398) |
| Log Salary[J] (Suburban Title I) | 0.672 (0.031)*** | 0.711 (0.066)*** | 0.760 (0.035)*** | 0.446 (0.797) |
| Log Auxiliary Spending[J] (Suburban Title I) | 2.270 (0.403)* | 0.242 (0.628)* | 1.064 (0.246) | 1.055 (0.929) |
| Log Salary[J] (Suburban Non-Title I) | 0.709 (0.055)*** | 0.748 (0.047)*** | 0.801 (0.037)*** | 0.812 (0.028)*** |
| Log Auxiliary Spending[J] (Suburban Non-Title I) | 0.965 (0.303) | 0.745 (0.364) | 0.769 (0.176) | 1.914 (0.935) |
| Log Salary[J] (Rural Title I) | 0.645 (0.046)*** | 0.646 (0.061)*** | 0.779 (0.042)*** | 0.801 (0.069)*** |
| Log Auxiliary Spending[J] (Rural Title I) | 1.261 (0.344) | 0.762 (0.342) | 0.678 (0.167)* | 0.526 (0.990) |
| Log Salary[J] (Rural Non-Title I) | 0.685 (0.06)*** | 0.704 (0.032)*** | 0.772 (0.039)*** | 0.570 (0.356) |
| Log Auxiliary Spending[J] (Rural Non-Title I) | 1.248 (0.300) | 1.159 (0.277) | 1.425 (0.146)* | 0.955 (0.753) |
| Log Salary[J] (Charter Schools) | 0.833 (0.064)** | 0.978 (0.070) | 1.024 (0.052) | 0.098 (0.656)*** |
| Log Auxiliary Spending[J] (Charter Schools) | 0.842 (0.281) | 0.698 (0.320) | 1.270 (0.311) | 0.552 (0.534) |

[J]Hazard ratios are the main effect of Log Salary/Log Auxiliary Spending conditioned on the specified (LEA/High Need Subject) reference categories for all experience/education levels.

Note: There is an insufficent sample of high need educators in Career & Technical Schools in order to execute a viable model. (See Table 4.6)

*p≤0.05, **p<0.01, *p<0.001

**Table 4.21 • Interaction of High Need Subject Area and (Log) Salary/Auxiliary Spending [Percent Change in Turnover Risk] | Greater Philadelphia CSA [n(educators)=18,840]**

| | Mathematics | | Natural Sciences | | Special, Alternative & Remedial Education | | English as Second Language | |
|---|---|---|---|---|---|---|---|---|
| | 10%↑ | 20%↑ | 10%↑ | 20%↑ | 10%↑ | 20%↑ | 10%↑ | 20%↑ |
| Log Salary[J] (School District of Philadelphia) | -6.22% | -11.55% | -12.68% | -22.85% | -5.34% | -9.97% | -15.21% | -27.07% |
| Philadelphia) | | | | | | | | |
| Log Salary[J] (Suburban Title I) | -1.44% | -2.73% | -1.30% | -2.47% | -1.81% | -3.43% | -1.30% | -2.47% |
| Log Auxiliary Spending[J] (Suburban Title I) | | | | | 9.54% | 19.05% | 25.46% | 54.31% |
| Log Salary[J] (Suburban Non-Title I) | -3.61% | -6.79% | -2.78% | -5.25% | -2.55% | -4.81% | -4.54% | -8.51% |
| Log Auxiliary Spending[J] (Suburban Non-Title I) | | | | | | | | |
| Log Salary[J] (Charter Schools) | | | | | -1.73% | -3.28% | -7.85% | -14.48% |
| Log Auxiliary Spending[J] (Charter Schools) | | | | | | | | |

JPercent change is the main effect of Log Salary/Log Auxiliary Spending conditioned on the specified (LEA/High Need Subject) reference categories for all experience/education levels.

Note #1: There is an insufficent sample of high need educators in Career & Technical Schools in order to execute a viable model. (See Table 4.6)

Note #2: Only statistically significant (p<0.05) values are shown.

**Table 4.22 • Interaction of High Need Subject Area and (Log) Salary/Auxiliary Spending [Percent Change in Turnover Risk] | Greater Pittsburgh CSA [n(educators)=9,284]**

| | Mathematics | | Natural Sciences | | Special, Alternative & Remedial Education | | English as Second Language | |
|---|---|---|---|---|---|---|---|---|
| | 10%↑ | 20%↑ | 10%↑ | 20%↑ | 10%↑ | 20%↑ | 10%↑ | 20%↑ |
| Log Salary[J] (Pittsburgh Public Schools) | -7.83% | -14.44% | -19.94% | -34.65% | -8.19% | -15.08% | | |
| Log Auxiliary Spending[J] (Pittsburgh Public Schools) | -21.30% | -36.76% | 7.99% | 15.85% | | | | |
| Log Salary[J] (Suburban Title I) | -4.14% | -7.76% | -7.15% | -13.24% | -2.07% | -3.92% | -11.73% | -21.24% |
| Log Auxiliary Spending[J] (Suburban Title I) | | | | | | | | |
| Log Salary[J] (Suburban Non-Title I) | -3.51% | -6.62% | -5.97% | -11.12% | -2.59% | -4.90% | -3.68% | -6.92% |
| Log Auxiliary Spending[J] (Suburban Non-Title I) | -11.37% | -20.61% | | | | | | |
| Log Salary[J] (Charter Schools) | -12.21% | -22.05% | -0.70% | -1.33% | | | | |
| Log Auxiliary Spending[J] (Charter Schools) | 7.12% | 14.05% | | | | | | |

JPercent change is the main effect of Log Salary/Log Auxiliary Spending conditioned on the specified (LEA/High Need Subject) reference categories for all experience/education levels.

Note #1: There is an insufficent sample of high need educators in Career & Technical Schools in order to execute a viable model. (See Table 4.6)

Note #2: Only statistically significant (p<0.05) values are shown.

**Table 4.23 • Interaction of High Need Subject Area and (Log) Salary/Auxiliary Spending [Percent Change in Turnover Risk] | Central Pennsylvania MSAs & µSAs [n(educators)=23,434]**

| | Mathematics | | Natural Sciences | | Special, Alternative & Remedial Education | | English as Second Language | |
|---|---|---|---|---|---|---|---|---|
| | 10%↑ | 20%↑ | 10%↑ | 20%↑ | 10%↑ | 20%↑ | 10%↑ | 20%↑ |
| Log Salary[J] (Regional Urban Districts) | -4.78% | -8.95% | -2.58% | -4.88% | -2.12% | -4.01% | -2.46% | -4.65% |
| Log Auxiliary Spending[J] (Regional Urban Districts) | 8.67% | 17.24% | | | 10.49% | 21.02% | | |
| Log Salary[J] (Suburban Title I) | -3.72% | -6.99% | -3.20% | -6.03% | -2.58% | -4.88% | | |
| Log Auxiliary Spending[J] (Suburban Title I) | 8.13% | 16.12% | -12.65% | -22.79% | 0.59% | 1.14% | | |
| Log Salary[J] (Suburban Non-Title I) | -3.22% | -6.08% | -2.73% | -5.16% | -2.09% | -3.96% | -1.97% | -3.73% |
| Log Auxiliary Spending[J] (Suburban Non-Title I) | | | | | | | | |
| Log Salary[J] (Rural Title I) | -4.09% | -7.68% | -4.08% | -7.66% | -2.35% | -4.45% | -2.09% | -3.96% |
| Log Auxiliary Spending[J] (Rural Title I) | | | | | -3.64% | -6.84% | | |
| Log Salary[J] (Rural Non-Title I) | -3.54% | -6.67% | -3.29% | -6.20% | -2.44% | -4.61% | | |
| Log Auxiliary Spending[J] (Rural Non-Title I) | | | | | 3.43% | 6.67% | | |
| Log Salary[J] (Charter Schools) | -1.73% | -3.28% | | | | | -19.86% | -34.52% |
| Log Auxiliary Spending[J] (Charter Schools) | | | | | | | | |

JPercent change is the main effect of Log Salary/Log Auxiliary Spending conditioned on the specified (LEA/High Need Subject) reference categories for all experience/education levels.

Note #1: There is an insufficent sample of high need educators in Career & Technical Schools in order to execute a viable model. (See Table 4.6)

Note #2: Only statistically significant (p<0.05) values are shown.

# CHAPTER 5

# DISCUSSION

> "I began to think like a policymaker, especially a federal policymaker. That meant, in the words of a book by James C. Scott that I later read and admired, I began 'seeing like a state,' looking at schools and teachers and students from an altitude of 20,000 feet and seeing them as objects to be moved around by big ideas and great plans."
>
> –Diane Ravitch (2016), *The Death and Life of the Great American School System*

These words from former Assistant Secretary of Education serve as a cautionary reminder for both academics and politicians that in the complex and dynamic ecosystem that is public education, policy decisions can quickly become products of ideology distant from the lives of those most affected by it. Perhaps it is this powerful combination of disassociation and fantasy that makes education reform so elusive, especially when attempted on a grand scale. In this final chapter, I divide the discussion into three parts, keeping in mind the spirit of Ravitch's words. In the first part, I analyze descriptive and inferential results using the Maslowian theoretical approach presented in Chapter 2 in an attempt to understand what encourages teachers to leave their positions. In the second part, I consider the implications of those findings with an eye toward educational practice, particularly in the realm of school leadership. Finally, in the third, I offer some possible policy solution both at the state and LEA level.

**Analysis of Results via a Synthetic Maslowian Framework**

Chapter 2 outlined a theoretical framework built on Maslow's Hierarchy of Needs but modified to include three theories – Human Capital Theory, Motivation-Hygiene Theory, and Person-Environment Theory. Recall that Human Capital Theory, was taken to mean survival, but in a purely economic sense (Does this job pay enough for my needs?). The second theory, Motivation-Hygiene Theory, introduced the concept of motivator and hygiene, the latter of which was taken to mean security, this time in terms of self-confidence (Do I have what I need to do this job?). The third theory, person-environment (P-E) extended dual factor's concept of motivators by presenting gradations of fit (with both the organization and the job) from "demands-abilities" fit (I am here to get my job done.) to "highly congruent" fit (I can go beyond my job and makes this organization and beyond better.). This last theory corresponded the apex of Maslow's Hierarchy, in which self-actualization (in the employment sense) meant the assumption of leadership responsibilities.

As presented in the theoretical framework, wages do not serve as good motivators since employees, and especially teachers, believe that they are overworked and underpaid and the initial euphoria associated with a pay raise quickly evaporates. In responding to the two research questions, it is essential to keep this distinction in mind because both questions are asking about how to *minimize* turnover as a function of the bottom two rungs of Maslow's Hierarchy – salary (survival) and supports (security). Yet, at a time when there is a declining interest in teaching, coupled with one of the largest generations of workers preparing for retirement, understanding if, how much, and where supplemental funds might result in the most significant return on investment can yield policy insight that goes beyond a "one-size fits all" approach.

### ***Experiential Analysis***

New and experienced teachers face considerably different pressures in schools, both pedagogically and socially. On top of teaching the same number of courses as their more experienced peers, they are also saddled with the same amount of planning time and charged with excessive amounts of data collection and paperwork requirements. Often because of seniority rules, these recruits teach remedial courses, which enroll many HUS, and, for those who wish to pursue post-graduate credits to qualify for an Instructional II license or higher, there may be limited support for administrators, both in terms of instructional release time and financial support. Perhaps most unjustly, they are subject to the same evaluation framework without any consideration with regard to their novice status—a virtually unheard of practice in any other field, at a time when more organizations are reconsidering traditional performance evaluations as too rigid, dispiriting, and altogether unconducive to a collaborative workplace (Smith, 2018). All of these conditions coupled with low pay create a perfect storm for turnover related behaviors.

Chapter 2 discussed the concept of P-E fit in terms of two constituent components – P-J and P-O fit, and for this study, defined “job” as occupation and “organization” as either school or district.) New teachers, more than any other teacher group examined in this study, need to consider P-J and P-O fit simultaneously to determine if either the occupation or the organization is the poorer fit, which can be difficult for new teachers to distinguish, since a minimal number of organizational experiences form their perception of the occupation. By contrast, experienced teachers, by their very definition, have overcome the steep learning curve associated with teaching and, likely enjoy a robust P-J fit. Thus, apart from any economic or hygiene-related needs, they are likely to seek opportunities that provide them with a robust P-O fit as, beyond the survival and security stages of their career development, they seek to assume roles consistent with higher levels of Maslow's hierarchy. (Note that I examine traditional district LEAs in this section with a more detailed analysis of charter school turnover in the following pages.)

***Urban Risk Assessment.***

The School District of Philadelphia. The SDP has a history of losing both new and experienced new teachers, except for entirely different reasons. For new teachers, there are some subtle, yet significant, differences between new teacher leavers and new teacher movers. Leavers have an experience/salary profile (2.6 years of experience with a high salary of $48,210) like that of movers (4.4 years of experience with a high salary of $47,598). What is worth noting is the difference in years' experience and not the salary difference. Leavers, who account for 42 percent of all new educators, leave the district in less than three years, the minimum number of years to obtain tenure. By contrast, movers depart closer to the five-year mark and account for only 4 percent of all new teachers. It is possible that some of these leavers are likely to be graduates of alternative teacher certification program such as TFA or are teaching on some temporary license (e.g., an Emergency of Intern License). In either case, once leavers have completed the minimum number of years associated with their obligation (e.g., TFA, Relay Graduate School of Education), they appear to start pursuing other opportunities (outside the field) rather quickly. It is difficult to gauge if this is a result of a problem of P-J or P-O fit since these individuals have known only one employer in the field and may associate the profession with that employer.

Conversely, movers have decided to commit to the profession (good P-J fit) and not to the organization (poor P-O fit). Nonetheless, these individuals are a select minority of 4 percent, and their experience profile suggests they are accumulating the prerequisite three to five years' experience needed to move into positions elsewhere. In either case, a simple human capital approach (survival) is guiding their decision making, since even a 10 percent increase in pay for new teachers can reducing their risk of leaving by 12 percent, with a 20 percent increase yielding a dramatic 21 percent decrease.

Experienced educators are also leaving the district for different reasons. First, the experience/salary profile of leavers and movers is highly similar. Leavers have an experience/salary profile (20 years of experience with a high salary of $68,924) like that of movers (17 years of experience with a high salary of $66,770). In sharp contrast to new teachers, the percent of movers and leavers is almost the same. As alluded to in the previous chapter, there appears to be some "mid-career" crisis around the 17-20 year mark (since superannuation for a pension is 35 years), in which senior teachers in the SDP either experience burnout and leave the profession. A possible reason might be that they feel they have achieved a career plateau in their current placement, thereby motivating a decision to leave for other opportunities in the field. In either case, this is an example of a poor P-O fit; for leavers, this is an issue regarding the lack of hygiene (support/job) security, whereas, for movers, it is an issue of "stalling" (i.e., there is no more room for growth in the organization).

Pittsburgh Public Schools. The PPS also shares many of the same turnover behaviors as does the SDP, except experienced teachers here do not have higher than baseline rates of turnover, implying that the issues of poor P-O fit in the SDP are not at play here. With respect to new PPS teachers, the leaver/mover profile is analogous to that of their peers in the SDP, with PPS leavers (2.3 years of experience and a high salary of $46,804) have half of the experience and are earning $10,000 less than movers (5 years of experience with a high salary $56,486). Here, too, a pay raise aids in reducing the risk of turnover with a 10 percent increase delivering an 11 percent reduction in turnover risk and a 20 percent pay increase resulting in a 20 percent risk reduction. As is the case with new teachers in the SDP, economic survival motivates new teachers in PPS. Furthermore, it is likely that this increase would have the most effect on leavers since they greatly outnumber the movers by a ratio of 153 to 4.

Regional City Districts. Like its peers in the PHL and PGH regions, RCDs in the CPA region also suffer from above baseline rates of turnover. Moreover, as expected, leaver experience/salary profiles (2.5 years of experience with a high salary of $49,266) are less, both in terms of experience and pay, than movers (4.4 years with a high salary of $56,673). One would expect, then, a pay increase to have the same effect on teacher retention as it did in the SDP and PPS. However, this is not the case. Even a 20 percent pay raise has a <3 percent effect on reducing the risk of turnover. It might be possible, given the economic and demographic profiles of these cities, because they are small urban schools with high poverty and chronic underfunding, that their loss is a product of the same hygiene (support/job) security-related issues common to urban schools. It is worth mention that leavers constitute the overwhelming majority of new teacher turnover, with 603 teachers annually compared to only 12 movers (which would be an average of 1 in each district that constitutes this group). A possible explanation and one that has been frequently cited in rural turnover studies nationally is geography. As mentioned above, it is difficult to tell if new teacher leavers are leaving because of poor P-J fit or poor P-O fit. Teachers in the SDP and PPS might have the opportunity to teach elsewhere without too drastic of a life change, whereas the same is not true for RCDs leavers. As Figures 1.3 & 1.4 illustrate, many districts in the CPA region are so expansive (because of low population density), it would be a significant logistical hurdle to seek employment anywhere else except in immediately neighboring districts, thereby diminishing other possibilities.

***Suburban & Rural Risk Assessment.***

PHL Suburban Title I Districts. New teachers in this LEA type also share similarities with their counterpart teachers in the SDP. Profiles of leavers (2.5 years of experience with a high salary of $42,986) and movers (4 years of experience with a high salary of $46, 803) closely mirror those of new teacher leavers and movers in the SDP. The application of a 10 or 20 percent increase has a minimal effect (<2 percent decrease in turnover risk). The lack of hygiene (teacher support) may be at play here as a function of educational leadership. SDP and Suburban Title I Teachers have a similar high poverty, minority-majority student population, in under-resourced schools; still, the fact that the SDP *would retain more teachers if it had the money* suggests that many new teachers believe there are at least some hygienic (support) factors in place to assist in their teaching (job security). The same cannot be said of these Suburban Title I Districts.

A similar situation emerges concerning experienced teachers in Suburban Title I Districts. Again, the leaver (18.5 years of experience with a high salary of $61,753) and mover (18 years of experience with a high salary $63,553) profiles of these educators closely /mirror those of their peers in the SDP. Both movers and leavers, of which there are roughly equal numbers, are also in the "mid-career" crisis stage at the 20-year mark. Here, neither a 10 nor a 20 percent pay raise results in any substantive reduction of risk (<4 percent).

PGH Suburban Title I Districts. New teachers in PGH Suburban Title I Districts experience a leaver and mover profile that closely tracks with PPS. Not only do leavers (2.5 years of experience with a high salary of $40,065) have a weaker profile compared to movers (4.5 years of experience with a high salary of $49,191), but also outnumber the latter by a ratio of 377 to 11, with nearly 36 percent of new teachers in this LEA type leaving in a five period. Moreover, even a 20 percent increase in salary only reduces the risk of turnover by <6 percent, suggesting that some hygiene-related factor (support/job security) is at play here leading to either a misfit of P-O or P-J.

Lastly, there is a striking contradiction between the effect of a pay increase in the SDP and PPS for new and experienced educators and their Suburban Title I counterparts that may not be clear at first sight: economy of scale. The SDP and PPS are the first and second largest districts in the state, with budgets of $3 billion and $600 million, respectively. This means that if each district set aside $6 million, which would correspond to a 0.2 percent or 1 percent financial commitment, for a professional support program for new teachers or a leadership development program for experienced teachers, it would lead to a higher return on investment as measured by reduced turnover compared to the costs of these districts. Such an investment might not be feasible for any single Suburban Title I District since a $6 million program could be 10 percent or more of such a district's budget (and roughly the entire finance and facilities portion for PHL Suburban Title I Districts, according to Table 4.2). In short, larger urban districts may have an advantage in terms of providing teacher support, and ultimately attracting both new and experienced teachers, compared to their poor suburban peers.

CPA Rural Districts. Lastly, the study suggests in the CPA's suburban and rural regions, not only does a 10 or 20 percent increase in remuneration have little to no effect in reducing turnover risk amongst new and experienced teachers, but also there is an altogether low (below average) turnover for these LEA types. Such a finding might appear to clash with the extant literature concerning teacher shortages in these areas. However, both statements complement one another when considering (a) this study examines turnover risk for teachers *already employed* in the state's public school system and (b) the broader socioeconomic conditions in which rural schools operate prevents a massive exodus in the profession in these areas.

Whereas several researchers continue to argue that teaching is a profession that deserves more respect compared to other white-collar vocations, this thinking reveals a hidden bias in favor of urban regions, where economic opportunities are bountiful, and there is a large concentration of individuals with post-secondary qualifications. However, teaching enjoys a highly favorable status in rural regions, where economic opportunities are scarce, and the percentage of college graduates is considerably lower than in the urban regions. PSDC (2018) data reveals that the while the percentage of college graduates in the PHL and PGH region are 34 and 32 percent of the total population, the CPA region has a considerably lower share of only 24 percent. This percentage complements findings in Table 1.2 in which the CPA region has the lowest percentage of the state's GDP in private services production, a proxy for professional positions (outside of public education). Perhaps the most vivid description of this lack of economic opportunity is by best described by Appalachian. J.D. Vance in his book *Hillbilly Elegy* states, "The statistics tell you that kids like me face a grim future—that if they're lucky, they'll manage to avoid welfare; and if they're unlucky, they'll die of a heroin overdose" (Vance (2016).

In this socioeconomic context, it is easy to see the allure of teaching jobs, which (in non-charter LEAs) have higher than average salaries thanks to unionization, offer high-quality healthcare benefits, and pay into the state pension system (PSERS). In fact, in some rural regions, competition for these jobs has led to dishonest community behavior. For instance, in 2009, FBI agents charged members of the Wyoming Valley West School District Board of Education in Luzerne County with nepotism and cronyism by circumventing hiring and labor laws (Janoski & Sisak, 2009).

### ***High Needs Subject Analysis***

As discussed in Chapter 2 and reiterated here, the motivations for high need content teachers (math and science) and high need support teachers (special education and ESL) are considerably different. STEM teachers, like other content area teachers, have a strong affinity for and technical expertise in their subject matter, earning them the moniker "little professors." Special education and ESL teachers choose to work with a specific student population (although the Commonwealth now require special education and ESL certification to be granted with an instructional license in some content area). In contrast to the reasoning, given the intensive nature of pursuing these subjects, high need teachers already possess some degree of P-J fit. So, along with Human Capital Theory and Motivation-Hygiene theory, P-O fit is also considered in this analysis.

#### ***Mathematics & Science Teacher Risk Assessment.***

<u>Greater Philadelphia Region.</u> For math teachers, the SDP and Suburban Title I schools have the most difficulty retaining teachers above baseline. For the SDP, the difficulty

stems from an inability to pay enough salary to keep math teachers from leaving the district. Leavers have four years' less experience than movers, coupled with an $8,000 wage difference. Also, math teachers in the SDP have a student load of 98—well below the 125-student threshold. A 20 percent increase in salary does reduce turnover by almost 12 percent.

Similarly, in science, there is also a four-year experience difference between leavers and movers with a smaller, $5,000, wage difference. Problematically, science teachers in the SDP are dramatically overworked, with a student load of 185. So, not surprisingly, even a 10 percent increase can reduce the risk of turnover by 13 percent. Both cases are a clear example of movement because of possessing valuable human capital. Since these teachers have technical knowledge that is transferable in education as well as service sector fields like finance and healthcare, both of which are significant contributors to the region's GDP, they can command a certain degree of desirability in the job market.

For Suburban Title I Districts, the reasons for teacher turnover appear to be a little bit more complicated. Here, too, leavers and movers in both math and science differ by only three years of experience as well as $5,000. Moreover, both subjects are within the 125-student threshold, with math teachers teaching 113 students annually compared to science teachers who teach 117 students annually. Unlike the SDP, an increase in pay does not lead to any effect at all, suggesting that both teacher groups might be experiencing poor P-O fit because of pressures from administrators to deliver on high stakes exams, given that performance on both standardized tests tend to be lower compared to ELA.

Greater Pittsburgh Region. The trend for math and science teacher turnover appears to follow the same pattern as in the PHL region. For math teachers in PPS, leavers and movers have only a three-year difference in experience, and despite a $5,000 pay difference, both enjoy high salaries ($75,900-$81,889). Math teachers here do not appear to be experiencing stress from a student load of 90 students—well below the 125-student guideline; nonetheless, a 20 percent increase in pay does lead to a 14 percent decrease in risk of turnover. Similarly, for science teachers, leavers and movers have a five-year experience difference, yet unlike their math colleagues, have a much higher difference in pay, with leavers earning a little over $15,000 less than movers. Predictably, even a 10 percent increase in pay leads a 20 percent decrease in the risk of turnover. The situation is repeated for science teachers in Suburban Title I schools, where movers and leavers have almost no difference in years' experience, and despite a smaller difference of $3,000, these teachers enjoy a high salary ($69,997). Here, too, the workload appears reasonable, with science teachers assigned 93 students.

The possible connection between all three teacher groups is the same as it was for SDP teachers, except with a geographic caveat. Again, math and science teachers possess a certain amount of human capital but, in Pittsburgh, this capital has more value. Chapter 1 mentioned that Pittsburgh is the largest city in both the Ohio River Valley and the Appalachia region (earning it the nickname "the Paris of Appalachia"). While Pittsburgh is most famously associated with steel (with the offices of both U.S. Steel and the United Steelworkers labor union across the street from one another), it is currently going through a hi-tech renaissance led by Carnegie Mellon University and the University of Pittsburgh (Kurutz, 2017). Such a revival has led several high profiles companies such as Uber, Amazon, and Google to establish regional AI, robotics, and engineering research labs alongside several smaller tech startups. Still, because of its location, these companies do not have a ready supply of high skilled labor like Philadelphia, which is near other major cities along the I-95 corridor. Consequently, skilled math and science teachers are being courted by these new arrivals, leaving PPS and Suburban Title I Districts to compete with IT salaries for a limited supply of labor.

Central Pennsylvania Region. Interestingly, when examining math teacher turnover in the CPA region, no LEA type, apart from charters, has math teacher turnover that is above baseline. For science teachers, this is not the case, as RCDs and both Rural Title I and Rural Non-Title I Districts have above average rates of turnover. In the RCD, leavers have about five years less experience than movers. Considering leavers earn almost $11,000 less than movers, both groups make at least on par with the regional average. They also experience a heavier workload than other LEA types, with 119 students and an increase in either 10 or 20 percent salary does very little to reduce the risk of turnover significantly. While the number of movers is relatively small and can be attributed to chance, the same is not true of leavers. Likewise, the situation in Rural Title I and Rural Non-Title I Districts is virtually identical. There, leavers and movers are separated by one year of experience and, in neither district, does the student load exceed 94 students. Moreover, like the RCDs, neither a 10 or 20 percent raise has a substantial effect on reducing the risk of turnover.

Human Capital Theory might explain these findings, but in a context that is entirely different from either the PHL or PGH regions. Many of the CPA region's small cities (e.g., Harrisburg, Scranton, Wilkes-Barre, and Erie) never recovered after the loss of industrial manufacturing in the 1970s and 1980s. Because they are small population centers that do not have a connection to more prominent regions or a commercial thoroughfare, they have struggled to attract labor and capital. Consequently, for a science teacher with valuable technical expertise, there may not even be other opportunities without leaving the area altogether. This reasoning is, even more, the case with rural districts. Recall from Table 1.2 that all 37 rural counties together account for a minor 12 percent of the state's GDP. It stands to reason than that there is also little economic opportunity outside farming or the occasional factory in these areas. These science teachers might seek to escape the economic isolation of their communities to pursue opportunities elsewhere, a proposition that is supported by Table 1.1, which outlines significant population decline in the CPA region.

***Special Education & ESL Teacher Risk Assessment***

Greater Philadelphia Region. In special education, both the SDP and Suburban Title I Districts suffer from an above average rate of turnover when compared to baseline, although the SDP's rate (14.5 percent) is considerably higher than that of Suburban Title I Districts' (9 percent). In the SDP, the relative difference in years of experience between movers and leavers is only two years, suggesting that the same phenomenon is acting on both groups. A possible reason then is the student load special education teachers have, which at 25, is well beyond the established 12-student limit. While a 20 percent increase in pay does lead to decrease in turnover of 10 percent, the most likely reason that turnover is so high for special education teachers in the SDP are demotivators that lead to feelings of inadequacy such as being overworked, underpaid, and underappreciated. This finding is confirmed when comparing the turnover rate for Suburban Title I and Suburban Non-Title I Districts which are only a percentage point difference. In both LEA types, monetary increases also have a negligible effect in reducing turnover.

For ESL, it is Suburban Title I Districts that have higher rates of turnover compared to the baseline. First, leavers here have considerably less experience (by six years) compared to movers and have an abnormally low salary ($50,8110). Second, the ESL teacher ratio is 28, which is under the 35-student guideline. Lastly, while the data suggests that young ESL teachers are leaving the field because of low money and not necessarily because of student load, the model appears to refute the above argument since neither a 10 percent nor a 20 percent pay increase results in any meaningful dent in risk of turnover. One possibility is a combination of hygiene (teacher support) and poor P-O fit, with Table 4.1 providing some evidence of this assertion. Suburban Title I Districts have the highest Hispanic and second highest ELL population percentages in the region. Consequently, like their special education peers, these teachers also feel a sense of being overworked and grossly underpaid, combined with the lack of administrative support, especially given the rapidly changing student demographics.

Greater Pittsburgh Region. In special education, only Suburban Title I Districts have a higher than the baseline average. Leavers tend to have less than five years' experience compared to movers yet are by no means underpaid ($63,973). This finding is confirmed by the model, which indicates that a 10 or 20 percent increase has a minimal impact on reducing the risk of turnover. One possibility is burnout because of hygiene (teacher support) coupled with poor P-O fit, to which special educations are especially susceptible because of "role confusion" (i.e., assigned a host of responsibilities that may be outside of the job description). Table 4.1 provides some evidence of this since this LEA type has amongst the highest percentage of identified students in the region (and even higher than the SDP). While Suburban Title I LEAs are at their maximum capacity of 12-students to a teacher, it is worth remembering that this number is an FTE number. Depending on whether the students are assigned itinerant or push-in status, these special education teachers might support well above 12 students. Lastly, when considering ESL teachers, both the PPS and Suburban Title I Districts have an above-average turnover. As Table 4.8 shows, there are very few individuals moving or leaving, so this turnover may also be due to chance actors. There is a significant trend concerning ESL teachers in Suburban Title I Districts. Leavers have significantly less experience (7 years) and quite low pay ($32,606), with both a 10 percent and a 20 percent increase in pay resulting in a 12 percent and 21 percent decrease in risk of turnover. Such a finding is a clear example of how low pay, even if there is an excellent P-J fit, can serve as a powerful demotivator, as these relatively young and underpaid teachers are looking for other opportunities, possibly convinced that the education field may not satisfy their financial needs.

Central Pennsylvania Region. Interestingly, for special education turnover, all LEA types, except charters, are within one or less percentage point of baseline – a finding that does not hold for ESL teacher turnover. Both RCDs and Rural Non-Title I Districts have higher than average ESL teacher turnover. First, leavers have seven years less experience than movers, yet their pay is still above the regional average ($60,720), implying that higher pay may not be a motivating factor here. Such reasoning is confirmed by the model analysis, which shows that a 10 or 20 percent increase has very minimal effects on reducing the risk of turnover. For Rural Non-Title I Districts, the conditions are similar. While leavers have only two years less experience than movers, they too have a higher than average regional pay ($60,655), and consequently, a pay raise of any amount does not affect turnover.

Furthermore, their student load is 19, almost half the 35-student guideline. In both cases, and like their PHL colleagues, demographic changes suggest that turnover here might be the result of hygiene (teacher support)/P-O fit. Even more so than their PHL colleagues, these teachers are witness to the almost overnight transformation of certain parts of the CPA region, which in the last decade has seen some cities tip the scales at >50 percent Hispanic demographic. Teachers here may be feeling overwhelmed just attending to the needs of increasing Hispanic student enrollment, with the added pressure of "role confusion" in which administrators, teachers, and others might seek an ESL teacher's insight about Hispanic families, students, language, and so on rather than developing the knowledge themselves.

### ***The Curious Case of Charters***

The issue of turnover in charter schools warrants an independent investigation for several reasons:

(1) the extraordinarily high rates of turnover in all teacher groups across all three regions beckon a more nuanced discussion about how charters function,

(2) the mission, culture, structure, and function of charters is highly uniform throughout the state, regardless of region, *and*

(3) the different practices and policies charters adopt in order to maintain their viability despite these abnormal rates of turnover.

***Addressing Experiential Turnover.*** Whereas the approach throughout this study has been that teacher turnover is a negative occurrence that is indicative of some more significant organizational issue, the study of teacher turnover in charters challenges that assumption. In all three regions, new teacher turnover rates for charter schools range from 24 percent in the PGH and 26 percent in the CPA region to 31 percent in the PHL region. Comparatively, in all three regions, teacher salaries were less than the regional average, ranging from -4 percent in the PHL region to -12 percent and -18 percent in the PGH and

CPA regions, respectively. While these two statistics alone would suggest some relationship between wages and attrition, model results show that a 10 or 20 percent increase in salary has little to no impact on reducing the risk of turnover, suggesting that there may be a powerful reinforcing effect between hygiene-related factors (lack of support) and P-E fit that pushes new teachers out the door.

While most organizations would see this amount of churn as a clarion call for major organizational restructuring, oddly the opposite is the case for charters. Table 4.3 confirms that charters across all three regions have a disproportionate experience profile and the number of new teachers employed in these schools is almost on par with the number of experienced teachers. Such a skewed distribution is not the result of chance but deliberate policy. Rather than view such high turnover as a problem with their management approach (a P-O issue), they contend that their approach to urban teaching is a response to the lack of high teacher preparation standards in the field, in effect making the argument that the environment and not the organization is the issue (an inversion of P-E fit). Act 82, which requires traditional districts to adopt the Danielson framework for teacher evaluations, exempts charters from this requirement, resulting in some novel, if not altogether controversial, teacher evaluation protocols. For instance, Mastery Charter Schools, one of the largest charter operators in Pennsylvania, received over $2 million in grant support from the Bill & Melinda Gates Foundation to expand its teacher coaching and evaluation program in public and parochial urban schools throughout in the PHL region, including across the Delaware River in Camden, NJ (Graham, 2012). Critics accused Mastery of employing an austere approach to teacher evaluations, complemented by a heavy emphasis on draconian classroom management techniques that placed a high premium on order, conformity, and control for both students and teachers. The network justified this approach it arguing that it delivered “student-centered” results, despite periodic reports of a high incidence of fatigue, burnout, turnover amongst teachers in the Mastery network (Mezzacappa, 2012).

Interestingly, a cottage industry of alternative teacher preparation programs has sprouted that supports and share the philosophies of the charter movement. Although the most famous of these is TfA, which has repeatedly faced criticism from the research community for its high rate of turnover, the organization has historically partnered with traditional teacher preparation programs which emphasize both theory and practice. However, more recent incarnations of alternative teacher preparation programs have abandoned this approach altogether. In 2011, three prominent charter school networks which are known for their “no excuses” approach – KIPP, Achievement First, and Uncommon Schools – formed the Relay Graduate School of Education utilizing a curriculum that heavily emphasized practice over theory. In what can only be described as an altogether bold and extreme move, CEO of Success Academy Charter Schools Eva Moskovitz lobbied the State University of New York (SUNY), one of two charter authorizers in the state, to permit charters the right to issue state-sanctioned teacher certifications in the hope of stemming a perennial shortage of teachers borne of high turnover (Taylor, 2017). Though the Board of Regents did approve this proposal in 2017, the New York State Supreme Court ruled against SUNY’s backdoor attempt at certification in June 2018.

This “no excuses” approach to schooling appears to have convinced some teachers, particularly more experienced ones, to rally to the cause of charters. Malloy & Wohlstetter (2003) found that despite the reality of more extended work hours, less job security, and less pay, most of the charter school teachers interviewed in the study that had at least a few years of experience enjoyed working in their schools, particularly the camaraderie with colleagues, their school's instructional approaches, and more autonomy because of less bureaucratic oversight. Furthermore, Ni (2012) found that charter school teachers believed that they had significantly more influence over school policies than their traditional public school counterparts, despite the reality that their working environment offers highly similar working conditions regarding principal leadership, school collegiality, classroom autonomy, and professional growth opportunities.

***Addressing High Needs Subject Turnover***. In terms of high need subject turnover, the results of this study suggest that churn in both high needs content and high needs support areas is on par with or higher than overall churn for these LEA types. Apart from special education (which I analyze in the following pages), Table 4.9 does not appear to show any shortage areas concerning math, science, and ESL student loads below their recommended or required levels. Charters are often quick to mention that their schools have an adequate supply of math and science teachers because they have more discretion compared to their district counterparts when it comes to offering a "market based" salary for high need subject areas. Some researchers have challenged this assertion, arguing that many charter employment contracts have significantly less pay and security provisions (e.g., year-to-year contracts, no tenure, merit-based pay) compared to district schools, which effectively establish the "prevailing wage" in their CBAs (Hunter, 2010; Podgursky & Springer, 2007). This study does not validate the "market based" argument. There is a minor difference in the average pay between high-need and low-need teachers for charters in all three regions, with pay increases in select subjects having a demonstrable effect on reducing the risk of turnover. For ESL teachers in PHL and CPA regions, a 20 percent increase (for PHL charters) and a 10 percent increase (for CPA charters) in pay delivers a corresponding reduction of turnover risk by 20 percent and 14.5 percent, respectively. Similarly, in the PGH region, a 10 percent increase for math teachers reduces turnover by a little over 12 percent. Increases in science teacher pay result in a minimal, if any, decrease in risk across all three regions.

For special education, charters have received considerable public criticism for intentionally admitting low numbers of special education students so as not to negatively influence their standardized test performance (Dee & Fu, 2004; Ni, 2012). This study does not confirm that assertion on two levels: first, charter LEA types in all three regions, excluding CTEs, have some of the highest special education population percentages, and secondly, special education teachers in all three LEA types have caseloads well above the state's 12-student limit. Another possible, and more illicit, explanation may better explain the high rate of special education turnover. Researchers have exhaustively studied the issue of selective admission criterion used by charter schools, However, what may not be so apparent is that, just like their traditional counterparts, charters are public schools and therefore cannot screen any special education student. Additionally, as outlined under IDEA, charters must provide a "free and appropriate education" (FAPE), a provision that stipulates if a special education student enrolls in a school that cannot accommodate that student's disability, the school must pay for the necessary services through a contractor or tuition payment at a school that can offer that service (Bordelon, 2009).

Consequently, because of their relatively small size compared to their much larger parent districts, charters "informally" prescreen those special education students to identify those for whom they cannot provide services, thereby circumventing the FAPE requirement. Since these students tend to have the most challenging conditions (e.g., autism, intellectual disability/mental retardation) and require the most expensive services, it gives the illusion that they are consciously selecting the most academically capable, when it is the side effect of a deviant policy (Zetino, 2017). However, once the academic year begins, charters begin to *over*identify already admitted students to take advantage of the increased per-student subsidy awarded in the Commonwealth's funding formula (see Figure 5.1), resulting in increased revenue with minimal obligations, since, the school reasons, the newly identified student required little to no support before arrival (Fierros & Blomberg, 2005; Gilliland & DiRocco, 2018; Miron, 2014). As parents begin to ask for services listed in the Individualized Education Plan (IEP), the onus of managing yet another case falls on already-taxed special education teachers, thereby increasing their chances of burnout.

### *The Realities of Auxiliary Spending*

Thus far, the discussion has primarily centered upon the teacher decision-making process, particularly about remuneration (survival) with working conditions as an ancillary consideration (hygiene). Taxpayers and politicians alike frequently equate public education spending with teacher salaries, but they often overlook the influence of auxiliary spending, possibly because this share of school spending requires a certain degree of careful management and allocation that rarely makes for an interesting newspaper story.

Although the results of this study indicate that most increases in auxiliary spending did not reduce the risk of teacher turnover in regions and LEA types with above-average rates, this finding does not mean that auxiliary funds are destined not to affect outcomes. As noted by several researchers cited in Chapter 2, support services play a crucial role in promoting student physical and mental wellbeing as well as aiding in socioemotional development. However, the findings may suggest that, in some cases either (a) some LEA types are unable to employ these funds to support teachers effectively judiciously, and by extension, the teaching and learning process, or (b) there is just not enough auxiliary funds for a sustainable support system.

It is essential to keep in mind that statistical models in the social sciences reflect *the past or present state* of the social environment but cannot predict a future in which actors make conscious decisions to change the course of their mathematical destiny. Rury and Mirel (1997) offer some pearls of wisdom to this end stating that "educational researchers [in the United States] too often accept the urban environment as a given natural setting, rather than one that has itself been determined by larger economic and political processes." Accordingly, auxiliary funds, like any dollar amounts, *can* pay dividends in terms of teacher retention and student achievement but only if used responsibly.

***Auxiliary Support in the Service of Teaching and Learning.*** Studies have shown that when these funds are used to employ support staff *with clearly defined roles that fulfill a preexisting need*, these new hires can help improve teacher efficacy, productivity, and ultimately, student achievement—all of which will likely result in reduced turnover-related behavior (House & Hayes, 2002; Lance, 2000; Smith, 2001). One possibility is that clearly defined roles and supports create a "work ready" environment that does not require some probationary period in which new hires are left to find their niche in an alien setting. LEAs also spend a considerable amount on instructional supplies, such as education technology, which qualify as auxiliary expenses. These expenditures may give the illusion of learning, yet not have a meaningful impact on curricular or instructional practice. For instance, in what amounts to the educational analog of "keeping up with the Joneses," districts are quick to purchase new technologies such as Smart Boards, iPads, and even 3D printers without any consideration of whether teachers even an intention have to use these expensive teaching aids in their lessons. Johnson et al. (2016) noted that training is not enough for teachers to adapt to classroom technology. They claim that these “training” sessions are usually part of a professional development day and cover generic basics rather than provide concrete ways teachers, teams, and departments can collaborate on a comprehensive approach that focuses on student achievement. Without any adequate support to aid in this process, teachers are likely to shun the technology altogether, in favor of their classic “tried and true” approach.

Outside the classroom, several researchers have commented on the problem of *excess* administration and support personnel. Richmond (2014) notes that there has not only been a surge in the number of non-teaching staff since the 1970s, with this population now accounting for half the teaching force nationally, but also that areas with a low labor supply of teachers, such as rural areas and small towns, have the highest ratio of non-teaching staff to students. In two studies, Scafidi (2012, 2013) offered an even more critical analysis noting that that the sharp increase in administrators has had little to no effect on learning outcomes a sentiment echoed by Chingos, Whitehurst, and Lindquist (2014) in Brookings report examining the effectiveness of school superintendents and cabinet staff on learning outcomes. In what amounts to a “too many cooks in the kitchen” situation, a high number of non-teaching staff bloat can have the unintended consequence of hampering teachers rather than aiding them. Organizational researchers within and outside the United States have repeatedly identified an inverse relationship between managerial bloat and organizational efficiency noting that employees can receive conflicting messages or directives from supervisors – a practice this is often coupled with multiple and possible redundant amounts of paperwork (Martin et al. 2012; Jung, 2012, 2013; Patilbanda, 1998). The results of this study suggest that this may well be the case. For instance, an increase in auxiliary spending does not affect special education turnover in any LEA type, and in the CPA region, which is comprised mostly of rural areas and small towns, the turnover risk *increases* with more spending. As Table 4.9 indicates, special education teachers are experiencing high student caseloads throughout the state. However, instead of investing in more special education teachers, many districts may have opted to invest this additional money into special education administrative staff, who struggle under an avalanche of IEPs, data reports, and litigation paperwork in an administrative office rather than supporting curriculum and instruction in the classroom.

***Schooling without Supplementals.*** A small amount of auxiliary funding can hobble teachers' ability to teach specific subjects such as science effectively or support certain types of special education students. Several STEM fields require qualified (certificate holding) teachers, specialized equipment, and specially-outfitted classrooms to promote effective teaching and learning. Regrettably, the lack of qualified teachers and facilities, particularly in urban schools, has led to a "chicken-and-egg" problem. Without qualified staff, districts do not offer the course, which, in turn, eliminates the need to spend auxiliary (facilities) funds to make the necessary modifications (e.g., installing water/gas lines for sinks and chemical showers, converting a classroom into a computer lab). Without either a vacancy or the facilities in place, qualified candidates will likely seek opportunities elsewhere. The results of this study appear to provide evidence for this reasoning. For Suburban Title I Districts in the CPA region, a 10 and 20 percent increase in auxiliary spending reduced the risk of turnover for science teachers by nearly 13 and 23 percent, respectively.

The lack of support funding is especially problematic for special education students since this subgroup has a greater need to perform well, both within and outside of the classroom. Recall from the start of the study how special education costs are becoming an increasing burden on LEAs, as state funding has failed to keep pace with the exponential rise in identified students. Lavelle et al. (2014) found that school districts assume $8,600 of that amount. When considering that the current autism rate for children in the United States is 1 in 88, the costs for many LEAs rise faster than their ability to accommodate these students. The consequence is an unfortunate situation for some LEA types that are spread too thin; administrators must decide between using instructional costs to hire more special education teachers, who can alleviate overtaxed special education staff or invest in more support staff, such as counselors and nurses that can benefit the whole student population. DuPaul et al. (2018) found that 20 percent of ADHD students nationally do not receive support services, with higher percentages for ELLs and low-income students. The researchers cited the need for more special education funding, especially in urban schools where many under-identified or under-serviced ADHD students are second fiddles to other special education students whose needs "outrank" their own. Again, the results of this study provide some support for these findings. In the CPA region, Rural Title I Districts may experience a near 7 percent decrease in turnover risk for special education teachers when auxiliary spending increases by 20 percent.

Lastly, in addition to impeding a district's ability to staff high need subjects, the lack of ancillary supports serves as a strong demotivator for current teachers. An Education

Law Center (2013) study examining the effects of a school nurse shortage in the SDP found that 70 percent of respondents reported that teachers or aides were administering medications or treatments with an additional 52 percent noting that children were missing classroom instruction time. These are disturbing findings given prior research indicates the presence of a school nurse improves school attendance, especially for children who suffer from chronic conditions and those who hail from low-income families who have either inadequate or no health insurance (Allen, 2003; Pennington & Delaney, 2008). Schneider (2003) found in his study of Chicago and Washington, D.C. classrooms that poor working conditions hurt teachers' health (both psychologically and physiologically) and increased the likelihood that teachers will leave their school. In both cases, the lack of hygiene (both literally and theoretically), serve as powerful demotivators for teachers who would otherwise be committed to teaching in low-income schools.

## Implications

In analyzing how turnover decision making can vary by teacher group, with considerable depth, it is easy to believe that there may be no shared commonality since different factions have differing motivators by region and LEA type. While it is true that there is no “one size fits all” approach (a simplistic perspective that has dangerous implications for education policy), there are some common themes that deserve attention. Whereas the preceding analysis focused heavily on money and working conditions as a strong demotivator, this section examines how teachers might be motivated to stay and thrive, ultimately achieving higher levels of job satisfaction as outlined in the Maslowian framework.

### ***The Importance of Educational Leadership***

Educational leadership is complex and demanding, requiring school administrators at both the building and LEA level to assume dual roles as instructional and organizational leaders. While, at face value, these roles appear distinct, they are mutually inclusive, as leaders with a convincing instructional vision for their schools must also be able to effectively manage and strategically employ resources in facilitating that vision to bear fruit. However, educational leadership does not happen in a vacuum. While administrators do need to provide decisive leadership that directs, supervises, and supports teachers, they also need to thoughtfully implement mechanisms of shared governance that are designed to elicit teacher support for the school leader's visions, since, once the class bell rings and the door is shut closed, all that remains in the room are the teacher and students.

***Leadership as the Confluence of Talent, Vision, Charisma.*** The Maslowian framework presented in Chapter 2 suggested that only a small fraction of an organization's workforce attain self-actualization, a state in which employees create projects that benefit the organization and guide colleagues also to achieve their maximum potential. However, while leadership summons a widespread belief that supervisors and bosses are omniscient, have posh salaries, and are even dictatorial, these misunderstandings do a disservice to the meaning of leadership. Leadership requires three essential components – talent, vision, and charisma – all in that order. The absence of any one characteristic leads to leadership incapable of either growth or reform. A leader with vision and talent, but no charisma will face difficulty in garner collegial support for initiatives. A leader with talent and charisma but has no vision risks squandering that talent on small ventures that may be inconsequential to the organization in the long term. In arguably the most problematic situation, a leader with vision and charisma but without talent cultivates a reputation as a charlatan who outsources projects to more capable individuals who, in turn, will likely seek to supplant the leader.

In education, a lack of high-quality leadership can have serious implications. March (1991) found that organizations that are large and poor (i.e., lacking in financial and human resources) have considerably less leeway than their smaller, wealthier peers to experiment with new approaches. Thus, urban districts, which generally fit the large and poor criterion, have much to lose in hiring school leaders who do not have either the talent, vision, or charisma to lead their schools in reform or long-term growth.

Furthermore, as discussed above, administrative bloat can lead to organizational inefficiencies, mixed messages, and the squandering of valuable resources. Concerning the most critical element, talent, Lochmiller (2016) and Boston et al. (2017) all noted that the feedback provided by principals to mathematics and science teachers via teacher evaluations focused on pedagogy as opposed to content understanding, leading many of these teachers to view such feedback as immaterial. Moreover, Lochmiller argued that administrator embedded feedback in their teaching experience and, therefore, they approached mathematics and science education with the same instructional lens as they did with their non-STEM peers. Merely adding more administrators and supervisors leads to a perpetual hiring frenzy in which a virtually endless parade of non-teaching staff is hired to compensate for one another's preparational shortcomings, a phenomenon that has received much attention in higher education settings (Bergmann, 1991; Hogan, 2011; Leslie & Rhoades, 1995). Unfortunately, urban schools do not have the luxury of dabbling in this practice due to budgetary constraints making the argument for competent and robust leadership all the more critical.

***Promoting Teacher Autonomy and Leadership.*** While teacher leadership tends to be an organic process in schools with low teacher turnover, high staff morale, and a shared feeling of community and collective responsibility, engaging in teacher leadership in urban schools that need serious reform can be challenging to navigate for both administrators and teachers. While a certain amount of "top-down" reform is necessary to stabilize an inherently chaotic learning environment in which a cavalcade of teachers enters and departs the school at any given time, Fullan (2005) noted that 'after this immediate year or so' devotion to arresting decline, this unsmiling approach must give way to near-term sustainable reform and long-term growth. Such growth is possible through a process known as capacity building, in which school leaders build a self-reflective and self-sustaining teaching staff that becomes less dependent on building administrators for direction. Fullan's approach to teacher leadership was recently validated in a large scale study by Ingersoll, Sirinides, and Dougherty (2017), who found that students in schools with higher levels of instructional leadership and teacher leadership performed at least ten percentage points higher in both mathematics and English language arts proficiency on their state assessments. Still, they caution that schools, and especially urban schools, are rarely able to implement the most critical aspects of strong instructional leadership, such as developing an effective school improvement team and holding teachers to high instructional standards, because of limited resources, weak workplace cohesion, and high levels of teacher and principal turnover.

School leaders often confuse teacher leadership with teacher representation, possibly because the latter is far more visible in schools than the former. Teachers have always served as school-wide committee members or as team leaders and department chairs; still, these are teacher representative positions because they are generally limited to an exclusive few who qualify (based on established criterion) and they do not serve as agents who enact a senior's expectations rather than their own (Livingston, 1992). Moreover, while the traditional solution has been for qualified teachers to move into administration positions, so they are the masters of the school's priorities, moving into such positions requires the abandonment of teaching altogether. In the absence of an enticing option, many experienced teachers never really advance to the two highest levels of Maslow's hierarchy—self-fulfillment and importance. As mentioned in the preceding analysis, this professional "stalling" provides fertile ground for turnover behaviors since these teachers crave engagement, yet do not receive it in their current employment. As the study shows, across all three regions, the leaver/mover phenomena appear to manifest at the mid-career point (in the 20-year experience range); so, unsurprisingly, research has long recognized that without providing access and opportunity for every teacher to develop leadership qualities, districts will experience difficulties hiring and retaining qualified staff (Boyd-Dimock & McGree, 1995; Howey, 1988). One of the hallmarks of teacher leadership is a shared sense of responsibility in which teachers trust one another enough to seek collegial wisdom independent of an administrative directive. Goddard, Hoy, and Hoy (2000) observed that when there is a free flow of curricular and instructional practices, combined with an open air of collaboration that welcomes innovation, both teachers and students found the teaching and learning process to be gratifying. In line with Fullan's (2005) argument, this culture of collective responsibility then spurs teachers to seek new professional development opportunities, either alone or in-person; in turn, leading to a self-reflective faculty.

### ***The Flaw in Applying a Mechanical Approach to Schools***

Imagine if the schoolhouse was a playhouse. Students, like audience members at a play, would only see the carefully rehearsed and honed craft performed during the show, with little regard for the planning and work that went into the performance before, and even during, the event. Afterward, some audience members walk away inspired, energized, and motivated, and others bored, tired, and disengaged. Once the playhouse clears, all that remains is the stage crew, the managers and staff, and of course, the actors. Just as the quality of a theatrical performance depends on the chemistry of all of these individuals, so too is a successful teaching experience predicated on the relationship between administrators, parents, students, and staff. Since teachers are members of a broader educational ecosystem, attempts to modify their actions will inevitably reverberate throughout the entire system. This part explores two such attempts at modifying teachers' behavior and ponder how their application can diminish a teacher's sense of self-actualization, importance, and belonging.

***The Wisdom in Maslow's Law of the Instrument.*** Over 50 years ago, Maslow (1966) cautioned social scientists to avoid the temptation that, "if the only tool you have is a hammer, to treat everything as if it were a nail," giving rise to Maslow's Law of the Instrument. Even though Maslow was speaking to members of the research community, his words carry special significance for policymakers who readily commit to approaches that bill themselves as a panacea to all policy-related ailments. In public education, this hammer-nail approach invariably oversimplifies the educational ecosystem, and as stated by Ravitch (2016), treats schools, teachers, and students as, "objects to be moved around." Teacher pay is one such hammer-nail issue. Employees treat salaries as a psychological evaluation of their worth, and poor pay can lead employees to question both their employment and their self-worth (Wickelgren, 2012). In the case of teachers, shortchanging their pay can lead to feelings that their efforts, especially when working in high pressure or isolated urban and rural schools, are largely unnoticed and societally unappreciated. So, unsurprisingly, a perennial question that employers and employees commonly ask themselves, especially around the time of a job offer, is: what is the (dollar) value of a good teacher? In a mathematical sense, this study can provide a reasonable estimate. Since survival models provide hazard rates (i.e., rates of change), the “ideal” salary would be one wherein there is no risk of turnover. Equations 5.1 and 5.2 illustrate this mathematically through a differential equation in which the partial derivative of salary and per-student spending is set to ‘0’.

$$\frac{\partial(\mathbf{logadjsalary})}{\partial(\mathbf{h(t)})} = \mathbf{0} \qquad (5.1)$$

$$\frac{\partial(\mathbf{logadjauxspend})}{\partial(\mathbf{h(t)})} = \mathbf{0} \qquad (5.2)$$

As Maslow’s Law of the Instrument and the findings of this study suggest, obtaining these values is ultimately meaningless since, firstly, this value may not be applicable to any one individual, since it’s calculated using the whole population, and secondly, the value obtained may be so high that it would be impractical to attempt. Both limitations highlight a valuable lesson for policymakers at all levels, down to LEA administrators: teachers are products of and contributors to their environment, and by treating them as “objects to be moved” dehumanizes their work.

***The Perils of Succumbing to Ideology.*** A related problem that follows from Maslow's Law of the Instrument is the promotion of ideology over substance, which is problematic in a highly partisan political environment, where political party and regional loyalties can breed a type of "groupthink." One such issue is the General Assembly's almost fanatical devotion to charter schools as a panacea to "fix" urban education. Chapter 1 noted that charters have a loyal following amongst RtW advocates, who universally regard teachers' unions as defenders of indolent teachers who are more than happy to coast their way to a publicly supported retirement by putting themselves ahead of students. (In fact, one prominent lobby group for charters *is* titled StudentsFirst.) The RtW movement, which is closely allied to the Republican Party, has a strong presence in the General Assembly, in large part because of that legislature's skewed political composition. Despite the RtW movement's almost panegyric admiration for charter schools and their professed ability to improve student outcomes, the reality is far more lackluster. As this study shows, charter schools have concocted a volatile mix of low pay, diminished teacher autonomy, lack of teacher input in school-based decision making, and a model that thrives on recruits, which combine to produce extraordinarily high rates of turnover. Also, the churn is not just limited to teachers. In their study of Utah charters, Ni, Sun, and Rorrer (2015) maintained that turnover rates amongst principals were equally as high when compared to charter school teachers. The difference is, whereas those leaving charter teaching positions remained in education, either teaching in other schools or a different capacity, charter school principals are at high risk of burnout, with a disproportionately large number leaving either the state or the profession altogether. As the results of this analysis indicate, increasing pay has little, if any, effect on this high rate of turnover for most teacher groups, since even a sizeable pay raise cannot compensate for the other workplace deficits.

While there are some high performing charter schools in the Commonwealth with stable staff, leadership, and concomitantly high academic achievement (e.g., MaST Community Charter School in the PHL region, Lincoln Park Performing Arts Charter School in the PGH region, and Lehigh Valley Arts Charter High School in the CPA region), these schools are few and far between. Despite the Auditor General's characterization of Pennsylvania's charter school law as "the worst in the nation," the General Assembly has continually rebuffed any attempt at charter school legislation on principle alone, even though evidence points to success in other states (PDAG, 2018). For example, New York state places a limit on how many charters can operate at any given time – a move that the New York State Schools Board Association has applauded, arguing that the restriction in supply helps traditional districts effectively manage costs (New York State School Boards Association, 2006). Also, this restriction can promote competition *within* the charter school sector, since those schools with subpar student achievement will likely see their charters revoked and awarded to a more capable operator. Even the National Alliance for Public Charter Schools (2019), which, as expected, is a strong promoter of charter school autonomy, has ranked Pennsylvania 34$^{th}$ amongst the 44 states with charter school laws, citing a lack of "transparency regarding educational service providers and [to emphasize] strengthening accountability for full-time virtual charter schools". Both cases illustrate that the Republican-dominated General Assembly's blind acceptance of charter schools is at odds with the party's commitment to competition and fiscal responsibility.

## Recommendations

The results show that the same monetary intervention (a 10 or 20 percent increase) can have highly variable effects, ranging from none to an impressive 42 percent decrease in turnover risk. The results of this study offer some practical recommendations for both state-level and LEA-level decision makers. In the first chapter, I presented a wealth of background information regarding the state's unique geographic, political, economic, and demographic indicators, and how school funding policy is first created in the crucible of this heterogeneous environment and subsequently parceled to LEA administrators who must balance student and teacher needs with limited resource availability and increasing fiscal pressures.

### *For State Policy Makers: Revisiting Policy Context I*

While state-level policymakers do have enormous sway over the structure and function of schools vis-à-vis the levers of power under their control, they are equally limited in their ability to apply this power effectively. State policymakers are several strata removed from the level of intended effect (generally schools or classrooms), and without context or consideration for the complexities of schools, their teachers, and their students, policy decisions can quickly become the victims of partisan debates that prioritize a parochial mindset over a progressive one as well as ideology over any empirical evidence.

***The Cost of Identity Politics.*** While political partisanship on Capitol Hill is a favorite topic of many news pundits, partisanship in Harrisburg is so well-rooted that Pennsylvanians have come to accept it as a way of life. In what has become an "us vs. them" mentality, an air of animosity exists between the PHL region (specifically Philadelphia) and the rest of the state (outside Pittsburgh). Other states too have similar divides (e.g., Texas and California), but Nathaniel Popkin (as cited in Spikol, 2016), a former Philadelphia newspaper columnist turned historian, argues that, while Philadelphia and the rest of the state have had distinct identities dating the Colonial Era, their shared economic fortunes bred a common "Pennsylvanian" identity. However, in the wake of post-World War II demographic changes (e.g., the Great Migration, White Flight, the creation of suburbs, of which, Levittown, PA was among the first in the country), a mental decoupling occurred between the PHL region and the rest of the state. The PHL region came to view the rest of the state as uneducated and underdeveloped, and the CPA and PGH regions regarded the PHL region as elitist and crime-riddled. Figures 1.1 and 1.2 illustrate the degree to which this atmosphere of mutual distrust and hostility has become entrenched in the General Assembly's political composition, with dire consequences for the PHL region.

Long gone are the days when economies were predominantly local and the effects of policy limited in their scope. In modern democratic societies, legislators may hail from diverse regions, each with their own demographic and economic idiosyncrasies; nevertheless, this experiment in self-represented government is sustainable insofar as legislators choose to compromise and take action over intransigence and complacency, with the latter giving rise to a disconnect between intention, policy, and effect. One such example is the link between urban dropout rates and state expenditures. Research has shown that the nearly three-quarters of students who fail to achieve reading proficiency by the end of fourth grade are low-income students, with two-thirds of these students likely to become high school dropouts (Fiester, 2013; Haney, 2001; Temple, Reynolds, & Ou, 2004). While some Harrisburg politicians may dismiss this finding as an "urban schools" issue that had little bearing on their constituents, the costs of dropout rates are shouldered by all taxpayers, statewide. High school dropouts are more likely to be employed in minimum wage jobs, which apart from the rare exception, results in these individuals becoming "stuck in place," with little chance of achieving social mobility. Moreover, because these jobs simply do not pay enough to sustain a single individual, let alone a whole family, these individuals also become long-term subscribers to supplemental support programs such as subsidized housing, healthcare, and food, which cost Pennsylvania taxpayers $12 billion annually at the state and local level compared to its $47.5 billion expenditure on education (U.S. Census Bureau, 2018). In effect, by underfunding its schools, Harrisburg legislators have created its own perverse "cradle to grave" social system.

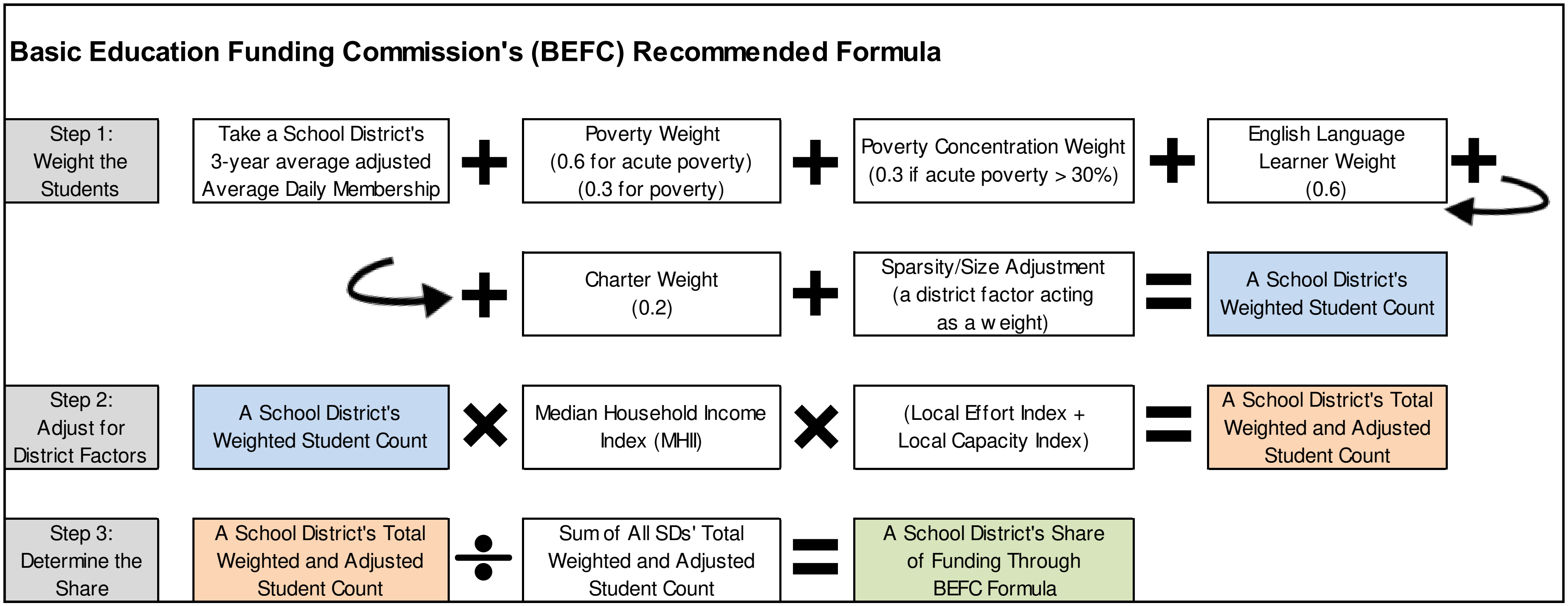
A more concrete example that draws from this study's results is the issue of science teacher turnover in the SDP. In 2015, Overbrook High School was cited in the State Senate as a high school without a (certified) biology teacher, which was likely a contributing factor to the school's Keystone Biology proficiency rate of slightly less than 7 percent that year (Mezzacappa, 2015). As Table 4.14(b) indicates, even a 2 percent annual increase in remuneration would lead to a reduction in risk of turnover by almost 13 percent in five years and a 4 percent annual increase would result in an almost 23 percent decrease in the turnover rate. If a biology teacher in the SDP earned $50,000 annually, a 4 percent annual raise would increase of $10,000 over five years. Invoking Carver Thomas & Darling-Hammond's (2017) research, teacher turnover can cost urban schools $10,000+ per employee. Since the General Assembly funds nearly half of the SDP's $3 billion budget, it would be more *cost-effective* for the legislature to make the initial investment, rather than suffer through successive waves of turnover of the same position. Moreover, in providing a more stable school environment that promotes academic growth for students and professional growth for teachers, the state is likely to witness long-term savings as a result of more high school graduates moving into self-sustaining jobs.

***Reforming the State's Funding Formula.*** Chapter 1 elaborated on the state's regressive formula, including its hold harmless provision. On June 1, 2016, Governor Wolf signed into law an improved funding formula called the Basic Education Funding Commission

(BEFC) formula, attempting to remedy the effects of the hold harmless provision spanning over two effects and resulting in chronic underfunding in the PHL region for both the SDP and surrounding Suburban Title I schools. Instead of allocating a defined amount to a district based on the hold harmless principle, the BERC formula moves toward a defined percentage in which a district receives a percentage share of the basic education budget using the weighted and unweighted variables outlined in Figure 5.1.

While the passage of the BERC formula is a long-awaited and sincere effort toward fair funding in Pennsylvania, there are limitations to its ability to completely remedy the effects of hold harmless. In abandoning the hold harmless provision, the state implemented a “base positive” or “base negative” calculation, both of which use AY2014-15 basic education funding as a baseline for the formula’s implementation. Districts that are base positive are those that have benefited from hold harmless, while base negative districts are those who are owed funding under the new formula. The BERC formula posits that base positive districts will have their funding slowly reduced while base positive districts will have their funding slowly increased to prevent wild fluctuations in per-student spending. According to the House Appropriations Committee’s analysis, only the Top 10 percent and Bottom 10 percent of school districts by median household income are base negative districts. These deciles correspond with Suburban Non-Title I Districts and the SDP, respectively, with each owed a corresponding $25.2 million and $719.9 million (2018). The money owed to the SDP would, as this study suggests, would decrease the risk of turnover by double digits for new and experienced educators as well as math, science, and special education teachers. Additionally, the funds would help Suburban Non-Title I Districts straining under high property taxes, especially in those districts like Lower Merion School District, which assume the highest share of special education costs.

**Figure 5.1**


Basic Education Funding Commission's (BEFC) Recommended Formula
Step 1: Weight the Students
Take a School District's 3-year average adjusted Average Daily Membership
Poverty Weight (0.6 for acute poverty) (0.3 for poverty)
Poverty Concentration Weight (0.3 if acute poverty > 30%)
English Language Learner Weight (0.6)
Charter Weight (0.2)
Sparsity/Size Adjustment (a district factor acting as a w eight)
A School District's Weighted Student Count
Step 2: Adjust for District Factors
A School District's Weighted Student Count
Median Household Income Index (MHII)
(Local Effort Index + Local Capacity Index)
A School District's Total Weighted and Adjusted Student Count
Step 3: Determine the Share
A School District's Total Weighted and Adjusted Student Count
Sum of All SDs' Total Weighted and Adjusted Student Count
A School District's Share of Funding Through BEFC Formula

*See Next Page

| Step 1: | Take a School District's 3-year average adjusted Average Daily Membership | + | Poverty Weight (0.6 for acute poverty) (0.3 for poverty) | + | Poverty Concentration Weight (0.3 if acute poverty > 30%) | + | English Language Learner Weight (0.6) | + | Charter Weight (0.2) | + | Sparsity/Size Adjustment (an adjustment factoring in as a weight) | = | A School District's Weighted Student Count |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|

| Table 1: Weighted Student Count | 3-year average adjusted Average Daily Membership | Poverty Weight | Poverty Concentration Weight | English Language Learner Weight | Charter Weight |
|---|---|---|---|---|---|
| Rationale | A student-based formula needs to start with an accurate count of students. A 3-year average of adjusted ADM is used in order to smooth out any sudden changes in enrollment and allow districts more time to make adjustments due to enrollment changes. | "Various studies have shown that children living in poverty often begin their educational careers behind their non-impoverished peers and thus require additional supports and services in order for them to meet the same academic standards." – BEFC Final Report, page 45 | Research indicates that not only does a low-socioeconomic household have a negative effect on student achievement, but it also demonstrates that the socioeconomic status of the student's community plays a large role. The negative effect that poverty has on student outcomes is compounded when the poverty is concentrated in a community. | In addition to the regular education curriculum, Pennsylvania requires that ELL students receive language instruction, which translates into higher costs to educate ELL students (dual language curriculum material, after school programs, etc). | When a student leaves the school district to attend a charter school, there are fixed costs (e.g. classroom, teacher) that are spread out over fewer remaining students, meaning the cost to educate the remaining students goes up. |
| Statistic | PA's 2015/16 statewide adjusted ADM was 1,708,454. Philadelphia City SD is by far PA's largest district with an adjusted ADM of 204,058 or 12 percent of the state total with the next closest being Pittsburgh City SD with 27,227 or 1.6 percent of the total. | "One analysis revealed that children from professional families heard an average of 2,153 words per hour, while children in working class families heard an average of 1,251 words per hour, meaning that by age four, a child from a welfare-recipient family may have heard 32 million fewer words than a classmate from a professional family." – BEFC Final Report, page 45 | "For example, 86 percent of students are proficient in 3rd grade reading when attending Pennsylvania districts with fewer than 25 percent of children in poverty, but only 52 percent of students are proficient in 3rd grade reading if they attend a district with 50 percent or more of their students in poverty." – Joan Benso's testimony at BEFC hearing December 10, 2014 | "Research has long investigated the amount of time it takes for ELL students to obtain complete proficiency, with estimates for academic proficiency often ranging between four and seven years, while oral proficiency may be obtained in as little as three to five years." – BEFC Final Report, page 30 | In the IFO survey commissioned by the BEFC, the school districts that were sampled reported that, under the hypothetical scenario where 10 percent of students departed for charter schools, the average base cost to educate the remaining students increased by 18 percent. See page 84 of BEFC Final Report. |
| Weight | Every student counts as 1.0 except half-day kindergarten students count as 0.5 (this is how adjusted ADM differs from regular ADM which counts all students as 1). | 0.6 for acute poverty; 0.3 for poverty | 0.3 | 0.6 | 0.2 |
| Making Sense of the Weight | This is basically a school district's annual enrollment. The foundation of the formula is every student counts as 1. | Students in poverty are already counted as 1.0 in the ADM. The 0.6 and 0.3 weights for students in poverty are a recognition that it costs an additional 60 or 30 percent more to educate impoverished students. | The BEFC formula determined it costs 60 percent more to educate acute poverty students in every district, but it costs 90 percent more to educate acute poverty students in districts with a high percentage of acute poverty. So there is an additional 0.3 weight on top of the 0.6 acute poverty weight for high poverty rate districts. | ELL students are already counted as 1.0 in the ADM. The 0.6 additional weight for these students accounts for the 60 percent higher costs to educate students with a non-English-speaking background. | Charter school students are counted in a district's ADM. The BEFC determined that an additional 20 percent was an appropriate amount to compenstate school districts for the 'stranded costs.' |
| Definition/ Notes | The PA Dept. of Education defines average daily membership as "the term used for all resident pupils of the school district for whom the school district is financially responsible. It is calculated by dividing the aggregate days membership for all children on active rolls by the number of days the school district is in session." | The acute poverty weight applies to students falling in the 0-99% range of the federal poverty level while the poverty weight factors in for students between 100-184% of the federal poverty level. | School districts qualifying for the poverty concentration weight have over 30% of their students in the 0-99% range of the federal poverty level. | Oftentimes also called Limited English Proficient (LEP) | A school district pays the tuition amount (the district's spending per student less some expenses) for its students that choose to attend a charter school. |
| Calculation | See Appendix A | See Appendix A | See Appendix A | See Appendix A | See Appendix A |
| Data Source(s) | PA Department of Education | Most recent 5-year estimate of the U.S. Census Bureau's American Community Survey ACS Series ID: B17024 | Most recent 5-year estimate of the U.S. Census Bureau's American Community Survey ACS Series ID: B17024 | PA Department of Education | PA Department of Education |

| Step 2: | | A School District's Weighted Student Count | X | Median Household Income Index (MHII) | X | (Local Effort Index + Local Capacity Index) | = | A School District's Total Weighted and Adjusted Student Count |
|---|---|---|---|---|---|---|---|---|

| **Table 2: Weighted & Adjusted Student Count** | **Sparsity/Size Adjustment** | **Median Household Income Index** | **Local Effort Capacity Index** | Local Effort Index | Local Capacity Index |
|---|---|---|---|---|---|
| **Rationale** | Testimony at BEFC hearings revealed that PA school districts in rural areas have unique challenges leading to higher costs. Some examples include difficulty to consolidate services due to the geographic size of a district, extraordinary transportation challenges, and higher per-pupil costs due to a loss of economies of scale. | A fair formula for state funding needs to account for the vastly different amounts of local wealth between districts. The MHII replaces the Market Value / Personal Income Aid Ratio as the measure of a district's relative wealth. | "Local tax effort and wealth are critical factors impacting the ability of school districts to raise local revenue." – BEFC Final Report, page 40 | The local effort index is designed to determine whether a school district is making a fair local tax effort. It compares the tax burden in each school district to the statewide median tax burden. Importantly, it includes an adjustment for school districts spending above the statewide median expenditures per weighted student so as to not reward wealthier districts that choose to have high taxes so that they may spend more per pupil. | Asks the question, how much spending per weighted student could a district afford if it taxed at the statewide median effort? The local capacity index component provides more state funding for districts that are unable to raise enough funds locally even if taxing at the statewide median rate. |
| **Statistic** | "Specifically, when studying economies of scale in education, [researchers Baker and Levin] found per-pupil costs tend to be flat as district enrollment surpasses 2,000 students, while below this enrollment, costs tend to increase, dramatically so as enrollment dips below 500." – BEFC Final Report, page 35 | In 2015, the median household income in PA was $53,599 and the number of households was 4,958,859.<br>Using 2017/18 distribution data: 278 school districts have a MHII greater than 1, while 222 have a MHII index value below 1. The median MHII value is 1.0423. | Using 2017/18 distribution data: PA's 125 poorest school districts based on the median household income index spent $9,485 per weighted student while the wealthiest 125 districts spent $14,472 per weighted student, or 53% more. | Using 2017/18 distribution data: The median local effort index is 0.92. Pocono Mountain School District has the highest local effort index at 1.90. | Using 2017/18 distribution data:<br>Of PA's 500 school districts, 252 receive a local capacity index of zero, and 248 have an index value above zero. Reading School District's local capacity index value of 0.84 is the highest. |
| **Adjustment Definition** | The sparsity/size adjustment weight is unique in the BEFC formula in that it is a district factor treated as a student weight. The weight is 0.7, and it applies to school districts at or above the 70th percentile of sparsity size index. In other words, out of PA's 500 school districts, the 150 districts with the lowest population density receive additional support. The sparsity/size adjustment is part of the weighted student count. The special education formula uses the same sparsity/size ratio. | The MHII measures a school district's median household income compared to the statewide median household income. The higher the MHII, the less income a school district has. The weighted student count is multiplied by the MHII in the formula. This means a MHII value greater than 1 increases a school district's share of the funding, while a value below 1 decreases a school district's share of the funding. | The Local Effort Capacity Index is the sum of the Local Effort Index and the Local Capacity Index. In the BEFC formula, the Local Effort Capacity Index is multiplied by the weighted student count. This means an index value greater than 1 increases a school district's share of funding, while a value below 1 decreases a school district's share of the funding. | The local effort index is added to the local capacity index in the BEFC formula. The stronger the local effort is (after accounting for spending above the median), the higher the index value will be. | If the district's hypothetical capacity for spending per weighted student is lower than the hypothetical statewide median amount, the district's local capacity index is above zero. If higher, the index is zero. The local capacity index is added to the local effort index in the BEFC formula. |
| **Calculation** | See Appendix A | See Appendix A | See Appendix A | See Appendix A | See Appendix A |
| **Data Source(s)** | PA Department of Education - for adjusted ADM<br>U.S. Census Bureau's latest decennial census - for Total Square Miles | Most recent 5-year estimate of the U.S. Census Bureau's American Community Survey ACS Series ID: S1903 | Most recent 5-year estimate of the U.S. Census Bureau's American Community Survey - for median income - ACS Series ID: S1903<br>PA Department of Education - for local tax related revenue, current expenditures, adj. ADM, and state property tax reduction allocation<br>PA Department of Community and Economic Development's Tax Equalization Division - for market values and adjusted personal income (reported to PDE) | | |

While this deficit to the PHL region will likely take many years to correct, the state's ESSA plan has established an ambitious school accountability goal of reducing, amongst other metrics, the number of students who are not proficient on the state's PSSA/Keystone ELA/Literature and PSSA/Keystone Math/Algebra I exams to half by 2030. Ironically, although many states objected to NCLB's 13-year timeline in which 100 percent of kindergarten students starting in AY2002-03 would achieve proficiency in ELA and mathematics by high school graduation in AY2014-15, they replicated the same 13-year timeline for their own ESSA ambitious goals hoping to achieve similarly high gains by 2030. As indicated in Table 4.1, the SDP has the lowest proficiency rates on standardized state assessments amongst all LEA types. It is conceivable then that the correction period associated with the funding imbalance may not prove helpful in either stemming teacher loss or providing the adequate learning environment needed to meet PDE's progressively increasing ESSA targets.

Second, while the BERC formula does redistribute funds more fairly, despite the extended correction period, it does not address a fundamental issue highlighted at the start of this study—the state's declining portion of school funding resulting from decades of divestment. Since the formula only makes a *relative* guarantee in the form of the AY2014-15 baseline, there is no mandate for the state to find new tax revenues (e.g., Marcellus Shale) to fund what *should* be an education budget that seeks to increase teacher hiring, renovating old facilities, and paying for more support services.

Lastly, while the new formula does include a Median Household Income Index (MHII), which measures a school district's median household income compared to statewide median household income, it does not include a CoLI adjustment. It is possible that two districts could have the same district median household income, and therefore the same MHII value, albeit with conflicting results. For example, according to data from the U.S. Census Bureau (2010), Philadelphia and Sullivan counties have almost identical median household incomes differing only by $1 ($36,250). According to Table 1.1, Philadelphia County has a CoLI of 109.7, whereas Sullivan County has a CoLI of 93.0, mainly resulting in median household income of $33,045 and $38,990 for Philadelphia County and Sullivan County, respectively.

***Critiquing Current Proposals.*** In the wake of several prominent national strikes, several politicians are seeking to capitalize on the movement by promising support to America's struggling teachers. Senator Cory Booker (D-NJ) is attempting an about-face to his record on education policy as he prepares for his presidential candidacy. When Booker was mayor of Newark, N.J., he embraced private school vouchers and even collaborated with then Governor Chris Christie to introduce merit pay for teachers in that city. Another presidential candidate, Senator Kamala Harris (D-CA), entered the fray in March 2019, with a plan to give every teacher a $13,500 raise—echoing Herbert Hoover's famous 1928 campaign slogan of "a chicken in every pot" (Epstein, 2019). While Harris's promise is admirable, such a lofty goal is likely to come into conflict with fiscal realities. In the wake of the Jobs and Tax Cuts Act of 2017, the Congressional Budget Office (2018) estimated that deficit would increase $1.9 trillion by 2028 - roughly the same period when Senator Harris's $315 billion plan would go into effect and therefore likely tempering support amongst more fiscally conscious politicians on both sides of the political aisle.

This past February, Governor Wolf announced that he was seeking to raise Pennsylvania's minimum teacher salary to $45,000. The plan only seeks to cover districts that currently pay less than the established minimum, with the state compensating for the wage difference (Mahon, 2019). Like Senator Harris's plan, Governor Wolf's proposal raises more questions than it answers. For one, Wolf's plan does not account for CoLI adjustments, and consequently, most districts that would receive funding are in the PGH and CPA regions, with only Reading School District (Berks County) in the PHL region set to receive any substantial amount. Without adjusting for CoLI values, the policy will likely fail to have any substantive effect on teacher retention in the PHL region, which as this study indicates, has the highest rate of teacher turnover. For instance, Wolf's proposal would result in no supplemental salary subsidies for the SDP, where a starting salary for a regular teacher with a bachelor's degree ($45,360) is marginally above the proposed minimum, yet when adjusted for CoLI drops to $41,350. Second, it is difficult to imagine, given Harrisburg's record of divestment in public education funding, its highly partisan state legislature, and ever-increasing pension obligations, whether the state's commitment to these underpaid teachers is even feasible in the immediate future, let alone years into the future. Third, the plan does not appear to include a similar subsidy for support staff, whose salaries will presumably continue their normal trajectory, possibly resulting in some intra-LEA side effects.

Finally, a growing contingent of Pennsylvanians has adopted a radical standard—the elimination of property taxes altogether. In 2015, two conservative groups—the Pennsylvania Liberty Alliance and the Pennsylvania Property Rights Association—lobbied for a bill before the General Assembly Senate that would have eliminated school property taxes statewide (Murphy, 2015). The bill was ultimately defeated by a razor-thin margin of 24-24, with Lt. Governor Michael Stack breaking the tie. Nonetheless, a relatively quiet campaign and closeness of the vote, suggests that powerful lobbies are exerting influence on Harrisburg politics under the guise of night. Despite the controversial and, at times, unpopular nature of property taxes, it is critical to keep in mind that they remain by far the largest and most reliable source of public funding. Less so than wages, sales, and sin (e.g., alcohol, tobacco), property values do not dramatically fluctuate over time and are generally assumed to increase in value over the long term, therefore netting the successive revenue needed to sustain school expenditures.

### *For LEA Administrators: Revisiting Policy Context II*

These findings can also provide some insight for LEA administrators, albeit with differing implications. Ironically, for many administrators who attempt to imbibe elements of student wellbeing into their school climate (e.g., caring for others, developing a sense of community, encouraging the pursuit of individualized learning, highlighting the importance of physical and mental health), they appear to forgot them when it comes to their teachers – as if Maslowian needs somehow become irrelevant once a teacher obtains certification. In some extreme cases, particularly in urban schools that are facing pressure from various stakeholders to produce immediate results, teachers can be treated, even by administrators, as problems to manage, rather than potential to be cultivated. This last policy section offer ways that school administrators can eschew this type of counterproductive reasoning by revisiting some of the findings in Chapter 2 with this study's results in hand. Horace Mann (as cited in Howe, 2006), a staunch advocate of the Common Schools movement, recognized the need to support teacher growth long before business schools offered courses on employee motivation and management when he commented that "teachers teach because they care. Teaching young people is what they do best. It requires long hours, patience, and care".

***Strategies for Attracting and Retaining Teachers.*** Organizational leaders and their human resources officers can (and often do) fall into the trap of believing there exists some mystical formula to hiring and retaining, as if by merely entering values (e.g., experience, education, salaries) will yield the desired result. Perhaps a better analogy is the twin processes of courtship and building a long-term relationship, respectively. During the courtship period, both the employee and employer strive to understand one another's needs and desires and, in the long term, build a positive rapport assembled on a foundation of trust and communication. Both the theoretical framework and the results of this study suggest that low pay (and, by extension, compensation) can be a significant demotivator that leads to turnover yet is a poor motivator when used to encourage productivity, with ephemeral results, at best. As the reviewed literature indicates, intangible factors, such as autonomy and a concern for their physical and mental wellbeing are far better motivators.

Teachers, like any other professional worker, value autonomy since it permits flexibility and feeds a sense of competence and trust. Despite reports that several Fortune 500 companies (e.g., Apple, Google, Microsoft) offer their employees a high degree of flexibility, a survey by Harvard Business Review found that over 96 percent of professionals listed flexibility and autonomy of high importance in choosing a job. Moreover, half of those surveyed said that they would seriously consider a job offer from another employer who fulfilled that expectation (Dean & Auerbach, 2018). While the structure of school schedules makes it difficult to offer the degree of autonomy or flexibility often seen in an office environment, some are possible if administrators are willing to embrace more innovative practices. One possible approach is to allow those who teach challenging students the opportunity to create their electives free from the constraints of standardized testing. Such an approach would have the dual effect of promoting competency and trust, which leads to a sense of importance and self-actualization—the highest of Maslow's needs.

Nonetheless, some administrators believe that allowing teachers to create and teach electives of their design might result in scheduling complications due to under-enrollment or detract from valuable class time that would otherwise be spent teaching ELA and mathematics. This concern can quickly be remediated by first, surveying students about topics of interest, and second, encouraging teachers to create interdisciplinary courses, which would also have the added benefit of bringing together colleagues in a collaboration that likely have little to no contact with one another daily. Another possible approach is to provide teachers with more professional development choices, both in terms of pursuits and modalities (e.g., in-person, online, before/after-school). If offered a selection of topics, teachers will likely choose those that are most relevant to their immediate classroom needs and personal schedules. Dymoke & Harrison (2006) noted that this is especially helpful for new teachers, who can feel overwhelmed by a range of pressing issues yet find that schoolwide professional development is too generic and fails to address their concerns.

With a growing emphasis on physical and health on overall happiness, especially amongst Millennials, wellness support programs are becoming more critical in aiding employee wellbeing. Mental health programs that assist employees in managing workplace stress can reduce the risk of burnout and eventual turnover. Beyond the obligatory induction or mentorship program for new teachers, schools rarely invest in teacher wellness, let alone one that is custom tailored. A study by Grant, Dutton, and Rosso (2018) asserted that the success underpinning the most effective of mental health support programs is due to employees both receiving help from their colleagues and providing it since coworkers are generally more cognizant of one other's needs compared to management. In the school setting, this could be as simple as permitting teachers to "share" sick and personal days with one another, a practice in which teachers donate some portion of their allocated days to another member of the faculty who may be experiencing some exceptional event.

As many CBAs have clauses that reserve a teacher's position for a year or so when she takes a leave of absence, these districts do not provide either pay or benefits during that period—a shortcoming that can be doubly difficult for teachers on maternity leave. The sharing of personal time can promote a sense of caring for fellow teachers. Some administrators might rebuff this suggestion, saying that it may lead to increased costs, implying that teachers will donate days without discretion. This reasoning is more indicative of poor budgeting practices since sound accounting principles dictate that employers should only offer as many benefits as they can maximally cover. In terms of physical wellbeing, some districts have even offered employees discounted gym membership or niche on-campus yoga and meditation classes. Still, the reality of teachers' demanding schedules presents a hurdle for many wishing to take advantage of this benefit, which, in turn, leads administrators to stop offering the perk altogether. However, Sonnentag & Fritz (2015) found that employers who reinforced the value of exercise, breaks, relaxation practices, and better defined work-home boundaries found that their employees felt physically energetic, engaged, and productive during working hours.

As Millennials begin to eclipse Baby Boomers in classrooms, administrators may need to rethink those hiring and retention processes that have long been codified or considered sacrosanct to meet the expectation of this large labor pool. Comet Financial

Intelligence, a firm that specializes in student loan repayment services, found in its survey of Millennial educators that respondents cited the lack of appreciation and recognition as one of the top three reasons for job dissatisfaction – on par with other service sectors such as hospitality, healthcare, and transportation (Comet, 2018). As discussed in Chapter 2, teaching is a profession that requires intense emotional energy to connect with one let alone 125 students daily. When administrators take this emotional commitment for granted, teachers may consider this attitude alongside other metrics (e.g., pay and benefits, amount of vacation/sick time, opportunities for professional growth) as indicators of their value (or lack thereof) in the eyes of their employer.

***Engaging in Constructive Collective Bargaining***. The concept of labor negotiations can stir images of two adversarial parties shouting at one another across a room, but the process can offer more progressive administrators the opportunity to use the bargaining table to promote policies that can aid in teacher retention. Even though the inevitable "give-and-take" nature of collective bargaining can lead to heated exchanges, and the expected airing of grievances, administrators should keep in mind that today's striking teachers are tomorrow's coworkers, once the ink dries on the new agreement. Possibly more important is the essential atmosphere of trust that permeates all aspects of the school environment, which can lead to productive employee engagement or, conversely, induce turnover related behavior.

Understandably, the weight of specific financial stressors can often lead administrators to falsely believe that money is both a means and an end for teachers who, like a tapeworm, can only be satisfied with ever-increasing pay raises. As this study argues, money is only one variable in the turnover arithmetic, with some teacher groups in certain LEA types experiencing little to no reduced risk on turnover despite considerable increases in pay. Perhaps, then, the best approach for administrators is to ask union leaders to identify the most pressing needs in the classroom, placing the onus on union leaders to effectively communicate with their bargaining unit to understand the needs of various demographic groups.

As the results suggest, for new teachers, the issue may be monetary, with two possible solutions. First, negotiators might consider higher salary increases at lower steps compared to smaller increases at higher steps. Thus, instead of traditional "across-the-board" percentage salary increases, financially astute negotiators might fashion a salary schedule in which costs reserved at the top end of the schedule shift to the bottom end of the schedule. Doing so can result in higher new teacher salary increases without incurring the need to raise additional revenue. Second, since post-secondary graduates continue to assume increasing amounts of student debt with each successive year, administrators may want to consider offering a benefits package that includes a student loan payment subsidy paid over several years of service. For experienced teachers who may be suffering from a "mid-career" crisis, administrators may wish to offer a greater amount in professional development funds for attending academic conferences or for pursuing advanced leadership or academic study, both of which can be an asset when promoting teachers for advancing teacher leadership. Finally, for both new and experienced teachers, a financially savvy contract negotiation team might consider establishing a salary schedule with breaks immediately before reaching the next IRS tax bracket, thereby resulting in greater "take-home" pay for employees.

However, in any case, these negotiation strategies should not be taken as a license to engage with deceptive or "hardball" tactics. A popular ploy used by some LEAs is to offer signing bonuses, a one-time payment used to entice a prospective employee, especially in high need subjects. There is a seductive quality to this approach, evoking a simpler time when banks offered a new toaster if a prospective customer opened an account at the local branch. However, researchers have argued that, like the free toaster offer, singing bonuses not only fail to encourage long term retention, but also breed adverse behaviors such as disloyalty or "cash and dash" in which the new hire leaves for a better position shortly after collecting the bonus – all of which ultimately cost the organization more in the long run. (Choi, 2013; Liu, Johnson, and Peske, 2004; Segars & Hendrickson, 2002)

Another problematic maneuver is concession bargaining, in which employees win gains in one area of the CBA (such as a pay increase) but this additional money is used to finance costs in another area (e.g., less health insurance subsidy). While such an approach might result in zero-sum gain for labor (and money saved for the employers), this type of negotiation displaces problems and lay the foundation for future hostilities, since teachers will likely feel that administrators are cavalierly dismissing their concerns or see them as more of a cost than an asset (Cooper & Greenhouse, 2011). Above all, administrators should adhere to the spirit of collective bargaining, in which teachers (like any other employee) want recognition for their efforts, competence, and commitment to the workplace and the community.

***Effectively Managing Per-Student Spending.*** Lastly, on top of fulfilling financial obligations outlined in the CBA, school administrators must also serve as good stewards of public funds. Historically, school districts have had the power to raise school taxes to finance CBAs, new construction projects, supplemental services, and so on. After the passage of Act I, districts have been forced to be more conservative in their spending.

Whereas Act I allows for a maximum of 10 exemptions (e.g., special education, pension payments), it also includes a provision in which school boards must call a special tax election if they wish to increase school taxes beyond the Act I Index limit. Suffice it to say that these referendums are generally rare and highly unpopular. For instance, in 2009, Crestwood School District, a Suburban Title I District (Luzerne County) and Northampton Community College (Monroe County), both of which are in the CPA region, held school tax referendums to finance construction-related projects, their requests were roundly defeated by an 85 percent and 62 percent majority.

In terms of general resource management, sharing resources has become a popular stopgap measure for some districts. The opening chapter of this study described several stressor costs on LEAs and provided the example of the healthcare consortium between Bucks and Montgomery County schools in Southeastern PA, a project designed to tame healthcare resources through a mutual pooling of resources and cost sharing. In the PGH region, some poorer districts have pushed the boundaries of cost sharing due to extreme financial distress. Aliquippa School District, a Suburban Title I Districts in Beaver County, does not have the student population or the funds to offer advanced coursework such as AP courses and even some Honors level courses. Consequently, the district has partnered with neighboring Hopewell Area School District so that students have access to this coursework (Niederberger, 2018).

It likely comes as no surprise that the state is currently experiencing a crisis level shortage of substitute teachers in addition to full-time teachers to staff classrooms (Benshoff, 2016). When there is no substitute teacher, the burden of coverage falls on either principals or fellow teachers, both of whom must digress from their already taxed schedules to supervise unfamiliar classrooms. One possibility that may reduce this "substitute teacher anxiety" (i.e., the time and frustration associated with finding a substitute) is to hire retired teachers on retainer. Some retirees leave the public school system either before reaching the age of superannuation or as the result of an early retirement package, they may not immediately qualify for Medicaid, and even those who do must pay out-of-pocket for Medicare Part D supplemental coverage. As such, offering a monthly healthcare subsidy in place of a base rate may sound financially imprudent at first, but if conditioned on a minimum number of days worked, the proposition could be cost-effective and aid in developing a robust pool of competent and experienced teachers.

## Limitations and Opportunities for Future Research

As is the case with any research, it is worth bearing in mind that some limitations manifest due to imperfections associated with either the data or the methodological approach. In this study, there are a few caveats to consider when deciphering the analysis. First, although the study does provide insight into leaver-related behaviors, it does not provide insight into whether a teacher left to pursue opportunities elsewhere in the field (e.g., independent or parochial schooling) and it does not account for life-related events, such as maternity leave or sabbaticals, since the PDE did not publish such data for this period. Moreover, there is no analysis of race or gender, despite the well-researched effects of both, especially at a time when nearly 55 percent of Pennsylvania's public schools do not have an educator of color and the few such teachers often feel the burden of being the "spokesperson for their ethnic or racial group" (Liu & Mezzacappa, 2018). By extension, the dataset for this study does not account for transgender or non-conforming teachers, who may experience unique stressors (Kamenetz, 2018). Furthermore, this study does attempt to investigate the effect of student support funding on teacher turnover using a global measure that does not differentiate between types of student spending. Recall from Chapter 3 that, since this study spans only a five-year observation period, results can change with protracted observation periods, as hazards fluctuate over much more extended periods.

However, these limitations also provide an opportunity for future research. To the first limitation, the dataset can be modified to include competing (multiple) hazards, such as a teachers' option to switch assignment, school, or LEA. To the second point, Pennsylvania's Sunshine Act can accommodate requests for more comprehensive datasets that incorporate race as well as other demographic variables, although the availability of these measures, coupled with the time needed to process the data for public consumption can be substantial. To the third point, per-student spending has multiple components as per Table 4.1. Attempting to incorporate them all in one model could lead to issues of collinearity that may, in turn, heighten the possibility that the model will fail in convergence. One possible approach would be to examine each measure individually over a series of studies to adequately study each facet of expenditure. Finally, to the last point, the methodological approach to this study might not only inspire subsequent research that either extends the observation period as more population data becomes available but also might apply to other states that also have a diverse demographic.

## Concluding Thoughts

When King Charles II granted William Penn a royal charter for the Province of Pennsylvania, he was merely seeking to repay debts owed to Penn's father, Admiral

William Penn, for his assistance in restoring the Crown following the English Civil War. In a historical irony of sorts, little did the second Charles Stuart realize that he was providing the imprimatur for a colony that would come to embody the very principles of equality, shared governance, and religious plurality that claimed the life of his father.

Since the establishment of the Commonwealth, the State of Independence has repeatedly sought to model these democratic Quaker principles first enshrined in the colony's Frame of Government, which Penn authored himself in 1682. In the nearly 340 years since Pennsylvania has led the nation in noteworthy firsts, within and outside of the realm of education. In the 18th century, Benjamin Franklin founded the first subscription library (The Library Company of Philadelphia) and the first hospital (Pennsylvania Hospital), both of which remain in operation today. In the 19th century, the state became home to the country's first off-reservation school for Native Americans (Carlisle Indian School) and the first professional organization committed to the cause of public education (the National Teachers Association which became the National Education Association). Moreover, in the 20th century, Pennsylvania became a champion for civil rights, with Sadie Alexander becoming the first African-American woman to receive a Ph.D. in Economics in the United States (and the second black woman to receive any doctorate), and in 1965, Independence Hall hosted the first national LGBT demonstrations—four years before the famed Stonewall Riots in New York City.

Although attempts at achieving more just public education funding can invoke fierce resistance from those who seek to propagate the status quo, the challenge serves as an opportunity to bring the community one step closer to the idyllic vision of the harmonious state first articulated by Aristotle more than two millennia ago. The

Commonwealth has historically been a testament to that progressive leadership ever since William Penn set foot on the banks of the Delaware River.

In the waning years of the House of Stuart, Joseph Addison, editor of the daily periodical *The Spectator*, reflected on the bitter partisanship between the newly formed Whig and Tory political parties that had consumed Westminster,

> "There cannot be a greater judgment befall a country than such a dreadful spirit of division as rends a government into two distinct people and makes them greater strangers and more averse to one another than if they were actually two different nations...A furious party spirit, when it rages in its full violence, exerts itself in civil war and bloodshed; and when it is under its greatest restraints naturally breaks out in falsehood, detraction, calumny, and a partial administration of justice. In a word, it fills a nation with spleen and rancour, and extinguishes all the seeds of good nature, compassion, and humanity."
>
> –Joseph Addison (1711), *The Spectator No. 125*.

Although Addison's warning separates us by over 300 years and 3000 miles, his words serve as a clarion call for legislators within the Commonwealth to eschew personal bias and prejudice in favor of the public good.

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This study references over 300 works were spanning academic research (e.g., books, journal articles, professional research reports) and public or popular media (e.g., state and federal datasets, interviews, newspaper and magazine articles). While all of these works are citied within the study text using appropriate APA formatting, I have listed them first by the character of the reference and second in alphabetical sets for easier reference.

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# Appendix A: Marked Data Preparation Procedures

## Appendix A.1: Teacher and LEA Data Restructuring

### I. Teacher Data Preparation Procedures [FOR EACH ACAD YEAR DATASET]

**Datasets:**

**(1) Pennsylvania Department of Education Professional Personnel Individual Staff Data (AY2012-13 through AY2017-18)**

A. In Microsoft Excel

1. Remove the following errant terms (i.e.

| | | |
|---|---|---|
| ACDC | GATEWAY | STAFF |
| COLLEGE | HIGHER | TEACHER |
| (SUB) CONTRACT | INC | TECHNOLOGY |
| (OR) | INSTRUCTOR | USER |
| CYBER | INTERACTIVE | VENDOR |
| DISTRICT | LEARNING | VIRTUAL |
| DUAL | LVC | |
| DUMMY | ONLINE | |
| EDUCATION | PARTY | |
| EMPLOYEE | PLATO | |
| ENROLLMENT | PRIVATE | |
| FICTITIOUS | PROFESSOR | |

fictitious entries):

2. Recode the following variables:
   a. *higheduc*: [High School Equivalent or Less, Vocational Certificate, Associate Degree or Some College] → '1'; [Bachelor's Degree] → '2'; [Master's Degree] → '3'; [Specialist's Degree, Doctoral Degree] → '4'
   b. *position:*
      a. [Elementary Special Ed. Teacher (PA); Elementary Teacher (PA); Specialist (PA); Elementary Teachers (US); Kindergarten Teachers (US); Pre-Kindergarten Teachers (US)] → '1' (Primary Teacher)
      b. [Secondary Special Ed. Teacher (PA); Secondary Teacher (PA); Specialist (PA); Ungraded Teacher (PA); Secondary Teachers (US)] → '2' (Secondary Teacher)
      c. [Guidance (PA); Elementary School Counselors (US); Secondary School Counselors (US)] → '3' (Guidance Counselor)
      d. [Operations (PA); Specialist (PA); Ungraded Special Ed. Teacher (PA); Ungraded Teacher (PA); Librarians or Media Specialists (US); Ungraded Teachers (US)] → '4' (Instructional Support Staff)
      e. [(Security) (PA); Health/Welfare (PA); Operations (PA); Other Support Staff (US); Student Support Services Staff (US); All Other Support Staff (US)] → '5' (Building & Student Support Staff)
      f. [Operations (PA); Other (PA); Specialist (PA); Supervisor/Coordinator (PA); Instructional Coordinators & Supervisors to the Staff (US)] → '6' (Coordinator & Staff Supervisor)
      g. [Chief School Administrator (PA); LEA Administrator (PA); Operations (PA); Other (PA); Supervisor/Coordinator (PA); School Administrator (PA); LEA Administrators (US); School Administrators (US)] → '7' (School Administrator)

c. *instarea*: (See Table 1 for full classification) Administrative Support → '1'; Elementary Education → '2'; English/Language Arts → '3'; English as Second Language Education → '4'; Foreign Languages → '5'; Health, Driver & Physical Education → '6'; Instructional & Building Support → '7'; Mathematics & Computer Science → '8'; Miscellaneous Positions → '9'; Natural Sciences → '10'; Social Studies/Sciences → '11'; Special/Alternate/Remedial Education → '12'; Visual & Performing Arts → '13'; Vocational & Technical Education → '14'
d. *highneed*: {2, 3, 5, 6, 9, 11, 13, 14} → '1' (Low Needs Subjects); {8} → '2' (Mathematics); {10} → '3' (Natural Sciences); {12} → '4' (Special Education); {4} → '5' (ESL); {1, 7} → '6' (Other)
e. *gender*: IF "M" THEN '1' ELSE '2'

3. Create the following variables:
    a. *expstatus*: IF *yearsexp* ≤ 5 THEN "New Educator" ELSE "Experienced Educator"

B. In IBM SPSS
3. Identify duplicate cases using the following variables: *uniqueid* and within cases by *fte, rawsalary, LEAAUN, and schnum* (all descending in that order)
4. Create new variable *within_caseid* by executing the following code:

```
DO IF (PrimaryFirst EQ 1).
compute caseid = $casenum.
ELSE.
compute caseid = lag(caseid).
END IF.
EXECUTE.Replace uniqueid with within_caseid
```

5. Aggregate by *within_caseid*; summate *numassign* and average *fte*
6. Replace variables *numassign* with *numassign_sum* and *fte* with *fte_avg*
7. Select {1} *uniquekey* value (created from identification of duplicate cases) and delete unselected cases
8. Create new variable *ftpt*: IF *fte_avg* ≥ 75, THEN "Full Time" ELSE "Part-Time"

C. In Microsoft Excel
9. Remove {#NULL!} values and renumber *within_caseid* by itemizing cases

**II. LEA Data Preparation Procedures [FOR EACH ACAD YEAR DATASET]**
**Datasets:**
**(2) Pennsylvania Department of Education School Performance Profile (AY2012-13 through AY2016-17)**
**(3) Pennsylvania Department of Education Annual Financial Report (AY 2012-13 through AY2016-17)**
**(4) 2017 Council for Community and Economic Research Cost of Living Index (Pennsylvania by County)**

A. In Microsoft Excel
1. Remove all {NA} and {IS} values
2. Sum Pacific-Islander, American-Indian, Multiracial, and Other racial designations into one variable: *other*
3. Recode Grades Served designation to *gradelvl* variable as follows:

B. In IBM SPSS
4. Impute Missing Values
    a. Conduct Missing Values Analysis to obtain before values for "missingness"

b. Conduct linear interpolation on the following variables *readprof*, *mathprof*, and *sciprof*
c. Conduct cubic interpolation on the following variables: *buildscore*, *readgrowth*, *mathgrowth*, and*scigrowth*
d. Replace missing values with saved predicted values
e. Rerun Missing Values Analysis to obtain after values for "missingness"

5. Create LEA Aggregated District & Charter Values
   a. Create new variable *distenroll* by summating all school enrollment grouped by *leaaun* and dividing by 1,000 (to minimize variation in values between large districts and smaller ones)
   b. For *title1*, average Title I percent of LEA using *distenroll* as weight
   c. Create new variable *title1stat*: IF *title1* ≥ 0.40 THEN "Title I" ELSE "Non-Title I"
   d. For all other district/charter variables summate using *distenroll* as weight (*disadvan, sped, ell, gifted, male, female, white, black, hisp, asian, other, buildscore, readprof, readgrowth, mathprof, mathgrowth, sciprof, scigrowth*)
6. Create LEA Aggregated Values
   a. Using *leaaun* as grouping variable, summate *distenroll* for all LEA enrollment
   b. For *title1*, average Title I percent of LEA using *distenroll* as weight
   c. For *title1stat*: IF *title1* ≥ 0.40 THEN "Title I" ELSE "Non-Title I"
7. Create Region and LEA Class Distinctions
   a. Create variable *region* with value of '1' for "Greater Philadelphia CSA"; '2' for Greater Pittsburgh CSA; and '3' for "Central Pennsylvania MSAs and μSAs" → Use U.S. Census Bureau definitions to manually code regions 1, 2, and 3
   b. Create variable *leaclass* with value of '1' for "Urban District"; '2' for "Suburban Title I District"; '3' for "Suburban Non-Title I District"; '4' for "Rural Title I District"; '5' for "Rural Non-Title I District"; '6' for "Charter Schools"; and '7' for "CTE Schools" → Use *region*, *countynm* and *title1stat* to classify LEAs
8. Delete all *schnum* cases so that only LEA cases are present in dataset
9. Add variable *coli* (from C2ER data) by matching with *countnm*
10. Import Per Student Spending Data (from PDE AFR File)
    a. In PDE AFR File, create variable *perstud* by dividing total LEA budget by total enrollment
    b. In PDE AFR File, create variables *pcntinst*, *pcntsup, pcntnoninst, pcntfacil,* and *pcntfin* by diving portion of budget devoted to category by total LEA budget
    c. Import into School Performance Profile Data and match *perstud, pcntinst*, *pcntsup, pcntnoninst, pcntfacil,* and *pcntfin* with *leaaun*
       i. Create new variable *adjperstud* by multiplying *perstud* by (*coli*/100)
11. Ensure the following variables are on 1 to 100-point scale: *dsadvan, sped, ell, gifted, male, female, white, black, hisp, asian, other, buildscore, readprof, readgrowth, mathprof, mathgrowth, sciprof, scigrowth*

C. In Microsoft Excel
   12. Remove all {#NULL!} Values

**III. Combining Teacher and LEA Datasets into One File [FOR EACH ACAD YEAR]**

**(5) [Modified] Professional Personnel Individual Staff Data (AY2012-13 through AY2017-18)**

**(6) [Modified] School Performance Profile Data (AY2012-13 through AY2016-17)**

A. In IBM SPSS
   1. Merge all datasets by adding variables (SPP dataset is the keyed table) and save as XLSX file

B. In Microsoft Excel
   2. Remove {#NULL!} and make UPPERCASE *lastnm, firstnm, middlenm,* and *suffixnm*
   3. Merge both Teacher and LEA Data files by academic year and sort descending by *lastnm, firstnm, middlenm, suffixnm, gender, datayear, yearsexp,* and *leanum*

C. In IBM SPSS
   4. Execute Grouping Algorithm (Appendix A.2)
   5. Once complete, identify duplicate cases by *within_caseid* + recode *within_caseid* by itemizing
   6. Execute Outcome Coding Algorithm (See Appendix A.3)
   7. Create new variable *adjsalary* by multiplying *rawsalary* by (*coli*/100)
   8. Reformat data as needed, merge all files (AY2012-13 through AY2016-17) and save as both XLSX and SAV files

## Appendix A.2: Educator Grouping Algorithm

**I. Male Educators [ONLY]**

A. In IBM SPSS
   1. Split file by *gender* and save male dataset as a 'Male Working File' and 'Female Working File'
   2. Split file by *datayear* and save as Dataset: {6, 5, 4, 3, 2, 1}yr. Cases
   3. Procedure to performing extractions by Groups A → F
      i. Group A: Same Educator, Same LEA, Same Position, Same Inst. Area
         a. Identify duplicate cases by matching *lastnm*, *firstnm*, *leanum*, *position*, *instarea* and organize ascending *datayear*, *yearsexp*, *higheduc*
         b. Run *newcaseid* SPSS variable creation code
         c. Create *N_BREAK* variable by aggregating (any variable) by *newcaseid*
         d. Split file by *newcaseid*; IF *N_BREAK*=6 THEN save file as Group[6]A_[M] ELSE delete unselected cases
      ii. Group B: Same Educator, Same LEA, Same Position
         a. Identify duplicate cases by matching *lastnm*, *firstnm*, *leanum*, *position*, and organize ascending *datayear*, *yearsexp*, *higheduc, and instarea*
         b. Run *newcaseid* SPSS variable creation code (start numbering after last Group A *newcaseid* value
         c. Create *N_BREAK* variable by aggregating (any variable) by *newcaseid*
         d. Split file by *newcaseid*; IF *N_BREAK*=6 THEN save file as Group[6]B_[M] ELSE delete unselected cases
      iii. Group C: Same Educator, Same LEA
         a. Identify duplicate cases by matching *lastnm*, *firstnm*, *leanum*, and organize ascending *datayear*, *yearsexp*, *higheduc, position, and instarea*

b. Run *newcaseid* SPSS variable creation code (start numbering after last Group B *newcaseid* value
c. Create *N_BREAK* variable by aggregating (any variable) by *newcaseid*
d. Split file by *newcaseid*; IF *N_BREAK*=6 THEN save file as Group[6]C_[M] ELSE delete unselected cases

iv. Group D: Same Educator, Same Position, Same Instructional Area
a. Identify duplicate cases by matching *lastnm*, *firstnm*, *leanum*, and organize ascending *datayear*, *yearsexp*, *higheduc, position*, *and instarea*
b. Run *newcaseid* SPSS variable creation code (start numbering after last Group C *newcaseid* value
c. Create *N_BREAK* variable by aggregating (any variable) by *newcaseid*
d. Split file by *newcaseid*; IF *N_BREAK*=6 THEN save file as Group[6]D_[M] ELSE delete unselected cases

v. Group E: Same Educator, Same Position
a. Identify duplicate cases by matching *lastnm*, *firstnm*, *position*, and organize ascending *datayear*, *yearsexp*, *higheduc, leaaun*, *and instarea*
b. Run *newcaseid* SPSS variable creation code (start numbering after last Group D *newcaseid* value
c. Create *N_BREAK* variable by aggregating (any variable) by *newcaseid*
d. Split file by *newcaseid*; IF *N_BREAK*=6 THEN save file as Group[6]E_[M] ELSE delete unselected cases

vi. Group F: Same First Name of Educator, Same LEA, Same Position, and Same Instructional Area
a. Identify duplicate cases by matching *firstnm*, *leaaun, position*, and *instarea* organize ascending *lastnm, datayear*, *yearsexp*, and *higheduc*
b. Run *newcaseid* SPSS variable creation code (start numbering after last Group E *newcaseid* value
c. Create *N_BREAK* variable by aggregating (any variable) by *newcaseid*
d. Split file by *newcaseid*; IF *N_BREAK*=6 THEN save file as Group[6]F_[M] ELSE delete unselected cases

4. Merge all Group[6]A_M → Group[6]F_M
5. Refine dataset to distill only cases with complete 6yr. records
   a. Split case by *newcaseid* and count cases (by *datayear*) to create *countyr1 → countyr6*
   b. Aggregate by *newcaseid* and summate variables *countyr1 → countyr6* and delete *countyr1 → countyr6* variables
   c. Select if *countyr1_sum*>1 or *countyr_sum2*>1 or *countyr3_sum*>1 or *countyr4_sum*>1 or *countyr5_sum*>1 or *countyr6_sum*>1 and create SPSS file Residual[6]_[M]
   d. Split by *newcaseid*, select *countyr1_sum*=1 and *countyr2_sum*=1 and *countyr3_sum*=1 and *countyr4_sum*=1 and *countyr5_sum*=1 and *countyr6_sum*=1 and unselected cases
   e. Save as Group6_REFINED[Male]
6. Merge Residual[6]_M file with (Male) Working File
7. Repeat steps #1-#6 for Groups {5, 4, 3, 2, 1}
   a. For Step 5, modify conditions such that Group[5] is *countyr1 → countyr5*; Group[4] is *countyr1 → countyr4;* and so on

B. In Microsoft Excel

1. Merge all Group{6, 5, 4, 3, 2, 1}_REFINED[Male] files into single file RefinedMale

**II. Female Educators [ONLY]**

A. Repeat all Part A Steps
B. Repeat All Part B Steps

**III. Master File**

A. Merge RefinedMale and RefinedFemale

## Appendix A.3: Educator Turnover (Outcome) Algorithm

1. Create *lead_caseid* (*newcaseid* +1)
2. Run SPSS Code:

   LOOP.
   DO IF (*newcaseid*=lag(*newcaseid*)) AND (*leaaun*=lag(*leaaun*)).
   COMPUTE *outcome*=0.
   ELSE.
   COMPUTE *outcome*=1.
   END IF.
   END LOOP IF (*newcaseid* NE *lead_newcaseid*).
3. Create *lead_outcome* (*outcome*+1)
4. Delete *lead_caseid* and *outcome* and rename *lead_outcome* → *outcome*

**Appendix B • Categorization of All Instructional Areas Offered During Study Period (AY2012-13 Through AY2016-17)**

**Elementary Education**

Pre Kindergarten (PreK)
Kindergarten, age 4 (K4)
Kindergarten, age 5 (K5)
Elementary, Primary Grades 1-3 1/
Elementary, Intermediate Grades 4-6 1/
Elementary Education
Elementary, Primary Grades 1-3
Elementary, Intermediate Grades 4-6

**English/Language Arts**

Middle Level English, 7-9
English/Communication, 10-12
Journalism
Philosophy

**Mathematics & Computer Science**

Middle Level Mathematics, 7-9
Mathematics, 10-12
Computer Science, Elementary, PreK-6
Computer Science, Secondary, 7-12

**Natural Sciences**

Middle Level Science, 7-9
General Science, Intermediate, 10-12
General Science, Advanced, 10-12
Earth and Space Science, Intermediate
Earth and Space Science, Advanced
Biology
Chemistry
Physics, 10-12
Nuclear Science
Environmental Education
Life Science, Intermediate, 10-12
Physical Science, Intermediate, 10-12
Physical Science, Advanced, 10-12
Science, Interdisciplinary Advanced, 10-12

**Social Studies/Sciences**

Middle Level Social Studies, 7-9
Geography, 10-12
Citizenship
Government, 10-12
History, 10-12
Anthropology
Sociology, 10-12
Psychology, Social or Behavioral Science
Psychology, Interdisciplinary Science
Economics
Social Science
Social Studies, 10-12

**Foreign Languages**

Spanish, Elementary, PreK-6
Spanish, 7-12
French, Elementary, PreK-6
French, 6-12
German, Elementary, PreK-6
German, 7-12
Latin, Elementary, PreK-6
Latin, 7-12
Portuguese
Italian
Russian
Hebrew
Arabic
Sanskrit
Chinese
Japanese

**Visual & Performing Arts**

Art, Elementary (PreK-6)
Art, Secondary (7-12)
Ceramics, Vocational
Music, Elementary, PreK-6
Music, Secondary, 7-12
Electronic Composition
Drama
Dance
Radio/Television

**Health, Driver & Physical Education**

Health and Physical Education, Elementary, PreK-6
Health and Physical Education, Secondary, 7-12
Driver Education
Health
Physical Education
Safety Education
Supervisor, Safety Education/Driver Education

**English as a Second Language**

English as Second Language, Elementary, PreK-6
English as Second Language, Middle Level English, 7-9
English as Second Language, Secondary English, 10-12
English as Second Language, Middle Level Math, 7-9
English as Second Language, Secondary Math, 10-12
English as Second Language, Middle Level Science, 7-9
English as Second Language, Secondary Science, 10-12
English as Second Language, Middle Level Social Studies, 7-9
English as Second Language, Secondary Social Studies, 10-12
English as Second Language, K-12 Resource

**Special, Remedial & Alternate Education**

Gifted Classes, Elementary. PreK-6
Gifted Classes, Tutorial/Resource, Secondary, 7-12
Speech
Speech Correction, Elementary, PreK-6
Speech Correction, Secondary, 7-12
Hearing Impaired, Elementary
Hearing Impaired Elementary, PreK-6
Hearing Impaired, Secondary
Hearing Impaired Resource, PreK-12
Hearing Impaired Middle Level English, 7-9
Hearing Impaired Secondary English, 10-12
Hearing Impaired Middle Level Math, 7-9
Hearing Impaired Secondary Math, 10-12
Hearing Impaired Middle Level Science, 7-9
Hearing Impaired Secondary Science, 10-12
Hearing Impaired Middle Level Social Studies, 7-9
Hearing Impaired Secondary Social Studies, 10-12
Visually Impaired, Elementary
Visually Impaired Elementary, PreK-6
Visually Impaired, Secondary
Visually Impaired Middle Level English, 7-9
Visually Impaired Secondary English, 10-12
Visually Impaired Middle Level Math, 7-9
Visually Impaired Secondary Math, 10-12
Visually Impaired Middle Level Science, 7-9
Visually Impaired Middle Level Social Studies, 7-9
Visually Impaired Secondary Social Studies, 10-12
Visually Impaired Resource, PreK-12
Special Ed, Elementary Areas, PreK-6
Special Ed, Middle Level English, 7-9
Special Ed, Secondary English, 10-12
Special Ed, Middle Level Math, 7-9
Special Ed, Secondary Math, 10-12
Special Ed, Middle Level Science, 7-9
Special Ed, Secondary Science, 10-12
Special Ed, Middle Level Social Studies, 7-9
Special Ed, Secondary Social Studies, 10-12
Special Ed, Resource PreK-12
Title I/Remedial Math, Elementary, PreK-6
Title I/Remedial Math, Secondary, 7-12
Developmental Reading, Elementary Classes, PreK-6
Developmental Reading, Secondary Classes, 7-12
Diagnostic/Prescriptive Reading, Elementary, PreK-6
Diagnostic/Prescriptive Reading, Secondary, 7-12
Alternate Education Program, K-6
Alternate Education, Middle Level English, 7-9
Alternate Education, Secondary English, 10-12
Alternate Education, Middle Level Math, 7-9
Alternate Education, Secondary Math, 10-12
Alternate Education, Middle Level Science, 7-9
Alternate Education, Secondary Science, 10-12
Alternate Education, Middle Level Social Studies, 7-9
Alternate Education, Secondary Social Studies, 10-12
Alternative Education, K-12 Resource Room

**Instructional & Building Support**

School Psychologist
Psychological Examiner
Elementary School Counselor
Secondary School Counselor
School Social Worker
School Nurse
Physical Therapist
Dental Hygienist
Occupational Therapist
Library Sciences, Elementary, PreK-6
Library Sciences, Secondary, 7-12
Instructional Support Teachers

**Miscellaneous Positions**

ROTC Instructor
Military Science (ROTC)
Related Areas
School Security Personnel
Home and School Visitor
Food Service Manager
Other Not Listed Above (certificated personnel)
Other Not Listed Above (non-certificated personnel)

**Administrative Support**

Intermediate Unit Executive Director
Intermediate Unit Assistant Executive Director
Intermediate Unit Program Specialist
Superintendent
Substitute Superintendent
Acting Superintendent
Assistant Superintendent
Acting Assistant Superintendent
Assistant to the Superintendent in Charge of Business Affair
Assistant to the Superintendent in Charge of Instruction
Chief Administrative Officer (charter schools only)
Business Manager
Secondary Principal
Assistant or Vice Secondary Principal
Middle School Principal
Assistant or Vice Middle School Principal
Elementary Principal
Assistant or Vice Elementary Principal
Director of Personnel
Director of Recreation
Director of Athletics
Director, Vocational Education
Assistant Vocational Director
Director of Management Information Systems
Education Program Specialist
School Program Specialist
Instructional Technology Specialist
Coordinator, Audio-visual Materials
Coordinator, Specially Funded Programs
Coordinator, Practical Nursing

**Administrative Support (Con't)**

Computer Technology Specialist
Coordinator, Vocational Education
Coordinator, Marketing/Distributive Education
Supervisor, Curriculum and Instruction
Supervisor, Early Childhood
Supervisor, Elementary Education
Supervisor, Secondary Education
Supervisor, English/Communication
Supervisor, Reading
Supervisor, Mathematics
Supervisor, Science
Supervisor, Environmental Education
Supervisor, Social Studies
Supervisor, Foreign Languages
Supervisor, Art, K-12
Supervisor, Music, Elementary
Supervisor, Music, K-12
Supervisor, Health and Physical Education, Elementary
Supervisor, Health and Physical Education, Secondary
Supervisor, Health and Physical Education, K-12
Supervisor, Special Education
Supervisor, Gifted Programs
Supervisor, Comprehensive Vocational Education
Supervisor, Vocational Education
Supervisor, Library Science
Supervisor, Trade-Industrial Education
Supervisor, Cooperative Education
Supervisor, Distributive Education
Supervisor, Business Education
Supervisor, Industrial Arts
Supervisor, Instructional Technology
Supervisor, Home Economics
Supervisor, School Health Services
Supervisor, Pupil Personnel Services
Supervisor, School Psychological Services
Supervisor, School Guidance Services
Supervisor, School Social Services
Literacy, Staff Coach
Mathematics, Staff Coach
Science, Staff Coach
Special Ed, Staff Coach
Other, Staff Coach (Not Math, Literacy, Science, or Special Education)

**Vocational & Technical Education**

Technology Education, Elementary, PreK-6
Technology Education, Secondary, 7-12
Business Education, Elementary
Business Education, Secondary
Family/Consumer Sciences, Elementary, PreK-6
Family/Consumer Sciences, Secondary, 7-12
Accounting/Bookkeeping
Aeronautical Technology
Agricultural Mechanics
Agricultural Power and Machinery

**Vocational & Technical Education (Con't)**

Agriculture
Air Conditioning
Air Conditioning/Refrigeration
Allied Health Science Technology
Appliance Repair
Arboretum, Aviary, Greenhouse
Architectural-Design Technology
Audio-visual Communications Technology
Auto Parts Counterman
Auto-Diesel Mechanic
Automotive Body and Fender
Automotive Maintenance
Automotive Mechanics
Automotive Technician
Automotive Technology
Baker
Barbering
Biological Technology
Blue Print Reading
Brick Masonry
Building Construction Trades
Building Trades Maintenance
Business Machine Maintenance
Carpentry
Chemical Technology
Child Care Services
Civil Technology
Commercial Art
Commercial Photography
Computer Servicing Technology
Computer Technology
Consumer Services
Cook/Chef
Cooperative Education
Cosmetology
Custodial Services
Data Processing
Dental Assistant
Diesel Mechanic
Digital Technology
Distributive Education
Drafting
Drafting-Architectural
Drafting-Mechanical
Dressmaking
Electrical Occupations
Electrical Power and Comm. Lineperson
Electrical Technology
Electrical, Construction/Maintenance
Electrical, General
Electrical, Industrial
Electro-Mechanical Technology
Electronics
Electronics Communications

**Vocational & Technical Education (Con't)**

Electronics Technology
Engineering Related Technology
Environmental Control Technology
Environmental Health Assistant
Floriculture
Graphic Arts
Graphic Occupations
Health Assistant
Health Related Technology
Heating
Heavy Equipment Construction
Home Economics
Horticulture/Floriculture
Hotel/Motel Management
Industrial Arts, Art Crafts Unit Shop
Industrial Arts, Automotives Unit Shop
Industrial Arts, Drawing Unit Shop
Industrial Arts, Electricity Unit Shop
Industrial Arts, Graphic Arts Unit Shop
Industrial Arts, Metal Unit Shop
Industrial Arts, Plastics Unit Shop
Industrial Arts, Printing Unit Shop
Industrial Arts, Textiles Unit Shop
Industrial Arts, Wood Unit Shop
Industrial Arts/Technology Education
Industrial Production and Maintenance
Industrial Technology
Instrumentation Technology
Interior Decorating
Law Enforcement
Lumbering
Machine Shop
Marketing/Sales
Masonry
Masonry Occupations
Masonry/Bricklaying
Material Handling
Meat Cutting
Mechanical Design Technology
Mechanical Drawing (Vocational)
Mechanical Technology
Medical Assistant
Medical Laboratory Assistant
Medical Records Technology
Metal Fabrication
Metallurgical Technology
Metalworking Occupations
Millwork and Cabinet Making
Network Systems Technology
Nurses Aide
Occupational Therapy Assistant
Occupations - Retarded Youth
Office Technologies
Ornamental Horticulture

**Vocational & Technical Education (Con't)**

Other Business Areas
Painting and Decorating
Passenger Transportation Marketing
Patternmaking
Petroleum Production
Photogrammetry
Physical Therapy Assistant
Planetarium, Meteorological Station
Plumbing
Power Mechanics Occupations
Practical Nursing
Printing
Protective Service Occupations
Quantity Foods
Refrigeration
Research Laboratory Assistant
Restaurant Practice
Retail Commercial Baking
Secretarial, Shorthand, and Office Practice
Security Services
Sewing
Sheet Metal
Small Engine Repair
Social Restoration
Telecommunications Technology
Textile Production/Fabrication
Tool and Die Design Technology
Trade and Industrial
Typewriting
Vending Machine Repair
Veterinarian Assistant
Vocational Instruction
Warehousing
Welding
Automotive Machinist

## Appendix C: Marked Study R Code

```
#Step 1: Download and load relevant R packages
install.packages('haven')
install.packages('tidyverse')
install.packages('psych')
install.packages('robumeta')
install.packages('survival')
install.packages('coxme')
library('haven')
library('tidyverse')
library('psych')
library('robumeta')
library('survival')
library('coxme')

#Step 2: Set Working Directory and read/save data as a dataframe object.
dissert<-read_spss('PA Educator Turnover Final Dataset.sav')
save(dissert, file='educturnover.rda')

#Step 3: Subsetting the data By PA Regions and performing listwise analysis.
    #Philadelphia CSA
phila<-filter(dissert, region==1)
phila_ss<-phila[!is.na(phila$datayear) & !is.na(phila$stopyear) & !is.na(phila$startyear) &
!is.na(phila$educatorid) & !is.na(phila$outcome) & !is.na(phila$rawsalary) &
!is.na(phila$adjsalary) & !is.na(phila$yearsexp) & !is.na(phila$expstatus) &
!is.na(phila$higheduc) & !is.na(phila$highneed) & !is.na(phila$numassign)  &
!is.na(phila$leaaun) & !is.na(phila$leaclass) & !is.na(phila$rawperstud) &
!is.na(phila$adjperstud) & !is.na(phila$adjauxspend) & !is.na(phila$sped) &
!is.na(phila$ell) & !is.na(phila$black) & !is.na(phila$hisp) & !is.na(phila$readprof) &
!is.na(phila$mathprof) & !is.na(phila$sciprof), c("datayear", "stopyear", "startyear",
"educatorid", "outcome", "rawsalary", "adjsalary", "yearsexp", "expstatus", "higheduc",
"highneed", "numassign", "leaaun", "leaclass", "rawperstud", "adjperstud", "adjauxspend",
"sped", "ell", "black", "hisp", "readprof", "mathprof", "sciprof")]
phila_ss<-phila_ss[phila_ss$educatorid %in% phila_ss$educatorid[phila_ss$highneed!=6],
]
phila_ss<-phila_ss[phila_ss$educatorid %in% phila_ss$educatorid[phila_ss$highneed!=7],
]

    #Pittsburgh CSA
pitt<-filter(dissert, region==2)
pitt_ss<-pitt[!is.na(pitt$datayear) & !is.na(pitt$stopyear) & !is.na(pitt$startyear) &
!is.na(pitt$educatorid) & !is.na(pitt$outcome) & !is.na(pitt$rawsalary) &
!is.na(pitt$adjsalary) & !is.na(pitt$yearsexp) & !is.na(pitt$expstatus) &
!is.na(pitt$higheduc) & !is.na(pitt$highneed) & !is.na(pitt$numassign) &
!is.na(pitt$leaaun) & !is.na(pitt$leaclass) & !is.na(pitt$rawperstud) &
!is.na(pitt$adjperstud) & !is.na(pitt$adjauxspend) & !is.na(pitt$sped) & !is.na(pitt$ell) &
!is.na(pitt$black) & !is.na(pitt$hisp) & !is.na(pitt$readprof) & !is.na(pitt$mathprof) &
!is.na(pitt$sciprof), c("datayear", "stopyear", "startyear", "educatorid", "outcome",
"rawsalary", "adjsalary", "yearsexp", "expstatus", "higheduc", "highneed", "numassign",
"leaaun", "leaclass", "rawperstud", "adjperstud", "adjauxspend", "sped", "ell", "black",
"hisp", "readprof", "mathprof", "sciprof")]
```

```
pitt_ss<-pitt_ss[pitt_ss$educatorid %in% pitt_ss$educatorid[pitt_ss$highneed!=6], ]
pitt_ss<-pitt_ss[pitt_ss$educatorid %in% pitt_ss$educatorid[pitt_ss$highneed!=7], ]

    #Central Pennsylvania MSAs & uSAs
central<-filter(dissert, region==3)
central_ss<-central[!is.na(central$datayear) & !is.na(central$stopyear) &
!is.na(central$startyear) & !is.na(central$educatorid) & !is.na(central$outcome)  &
!is.na(central$rawsalary) & !is.na(central$adjsalary) & !is.na(central$yearsexp) &
!is.na(central$expstatus) & !is.na(central$higheduc) & !is.na(central$highneed) &
!is.na(central$numassign) & !is.na(central$leaaun) & !is.na(central$leaclass) &
!is.na(central$rawperstud) & !is.na(central$adjperstud) & !is.na(central$adjauxspend) &
!is.na(central$sped) & !is.na(central$ell) & !is.na(central$black) & !is.na(central$hisp) &
!is.na(central$readprof) & !is.na(central$mathprof) & !is.na(central$sciprof), c("datayear",
"stopyear", "startyear", "educatorid", "outcome", "rawsalary", "adjsalary", "yearsexp",
"expstatus", "higheduc", "highneed", "numassign", "leaaun", "leaclass", "rawperstud",
"adjperstud", "adjauxspend", "sped", "ell", "black", "hisp", "readprof", "mathprof",
"sciprof")]
central_ss<-central_ss[central_ss$educatorid %in%
central_ss$educatorid[central_ss$highneed!=6], ]
central_ss<-central_ss[central_ss$educatorid %in%
central_ss$educatorid[central_ss$highneed!=7], ]

#Step 4: Obtaining descriptive statistics to compare the old and new dataframes.
    #Philadelphia CSA
nrow(phila)
nrow(phila_ss)
describe(phila_ss)
phila_out<-with(phila_ss, table(educatorid, outcome))
length(unique(phila_ss$educatorid))
table(phila_out[,2])

    #Pittsburgh CSA
nrow(pitt)
nrow(pitt_ss)
describe(pitt_ss)
pitt_out<-with(pitt_ss, table(educatorid, outcome))
length(unique(pitt_ss$educatorid))
table(pitt_out[,2])

    #Central Pennsylvania MSAs and uSAs
nrow(central)
nrow(central_ss)
describe(central_ss)
central_out<-with(central_ss, table(educatorid, outcome))
length(unique(central_ss$educatorid))
table(central_out[,2])

#Step 5: Creating lagged money and group centered LEA student demographic and
academic profile variables [by PA region].
    #Philadelphia CSA
phila_ss$educatorid<-as.character(phila_ss$educatorid)
phila_ss$leaaun<-as.character(phila_ss$leaaun)
```

```
phila_ss$logadjsalary<-log(phila_ss$adjsalary)
phila_ss$logadjauxspend<-log(phila_ss$adjauxspend)

phila_ss$sped<-(phila_ss$sped)/5
phila_ss$spedm<-group.mean(phila_ss$sped, phila_ss$leaaun)
phila_ss$ell<-(phila_ss$ell)/5
phila_ss$ellm<-group.mean(phila_ss$ell, phila_ss$leaaun)
phila_ss$black<-(phila_ss$black)/5
phila_ss$blackm<-group.mean(phila_ss$black, phila_ss$leaaun)
phila_ss$hisp<-(phila_ss$hisp)/5
phila_ss$hispm<-group.mean(phila_ss$hisp, phila_ss$leaaun)
phila_ss$readprof<-(phila_ss$readprof)/5
phila_ss$readprofm<-group.mean(phila_ss$readprof, phila_ss$leaaun)
phila_ss$mathprof<-(phila_ss$mathprof)/5
phila_ss$mathprofm<-group.mean(phila_ss$mathprof, phila_ss$leaaun)
phila_ss$sciprof<-(phila_ss$sciprof)/5
phila_ss$sciprofm<-group.mean(phila_ss$sciprof, phila_ss$leaaun)

    #Pittsburgh CSA
pitt_ss$educatorid<-as.character(pitt_ss$educatorid)
pitt_ss$leaaun<-as.character(pitt_ss$leaaun)
pitt_ss$logadjsalary<-log(pitt_ss$adjsalary)
pitt_ss$logadjauxspend<-log(pitt_ss$adjauxspend)

pitt_ss$sped<-(pitt_ss$sped)/5
pitt_ss$spedm<-group.mean(pitt_ss$sped, pitt_ss$leaaun)
pitt_ss$ell<-(pitt_ss$ell)/5
pitt_ss$ellm<-group.mean(pitt_ss$ell, pitt_ss$leaaun)
pitt_ss$black<-(pitt_ss$black)/5
pitt_ss$blackm<-group.mean(pitt_ss$black, pitt_ss$leaaun)
pitt_ss$hisp<-(pitt_ss$hisp)/5
pitt_ss$hispm<-group.mean(pitt_ss$hisp, pitt_ss$leaaun)
pitt_ss$readprof<-(pitt_ss$readprof)/5
pitt_ss$readprofm<-group.mean(pitt_ss$readprof, pitt_ss$leaaun)
pitt_ss$mathprof<-(pitt_ss$mathprof)/5
pitt_ss$mathprofm<-group.mean(pitt_ss$mathprof, pitt_ss$leaaun)
pitt_ss$sciprof<-(pitt_ss$sciprof)/5
pitt_ss$sciprofm<-group.mean(pitt_ss$sciprof, pitt_ss$leaaun)

    #Central Pennsylvania MSAs & uSAs
central_ss$educatorid<-as.character(central_ss$educatorid)
central_ss$leaaun<-as.character(central_ss$leaaun)
central_ss$logadjsalary<-log(central_ss$adjsalary)
central_ss$logadjauxspend<-log(central_ss$adjauxspend)

central_ss$sped<-(central_ss$sped)/5
central_ss$spedm<-group.mean(central_ss$sped, central_ss$leaaun)
central_ss$ell<-(central_ss$ell)/5
central_ss$ellm<-group.mean(central_ss$ell, central_ss$leaaun)
central_ss$black<-(central_ss$black)/5
central_ss$blackm<-group.mean(central_ss$black, central_ss$leaaun)
central_ss$hisp<-(central_ss$hisp)/5
```

```
central_ss$hispm<-group.mean(central_ss$hisp, central_ss$leaaun)
central_ss$readprof<-(central_ss$readprof)/5
central_ss$readprofm<-group.mean(central_ss$readprof, central_ss$leaaun)
central_ss$mathprof<-(central_ss$mathprof)/5
central_ss$mathprofm<-group.mean(central_ss$mathprof, central_ss$leaaun)
central_ss$sciprof<-(central_ss$sciprof)/5
central_ss$sciprofm<-group.mean(central_ss$sciprof, central_ss$leaaun)
```

**#Step 6: Specifying factor variables and initial reference categories [by PA Region].**

**#Philadelphia CSA**

```
phila_ss$datayearf<-factor(phila_ss$datayear, levels=c(1, 2, 3, 4, 5), labels=c("AY2012-13", "AY2013-14", "AY2014-15", "AY2015-16", "AY2016-17"))

phila_ss$expstatusf<-factor(phila_ss$expstatus, levels=c(1, 2), labels=c("New Educator", "Experienced Educator"))

phila_ss$neweduc<-phila_ss$higheduc
phila_ss$neweduc[phila_ss$neweduc==1]<-1
phila_ss$neweduc[phila_ss$neweduc==2]<-1
phila_ss$neweduc[phila_ss$neweduc==3]<-1
phila_ss$neweduc[phila_ss$neweduc==4]<-2
phila_ss$neweduc[phila_ss$neweduc==5]<-3
phila_ss$neweduc[phila_ss$neweduc==6]<-4
phila_ss$higheducf<-factor(phila_ss$neweduc, levels=c(1, 2, 3, 4), labels=c("Some College (inc. Vocational Certification)", "Bachelor's Degree", "Master's Degree", "Specialist's or Doctoral Degree"))
phila_ss$higheducf<-relevel(phila_ss$higheducf, ref=2)

phila_ss$newneed<-phila_ss$highneed
phila_ss$newneed[phila_ss$newneed==1]<-1
phila_ss$newneed[phila_ss$newneed==2]<-2
phila_ss$newneed[phila_ss$newneed==3]<-3
phila_ss$newneed[phila_ss$newneed==4]<-4
phila_ss$newneed[phila_ss$newneed==5]<-5
phila_ss$newneed[phila_ss$newneed==6]<-6
phila_ss$newneed[phila_ss$newneed==7]<-6
phila_ss$highneedf1<-factor(phila_ss$newneed, levels=c(1, 2, 3, 4, 5, 6), labels=c("Non-High Needs Subject", "Mathematics", "Natural Sciences", "Special Education", "English as Second Language", "Other Educators (inc. Admin)"))
phila_ss$highneedf2<-factor(phila_ss$newneed, levels=c(1, 2, 3, 4, 5, 6), labels=c("Non-High Needs Subject", "Mathematics", "Natural Sciences", "Special Education", "English as Second Language", "Other Educators (inc. Admin)"))
phila_ss$highneedf3<-factor(phila_ss$newneed, levels=c(1, 2, 3, 4, 5, 6), labels=c("Non-High Needs Subject", "Mathematics", "Natural Sciences", "Special Education", "English as Second Language", "Other Educators (inc. Admin)"))
phila_ss$highneedf4<-factor(phila_ss$newneed, levels=c(1, 2, 3, 4, 5, 6), labels=c("Non-High Needs Subject", "Mathematics", "Natural Sciences", "Special Education", "English as Second Language", "Other Educators (inc. Admin)"))

phila_ss$newclass<-phila_ss$leaclass
phila_ss$newclass[phila_ss$newclass==1]<-1
phila_ss$newclass[phila_ss$newclass==2]<-2
```

```
phila_ss$newclass[phila_ss$newclass==3]<-3
phila_ss$newclass[phila_ss$newclass==6]<-4
phila_ss$newclass[phila_ss$newclass==7]<-5
phila_ss$leaclassf1<-factor(phila_ss$newclass, levels=c(1, 2, 3, 4, 5), labels=c("School
District of Philadelphia", "Suburban Title I", "Suburban Non-Title I", "Charter Schools",
"CTE Schools"))
phila_ss$leaclassf2<-factor(phila_ss$newclass, levels=c(1, 2, 3, 4, 5), labels=c("School
District of Philadelphia", "Suburban Title I", "Suburban Non-Title I", "Charter Schools",
"CTE Schools"))
phila_ss$leaclassf3<-factor(phila_ss$newclass, levels=c(1, 2, 3, 4, 5), labels=c("School
District of Philadelphia", "Suburban Title I", "Suburban Non-Title I", "Charter Schools",
"CTE Schools"))

    #Pittsburgh CSA
pitt_ss$datayearf<-factor(pitt_ss$datayear, levels=c(1, 2, 3, 4, 5), labels=c("AY2012-13",
"AY2013-14", "AY2014-15", "AY2015-16", "AY2016-17"))

pitt_ss$expstatusf<-factor(pitt_ss$expstatus, levels=c(1, 2), labels=c("New Educator",
"Experienced Educator"))

pitt_ss$neweduc<-pitt_ss$higheduc
pitt_ss$neweduc[pitt_ss$neweduc==1]<-1
pitt_ss$neweduc[pitt_ss$neweduc==2]<-1
pitt_ss$neweduc[pitt_ss$neweduc==3]<-1
pitt_ss$neweduc[pitt_ss$neweduc==4]<-2
pitt_ss$neweduc[pitt_ss$neweduc==5]<-3
pitt_ss$neweduc[pitt_ss$neweduc==6]<-4
pitt_ss$higheducf<-factor(pitt_ss$neweduc, levels=c(1, 2, 3, 4), labels=c("Some College
(inc. Vocational Certification)", "Bachelor's Degree", "Master's Degree", "Specialist's or
Doctoral Degree"))
pitt_ss$higheducf<-relevel(pitt_ss$higheducf, ref=2)

pitt_ss$newneed<-pitt_ss$highneed
pitt_ss$newneed[pitt_ss$newneed==1]<-1
pitt_ss$newneed[pitt_ss$newneed==2]<-2
pitt_ss$newneed[pitt_ss$newneed==3]<-3
pitt_ss$newneed[pitt_ss$newneed==4]<-4
pitt_ss$newneed[pitt_ss$newneed==5]<-5
pitt_ss$newneed[pitt_ss$newneed==6]<-6
pitt_ss$newneed[pitt_ss$newneed==7]<-6
pitt_ss$highneedf1<-factor(pitt_ss$newneed, levels=c(1, 2, 3, 4, 5, 6), labels=c("Non-
High Needs Subject", "Mathematics", "Natural Sciences", "Special Education", "English as
Second Language", "Other Educators (inc. Admin)"))
pitt_ss$highneedf2<-factor(pitt_ss$newneed, levels=c(1, 2, 3, 4, 5, 6), labels=c("Non-
High Needs Subject", "Mathematics", "Natural Sciences", "Special Education", "English as
Second Language", "Other Educators (inc. Admin)"))
pitt_ss$highneedf3<-factor(pitt_ss$newneed, levels=c(1, 2, 3, 4, 5, 6), labels=c("Non-
High Needs Subject", "Mathematics", "Natural Sciences", "Special Education", "English as
Second Language", "Other Educators (inc. Admin)"))
pitt_ss$highneedf4<-factor(pitt_ss$newneed, levels=c(1, 2, 3, 4, 5, 6), labels=c("Non-
High Needs Subject", "Mathematics", "Natural Sciences", "Special Education", "English as
Second Language", "Other Educators (inc .Admin)"))
```

```
pitt_ss$newclass<-pitt_ss$leaclass
pitt_ss$newclass[pitt_ss$newclass==1]<-1
pitt_ss$newclass[pitt_ss$newclass==2]<-2
pitt_ss$newclass[pitt_ss$newclass==3]<-3
pitt_ss$newclass[pitt_ss$newclass==6]<-4
pitt_ss$newclass[pitt_ss$newclass==7]<-5
pitt_ss$leaclassf1<-factor(pitt_ss$newclass, levels=c(1, 2, 3, 4, 5), labels=c("Pittsburgh
Public Schools", "Suburban Title I", "Suburban Non-Title I", "Charter Schools", "CTE
Schools"))
pitt_ss$leaclassf2<-factor(pitt_ss$newclass, levels=c(1, 2, 3, 4, 5), labels=c("Pittsburgh
Public Schools", "Suburban Title I", "Suburban Non-Title I", "Charter Schools", "CTE
Schools"))
pitt_ss$leaclassf3<-factor(pitt_ss$newclass, levels=c(1, 2, 3, 4, 5), labels=c("Pittsburgh
Public Schools", "Suburban Title I", "Suburban Non-Title I", "Charter Schools", "CTE
Schools"))

    #Central Pennsylvania MSAs & uSAs
central_ss$datayearf<-factor(central_ss$datayear, levels=c(1, 2, 3, 4, 5),
labels=c("AY2012-13", "AY2013-14", "AY2014-15", "AY2015-16", "AY2016-17"))

central_ss$expstatusf<-factor(central_ss$expstatus, levels=c(1, 2), labels=c("New
Educator", "Experienced Educator"))

central_ss$neweduc<-central_ss$higheduc
central_ss$neweduc[central_ss$neweduc==1]<-1
central_ss$neweduc[central_ss$neweduc==2]<-1
central_ss$neweduc[central_ss$neweduc==3]<-1
central_ss$neweduc[central_ss$neweduc==4]<-2
central_ss$neweduc[central_ss$neweduc==5]<-3
central_ss$neweduc[central_ss$neweduc==6]<-4
central_ss$higheducf<-factor(central_ss$neweduc, levels=c(1, 2, 3, 4), labels=c("Some
College (inc. Vocational Certification)", "Bachelor's Degree", "Master's Degree",
"Specialist's or Doctoral Degree"))
central_ss$higheducf<-relevel(central_ss$higheducf, ref=2)

central_ss$newneed<-central_ss$highneed
central_ss$newneed[central_ss$newneed==1]<-1
central_ss$newneed[central_ss$newneed==2]<-2
central_ss$newneed[central_ss$newneed==3]<-3
central_ss$newneed[central_ss$newneed==4]<-4
central_ss$newneed[central_ss$newneed==5]<-5
central_ss$newneed[central_ss$newneed==6]<-6
central_ss$newneed[central_ss$newneed==7]<-6
central_ss$highneedf1<-factor(central_ss$newneed, levels=c(1, 2, 3, 4, 5, 6),
labels=c("Non-High Needs Subject", "Mathematics", "Natural Sciences", "Special
Education", "English as Second Language", "Other Educators (inc. Admin)"))
central_ss$highneedf2<-factor(central_ss$newneed, levels=c(1, 2, 3, 4, 5, 6),
labels=c("Non-High Needs Subject", "Mathematics", "Natural Sciences", "Special
Education", "English as Second Language", "Other Educators (inc. Admin)"))
```

```
central_ss$highneedf3<-factor(central_ss$newneed, levels=c(1, 2, 3, 4, 5, 6),
labels=c("Non-High Needs Subject", "Mathematics", "Natural Sciences", "Special
Education", "English as Second Language", "Other Educators (inc. Admin)"))
central_ss$highneedf4<-factor(central_ss$newneed, levels=c(1, 2, 3, 4, 5, 6),
labels=c("Non-High Needs Subject", "Mathematics", "Natural Sciences", "Special
Education", "English as Second Language", "Other Educators (inc .Admin)"))
central_ss$highneedf5<-factor(central_ss$newneed, levels=c(1, 2, 3, 4, 5, 6),
labels=c("Non-High Needs Subject", "Mathematics", "Natural Sciences", "Special
Education", "English as Second Language", "Other Educators (inc .Admin)"))
central_ss$highneedf6<-factor(central_ss$newneed, levels=c(1, 2, 3, 4, 5, 6),
labels=c("Non-High Needs Subject", "Mathematics", "Natural Sciences", "Special
Education", "English as Second Language", "Other Educators (inc .Admin)"))

central_ss$newclass<-central_ss$leaclass
central_ss$newclass[central_ss$newclass==1]<-1
central_ss$newclass[central_ss$newclass==2]<-2
central_ss$newclass[central_ss$newclass==3]<-3
central_ss$newclass[central_ss$newclass==6]<-4
central_ss$newclass[central_ss$newclass==7]<-5
central_ss$leaclassf1<-factor(central_ss$newclass, levels=c(1, 2, 3, 4, 5, 6, 7),
labels=c("Urban Schools", "Suburban Title I", "Suburban Non-Title I", "Rural Title I", "Rural
Non-Title I", "Charter Schools", "CTE Schools"))
central_ss$leaclassf2<-factor(central_ss$newclass, levels=c(1, 2, 3, 4, 5, 6, 7),
labels=c("Urban Schools", "Suburban Title I", "Suburban Non-Title I", "Rural Title I", "Rural
Non-Title I", "Charter Schools", "CTE Schools"))
central_ss$leaclassf3<-factor(central_ss$newclass, levels=c(1, 2, 3, 4, 5, 6, 7),
labels=c("Urban Schools", "Suburban Title I", "Suburban Non-Title I", "Rural Title I", "Rural
Non-Title I", "Charter Schools", "CTE Schools"))

#Step 7: Creating CoxPH Survival Model (GEE based) with clustering, stratification,
and two (2) three-way interaction groupings [by PA Region].
    #Models WITHOUT Interactions: Main Effects (Table 4.8)
        #Reference Category: An educator who (1) began the study in AY2012-13/
        (2) is an NEW educator/ (3) holds a BACHELOR'S Degree/ (4) in a Suburban
        Non-Title I District.
modelwophila<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf + yearsexp +
logadjsalary + expstatusf + higheducf + highneedf1 + leaclassf1 + numassign +
logadjauxspend + spedm + ellm + blackm + hispm + readprofm + mathprofm +
sciprofm + cluster(educatorid) + strata(leaclassf1), data=phila_ss)

modelwopitt<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf + yearsexp +
logadjsalary + expstatusf + higheducf + highneedf1 + leaclassf1 + numassign +
logadjauxspend + spedm + ellm + blackm + hispm + readprofm + mathprofm +
sciprofm + cluster(educatorid) + strata(leaclassf1), data=pitt_ss)

modelwocentral<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf + yearsexp +
logadjsalary + expstatusf + higheducf + highneedf1 + leaclassf1 + numassign +
logadjauxspend + spedm + ellm + blackm + hispm + readprofm + mathprofm +
sciprofm + cluster(educatorid) + strata(leaclassf1), data=central_ss)
    #Models WITH Interactions (Tables 4.9-4.14)
        #Q1: Change in Educator Exp, Education, and LEA Type (Tables 4.9-4.11)
```

```
#Reference Category: An educator who (1) began the study in AY2012-13/
(2) is an [Swapped Experience Level] educator/ (3) holds a [Swapped
Education Level] Degree/ (4) in a [Swapped LEA] for Any Subject Area
    #Greater Philadelphia CSA Models: New Educator w/Bachelor's Degree
modelwithphilasd.newref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + expstatusf + higheducf + leaclassf1 + numassign +
logadjauxspend + spedm + ellm + blackm + hispm + readprofm + mathprofm +
sciprofm + expstatusf*leaclassf1*logadjsalary + expstatusf*leaclassf1*logadjauxspend +
cluster(educatorid) + strata(leaclassf1), data=phila_ss)

phila_ss$leaclassf1<-relevel(phila_ss$leaclassf1, ref=2) #Suburban Title I Districts
modelwithphilasubt1.newref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + expstatusf + higheducf + leaclassf1 + numassign +
logadjauxspend + spedm + ellm + blackm + hispm + readprofm + mathprofm +
sciprofm + expstatusf*leaclassf1*logadjsalary + expstatusf*leaclassf1*logadjauxspend +
cluster(educatorid) + strata(leaclassf1), data=phila_ss)

phila_ss$leaclassf1<-relevel(phila_ss$leaclassf1, ref=3) #Suburban NonTitle I Districts
modelwithphilasubnt1.newref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + expstatusf + higheducf + leaclassf1 + numassign +
logadjauxspend + spedm + ellm + blackm + hispm + readprofm + mathprofm +
sciprofm + expstatusf*leaclassf1*logadjsalary + expstatusf*leaclassf1*logadjauxspend +
cluster(educatorid) + strata(leaclassf1), data=phila_ss)

phila_ss$leaclassf1<-relevel(phila_ss$leaclassf1, ref=4) #Charter Schools
modelwithphilachart.newref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + expstatusf + higheducf + leaclassf1 + numassign +
logadjauxspend + spedm + ellm + blackm + hispm + readprofm + mathprofm +
sciprofm + expstatusf*leaclassf1*logadjsalary + expstatusf*leaclassf1*logadjauxspend +
cluster(educatorid) + strata(leaclassf1), data=phila_ss)

phila_ss$leaclassf1<-relevel(phila_ss$leaclassf1, ref=5) #CTE Schools
modelwithphilacte.newref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + expstatusf + higheducf + leaclassf1 + numassign +
logadjauxspend + spedm + ellm + blackm + hispm + readprofm + mathprofm +
sciprofm + expstatusf*leaclassf1*logadjsalary + expstatusf*leaclassf1*logadjauxspend +
cluster(educatorid) + strata(leaclassf1), data=phila_ss)

    #Greater Philadelphia CSA Models: Exp Educator w/Master's Degree
phila_ss$expstatusf<-relevel(phila_ss$expstatusf, ref=2)
phila_ss$higheducf<-relevel(phila_ss$higheducf, ref=3)
modelwithphilasd.expref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + expstatusf + higheducf + leaclassf2 + numassign +
logadjauxspend + spedm + ellm + blackm + hispm + readprofm + mathprofm +
sciprofm + expstatusf*leaclassf2*logadjsalary + expstatusf*leaclassf2*logadjauxspend +
cluster(educatorid) + strata(leaclassf2), data=phila_ss)

phila_ss$leaclassf2<-relevel(phila_ss$leaclassf2, ref=2) #Suburban Title I Districts
modelwithphilasubt1.expref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + expstatusf + higheducf + leaclassf2 + numassign +
logadjauxspend + spedm + ellm + blackm + hispm + readprofm + mathprofm +
```

sciprofm + expstatusf*leaclassf2*logadjsalary + expstatusf*leaclassf2*logadjauxspend + cluster(educatorid) + strata(leaclassf2), data=phila_ss)

phila_ss$leaclassf2<-relevel(phila_ss$leaclassf2, ref=3) **#Suburban NonTitle I Districts**
modelwithphilasubnt1.expref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf + yearsexp + logadjsalary + expstatusf + higheducf + leaclassf2 + numassign + logadjauxspend + spedm + ellm + blackm + hispm + readprofm + mathprofm + sciprofm + expstatusf*leaclassf2*logadjsalary + expstatusf*leaclassf2*logadjauxspend + cluster(educatorid) + strata(leaclassf2), data=phila_ss)

phila_ss$leaclassf2<-relevel(phila_ss$leaclassf2, ref=4) **#Charter Schools**
modelwithphilachart.expref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf + yearsexp + logadjsalary + expstatusf + higheducf + leaclassf2 + numassign + logadjauxspend + spedm + ellm + blackm + hispm + readprofm + mathprofm + sciprofm + expstatusf*leaclassf2*logadjsalary + expstatusf*leaclassf2*logadjauxspend + cluster(educatorid) + strata(leaclassf2), data=phila_ss)

phila_ss$leaclassf2<-relevel(phila_ss$leaclassf2, ref=5) **#CTE Schools**
modelwithphilacte.expref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf + yearsexp + logadjsalary + expstatusf + higheducf + leaclassf2 + numassign + logadjauxspend + spedm + ellm + blackm + hispm + readprofm + mathprofm + sciprofm + expstatusf*leaclassf2*logadjsalary + expstatusf*leaclassf2*logadjauxspend + cluster(educatorid) + strata(leaclassf2), data=phila_ss)

**#Greater Pittsburgh CSA Models: New Educator w/Bachelor's Degree**
modelwithpittsd.newref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf + yearsexp + logadjsalary + expstatusf + higheducf + leaclassf1 + numassign + logadjauxspend + spedm + ellm + blackm + hispm + readprofm + mathprofm + sciprofm + expstatusf*leaclassf1*logadjsalary + expstatusf*leaclassf1*logadjauxspend + cluster(educatorid) + strata(leaclassf1), data=pitt_ss)

pitt_ss$leaclassf1<-relevel(pitt_ss$leaclassf1, ref=2) **#Suburban Title I Districts**
modelwithpittsubt1.newref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf + yearsexp + logadjsalary + expstatusf + higheducf + leaclassf1 + numassign + logadjauxspend + spedm + ellm + blackm + hispm + readprofm + mathprofm + sciprofm + expstatusf*leaclassf1*logadjsalary + expstatusf*leaclassf1*logadjauxspend + cluster(educatorid) + strata(leaclassf1), data=pitt_ss)

pitt_ss$leaclassf1<-relevel(pitt_ss$leaclassf1, ref=3) **#Suburban Non-Title I Districts**
modelwithpittsubnt1.newref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf + yearsexp + logadjsalary + expstatusf + higheducf + leaclassf1 + numassign + logadjauxspend + spedm + ellm + blackm + hispm + readprofm + mathprofm + sciprofm + expstatusf*leaclassf1*logadjsalary + expstatusf*leaclassf1*logadjauxspend + cluster(educatorid) + strata(leaclassf1), data=pitt_ss)

pitt_ss$leaclassf1<-relevel(pitt_ss$leaclassf1, ref=4) **#Charter Schools**
modelwithpittchart.newref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf + yearsexp + logadjsalary + expstatusf + higheducf + leaclassf1 + numassign + logadjauxspend + spedm + ellm + blackm + hispm + readprofm + mathprofm + sciprofm + expstatusf*leaclassf1*logadjsalary + expstatusf*leaclassf1*logadjauxspend + cluster(educatorid) + strata(leaclassf1), data=pitt_ss)

```
pitt_ss$leaclassf1<-relevel(pitt_ss$leaclassf1, ref=5) #CTE Schools
modelwithpittcte.newref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + expstatusf + higheducf + leaclassf1 + numassign +
logadjauxspend + spedm + ellm + blackm + hispm + readprofm + mathprofm +
sciprofm + expstatusf*leaclassf1*logadjsalary + expstatusf*leaclassf1*logadjauxspend +
cluster(educatorid) + strata(leaclassf1), data=pitt_ss)

        #Greater Pittsburgh CSA Models: Exp Educator w/Master's Degree
pitt_ss$expstatusf<-relevel(pitt_ss$expstatusf, ref=2)
pitt_ss$higheducf<-relevel(pitt_ss$higheducf, ref=3)
modelwithpittsd.expref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + expstatusf + higheducf + leaclassf2 + numassign +
logadjauxspend + spedm + ellm + blackm + hispm + readprofm + mathprofm +
sciprofm + expstatusf*leaclassf2*logadjsalary + expstatusf*leaclassf2*logadjauxspend +
cluster(educatorid) + strata(leaclassf2), data=pitt_ss)

pitt_ss$leaclassf2<-relevel(pitt_ss$leaclassf2, ref=2) #Suburban Title I Districts
modelwithpittsubt1.expref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + expstatusf + higheducf + leaclassf2 + numassign +
logadjauxspend + spedm + ellm + blackm + hispm + readprofm + mathprofm +
sciprofm + expstatusf*leaclassf2*logadjsalary + expstatusf*leaclassf2*logadjauxspend +
cluster(educatorid) + strata(leaclassf2), data=pitt_ss)

pitt_ss$leaclassf2<-relevel(pitt_ss$leaclassf2, ref=3) #Suburban Non-Title I Districts
modelwithpittsubnt1.expref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + expstatusf + higheducf + leaclassf2 + numassign +
logadjauxspend + spedm + ellm + blackm + hispm + readprofm + mathprofm +
sciprofm + expstatusf*leaclassf2*logadjsalary + expstatusf*leaclassf2*logadjauxspend +
cluster(educatorid) + strata(leaclassf2), data=pitt_ss)

pitt_ss$leaclassf2<-relevel(pitt_ss$leaclassf2, ref=4) #Charter Schools
modelwithpittchart.expref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + expstatusf + higheducf + leaclassf2 + numassign +
logadjauxspend + spedm + ellm + blackm + hispm + readprofm + mathprofm +
sciprofm + expstatusf*leaclassf2*logadjsalary + expstatusf*leaclassf2*logadjauxspend +
cluster(educatorid) + strata(leaclassf2), data=pitt_ss)

pitt_ss$leaclassf2<-relevel(pitt_ss$leaclassf2, ref=5) #CTE Schools
modelwithpittcte.expref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + expstatusf + higheducf + leaclassf2 + numassign +
logadjauxspend + spedm + ellm + blackm + hispm + readprofm + mathprofm +
sciprofm + expstatusf*leaclassf2*logadjsalary + expstatusf*leaclassf2*logadjauxspend +
cluster(educatorid) + strata(leaclassf2), data=pitt_ss)

        #Central Penn MSAs and uSAs Models: New Educ w/Bachelor's Degree
modelwithcentralsd.newref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + expstatusf + higheducf + leaclassf1 + numassign +
logadjauxspend + spedm + ellm + blackm + hispm + readprofm + mathprofm +
sciprofm + expstatusf*leaclassf1*logadjsalary + expstatusf*leaclassf1*logadjauxspend +
cluster(educatorid) + strata(leaclassf1), data=central_ss)

central_ss$leaclassf1<-relevel(central_ss$leaclassf1, ref=2) #Suburban Title I Districts
```

```
modelwithcentralsubt1.newref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + expstatusf + higheducf + leaclassf1 + numassign +
logadjauxspend + spedm + ellm + blackm + hispm + readprofm + mathprofm +
sciprofm + expstatusf*leaclassf1*logadjsalary + expstatusf*leaclassf1*logadjauxspend +
cluster(educatorid) + strata(leaclassf1), data=central_ss)

central_ss$leaclassf1<-relevel(central_ss$leaclassf1, ref=3) #Suburban NTI Districts
modelwithcentralsubnt1.newref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + expstatusf + higheducf + leaclassf1 + numassign +
logadjauxspend + spedm + ellm + blackm + hispm + readprofm + mathprofm +
sciprofm + expstatusf*leaclassf1*logadjsalary + expstatusf*leaclassf1*logadjauxspend +
cluster(educatorid) + strata(leaclassf1), data=central_ss)

central_ss$leaclassf1<-relevel(central_ss$leaclassf1, ref=4) #Rural Title I Districts
modelwithcentralruralt1.newref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + expstatusf + higheducf + leaclassf1 + numassign +
logadjauxspend + spedm + ellm + blackm + hispm + readprofm + mathprofm +
sciprofm + expstatusf*leaclassf1*logadjsalary + expstatusf*leaclassf1*logadjauxspend +
cluster(educatorid) + strata(leaclassf1), data=central_ss)

central_ss$leaclassf1<-relevel(central_ss$leaclassf1, ref=5) #Rural Non-Title I District
modelwithcentralruralnt1.newref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf
+ yearsexp + logadjsalary + expstatusf + higheducf + leaclassf1 + numassign +
logadjauxspend + spedm + ellm + blackm + hispm + readprofm + mathprofm +
sciprofm + expstatusf*leaclassf1*logadjsalary + expstatusf*leaclassf1*logadjauxspend +
cluster(educatorid) + strata(leaclassf1), data=central_ss)

central_ss$leaclassf1<-relevel(central_ss$leaclassf1, ref=6) #Charter Schools
modelwithcentralchart.newref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + expstatusf + higheducf + leaclassf1 + numassign +
logadjauxspend + spedm + ellm + blackm + hispm + readprofm + mathprofm +
sciprofm + expstatusf*leaclassf1*logadjsalary + expstatusf*leaclassf1*logadjauxspend +
cluster(educatorid) + strata(leaclassf1), data=central_ss)

central_ss$leaclassf1<-relevel(central_ss$leaclassf1, ref=7) #CTE Schools
modelwithcentralcte.newref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + expstatusf + higheducf + leaclassf1 + numassign +
logadjauxspend + spedm + ellm + blackm + hispm + readprofm + mathprofm +
sciprofm + expstatusf*leaclassf1*logadjsalary + expstatusf*leaclassf1*logadjauxspend +
cluster(educatorid) + strata(leaclassf1), data=central_ss)

            #Central Penn MSAs and uSAs Models: Exp Educator w/Master's Degree
central_ss$expstatusf<-relevel(central_ss$expstatusf, ref=2)
central_ss$higheducf<-relevel(central_ss$higheducf, ref=3)
modelwithcentralsd.expref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + expstatusf + higheducf + leaclassf2 + numassign +
logadjauxspend + spedm + ellm + blackm + hispm + readprofm + mathprofm +
sciprofm + expstatusf*leaclassf2*logadjsalary + expstatusf*leaclassf2*logadjauxspend +
cluster(educatorid) + strata(leaclassf2), data=central_ss)

central_ss$leaclassf2<-relevel(central_ss$leaclassf2, ref=2) #Suburban Title I Districts
```

modelwithcentralsubt1.expref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf + yearsexp + logadjsalary + expstatusf + higheducf + leaclassf2 + numassign + logadjauxspend + spedm + ellm + blackm + hispm + readprofm + mathprofm + sciprofm + expstatusf*leaclassf2*logadjsalary + expstatusf*leaclassf2*logadjauxspend + cluster(educatorid) + strata(leaclassf2), data=central_ss)

central_ss$leaclassf2<-relevel(central_ss$leaclassf2, ref=3) **#Suburban NT I Districts**
modelwithcentralsubnt1.expref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf + yearsexp + logadjsalary + expstatusf + higheducf + leaclassf2 + numassign + logadjauxspend + spedm + ellm + blackm + hispm + readprofm + mathprofm + sciprofm + expstatusf*leaclassf2*logadjsalary + expstatusf*leaclassf2*logadjauxspend + cluster(educatorid) + strata(leaclassf2), data=central_ss)

central_ss$leaclassf2<-relevel(central_ss$leaclassf2, ref=4) **#Rural Title I Districts**
modelwithcentralruralt1.expref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf + yearsexp + logadjsalary + expstatusf + higheducf + leaclassf2 + numassign + logadjauxspend + spedm + ellm + blackm + hispm + readprofm + mathprofm + sciprofm + expstatusf*leaclassf2*logadjsalary + expstatusf*leaclassf2*logadjauxspend + cluster(educatorid) + strata(leaclassf2), data=central_ss)

central_ss$leaclassf2<-relevel(central_ss$leaclassf2, ref=5) **#Rural NT I Districts**
modelwithcentralruralnt1.expref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf + yearsexp + logadjsalary + expstatusf + higheducf + leaclassf2 + numassign + logadjauxspend + spedm + ellm + blackm + hispm + readprofm + mathprofm + sciprofm + expstatusf*leaclassf2*logadjsalary + expstatusf*leaclassf2*logadjauxspend + cluster(educatorid) + strata(leaclassf2), data=central_ss)

central_ss$leaclassf2<-relevel(central_ss$leaclassf2, ref=6) **#Charter Schools**
modelwithcentralchart.expref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf + yearsexp + logadjsalary + expstatusf + higheducf + leaclassf2 + numassign + logadjauxspend + spedm + ellm + blackm + hispm + readprofm + mathprofm + sciprofm + expstatusf*leaclassf2*logadjsalary + expstatusf*leaclassf2*logadjauxspend + cluster(educatorid) + strata(leaclassf2), data=central_ss)

central_ss$leaclassf2<-relevel(central_ss$leaclassf2, ref=6) **#CTE Schools**
modelwithcentralcte.expref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf + yearsexp + logadjsalary + expstatusf + higheducf + leaclassf2 + numassign + logadjauxspend + spedm + ellm + blackm + hispm + readprofm + mathprofm + sciprofm + expstatusf*leaclassf2*logadjsalary + expstatusf*leaclassf2*logadjauxspend + cluster(educatorid) + strata(leaclassf2), data=central_ss)

**#Q2: Change in High Need Area and LEA Type (Tables 4.12-4.14)**
**#Reference Category: An educator who (1) began the study in AY2012-13/ (2) teaches a [Swapped High Need Area]/ (3) in a [Swapped LEA] with Any Experience/Education Level.**

**#Greater Philadelphia CSA**

**#School District of Philadelphia**

phila_ss$highneedf1<-relevel(phila_ss$highneedf1, ref=2) *#For Mathematics*
modelwithphilasd.mathref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf + yearsexp + logadjsalary + highneedf1 + leaclassf3 + numassign + logadjauxspend + disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm +

```
sciprofm + highneedf1*leaclassf3*logadjsalary + highneedf1*leaclassf3*logadjauxspend
+ cluster(educatorid) + strata(leaclassf3), data=phila_ss)

phila_ss$highneedf1<-relevel(phila_ss$highneedf1, ref=3) #For Natural Sciences
modelwithphilasd.sciref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + highneedf1 + leaclassf3 + numassign + logadjauxspend +
disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm +
sciprofm + highneedf1*leaclassf3*logadjsalary + highneedf1*leaclassf3*logadjauxspend
+ cluster(educatorid) + strata(leaclassf3), data=phila_ss)

phila_ss$highneedf1<-relevel(phila_ss$highneedf1, ref=4) #For Special Education
modelwithphilasd.spedref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + highneedf1 + leaclassf3 + numassign + logadjauxspend +
disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm +
sciprofm + highneedf1*leaclassf3*logadjsalary + highneedf1*leaclassf3*logadjauxspend
+ cluster(educatorid) + strata(leaclassf3), data=phila_ss)

phila_ss$highneedf1<-relevel(phila_ss$highneedf1, ref=5) #For ESL
modelwithphilasd.eslref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + highneedf1 + leaclassf3 + numassign + logadjauxspend +
disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm +
sciprofm + highneedf1*leaclassf3*logadjsalary + highneedf1*leaclassf3*logadjauxspend
+ cluster(educatorid) + strata(leaclassf3), data=phila_ss)

                    #Suburban Title I Districts
phila_ss$leaclassf3<-relevel(phila_ss$leaclassf3, ref=2)
phila_ss$highneedf2<-relevel(phila_ss$highneedf2, ref=2) #For Mathematics
modelwithphilasubt1.mathref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + highneedf2 + leaclassf3 + numassign + logadjauxspend +
disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm +
sciprofm + highneedf2*leaclassf3*logadjsalary + highneedf2*leaclassf3*logadjauxspend
+ cluster(educatorid) + strata(leaclassf3), data=phila_ss)

phila_ss$highneedf2<-relevel(phila_ss$highneedf2, ref=3) #For Natural Sciences
modelwithphilasubt1.sciref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + highneedf2 + leaclassf3 + numassign + logadjauxspend +
disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm +
sciprofm + highneedf2*leaclassf3*logadjsalary + highneedf2*leaclassf3*logadjauxspend
+ cluster(educatorid) + strata(leaclassf3), data=phila_ss)

phila_ss$highneedf2<-relevel(phila_ss$highneedf2, ref=4) #For Special Education
modelwithphilasubt1.spedref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + highneedf2 + leaclassf3 + numassign + logadjauxspend +
disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm +
sciprofm + highneedf2*leaclassf3*logadjsalary + highneedf2*leaclassf3*logadjauxspend
+ cluster(educatorid) + strata(leaclassf3), data=phila_ss)

phila_ss$highneedf2<-relevel(phila_ss$highneedf2, ref=5) #For ESL
modelwithphilasubt1.eslref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + highneedf2 + leaclassf3 + numassign + logadjauxspend +
disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm +
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sciprofm + highneedf2*leaclassf3*logadjsalary + highneedf2*leaclassf3*logadjauxspend + cluster(educatorid) + strata(leaclassf3), data=phila_ss)

**#Suburban Non-Title I Districts**

phila_ss$leaclassf3<-relevel(phila_ss$leaclassf3, ref=3)
phila_ss$highneedf3<-relevel(phila_ss$highneedf3, ref=2) *#For Mathematics*
modelwithphilasubnt1.mathref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf + yearsexp + logadjsalary + highneedf3 + leaclassf3 + numassign + logadjauxspend + disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm + sciprofm + highneedf3*leaclassf3*logadjsalary + highneedf3*leaclassf3*logadjauxspend + cluster(educatorid) + strata(leaclassf3), data=phila_ss)

phila_ss$highneedf3<-relevel(phila_ss$highneedf3, ref=3) *#For Natural Sciences*
modelwithphilasubnt1.sciref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf + yearsexp + logadjsalary + highneedf3 + leaclassf3 + numassign + logadjauxspend + disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm + sciprofm + highneedf3*leaclassf3*logadjsalary + highneedf3*leaclassf3*logadjauxspend + cluster(educatorid) + strata(leaclassf3), data=phila_ss)

phila_ss$highneedf3<-relevel(phila_ss$highneedf3, ref=4) *#For Special Education*
modelwithphilasubnt1.spedref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf + yearsexp + logadjsalary + highneedf3 + leaclassf3 + numassign + logadjauxspend + disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm + sciprofm + highneedf3*leaclassf3*logadjsalary + highneedf3*leaclassf3*logadjauxspend + cluster(educatorid) + strata(leaclassf3), data=phila_ss)

phila_ss$highneedf3<-relevel(phila_ss$highneedf3, ref=5) *#For ESL*
modelwithphilasubnt1.eslref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf + yearsexp + logadjsalary + highneedf3 + leaclassf3 + numassign + logadjauxspend + disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm + sciprofm + highneedf3*leaclassf3*logadjsalary + highneedf3*leaclassf3*logadjauxspend + cluster(educatorid) + strata(leaclassf3), data=phila_ss)

**#Charter Schools**

phila_ss$leaclassf3<-relevel(phila_ss$leaclassf3, ref=4)
phila_ss$highneedf4<-relevel(phila_ss$highneedf4, ref=2) *#For Mathematics*
modelwithphilachart.mathref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf + yearsexp + logadjsalary + highneedf4 + leaclassf3 + numassign + logadjauxspend + disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm + sciprofm + highneedf4*leaclassf3*logadjsalary + highneedf4*leaclassf3*logadjauxspend + cluster(educatorid) + strata(leaclassf3), data=phila_ss)

phila_ss$highneedf4<-relevel(phila_ss$highneedf4, ref=3) *#For Natural Sciences*
modelwithphilachart.sciref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf + yearsexp + logadjsalary + highneedf4 + leaclassf3 + numassign + logadjauxspend + disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm + sciprofm + highneedf4*leaclassf3*logadjsalary + highneedf4*leaclassf3*logadjauxspend + cluster(educatorid) + strata(leaclassf3), data=phila_ss)

phila_ss$highneedf4<-relevel(phila_ss$highneedf4, ref=4) *#For Special Education*
modelwithphilachart.spedref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf + yearsexp + logadjsalary + highneedf4 + leaclassf3 + numassign + logadjauxspend +

disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm + sciprofm + highneedf4*leaclassf3*logadjsalary + highneedf4*leaclassf3*logadjauxspend + cluster(educatorid) + strata(leaclassf3), data=phila_ss)

phila_ss$highneedf4<-relevel(phila_ss$highneedf4, ref=5) *#For ESL*
modelwithphilachart.eslref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf + yearsexp + logadjsalary + highneedf4 + leaclassf3 + numassign + logadjauxspend + disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm + sciprofm + highneedf4*leaclassf3*logadjsalary + highneedf4*leaclassf3*logadjauxspend + cluster(educatorid) + strata(leaclassf3), data=phila_ss)

**#Greater Pittsburgh CSA**
**#Pittsburgh Public Schools**
pitt_ss$highneedf1<-relevel(pitt_ss$highneedf1, ref=2) *#For Mathematics*
modelwithpittsd.mathref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf + yearsexp + logadjsalary + highneedf1 + leaclassf3 + numassign + logadjauxspend + disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm + sciprofm + highneedf1*leaclassf3*logadjsalary + highneedf1*leaclassf3*logadjauxspend + cluster(educatorid) + strata(leaclassf3), data=pitt_ss)

pitt_ss$highneedf1<-relevel(pitt_ss$highneedf1, ref=3) *#For Natural Sciences*
modelwithpittsd.sciref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf + yearsexp + logadjsalary + highneedf1 + leaclassf3 + numassign + logadjauxspend + disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm + sciprofm + highneedf1*leaclassf3*logadjsalary + highneedf1*leaclassf3*logadjauxspend + cluster(educatorid) + strata(leaclassf3), data=pitt_ss)

pitt_ss$highneedf1<-relevel(pitt_ss$highneedf1, ref=4) *#For Special Education*
modelwithpittsd.spedref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf + yearsexp + logadjsalary + highneedf1 + leaclassf3 + numassign + logadjauxspend + disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm + sciprofm + highneedf1*leaclassf3*logadjsalary + highneedf1*leaclassf3*logadjauxspend + cluster(educatorid) + strata(leaclassf3), data=pitt_ss)

pitt_ss$highneedf1<-relevel(pitt_ss$highneedf1, ref=5) *#For ESL*
modelwithpittsd.eslref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf + yearsexp + logadjsalary + highneedf1 + leaclassf3 + numassign + logadjauxspend + disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm + sciprofm + highneedf1*leaclassf3*logadjsalary + highneedf1*leaclassf3*logadjauxspend + cluster(educatorid) + strata(leaclassf3), data=pitt_ss)

**#Suburban Title I Districts**
pitt_ss$leaclassf3<-relevel(pitt_ss$leaclassf3, ref=2)
pitt_ss$highneedf2<-relevel(pitt_ss$highneedf2, ref=2) *#For Mathematics*
modelwithpittsubt1.mathref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf + yearsexp + logadjsalary + highneedf2 + leaclassf3 + numassign + logadjauxspend + disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm + sciprofm + highneedf2*leaclassf3*logadjsalary + highneedf2*leaclassf3*logadjauxspend + cluster(educatorid) + strata(leaclassf3), data=pitt_ss)

pitt_ss$highneedf2<-relevel(pitt_ss$highneedf2, ref=3) *#For Natural Sciences*

```
modelwithpittsubt1.sciref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + highneedf2 + leaclassf3 + numassign + logadjauxspend +
disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm +
sciprofm + highneedf2*leaclassf3*logadjsalary + highneedf2*leaclassf3*logadjauxspend
+ cluster(educatorid) + strata(leaclassf3), data=pitt_ss)

pitt_ss$highneedf2<-relevel(pitt_ss$highneedf2, ref=4) #For Special Education
modelwithpittsubt1.spedref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + highneedf2 + leaclassf3 + numassign + logadjauxspend +
disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm +
sciprofm + highneedf2*leaclassf3*logadjsalary + highneedf2*leaclassf3*logadjauxspend
+ cluster(educatorid) + strata(leaclassf3), data=pitt_ss)

pitt_ss$highneedf2<-relevel(pitt_ss$highneedf2, ref=5) #For ESL
modelwithpittsubt1.eslref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + highneedf2 + leaclassf3 + numassign + logadjauxspend +
disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm +
sciprofm + highneedf2*leaclassf3*logadjsalary + highneedf2*leaclassf3*logadjauxspend
+ cluster(educatorid) + strata(leaclassf3), data=pitt_ss)

                    #Suburban Non-Title I Districts
pitt_ss$leaclassf3<-relevel(pitt_ss$leaclassf3, ref=3)
pitt_ss$highneedf3<-relevel(pitt_ss$highneedf3, ref=2) #For Mathematics
modelwithpittsubnt1.mathref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + highneedf3 + leaclassf3 + numassign + logadjauxspend +
disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm +
sciprofm + highneedf3*leaclassf3*logadjsalary + highneedf3*leaclassf3*logadjauxspend
+ cluster(educatorid) + strata(leaclassf3), data=pitt_ss)

pitt_ss$highneedf3<-relevel(pitt_ss$highneedf3, ref=3) #For Natural Sciences
modelwithpittsubnt1.sciref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + highneedf3 + leaclassf3 + numassign + logadjauxspend +
disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm +
sciprofm + highneedf3*leaclassf3*logadjsalary + highneedf3*leaclassf3*logadjauxspend
+ cluster(educatorid) + strata(leaclassf3), data=pitt_ss)

pitt_ss$highneedf3<-relevel(pitt_ss$highneedf3, ref=4) #For Special Education
modelwithpittsubnt1.spedref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + highneedf3 + leaclassf3 + numassign + logadjauxspend +
disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm +
sciprofm + highneedf3*leaclassf3*logadjsalary + highneedf3*leaclassf3*logadjauxspend
+ cluster(educatorid) + strata(leaclassf3), data=pitt_ss)

pitt_ss$highneedf3<-relevel(pitt_ss$highneedf3, ref=5) #For ESL
modelwithpittsubnt1.eslref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + highneedf3 + leaclassf3 + numassign + logadjauxspend +
disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm +
sciprofm + highneedf3*leaclassf3*logadjsalary + highneedf3*leaclassf3*logadjauxspend
+ cluster(educatorid) + strata(leaclassf3), data=pitt_ss)

                    #Charter Schools
pitt_ss$leaclassf3<-relevel(pitt_ss$leaclassf3, ref=4)
```

```
pitt_ss$highneedf4<-relevel(pitt_ss$highneedf4, ref=2) #For Mathematics
modelwithpittchart.mathref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + highneedf4 + leaclassf3 + numassign + logadjauxspend +
disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm +
sciprofm + highneedf4*leaclassf3*logadjsalary + highneedf4*leaclassf3*logadjauxspend
+ cluster(educatorid) + strata(leaclassf3), data=pitt_ss)

pitt_ss$highneedf4<-relevel(pitt_ss$highneedf4, ref=3) #For Natural Sciences
modelwithpittchart.sciref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + highneedf4 + leaclassf3 + numassign + logadjauxspend +
disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm +
sciprofm + highneedf4*leaclassf3*logadjsalary + highneedf4*leaclassf3*logadjauxspend
+ cluster(educatorid) + strata(leaclassf3), data=pitt_ss)

pitt_ss$highneedf4<-relevel(pitt_ss$highneedf4, ref=4) #For Special Education
modelwithpittchart.spedref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + highneedf4 + leaclassf3 + numassign + logadjauxspend +
disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm +
sciprofm + highneedf4*leaclassf3*logadjsalary + highneedf4*leaclassf3*logadjauxspend
+ cluster(educatorid) + strata(leaclassf3), data=pitt_ss)

pitt_ss$highneedf4<-relevel(pitt_ss$highneedf4, ref=5) #For ESL
modelwithpittchart.eslref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + highneedf4 + leaclassf3 + numassign + logadjauxspend +
disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm +
sciprofm + highneedf4*leaclassf3*logadjsalary + highneedf4*leaclassf3*logadjauxspend
+ cluster(educatorid) + strata(leaclassf3), data=pitt_ss)

            #Central Pennsylvania MSAs and uSAs
                #Regional Urban Districts
central_ss$highneedf1<-relevel(central_ss$highneedf1, ref=2) #For Mathematics
modelwithcentralsd.mathref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + highneedf1 + leaclassf3 + numassign + logadjauxspend +
disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm +
sciprofm + highneedf1*leaclassf3*logadjsalary + highneedf1*leaclassf3*logadjauxspend
+ cluster(educatorid) + strata(leaclassf3), data=central_ss)

central_ss$highneedf1<-relevel(central_ss$highneedf1, ref=3) #For Natural Sciences
modelwithcentralsd.sciref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + highneedf1 + leaclassf3 + numassign + logadjauxspend +
disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm +
sciprofm + highneedf1*leaclassf3*logadjsalary + highneedf1*leaclassf3*logadjauxspend
+ cluster(educatorid) + strata(leaclassf3), data=central_ss)

central_ss$highneedf1<-relevel(central_ss$highneedf1, ref=4) #For Special Education
modelwithcentralsd.spedref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + highneedf1 + leaclassf3 + numassign + logadjauxspend +
disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm +
sciprofm + highneedf1*leaclassf3*logadjsalary + highneedf1*leaclassf3*logadjauxspend
+ cluster(educatorid) + strata(leaclassf3), data=central_ss)

central_ss$highneedf1<-relevel(central_ss$highneedf1, ref=5) #For ESL
```

```
modelwithcentralsd.eslref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + highneedf1 + leaclassf3 + numassign + logadjauxspend +
disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm +
sciprofm + highneedf1*leaclassf3*logadjsalary + highneedf1*leaclassf3*logadjauxspend
+ cluster(educatorid) + strata(leaclassf3), data=central_ss)

                    #Suburban Title I Districts
central_ss$leaclassf3<-relevel(central_ss$leaclassf3, ref=2)
central_ss$highneedf2<-relevel(central_ss$highneedf2, ref=2) #For Mathematics
modelwithcentralsubt1.mathref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + highneedf2 + leaclassf3 + numassign + logadjauxspend +
disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm +
sciprofm + highneedf2*leaclassf3*logadjsalary + highneedf2*leaclassf3*logadjauxspend
+ cluster(educatorid) + strata(leaclassf3), data=central_ss)

central_ss$highneedf2<-relevel(central_ss$highneedf2, ref=3) #For Natural Sciences
modelwithcentralsubt1.sciref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + highneedf2 + leaclassf3 + numassign + logadjauxspend +
disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm +
sciprofm + highneedf2*leaclassf3*logadjsalary + highneedf2*leaclassf3*logadjauxspend
+ cluster(educatorid) + strata(leaclassf3), data=central_ss)

central_ss$highneedf2<-relevel(central_ss$highneedf2, ref=4) #For Special Education
modelwithcentralsubt1.spedref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + highneedf2 + leaclassf3 + numassign + logadjauxspend +
disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm +
sciprofm + highneedf2*leaclassf3*logadjsalary + highneedf2*leaclassf3*logadjauxspend
+ cluster(educatorid) + strata(leaclassf3), data=central_ss)

central_ss$highneedf2<-relevel(central_ss$highneedf2, ref=5) #For ESL
modelwithcentralsubt1.eslref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + highneedf2 + leaclassf3 + numassign + logadjauxspend +
disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm +
sciprofm + highneedf2*leaclassf3*logadjsalary + highneedf2*leaclassf3*logadjauxspend
+ cluster(educatorid) + strata(leaclassf3), data=central_ss)

                    #Suburban Non-Title I Districts
central_ss$leaclassf3<-relevel(central_ss$leaclassf3, ref=3)
central_ss$highneedf3<-relevel(central_ss$highneedf3, ref=2) #For Mathematics
modelwithcentralsubnt1.mathref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf
+ yearsexp + logadjsalary + highneedf3 + leaclassf3 + numassign + logadjauxspend +
disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm +
sciprofm + highneedf3*leaclassf3*logadjsalary + highneedf3*leaclassf3*logadjauxspend
+ cluster(educatorid) + strata(leaclassf3), data=central_ss)

central_ss$highneedf3<-relevel(central_ss$highneedf3, ref=3) #For Natural Sciences
modelwithcentralsubnt1.sciref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + highneedf3 + leaclassf3 + numassign + logadjauxspend +
disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm +
sciprofm + highneedf3*leaclassf3*logadjsalary + highneedf3*leaclassf3*logadjauxspend
+ cluster(educatorid) + strata(leaclassf3), data=central_ss)
```

central_ss$highneedf3<-relevel(central_ss$highneedf3, ref=4) *#For Special Education*
modelwithcentralsubnt1.spedref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf + yearsexp + logadjsalary + highneedf3 + leaclassf3 + numassign + logadjauxspend + disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm + sciprofm + highneedf3*leaclassf3*logadjsalary + highneedf3*leaclassf3*logadjauxspend + cluster(educatorid) + strata(leaclassf3), data=central_ss)

central_ss$highneedf3<-relevel(central_ss$highneedf3, ref=5) *#For ESL*
modelwithcentralsubnt1.eslref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf + yearsexp + logadjsalary + highneedf3 + leaclassf3 + numassign + logadjauxspend + disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm + sciprofm + highneedf3*leaclassf3*logadjsalary + highneedf3*leaclassf3*logadjauxspend + cluster(educatorid) + strata(leaclassf3), data=central_ss)

**#Rural Title I Districts**

central_ss$leaclassf3<-relevel(central_ss$leaclassf3, ref=4)
central_ss$highneedf4<-relevel(central_ss$highneedf4, ref=2) *#For Mathematics*
modelwithcentralruralt1.mathref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf + yearsexp + logadjsalary + highneedf4 + leaclassf3 + numassign + logadjauxspend + disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm + sciprofm + highneedf4*leaclassf3*logadjsalary + highneedf4*leaclassf3*logadjauxspend + cluster(educatorid) + strata(leaclassf3), data=central_ss)

central_ss$highneedf4<-relevel(central_ss$highneedf4, ref=3) *#For Natural Sciences*
modelwithcentralruralt1.sciref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf + yearsexp + logadjsalary + highneedf4 + leaclassf3 + numassign + logadjauxspend + disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm + sciprofm + highneedf4*leaclassf3*logadjsalary + highneedf4*leaclassf3*logadjauxspend + cluster(educatorid) + strata(leaclassf3), data=central_ss)

central_ss$highneedf4<-relevel(central_ss$highneedf4, ref=4) *#For Special Education*
modelwithcentralruralt1.spedref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf + yearsexp + logadjsalary + highneedf4 + leaclassf3 + numassign + logadjauxspend + disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm + sciprofm + highneedf4*leaclassf3*logadjsalary + highneedf4*leaclassf3*logadjauxspend + cluster(educatorid) + strata(leaclassf3), data=central_ss)

central_ss$highneedf4<-relevel(central_ss$highneedf4, ref=5) *#For ESL*
modelwithcentralruralt1.eslref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf + yearsexp + logadjsalary + highneedf4 + leaclassf3 + numassign + logadjauxspend + disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm + sciprofm + highneedf4*leaclassf3*logadjsalary + highneedf4*leaclassf3*logadjauxspend + cluster(educatorid) + strata(leaclassf3), data=central_ss)

**#Rural Non-Title I Districts**

central_ss$leaclassf3<-relevel(central_ss$leaclassf3, ref=5)
central_ss$highneedf5<-relevel(central_ss$highneedf5, ref=2) *#For Mathematics*
modelwithcentralruralnt1.mathref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf + yearsexp + logadjsalary + highneedf5 + leaclassf3 + numassign + logadjauxspend + disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm + sciprofm + highneedf5*leaclassf3*logadjsalary + highneedf5*leaclassf3*logadjauxspend + cluster(educatorid) + strata(leaclassf3), data=central_ss)

```
central_ss$highneedf5<-relevel(central_ss$highneedf5, ref=3) #For Natural Sciences
modelwithcentralruralnt1.sciref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + highneedf5 + leaclassf3 + numassign + logadjauxspend +
disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm +
sciprofm + highneedf5*leaclassf3*logadjsalary + highneedf5*leaclassf3*logadjauxspend
+ cluster(educatorid) + strata(leaclassf3), data=central_ss)

central_ss$highneedf5<-relevel(central_ss$highneedf5, ref=4) #For Special Education
modelwithcentralruralnt1.spedref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf
+ yearsexp + logadjsalary + highneedf5 + leaclassf3 + numassign + logadjauxspend +
disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm +
sciprofm + highneedf5*leaclassf3*logadjsalary + highneedf5*leaclassf3*logadjauxspend
+ cluster(educatorid) + strata(leaclassf3), data=central_ss)

central_ss$highneedf5<-relevel(central_ss$highneedf5, ref=5) #For ESL
modelwithcentralruralnt1.eslref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + highneedf5 + leaclassf3 + numassign + logadjauxspend +
disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm +
sciprofm + highneedf5*leaclassf3*logadjsalary + highneedf5*leaclassf3*logadjauxspend
+ cluster(educatorid) + strata(leaclassf3), data=central_ss)

                #Charter Schools
central_ss$leaclassf3<-relevel(central_ss$leaclassf3, ref=6)
central_ss$highneedf6<-relevel(central_ss$highneedf6, ref=2) #For Mathematics
modelwithcentralchart.mathref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + highneedf6 + leaclassf3 + numassign + logadjauxspend +
disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm +
sciprofm + highneedf6*leaclassf3*logadjsalary + highneedf6*leaclassf3*logadjauxspend
+ cluster(educatorid) + strata(leaclassf3), data=central_ss)

central_ss$highneedf6<-relevel(central_ss$highneedf6, ref=3) #For Natural Sciences
modelwithcentralchart.sciref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + highneedf6 + leaclassf3 + numassign + logadjauxspend +
disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm +
sciprofm + highneedf6*leaclassf3*logadjsalary + highneedf6*leaclassf3*logadjauxspend
+ cluster(educatorid) + strata(leaclassf3), data=central_ss)

central_ss$highneedf6<-relevel(central_ss$highneedf6, ref=4) #For Special Education
modelwithcentralchart.spedref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + highneedf6 + leaclassf3 + numassign + logadjauxspend +
disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm +
sciprofm + highneedf6*leaclassf3*logadjsalary + highneedf6*leaclassf3*logadjauxspend
+ cluster(educatorid) + strata(leaclassf3), data=central_ss)

central_ss$highneedf6<-relevel(central_ss$highneedf6, ref=5) #For ESL
modelwithcentralchart.eslref<-coxph(Surv(startyear, stopyear, outcome) ~ datayearf +
yearsexp + logadjsalary + highneedf6 + leaclassf3 + numassign + logadjauxspend +
disadvanm + spedm + ellm + femalem + blackm + hispm + readprofm + mathprofm +
sciprofm + highneedf6*leaclassf3*logadjsalary + highneedf6*leaclassf3*logadjauxspend
+ cluster(educatorid) + strata(leaclassf3), data=central_ss)
```

```
#Step 8: Obtaining baseline hazards and (truncated) model summaries.
    #Truncating Output to Three Decimal Places
specify_decimal<-function(x, k) format(round(x, k), nsmall=k)
simpsummary<- function(lmcoef, digits) {
 coefs <- as.data.frame(lmcoef)
 coefs[] <- lapply(coefs, function(x) specify_decimal(x, digits))
 coefs
}

    #Baseline Hazards and Kaplan-Meier Curves of Models
      (WITHOUT Interactions)
basehaz(modelwophila, centered=FALSE)
basehaz(modelwopitt, centered=FALSE)
basehaz(modelwocentral, centered=FALSE)

N<-length(unique(modelwophila))
plot(survfit(modelwophila), xlab="Year of Study", ylab="Survival Rate of Educator",
mark.time=F, col=1:N)
N<-length(unique(modelwopitt))
plot(survfit(modelwopitt), xlab="Year of Study", ylab="Survival Rate of Educator",
mark.time=F, col=1:N)
N<-length(unique(modelwocentral))
plot(survfit(modelwocentral), xlab="Year of Study", ylab="Survival Rate of Educator",
mark.time=F, col=1:N)

    #Summary of Models (WITHOUT Interactions)
simpsummary(summary(modelwophila)$coefficients, 3)
simpsummary(summary(modelwopitt)$coefficients, 3)
simpsummary(summary(modelwocentral)$coefficients, 3)

    #Summary of Models: Experience & Education Level Based
        #Greater Philadelphia CSA Models: New Educator w/Bachelor's Degree
simpsummary(summary(modelwithphilasd.newref)$coefficients, 3)
simpsummary(summary(modelwithphilasubt1.newref)$coefficients, 3)
simpsummary(summary(modelwithphilasubnt1.newref)$coefficients, 3)
simpsummary(summary(modelwithphilachart.newref)$coefficients, 3)
simpsummary(summary(modelwithphilacte.newref)$coefficients, 3)

        #Greater Philadelphia CSA Models: Experienced Educator w/Master's Degree
simpsummary(summary(modelwithphilasd.expref)$coefficients, 3)
simpsummary(summary(modelwithphilasubt1.expref)$coefficients, 3)
simpsummary(summary(modelwithphilasubnt1.expref)$coefficients, 3)
simpsummary(summary(modelwithphilachart.expref)$coefficients, 3)
simpsummary(summary(modelwithphilacte.expref)$coefficients, 3)

        #Greater Pittsburgh CSA Models: New Educator w/Bachelor's Degree
simpsummary(summary(modelwithpittsd.newref)$coefficients, 3)
simpsummary(summary(modelwithpittsubt1.newref)$coefficients, 3)
simpsummary(summary(modelwithpittsubnt1.newref)$coefficients, 3)
simpsummary(summary(modelwithpittchart.newref)$coefficients, 3)
simpsummary(summary(modelwithpittcte.newref)$coefficients, 3)
```

```
#Greater Pittsburgh CSA Models: Experienced Educator w/Master's Degree
simpsummary(summary(modelwithpittsd.expref)$coefficients, 3)
simpsummary(summary(modelwithpittsubt1.expref)$coefficients, 3)
simpsummary(summary(modelwithpittsubnt1.expref)$coefficients, 3)
simpsummary(summary(modelwithpittchart.expref)$coefficients, 3)
simpsummary(summary(modelwithpittcte.expref)$coefficients, 3)

#Central Penn MSAs and uSAs Models: New Educator w/Bachelor's Degree
simpsummary(summary(modelwithcentralsd.newref)$coefficients, 3)
simpsummary(summary(modelwithcentralsubt1.newref)$coefficients, 3)
simpsummary(summary(modelwithcentralsubnt1.newref)$coefficients, 3)
simpsummary(summary(modelwithcentralruralt1.newref)$coefficients, 3)
simpsummary(summary(modelwithcentralruralnt1.newref)$coefficients, 3)
simpsummary(summary(modelwithcentralchart.newref)$coefficients, 3)
simpsummary(summary(modelwithcentralcte.newref)$coefficients, 3)

#Central Penn MSAs and uSAs Models: Exp Educator w/Master's Degree
simpsummary(summary(modelwithcentralsd.expref)$coefficients, 3)
simpsummary(summary(modelwithcentralsubt1.expref)$coefficients, 3)
simpsummary(summary(modelwithcentralsubnt1.expref)$coefficients, 3)
simpsummary(summary(modelwithcentralruralt1.expref)$coefficients, 3)
simpsummary(summary(modelwithcentralruralnt1.expref)$coefficients, 3)
simpsummary(summary(modelwithcentralchart.expref)$coefficients, 3)
simpsummary(summary(modelwithcentralcte.expref)$coefficients, 3)

#Summary of Models: High Needs Based
#Greater Philadelphia CSA
#School District of Philadelphia
simpsummary(summary(modelwithphilasd.mathref)$coefficients, 3)
simpsummary(summary(modelwithphilasd.sciref)$coefficients, 3)
simpsummary(summary(modelwithphilasd.spedref)$coefficients, 3)
simpsummary(summary(modelwithphilasd.eslref)$coefficients, 3)

#Suburban Title I Districts
simpsummary(summary(modelwithphilasubt1.mathref)$coefficients, 3)
simpsummary(summary(modelwithphilasubt1.sciref)$coefficients, 3)
simpsummary(summary(modelwithphilasubt1.spedref)$coefficients, 3)
simpsummary(summary(modelwithphilasubt1.eslref)$coefficients, 3)

#Suburban Non-Title I Districts
simpsummary(summary(modelwithphilasubnt1.mathref)$coefficients, 3)
simpsummary(summary(modelwithphilasubnt1.sciref)$coefficients, 3)
simpsummary(summary(modelwithphilasubnt1.spedref)$coefficients, 3)
simpsummary(summary(modelwithphilasubnt1.eslref)$coefficients, 3)

#Charter Schools
simpsummary(summary(modelwithphilachart.mathref)$coefficients, 3)
simpsummary(summary(modelwithphilachart.sciref)$coefficients, 3)
simpsummary(summary(modelwithphilachart.spedref)$coefficients, 3)
simpsummary(summary(modelwithphilachart.eslref)$coefficients, 3)

#Greater Pittsburgh CSA
```

```
        #Pittsburgh Public Schools
simpsummary(summary(modelwithpittsd.mathref)$coefficients, 3)
simpsummary(summary(modelwithpittsd.sciref)$coefficients, 3)
simpsummary(summary(modelwithpittsd.spedref)$coefficients, 3)
simpsummary(summary(modelwithpittsd.eslref)$coefficients, 3)

        #Suburban Title I Districts
simpsummary(summary(modelwithpittsubt1.mathref)$coefficients, 3)
simpsummary(summary(modelwithpittsubt1.sciref)$coefficients, 3)
simpsummary(summary(modelwithpittsubt1.spedref)$coefficients, 3)
simpsummary(summary(modelwithpittsubt1.eslref)$coefficients, 3)

        #Suburban Non-Title I Districts
simpsummary(summary(modelwithpittsubnt1.mathref)$coefficients, 3)
simpsummary(summary(modelwithpittsubnt1.sciref)$coefficients, 3)
simpsummary(summary(modelwithpittsubnt1.spedref)$coefficients, 3)
simpsummary(summary(modelwithpittsubnt1.eslref)$coefficients, 3)

        #Charter Schools
simpsummary(summary(modelwithpittchart.mathref)$coefficients, 3)
simpsummary(summary(modelwithpittchart.sciref)$coefficients, 3)
simpsummary(summary(modelwithpittchart.spedref)$coefficients, 3)
simpsummary(summary(modelwithpittchart.eslref)$coefficients, 3)

    #Central Pennsylvania MSAs and uSAs
        #Regional Urban Districts
simpsummary(summary(modelwithcentralsd.mathref)$coefficients, 3)
simpsummary(summary(modelwithcentralsd.sciref)$coefficients, 3)
simpsummary(summary(modelwithcentralsd.spedref)$coefficients, 3)
simpsummary(summary(modelwithcentralsd.eslref)$coefficients, 3)

        #Suburban Title I Districts
simpsummary(summary(modelwithcentralsubt1.mathref)$coefficients, 3)
simpsummary(summary(modelwithcentralsubt1.sciref)$coefficients, 3)
simpsummary(summary(modelwithcentralsubt1.spedref)$coefficients, 3)
simpsummary(summary(modelwithcentralsubt1.eslref)$coefficients, 3)

        #Suburban Non-Title I Districts
simpsummary(summary(modelwithcentralsubnt1.mathref)$coefficients, 3)
simpsummary(summary(modelwithcentralsubnt1.sciref)$coefficients, 3)
simpsummary(summary(modelwithcentralsubnt1.spedref)$coefficients, 3)
simpsummary(summary(modelwithcentralsubnt1.eslref)$coefficients, 3)

        #Rural Title I Districts
simpsummary(summary(modelwithcentralruralt1.mathref)$coefficients, 3)
simpsummary(summary(modelwithcentralruralt1.sciref)$coefficients, 3)
simpsummary(summary(modelwithcentralruralt1.spedref)$coefficients, 3)
simpsummary(summary(modelwithcentralruralt1.eslref)$coefficients, 3)

        #Rural Non-Title I Districts
simpsummary(summary(modelwithcentralruralnt1.mathref)$coefficients, 3)
simpsummary(summary(modelwithcentralruralnt1.sciref)$coefficients, 3)
```

```
simpsummary(summary(modelwithcentralruralnt1.spedref)$coefficients, 3)
simpsummary(summary(modelwithcentralruralnt1.eslref)$coefficients, 3)

            #Charter Schools
simpsummary(summary(modelwithcentralchart.mathref)$coefficients, 3)
simpsummary(summary(modelwithcentralchart.sciref)$coefficients, 3)
simpsummary(summary(modelwithcentralchart.spedref)$coefficients, 3)
simpsummary(summary(modelwithcentralchart.eslref)$coefficients, 3)
```