STAYING OR LEAVING? EVALUATION OF THE 2024 TEACHER COMPENSATION PROVISION'S EFFECT ON HEAD START CLASSROOM TEACHERS' TURNOVER AND WAGE

by

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Boyun Kim

ABSTRACT

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High teacher turnover rates (TTR) significantly impact Early Care and Education (ECE) environments by decreasing instructional quality and threatening the fiscal stability of programs, especially in under-resourced communities (Barnes et al., 2007; Kwon et al., 2025; Schaack et al., 2022). Between 2019 and 2023, Head Start (HS) teachers vacancies rose from 13.5% to 17% (DHHS, 2024b). HS teachers frequently cite low wages and insufficient benefits as key reasons for leaving (Hur et al., 2023; Vicente et al., 2024). In response, the Department of Health and Human Services announced revisions to the Head Start Program Performance Standards (HSPPS) in November 2023 (ACF, 2023b), which took effect in August 2024. The 2024 HSPPS implemented changes related to wage scales, benefits, and staff well-being (DHHS, 2024b).

This study investigated the impact of the early stage of 2024 HSPPS revision on classroom TTR and wage, examining the relationship between TTR and wages before and after the policy period by addressing the following questions: *What is the impact of the 2024 HSPPS on classroom TTR and wage, and to what extent does wage predict classroom TTR, before and after in 2024?*

Adopting a quantitative design, secondary data from 2022 to 2025 were utilized. difference-in-differences and multilevel modeling analysis were used to evaluate the 2024

HSPPS impact. Results revealed that the early stage of policy implementation successfully reduced teacher turnover rates at the national-level. Similar to previous research, this study confirmed that classroom teachers' actual wage increase rates are a direct driver of reduced turnover. Given the early stage of implementation, findings show encouraging results, emphasizing the effectiveness of the 2024 HSPPS. Evidence of policy success catalyzes improvement in working environments that allow teachers to thrive, influencing the broader ECE system.

Keywords: Head Start, ECE policy, policy evaluation, teacher wage, teacher turnover, teacher workforce

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CHAPTER ONE

THE PROBLEM AND ITS BACKGROUND

Introduction

Early Care and Education (ECE) programs have long suffered from high operational costs, staffing shortages, and program closures (Kashen & Valle-Gutierrez, 2024). COVID-19 exacerbated this phenomenon, particularly regarding staffing shortages, due to the abrupt transition to remote learning, the need to acquire new technological skills, and concerns regarding personal health (Bacher-Hicks et al., 2023; Kwon et al., 2025). ECE teacher turnover rates (TTR) have rapidly increased, with annual turnover rates estimated at 26% to 40% (Totenhagen et al., 2016). America's federally funded preschool program, Head Start (HS), is not an exception; in fact, the annual TTR among general school teachers is 1.28 times lower than that of HS teachers (Bassok et al., 2021b).

Head Start programs serve eligible children ages three to five. Early Head Start (EHS) programs are designed for infants and toddlers, up to age three, as well as pregnant women (Lynch, 2019). The 2024 reauthorization of the Head Start Act (Title 45, Code of Federal Regulations, §1302.12, 2024) established the eligibility criteria for HS program enrollment, which were limited to 100% of the Federal Poverty Level (FPL), with 35% of program seats being eligible to children from families at 130% of the FPL (NHSA, 2021). It is mandatory that HS programs guarantee that children with disabilities occupy a minimum of 10% of enrollment spaces (ECLKC, n.d.). According to the Department of Health and Human Services (DHHS) (2024b), the turnover rate by HS positions (not including EHS) increased from 13.5% in 2019 (e.g., prior to the COVID-19 pandemic) to 17% in 2023. This metric is alarming considering the widespread impact that HS programs have in underserved communities (Kwon et al., 2025). In fiscal year (FY) 2023 alone, 778,420 children and pregnant women across the U.S. were served by HS/EHS programs in centers, family homes, and family child care homes (ECLKC, 2024d). Notably, HS/EHS programs have strong relationships and align with other ECE communities.

Head Start and Early Head Start

The HS program started in 1965 and has offered extensive early education and child development support to children and their families. All 50 states offer HS preschool services (ACF, 2024b). Building upon the HS's success and the growing need for programs that support children from birth to age two, as well as pregnant mothers (Lynch, 2019), EHS was launched in 1995. The Office of Head Start within Administration for Children and Families (ACF) offers HE/EHS, which are the largest ECE programs offered by the federal government across the United States (NHSA, 2023). ACF is operated within the U.S. Department of Health and Human Services (DHHS). Children and pregnant women are eligible for HS or EHS at no cost if their family income does not exceed the FPL (Lynch, 2019). The DHHS grants money is appropriated to various organizations, such as local grantees, school districts, and community action agencies, to support programs. HS/EHS are divided into three program types: 1) Head Start; 2) Early Head Start; and 3) Migrant & Seasonal Head Start. Dating back to 1965, HS programs have served more than 38 million children and their families.

Those who attend HS programs are more likely to complete high school, go on to college, and show better social, emotional, and behavioral development (ACF, 2024b). They are also better prepared for parenthood than children who do not participate in the program (ACF, 2024b). Compared to other programs without HS funding, HS shows relatively strong program quality (Aber et al., 2007).

While there are multiple programs that serve children prenatal to age 5, under diverse funding sources, including public and tuition-based, my research focused on the federally funded Head Start (HS) and Early Head Start (EHS) programs. HS served from three to five years old, and EHS served from birth to two years old and pregnant women. Thus, encompassing HS/EHS allows for the inclusion of a wide range of ages served. Ultimately, this expanded focus helps us examine patterns and trends among overall ECE age groups, not limited to a specific age group. Additionally, looking at the HS/EHS's TTR potentially helps us interpret the impact on children from birth to five years. The creation of EHS-Child Care Partnerships (EHS-CCP) in 2014 expanded access of EHS (Start Early, 2025) to community-based early care and education programs. The EHS-CCP initiative integrates EHS and child care resources to offer comprehensive, continuous services for low-income infants, toddlers, and parents (ACF, 2024c). EHS and child care program strengths are unified by the EHS-CCP (Office of Early Childhood Development, 2020). As a federally funded program, HS/EHS have similar program implementation standards across the U.S. According to Section 644(a)(2) of the Head Start Act, which is the federal statute that authorizes the program (Improving Head Start for School Readiness Act, 2007), every HS agency is mandated to release an annual report for the general public (ACF 2024c; Improving Head Start for School Readiness Act, 2007). This annual report includes metrics on the following: (a) total public and private funds received, (b) expenditures and budget plans, (c) number of children and families served, (d) results of federal reviews and audits, (e) health services data (e.g., medical and dental exams), (f) parent involvement activities, and (g) efforts to prepare children for kindergarten (Improving Head Start for School Readiness Act, 2007). This annual report is mandated due to accountability to tax payers, the government must annually assess implementation quality.

Furthermore, HS has led the field in terms of setting standards, such as the Early Learning Outcomes Framework (ELOF). The ELOF covers children from birth to five years old and details five key early learning domains (ACF, 2024d). This framework highlights the unbroken progression of learning from infancy through preschool based on extensive research into early childhood development milestones (ACF, 2024d).

Head Start Program Performance Standards

Head Start Program Performance Standards (HSPPS) is a regulation document for all HS programs nationwide (DHHS, 2024b). The Office of Head Start (OHS) and Administration for Children and Families (ACF), which fall under the purview of the U.S. Department of Health and Human Services (DHHS), announced “Supporting the Head Start Workforce and Consistent Quality Programming” as a final rule in August 2024. This final rule modified the Head Start Program Performance Standards (HSPPS) regulations (DHHS, 2024b).

Introduced in 1975, the HSPPS details mandatory requirements for grantees to guarantee high-quality, comprehensive Head Start services promoting school readiness (Bergeron, 2024). The recently revised and adopted HSPPS mainly addressed wages and benefits, training and professional development plans, staff wellness, and employee engagement. The revision and update to this final rule were originally forecasted by ACF on November 20th, 2023 (Supporting the Head Start Workforce and Consistent Quality Programming, 2023). First, a new wage scale was implemented to reduce the wage disparity between Head Start educators and preschool teachers in public schools. Currently, data show there is a disparity between the wages of HS teachers and preschool teachers in public schools, with HS teachers earning less than their public school counterparts. The revised and reprioritized implementation of these requirements aimed to address the existing pay disparity by working toward wage parity—or at a minimum ensuring Head Start teachers earn 90% of what K-3 public school teachers make (DHHS, 2024b).

Additionally, per the new regulations, all HS staff must be paid wages that are sufficient to cover the cost of living in their area. Wages should be equal for comparable positions, qualifications, and experience across HS/EHS programs (DHHS, 2024b). HSPPS indicated that there is a seven-year timeframe to fully update the wage scale, with a prospective completion date of August 1, 2031 (DHHS, 2024b).

Second, per the new HSPPS, staff benefits must include access to health care coverage, paid leave for full-time staff, and access to free or low-cost, short-term behavioral health services for full-time staff. Furthermore, staff benefits, such as access to high-quality, affordable health care and paid leave, now vary based on enrollment status (part-time or full-time) (DHHS, 2024b). The staff benefits timeline for implementation is August 1, 2028, or approximately four years (DHHS, 2024b).

Third, the HSPPS addressed staff health and wellness. All staff need regular breaks, with their duration and frequency depending on hours worked, and must include meal breaks when appropriate. These changes must be implemented before August 1, 2027, or approximately three years after publication of the final rule (DHHS, 2024b).

Furthermore, the 2024 HSPPS policy focused on matching the wage parity between HS and EHS teachers who have the same qualifications. Thus, evaluating the effectiveness of the 2024 HSPPS is a fundamental resource for understanding ways to mitigate teacher turnover. The revised performance standards will empower committed HS personnel to establish long-lasting careers in supporting vulnerable children and families. It is evident that the revision of HSPPS in August of 2024 was not temporary; it included a multi-year, incremental implementation period that seeks to reduce teacher turnover rates and, in doing so, deliver higher-quality education to students. To align with these changes, FY 2024 HS programs under the Head Start Act now have $12,271,820,000 in funding, around $275 million more than in FY 2023 (ECLKC, 2024b).

According to Rouse et al.'s (2023) research, many HS/EHS teachers who departed early childhood education indicated they would consider returning to the profession if compensation and benefits were improved. Furthermore, teachers expressed conditions of staying if they could pursue part-time work but noted they had trouble finding jobs that offered desirable working hours (Blöchliger & Bauer, 2024). It is important to investigate how the updated 2024 HSPPS is driving changes in teacher turnover rates. In other words, to what degree have revised standards improved retention rates in the announcement and the first year after their implementation? As mentioned, over the next seven years, from 2024 to 2031, in keeping with the HSPPS, HS will roll out incremental wage increases. Thus, this study also explored the relationship between HS/EHS teachers' turnover rates and how each of the states is responding to changes in wage announcement and the first year after their implementation. With increased funding in alignment with the change in 2024 HSPPS, there is an accountability to show that the increased funding actually made a difference. Importantly, high-quality education at the preschool level has the potential to positively impact the lives of impoverished children, leading to improved academic outcomes, school progression, and educational attainment (Aber et al., 2007).

Eventually, having and building strengths in teacher compensation policy to reduce teacher turnover in the HS/EHS could spill over to other and future programs (ECLKC, 2024c). Additionally, the operational circumstances in each state, such as the fulfillment of living wage standards, were investigated. Importantly, the 2024 HSPPS revision is not a mandate for temporary funding, like the prior Coronavirus Aid, Relief, and Economic Security (CARES) Act or the American Rescue Plan (ARPA). Recent Trump administration trends, policies, and priorities have shifted, which could impact the feasibility or implementation of this sustainable plan. However, as of now (January 2026), no changes have been announced. Thus, this study focused on the period before and after the policy update's forecast announcement, examining the anticipation effect and the first-year policy implementation. It also means presidential administration changes will not likely directly impact the current study.

Theory

Bronfenbrenner's Ecological Environment

Ecological environment by Bronfenbrenner explained "ecological environment is conceived as a set of nested structures" (Bronfenbrenner, 1979, p. 3). Bronfenbrenner's Ecological Environment is particularly well-suited for examining how teacher turnover affects individual children, teachers, and families. This is because it allows us to examine how teacher turnover affects not only the immediate relationships children have with their teachers but also the broader social, cultural, and political environments that contribute to workforce instability in early childhood education. This relationship is also bi-directional, with sociocultural and political factors that impact early childhood education.

Children directly interact with the people in their surrounding environment, such as parents, friends, and teachers. Children are also influenced by indirect interactions with other elements, such as community, media, and cultural values. Similarly, teachers, as individuals, both influence and are influenced by their environments, such as policies that impact their decisions regarding job retention or departure, as well as their workloads, responsibilities, and wages. Therefore, from the perspective of teacher turnover, it is crucial to examine how and to what extent these policy shifts affect turnover rates. This phenomenon is explained by Bronfenbrenner's Ecological model, which includes five systems: the microsystem, the mesosystem, the exosystem, the macrosystem, and the chronosystem (Figure 1.1). These systems deal with the environment that encompasses a phenomenon. First, the microsystem includes the immediate environmental surroundings of the child, such as families and early childhood education, which are considered to be the most critical factors (Bronfenbrenner & Ceci, 1994; Guy-Evans, 2020) because children are constantly interacting with the environment surrounding them. The microsystem refers to the place where face-to-face interaction occurs, and this experience is critical (Bronfenbrenner, 1979). Through experience, people in these environments perceive its properties (Bronfenbrenner, 1979). Children experience fluctuating environments when teachers continue to turn over. Eventually, higher teacher turnover can disrupt the microsystem of each individual child, and children no longer expect consistent support from their teachers. Second, the mesosystem refers to the connections or relationships between different microsystems. For instance, the interactions between families and teachers are part of the mesosystem. As Bronfenbrenner (1994) explained, "A mesosystem is a system of microsystems" (p. 40). Therefore, teachers are integral components of the mesosystem. In the mesosystem, there are four different types of interrelations: multi-setting participation, indirect linkage, intersetting communications, and intersetting knowledge (Bronfenbrenner, 1979). In particular, multi-setting participation is the most fundamental type of link between two contexts (Bronfenbrenner, 1979). It happens when an individual participates in activities in many contexts, for example, when a child experiences both home and child care center (Bronfenbrenner, 1979). One person has a linkage with multiple environments, and the mesosystem explains how a developing child interacts in multiple environments and how connections between them are made, and explains that these connections have a significant impact on development (Bronfenbrenner, 1979). Third, the exosystem encompasses environmental factors that indirectly affect a child. Although children are not directly involved, these external influences still impact their development. Examples include parents' workplaces (Eckenrode & Gore, 1990), family social networks (Cochran et al., 1990), and neighborhood-community contexts (Bronfenbrenner, 1994). For example, if parents get stressed from work, this stress can be reflected in the parent-child interaction. Vice versa, if parents are stressed by their child, it could have an impact on the workplace. Thus, this causal sequence occurs bi-directionally (Bronfenbrenner, 1979).

All three levels (the microsystem, the mesosystem, and the exosystem) of the ecological environment are outlined by society or subculture. The organization of these three systems is referred to as a blueprint (Bronfenbrenner, 1979). Blueprints are modified by the arrangement of societal settings. Every culture has different blueprints, which can be significantly transformed, leading to corresponding shifts in behavior and development. For example, research has shown that procedures that impact maternity wards, namely those that may have influenced the mother-child bond, have consequences that are noticeable, affecting the child's development (Bicking Kinsey & Hupcey, 2013).

Similarly, depending on the child's age at the time of financial hardship, a serious socio-economic crisis may be perceived to have either a beneficial or negative effect on the child's development later in life (Bronfenbrenner, 1979). However, individual children may react differently even when they seem to be experiencing similar environments. This is because children's development is affected by the environment as perceived rather than as it exists in "object" reality (Bronfenbrenner, 1979). This same concept can be applied to teachers. Even if they worked in the same centers with the same policies, benefits, and wages. Individuals' perceptions will differ, which leads to different decisions, such as to stay or leave.

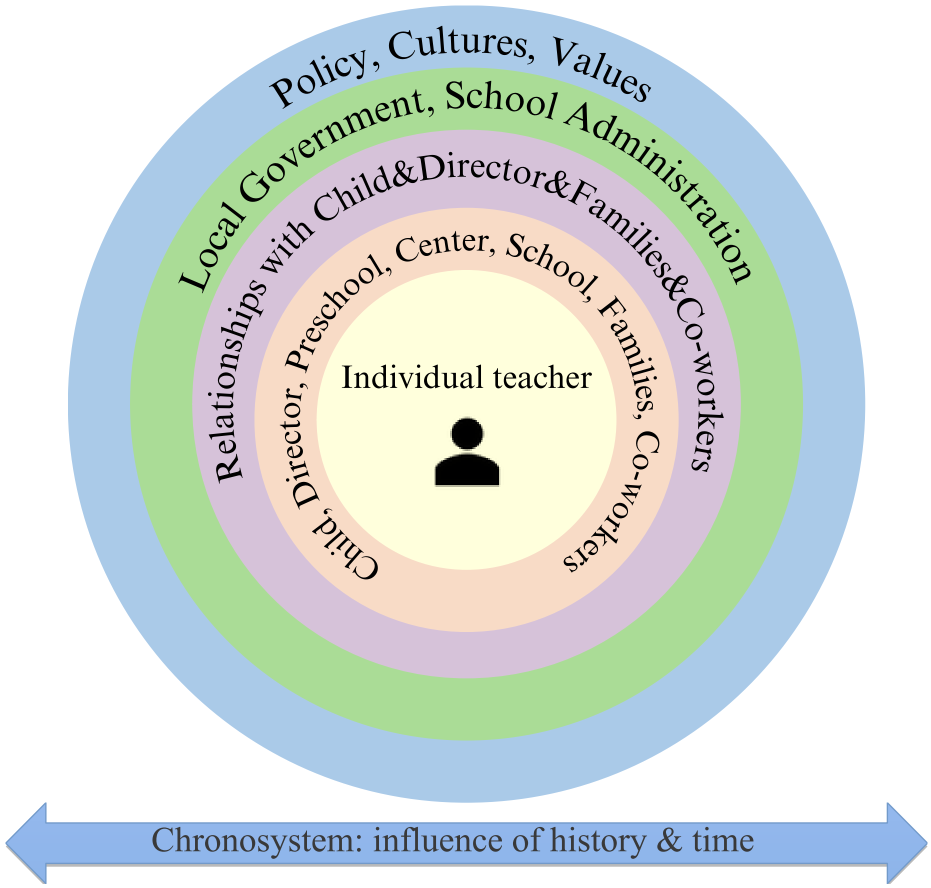
The macrosystem encompasses the broader societal influences, such as social values, cultural aspects, and laws. Policies fall within the macrosystem. Although policies are not direct tools for interacting with children and teachers, they have significant impacts, as demonstrated by the effects of COVID-19 policies. Understanding the pivotal role that policies play in shaping practices is crucial for establishing a solid foundation for children's education. Recognizing this role is essential for developing and offering high-quality educational environments. Policies are key indicators of society's understanding and priorities, reflecting the current trajectory of early childhood education and the comprehension of policymakers regarding its importance.

Additionally, policies fall under the umbrella term “linkage effect.” This term suggests that policy can change society and is strongly connected with support funding mechanisms in the education field, especially for primary caregivers. Changing policies are palpable reasons to stay or leave for many teachers. For instance, according to Sun et al. (2016), the No Child Left Behind (NCLB) Act decreased the likelihood of involuntary attrition (or, in other words, teachers leaving the profession involuntarily) as schools adjusted to the policy. This phenomenon can be thought of as a chain or “linkage” effect, wherein the social problem is examined, policies are changed, retention increases, remaining teachers and children are exposed to less stressful environments, and overall working education conditions improve. Eventually, this linkage circles back to children’s microsystems. Children who interact with a stable environment are more likely to achieve emotional stability. This study examines how macrosystemic policy changes can stabilize the ECE workforce and mitigate teacher turnover, eventually overcoming a primary systemic deficit within the ECE field.

Lastly, the Chronosystem “encompasses change or consistency over time not only in the characteristics of the person but also of the environments in which the person lives” (Bronfenbrenner, 1994, p. 40). Examples include socioeconomic status and changes in family structure throughout life. The changes set forth by the HSPPS will gradually impact children’s development as they will take place in the chronosystem over the span of seven years.

Figure 1.1

Original Ecological Model



Note. Bronfenbrenner, (1979)

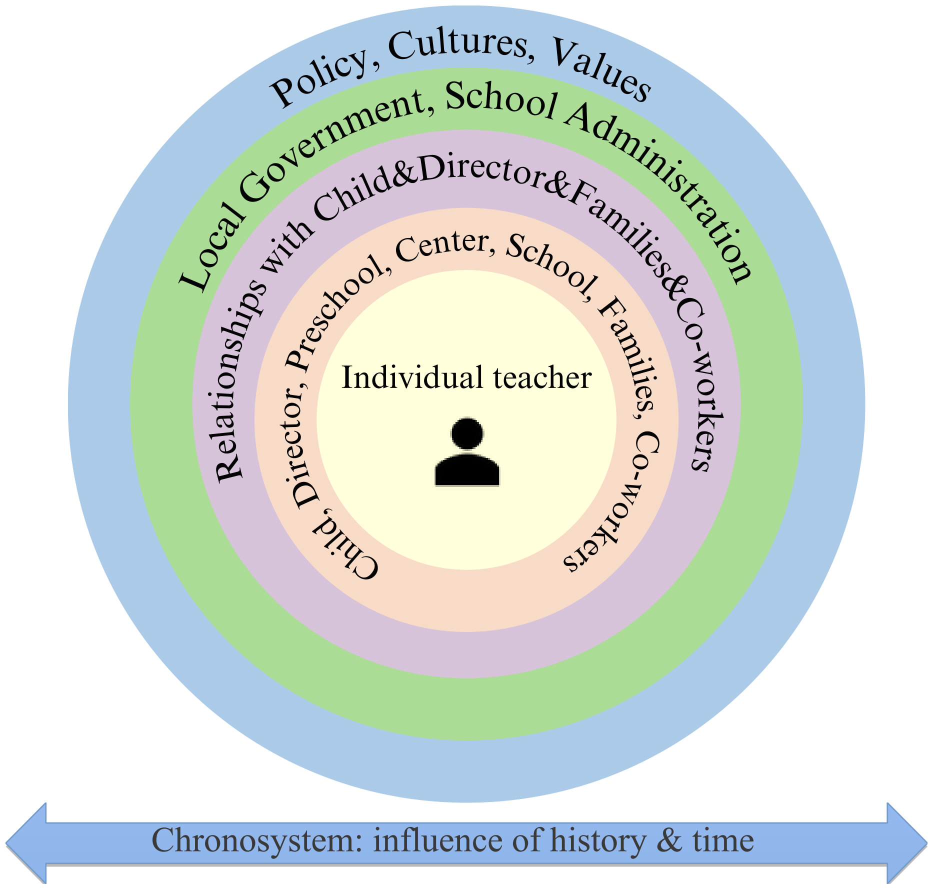
The Ecological model was later expanded upon and became known as the PPCT model. PPCT refers to process, person, context, and time. The process indicates interaction between organisms and the environment. More specifically, this interaction is termed “proximal processes,” which are defined as “progressively more complex reciprocal interaction between an active, evolving biopsychological human organism and the persons, objects, and symbols in its immediate external environment” (Bronfenbrenner

& Morris, 1998, p. 996). In other words, the interacting relationship between children and their teacher is part of “proximal processes.”

Moreover, the Ecological model can be reframed to place the teacher—alongside the child—at its center (Figure 1.2) (Fenech et al., 2021). This teacher-centered version explains how teachers correspond with the environment surrounding them. The microsystem includes the child, director, the early childhood education institutions, families, and co-workers. Teachers also experience these changes as individuals. With ongoing teacher turnover, teachers come to expect that their working environment is not continuously supportive, as co-worker changes create fluctuating environments for them as well. The mesosystem includes relationships between child, director, the early childhood education institutions, families, and co-workers. The exosystem includes local government or school district administration (e.g., policies about wages, hiring freezes, school closures). The macrosystem includes policy, cultures, and values like the original Ecological model. When the teacher is in the center, individuals connect more directly to policies such as wages or compensation rates compared to the original Ecological model, which more collectively impacts on teachers (Fenech et al., 2021). Eventually, the teacher-centered model helped us understand the impact of teacher turnover. Through the lens of Bronfenbrenner’s Ecological Environment, it is easy to conceptualize that teachers have a direct impact on children, and moreover, the teacher’s relationship with other teachers also has an indirect impact on children and overall learning outcomes (Bronfenbrenner, 1979).

Figure 1.2

Teacher-Centered Ecological Model



Note. Adapted from Fenech et al. (2021)

Both the original Ecological model and the reframed teacher-centered model explain how teacher turnover affects multiple individuals, while also highlighting the different ways children and teachers are interrelated.

Bowlby's Attachment Theory

According to research, a child's connection to a primary caregiver in out-of-home child care is just as significant as their attachment to their mothers (Cummings, 1980;

Goossens & van Ijzendoorn, 1990; Howes & Hamilton, 1992). When children receive consistent and regular responses from their teachers, they are able to build stable relationships with them (Resources for Infant Educarers®, 2025). This stability is crucial for young children's development (Bellows et al., 2022; Hur et al., 2023; Kwon et al., 2025). In other words, high teacher turnover consistently changes the environment in which children and parents interact (Whitebook et al., 1989). Ultimately, this disruption leads to decreased chances for children to develop a stable relationship with their teacher, as evidenced by attachment theory.

Attachment theory, first introduced by Bowlby (1982), is a key theory to rely on when investigating teacher turnover because it considers the impact that abrupt changes in staffing can have on students in ECE environments. Teacher turnover disrupts the bonds children have formed with their teachers, often resulting in emotional distress. When a teacher leaves, children lose the person to whom they have already formed an attachment and must start the attachment process anew with a new teacher, all within the same academic year. This sudden loss of attacfhment can lead to what Bowlby (1988) referred to as a broader concept of "separation anxiety" among children. Bowlby suggested that children experience separation anxiety from their mother or primary caregiver when they become separated from them. This separation anxiety is considered to be beyond just anxiety; however, sometimes, it provokes anger (Bowlby, 1988), which could lead to behavioral issues in the classroom later in life. Connecting this idea to ECE environments, prior studies have suggested parallels between not only separation anxiety from mothers and primary caregivers but also separation anxiety from teachers (O'Brien et al., 2016; Robbins, 1997). Additionally, when children are faced with a new teacher, they are forced to readjust and start from scratch to form a new bond (Howes & Hamilton, 1992).

Thus, attachment theory emphasizes emotional bonds between individuals, such as dyadic relationships (Bowlby, 1988). Dyads are also relevant to the Ecological

Environment. Bronfenbrenner insisted that a dyad includes people. Thus, a dyad is a group that can be utilized to analyze the interaction between two people. A dyad is explained when one partner in the pair goes through a developmental phase, and the other does too. In other words, children and parents, and children and teachers, experience reciprocal relations with each other (Bronfenbrenner, 1979). Securely attached children are more likely to develop better relationships, have greater capacity for concentration and cooperation, and demonstrate more confidence and resilience by the age of six (Gomez, 1997). Thus, if children can't form secure attachments with their caregivers and teachers, it leads to decreased social and behavioral development. Additionally, those who care for children in such settings have a significant impact on children's developmental journeys (Markowitz, 2024). Eventually, secure and positive relations with teachers help children's success (NAEYC, 2021). Thus, a higher rate of teacher turnover may reduce children's opportunities to build trusting relationships with their teachers (Erikson, 1963; Helburn et al., 1995). John Bowlby's attachment theory was developed to explain specific behavioral patterns that were previously thought to be associated with an overreliance in infants and toddlers, children, adolescents, and adults on the primary adults in their lives. When it was first formulated, observations of how young children reacted in unfamiliar situations with unfamiliar people, and the impact those experiences had on a child's future relationships with his parents, were particularly relevant (Ainsworth et al., 1978). Teacher turnover can negatively impact the teacher-child attachment relationship, causing anxiety in children due to a lack of trust in having a consistent teacher to support them (Howes & Smith, 1995). Furthermore, teachers need relationships with children to maintain their professional identity (Riley, 2010). For example, when children rejected a teacher, they often had unarticulated fear (Riley, 2010). Thus, a reciprocal relationship, with changes in both parties of the dyad. There is an impact on teachers when the attachment of this dyad is disrupted, not just on children.

Theory of Reasoned Action and Theory of Planned Behavior

The Theory of Reasoned Action (TRA) and the Theory of Planned Behavior (TPB) examine how individual motivations shape behavior (Glanz et al., 2015). Both theories propose that attitudes and social norms are key factors influencing intentions, which ultimately predict behavior (Glanz et al., 2015). The TRA operates on the belief that behavioral intention is the primary factor influencing behavior (Glanz et al., 2015). The TPB extends the TRA by adding perceived behavioral control as an additional factor (Glanz et al., 2015).

While TRA and TPB suggest that turnover is the result of individual intention for teachers. However, reasons for leaving are not always a choice unless there is a change in living circumstances or an alternative to the current position. According to Ajzen (1991), behavior is constrained by the availability of requisite opportunities and resources. Connecting with Bronfenbrenner's Ecological Environment, individuals interact with their environment based on their nested environments. Consequently, this dissertation is interested in exploring how teachers' behaviors are shaped by their perceptions of exosystem and macrosystem changes, specifically regarding wages and benefits resulting from policy implementation.

Eventually, Ecological Environment explains how policy revisions impact children and the overall ECE environment. Attachment theory illustrates how children's emotional responses are affected by the stability or changes in their teachers; TRA and TPB explain how policy changes influence teachers' decisions regarding turnover.

Research Questions

This study addressed the following research questions: *What is the impact of the 2024 HSPPS announcement (as an anticipation effect) and its initial implementation in*

2025 on classroom TTR, actual wage increase rates, and raw wages? To what extent does actual wage increase rates predict classroom TTR, before and after in 2024?

While the 2024 HSPPS revision was announced in November 2023 and the programs started implementation in 2024, the purpose of this study focused on the early stage behavioral responses triggered by its announcement and the first year of implementation. By employing a difference-in-differences (DiD) and multilevel modeling (MLM) approach, this study evaluated the anticipation effects of policy changes on classroom teacher turnover and wage structures while accounting for the nested nature of the data. Moreover, wages are important for ECE professional quality, examining the general relationship between classroom teacher turnover and classroom teachers' actual wage increase rates before and after 2024. Eventually, this study will offer the effectiveness of compensation policy in the reduction of the classroom teachers' turnover rates, which leads to increasing ECE quality. This study supports the effectiveness of the policy and the impact of raising wages on ECE. Thus, this study followed APA Journal Article Reporting Standards for Quantitative Research (Association, 2019) as to a quantitative research design and utilized secondary data from the Head Start Program Information Report (PIR).

CHAPTER TWO

OVERVIEW OF MAIN FINDINGS FROM PREVIOUS LITERATURE

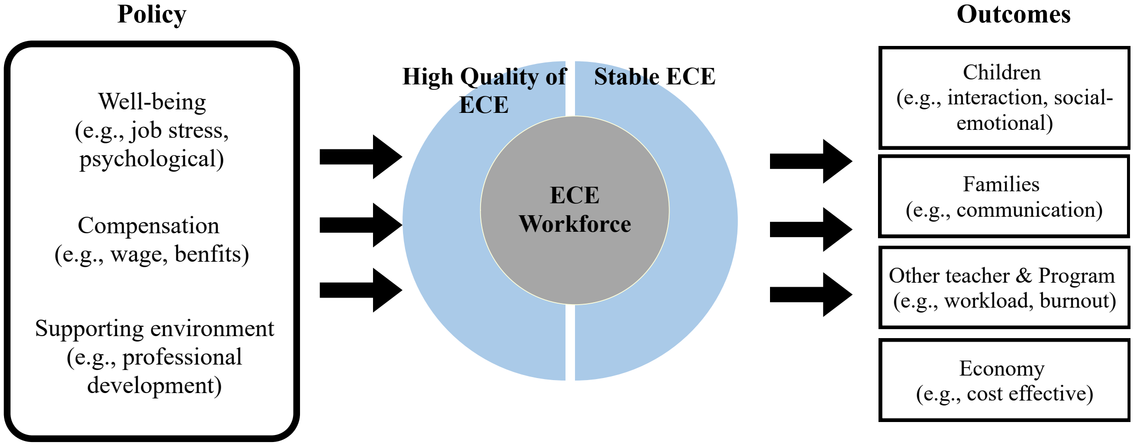
Introduction

In the literature review for this study, consider the changes of the 2024 Head Start Performance Standard (HSPPS) on teacher turnover through the lens of Bronfenbrenner's Ecological Environment (1979). Importantly, teacher turnover impacts children, parents, and other staff. Especially, Bowlby's Attachment Theory supports how turnover disrupts consistent teacher-child relationships. Thus, to understand the overall picture in Early Care and Education (ECE), both Head Start (HS) and non-HS settings will be noted. Non-HS setting refers to school-based preschool, state-funded preschool, and subsidized child care. Including and comparing both sets of metrics helps to understand the overall picture in ECE. Furthermore, to help establish future directions, reviewing literature on both HS and non-HS will be beneficial for future offerings and adaptations.

Based on the literature review, I adapted a conceptual framework from Kwon and colleagues (2020) to represent components that affect ECE teacher turnover, which in turn affects the overall ECE environment (see Figure 2.1).

Figure 2.1

Conceptual Model of the Impact and Effect of the ECE Workforce in the ECE Environment



Note Adapted from Kwon et al. (2020)

Search and Compilation Strategies

The main search engine I used was ERIC through the Oakland University Kresge Library OneSearch function. For every search term, I filtered by peer-reviewed articles published between 2010 and 2024. The following key term was used to conduct the search: “teacher turnover” AND “policy”. This yielded 195 records. Following, I examined the reference list of each record to identify articles not captured by the key term search. Afterward, I reviewed the abstract of each article to identify those that included populations from birth to age five.

For a clearer, I refined my search to focus on specific topics: “Head Start,” “quality,” and “cost.” And to investigate the broad impact of the teacher turnover impact on children: adding keywords such as “achievement,” “behavior.” Terms like "achievement" and "behavior" helped me to better understand teacher turnover relationships with children’s outcomes. Those results showed literature on teacher-child relationships, which includes “attachment.” Thus, "attachment" was not included in the search.

Regarding HS more specifically, I referenced the Office of Head Start website, which is managed by the Administration for Children and Families (ACF). The findings from the search provided valuable insights for shaping my research questions, a partial discussion of this research is included below. There are several theories and theorists that I found relevant to my research questions, many of which were also mentioned in the articles I reviewed. To explore these further, I sought out the original sources of each theory. During this process, I occasionally referenced my qualifying exam reading list for additional insights. Once I had gathered all the searches, I organized them using Zotero, which is linked to Google Docs. This setup made it easy to add citations while writing and generating a full reference list efficiently.

Primarily, I focused on articles that have a quantitative design. In a 2023 article by Hur and colleagues entitled "Why Are They Leaving? Understanding Associations between Early Childhood Program Policies and Teacher Turnover Rates," the authors explored the outcomes of teacher turnover in the early childhood education field. Hur et al.'s (2023) research was published after COVID-19 by using the Fragile Families and Child Wellbeing Study (FFCWS). Hur et al. (2023) analyzed responses from 354 lead teachers and assistant teachers from FFCW data on center-based programs. This study found that teacher turnover rates were generally higher in programs without available policies. Additionally, the study examined the difference in lead and assistant teacher turnover. Lead teachers with few wage and benefit policies tended to have higher turnover rates. Assistant teachers showed higher turnover rates without supportive policies, including wages, benefits, and teacher support (Hur et al., 2023).

Findings from the Review of Literature

Sun et al.'s (2016) research offered great standards for identifying the categories of leaving, such as stayer, voluntary mover, involuntary mover, voluntary leaver, and involuntary leaver, using pre-pandemic data. Sun et al.'s (2016) study provided insight into the impact of federal accountability policies on teacher labor markets, highlighting the possibility of schools reassigning teachers (involuntary mobility) rather than decreasing their turnover rates. Thus, it focused on the examination of the factor "school accountability" and its relationship to teacher turnover. Overall, federal accountability policies did not decrease involuntary teacher turnover. In addition, the study discussed that there is a possibility that school accountability policies might push teachers to leave due to increased job-related stress and create difficult working conditions for teachers. An example of this is provided in the conceptual framework (Figure 2.1) to ECE teachers' workforces.

Markowitz's recent research investigated the relationship between "achievement" and "teacher turnover." Markowitz (2024) examined how teacher turnover in HS programs affected children's school readiness, which provided valuable insights into the dynamics of HS teacher turnover. Choi et al. (2019) used secondary data from an EHS family and child experiences study. Children with stable caregiving tend to exhibit fewer behavioral problems and greater social competence (Choi et al., 2019), which is illustrated in the outcomes column of the conceptual framework (Figure 2.1).

Differences in Key Definitions in Literature

Definitions of Early Childhood Education

According to the National Association for the Education of Young Children (NAEYC), early childhood education is defined as "a term defined using the developmental definition of birth through approximately age eight, regardless of programmatic, regulatory, funding, or delivery sectors or mechanisms" (NAEYC, n.d.b.). Thus, the goal of early childhood education is to promote high-quality early learning for children from birth to 8 years old (NAEYC, n.d.a). Through these definitions, NAEYC recognizes that early childhood education refers to the place of early learning. It could include child care, which is defined as “the action or skill of looking after children” and “the care of children by a day-care center, babysitter, or other providers while parents are working” (Oxford Languages, n.d.).

Definitions of Head Start and Early Head Start

Head Start (HS) and Early Head Start (EHS) are federally funded ECE programs for pregnant women and birth to five (ECLKC, 2024d). Thus, this study defines the ECE age range as between birth and five years. However, some literature reviews did not indicate ECE as the overarching term for early childhood care and education. Thus, some of the categories were not the same as those in my research. For example, Fee’s (2024) research used ECE as an overarching term that includes care and education. Head Start settings include HS, EHS, and EHS-CCP. However, the PIR report did not distinguish between EHS and EHS-CCP. Thus, PIR data have the potential to contain information about EHS-CCP. Within the HS setting, this study examined the difference between HS and EHS. According to McLean et al. (2024), the mean annual wage for Head Start teachers was $39,600 in 2019. On the other hand, other public pre-K teachers earned $43,200, while school-sponsored pre-K teachers’ mean annual wage was $56,500. Consequently, Head Start classroom teachers earn approximately 30% lower mean annual wages than school-sponsored pre-K teachers.

Definition of Teacher Turnover in Early Childhood Education

There were several studies about teacher turnover in the ECE field, each of which offers slightly different definitions of teacher turnover in the context of early childhood education. First, in Bassok et al.’s (2021b) research, teacher turnover was defined as those educators who dealt with children aged birth to five and did not fulfill their obligations at the program’s conclusion, including teachers who either stopped working or cut back on their hours yet continued to work at their locations. Participating teachers worked in over 1,500 centers, not only in HS but also in childcare sites and school-based pre-K programs (Bassok et al., 2021b).

Similarly, the definition offered in Bellows et al. 's (2022) research included teachers working not only in HS but also in any publicly funded, center-based programs. Teacher turnover in Bellows et al. 's (2022) study was defined as the proportion of teachers who were no longer present at the same site in subsequent time periods. As Bellows et al. (2022) underscored, this site-level turnover is likely the most disruptive for children, families, and the sites themselves. Notably, some teachers may leave and then return to their sites (e.g., after maternity leave). If a teacher was absent during one time period but was observed in both the preceding and following periods, they were considered the teacher to have continued teaching. Additionally, in the federal definition of teacher turnover rates (TTR), three different parts are classified: childcare, preschool, and kindergarten.

However, in this study, the teacher turnover definition follows the 2023-2024 Head Start Program Information Report (ACF, 2024a), which states TTR is reflective of the number of teachers who departed during the program year, including a turnover that occurred while classes and home visits were not in session (for example, during summer break; ACF, 2024a).

Teacher Turnover Rates in Head Start and Non-Head Start

The ECE field is not immune to issues surrounding increased teacher turnover. When comparing TTR with other occupations outside of ECE, ECE teachers have a noticeably higher turnover rate at 65% (Fee, 2024).

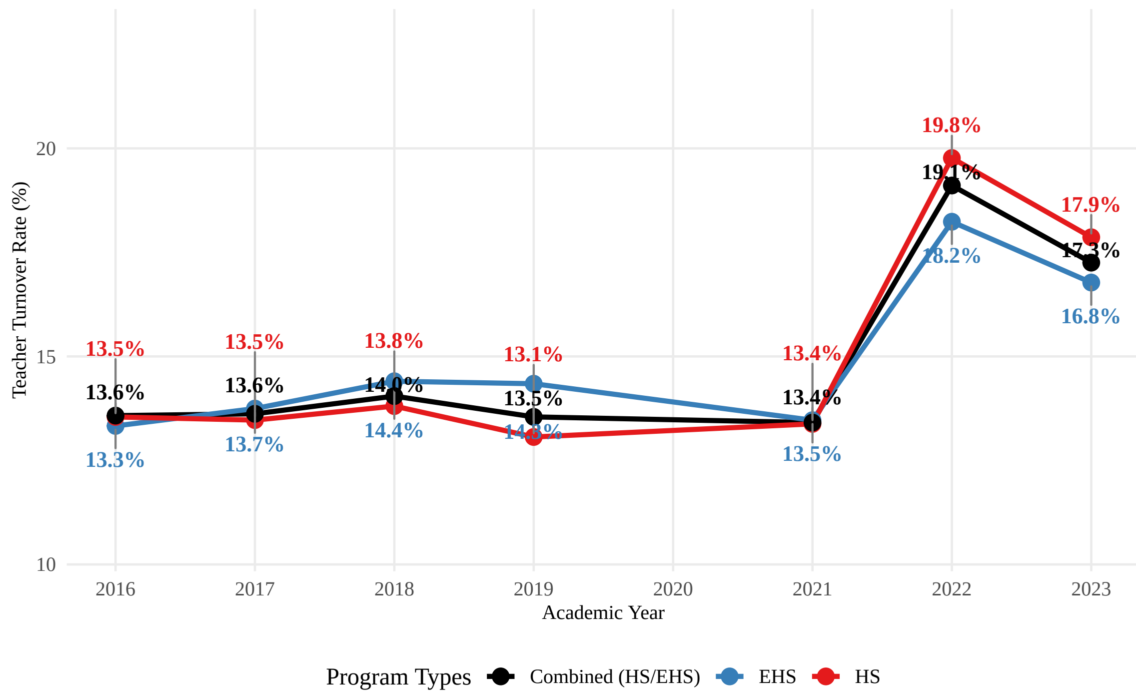
Approximately 25% of ECE teachers quit their jobs annually, a turnover rate four times greater than other elementary school teachers (Bassok et al., 2013; Whitebook et al., 2014). Moreover, recent data suggest this issue has continued to worsen, rising from 25% in 2014 to 33% in 2021 (Bassok et al., 2021b). Moreover, the bigger problem caused by TTR is that early childhood education workers not only left their jobs but also departed the field of teaching altogether (Vicente et al., 2024). For example, according to findings from 2024, about 50% of ECE teachers left their field permanently when they quit their current jobs (Fee, 2024).

Focusing on HS/EHS TTR more specifically, children enrolled in HS and child care programs suffered from heightened instabilities in care and education when compared to those in school settings. From spring 2019 to fall 2019, 21% of teachers left during the program year in HS, and 23% of teachers in child care, whereas only 17% of preschool teachers departed (Bellows et al., 2022). In Bellows et al. 's (2022) research, preschool teachers were defined as local, school-based pre-kindergarten programs that primarily serve three-to-four-year-olds. HS/EHS teachers were considered as those who serve children from birth through five. Moreover, the research showed that the teacher turnover rate is higher in programs serving younger age groups that are most likely to benefit from stable relationships (Bellows et al., 2022). Similarly, EHS teachers' turnover rate has significantly increased since COVID-19. According to Sandstrom et al. (2024), during the 2021-22 program year, the number of education and child development (ECD) staff who left their positions in EHS programs across the country reached 9,600, with an average turnover rate of 29% for EHS programs.

When comparing teacher turnover rates in all of the teacher positions (i.e., classroom, assistant) between HS and EHS during the 2015-2016 academic year, HS was at 13.5%, and EHS was at 13.3%, illustrating that HS experienced greater turnover (ACF, 2016). When examining rates for 2017 to 2019, the EHS turnover overtook HS turnover. In 2020, data were not available due to COVID-19. Following the pandemic in 2021, HS and EHS showed similar turnover rates, with HS at 13.4% and EHS at 13.5%. However, in 2022 and 2023, HS turnover began to overtake EHS in terms of turnover rates. As of 2022, HS turnover was at 19.8% and EHS turnover was at 18.2%. Figure 2.2 represents seven years of data (2016-2019 and 2021-2023) released by the Administration for Children and Families in their annual Head Start Program Information Report (ACF, 2016, 2017, 2018, 2019, 2021, 2022, 2023a).

Figure 2.2

HS and EHS Teacher Turnover Rates from 2017 to 2023



Note. Source: PIR data (ACF, 2016, 2017, 2018, 2019, 2021, 2022, 2023a)

TTR increased after COVID-19. Reducing the high turnover trend in HS programs across the nation will be possible through the ability to hire and retain qualified and experienced staff (ECLKC, 2024c).

Impacts of Teacher Turnover

Major research addressing high teacher turnover rates has demonstrated countless negative effects it has on the ECE environment and beyond. In addition to an overall decreased quality of education, other impacts include negative effects on children, families, and staff, increased strains in under-resourced communities, and various social and fiscal costs.

Impacts on Children

Teacher turnover impacts student development, including achievement, social-emotional growth, and stability across all school-age children, not only HS/EHS. Stability in this context refers to offering a non-fluctuating environment in ECE settings (King et al., 2015). According to Bowlby's attachment theory and Bronfenbrenner's Ecological Environment, children, especially from birth to five years old, are highly affected by the environment that surrounds them. Over time, frequent significant changes may lead to children developing anxiety. Children from birth to age five are more significantly impacted in children's holistic development. Markowitz's (2024) research focused on the relationship between within-year teacher turnover rates and children's achievement in the HS setting. Markowitz (2024) used the 2006 and 2009 data from the Head Start Family and Child Experiences Survey (FACES). Children's achievement scores were divided into children's school readiness with math, literacy, social, and behavioral outcomes. This study also used a fixed effects model to control for the time-invariant and program characteristics. It helped to examine the relationship between teacher turnover and children's outcomes. This approach included centers as fixed effects to account for unobserved center traits through within-center comparisons. Programs were also added as fixed effects. Findings showed teacher turnover was negatively related to student outcomes, especially in language development.

Markowitz's (2024) work revealed that children's language development was most impacted by the within-year teacher turnover. Importantly, compared with K-12 data, HS children were 1.5 times more negatively impacted by within-year teacher turnover (Henry & Redding, 2020; Markowitz, 2024). This impact is greater among younger children, such as those in HS programs, who are in the early stages of language development. Markowitz's results demonstrate the impact of teacher turnover; however, Markowitz (2024) did not address policy implementations or their impact on teacher turnover rates. Additionally, data from 2006 and 2009 were gathered pre-COVID-19 and therefore may not be representative of recent changes in the ECE environment.

Furthermore, turnover is connected with low quality in instructional activities, class management, and teacher-child interactions, contributing to increasing workload and emotional pressures among teachers who did not leave (Hur et al., 2023; Kwon et al., 2025). When teachers depart, often in the middle of the year, they carry away the knowledge, skills, and social connections they have built with the young students in their classrooms, which are not easily or swiftly replaced (Schaack et al., 2020). These findings are evidence that high teacher turnover has a bigger burden on HS/EHS programs as compared with teachers in school-aged children's programs (Choi et al., 2019), which is particularly evident as higher teacher turnover also strongly correlates with children's achievement (Markowitz, 2024).

Additionally, children who have lost emotional connections struggle to undertake everyday tasks with fewer staff members until new teachers are hired (Hur et al., 2023; Kwon et al., 2025), highlighting the fact that children are struggling with the transition to new teachers (Cryer et al., 2001). More evidence was provided to support this argument in 2018 when a study found that children who worked with the same lead teacher at EHS for more than 18 months demonstrated higher social-cognitive and emotional skills throughout their EHS years compared to children who did not (Horm et al., 2018).

Children who stayed with the same teachers in EHS for at least 18 months were rated as demonstrating higher social-cognitive and emotional skills throughout their EHS years by teacher rating (Horm et al., 2018). As depicted in the conceptual framework (Figure 2.1), the ECE teacher workforce impacts children's interactions and social-emotional development outcomes.

Impacts on Families

Parents often express concerns about teacher-parent relationships, particularly regarding the well-being of their children and the quality of communication with classroom staff as a result of changes in or a loss of contact with teachers (Bryant et al., 2023; Cassidy et al., 2011). Thus, teacher turnover is a mediator that weakens teacher-child relationships and the rapport between teachers and parents. According to Bronfenbrenner's Ecological Environment, the relationship between teachers and families best conforms to the exosystem. Additionally, teacher turnover creates staffing shortages, which eventually leads to low child center enrollment. According to the 2023-2024 Head Start Program Information Report (ACF, 2024a), 592,271 children were enrolled in the HS program and 191,807 children in EHS, with 248,000 staff (Office of Head Start, 2022). The HS enrollment rate has continued decreasing since 2015. More specifically, there was a decrease from 680,000 children in 2018 to just under 537,000 in 2023 (Hutton, 2024). There are several reasons for enrollment decline, such as parent information shortage especially, single parents, families who live in urban areas (Kim et al., 2024), and a shortage of teachers created barriers to access. This lower enrollment phenomenon increased the burden on parents and families, who need to find someone to take care of their children or adjust their work schedules. Through the conceptual framework (Figure 2.1), we see that the ECE teacher workforce impacts families, too, such as affecting communication.

Impacts on Teachers

TTR not only affects children and families but also affects teachers who remain, or the remaining teachers. To manage the classrooms, remaining teachers must cope with a heavier workload and address the varying reactions of students, necessitating adjustments to the schedule and instructional activities (Bryant et al., 2023; Cassidy et al., 2011). Teachers' perceptions of children's behavior are crucial for fostering engagement, providing cognitive stimulation, and nurturing relationships (Markowitz, 2024). If a lead teacher leaves during the school year, the remaining or new teacher must fill the knowledge gap about the children, which can disrupt the continuity of care and support. Moreover, the turnover has made it harder to teach effectively because of the increased workload (Bryant et al., 2023; Cassidy et al., 2011; Vicente et al., 2024), which in turn encourages other teachers to leave and start a cycle of turnover (Whitebook et al., 2014). This phenomenon is akin to the "domino effect" (Vicente et al., 2024). For instance, Vicente et al. (2024) highlighted the high volumes of paperwork that accrue for remaining staff with the following quote from a participant in their study: "....so you have this paperwork that piles up, up, up that eventually you feel like the paperwork becomes more important than the children" (p. 7). According to Hutton (2024), in some cases, HS programs "... have the funds, but with fewer classrooms, they can't use them. Yet, without enough teachers, they can't open additional classrooms". Together, these dynamics create a feedback loop that links workforce shortage to high turnover rates. This relationship shows that over time, higher teacher turnover rates lead to various social problems, such as under-enrollment and emotional and behavioral instability among children, which ultimately impact a child's classroom quality. Eventually, this relationship affects the stability and quality of HS/EHS programs. Through the conceptual framework (Figure

2.1), it is evident that the ECE teacher workforce has impacts on teachers themselves as well, such as increasing the workload, ultimately accelerating burnout.

Impacts on Decreased Education Quality

According to the Child Care & Early Education Research Connections (n.d.), child care and early education quality are organized into three categories: process quality, structural quality, and quality initiatives. Process quality includes the quality of children's interactions with caregivers/teachers (Child Care & Early Education Research Connections, n.d.; Vicente et al., 2024). Attending high-quality early education programs increases a child's likelihood of meeting school goals, adjusting to demands, performing better in reading and arithmetic, having advanced language abilities, having good attitudes and self-perceptions, and having a tighter bond with teachers (Vicente et al., 2024). Thus, to check and offer higher quality ECE settings, HSPPS indicated and emphasized the importance of state Quality Rating and Improvement Systems as quality indicators and encouraged participation (DHHS, 2024b). Critical high-quality education continues to be impeded by teacher turnover, especially pertaining to teacher and child interaction (Markowitz et al., 2024). Research indicated a correlation between depressive symptoms and teacher turnover among those working in pre-K, HS, and subsidized childcare settings serving children from birth to five, as well as a negative correlation between depressive symptoms and teacher-child interactions, specifically among preschool teachers (Markowitz et al., 2024).

Impacts on Under-resourced Communities and Under-enrollment

Children in under-resourced communities are particularly vulnerable to the negative effects of teacher turnover, disproportionately hindering their development (Bitler et al., 2017; Vicente et al., 2024; Kwon et al., 2025). In other words, HS/EHS programs that operate to benefit low-income families need to address the challenges of increased teacher turnover first (Kwon et al., 2025). In 2024, the federal poverty level was referred to individuals who earn less than $15,060 per year, with an additional $5,380 per additional family member (DHHS, 2024a). This metric is used to determine qualification for HS and EHS (DHHS, 2024b).

According to Roos et al.'s (2019) research, 46,589 children lived in low-income neighborhoods across Manitoba, Canada, between 2000 and 2009. This study showed that children from poverty-stricken backgrounds were more likely to be unprepared for school than children from more affluent families in the five different domains: physical health and well-being, social competence, emotional maturity, language, cognitive development, and communication skills and general knowledge. The goal of HS/EHS is to help create children's school readiness through the provision of educational, health, nutritional, social, and other services (Lynch, 2019) and eventually lead to the school's success by offering transition support to children living in poverty. This is because there is a relationship between poverty and school readiness/success (Brooks-Gunn & Duncan, 1997). Overall, HS/EHS are offering a foundation for children's holistic development. In other words, HS/EHS programs are at the front line of this phenomenon because HS/EHS programs serve approximately a third to half of families at the federal poverty level.

Since HS/EHS began, they have served 40 million children (ECLKC, 2024d), and in the 2023 fiscal year, 250,000 teachers were contracted across all of the United States. Between 2018-2019, HS served 49.4% of children in poverty. However, during COVID-19, from 2020-2021, HS covered only 31.2% of children in poverty (Schneider & Gibbs, 2023). This reduction occurred because HS/EHS are currently experiencing significant challenges, with many programs facing under-enrollment (DHHS, 2024b). The workforce shortage is considered a significant bi-directional factor affecting the quality of HS/EHS, which has led to under-enrollment. HS/EHS enrollment rates have continued to decrease since FY 2015. More specifically, a major decrease occurred in 2023, when enrollment fell to just under 537,000, as compared to the 680,000 children enrolled in HS programs in 2018 (Hutton, 2024).

Moreover, issues related to program quality — under-enrollment and turnover — can have potentially serious impacts on the experiences children have across all early childhood education settings (Blöchliger & Bauer, 2024). Eventually, a higher teacher turnover rate impacts overall ECE quality and leads to ECE outcomes. For example, children's academic and social-emotional skills, teacher and parent/family relationships, and teachers' working environment.

Social and Fiscal Costs of Teacher Turnover

Popular cost-benefit analyses of successful ECE programs have also demonstrated that it is wise for society to invest in teachers' wages and benefits, with society realizing savings from children's decreased need for remedial education, their decreased involvement in the criminal justice system, and their increased adult employment earnings (Heckman et al., 2010; Reynolds & Temple, 2008). A higher teacher turnover rate not only decreases children's development but also has social and fiscal costs.

Social Costs

Teacher turnover does not occur in a vacuum; it impacts society in a number of ways, as will be outlined below. First, educational administrators express frustration with hiring and training new teachers (Bassok et al., 2021a; Bassok et al., 2021c). Eventually, this strain trickles down to affect parents and families (Hur et al., 2023) who rely on their children attending educational programs so they can go to work during the day (Bassok et al., 2021a). For example, parents from low-income, do not have paid leave to take care of their children, when ECE centers close due to the teacher shortage (Jenkins & Nguyen, 2022). If this situation continues, parents may be forced to quit their jobs, resulting in children's households losing social benefits beyond just potential wage increases and contributions (Spector, 2017). Ultimately, this can lead to financial burdens for partners and families, potentially resulting in broader social problems in the future.

Contrarily, when HS programs are staffed appropriately and retain teachers, the social benefits amass. For example, prior research has shown that HS children made noticeable progress in reading and arithmetic in kindergarten compared to non-parental or parental care (Lee et al., 2013) and continued to improve through the early elementary years, performing about on par with national norms by the third grade (Puma et al., 2012).

Fiscal Costs

Economic mobility in the labor force is thought to be significantly influenced by education (Maier & Roach, 2024). More financially specific, the teacher turnover calculator – an interactive tool developed by the Learning Policy Institute (2024) that models the estimated costs and savings associated with teacher turnover – shows how much would be saved by cutting teacher turnover in half. This is an interactive tool that asks two questions to estimate the cost of turnover. First, the teacher turnover calculator asks about “How many teachers left your school or district?” Second, “What’s the cost of replacing a teacher?” Using this tool, educators can estimate how much it costs the district to replace teachers based on how many students are enrolled in the district. For example, a small district with 10,000-12,000 enrollees would incur a cost of about $12,000 per teacher who leaves. In addition to the costs of recruiting, hiring, and training new teachers, there are also expenditures and many hours associated with processing a teacher’s departure (Learning Policy Institute, 2024). Given this calculation, it is easy to see how much it costs a district when even as many as five teachers depart the district during an academic year. To see these costs in a real-world context, consider the Chicago school district. Each teacher who leaves the Chicago Public Schools system costs the district $17,872. Chicago could save millions of dollars and lower teacher turnover by implementing an efficient retention plan, such as a top-notch induction program that costs $6,000 per teacher (Barnes et al., 2007). The staffing crisis puts too much strain on the directors as they have to spend a lot of time recruiting and training new staff (Blöchliger & Bauer, 2024). Eventually, higher turnover eventually creates an unhealthy environment in early childhood care and education, leading to overall higher financial costs, in addition to the social risks associated with this issue. Through the conceptual framework (Figure 2.1), it is clear that the ECE teacher workforce also has broader impacts on the overall economy.

Reasons for Teachers' Departure

Why are teachers leaving, and when they leave, why are they not staying in the ECE profession? ECE teachers suffer from low compensation packages, such as benefit policies and low wages, which are some of the major reasons that make teachers leave (Cassidy et al., 2011; Hur et al., 2023; Vicente et al., 2024). Moreover, increased responsibilities come with extremely low compensation and inadequate benefits for the majority of early childhood educators.

Low Wages and Benefits

According to Schaack et al. (2020), in recent national studies of the birth to-five ECE workforce, most teachers working outside of district-based pre-kindergarten programs are paid so little that they are eligible for public benefits in almost every state, including food stamps and free or reduced lunch rates for their own children (Whitebook et al., 2016). Schaack et al. (2020) conducted a qualitative study to explore the factors influencing teacher turnover and retention decisions.

Grunewald et al. (2022) divided three different categories for ECE teachers based on center type and funding source. First, the Head Start-funded, not school-sponsored teachers make $14.95 per average hourly wage. Second, teachers in public pre-K funded programs that are neither school-sponsored nor HS-funded earn $16.45 per average hourly wage. Third, those in school-sponsored programs receive $20.99 per average hourly wage (Grunewald et al. 2022). Thus, HS teachers received the lowest wages among the center types. This phenomenon of low wages and compensation is directly connected with higher teacher turnover rates. Teachers' wages and turnover rate are correlated by an average turnover decrease as wages increase (Grunewald et al., 2022).

The study focused on understanding why some early childhood education teachers stayed in their jobs while others chose to leave. The research involved 26 teachers from HS/EHS, and state preschool programs, who were divided into two groups: stayers and leavers. Interviews with both groups were coded and analyzed using a job demands and resources framework (Schaack et al., 2022). The findings revealed that teachers' financial instability and distress led to economic anxiety, which eventually caused them to leave (Kwon et al., 2025; Schaack et al., 2020). Thus, for many years, it has been recognized that early education working conditions, including compensation, need to be improved (Vicente et al., 2024). In particular, earnings are not enough to cover the state's cost of living. To illustrate, one of the teachers stated: "Our staff is so poor. Sometimes they are struggling as much as the families that they're serving" (Vicente et al., 2024, p. 1472). It is important to note that stayers stated that one of the factors that contributed to their decision to stay after receiving a pay raise was the availability of benefits, such as reduced-rate child care and professional development opportunities (Vicente et al., 2024).

Vicente et al.'s (2024) research used a descriptive research design and analyzed secondary data using qualitative and quantitative methods. The majority of survey participants were directors, supervisors, and managers. They also held a focus group to speak with employees who worked in the HS/EHS programs. One drawback of their findings was that they are focused on the narratives of directors and supervisors, rather than underscoring the voices and stories of ECE teachers in HS/EHS programs.

Additionally, reasons for leaving low-wage and low-benefit jobs are not only constrained to the lead teachers; assistant teachers are affected (Hur et al., 2023). However, depending on the teacher's position (e.g., lead or assistant), reasons for leaving slightly differ. For instance, it appears that paid maternity/paternity leave and retirement or pension plans may be more significant to lead teachers than other benefits. On the other hand, the availability of several additional benefits, such as health insurance, paid maternity and paternity leave, paid sick days, and health benefits, may be critical to assistant teachers (Hur et al., 2023). Furthermore, heavy-duty work and low pay do not align with teacher's higher job satisfaction (Jeon & Wells, 2018). Several previous research findings reveal that increasing teachers' compensation packages is considered one of the most critical ways to alleviate teacher turnover and create a high-quality early childhood environment. Historically, higher-wage teachers are expected to have a better quality of education compared with lower-wage teachers (Helburn & Howes, 1996). This dissatisfaction with wages and benefits pushed many teachers to leave the field altogether. This phenomenon acutely impacted various sectors mentioned above.

Low wages and compensation are not the only factors that determine whether teachers leave or stay; there are other mediating or moderating variables to consider. Yet, many researchers have indicated that low wages and compensation are the strongest factors associated with TTR.

Lack of Supporting Environment

The lack of a supporting environment can contribute significantly to teacher turnover. Teachers desire professional development and communication with other teachers (Vicente et al., 2024). According to Blöchliger and Bauer (2024), one of the strategies to retain teachers is a good team climate. In their recent study, they conducted structural equation modeling to develop a Job Demands-Resources (JD-R) model. In the

JD-R model, the research included not only job demands and job resources but also burnout and job satisfaction as turnover intention indicators. Collecting data from teachers and directors via a questionnaire, the study assessed reasons for staying or leaving. Job intentions were categorized into six different factors, team and work climate being one of them. When teachers can connect with other teachers and the environment, they are motivated to stay at their jobs (Blöchliger & Bauer, 2024). For example, the teacher expressed, "I think, if I could have got more time away from the classroom to actually plan, clean, do stuff like that, the job would have been less frustrating" (Schaack et al., 2020, p.334).

Personal Reasons

Personal reasons, like motherhood or caregiving for ill parents, are a common reason that leads ECE teachers to depart (Blöchliger & Bauer, 2024). According to Fee's (2024) research on child care workers 94.8% are women, and preschool and kindergarten teachers are 97.7% women. One of the reasons teachers leave child care and early education jobs is that they cannot find a center to bring their own children to, forcing them to call in to work themselves. Additionally, teachers are not able to afford the cost of child care, which is one-third or more than their income (Gould, 2015). Alarmingly, many preschool and child care educators cannot afford child care for their own children, since the cost of child care in many states is equivalent to one-third or more of child care workers' earnings (Gould, 2015). This situation shows that this is a problem that extends beyond merely child care and the early education sector. Moreover, having access to adequate child care opens the door to employment opportunities for all families, it is especially critical for low-income families (Cohen, 1996). Cumulatively, all occupations are impacted by a lack of early childhood educational practitioners, but notably, this phenomenon impacts women the most.

Overlooking the Importance of ECE

Overlooking the critical role of the ECE workforce hinders the amount of care that families are able to access (McLean et al., 2024). Caring for others is a fundamental human experience that transcends cultural boundaries (Minof & Coccia, 2024). The act of caregiving serves a crucial social and economic function while also fostering deep, lasting connections between individuals (Minof & Coccia, 2024). This reciprocal process reinforces our sense of belonging within a community (Minof & Coccia, 2024). However, despite its immense societal and economic importance, caregiving responsibilities frequently fall on the shoulders of individuals who receive minimal or no support from the broader community (Minof & Coccia, 2024). Markowitz (2024) offered a critical connection between HS teacher turnover and children's outcomes. Children's school readiness has been adversely affected by HS teacher turnover, and there is suggestive evidence pointing to impacts on their behavior.

Systemic Undervaluing of Women

Historically, education has been considered a female profession, and over time, women have continued to be significantly underpaid compared to men. The expansion of the public education system was driven by common school reformers who advocated for hiring more female teachers at lower wages (Merlin, 2022). These discrepancies in income between male and female teachers are critically connected with the devaluation of education (Merlin, 2022). Among all school-aged teachers (i.e., grades K-12), female teachers on average make about $2,200 less than male teachers (Will, 2023). Furthermore, this vital work often goes undervalued and inadequately compensated, failing to reflect its true worth to society (Minof & Coccia, 2024). Every day, millions of young children are nurtured and their development is facilitated by early childhood educators, who are mostly women and frequently women of color (McLean et al., 2024). The working circumstances for early educators today jeopardize their well-being and cause terrible financial uncertainty far into retirement age, despite their significant expertise, complicated abilities, and crucial profession (McLean et al., 2024). Eventually, increasing wages is a way to overcome the perpetually undervalued ECE system—a female-dominated field, in which more than 98% of teachers in HS are female (SEE-Partnerships, 2023). Among ECE teachers, women of color face greater pay inequality, earning thousands of dollars less than their coworkers (McLean et al., 2024).

Again, based on the findings from the literature review, I conceptualize that the ECE workforce impacts the surrounding environment, and is also impacted at the macrosystem level, by policy-level decisions. These components affect teacher turnover, which in turn affects the overall ECE environment (see Figure 2.1). Therefore, my research focuses on how wages and compensation relate to TTR by investigating the existing PIR data sets. While there are other potential factors that influence the TTR, they are not a part of the data set being used in this analysis. Understanding and examining teacher turnover in ECE environments is important, as it becomes a key leverage for policymakers aiming to narrow the opportunity gap for children from low-income families (Duncan & Sojourner, 2013; Schaack et al., 2020).

CHAPTER THREE

METHODS AND DATA ANALYSIS

Research Questions and Research Hypotheses

This study evaluates the effects of the anticipated and first year implementation of the 2024 HSPPS revision on: 1) classroom teachers' turnover rates [Class_TTR], 2) classroom teachers' actual wage increase rates [ClassT_Real_Wage_Growth]; and 3) classroom teachers' raw wages [ClassT_Raw_Wage]. To explore these phenomena, this study addressed the following research questions (RQs):

RQ1: What is the impact of the 2024 HSPPS announcement (as an anticipation effect) and its initial implementation in 2025 on classroom teachers' turnover rates when considering:

a. Program type (Head Start vs Early Head Start);
b. State; and
c. Representative education level of classroom teachers within each program?

RQ2: What is the impact of the 2024 HSPPS announcement (as an anticipation effect) and its initial implementation in 2025 on classroom teachers' actual wage increase rates when considering:

a. Program type (Head Start vs Early Head Start);
b. State; and
c. Representative education level of classroom teachers within each program?

RQ3: What is the impact of the 2024 HSPPS announcement (as an anticipation effect) and its initial implementation in 2025 on classroom teachers' raw wages when considering:

a. Program type (Head Start vs Early Head Start);

b. State; and

c. Representative education level of classroom teachers within each program?

RQ4: To what extent do classroom teachers' actual wage increase rates predict classroom turnover rates, before and after 2024, when considering:

a. Program type (Head Start vs Early Head Start);

b. State; and

c. Representative education level of classroom teachers within each program?

Table 3.1 provides hypotheses associated with each research question.

Table 3.1

Research Hypotheses Categorized by Research Questions

RQ	Hypotheses
RQ1	H1: The 2024 HSPPS leads to a significant decrease in the turnover rates of classroom teachers in the treatment group compared to the comparison group. H1a-c: The impact of the HSPPS on classroom teacher turnover varies significantly by (a) program type, (b) state, and (c) representative education level of classroom teachers within each program
RQ2	H2: The 2024 HSPPS leads to a significant increase in the classroom teachers' actual wage increase rates in the treatment group compared to the comparison group. H2a-c: The impact of the 2024 HSPPS on classroom teachers' actual wage increase rates varies significantly by (a) program type, (b) state, and (c) representative education level of classroom teachers within each program

Table 3.1 – Continued

RQ	Hypotheses
RQ3	H3: The 2024 HSPPS leads to a significant increase in the classroom teachers' raw wages in the treatment group compared to the Comparison Group. H3a-c: The impact of the 2024 HSPPS on classroom teachers' raw wages varies significantly by (a) program type, (b) state, and (c) representative education level of classroom teachers within each program
RQ4	H4: There is a relationship between the classroom teacher's turnover rate and the classroom teachers' actual wage increase rates before and after 2024 H4a-c: The relationship between the classroom teacher's turnover rate and classroom teachers' actual wage increase rates before and after 2024 varies significantly by (a) program type, (b) state, and (c) the representative education level of classroom teachers within each program

To address the research questions, I used a quantitative design to analyze secondary data from the Head Start Program Information Report (PIR). Head Start (HS) and Early Head Start (EHS) PIR data contain five different levels of information: state, city, grantee, region, and program-level. PIR data included the same programs across multiple years, hence it is panel data (Princeton University Library, 2024).

Sample

Data Source

The PIR disseminates data each year as a target for the HS/EHS programs. It also included a combination of survey data and established records, such as student enrollment and family records. The PIR is considered the official data set from the federal agency in charge (i.e., DHHS). Each year, the PIR includes information for more than 2,900 programs across the nation, which helps this study have strong generalizability with a large sample size (Creswell, 2019; see Table 2). Moreover, it contains robust data on program information, program staff and qualifications, and child and family services. Overall, this study employed a cross-sectional survey research design, which means data were collected all at one time, without a control condition (Creswell, 2019). I downloaded data sets from the Head Start Enterprise System (HSES), which is operated by the Office of Head Start (OHS). Comprehensive services are provided to specific communities through grants that the OHS appropriates to public and private agencies in a competitive process. This grant appropriation approach is one of the major characteristics of HS/EHS. Head Start grantees deliver services following the Head Start Program Performance Standards (HSPPS) and the 2007 Head Start Act (Office of Head Start, n.d.). Thus, each of the programs is nested within the grantee, and in turn, the grantee is nested within the state. Some of the grantees are within the city, and the city is nested within the state. However, there is an exception; for example, Oakland Livingston Human Service Agency (OLHSA) is a grantee for Oakland and Livingston counties in Michigan.

Time Frame

This study followed the time frames stipulated by PIR. PIR data were collected and released based on each academic school year (i.e., 2023.09.01-2024.08.31). This study used a total of four academic years of PIR data – 2022 to 2025 – to include before and after the 2024 HSPPS announcement (which occurred November 20, 2023) and the first year of policy execution (i.e., the 2024-2025 academic year). Due to changes in the questionnaire methodology implemented in 2021, data collected prior to that year were not included in this study.

Sampling Procedure

I limited the program type to HS and EHS for the purposes of this study. The PIR data sets include six program types: HS, EHS, American Indian and Alaska Native (AIAN) HS, AIAN EHS, Migrant and Seasonal Head Start (MSHS) HS, and MSHS EHS. Except for HS and EHS, the remaining four program types serve highly specific populations, such as tribal communities and families engaged in agricultural or seasonal work (ACF, 2025b). These specialized programs are not representative of the broader HS and EHS population. While they also comprise a relatively small number of programs (e.g., only 264 programs across AIAN HS/EHS and MSHS HS/EHS in the 2024 PIR data set), their exclusion is based primarily on their targeted nature rather than on sample size alone.

Although the PIR data set included the 50 U.S. states, Washington, D.C. and several U.S. territories (e.g., Puerto Rico, Guam, and the U.S. Virgin Islands), this study was restricted to the 50 states. Consequently, I removed observations from the territories and Washington, D.C.

Mitigating Data Limitations

In the data sets, PIR data sets provided average rather than median wage information at the state-level. Additionally, PIR data sets only offer wage data by state. Nevertheless, to prevent multicollinearity, I assigned data based on the representative education level of classroom teachers within each program. Thus, over 76% of the wage variation stems from within-state differences among programs, as confirmed (see Appendix B). This finding demonstrates that the estimated wage variable captures sufficient variation to ensure that the estimation of policy affects classroom teachers' real growth and classroom teachers' raw wages.

Study Design

Sun et al. 's (2016) research considered the relationship between policy and teacher turnover and the No Child Left Behind (NCLB) Act of 2001. Sun et al. (2016) offered methodology standards for the policy impact on the education environment, namely the difference-in-differences (DiD) approach. The DiD approach allows for the calculation of the treated effect by examining the difference in average teacher turnover probability. In their work, Sun et al. (2016) found a disparity in the average probability of teacher turnover between pre- and post-NCLB implementation for both the treatment and comparison group (Sun et al., 2016). In other words, the main point of the DiD approach is that there are treatment and comparison groups. The 2024 HSPPS revisions regarding wages and benefits are applicable only when the total funded enrollment exceeds 200 slots. This indicates that most of the rules regarding wage and benefit conditions do not apply to small agencies with 200 or fewer funded slots (DHHS, 2024b). Small HS agencies (defined as those with 200 or fewer funded slots) are exempt from the wages, and some of the benefits still have a pay scale or structure that promotes competitive wages (DHHS, 2024b). Thus, this study used programs with more than 200 slots and after the 2024 academic year as the treatment group and those with 200 or fewer funded slots and before the 2024 academic year as the comparison group. Programs with more than 200 funded slots, but before the 2024 academic year considered as baseline. This baseline, before treatment, offered an initial reference point for evaluating the policy's impact and offers a valuable criterion (Corral & Yang, 2024; See Table 3.2).

Table 3.2

DiD Design: Treatment and Comparison Group Definitions

	Pre - 2024	**Post - 2024**
More than 200 funded slots	Treatment Group (Status: before treated / Baseline)	Treatment Group (Status: after treated / Treated)
200 or fewer funded slots	Comparison Group (Status: not treated)	Comparison Group (Status: not treated)

To address the first three research questions, I employed a DiD approach. Accordingly, I conducted the analyses through the following four steps: (1) calculating the intraclass correlation coefficient (ICC) to assess the proportion of variance at each level; (2) applying variables into the fixed effects depending on the ICC results; (3) analyzing DiD to evaluate the policy; (4) conducting a placebo test using the 2022 to 2023 year for the period following the announcement of the policy but prior its enactment to obtain pre-trend assumptions; (5) performing event study; and (6) conducting a heterogeneous analyses by program types, states and representative education level of classroom teachers within each program. Additionally, it is common to report DiD results with clustered standard errors (*SE*) at the institution or state-level (Corral & Yang, 2024). This study also reported clustered *SE* at the grantee-level for the first research question, and state-level *SE*s were reported for the second and third research questions.

To address the fourth research question, I employed a multilevel modeling (MLM) approach. I also applied ICC results from the first to third research questions, and accordingly, I conducted the analyses through the following three steps: (1) identified the best model fit, (2) analyzed MLM, (3) conducted heterogeneous analysis by program types, states, and representative education level of classroom teachers within each program. The current study offers the methodology of causal effect of natural experiments (Corral & Yang, 2024) in classroom teacher turnover outcomes before and after the 2024 HSPPS anticipation effects.

Data Analysis

Variables

This study relied on data from two sections of the PIR. PIR organized data by section, such as section A and B. Section A is program information, which includes funded enrollment and classes in center-based settings. Section B includes program staff & qualifications, such as total staff, education and child development staff, and staff turnover (ACF, 2024a). I also used Bureau of Labor Statistics data for this study. There are two types of variables, which are original variables from data sets and generated variables. Table 3.3 depicts the variables examined in the current study and distinguishes between original and generated variables.

Table 3.3

Variables

Variables	Abbr.	Equation	Source	Type
State	State	General information: Program state - Geographic location of program by state	PIR	Original
City	City	General information: Program city - Geographic location of program by city	PIR	Original
Grantee	Grantee	General information: Program grantee - Identification of the each of program's grantee	PIR	Original

Table 3.3 – Continued

Variables	Abbr.	Equation	Source	Type
Region	Region	General information: Program region - Geographic location of program by region	PIR	Original
Program	Program	General information: Program ncumber - Identification number for Each of program	PIR	Original
Program types (HS vs EHS)	Program types	General information: program types - HS - EHS	PIR	Original
Classroom teachers turnover rate	Class_TTR	Number of classroom teachers who left (B.17-c) / number of classroom teachers (B.3-1+B6) $\times$ 100 = TTR B.3-1: Total number of preschool education and child development staff by position of classroom teachers B.6: Total number of infant and toddler classroom teachers B.17-c: B17 of these, the number that were classroom teachers who left the program	PIR	Generated

Table 3.3 – Continued

Variables	Abbr.	Equation	Source	Type
Number of classroom teachers by education level	Classroom Teacher Education level	B.3-1 and B.6: Of the number of preschool education and child development staff by position of classroom teachers and infant and toddler classroom teachers: a. An advanced degree b. A baccalaureate degree c. An associate's degree d. A Child Development Associate (CDA) credential or state-awarded certification, credential, or licensure that meets or exceeds the CDA e. None of the qualifications listed in B.3 a through B.3.d	PIR	Original
Representative education level of classroom teachers within each program	Rep_ Teacher_ Edu	Number of classroom teachers in each of the education levels [Classroom_Teacher_Education_level] / number of classroom teachers (B.3-1+B6) x 100 = Percentage of each of the classroom teachers' Education level Selected the education level of more than 40% if there is none, categorized as Mixed-Multi	PIR	Generated

Table 3.3 – Continued

Variables	Abbr.	Equation	Source	Type
Classroom Teachers' raw wages by education level	ClassT_ Raw_Wage	Classroom teacher's wage by education level B.11: a. An advanced degree b. A baccalaureate degree c. An associate's degree d. A Child Development Associate (CDA) credential or state-awarded certification, credential, or licensure that meets or exceeds the CDA e. None of the qualifications listed in B.3 a through B.3.d	PIR	Original
Classroom teachers' wage increased percentage	ClassT_WIP	(Year's wage - (Year-1)'s wage) / (Year-1)'s wage × 100 (B.11)	PIR	Generated
State inflation rates (Consumer Price Index)	CPI_State	(Year's State CPI - (Year-1)'s State CPI) / (Year-1)'s State CPI Each of the state's yearly CPI × 100	U.S. Bureau of Labor Statistics	Generated

Table 3.3 – Continued

Variables	Abbr.	Equation	Source	Type
Classroom Teachers' actual wage increase rates	ClassT_ Real_Wage_ Growth	Year's ClassT_WIP - CPI_State = ClassT_Real_Wage_Growth		Generated
treat	treat	A dummy variable representing program size: - Funded enrollment by funding source > 200 = 1 - Funded enrollment by funding source $\leq$ 200 = 0 (at or below 200 slots)	PIR	Generated
prepost	prepost	A dummy variable to capture periods before and after the 2024 HSPPS - Before 2024 = 1 - After 2024 = 0	PIR	Generated
did	did	The interaction term between treat and prepost variables used to create comparison and treatment groups - treat $\times$ prepost		Generated

Original variables. Original variables refer to variables from the dataset without any additional processing, such as state, city, grantee, region, program, program type, classroom teachers' education level, and classroom teachers' raw wage.

First, the PIR data set included demographic information: [State], [City], [Grantee], [Region], and [Program Type], and other descriptive information, such as zip code. Second, PIR data included teachers' descriptive information such as education level, teacher's position, and ethnicity/race. There are four types of teacher positions: Classroom Teachers, Assistant Teachers, Home-Based Visitors, and Family Child Care Providers. Of note, this study only included classroom teacher positions. Due to the structure of the data, only wage data and turnover rates for different positions were available for classroom teachers; other teacher positions were not included. For example, only state-level wage data was available for assistant teachers, and a separate turnover rate was not provided.

Generated variables. On the other hand, by using the dataset, I generated variables such as classroom teachers' turnover rates, classroom teachers' wage increased percentage, State inflation rates (consumer price index), classroom teachers' actual wage increase rates, treat, prepost, and did.

First, the classroom teachers' turnover rate, represented as [Class_TTR], is mainly occupied in section B, which included survey questions and a recording of teachers' turnover information. The PIR data sets are organized into three staff turnover categories: (1) all staff turnover, (2) education and child development staff turnover, and (3) classroom teacher turnover. All staff turnover refers to the total number of staff who left during the program year, including turnover that occurred while the program was not in session, such as during the summer months (ACF, 2024a). Education and child development staff turnover refers to the number of classroom teachers, assistant teachers, home-based visitors, and family child care providers who left during the program year (including turnover that occurred while classes and home visits were not in session, such as during the summer months; ACF, 2024a). Classroom teacher refers to the number of only classroom teachers in both HS and EHS. Once again, the PIR data sets only provide a distinguishable turnover rate for classroom teachers.

Second, I created [Rep_Teacher_Edu] from [Classroom_Teacher_Education_level] to determine the representative education level of classroom teachers within each program. [Classroom_Teacher_Education_level] is divided into six categories: advanced degree, baccalaureate degree, associate's degree, Child Development Associate (CDA), none of the above qualifications, and mixed-multi. I calculated the number of classroom teachers in each education level as a percentage of all classroom teachers within each program. These percentages were then used to categorize each of the programs. For example, if more than 40% of program A's classroom teachers hold a bachelor's degree, Program A is categorized as a "bachelor-focused" program. If no single education level exceeds the 40% threshold and more than one exceeds the 40% threshold, the program is categorized as "mixed-multi." Consequently, the programs were classified into six distinct categories, including the "mixed-multi" designation. For clarity, I reframed the advanced degree as an advanced focus, bachelor's degree as a bachelor's focus, associate degree as an associate focus, CDA as a CDA focus, and none of the above qualifications as a no-qual focus. The mixed-multi remained the same.

Third, [ClassT_Raw_Wage] represents classroom teachers' raw wages data, which are primarily organized at the state-level into two different categories: wage by position (e.g., classroom teachers, assistant teachers) and classroom teacher wage by level of education. PIR data offers [Classroom_Teacher_Education_level] consisting of five different categories: advanced degree, baccalaureate degree, associate degree, child development associate (CDA), and "None of the qualifications above." For example, according to the PIR data set, in the State of California, these categories correspond to incremental wage levels: $65,722 (advanced), $60,421 (baccalaureate), $53,988 (associate), $52,659 (CDA), and $48,144 (none of the qualifications above). By using generated variables from [Rep_Teacher_Edu] that Programs that are categorized in mixed-multi's wage data were calculated from the average of all of the education levels of the teachers' wages.

This study selected and included classroom teacher wages by education level to provide variation in the wage data. A few states lacked wage data for certain education levels—particularly for the "None of the qualifications above." For example, the State of Alaska did not provide wage data for classroom teachers in this category. In such cases, I calculated the missing values based on the average wage of the other available education levels. After that, I assigned each program as [ClassT_Raw_Wage] accordingly [Rep_Teacher_Edu]. Thus, I assigned classroom teachers' raw wages by education level data based on the representative education level of classroom teachers within each program. This approach created variation within each state, enabling a state-level analysis even when only state-level wage data were available.

Fourth, [ClassT_WIP] represents the classroom teachers' wage increased percentage following [ClassT_Raw_Wage], which was assigned by [Rep_Teacher_Edu]. After that, the increased percentage of the previous wage data is calculated: [ClassT_WIP].

Fifth, [CPI_State], Mackenzie-Liu et al.'s (2024) research also used PIR as the primary average wage data sets and the U.S. Bureau of Economic to report unadjusted and adjusted wages for HS/EHS. I conducted an analysis of regional price parities for states to account for the cost of living, which included goods, services, and housing that were able to reflect the difference between states' economic statuses. Adapting this model, I also used consumer price index (CPI) data provided by the U.S. Bureau of Labor Statistics to calculate the exact percentage of increase by geographic difference (U.S. Bureau of Labor Statistics, n.d.). However, these data were presented by region, rather than by state (i.e., Southeast, Western, Southwest, Northeast, Mountain-Plains, and Mid-Atlantic). Some large metropolitan areas, like Dallas-Fort Worth-Arlington in Texas, are also provided. Thus, the U.S. Bureau of Labor Statistics did not offer a CPI for all 50 states. In the absence of such data, I used the regional CPI. All original data of CPIs for urban consumers were downloaded and calculated for the same duration as the program year (e.g., 2023.09.01-2024.08.31) and compared with the previous year to calculate the CPI increase percentage. This process helped to control exogenous variables that arise from different environments in each state.

Sixth, [ClassT_Real_Wage_Growth], which represents classroom teachers' actual wage increase rates, is reflected as [ClassT_WIP] subtracted from the [CPI_State]. I calculated [ClassT_Real_Wage_Growth] for every year, which is an indicator to compare each state, while the cost of living varies by state.

Lastly, I created three dummy variables to conduct the difference-in-differences (DiD) and multilevel modeling (MLM) analyses: [treat], [prepost], and [did]. First, I assigned and created a dummy variable [treat] to represent program size. If a program had more than 200 enrollment funded slots it was given a source value of 1, and otherwise it had a value of 0. Second, I assigned and created a dummy variable [prepost] to capture periods before and after the 2024 HSPPS. The period starting in 2024 (post-policy announcement) was valued as 1, and the period before 2024 was valued as 0. And, lastly, I created [did] as an interaction term between [treat] and [prepost]. A value of 1 indicated the treatment group during the post-policy period, while a value of 0 represented the baseline for comparison.

To consider the data structure, I calculated and evaluated across five distinct categorical levels using the intraclass correlation coefficient (ICC). The first and fourth research questions have the same dependent variable as [Class_TTR]. The second research question has dependent variables as [ClassT_Real_Wage_Growth], and the third research question has dependent variables as [ClassT_Raw_Wage]. Thus, I conducted three separate ICCs.

Intraclass Correlation Coefficient (ICC) for RQ1 and RQ4

I performed ICC with variable [Class_TTR]. The program showed large variability between groups (ICC = .223; see Table 3.4). Furthermore, the proportions of variance at the grantee (ICC = .176) and city (ICC = .146) levels were statistically meaningful, exceeding 0.05. The state (ICC = .036) was less than .05. However, given these significant proportions of variance at [Grantee] and [City] levels, and the fact that wage data was only offered at the state-level, the following model was used; thus, for the first research question, I included [State], [City], [Grantee] and [Program] as fixed effects. For the fourth research question, I implemented a three-level hierarchical structure for [State], [City], and [Grantee] to model the outcomes. I took this approach because MLM uses a programme as a unit of analysis.

Table 3.4

RQ1 and RQ4 ICC in State, City, Grantee, Region, Program

Level	Adjusted ICC	Unadjusted ICC
State	.036	.036
City	.146	.146
Grantee	.176	.176
Region	.012	.012
Program	.223	.223

Intraclass Correlation Coefficient (ICC) for RQ2 and RQ3

I also performed ICC with the variable [ClassT_Real_Wage_Growth]. The region showed large variability between groups (ICC = .231; see Table 3.5). Furthermore, the proportions of variance at the State (ICC = .123).

Table 3.5

RQ2 ICC in State, City, Grantee, Region, Program

Level	**Adjusted ICC**	**Unadjusted ICC**
State	.123	.123
City	.037	.037
Grantee	.039	.039
Region	.231	.231
Program	.011	.011

Furthermore, I performed ICC with the variable [ClassT_Raw_Wage]. The program showed large variability between groups (ICC = .574; see Table 3.6). Furthermore, all of the [State], [City], [Grantee], [Region], and [Program] showed larger proportions of variance (more than .05).

Table 3.6

RQ3 ICC in State, City, Grantee, Region, Program

Level	Adjusted ICC	Unadjusted ICC
State	.412	.412
City	.482	.482
Grantee	.526	.526
Region	.326	.326
Program	.574	.574

Wage data were only offered at the state-level, which is directly connected with the second and third research questions, also computed from wage data. Thus, for the second and third research questions, among [State], [City], [Grantee], [Region], [Program], only [State] was included as a fixed effect. For the first research question, the program-level was the unit of analysis to account for the nested data structure and characteristics.

RQ 1 to 3

The first to third research questions examined the anticipation and the first year of Implementation of the compensation policy; thus, I conducted the DiD approach.

RQ1 Main DiD. I performed two different equations to answer the first research question. First, I utilized DiD with fixed effects (MLM structured). This model did include [State], [City], and [Grantee] as fixed effects (See Equation1). This study utilized a nested data set, as ICC showed there are significant proportions of variance in the grantee, city, and state.

$$\text{Class\_TTR}_{igcst} = \alpha + \beta_1 \text{did}_{it} + \alpha_i + \phi_g + \delta_c + \theta_s + \gamma_t + \varepsilon_{igcst} \tag{3.1}$$

- $Class\_TTR_{igcst}$: classroom teachers' turnover rates for the program i in the year t.

- β_1 : Coefficient of interest
- α_i : Program Fixed Effects (Program Number)
- ϕ_g : Grantee Fixed Effects (Grantee)
- δ_c : City Fixed Effects (City)
- θ_s : State Fixed Effects (State)
- γ_t : Year Fixed Effects (Year)
- ε_{igcst} : Idiosyncratic Error Term, clustered at the grantee-level

RQ1 Placebo Test. DiD is a "natural experiment" (Corral & Yang, 2024). The strongest assumption underlying DiD is the parallel trends assumption (Corral & Yang, 2024). Furthermore, DiD raises concerns about whether a policy takes time to take effect or has an immediate impact. To check for policy anticipation and the policy's effect, DiD research generally conducts a placebo test (Corral & Yang, 2024). I used a placebo test to analyze the presence of a parallel trend before the 2024 policy announcement to confirm the effectiveness of the policy. Thus, as Equation 3.2 showed, there is a subset of the data between only 2022 and 2023 used to check DiD. Equation 3.2 followed the same structure and assumptions as Equation 3.1; however, the data sets ranges were different.

$$\text{Class\_TTR}_{igcst} = \alpha + \beta_p \text{Placebo\_Group\_did}_{it} + \alpha_i + \phi_g + \delta_c + \theta_s + \gamma_t + \varepsilon_{igcst} \tag{3.2}$$

- $Placebo\_Group\_DiD_{it}$: Placebo interaction term using pre-treated years (up to 2023).
- β_p : Placebo estimator; a non-significant result validates the parallel trends assumption

RQ1 Event Study. Along with a placebo test, conducting an event study enables researchers to investigate complex but common scenarios in education policy research, such as dynamic treated impacts across time, and provides evidence of parallel pre-trends (Corral & Yang, 2024). Thus, to address the event study specification, I performed Equation 3.3. Equation 3.3 references 2022 to calculate the difference between the years 2023, 2024, and 2025.

$$\text{Class\_TTR}_{igcst} = \alpha + \sum_{k \neq 2022} \beta_k (\text{Treat}_i \times \mathbb{1}\{t = k\}) + \alpha_i + \phi_g + \delta_c + \theta_s + \gamma_t + \varepsilon_{igcst} \quad (3.3)$$

- β_k : Coefficients representing the dynamic effect of the policy for each year k relative to the reference year 2022.
- Treat_i: Indicator for the treatment group.
- $\mathbb{1}\{t = k\}$: Time dummy variable equaling 1 if the year is k, and 0 otherwise.

RQ1 Heterogeneity Analysis. First, the first research question, I derived the main DiD (Equation 3.1) from a sub-sample based on program type (i.e., HS and EHS) to identify potential differences in policy impact across program structures (see Equation 3.4).

$$\text{Class\_TTR}_{igcst} = \alpha_p + \beta_{1p} \text{did}_{it} + \alpha_i + \phi_g + \delta_c + \theta_s + \gamma_t + \varepsilon_{igcst}, \quad p \in \{\text{HS, EHS}\} \quad (3.4)$$

- $p \in \{HS, EHS\}$: Head Start and Early Head Start denote the specific program type.
- β_{1p} : is the group-specific coefficient of interest, capturing the policy effect for either HS or EHS programs

Second, in the first research question, I performed the main DiD (Equation 3.1) separately by state to identify potential differences in policy impact across states (see Equation 3.5). Especially across states, I performed multiple testing to test the same hypotheses. In this case, there is a high probability that some true null hypotheses will be rejected (Romano et al., 2016). Thus, I used the Bonferroni adjustment to prevent this circumstance, also known as the family-wise error rate. However, in many multiple testing settings, minimizing the family-wise error rate is too strict (Noble, 2009). Thus, as an alternative to the Bonferroni test, I also used the false discovery rate (FDR)'s Benjamini-Hochberg (BH) test. Equation 3.5 also did not include the state in the fixed effect.

$$\text{Class\_TTR}_{igct} = \alpha_s + \beta_{1s}\text{did}_{it} + \alpha_i + \phi_g + \delta_c + \gamma_t + \varepsilon_{igct}, \quad \forall s \in \text{States} \tag{3.5}$$

Third, to identify potential variation in policy impact across [Rep_Teacher_Edu], six different categories of [Rep_Teacher_Edu] were added to Equation 3.6, which I developed from the first research question main DiD (Equation 3.1). Furthermore, I conducted subgroup analyses by subsetting program types and states using Equation 3.6.

$$\text{Class\_TTR}_{igcst} = \alpha_g + \beta_{1g}\text{did}_{it} + \alpha_i + \phi_g + \delta_c + \theta_s + \gamma_t + \varepsilon_{igcst}, \quad \forall g \in \{1,\ldots,6\} \tag{3.6}$$

- $g \in \{1,\ldots,6\}$ subgroups defined by [Rep_Teacher_Edu] :

1. An advanced degree
2. A baccalaureate degree
3. An associate's degree
4. A CDA credential or state-awarded certification/licensure
5. None of the qualifications
6. Mixed-Multi

RQ2 and 3

Unlike the first research question, in the nation-level analysis, the standard errors for the second and third research questions were clustered at the state-level. Thus, the fixed effects only included state and year. The second research question used [ClassT_Real_Growth] as dependable and the third research question used [ClassT_Raw_Wage] (See Table 3.1).

RQ2 Main DiD. Equation 3.7 did not include [City], [Grantee], and [Program] as fixed effects.

$$\text{ClassT\_Real\_Wage\_Growth}_{st} = \alpha + \beta_1 \text{did}_{st} + \theta_s + \gamma_t + \varepsilon_{st} \tag{3.7}$$

- $ClassT\_Real\_Wage\_Growth_{st}$: Classroom teachers' real wage growth for states in year t.
- β_1: Coefficient of interest
- θ_s: State Fixed Effects
- γ_t: Year Fixed Effects
- ε_{ist}: Idiosyncratic error term, clustered at the state-level

RQ2 Placebo Test. To validate the parallel trends assumption, DiD research generally conducts placebo tests (Corral & Yang, 2024). This involves using Equation 3.7 on a subset of the data between only the years 2022 and 2023, which is before policy announcement or implication (see Equation 3.8).

$$\text{ClassT\_Real\_Wage\_Growth}_{st} = \alpha + \beta_p \text{Placebo Group\_did}_{st} + \theta_s + \gamma_t + \varepsilon_{st} \tag{3.8}$$

- Placebo Group_DiD$_{st}$: Placebo interaction term using pre-treated years (up to 2023)
- β_p: Placebo estimator; a non-significant result validates the parallel trends assumption

RQ2 Event Study. In the event study specification, I performed Equation 3.9. Equation 3.9 references 2022 to calculate the difference with years 2023, 2024, and 2025.

$$\text{ClassT\_Real\_Wage\_Growth}_{st} = \alpha + \sum_{k \neq 2022} \beta_k (\text{Treat}_s \times \mathbb{1}\{t = k\}) + \theta_s + \gamma_t + \varepsilon_{st} \quad (3.9)$$

- β_k : Coefficients representing the dynamic effect of the policy for each year k relative to the reference year 2022.
- Treat_s: Indicator for the treatment group.
- $\mathbb{1}\{t = k\}$: Time dummy variable equaling 1 if the year is k, and 0 otherwise.

RQ2 Heterogeneity Analysis. First, the second research question, I derived the main DiD (Equation 3.7) from a sub-sample based on program type (i.e., HS and EHS) to identify potential differences in policy impact across program structures (see Equation 3.10).

$$\text{ClassT\_Real\_Wage\_Growth}_{st} = \alpha_p + \beta_{1p}\text{did}_{st} + \theta_s + \gamma_t + \varepsilon_{st}, \quad p \in \{\text{HS, EHS}\} \quad (3.10)$$

Second, the second research question, I performed the main DiD (Equation 3.8) separately by state to identify potential differences in policy impact across states (see Equation 3.11). Equation 3.11 did not include the state in the fixed effect. Again, considering multiple testing, I used the Bonferroni adjustment and false discovery rate (FDR)'s Benjamini-Hochberg (BH). Moreover, I did not specify cluster levels as state-level and instead used robust *SE*.

$$\text{ClassT\_Real\_Wage\_Growth}_{st} = \alpha_s + \beta_{1s}\text{did}_{st} + \gamma_t + \varepsilon_{st}, \quad \forall s \in \text{States} \quad (3.11)$$

Third, to identify potential variation in policy impact across [Rep_Teacher_Edu], six different categories of [Rep_Teacher_Edu] were added to Equation 3.12, which I developed from the second research question's main DiD (Equation 3.7). Furthermore, I conducted subgroup analyses by subsetting program types and states using Equation 3.12.

$$\text{ClassT\_Real\_Wage\_Growth}_{st} = \alpha_g + \beta_{1g}\text{did}_{st} + \theta_s + \gamma_t + \varepsilon_{st}, \quad \forall g \in \{1,\ldots,6\} \tag{3.12}$$

RQ3 Main DiD. Equation 3.13 did not include [City], [City], and [Grantee] as fixed effects.

$$\text{ClassT\_Raw\_Wage}_{st} = \alpha + \beta_1\text{did}_{st} + \theta_s + \gamma_t + \varepsilon_{st} \tag{3.13}$$

- $ClassT\_Raw\_Wage_{st}$: Classroom teachers' raw wage for states in year t.
- β_1: Coefficient of interest
- θ_s: State Fixed Effects
- γ_t: Year Fixed Effects
- ε_{ist}: Idiosyncratic error term, clustered at the state-level

RQ3 Placebo Test. To validate the parallel trends assumption, DiD research generally conducts placebo tests (Corral & Yang, 2024). This involves using Equation 3.13 on a subset of the data between only of the years 2022 and 2023, which before policy announcement or implication (see Equation 3.14).

$$\text{ClassT\_Raw\_Wage}_{st} = \alpha + \beta_p\text{Placebo Group\_did}_{st} + \theta_s + \gamma_t + \varepsilon_{st} \tag{3.14}$$

- Placebo Group_DiD$_{st}$: Placebo interaction term using pre-treated years (up to 2023)
- β_p: Placebo estimator; a non-significant result validates the parallel trends assumption

RQ3 Event Study. In the event study specification I performed Equation 3.15. Equation 3.16 references 2022 to calculate the difference between the years 2023, 2024, and 2025.

$$\text{ClassT\_Raw\_Wage}_{st} = \alpha + \sum_{k \neq 2022} \beta_k (\text{Treat}_s \times \mathbb{1}\{t = k\}) + \theta_s + \gamma_t + \varepsilon_{st} \tag{3.15}$$

- β_k : Coefficients representing the dynamic effect of the policy for each year k relative to the reference year 2022.
- Treat_s: Indicator for the treatment group.
- $\mathbb{1}\{t = k\}$: Time dummy variable equaling 1 if the year is k, and 0 otherwise.

RQ3 Heterogeneity Analysis. First, for the third research question, I derived the main DiD (Equation 3.13) from a sub-sample based on program type (i.e., HS and EHS) to identify potential differences in policy impact across program structures (see Equation 3.16).

$$\text{ClassT\_Raw\_Wage}_{st} = \alpha_p + \beta_{1p}\text{did}_{st} + \theta_s + \gamma_t + \varepsilon_{st}, \quad p \in \{\text{HS, EHS}\} \tag{3.16}$$

Second, the third research question, I performed the main DiD (Equation 3.13), separately by state to identify potential differences in policy impact across states (see Equation 3.17). Equation 3.17 did not include the state in the fixed effect. Again, considering multiple testing, I used the Bonferroni adjustment and false discovery rate (FDR) Benjamini-Hochberg (BH) test. Moreover, I did not specify cluster levels as state-level and instead used robust SE.

$$\text{ClassT\_Raw\_Wage}_{st} = \alpha_s + \beta_{1s}\text{did}_{st} + \gamma_t + \varepsilon_{st}, \quad \forall s \in \text{States} \tag{3.17}$$

Third, to identify potential variation in policy impact across [Rep_Teacher_Edu], I added six different categories of [Rep_Teacher_Edu] to Equation 3.18, which I developed from the third research question main DiD (Equation 3.13). Furthermore, I conducted subgroup analyses by subsetting program types and states using Equation 3.18.

$$\text{ClassT\_Raw\_Wage}_{st} = \alpha_g + \beta_{1g}\text{did}_{st} + \theta_s + \gamma_t + \varepsilon_{st}, \quad g \in \{1, \ldots, 6\} \tag{3.18}$$

RQ4

To examine the relationship on classroom TTR between classroom teacher actual wage increase rates and pre- and post- 2024 HSPPS, I used a multilevel modeling (MLM) approach. MLM allows for nested data where Level 1 (Time/Observation) is nested within Level 2 (Grantee), which is nested within Level 3 (City), and finally nested within Level 4 (State). This structure ensures that variance at each level is appropriately modeled. While there are some exception grantees like OLHSA, however, city-level ICC results showed higher than state-level thus, city-level included a more conservative and accurate estimation for analysis. Thus, the first to third research questions followed ICC results with added fixed effects, and the fourth research question was conducted using MLM.

Model Fit. Following the research question, I constructed three different models.

$$\text{ClassT\_TTR}_{it} = \beta_0 + \beta_1\text{PrePost}_{it} + \beta_2\text{ClassT\_Real\_Wage\_Growth}_{it} + u_s + v_{c(s)} + w_{g(cs)} + \varepsilon_{it} \tag{3.19}$$

$$\begin{aligned} \text{ClassT\_TTR}_{it} = \beta_0 + \beta_1\text{prepost}_{it} + \beta_2&\text{ClassT\_Real\_Wage\_Growth}_{it} \\ &+ \beta_3(\text{prepost}_{it} \times \text{ClassT\_Real\_Wage\_Growth}_{it}) \\ &+ u_s + v_{c(s)} + w_{g(cs)} + \varepsilon_{it} \end{aligned} \tag{3.20}$$

$$\begin{aligned} \text{ClassT\_TTR}_{it} = \beta_0 + \beta_1\text{prepost}_{it} + \beta_2&\text{ClassT\_Real\_Wage\_Growth}_{it} \\ &+ (u_{0s} + u_{1s}\text{ClassT\_Real\_Wage\_Growth}_{it}) \\ &+ (v_{0c(s)} + v_{1c(s)}\text{ClassT\_Real\_Wage\_Growth}_{it}) \\ &+ (w_{0g(cs)} + w_{1g(cs)}\text{ClassT\_Real\_Wage\_Growth}_{it}) + \varepsilon_{it} \end{aligned} \tag{3.21}$$

- β_1 is the coefficient for prepost, representing the average change over time.

- β_2 is the coefficient for classroom teachers real wage growth, representing the average effect of wage increases.

- $u_{0s}, v_{0c(s)}, w_{0g(cs)}$ are the **random intercepts** for State, City, and Grantee, representing the baseline differences at each level.

- $u_{1s}, v_{1c(s)}, w_{1g(cs)}$ are the random slopes, allowing the effect of ClassT_Real_Wage_Growth to vary across State, City, and Grantee.

- $\varepsilon_{it} \sim N(0, \sigma_\varepsilon^2)$ is the residual error term.

Multilevel Model Specification. Based on the ICC and Model fit, the final model (Equation 3.19) was selected as the main MLM for the fourth research question. The data are nested as follows: Level 1 (Time/Observation), Level 2 (Program) is nested within Level 3 (Grantee), which is nested within Level 4 (City), which is finally nested within Level 5 (State). This structure ensures that variance at each level is appropriately modeled.

Level 1 Model (Time within Program)

$$\text{Class\_TTR}_{it} = \beta_{0i} + \beta_1(\text{prepost}_{it}) + \varepsilon_{it} \tag{3.22}$$

- β_{0i}: Intercept for program i (baseline turnover rate).

- β_1: Fixed effect of the policy (pre-post) on turnover rate.

- ε_{it}: Level-1 residual error.

Level 2 Model (Program within Grantee)

$$\beta_{0i} = \gamma_{00g} + \eta_{0i} \tag{3.23}$$

- γ_{00g}: Average intercept for grantee g.

- η_{0i}: Program-level random effect (deviation of program i from grantee average).

Level 3 Model (Grantee within City)

$$\gamma_{00g} = \kappa_{000c} + \zeta_{0g} \tag{3.24}$$

- κ_{000c}: Average intercept for city c.
- ζ_{0g}: grantee-level random effect.

Level 4 Model (City within State)

$$\kappa_{000c} = \delta_{0000s} + v_{0c} \tag{3.25}$$

- δ_{0000s}: Average intercept for state s.
- v_{0c}: City-level random effect.

Level 5 Model (State Level)

$$\delta_{0000s} = \theta_{00000} + \theta_{00001}(\text{ClassT\_Real\_Wage\_Growth}_s) + u_{0s} \tag{3.26}$$

- θ_{00000}: Grand mean intercept across all states.
- θ_{00001}: Effect of state-level wage growth on the baseline turnover rate.
- u_{0s}: state-level random effect.

RQ4 Heterogeneity Analysis. First, the fourth research question main MLM (Equation 3.19) was derived from a sub-sample based on Program type (i.e., HS and EHS) to identify potential differences in policy impact across program structures (see Equation 3.27)

$$\begin{aligned} \text{ClassT\_TTR}_{itp} = \beta_0 + \beta_1 \text{prepost}_{itp} + \beta_{2p} \text{ClassT\_Real\_Wage\_Growth}_{itp} \\ + u_s + u_c + u_g + \varepsilon_{itp} \end{aligned} \tag{3.27}$$

$$\text{where } p \in \{\text{HS, EHS}\}$$

Second, for the fourth research question, I performed the main MLM (Equation 3.19) separately by state to identify potential differences in [Class_TTR] impact from [ClassT_Real_Wage_Growth] across states (see Equation 3.28). Equation 3.28 did not include the state in the fixed effect. Again, considering multiple testing, I used the Bonferroni adjustment and false discovery rate (FDR) Benjamini-Hochberg (BH) test.

$$\begin{aligned}\text{ClassT\_TTR}_{its} = \beta_{0s} + \beta_{1s}\text{prepost}_{its} + \beta_{2s}\text{ClassT\_Real\_Wage\_Growth}_{its} \\ + u_c + u_g + \varepsilon_{its}, \quad \forall s \in \text{States}\end{aligned} \tag{3.28}$$

Third, to identify potential variation in the impact of [Class_TTR] from [ClassT_Real_Wage_Growth] across [Rep_Teacher_Edu], six different categories of [Rep_Teacher_Edu] were incorporated into Equation 3.29, which was derived from the fourth research question main MLM (Equation 3.19).

$$\begin{aligned}\text{ClassT\_TTR}_{itg} = \beta_{0g} + \beta_{1g}\text{prepost}_{itg} + \beta_{2g}\text{ClassT\_Real\_Wage\_Growth}_{itg} \\ + u_s + u_c + u_g + \varepsilon_{itg}, \quad g \in \{1, \dots, 6\}\end{aligned} \tag{3.29}$$

Table 3.7 below summarizes my research questions and the analysis for addressing each question. I conducted all of the analyses through statistical software RStudio, version 2026.1.0.392. I reported analysis results in a Table format that included the estimate (β), standard error *SE*), p-value (p), t-value (t), p-value from Bonferroni as p(Bonf) and p-value from False Discovery Rate Benjamini-Hochberg as p(FDR BH).

Table 3.7

Methodology with Dependent and Independent Variables

RQ	Data Frame	Y: : dependent variable	X: independent variable	Method	*SE*	Notes
RQ1						
Main DiD	Full sample	TTR	did	DiD	Grantee	
Placebo	2022-2023 (placebo group)	TTR	did	DiD	Grantee	
Event study	Full sample	TTR	year X treat	Event Study	Grantee	Reference year 2022
Heterogeneity DiD	By program types By State By Rep _Teacher_Edu	TTR	did	DiD	Grantee	*p*(Bonf) and *p*(FDR BH) only for state-level
RQ2						
Main DiD	Full sample	ClassT_Real _Growth	did	DiD	State	
Placebo	2022-2023 (placebo group)	ClassT_Real _Growth	did	DiD	State	

Table 3.7 – Continued

RQ	Data Frame	Y: : dependent variable	X: independent variable	Method	*SE*	Notes
Event study	Full sample	ClassT_Real _Growth	year X treat	Event Study	State	Reference year 2022
Heterogeneity DiD	By program types By State By Rep _Teacher_Edu	ClassT_Real _Growth	did	DiD	State, Robust *SE* only for state-level	p(Bonf) and p(FDR BH) for state-level
RQ3						
Main DiD	Full sample	ClassT _Raw_Wage	did	DiD	State	
Placebo Test	2022-2023 (placebo group)	ClassT _Raw_Wage	did	DiD	State	
Event study	Full sample	ClassT _Raw_Wage	year X treat		State	Reference year 2022
Heterogeneity DiD	By program types By State By Rep _Teacher_Edu	ClassT _Raw_Wage	did	DiD	State, Robust *SE* only for state-level	p(Bonf) and p(FDR BH) only for state-level

Table 3.7 – Continued

RQ	**Data Frame**	**Y: : dependent variable**	**X: independent variable**	**Method**	*SE*	**Notes**
RQ4						
Mian MLM	Full sample	TTR	prepost	MLM	-	
Heterogeneity MLM	By program types By State By Rep _Teacher_Edu	TTR	prepost	MLM	-	

CHAPTER FOUR

RESULT

Descriptive Results

From the academic year 2022 to 2025, the total number of Head Start (HS) and Early Head Start (EHS) programs was 11,871 (See Table 4.1). The state of Delaware (DE) had the fewest at 29, while the state of New York (NY) had the most at 1,097. The full data set is attached in Appendix C.

Table 4.1

Overview of the Study Sample from the 2022-2025 PIR Data Set

Academic years	**Data file name from HSES**	**Programs**			
		HS	**EHS**	**Total**	
2021.09.01-2022.08.31	2022 PIR data	1,526	1,524	3,050	
2022.09.01-2023.08.31	2023 PIR data	1,498	1,477	2,975	
2023.09.01-2024.08.31	2024 PIR data	1,485	1,461	2,946	2024 HSPPS policy revision forecast was announced
2024.09.01-2025.08.31	2025 PIR data	1,471	1,429	2,900	2024 HSPPS's first year implementation

Table 4.2 includes information of sample distribution by year and group. The groups included comparison and treatment groups. Variable did=1 and did=0 to examine policy and policy announcements. The total number of observations of [did]=1 is 2,064.

Table 4.2

Sample Distribution by Year and Group

Year	Comparison Group (treat=0) ($\leq$ 200 Slots)	Treatment group (treat=1) ($>$ 200 Slots)	Treatment group (did=1)
2022	1,891	1,159	Pre-Policy (Baseline)
2023	1,827	1,148	Pre-Policy (Baseline)
2024	1,859	1,087	Treated (did=1)
2025	1,923	977	Treated (did=1)

Table 4.3 includes information on the representative education level of classroom teachers within each program. Among these categories, programs focusing on a bachelor's degree had the largest number of observations (n = 4,395).

Table 4.3

Number of Observations by Representative Teachers' Education Level by Year

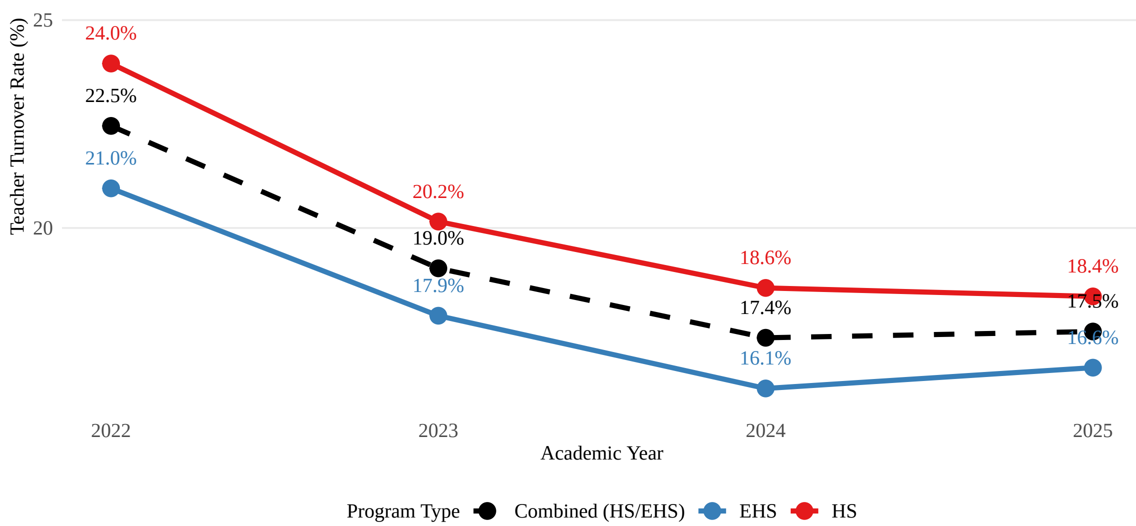
Year	Advanced Focus	Bachelor Focus	Associate Focus	CDA Focus	No-Qual Focus	Mixed-Multi	Total
2022	151	1032	234	13	11	1609	3050
2023	129	1159	495	557	151	484	2975
2024	132	1121	483	574	161	475	2946
2025	122	1083	484	623	135	453	2900
Total	**534**	**4395**	**1696**	**1767**	**458**	**3021**	**11871**

On the other hand, Figure 2.1 and Figure 4.1 are representative of the classroom teachers' turnover rates trend between 2022-2025 in both HS and EHS contexts. From

2022-2025, the HS classroom teachers' turnover rates decreased from 24% to 18.4%. EHS classroom teachers' turnover rates decreased steadily until the 2023-2024 academic year; however, the following year in 2024-2025, EHS classroom teacher turnover increased slightly, from 16.1% to 16.6%.

Figure 4.1

Classroom Teachers' Turnover Rates Between 2022 to 2025 Between HS and EHS and Combined

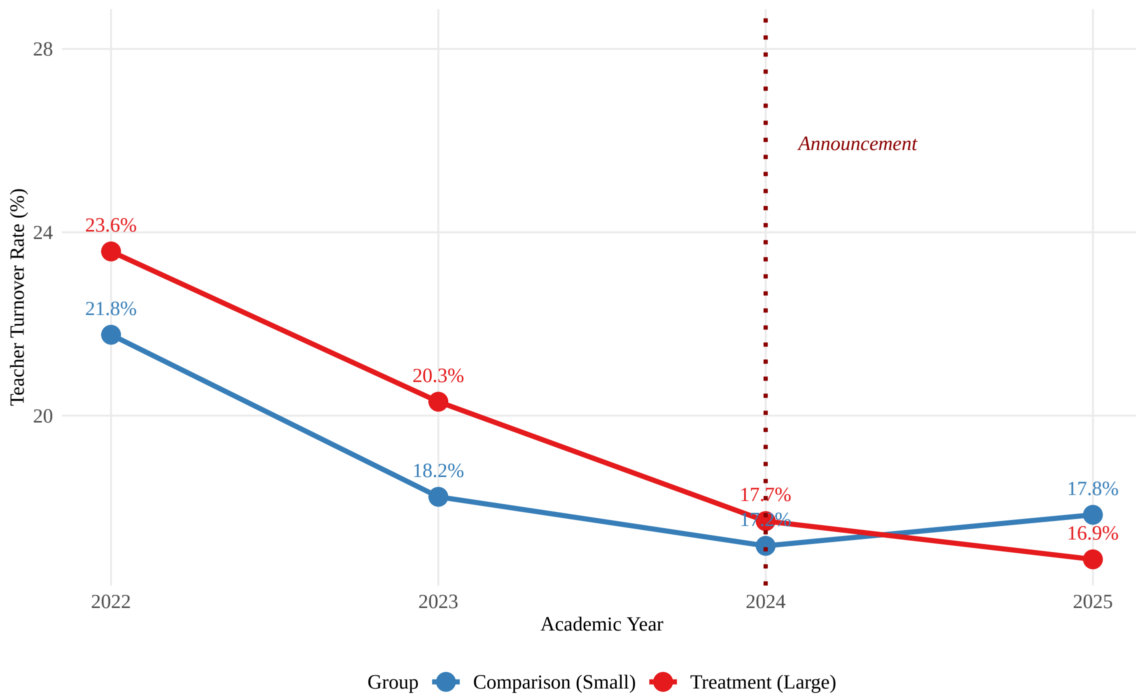


Note. The academic year followed the PIR data set, which 2022 indicates the 2021–2022 academic year. Black dashed lines indicate combined HS and EHS. Blue is EHS, and red is HS. Source: PIR data (ACF, 2022, 2023a, 2024, 2025a)

In 2021-2022, the treatment group's classroom teachers turnover rates were higher than the comparison group at 23.6% and 21.8%, respectively. Both the treatment and comparison group's classroom teachers' turnover rates consistently decreased; however, the treatment group's classroom teachers' turnover rates in 2024-2025, became lower (16.9%) than the comparison group's classroom teachers' turnover rates (17.8%), as shown in Figure 4.2. Figure 4.2 shows the classroom teachers' turnover rates between 2022 and 2025 for control and treatment groups.

Figure 4.2

Classroom Teachers' Turnover Rates Between 2022 to 2025 Between Treatment and Comparison Groups



Note. The academic year followed the program information report (PIR) data set, which 2022 indicates the 2021-2022 academic year. Red indicates the treatment group's classroom teachers' turnover rates (TTR), which funded enrollment slots larger than 200 slots, and after 2024. Blue indicates the comparison group's classroom teachers' turnover rates, which funded enrollment slots 200 or lower than 200 funded slots and before 2024.

In the section that follows, I report the results of each research question (RQ). The first research question is clustered at the grantee-level.

RQ1 Results

Difference-in-Difference Evidence on the Effects of the 2024 HSPPS on Classroom Teacher Turnover

To answer the first research question, I performed Equation 3.1. Additionally, to check the placebo effect, I performed Equation 3.2. After clustering standard errors (*SE*) at the grantee-level, the Difference-in-Difference (DiD) coefficient for the 2024 policy announcement remains significant at the .01 level ($\beta = -2.48$, $p = .001$**). The standard deviation (*SD*) of classroom teachers' turnover rates is 22.25 when calculated with $\beta = -2.48$, resulting in a standardized effect size of approximately 0.11 ($d = 0.11$). This result indicates a small impact of the 2024 Head Start Program Performance Standards (HSPPS) for the classroom teacher turnover rates based on Cohen's (1988) benchmarks for group differences. However, it also indicates that the 2.48 unit reduction in the classroom teachers' turnover rates, compared to the comparison group, is driven by the 2024 HSPPS changes and remains significant even after controlling all fixed variables (e.g., year, state, city, grantee, program). Also, this impact of policy confirmed from the placebo DiD result ($\beta = -.956$, $p = .42$), which was statistically insignificant. I found that there are no pre-existing trends in classroom teachers' turnover rates between the treatment and comparison group prior to the policy announcement in 2024. Table 4.4 shows a comparison of information between Equation 3.1 and Equation 3.2.

Table 4.4

DiD Results: Main and Placebo Test (Equations 3.1 and 3.2) in RQ1

Variable	**(1) Main DiD**	**(2) Placebo DiD**
[did]	-2.483^{**}	$-.956$
	$(.764)$	(1.18)
Period	2022–2025 (Policy)	2022–2023 (Placebo Group)
Fixed Effects	Year, State, City, Grantee, Program	
n	11,633	5,874
Adjusted R^2	.121	$-.0376$
Within R^2	.00127	.000176

Note. SE clustered at the grantee-level are reported in parentheses.

The placebo DiD used a period (2022–2023) assigned prior to the actual policy implementation (2024) to test for pre-existing trends.

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

Event Study in RQ1

Following Equation 3.4, I performed an event study. Equation 3.4 references 2022 to calculate differences with years (2023, 2024, and 2025). The event study analysis revealed a progressive decline in classroom teacher turnover following the policy intervention in the treatment group compared with the comparison group. In 2023 ($\beta = -1.33$, $p = .2$), none of the statistically significant anticipatory effects were observed. While I observed 2024 had a statistically significant anticipatory effect ($\beta = -2.28$, $p = .019$*) and by the implementation phase in 2025, the effect increased to $\beta = -3.59$ (p < .001***), representing an increase of 56.18% over the 2024 level. This trend confirms a robust, incremental reduction in classroom teachers' turnover rates.

Furthermore, the validity of this causal interpretation is supported by the placebo test, which showed no statistical difference between the treated and comparison group prior to the policy period, and the fact that the statistical significance and effect size reached their peak during the actual policy implementation years (i.e., 2024–2025), see Table 4.5.

Table 4.5

Event Study in RQ1 (Equation 3.3)

Interaction Term	β	*SE*	*t*	$Pr(>\|t\|)$
Year 2023	-1.33	1.04	-1.28	.2
Year 2024	-2.28	.98	-2.33	.019*
Year 2025	-3.59	.98	-3.68	.0002***
Fixed-Effects	Year, State, City, Grantee, Program			
n	11,633			
Adjusted R^2	.1211			
Within R^2	.0016			

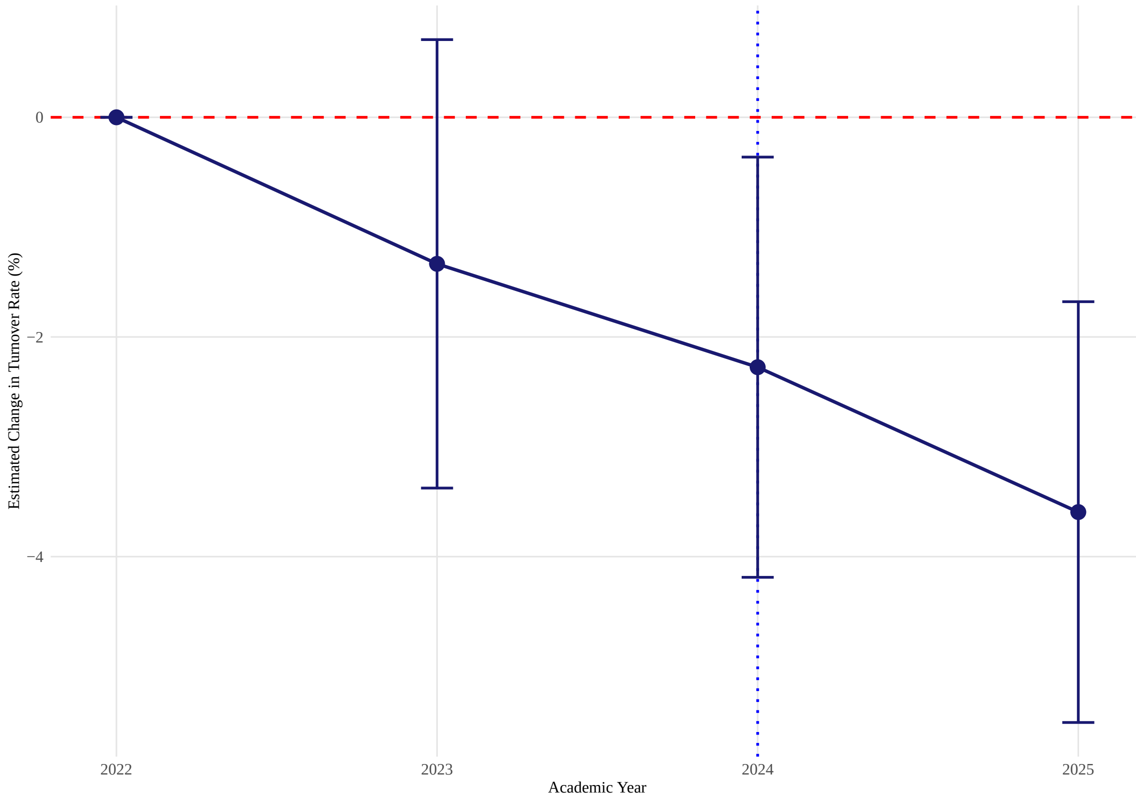
Note. Reference year is 2022. *SE* are clustered at the grantee-level.

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

Figure 4.3 shows the result of an event study with the same information as Table 4.5. The estimated change in the classroom teachers' turnover rates exhibits a consistent downward trajectory following the 2022 reference year. The red dashed line indicates the error bar. Notably, 2024 and 2025 are well under the error bar threshold, unlike 2023.

Figure 4.3

Event Study in RQ1 (Equation 3.3)



Note. Error bars represent 95% clustered confidence intervals at the grantee-level, based on the reference year 2022.

These findings suggest that the 2024 HSPPS announcement and its first year of implementation not only provided a signal to reduce classroom teacher turnover in the early stage of the HS and EHS classroom teacher workforce but also fostered long-term stability as its implementation progressed.

Difference-in-Difference Evidence on the Effects of the 2024 HSPPS on Classroom Teacher Turnover Based on Program Type

Following Equation 3.4, I performed sub-sample analyses between HS and EHS. For HS classroom teachers, the estimated effect was $\beta = -1.86$ (p =.18), while the estimated effect for EHS classroom teachers was $\beta = -.24$ (p =.84). Both program types showed negative estimates, which indicated that HS and EHS showed the same decrease in TTR between treated and comparison groups. Neither HS nor EHS showed a statistically significant difference (see Table 4.6). This result may be driven by sub-sampling data that creates a smaller number of programs for each sample.

Table 4.6

DiD Results: Impact on Classroom Teacher Turnover by Program Types (Equation 3.4) in RQ1

Dependent Variable:	**Class_TTR**	
	(1) Head Start	**(2) Early Head Start**
[did]	-1.86	$-.24$
	(1.37)	(1.2)
Fixed-Effects	Year, State, City, Grantee, Program	
n	5,674	5,602
Adjusted R^2	.002	.128
Within R^2	.0007	.000008

Note. SE clustered at the grantee-level are reported in parentheses.

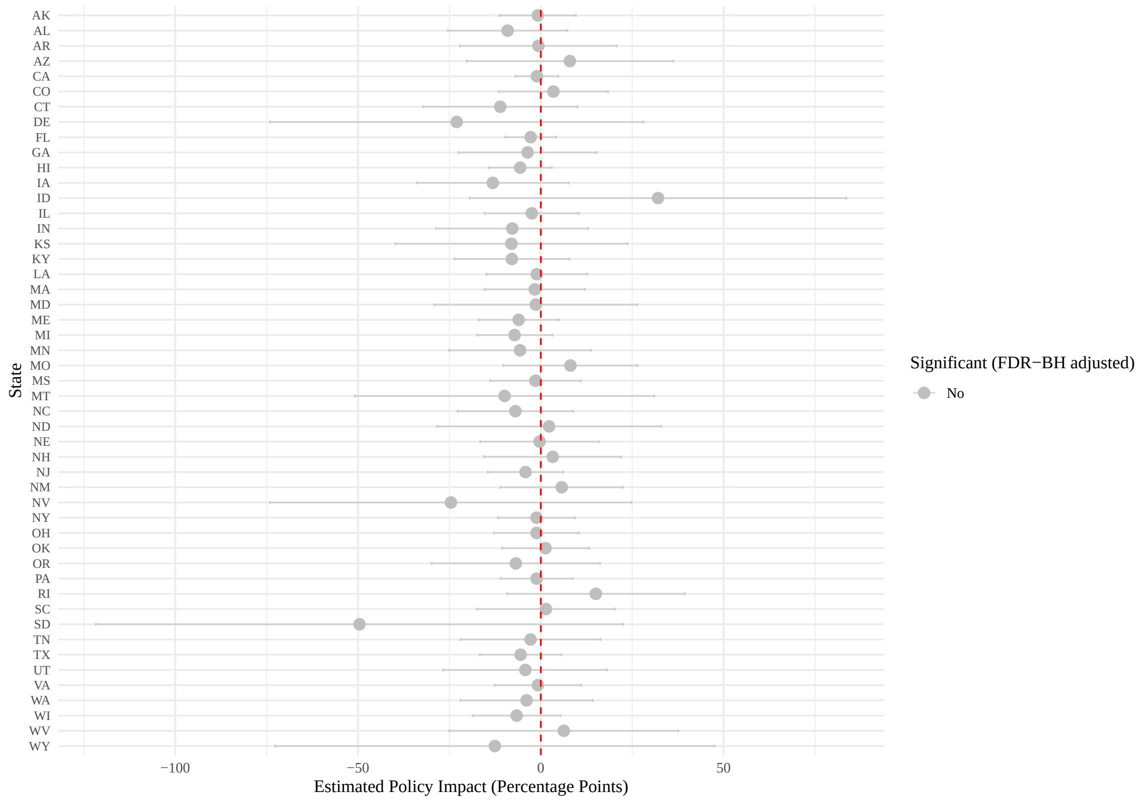
* $p < .05$. ** $p < .01$. *** $p < .001$.

Difference-in-Difference Evidence on the Effects of the 2024 HSPPS on Classroom Teacher Turnover Across States

Equations 3.5 and 3.6 followed multiple testing corrections, including a p-value adjustment before conducting the False Discovery Rate (FDR)'s Benjamini-Hochberg (BH) test. The FDR BH adjusted p-value analysis rendered a statistically significant result. While computing Equation 3.5, I removed the state of Vermont (VT). This omission was intentional because the state of VT did not have an observation in the control, which meant that there was no comparison group available. This omission only occurred in the state-level analysis. Following Equation 3.5, I performed sub-sample analyses at the state-level to examine regional heterogeneity. All of the states showed an insignificant difference. This result could also be the result of small observations from the subset. Figure 4.4 shows the result of Equation 3.5. In Figure 4.4, gray indicates an insignificant change in classroom TTR (p .05 after FDR BH adjustment). On the left side of the red dashed line, an indicated a negative estimate, the right side of the state, a positive estimate. The full version of the result of Equation 3.5 is attached in Appendix D.

Figure 4.4

DiD Results: Impact on Classroom Teacher Turnover Across States (Equation 3.5) in RQ1



Note. Gray points represent statistically insignificant states.

Difference-in-Difference Evidence on the Effects of the 2024 HSPPS on Classroom Teacher Turnover Based on Representative Teachers' Education Level

Following Equation 3.6, I performed sub-sample analyses based on representative teachers' education level (See Table 4.7). Only programs that had classrooms with more than 40% of teachers who held bachelor's degrees showed a statistically significant difference ($\beta = -3.667$, p = .018*) and a decrease in classroom teachers' turnover rates before and after the 2024 HSPPS policy implementation. The bachelor focused category's *SD* of classroom teachers' turnover rates is 22.2 when calculated with $\beta = -3.667$, resulting in a standardized effect size of approximately 0.165 (d = .65). This result aligns with Equation 3.1 as a small effect from the 2024 HSPPS for classroom teacher turnover rates based on Cohen's (1988) benchmarks for group differences.

Table 4.7

DiD Results: Impact on Classroom Teacher's Turnover by Representative Teachers' Education Level (Equation 3.6) in RQ1

	Advanced Focus	**Bachelor Focus**	**Associate Focus**	**CDA Focus**	**No-Qual Focus**	**Mixed-Multi**
[did]	$-.617$	-3.667^{*}	-2.94	$-.4703$	8.802	.049
	(5.087)	(1.56)	(2.21)	(2.558)	(13.08)	(2.68)
Fixed-Effects	Year, State, City, Grantee, Program					
n	382	4,031	1,399	1,443	292	2,361
Adjusted R^2	$-.43641$	.00476	$-.2847$	$-.26745$	-1.6446	.07099
Within R^2	.0000569	.0032	.0027	.0000425	.0084	.000000302

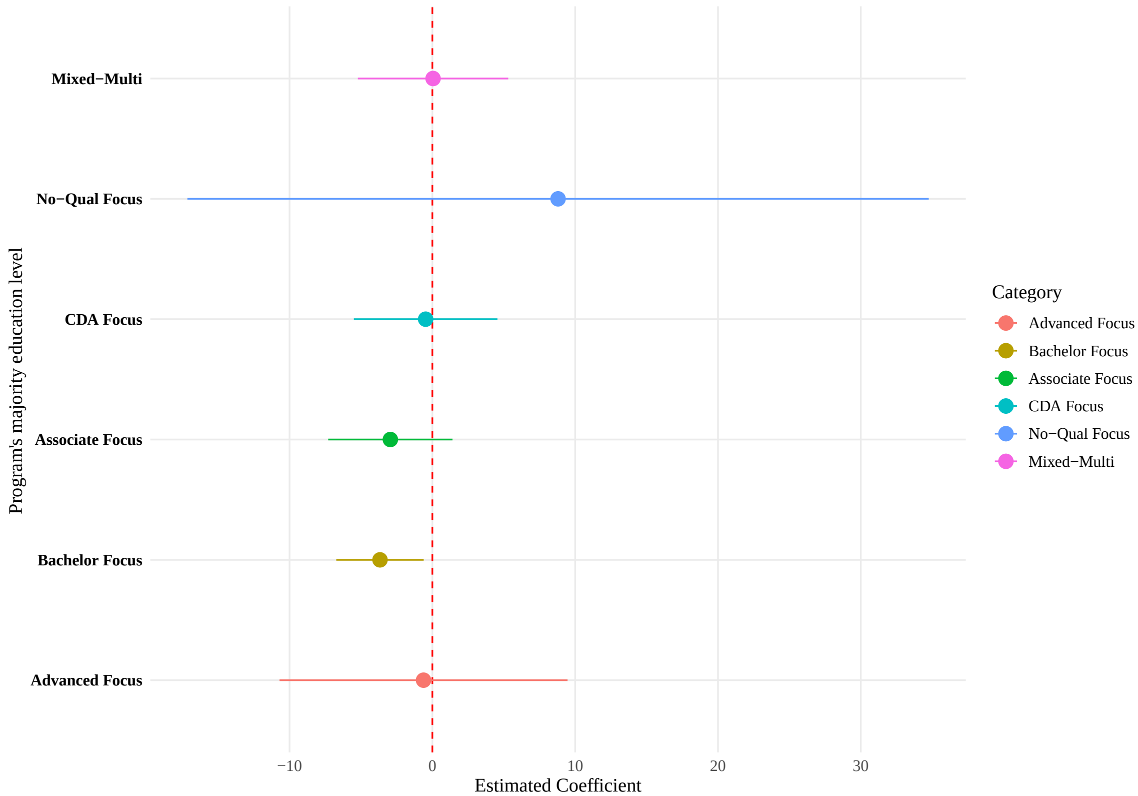
Note. SE clustered at the grantee-level are reported in parentheses.

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

Figure 4.5 is a visualization of Table 4.7. The area close to or over the red dashed line indicates no significance. For example, an advanced degree above the red dashed line indicates that it is not significant. The lines for each representative teacher's education level category indicate that a large number of estimates makes the line longer.

Figure 4.5

DiD Results: Impact on Classroom Teachers' Turnover by Representative Teachers' Education Level (Equation 3.6) in RQ1



Note. The category indicates the representative teachers' education level. The red dashed line indicates a null effect (zero).

Following Equation 3.6, I conducted a heterogeneity analysis on HS and EHS sub-samples. First, classroom teachers in HS also showed a significant difference in the bachelor focus category ($\beta = -4.475$, p =.014*), as demonstrated in Table 4.8. Aligned with the full-sample, neither the categories with no-qual focus (β=101.8, p =.75) nor the mixed-multi (=4.725, p =.64) category showed statistically significant differences, although both categories showed positive estimates. No-qual focus category showed a high number or estimate, which asserts that a lot of teachers who do not qualify move on from the program. Additionally, the CDA focus categories also showed positive estimates (β=.558, p β=.98), which did not align with the full-sample analysis. I was not able to perform EHS and state-level analyses due to the smaller number of programs resulting from sub-sampling.

Table 4.8

DiD Results: Impact on Classroom Teacher Turnover by Representative Teachers' Education Level (Equation 3.6) in HS in RQ1

	Advanced Focus	**Bachelor Focus**	**Associate Focus**	**CDA Focus**	**No-Qual Focus**	**Mixed-Multi**
[did]	$-.221$	-4.475^{*}	-3.522	.558	101.8	4.725
	(4.978)	(1.833)	(3.469)	(23.690)	(311.200)	(10.110)
Fixed-Effects	Year, State, City, Grantee, Program					
n	373	3,519	832	45	30	209
Adjusted R^2	$-.386$	$-.029$	$-.55$	3.033	2.559	-1.519
Within R^2	.0000073	.004	.003	.0001	.275	.005

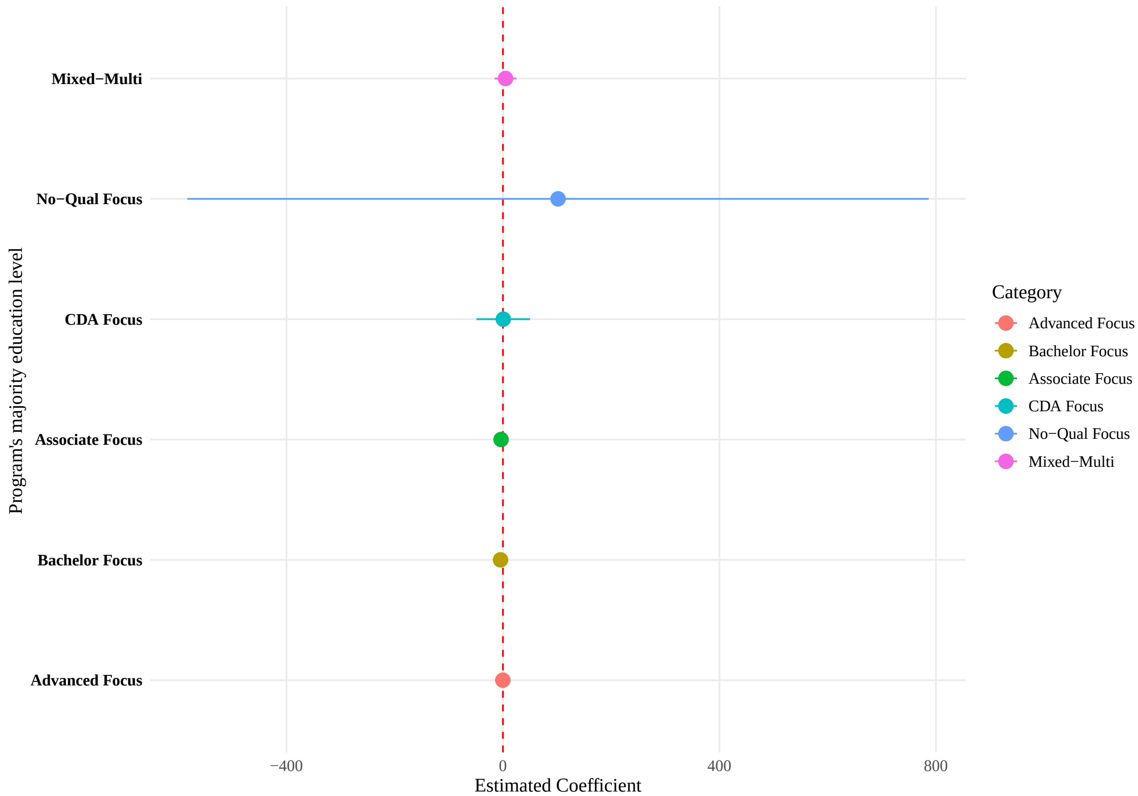
Note. Standard errors clustered at grantee-level.

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

Figure 4.6 demonstrates the visualized result of Table 4.8.

Figure 4.6

DiD Results: Impact on Classroom Teacher Turnover by Representative Teachers' Education Level (Equation 3.6) within HS in RQ1



Note. The category indicates the representative teachers' education level. The red dashed line indicates a null effect (zero).

Overall, the ***null*** hypotheses for RQ1 were ***rejected***. First, I established that the national impact of the 2024 HSPPS announcement and the first year of policy had a statistically significant impact on the reduction in classroom teacher turnover for large programs. Placebo tests and event study also support this result. Second, HS and EHS classroom teachers did not show any statistical significance. Third, the analysis revealed that there were no variations across the states. Again, this result could be driven from the small number of observations from sub-sampling at the state level. Finally, I decomposed the trend by the representative teachers' education level. The representative education level of classroom teachers within each program having bachelor's degrees experienced the highest reduction in turnover in the full sample (See Table 4.9).

Table 4.9

Summary of Empirical Findings for RQ1

Analysis Step	**Specification**	β	**Sig.**	**Key Findings & Implications**
1. National Level				
Main DiD Impact	Full Sample	−2.483	**	Overall policy introduction reduced turnover rates.
Placebo Test	2022–2023 (Pre)	−.956	*ns*	No pre-existing trends; validates DiD identification.
Dynamic Effect	2025	−3.59	***	Impact grows significantly during the implementation phase.
2. Program Type				
Head Start (HS)	Sub-sample	−1.86	*ns*	Consistent direction; strongest in high-credential centers.
Early HS (EHS)	Sub-sample	−.24	*ns*	Weaker impact; potentially due to different credential requirements.
3. State-level Analysis				
General Variation	49 States	Variable	*ns*	No state-specific patterns detected.
4. Education Level				

Table 4.9 – Continued

Analysis Step	Specification	β	Sig.	Key Findings & Implications
National	Bachelor Focus	-3.667	*	Policy most effective for programs with higher proportions of Bachelor's degree-holding teachers.
Head Start (HS)	Bachelor Focus	-4.475	*	Policy most effective for programs with higher proportions of Bachelor's degree-holding teachers.
Early HS (EHS)	Sub-sample	–	–	No computation due to small observations.
State-level	49 States	–	–	No computation due to small observations.

Note. ns = insignificant.

Significance levels are based on clustered *SE* at the grantee-level.

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

RQ2 Result

Difference-in-Difference Evidence on the Effects of the 2024 HSPPS on Classroom Teachers' Real Wage Growth

To answer the second research question, I performed Equation 3.7. Additionally, to check the placebo effect, I also performed Equation 3.8. In the second research question, neither the main DiD nor placebo DiD analyses showed a significant difference between the 2024 HSPPS policy announcement and the first year of implementation with classroom teachers' real wage growth (see Table 4.10). Interestingly, the main DiD result showed a negative estimate of $\beta = -.366$ (p =.13). On the other hand, the placebo DiD showed a positive estimate as β=.505 (p =.117).

Table 4.10

DiD Result of Main and Placebo Test (Equations 3.7 and 3.8) in RQ2

Variables	**(1) Main DiD**	**(2) Placebo DiD**
[did]	$-.366$	.505
	(0.23)	(0.31)
Period	2022–2025 (Policy)	2022–2023 (Placebo Group)
Fixed-Effects	Year, State	
n	11,836	6,006
Adjusted R^2	.405	.489
Within R^2	.00073	.0017

Note. SE clustered at the state-level are reported in parentheses.

The placebo DiD used a period (2022–2023) assigned prior to the actual policy implementation (2024) to test for pre-existing trends.

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

Event Study in RQ2

Following Equation 3.9, I performed an event study. Equation 3.9 references 2022 to calculate differences with years (2023, 2024, and 2025). Table 4.11 shows the result of the event study. Interestingly, 2025 showed statistical significance with a negative estimate ($\beta = -1.116$, p =.0021**) in the treatment group compared with the comparison group, as shown in Table 17. Per this result, along with the result in Table 17, the year 2025 showed a negative estimate; however, years 2024 (β=.358, p =.308) and 2023 (β=.517, p =.15) had positive estimates.

Table 4.11

Event Study in RQ2 (Equation 3.9)

Interaction Term	β	SE	t	$Pr(>\|t\|)$
Year 2023	.517	.354	1.46	.15
Year 2024	.368	.359	1.03	.308
Year 2025	−1.116	.345	−3.236	.0021**
Fixed-Effects		Year, State		
n		11,836		
Adjusted R^2		.408		
With R^2		.0048		

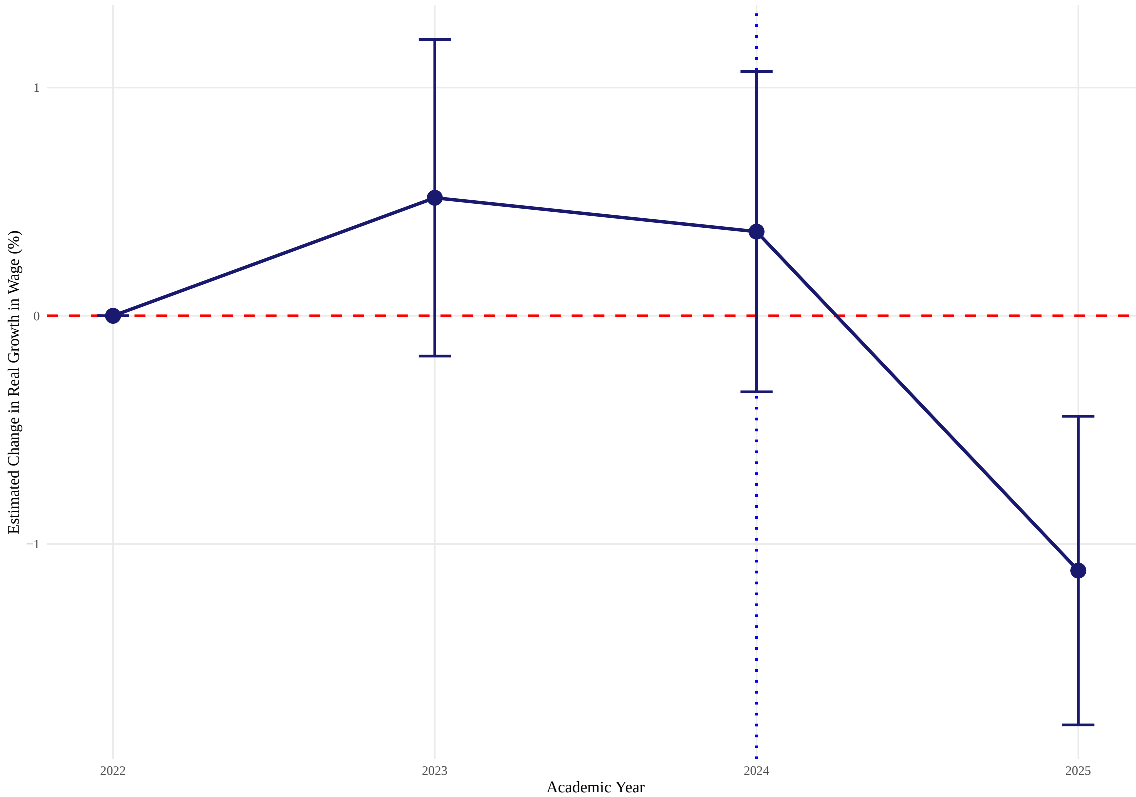
Note. Reference year is 2022. *SE* are clustered at the state-level.

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

Figure 4.7 shows the result of an event study with the same information as Table 4.11. The estimated change in the classroom teachers' real wage growth exhibits a consistent upward trajectory following the 2022 reference year; however, the year 2025 showed a downward trajectory. The red dashed line indicates the error bar. All of the years showed a distance from the error bar.

Figure 4.7

Event Study in RQ2 (Equation 3.9)



Note. Error bars represent 95% clustered confidence intervals at the state-level, based on the reference year 2022.

Difference-in-Difference Evidence on the Effects of the 2024 HSPPS on classroom teachers' real wage Growth Based on Program Type

Following Equation 3.10, I performed sub-sample analyses between HS and EHS. Although classroom teachers' real wage growth data were originally provided at the state-level, I assigned these data to each program based on the representative education level of its classroom teachers. I took this approach to prevent multicollinearity and to enable a program-level analysis, which also allowed for the sub-sample analysis between HS and EHS programs. The HS classroom teacher showed β=.16 (p =.94) and the EHS classroom teacher showed $\beta = -.001$ (p =.99). Although both program types showed different estimated directions, neither the HS nor the EHS showed a statistically significant difference (see Table 4.12). This result aligns with the main DiD result of RQ2.

Table 4.12

DiD Results: Impact on Classroom Teachers' Real Wage Growth by Program Types (Equation 3.10) in RQ2

Dependent Variable:	**ClassT_Real_Wage_Growth**	
	(1) Head Start	**(2) Early Head Start**
[did]	.016	$-.001$
	(.232)	(.348)
Fixed-Effects	Year, State	
n	5,961	5,875
Adjusted R^2	.444	.381
Within R^2	.00000165	.000000006791

Note. *SE* clustered at the state-level are reported in parentheses.

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

Difference-in-Difference Evidence on the Effects of the 2024 HSPPS on Classroom Teachers' Real Wage Growth Across States

Again, I excluded the state of VT, and computed a total of 49 states by following Equation 3.11. I performed sub-sample analyses at the state-level to examine regional heterogeneity. For Equation 3.11, I followed multiple testing corrections, performing a p-value adjustment before conducting the Benjamini-Hochberg test. The Benjamini-Hochberg adjusted p-value analysis rendered a statistically significant result. In addition, I did not specify the cluster and instead used robust *SE*. The states of Florida

(FL), Georgia (GA), Indiana (IN), Maine (ME), New Jersey (NJ), Pennsylvania (PA), Texas (TX), and West Virginia (WV) were statistically significantly different, and all of the states showed negative estimates. Targeting eight states, I performed placebo tests and used the same functions as Equation 3.11, but with sub-set data between 2022 and 2023. I excluded the states of FL, ME, PA, TX, and WV (See Table 4.13).

Table 4.13

Confirmed State-level Policy Effects (Passed Placebo Test) Classroom Teachers' Real Wage Growth in RQ2

	States	**Total**
Initial Significant States	FL, GA, IN, ME, NJ, PA, TX, WV	8
Showed Significant in Placebo Test	AL, AR, CT, FL, IA, ME, MI, MN, PA, TX, WV, WY	12
Confirmed Policy Effect	GA, IN, NJ	3

After this adjustment, three states remained (i.e., GA, IN, and NJ). I identified that there was variation in the 2024 HSPPS policy. The state of IN showed a positive estimate as $\beta = .939$ (p =.02*). In other words, the state of IN was the only state with positive classroom teacher actual wage increase rates after the 2024 HSPPS announcement and the first year of implementation. The state of IN's *SD* of classroom teachers' real wage growth is 3.78 when calculated with (β=.939), resulting in a standardized effect size of approximately 0.25 (d = 0.25). Thus, the state of IN has a small effect on the 2024 HSPPS for the classroom teachers' real wage growth based on Cohen's (1988) benchmarks for group differences. States of GA and NJ showed a negative estimate (See Table 4.14). The full version of Equation 3.11 results can be found in Appendix D.

Table 4.14

DiD Results: Impact on Classroom Teachers' Real Wage Growth Across States (Equation 3.11) in RQ2

State	β	*SE*	***p***	*p* **(Bonf)**	*p* **(FDR BH)**	*n*
GA	-1.63	.417	.000123	.00601	.0012*	252
IN	.939	.313	.00298	.146	.0209*	268
NJ	-1.7	.474	.000422	.0207	.00345**	211

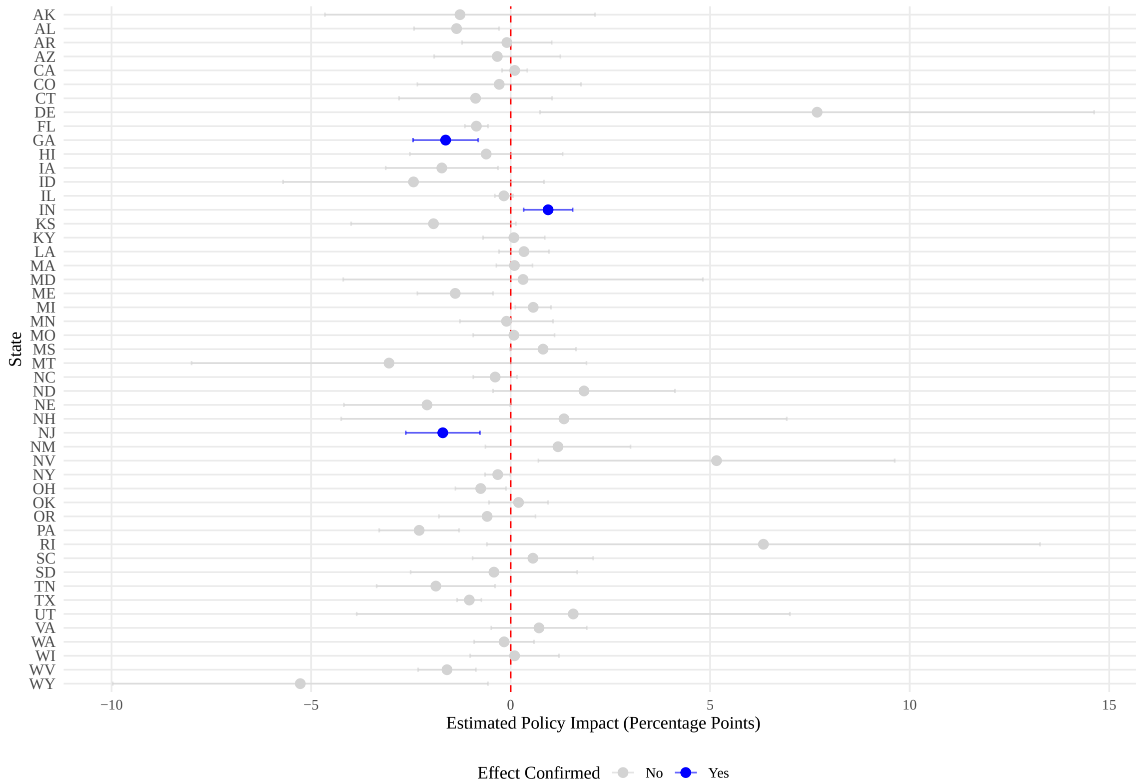
Note. *p* (Bonf) denotes Bonferroni-adjusted *p*-values; *p* (FDR BH) denotes Benjamini-Hochberg adjusted *p*-values.

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

Figure 4.8 shows the significant and insignificant state of policy impact by state. Blue indicated a significant change in classroom teachers' real wage growth (p < .05, after Benjamini-Hochberg adjustment). The left side of the red dashed line indicates a negative estimate, and the right side of the state indicates a positive estimate.

Figure 4.8

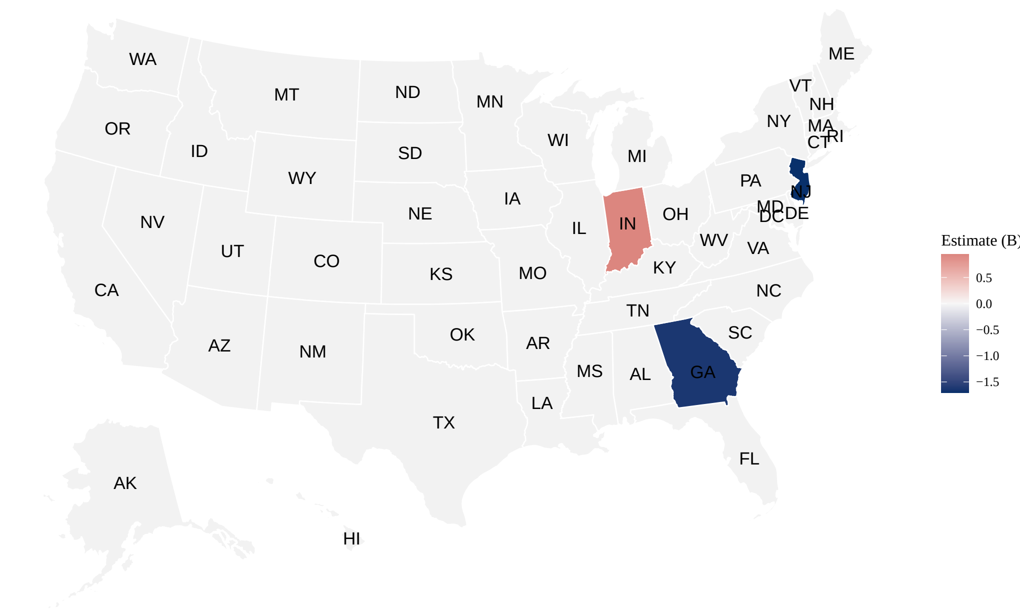
DiD Results: Impact on Classroom Teachers' Real Wage Growth Across States (Equation 3.11) in RQ2



Note. Blue points denote states with statistically significant effects (p < .05) that successfully passed the placebo validation. Gray points represent states that were either statistically insignificant or failed the placebo test.

Figure 4.9

DiD Results: Impact on Classroom Teachers' Real Wage Growth Across States (Equation 3.11) in RQ2 in Map



Note. Red areas represent states with statistically significant positive effects, respectively ($p < .05$ after FDR BH correction). Blue areas represent states with statistically significant negative effects, respectively ($p \geq .05$). Gray areas indicate insignificant results ($p \geq .05$) or missing data.

Difference-in-Difference Evidence on the Effects of the 2024 HSPPS on Classroom Teachers' Real Wage Growth by Representative Teachers' Education Level

Following Equation 3.12, I performed sub-sample analyses between representative teachers' education level. No-qual focus categories showed a result approaching significance at the 10% level ($p = .082$). Other than the no-qual focus categories, none of the representative teachers' education level categories showed statistically significant differences in classroom teachers' real wage growth before and after the 2024 HSPPS policy implementation (See Table 4.15).

Table 4.15

DiD Results: Impact on Classroom Teachers' Real Wage Growth by Representative Teachers' Education Level (Equation 3.12) in RQ2

	Advanced Focus	**Bachelor Focus**	**Associate Focus**	**CDA Focus**	**No-Qual Focus**	**Mixed-Multi**
[did]	.037	−.032	.03	−.413	−2.166	−.609
	(.615)	(.215)	(.405)	(.523)	(1.22)	(.43)
Fixed-Effects	Year, State					
n	528	4,383	1,690	1,766	453	3,009
Adjusted R^2	.227	.603	.459	.378	.179	.541
Within R^2	.00000638	.0000105	.00000729	.00079	.00673	.00128

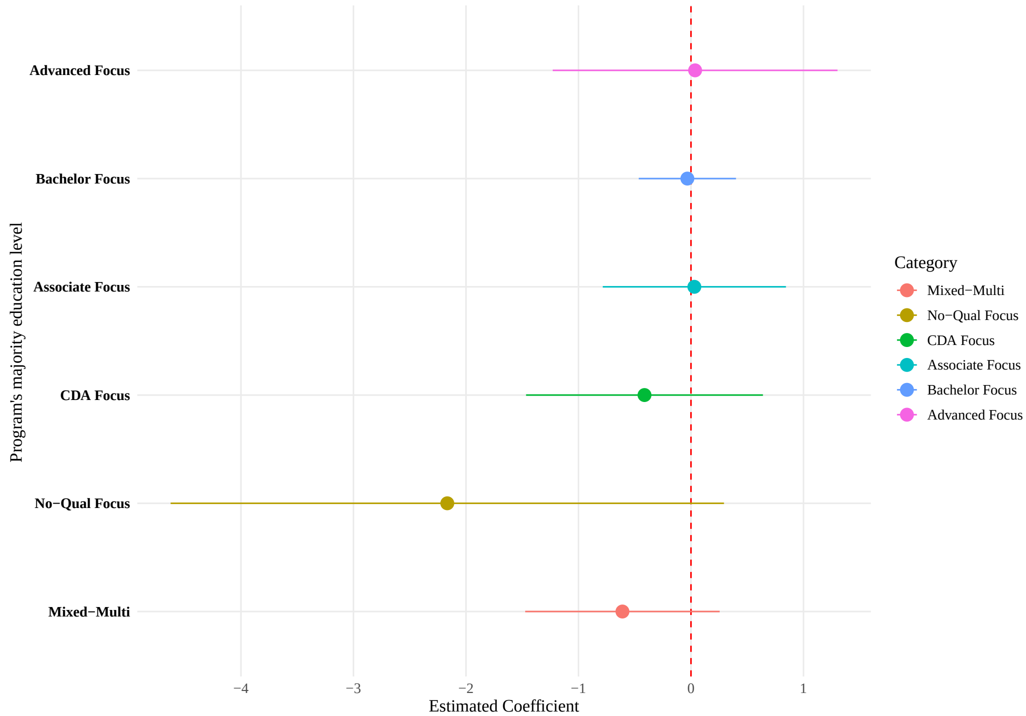
Note. SE clustered at the state-level are reported in parentheses.

· * $p < .05$. ** $p < .01$. *** $p < .001$.

Figure 4.10 is the visualization of Table 4.15.

Figure 4.10

DiD Results: Impact on Classroom Teachers' Real Wage Growth by Representative Teachers' Education Level (Equation 3.12) in RQ2



Note. The category indicates the representative teachers' education level. The red dashed line indicates a null effect (zero).

Following Equation 3.12, I conducted heterogeneity analysis on the sub-sample HS and EHS. First, for HS, similar to the full-sample size, none of the categories showed statistically significant differences (see Table 4.16). I was not able to perform EHS and state-level analyses due to the small number of observations resulting from sub-sampling.

Table 4.16

DiD Results: Impact on Classroom Teachers' Real Wage Growth by Representative Teachers' Education Level (Equation 3.12) within HS in RQ2

	Advanced Focus	**Bachelor Focus**	**Associate Focus**	**CDA Focus**	**No-Qual Focus**	**Mixed-Multi**
[did]	.125	-.04	.629	1.429	-.104	-.417
	(.623)	(.267)	(.444)	(1.152)	(4.249)	(.478)
Fixed-Effects	Year, State					
n	509	3,853	1,054	86	65	368
Adjusted R^2	.258	.594	.435	.259	.268	.437
Within R^2	.00008	.00001	.00261	.00520	.00001	.00126

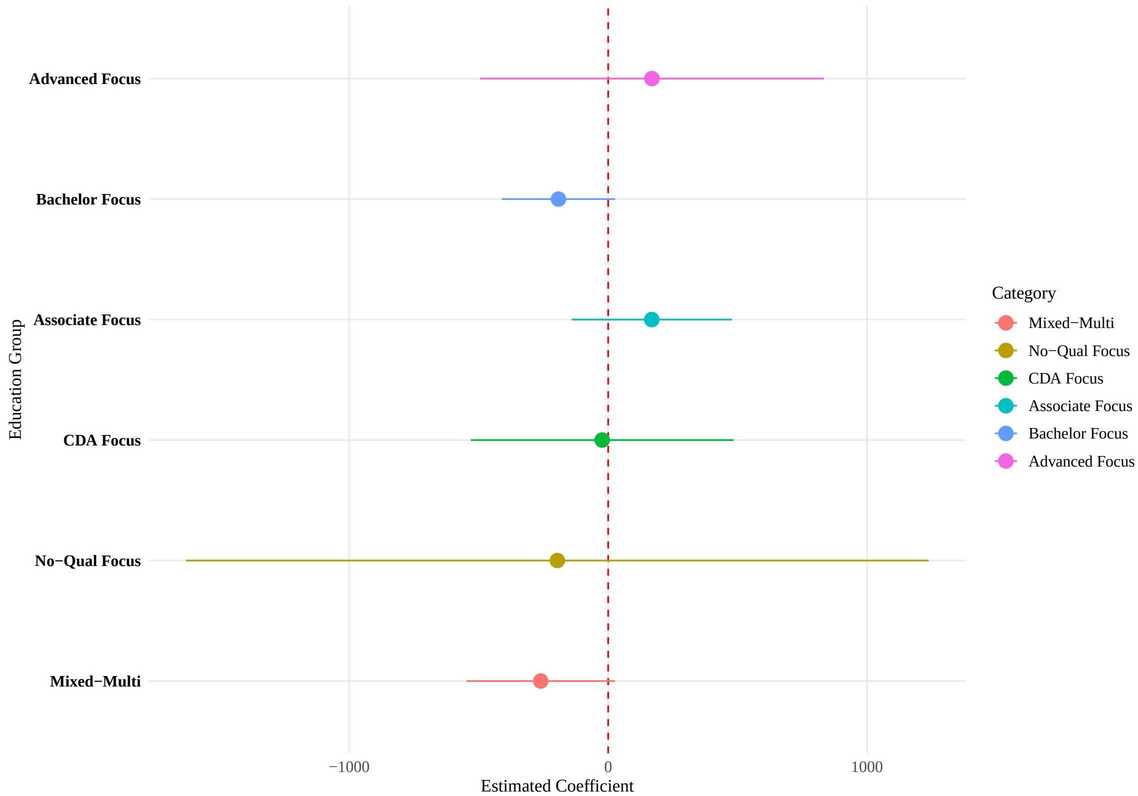
Note. SE clustered at the state-level are reported in parentheses.

$^{\cdot}$ $p < .1$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Figure 4.10 is the visualization of Table 4.16.

Figure 4.11

DiD Results: Impact on Classroom Teachers' Real Wage Growth by Representative Teachers' Education Level (Equation 3.12) within HS in RQ2



Note. The category indicates the representative teachers' education level. The red dashed line indicates a null effect (zero).

Overall, the ***null*** hypotheses for RQ2 were **not** rejected. First, statistically, there is no national impact of the 2024 HSPPS announcement and the first year of policy impact on classroom teachers' actual wage increase rates. Notably, the result of the event study for the year 2025 showed statistically significant differences with negative estimates. In other words, classroom teachers' actual wage increase rates significantly declined in 2025. Second, HS and EHS classroom teachers did not show any statistical significance. Third, I identified variation across states. A total of three different states showed statistically significant differences. Notably, the state of IN showed positive estimates in classroom teachers' actual wage increase rates. Finally, I decomposed the trend by the representative teachers' education level. In the national data, the no-qual focus categories showed a result approaching significance. The sub-sample of HS did not show any statistical significance. I was not able to perform EHS and state-level analyses due to the small number of observations resulting from sub-sampling (See Table 4.17).

Table 4.17

Summary of Empirical Findings for RQ2

Analysis Step	**Specification**	β	**Sig.**	**Key Findings & Implications**
1. National Level				
Main DiD Impact	Full Sample (Total)	−.366	*ns*	
Placebo Test	2022-2023 (Pre)	.505	*ns*	
Dynamic Effect	2025	−1.116	**	Directions differ differ between years.
2. Program Type				
Head Start (HS)	Sub-sample	.016	*ns*	
Early HS (EHS)	Sub-sample	−.001	*ns*	
3. State-level Analysis				

Table 4.17 – Continued

Analysis Step	Specification	β	Sig.	Key Findings & Implications
General Variation	49 States	Var.	*	State of GA and NJ showed significant negative effects. State of IN showed significant postative effects.
4. Education Level				
National (Total)	No-Qual Focus	-2.166	.	A result approaching significance ($p = .083$)
Head Start (HS)	Sub-sample	Var.	*ns*	
Early HS (EHS)	Sub-sample	-	-	No computation due to small observations.
State-level	49 States	-	-	No computation due to small observations.

Note. ns = insignificant. Significance levels are based on clustered *SE* at the state-level.
* $p < .05$. ** $p < .01$. *** $p < .001$.

RQ3 Results

Difference-in-Difference Evidence on the Effects of the 2024 HSPPS on Classroom Teachers' Raw Wages

To answer research question three, I performed Equation 3.13. Additionally, to check the placebo effect, I also performed a second Equation 3.14. In research question three, both the main DiD (β =2623.08, $p < .001 ***$) and placebo DiD (β =2688.42, $p < .001 ***$) values showed a significant difference between the 2024 HSPPS policy announcement and first year of implementation with classroom teachers' raw wages (see Table 4.18). In other words, statistically, it was unable to discern whether classroom teachers' raw wages increased from the 2024 HSPPS announcement and the first Implementation. However, I was able to identify that a constantly increasing trend in classroom teachers' raw wages was evident from 2022 to 2025.

Table 4.18

Difference-In-Differences Result of Main and Placebo Test (Equations 3.13 and 3.14) in RQ3

Variable	**(1) Main DiD**	**(2) Placebo DiD**
[did]	2623.08***	2686.42***
	(341.91)	(389.83)
Period	2022–2025 (Policy)	2022–2023 (Placebo Group)
Fixed-Effects	Year, State	Year, State
n	11,869	6,023
Adjusted R^2	.51	.49
Within R^2	.024121	.035243

Note. SE clustered at the state-level are in parentheses.

The placebo DiD used a period (2022–2023) assigned prior to the actual policy implementation (2024) to test for pre-existing trends.

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

Event Study in RQ3

Following Equation 3.15, I performed an event study. Equation 3.15 references the year 2022 to calculate the difference with years (2023, 2024, and 2025). Table 4.19 shows the results of the event study, which reveals a progressive increase in classroom teachers' raw wages from 2022 to 2025. Notably, estimates have consistently decreased since 2023: for instance, 2023's estimate showed (β =2741.87, $p < .001***$), 2024 was (β = 2689.63, $p < .001***$) and 2025 was (β =2495.37, $p < .001***$) in the treatment group compared with the comparison group. Thus, 2025 demonstrated a 5.26% decrease beginning in 2023 (See Table 25). This result does not align with the second research question.

Table 4.19

Event Study in RQ3 (Equation 3.15)

Interaction Term	β	SE	t	$Pr(>\|t\|)$
Year 2023	2741.87	474.18	5.78	$< .001$
Year 2024	2718.37	358.37	7.59	$< .001$
Year 2025	2597.56	367.95	7.06	$< .001$
Fixed-Effects		Year, State		
n		11,869		
Adjusted R^2		.52		
Within R^2		.038326		

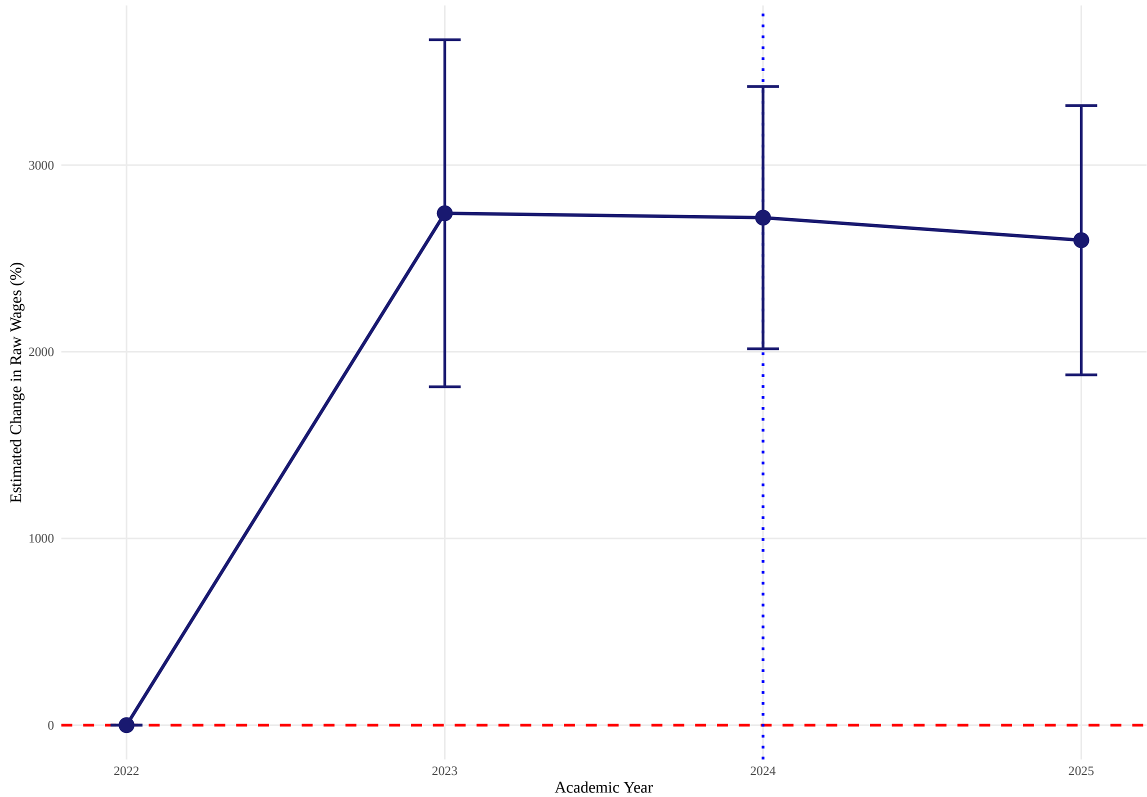
Note. Reference year is 2022. *SE* are clustered at the state-level.

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

Figure 4.11 shows the result of an event study with the same information presented in Table 4.19. The estimated change in the classroom teachers' raw wages were highest in the year 2023. Since 2023, it has consistently shown a downward trajectory. The red dashed line indicates the error bar. All of the years were well above the error line threshold.

Figure 4.12

Event Study in RQ3 (Equation 3.15)



Note. Error bars represent 95% clustered confidence intervals at the state-level, based on the reference year 2022.

Difference-in-Difference Evidence on the Effects of the 2024 HSPPS on Classroom Teachers' Raw Wages Based on Program Type

Again, classroom teachers' raw wages data were only provided at the state-level, so I assigned these data to each program based on the representative education level of its classroom teachers. I took this approach to prevent multicollinearity and to enable a program-level analysis, which also allowed for the sub-sample analysis between HS and EHS programs. Following Equation 3.16, I performed sub-sample analyses between HS and EHS. HS classroom teachers showed $\beta = -370.82$ (p =.13) and EHS classroom teachers showed $\beta = -386.003$ (p =.46); both program types showed negative estimates, but there was not a critical or significant difference (see Table 4.20). This result may be driven by the sub-sampling of the data, which creates a smaller number of programs for each sample.

Table 4.20

DiD Results: Impact on Classroom Teachers' Raw Wages by Program Types (Equation 3.16) in RQ3

Dependent Variable:	**ClassroomT_Raw_wage**	
	(1) Head Start	**(2) Early Head Start**
[did]	-370.82	-386.003
	(243.65)	(521.59)
Fixed-Effects	Year, State	
n	5,980	5,889
Adjusted R^2	.58	.66
Within R^2	.0006303	.000522

Note. SE are clustered at the state-level are reported in parentheses.

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

Difference-in-Difference in Evidence on the Effects of the 2024 HSPPS on Classroom Teachers' Raw Wages Across States

Again, excluding the state of VT, I computed a total of 49 states following Equation 3.17. I performed sub-sample analyses at the state-level to examine regional heterogeneity. Equation 3.17 followed multiple testing corrections; I used FDR BH adjusted p-values, and significance was reported based on these adjusted values. I performed Equation 3.17 to examine state-level variation; thus, unlike previous equations, clustered *SE* at the state-level were not used. Instead, I employed a robust *SE*. A total of 29 states (i.e., AL, DE, FL, GA, IA, IL) showed statistically significantly different results, and all of the states showed positive estimates. I performed Placebo tests. These tests used the same Equation 3.17, but only subset the data from 2022 to 2023. Thus, I excluded a total of 20 states (i.e., AL, FL, GA, IA, IL, MA, ME, NC, NJ, OH, OK, PA, TN, TX, WV, WY) (see Table 4.21).

Table 4.21

Confirmed State-level Policy Effects (Passed Placebo Test) Classroom Teachers' Raw Wages in RQ3

	States	**Total**
Initial Significant States	AL, DE, FL, GA, IA, IL, LA, MA, MD, ME, MI, MS, MT, NC, ND, NJ, NV, NY, OH, OK, PA, RI, SC, TN, TX, UT, WI, WV, WY	29
Showed Significant in Placebo Test	AL, AR, FL, GA, HI, IA, IL, IN, MA, ME, NC, NJ, OH, OK, PA, TN, TX, WA, WV, WY	20
Confirmed Policy Effect	DE, LA, MD, MI, MS, MT, ND, NV, NY, RI, SC, UT, WI	13

Therefore, a total of 13 states remained: Delaware (DE), Louisiana (LA), Maryland (MD), Michigan (MI), Mississippi (MS), Montana (MT), North Dakota (ND), Nevada (NV), New York (NY), Rhode Island (RI), South Carolina (SC), Utah (UT), Wisconsin (WI). This result confirmed that there is potential variation in impact across states in the 2024 HSPPS policy. For example, the state of MD showed the largest estimate as $\beta = 7719$ (p =.0109*), as shown in Table 4.22. The full version of Equation 3.17 results are attached in Appendix D.

Table 4.22

DiD Results: Impact on Classroom Teachers' Raw Wages Across States (Equation 3.17) in RQ3

State	β	*SE*	***p***	***p* (Bonf)**	***p* (FDR BH)**	*n*
DE	4418	1537	.008**	.408	.016*	29
LA	3434	706	< .001***	< .001***	< .001***	329
MD	7719	2701	.005**	.230	.011*	223
MI	1794	649	.006**	.292	.013*	410
MS	1701	475	< .001***	.021*	.001**	191
MT	2512	902	.007**	.334	.014*	78
ND	4931	1516	.002**	.092	.005**	65
NV	3929	1660	.024*	1.000	.040*	40
NY	3328	846	< .001***	.004**	< .001***	1097
RI	6509	1836	.001**	.043*	.002**	53
SC	3058	624	< .001***	< .001***	< .001***	157
UT	3361	1457	.024*	1.000	.040*	89
WI	2697	969	.006**	.287	.013*	221

Note. p (Bonf) denotes Bonferroni-adjusted p-values; p (FDR BH) denotes Benjamini-Hochberg adjusted p-values.

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

The state of MD's *SD* of classroom teachers' raw wages is 8,076 when calculated with β=7719, resulting in a standardized effect size of approximately 0.956 (d = 0.956).

This result shows that the state of MD has a large effect on the 2024 HSPPS for the classroom teachers' raw wages based on Cohen's (1988) benchmarks for group differences. Additionally, the states of RI, NV, DE, and SC also showed large effects (Cohen, 1988; see Table 4.23).

Table 4.23

Effective Size Classroom Teachers' Raw Wages Across States Result (Equation 3.17) in RQ3

State	**Estimate (did)**	**State *SD***	**Cohen's d**	**Effect Category**
RI	6,509	5,194	1.25	Large
NV	3,929	3,415	1.15	Large
DE	4,418	4,029	1.10	Large
MD	7,719	8,076	0.96	Large
SC	3,058	3,658	0.84	Large
LA	3,434	4,367	0.79	Medium
MT	2,512	3,339	0.75	Medium
ND	4,931	6,598	0.75	Medium
UT	3,361	4,801	0.70	Medium
MS	1,701	2,750	0.62	Medium
WI	2,697	5,157	0.52	Medium
NY	3,328	7,978	0.42	Small
MI	1,794	4,830	0.37	Small

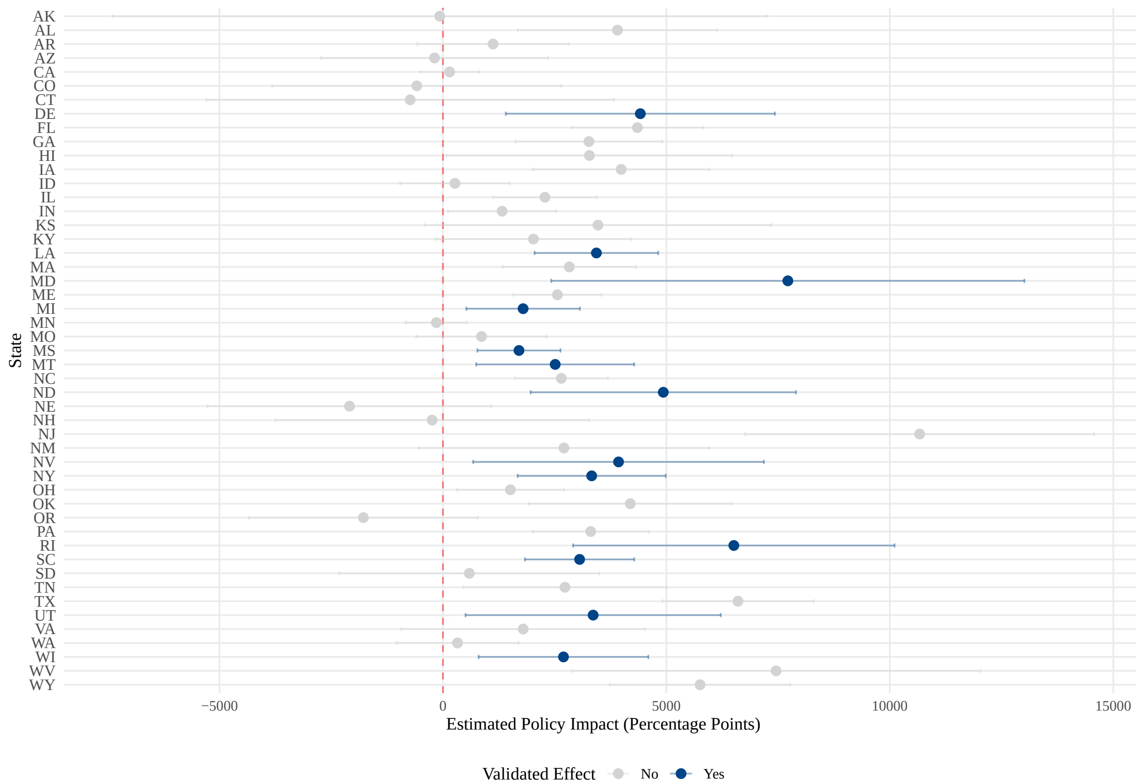
Note. Effect size thresholds: $d = 0.2$, a small effect, $d = 0.5$, a medium effect, and $d = 0.8$ a large effect (Cohen, 1988).

Figure 4.12 shows the significant and insignificant state of policy impact by state. Blue indicates a significant change in classroom teachers' raw wages (p < .05 after

Benjamini-Hochberg adjustment). On the left side of the red dashed line, an indicated a negative estimate, the right side of the state indicated a positive estimate.

Figure 4.13

DiD Results: Impact on Classroom Teachers' Raw Wages Across States (Equation 3.17) in RQ3

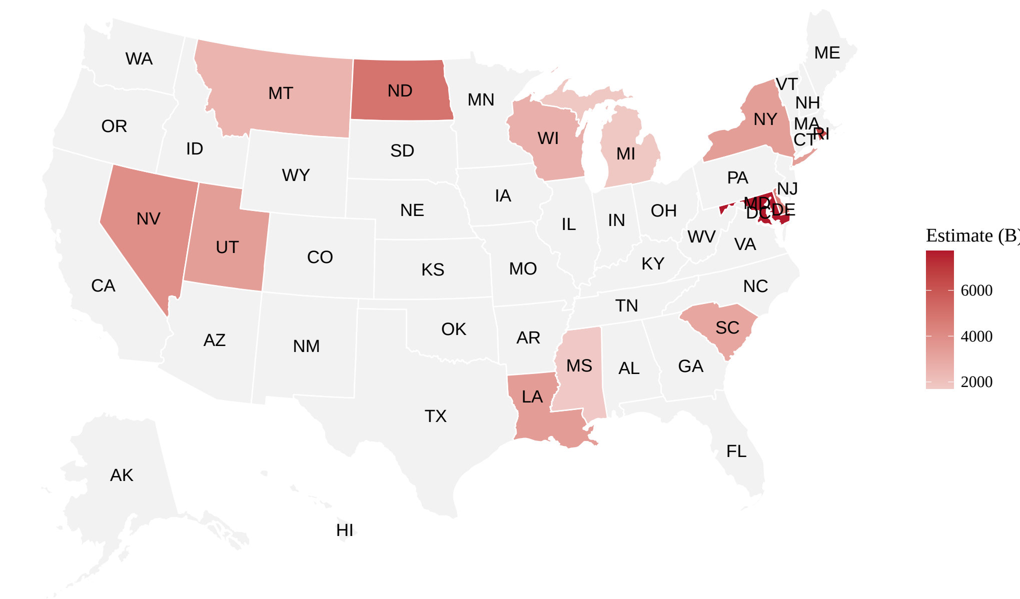


Note. Blue points denote states with statistically significant effects (p < .05) that successfully passed the placebo validation. Gray points represent states that were either statistically insignificant or failed the placebo test.

Figure 4.13 presents the same information as Table 4.22, highlighting 13 states with statistically significant effects. States with larger estimated coefficients are shown in darker shades of red.

Figure 4.14

DiD Results: Impact on Classroom Teachers' Raw Wages Across States (Equation 3.17) in RQ3 in Map



Note. Red areas represent states with statistically significant positive effects, respectively ($p < .05$ after FDR BH correction). Gray areas indicate insignificant results ($p \geq .05$) or missing data.

Difference-in-Difference Evidence on the Effects of the 2024 HSPPS on Classroom Teachers' Raw Wages by Representative Teachers' Education Level

Following Equation 3.18, I performed sub-sample analyses between [Rep_Teacher_Edu]. Only programs that have more than 40% of bachelor's degree classroom teachers showed a statistically significantly different decrease in classroom teachers' raw wages before and after the 2024 HSPPS policy ($\beta = -185.65$, $p = .036$*). Bachelor force category's *SD* of classroom teachers' raw wages is 6,251 when calculated with $\beta = -185.65$, resulting in a standardized effect size of approximately 0.03 (d =

0.03). This indicates a very small effect from the 2024 HSPPS for the bachelor focus category's raw wages based on Cohen's (1988) benchmarks for group differences.

Other categories did not show a statistically significant difference. Mixed-Multi ($\beta = -70.94$, p =.755) and No-qual focus categories ($\beta = -437.38$, p =.077) also showed a negative estimate (see Table 4.24). Other categories showed positive estimates. This result showed that classroom teachers who have bachelor's degrees experienced a reduction in raw wages before and after the 2024 HSPPS announcement and its first year of implementation.

Table 4.24

DiD Results: Impact on Classroom Teachers' Raw Wages by Representative Teachers' Education Level (Equation 3.18) in RQ3

	Advanced Focus	**Bachelor Focus**	**Associate Focus**	**CDA Focus**	**No-Qual Focus**	**Mixed-Multi**
[did]	106.96	-185.65*	73.08	32.6	-437.38.	-70.94
	(320.24)	(86.31)	(103.4)	(79.88)	(241.7)	(226.43)
Fixed-Effects	Year, State					
n	529	4,395	1,696	1,767	456	3,019
Adjusted R^2	.906	.961	.972	.956	.846	.965
Within R^2	.00036	.00271	.00054	.00011	.00605	.0002

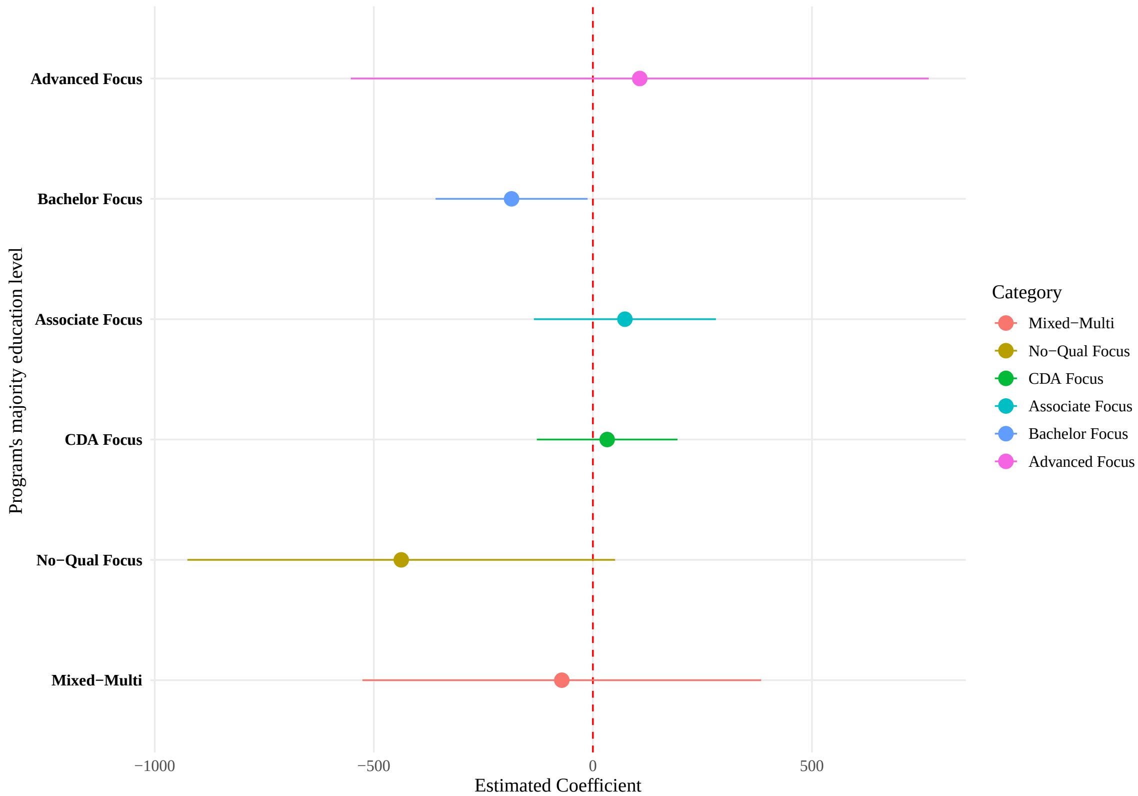
Note. SE clustered at the state-level are reported in parentheses.

. $p < .1$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Figure 4.14 is a visualization of Table 4.23.

Figure 4.15

DiD Results: Impact on Classroom Teachers' Raw Wages by Representative Teachers' Education Level (Equation 3.18) in RQ3



Note. The category indicates the representative teachers' education level. The red dashed line indicates a null effect (zero).

Following Equation 3.18, I conducted heterogeneity analysis on sub-samples of HS and EHS. First, for HS, none of the groups showed statistically significant differences (See Table 4.26). I was not able to perform EHS and state-level analyses due to the small number of observations resulting from sub-sampling.

Table 4.25

DiD Results: Impact on Classroom Teachers' Raw Wages by Representative Teachers' Education Level (Equation 3.18) within HS in RQ3

	Advanced Focus	**Bachelor Focus**	**Associate Focus**	**CDA Focus**	**No-Qual Focus**	**Mixed-Multi**
[did]	168.938	−191.97.	168.15	−23.16	−196.252	−260.36.
	(321.12)	(108.95)	(153.644)	(241.5)	(682.46)	(137.50)
Fixed-Effects	Year, State					
n	510	3,865	1,059	86	65	368
Adjusted R^2	.906	.96	.97	.935	.89	.962
Within R^2	.00088	.00277	.00248	.0000347	.00137	.00763

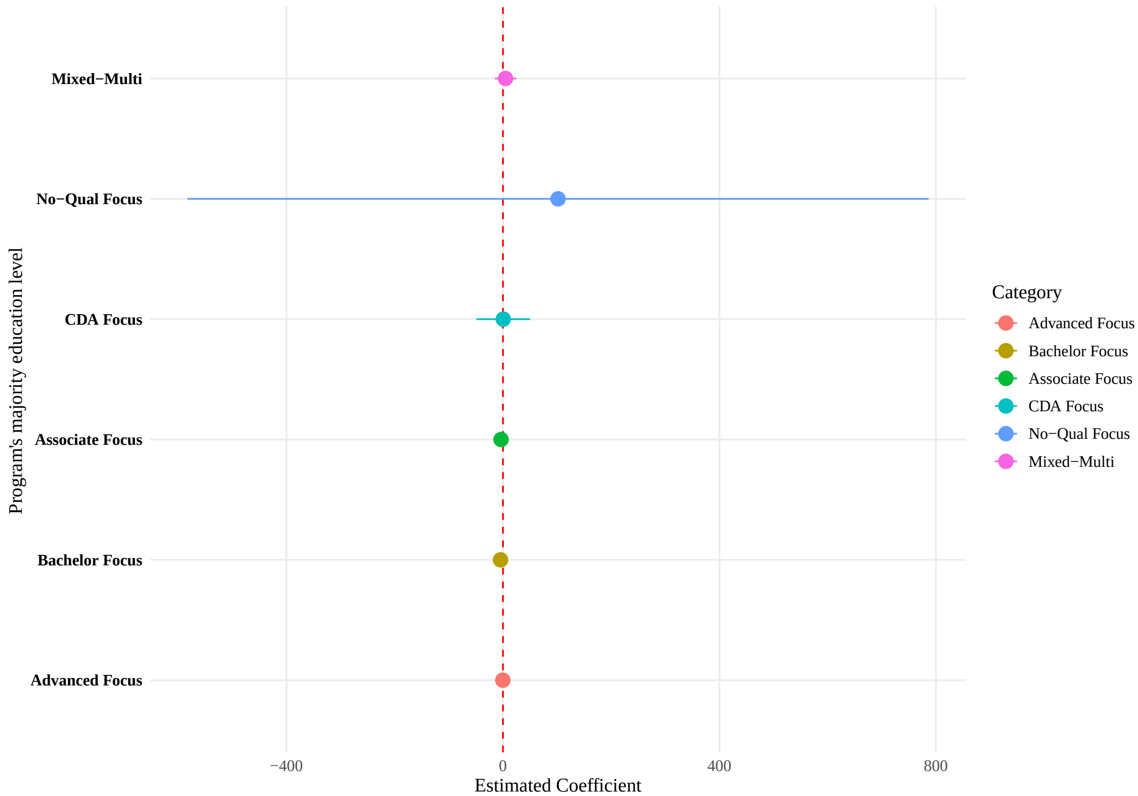
Note. SE clustered at the state-level are reported in parentheses.

. $p < .1$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Figure 4.15 is a visualization of Table 4.25.

Figure 4.16

DiD Results: Impact on Classroom Teachers' Raw Wages by Representative Teachers' Education Level (Equation 3.18) within HS in RQ3



Note. The category indicates the representative teachers' education level. The red dashed line indicates a null effect (zero).

Overall, the ***null*** hypotheses for RQ3 were **not** rejected. First, statistically, there is no national impact of the 2024 HSPPS announcement and the first year of policy impact on classroom teachers' raw wages. The placebo test showed statistical significance; thus, the parallel trends assumption was not validated. Also, the entire year in the event study showed statistical significance. Second, both HS and EHS classroom teachers showed no statistically significant change in classroom teachers raw wages resulting from the 2024 HSPPS. Third, I was able to identify variations across states. A total of 13 states showed statistically significant positive estimates. Finally, I decomposed the trend by the Representative Teachers' Education Level. Classroom teachers who held bachelor's degrees showed a reduction in raw wages before and after the 2024 HSPPS policy announcement and its first year of implementation (See Table 4.26).

Table 4.26

Summary of Empirical Findings for RQ3

Analysis Step	Specification	β	Sig.	Key Findings & Implications
1. National Level				
Main DID Impact	Full Sample (Total)	2623.08	***	Significant overall increase in salary after policy implementation.
Placebo Test	2022–2023 (Pre)	2686.42	***	High pre-trend indicates baseline growth prior to full policy effect.
Dynamic Effect	2023 / 2024 / 2025	Var.	***	Persistent positive impact across all policy years (2600–2740 range).
2. Program Type				
Head Start (HS)	Sub-sample	-370.82	*ns*	($p = .13$)
Early HS (EHS)	Sub-sample	-386.003	*ns*	($p = .46$)
3. State-level Analysis				
General Variation	Significant States	Var.	***	13 states (e.g., DE, LA, NY, SC) showed significant
4. Education Level				
National (Total)	Bachelor Focus	-185.65	*	($p = .036$)

Table 4.26

Table 4.26 (Continued)

Analysis Step	Specification	β	Sig.	Key Findings & Implications
	No-Qual Focus	-437.38	.	Approaching significance (p = .077)
Head Start (HS)	Bachelor Focus	-191.97	.	Approaching significance (p = .0843)
	Mixed-Multi	-260.36	.	Approaching significance (p = .0736)
Early HS (EHS)	Sub-sample	–	–	No computation (small observations)
State-level	Individual States	–	–	No computation (small observations)

Note. ns = insignificant

. $p < .1$, * $p < .05$, ** $p < .01$, *** $p < .001$.

RQ4 Results

Multilevel Modeling Evidence Between Classroom Teachers' Turnover Rates and Classroom Teachers' Real Wage Growth

First, I checked each of the model's singular fits (Equations 3.19, 3.20, and 3.21). Equations 3.19 and 3.20 showed non-singular convergence; however, Equation 3.21 showed a convergence failure, and thus I did not include it. Second, between Equations 3.19 and 3.20, I conducted likelihood ratio tests. The tests indicated that the inclusion of the interaction term did not significantly improve the model fit (see Equation 3.21). Therefore, I retained the simpler Equation 3.19 as the preferred model for final interpretation ($\chi^2(1)$ = 2.43, p = .119; see Table 4.27). Therefore, I selected Equation 3.19 for this study.

Table 4.27

Model Selection and Fit Statistics for Classroom Teachers' Turnover Rates

Model	df	**AIC**	**BIC**	**LogLik**	**Decision**
Equation 3.19	7	106094.6	106146.3	-53040.3	**Selected Model**: Best parsimony and stability.
Equation 3.20	8	106094.2	106153.3	-53039.1	Rejected: Interaction not significant ($p = .119$).
Equation 3.21	13	–	–	–	Excluded: Failed to converge (Singular Fit).

Note. Model 21 was excluded from formal comparison due to a singular fit ($\sigma^2 \approx 0$), indicating an over-specified random structure.

Equation 3.19 examined the relationship between classroom teachers' turnover rates and classroom teachers' real wage growth, and pre- and post-policy. First, classroom teachers' turnover rates are significantly different between pre- and post-policy ($\beta = -3.26$, p<.001***). This result implies that the turnover rate decreased by 3.26 units in the post-policy period relative to the pre-policy period. Second, classroom teachers' turnover rates also showed a statistically significant relationship with classroom teachers' real wage growth ($\beta = -.084$, p =.02*), as shown in Table 4.28. And when the classroom teacher's actual wage increase rates increased, the classroom teachers' turnover rates decreased by .084 units. This indicates that for every unit increase in a classroom teacher's actual wage increase rates, the classroom teachers' turnover rates decreased by .084 units. The standardized effect sizes for the effect of the pre/post-period and real wage growth on classroom teacher turnover were very small (Cohen, 1988).

Table 4.28

Multilevel Modeling Result (Equation 3.19) in RQ4

Fixed Effects	β	***SE***	
Intercept	21.3***	.65	
Pre-Post	$-3.26{*}{*}{*}$	.38	
ClassT_Real_Wage_Growth	-.08*	.03	
Random Effects	**Variance**	**Std. Dev.**	**Group Count**
Grantee:City:State	51.05	7.15	2,141 Grantees
City:State	32.65	5.71	1,308 Cities
State	11.95	3.46	50 States
Residual	403.73	20.09	$N = 11,835$

Note. * $p < .05$, ** $p < .01$, *** $p < .001$. AIC = 106,094.6.

Multilevel Modeling Evidence Between Classroom Teachers' Turnover Rates and Classroom Teachers' Real Wage Growth Based on Program Types

Following Equation 3.27, I performed sub-sample analyses between HS and EHS. First, HS classroom teachers' turnover rates showed a statistically significant difference between pre- and post- policy ($\beta = -3.53$, p < .001**); however, classroom teachers' real wage growth did not show a significant difference ($\beta = -.07$, p = .19). Second, EHS classroom teachers' turnover rates also showed a statistically significant difference between pre-post policy ($\beta = -2.95$, $p < .001$**). Unlike HS teachers, EHS teachers showed a result approaching significance with classroom teachers' real wage growth($\beta = -.08$, $p = .09$; see Table 4.29). Notably, estimates rendered a negative value, which means that when actual wage increase rates increased, EHS classroom teacher turnover decreased. Both HS and EHS's standardized effect sizes for the effect of the pre/post-period and real wage growth on classroom teacher turnover were very small (Cohen, 1988).

Table 4.29

MLM Results: Between Classroom Teachers' Turnover Rates and Classroom Teachers' Real Wage Growth by Program Types (Equation 3.27) in RQ4

	Head Start		Early Head Start	
Fixed Effects	*B*	*SE*	*B*	*SE*
Intercept	22.35***	.69	20.42***	4.81
Pre-Post	−3.53***	.55	-2.95***	.49
ClassT_Real_Wage_Growth	−.07	.05	-.08†	.05
Random Effects (σ^2)				
Grantee:City:State	80		59.12	
City:State	13.85		62.11	
State	9.95		16.68	
Residual	421.56		331.95	
Fit Statistics				
n	5,961		5,874	
AIC	53,917.3		51,997.5	

Note. $^{\dagger}p < .10$, *** $p < .001$.

Multilevel Modeling Evidence Between Classroom Teachers' Turnover Rates and Pre- and Post- and Classroom Teachers' Real Wage Growth Across States

Following Equation 3.28, I performed sub-sample analyses across states. Again, to follow multiple testing corrections, including a p-value adjustment before conducting the False Discovery Rate (FDR)'s Benjamini-Hochberg (BH) test. The FDR BH adjusted p-value analysis rendered a statistically significant result. The MLM results for classroom teachers' turnover rates showed negative estimates associated with pre- and post- across seven different states. Among these, Kansas (KS) exhibited the largest reduction in turnover, with an estimate of $\beta = -18.93$ ($p = .01**$). After that, the states of Maryland (MD), South Carolina (SC), West Virginia (WV), Colorado (CO), Georgia (GA), and New York (NY) followed (See Table 4.30). All of the significant states' standardized effect sizes for the impact of the pre/post-period and real wage growth on classroom teacher turnover were small (Cohen, 1988).

Table 4.30

MLM Results: Between Classroom Teachers' Turnover Rates and Pre- and Post- Policy Across States (Equation 3.28) in RQ4

State	**Term**	β	***SE***	***p***	*p* **(Bonf)**	*p* **(FDR BH)**
CO	prepost	-8.94	2.74	< 0.001***	.0619	.0124*
GA	prepost	-7.71	2.63	0.004**	.185	.0283*
KS	prepost	-18.9	5.29	< 0.001***	.0229	.00762**
MD	prepost	-11.8	2.98	< 0.001***	.00519	.0026**
NY	prepost	-7.55	1.71	< 0.001***	.000542	.000542***
SC	prepost	-10.4	3.07	< 0.001***	.0439	.011*
WV	prepost	-9.76	3.32	0.004**	.198	.0283*

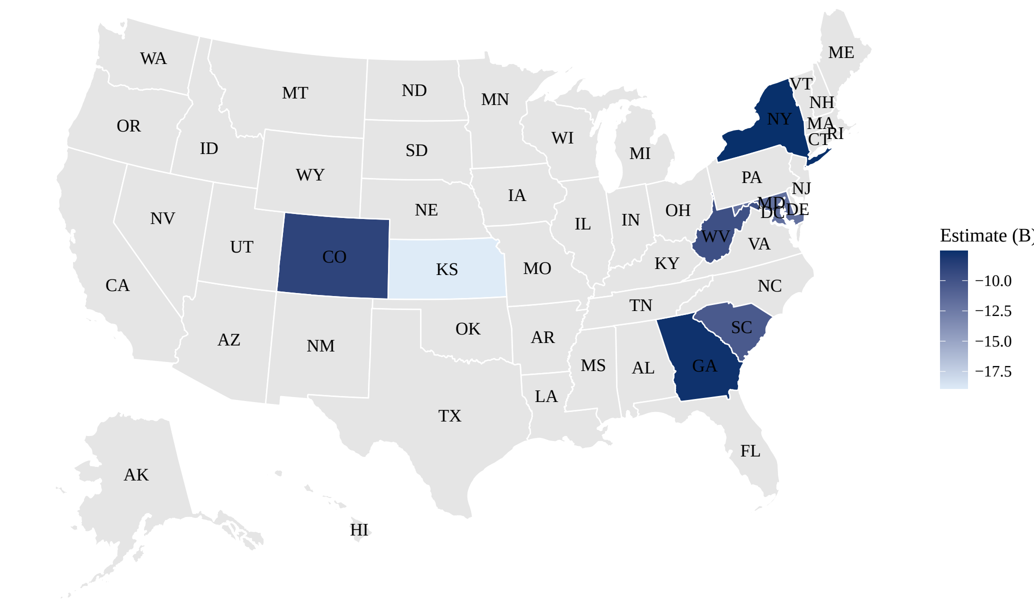
Note. p (Bonf) denotes Bonferroni-adjusted p-values; p (FDR BH) denotes Benjamini-Hochberg adjusted p-values.

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

Figure 4.16 shows the states that displayed statistical significance from Table 4.29. The states with larger estimated values are shown in dark blue.

Figure 4.17

MLM Results: Between Classroom Teachers' Turnover Rates and Pre- and Post- Across States (Equation 3.28) in RQ4 in Map



Note. Blue areas represent states with statistically significant negative effects, respectively ($p < .05$ after FDR BH correction). Gray areas indicate insignificant results ($p \geq .05$) or missing data.

Second, between classroom teachers' turnover rates and classroom teachers' real wage growth, only the state of PA showed a statistically significant difference ($\beta = -.44$, $p = .02*$; See Table 4.31). In contrast to the seven states previously mentioned, some of the remaining states exhibited positive estimates for the association between classroom teachers' turnover rates and classroom teachers' real wage growth, although these results were statistically insignificant. In other words, even though there is no statistically significant difference, there is variation by states between the classroom teachers' turnover rates and classroom teachers' real wage growth. The state of PA's standardized effect sizes for the impact of the pre/post-period and real wage growth on classroom teacher turnover were small (Cohen, 1988).

Table 4.31

MLM Results: Between Classroom Teachers' Turnover Rates and Classroom Teachers' Real Wage Growth Across States (Equation 3.28) in RQ4

State	Term	β	*SE*	*p*	*p* (Bonf)	*p* (FDR BH)
PA	Real_Wage_Growth	$-.437$	.12	<.001***	.0146*	.0146*

Note. *p* (Bonf) denotes Bonferroni-adjusted *p*-values; *p* (FDR BH) denotes Benjamini-Hochberg adjusted *p*-values.

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

Figure 24 shows the states that displayed statistical significance in Table 4.30. The states with larger estimated values are shown in dark blue.

Multilevel Modeling Evidence Between Classroom Teachers' Turnover Rates and Classroom Teachers' Real Wage Growth Based on Representative Teachers' Education Level

Following Equation 3.29, I performed sub-sample analyses by representative teachers' education level. First, classroom teachers' turnover rates and pre- and post-, besides the no-qual focus category, all of the representative teachers' education level categories showed significant differences. All of the categories in representative education level of classroom teachers within each program showed a negative estimate, whereas representative education level of classroom teachers within each program advanced focus category, classroom teachers showed the largest estimate ($\beta = -4.63$, p = .04*). After that, the mixed-multi, associate, bachelor focused and no-qual focus categories followed.

Second, classroom teachers' real wage growth was statistically significant with a representative education level of classroom teachers within each program category, with a mixed-multi value of $\beta = -.19$ (p =.02*), see Table 4.32. However, the advanced focus category did not show statistical significance ($\beta = .42$), though the result showed approaching statistical significance as p =.051 (See Figure 4.19). Additionally, the estimate showed a positive value, which none of the other representative teachers' education level categories exhibited (See Table 4.31). In other words, programs with advanced degree-holding teachers increased classroom teacher turnover by .42 units (See Figure 4.20). Across all representative teacher education level categories, the standardized effect sizes for the effect of the pre/post-period and real wage growth on classroom teacher turnover were very small (Cohen, 1988).

Table 4.32

MLM Results: Between Classroom Teachers' Turnover Rates and Classroom Teachers' Real Wage Growth and Pre- and Post- Policy by Representative Teachers' Education Level (Equation 3.29) in RQ24

Category	**Term**	β	*SE*	p **(FDR BH)**
Bachelor Focus	(Intercept)	21.8	.54	< .001***
	prepost	−3.27	.62	< .001***
	ClassT_Real_Growth	−.09	.06	.155
Mixed-Multi	(Intercept)	19.6	.62	< .001***
	prepost	−4.5	.79	< .001***
	ClassT_Real_Growth	−.19	.08	.016*
Advanced Focus	(Intercept)	18.2	1.56	< .001***
	prepost	-4.63	2.14	.046*
	ClassT_Real_Growth	.42	.2	.051
Associate Focus	(Intercept)	21.8	.83	< .001***
	prepost	−3.87	.93	< .001***

Table 4.32

Table 4.32 (Continued)

Category	**Term**	β	*SE*	*p* **(FDR BH)**
	ClassT_Real_Growth	−.12	.09	.174
CDA Focus	(Intercept)	22.4	.97	< .001***
	prepost	−2.89	.98	.006**
	ClassT_Real_Growth	−.02	.08	.892
No-Qual Focus	(Intercept)	30.1	2.29	< .001***
	prepost	−.38	2.61	.903
	ClassT_Real_Growth	.02	.14	.903

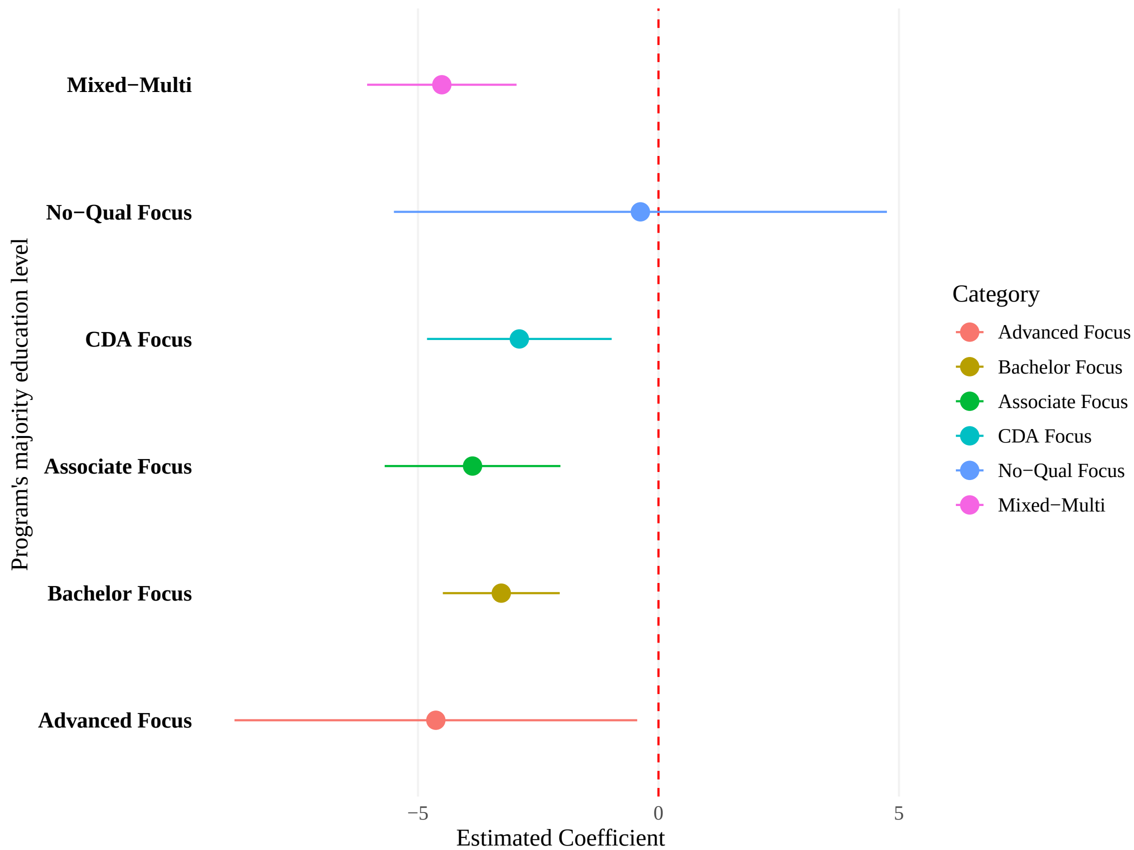
Note. *p* (FDR BH) denotes Benjamini-Hochberg adjusted *p*-values.

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

Figures 4.17 and 4.18 show the results of Table 4.32. Figure 4.17 shows the results of classroom teachers' turnover rates and pre- and post- by representative teachers' education level. Figure 4.18 shows the results of classroom teachers' turnover rates and classroom teachers' real wage growth by representative teachers' education level.

Figure 4.18

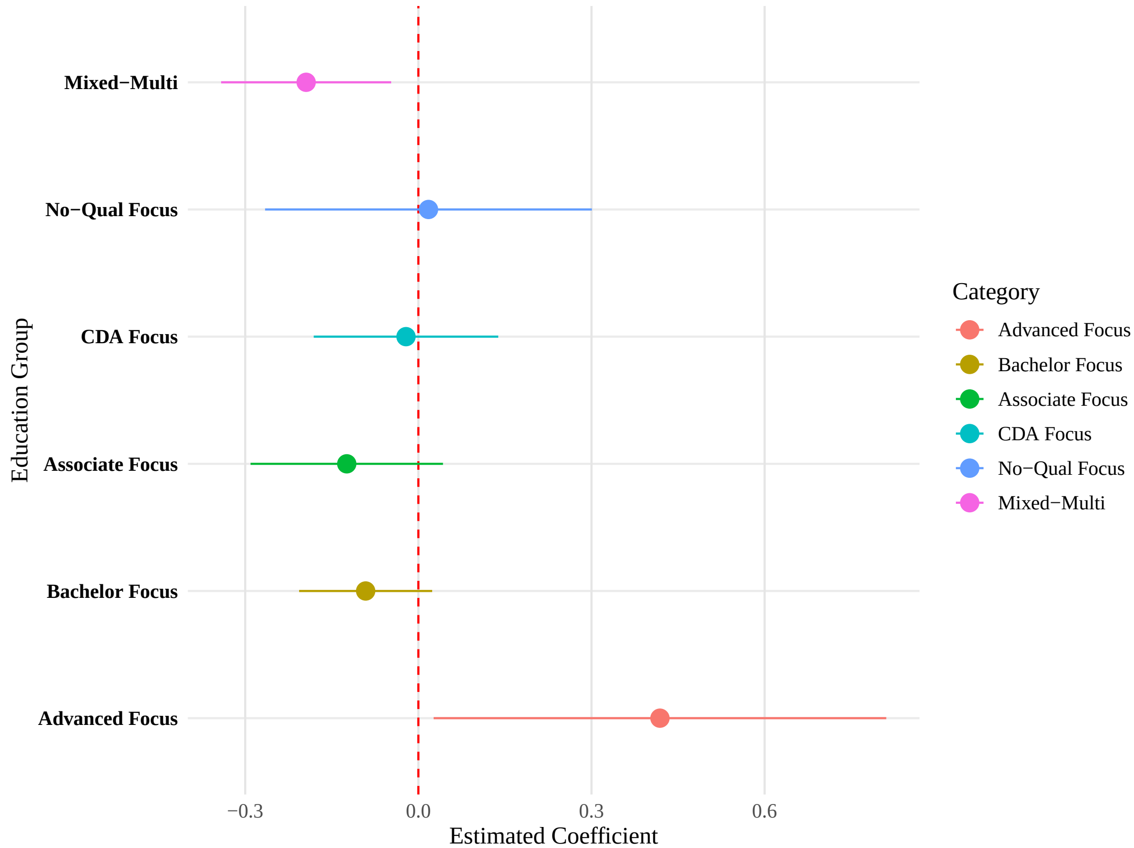
MLM Results: Between Classroom Teachers' Turnover Rates and Pre- and Post- by Representative Teachers' Education Level(Equation 3.29) in RQ4



*Note.*The category indicates the representative teachers' education level. The red dashed line indicates a null effect (zero).

Figure 4.19

MLM Results: Between Classroom Teachers' Turnover Rates and Classroom Teachers' Real Wage Growth by Representative Teachers' Education Level (Equation 3.29) in RQ4



Note. The category indicates the representative teachers' education level. The red dashed line indicates a null effect (zero).

Overall, the ***null*** hypotheses for RQ4 were ***rejected***. First, classroom teacher turnover decreased from pre- to post- policy. Noticeably, classroom teacher turnover decreased by the classroom teacher's actual wage increase rates. Second, based on program type, both HS and EHS classroom teacher turnover decreased from pre- to post-policy, which aligns with the result of the first research question. Third, I was able to identify variations across states. There were several states that showed statistically significant differences between classroom teachers' turnover rates and pre- post. However, between classroom teachers' turnover rates and classroom teachers' real wage growth only the state of PA showed a statistically significant difference. Finally, all of the categories in representative teachers' education level rendered statistically significant differences from pre- and post- policy in classroom teachers' turnover rates. On the other hand, the mixed-multiple categories showed statistical significance with classroom teachers' real wage growth (See Table 4.33). These results are consistent with the findings from RQ1, which indicated that classroom teacher turnover decreased before and after the policy announcement, as well as during the first year of implementation.

Table 4.33

Summary of Empirical Findings for RQ4

Analysis Step	Variable	Specification	β	Sig.	Key Findings & Implications
1. Main MLM	[prepost]	Full Sample	−3.263	***	Significant reduction in turnover rate post-policy.
	[Real_Wage_Growth]	Full Sample	−.084	*	Real wage growth showed a significant negative correlation.
2. Program Type	[prepost]	HS	−3.531	***	Strong policy impact observed in HS programs.
	[Real_wage_Growth]	HS	−.067	*ns*	Real wage growth was not significant in HS.
	[prepost]	EHS	−2.952	***	Significant policy impact also confirmed in EHS.
	[Real_Wage_Growth]	EHS	−.078	.	Real wage growth showed a result approaching significance.
3. State-level	[prepost]	CO, GA, KS, MD, NY, SC, WV	Var.	***	Robust reduction found in multiple states.

Analysis Step	Variable	Specification	β	Sig.	Key Findings & Implications
	[Real_Wage_ Growth]	PA	$-.437$	*	Significant interaction between growth and turnover in PA.
4. Education Level	[prepost]	All categories	Var.	*	All groups showed significant interaction between Class_TTR and prepost.
	[Real_Wage_ Growth]	Mixed-Multi	$-.19$	*	Significant effect of real wage growth for Mixed-Multi.

CHAPTER FIVE

DISCUSSION

Despite strong evidence that high-quality early care and education (ECE) has critical impacts on society, such as improving academic outcomes and return on investment (Aber et al., 2007; Blöchliger & Bauer, 2024), the professional status of ECE teachers remains systemically undervalued in comparison to their K-12 counterparts. This is especially apparent in pay disparity, leading to issues such as high teacher turnover rates.

In 2024, the office of Head Start announced a revision to the Head Start Program Performance Standards (HSPPS) to improve the working conditions of Head Start (HS) and Early Head Start (EHS) teachers in hopes of reducing teacher turnover. HS and EHS are two of the major national programs in the ECE field. Thus, the 2024 HSPPS is a policy that could set the standards for all early care and education programs. The 2024 HSPPS is a compensation policy to reduce classroom teacher turnover in HS and EHS by improving wages, benefits, staff health, and wellness (DHHS, 2024b). Each section has a different timeframe to fulfill, such as wages by August 1, 2031 (DHHS, 2024b). The implementation of benefits will be completed by the end of August 1, 2028, and staff health and wellness by the end of August 1, 2027 (DHHS, 2024b). Those actions were announced on November 20th, 2023, and were implemented during the 2024 academic year.

The purpose of this study was to evaluate the relationship between the 2024 HSPPS implementation and classroom teacher turnover, actual wage increase rates, and raw wages. Doing so is a starting point to understand and evaluate the early stages of the 2024 HSPPS's effectiveness in national, state, program types, and the representative education level of teachers within each program. Offering descriptive results—such as which states or program types showed the most or least impact—provides direction for the remaining policy timeframe to make 2024 HSPPS more effective. For example, in the second research question, the state of Indiana showed a positive estimate in classroom teachers' real wage growth from the 2024 HSPPS. In the third research question, the state of Maryland showed the largest estimate, which is the most impacted state in raw wages from the 2024 HSPPS.

National-level policy evaluation is necessary to support and develop strategies for the ECE teacher workforce because it is also impacting other programs and overall national education at the same time. In addition to customizing and developing the 2024 HSPPS at the local level, implementing this policy will eventually help fulfill equity in teachers' working environments, leading to a higher overall quality of ECE programming. The following sections will summarize the findings in relation to the research questions and sub-questions and explain how the findings support or contradict to the literature.

Review of Critical Findings by Research Questions

2024 HSPPS Effect on Teacher Turnover, Real Wage Growth and Raw Wages at the National-level

RQ1 Result: Policy Impact on Teacher Turnover Rates

Previous literature (Bryant et al., 2023; Hur et al., 2023) reveals that the reasons for teacher attrition are closely connected to compensation, including wage and working conditions such as meal breaks. The purpose of the 2024 HSPPS policy revision was to advance compensation, benefits, and staff health and wellness in HS and EHS programs to retain teachers and reduce turnover. Accordingly, the finding in RQ1 of this study strongly suggests that there is a causal impact of the 2024 HSPPS on classroom teacher retention.

The difference-in-differences (DiD) analysis revealed a statistically significant decline in classroom teachers' turnover rates within the treatment group following the 2024 HSPPS policy announcement and its first year of implementation. This finding confirms the effectiveness of the 2024 HSPPS in reducing classroom teacher turnover in larger programs with more than 200 slots, but not in smaller programs. Interestingly, the results suggest a powerful "announcement effect." This "announcement effect" is explained by the theory of reasoned action (TRA) and the theory of planned behavior (TPB). The 2024 HSPPS announcement may have impacted the teachers' perceptions of the benefits of remaining in HS and EHS classrooms. Previous literature has revealed that compensation is not the only reason for staying (e.g., Blöchliger & Bauer, 2024). The 2024 HSPPS revision includes more than compensation, which might also trigger them to stay. Even in the initial stage of implementation, the government's formal commitment to wage parity and improved working conditions served as a positive signal to the workforce, effectively reducing immediate turnover intentions, which evidenced a “linkage” effect (Bronfenbrenner, 1979).

RQ2 and 3 Result: Policy Impact on Real Wage Growth and Raw Wages

A critical contribution of this study is the nuance discovered regarding actual wage increase rates versus raw wages. The second research question’s actual wage increase rates did not show any impact from the 2024 HSPPS. Also, the third research question’s raw wages did not show any impact from the 2024 HSPPS.

However, the second research question, particularly in the year 2025, showed strong negative trends in terms of actual wage increase rates. In other words, the actual wage increase rates decreased in 2025. This finding reveals that the policy announcement and its first year of implementation did not correlate with significant actual wage increase rates for classroom teachers.

Although the third research question’s raw wages showed a significant difference between the treatment and comparison groups, the policy failed to produce a statistically significant change in raw wages growth, specifically attributed to the 2024 HSPPS. In other words, the 2024 HSPPS merely followed the trend rather than setting it. Raw wages have grown continuously since 2022.

While the 2024 HSPPS policy was designed to bolster compensation, the empirical data provide a sobering reality: classroom teacher actual wage increase rates did not show a statistically significant difference before and after the 2024 HSPPS. Instead, the increase in raw wages appears to be a consistent trend within the ECE field rather than a unique result of the 2024 HSPPS. For example, according to Gonzalez et al. (2024), consecutive wage growth was already observed in the spring of both 2021 and 2022.

Combined with findings from the second and third research questions, I found that while classroom teacher wages increased consistently, the rates of wage increase declined. Specifically, by 2025, inflation was too high to be compensated for by the increase in raw wages. I found that while the ECE field saw nominal pay raises, these did not translate into "real economic growth" for individual teachers, which is strongly connected to the “Educator Economic Well-being (McLean et al., 2024, p.62).” Educator economic well-being comprises strategies to improve wage, financial incentives (Bernardi et al., 2023). According to Walker (2024), nonetheless, accounting for inflation, teachers' average earnings have decreased by 5.3% over the past decade. Eventually, this finding extends the work of McLean et al. (2024), which argued that "early educators do not earn a living wage in any state" (p. 57) by highlighting that wage increases in the ECE field must be evaluated against the broader macroeconomic context to be truly effective.

RQ4 Result: TTR Between Real Wage Growth and Pre- and Post Policy

Lastly, from the fourth research question, I found that classroom teacher turnover has an inverse relationship with actual wage increase rates. In other words, when classroom teacher actual wage increase rates increase classroom teacher turnover rate decreases. This finding aligns with research by Hur et al. (2023) and Vicente et al. (2024). Therefore, future policy implementations must prioritize not just raw wages but also ensure that wage increases exceed inflation. Doing so will be a vital strategy for reducing turnover and retaining teachers.

2024 HSPPS Effect on Teacher Turnover, Real Wage Growth and Raw Wages based on HS, EHS

RQ1 to RQ3 Result: Policy Impact on Teacher Turnover Rates, Real Wage Growth, and Raw Wages

The effectiveness of the 2024 HSPPS policy has not yielded significant variations between HS and EHS regarding classroom teachers' turnover rates, nor has it produced strong distinctions in actual wage increase rates or raw wages between the two programs.

In the classroom, teachers' turnover there are mixed findings in the previous results regarding teachers ' turnover. For example, research by Bassok et al. (2021b) indicated that teachers who work with infants and toddlers have a higher chance of leaving the field. Contrarily, findings from Bryant et al. (2023) and Kwon et al. (2025) reported that preschool and kindergarten teachers have higher turnover than infant and toddler teachers. Also, teachers in both studies indicated different reasons for leaving. Both of the research teams also reported and understood the difference finding in their results across the literature. Those exciting findings might be reflected in this research and not show any variation.

RQ4 Result: Teacher Turnover Rates Between Real Wage Growth and Pre- and Post Policy

Among EHS teachers, there is a result approaching a significant relationship between classroom teachers' turnover rates and actual wage increase rates. When classroom teachers' actual wage increase rates increased, EHS classroom teachers tended to reduce their turnover rates. Similar to findings from Bryant et al. (2023), teachers who work with infants and toddlers indicated their main reasons for leaving were the stressful nature of the work, a negative work climate, and low compensation. However, unlike Lee et al. (2022), they found that working with infants and toddlers had an insignificant effect on ECE educators' wages. Historically, EHS teachers' wages were lower than HS (Mackenzie-Liu et al., 2024). There is a possibility that EHS teachers are more sensitive to wages than HS teachers. Lee et al. (2022) indicated that their research used data from different teacher settings (e.g., center-based, home-based). On the other hand, this present study did not. Therefore, I argue that the historical trend makes EHS teachers more sensitive to wages than HS teachers in the same setting.

2024 HSPPS Effect on Teacher Turnover, Real Wage Growth and Raw Wages Across States

RQ1 Result: Policy Impact on Teacher Turnover Rates

I found that from the first research question that the policy's impact on classroom teacher turnover did not show variation across all states. At the state-level, after accounting for clustered standard errors, I found that the differences between the treatment and comparison groups were statistically indistinguishable. In other words, while the 2024 HSPPS served as a powerful national-level "announcement" and "first year Implementation" that lowered turnover expectations broadly, it was still in an earlier stage of policy implementation to show the local level's reaction to turnover. Moreover, this research used program-level data, which shrank the overall sample size. This result may be driven by sub-sampling data that creates a smaller number of programs for each sample.

RQ2 Result: Policy Impact on Real Wage Growth

The states of Georgia (GA), Indiana (IN), New Jersey (NJ) showed significance with regard to the second research question; however, states of IN showed positive estimates on the other hand states of GA and NJ showed a negative estimate. The states of GA and NJ have a cost of living that is higher than the average wage. For example, the state of GA's treatment group' classroom teachers' actual wage increase rates was consistently lower than the comparison group since 2023. On the other hand, the state of IN's treatment group's classroom teachers' real wage growth increase rates were consistently higher than the comparison between 2023 and 2024. And in 2025, comparisons and teacher groups' classroom teachers' real wage growth were the same as 8.7%. Thus, the 2024 HSPPS was least effective in generating actual wage increase rates in the majority of states, especially the state of GA and NJ; it lacked the necessary economic strength to counteract localized factors in the majority of states.

However, again, this research's wage data were state-level data. Although wages were assigned by the representative education level of classroom teachers within each program, further analysis is still needed to examine a deeper relationship with the 2024 HSPPS.

RQ3 Result: Policy Impact on Raw Wages. A total of 13 states — Delaware (DE), Louisiana (LA), Maryland (MD), Michigan (MI), Mississippi (MS), Montana (MT), North Dakota (ND), Nevada (NV), New York (NY), Rhode Island (RI), South Carolina (SC), Utah (UT), Wisconsin (WI) — showed significance with regard to the third research question. Their pre-trend assumptions were confirmed, indicating insignificant differences in raw wage trends between the treatment and comparison groups prior to the 2024 HSPPS. I found that while these findings—specifically the increase in raw wages—provide evidence of the 2024 HSPPS's impact. However, none of the states above showed a positive estimate or significance in the second research question. The findings show that these states increased raw wages, but they were not enough to compensate for the cost of living. In other words, the impact of policy was not enough to show the actual wage increase rates. Mackenzie-Liu et al. (2024) pointed out that the state of NY had the lowest average wage for HS classroom teachers with an associate's degree. However, the state of NY showed significant differences in raw wages, which is a contradictory result indicating that the state of NY is one where the 2024 HSPPS was effective in terms of raw wages. Still, it is important to consider whether smaller programs within the state were able to consider inflation when implementing these wage increases.

When focusing solely on the state of Wisconsin (WI), it has the REWARD, which state of WI Stipend Program delivers crucial extra financial support to ECE teachers continuing in an underpaid and under-resourced sector (Wisconsin Early Childhood Association, 2023). The purpose of this program is to boost ECE teacher pay, enhance their job stability, and foster ongoing professional development (Wisconsin Early Childhood Association, 2023). WI did not show any pre-trend, but there is still a possibility of raw wages increases from other policies or a combination with the 2024 HSPPS. The state of Michigan (MI) also has the Great Start Readiness Program (GSRP), which serves four-year-old children from families with incomes at or below 400% of the federal poverty level (MiLEAP, n.d.). The HSPPS partially overlaps with the GSRP as it plans to increase teacher wages, such as the Early Educator Wage Initiative (Vibrant Futures, n.d.). Michigan's Department of Lifelong Education has launched the Early Childhood Educator Wage Initiative, allocating $16 million to bolster the workforce and ensure enduring wage stability for ECE teachers (MiLEAP, 2025). The MI wages initiative will run through September 2027 (MiLEAP, 2025), which partially overlaps with the 2024 HSPPS' seven-year timeframe.

Moreover, in Figure 4.13, I was able to identify the region group. States that showed statistical significance were mainly located along the Atlantic coast and in the midwest.On the other hand, I did not observe any statistically significant relationship in the western regions of the U.S.

RQ4 Result: Teacher Turnover Rates Between Real Wage Growth and Pre- and Post- Policy

As identified in the fourth research question, only six states — Colorado (CO), Georgia (GA), Kansas (KS), Maryland (MD), New York (NY), South Carolina (SC), and West Virginia (WV) — exhibited a significant relationship between classroom teacher turnover and the pre-post policy periods. Pennsylvania (PA) is the only state that showed a relationship between classroom teacher turnover and actual wage increase rates when sub-sampled by state-level in the fourth research question. According to Whitebook et al., (2018), teachers who work with infants and toddlers earn less than those who work with preschool-aged children. The state of PA showed larger program numbers in EHS than in HS. Thus, this result, coming from EHS teacher turnover, showed a relationship with actual wage increase rates and their turnover. Additionally, PA's HS and EHS classroom teachers could be more sensitive to wages than other states' teachers. This result could potentially be driven by their variation across states' characteristics, such as their close proximity to a state with a high cost of living (i.e., New York). Thus, the state of PA teachers may be more sensitive to wage increases. Therefore, future investigation into the reasons for this outcome is needed. Research by Nelson et al. (2025) indicated that libraries and childcare centers affected teachers' decisions to leave differently. This variation may come from neighborhood factors coupled with the 2024 HSPPS. Again, "object reality concept applied to the teacher, where individual perceptions differ, which leads to differ decisions (Bronfenbrenner, 1979). In other words, the neighborhood could be a factor in deciding to leave or stay.

Examining differences across states revealed that the majority of states were statistically insignificant. This lack of state-level significance suggests that the 2024 HSPPS may not have enough time to demonstrate actual changes or data structures that cause data to be insufficient. In addition, state-level wage data yield constraints on the dataset's diversity. This lag made it difficult to observe regional disparities, such as inflation and the cost of living, highlighting the need for a more geographically tailored policy approach based on thorough data.

2024 HSPPS Effect on Wages and Turnover by Education Level

RQ1 Result: Policy Impact on Teacher Turnover Rates

Programs representing the education level of classroom teachers, particularly those in the bachelor's degree category, showed statistically significant results in classroom teachers' turnover rates between the treatment and comparison groups. The 2024 HSPPS was effective in reducing turnover in the bachelor's focus category. Similar to Markowitz (2024), a teacher who had an associate degree showed a slightly higher likelihood of leaving the job than teachers of other higher levels of education. On the other hand, Kwon et al. (2025) found that teachers who had higher levels of education tended to leave the field at a higher rate.

HS also showed the same result at the national-level. A classroom teacher in HS education needs to hold at least an associate's or bachelor's degree, and nationally, 50% need to hold a bachelor's (ACF, n.d.b). On the other hand, the EHS teacher requirement is CDA (ACF, n.d.a). Given this prerequisite, HS teachers naturally have more teachers with bachelor's degrees than EHS. According to the NAEYC & The Education Trust, (2019), teachers who work in a non-public school pre-k setting tend to discriminate in wage or benefits even though they have the same level of experience. Thus, teachers who have a bachelor's degree might have high expectations of the 2024 HSPPS to reduce this discrimination. Also, 2024 HSPPS indicate that HS teachers' wages are comparable to public school preschool teachers (DHHS, 2024b). This result potentially comes from 2024 HSPPS characteristics that a classroom teacher in HS 50% need to hold a bachelor's degree.

RQ2 Result: Policy Impact on Real Wage Growth

In the no-qual focus category, the representative education level of classroom teachers within each program showed a result approaching significance as a negative relationship with actual wage increase rates.

RQ3 Result: Policy Impact on Raw Wages

I found that programs representing the education level of classroom teachers, particularly those in the bachelor's focus category reported lower raw wages in comparison to other programs with a non-bachelor's focus category. Notably, bachelor's degree classroom teachers' raw wages decreased.

Fortunately, it was not connected with the first and second research questions. This result comes from the 2024 HSPPS policy focused on matching the wage parity between HS and EHS teachers who have the same qualifications. In addition, the 2024 HSPPS focused not only on compensation but also considered other working environments. Thus, the bachelor's focus category showed the highest expectation and execution in reducing their turnover rates. Although wage is not the only reason for leaving or staying, it is one of the most important factors. Additionally, 35.2% of current HS and EHS teachers have bachelor's degrees. Notably, categories of teachers with bachelor's focus have been shown to significantly reduce turnover in the 2024 HSPPS. Bachelor's degrees will be an important portion of the consistent effectiveness of the 2024 HSPPS.

RQ4 Result: Teacher Turnover Rates Between Real Wage Growth and Pre- and Post Policy

The mixed-multi category classroom teachers' turnover showed a relationship with actual wage increase rates. This finding was confirmed again by all levels of education teachers, who indicated they cared about actual wage increase rates. Along with the results of Morrissey and Bowman's (2024) research, this finding underscores the importance of wages in reducing teacher turnover.

In summary, the 2024 HSPPS policy successfully triggered a reduction in classroom teacher turnover during the announcement and its first year of implementation. However, the shadow of 2025's inflation reveals that nominal success does not always equate to real-world stability. For the Head Start workforce to remain sustainable, future policy must ensure that wage enhancements exceed the rate of inflation, thereby securing the real economic growth of the educators who are foundational to the program's success.

Unique to this Research

Having and building strengths in teacher compensation policy to reduce classroom teacher turnover in the HS and EHS will spill over to other ECE programs and also to future education programs (ECLKC, 2024c). Despite the necessity and effectiveness of HS and EHS, compensation is one of the reasons that enrollment rates have continued to decrease since fiscal year (FY) 2015. Years of research indicate that offering high-quality preschool programs has the potential to positively impact the lives of impoverished children, leading to improved academic outcomes, school progression, and educational attainment (Aber et al., 2007).

The revision of HSPPS in August of 2024 was not temporary; it included a plan through the year 2031 and beyond that seeks to reduce classroom teachers' turnover rates and, in doing so, deliver higher-quality education to children. Thus, evaluating the effectiveness of the 2024 HSPPS is a fundamental resource for understanding ways to mitigate teacher turnover, ultimately improving overall school readiness among underserved student populations. Furthermore, HS and EHS programs have strong relationships and align with other ECE communities. EHS-ECE Partnerships enhance access to top-notch early learning settings for babies and toddlers from low-income families (ECLKC, 2024a). Therefore, HS and EHS programs exercise influence in all of the ECE sectors, such as private centers or communities. Follow the 2024 HSPPS model to adjust teachers' wages and benefits.

Limitations

This study incurred several limitations, mainly owing to data deficiency. First, this research used the PIR data set, which only offers program-level data. Thus, this research used the representative education level of classroom teachers within each program, which cannot capture the individual-level characteristics of teachers, such as their race or years of teaching experience.

Second, the consumer price index (CPI) data comes from the U.S. Bureau of Labor Statistics. The U.S. Bureau of Labor Statistics does not offer state-level CPI data. For example, Michigan's CPI comes from the metropolitan Detroit CPI. Even within the same state, suburban and rural areas could have different CPIs. However, it was not possible to consider these specific differences. Furthermore, some states did not provide their CPI data. In this case, the CPI calculations for some states are region-specific. Ultimately, this data deficiency rendered some states' exact CPI unmeasurable.

Third, wage data were only available at the state-level. Differences between grantee-level could not be observed. Additionally, I assigned the wage data to the representative education level of classroom teachers within each program to prevent multicollinearity; however, limitations remained in understanding trends in raw wages and actual wage increase rates.

Lastly, at some point, I acknowledged that each state, region, and perhaps even program could have tackled this issue prior to, or in conjunction with, the 2024 HSPPS. As mentioned above, research by Gonzalez et al. (2024) indicated that consecutive wage growth had already been observed in 2021 and 2022. Additionally, this research used small programs as comparison groups. However, the small programs still have responsibility in pay scale or structure that promotes competitive wages (DHHS, 2024b). The findings from this study also showed a pre-trend in raw wages, suggesting that 2024 HSPPS does not exist in a vacuum.

Directions for Future Research

Based on the results of this study, there are several recommendations for future research. First, this study examined the effects of policy announcements and the first year of policy implementation. The policy has a seven-year timeframe, so future research should examine the policy implementations of the next six years and determine to see long-term implementation pattern of 2024 HSPPS.

Second, this study was not able to examine differences between teacher positions. Due to the data structure, this study only focused on classroom teachers. Future research should distinguish between classroom teachers, assistant teachers, home-based visitors, and family child care providers by using different data sets that contain information of each teacher's turnover by each position. Moreover, prior studies indicate the reasons for staff turnover differ by teacher position (DHHS, 2024b; Hur et al., 2023). Therefore, further research is needed to address how effective the 2024 HSPPS is in reducing classroom teacher turnover differ by teacher positions (e.g., classroom or assistant).

Third, future research should include the exact CPI of each state, or consider each district individually. This research used CPI data from the U.S. Bureau of Labor Statistics, which offers CPI data based on region and large metropolitan areas, rather than by state. Thus, I am suggesting using state-level CPI data which provides more detailed information, such as county-level. This would allow us to calculate the pure effect of the 2024 HSPPS on actual wage increase rates in each state, moreover, at each grantee-level.

Fourth, a larger number of observations need to be conducted to understand and identify variations between program types (i.e., HS and EHS) and across states. For example, this study used program-level data; thus, future research at the teacher level is needed to gain a deeper understanding of each group. Additional investigation on the demographic characteristics of teachers will help us better target the 2024 HSPPS and understand the reaction to this research.

Fifth, analyzing classroom teachers' turnover through Bronfenbrenner's ecological framework provides a comprehensive understanding of how interconnected systems influence, especially for teachers and children. This perspective highlights the need for policies that address not only structural conditions but also the day-to-day experiences that shape retention and educational quality. Therefore, for future research, should include qualitative data to incorporate teacher voices to examine their exact perspectives.

Seventh, this study revealed that smaller programs were not impacted by the change in 2024 HSPSS as much as larger programs. However, teachers are still working in the same field and potentially in the same city, in some cases even across the street, suggesting that teachers do move between programs. This finding implies that teachers who work in smaller programs can simply move to larger programs within the same region. This occurrence could be the reason TTR either did not significantly change or slightly increased among smaller programs.

Additionally, this research also found that there are variations across states, such as the state of PA or the states of DE, ME, MI, and MS. Neighborhood factors—such as geography, infrastructure (e.g., childcare centers, hospital), and socioeconomic (Nelson et al., 2025) suggested that —may contribute to this variance, alongside the 2024 HSPPS. Thus, future research should examine the relationship between the 2024 HSPPS policy and neighborhood factors to understand trends in the workforce and other impact factors related to teacher turnover by using additional data sets, such as administration data that includes neighborhood factors. More specifically, research focused on why actual wage increase rates showed a negative effect by examining the economy and politics in those specific states would be noteworthy.

Seventh, from a broad perspective, this phenomenon is explained by Bronfenbrenner's Ecological model. Individuals' perceptions of three levels (the microsystem, the mesosystem, and the exosystem) of the ecological environment are different (Bronfenbrenner, 1979). Thus, teachers from different states, and even teachers within the same state, have different perceptions of the HHSPS policy actions of wages, benefits, and staff health and wellness. Further examining differences at the micro-level, such as the state-level policy, will help to more deeply understand this phenomenon.

Lastly, one of the 2024 HSPPS funding sources comes from under-enrollment slots, meaning vacant slots (DHHS, 2024b). Administration for Children and Families (ACF) is planning to reallocate funded slots that are currently vacant (DHHS, 2024b). Currently, HS programs face the conundrum of having vacant slots, but no staff to serve additional children. As a result, 2024 HSPPS provides an opportunity to restructure the budget to support fewer slots in some programs to deliver higher wages and benefits for staff (DHHS, 2024b). Hence, in the future, researchers should examine these vacant slots and actually move to the actual wage increase rates which will be important when evaluating the 2024 HSPSP. Unfortunately, the PIR data sets do not offer information on vacant slots, so future research on how vacant slots increase wages is another way to evaluate the implementation of the 2024 HSPPS policy.

Conclusions

This study evaluated the impact of the 2024 HSPPS announcement and its first year of implementation on classroom teacher turnover, actual wage increase rates, and raw wages at the national, state, program, and representative education level of classroom teachers within each program. While the combination resulted with other social factors, the policy marked a successful start to reduce turnover; it did not yield significant improvements in actual wage increase rates or raw wages. These results underscore the need for policy sustainability. The timeframe of this study may have been too early to capture the full impact of the changes in the HSPPS. Nevertheless, the 2024 HSPPS has already shown positive results in retaining teachers in the short term; thus, sustaining this successful trend is necessary. This approach will help ensure that the reduction in classroom teacher turnover is not temporary. Additionally, as inflation in 2025 was higher than normal, most people's wages did not keep pace with it. Furthermore, variations were observed across states and program types. Some states already have their own plan for ECE workforce development. Thus, to maximize the effectiveness of the 2024 HSPPS, I suggest that state-level policies are warranted, in coordination with revisions to HSPPS, such as customized strategies by consideration of local economic conditions and teacher characteristics. Moreover, observing this effectiveness in the early stages of the 2024 HSPPS suggested teachers' willingness to stay if their working conditions improved, not only wages but also on teachers' benefits and health wellness. Therefore, the core focus of future policy should be on the sustained preservation of actual wage increase rates. Evidence of the success of this policy is a starting point for improving and developing working environments that will allow teachers to thrive, potentially influencing broader ECE systems.

APPENDIX A

IRB APPROVAL

Figure A.1

IRB APPROVAL

OAKLAND UNIVERSITY

Institutional Review Board

Date: August 6, 2025

Study #: IRB-FY2026-31

Study Tile: Staying or Leaving? Head Start Teachers' Turnover and Retention Trends from 2022 to 2025 in the Early Adoption Phase of the 2024 Teacher Compensation Provision

Submission Type: Initial

IRB Decision: No Human Subjects Research

Research Team:
Boyun Kim
Tomoko Wakabayashi

The above referenced study has been has been determined to be No Human Subjects Research according to federal regulations.

The IRB decision is based on the following:

- The study does not meet the definition of human subjects research as it involves the use of de-identified public information that will be obtained from the Performance Indicator Report (PIR) available on the Head Start webpage. The PIR contains only aggregate data that can not be individually linked.

Please retain a copy of this correspondence for your records.

If you have any questions, please contact the IRB staff.

Thank you.

The Oakland University IRB

APPENDIX B

STATISTICAL SUMMARY OF WAGE VARIANCES

Table B.1
Wages Variance and Ratio by State

State	Within Var	Between Var	Ratio
AK	0.2861	0.0171	0.9435
AL	0.1618	0.0321	0.8344
AR	0.4945	0.0556	0.8989
AZ	3.8370	0.3948	0.9067
CA	2.6398	0.3623	0.8793
CO	0.4884	0.1179	0.8056
CT	2.4925	0.6828	0.7850
DE	1.0906	0.1661	0.8678
FL	1.1333	0.1396	0.8904
GA	1.2566	0.1283	0.9074
HI	0.9916	0.1251	0.8880
IA	1.1473	0.0468	0.9608
ID	1.2262	0.2047	0.8570
IL	0.9434	0.1279	0.8806
IN	1.3623	0.1841	0.8809
KS	0.7591	0.1746	0.8130
KY	0.6509	0.1284	0.8352
LA	1.8395	0.4166	0.8154
MA	2.1610	0.3526	0.8597
MD	1.5000	0.1693	0.8986
ME	0.9933	0.1526	0.8668
MI	0.7888	0.1327	0.8560

Table B.1 – Continued

State	Within Var	Between Var	Ratio
MN	2.2055	0.1676	0.9294
MO	1.4119	0.2769	0.8361
MS	0.3056	0.0275	0.9174
MT	1.8767	0.4090	0.8211
NC	0.5483	0.0536	0.9110
ND	0.7354	0.1802	0.8032
NE	0.4155	0.0773	0.8432
NH	2.8346	0.2034	0.9331
NJ	3.2634	0.1236	0.9635
NM	2.1808	0.2891	0.8829
NV	2.0264	0.1307	0.9394
NY	1.0967	0.3408	0.7629
OH	0.7672	0.1238	0.8610
OK	0.8400	0.0991	0.8945
OR	1.6324	0.3139	0.8387
PA	0.9855	0.0971	0.9103
RI	1.7861	0.0902	0.9519
SC	0.4744	0.0653	0.8790
SD	0.4605	0.0817	0.8493
TN	0.4168	0.0276	0.9379
TX	1.1272	0.2099	0.8430
UT	1.2538	0.1744	0.8779
VA	2.0660	0.3343	0.8607

Table B.1 – Continued

State	Within Var	Between Var	Ratio
VT	1.4949	0.1750	0.8952
WA	0.8826	0.0813	0.9157
WI	0.8324	0.1452	0.8515
WV	0.2533	0.0534	0.8258
WY	1.1897	0.1117	0.9142

APPENDIX C

DESCRIPTIVE RESULTS

Table C.1
Number of Observation Programs by State and Year (2022–2025)

State	2022		2023		2024		2025		Total
	HS	EHS	HS	EHS	HS	EHS	HS	EHS	
AK	5	4	5	4	5	4	5	4	36
AL	25	23	24	20	25	20	25	21	183
AR	22	27	22	26	22	25	22	25	191
AZ	8	12	8	12	8	11	8	11	78
CA	115	142	110	135	109	125	112	122	970
CO	46	31	46	33	48	37	45	37	323
CT	21	16	20	14	20	14	18	12	135
DE	3	5	3	4	3	4	3	4	29
FL	60	75	58	71	56	69	55	69	513
GA	32	33	32	32	30	31	31	31	252
HI	4	6	4	6	4	6	4	5	39
IA	18	18	18	18	18	18	18	19	145
ID	7	6	7	6	7	6	7	6	52
IL	77	104	75	100	74	96	73	91	690
IN	37	31	37	31	37	31	35	29	268
KS	25	18	24	18	24	18	24	18	169
KY	39	24	39	25	39	26	39	26	257
LA	51	33	51	33	50	32	48	31	329
MA	25	24	25	23	25	24	25	24	195
MD	21	37	21	35	21	34	21	33	223
ME	11	12	11	12	11	12	11	11	91

Table C.1 – Continued

State	2022		2023		2024		2025		Total
	HS	EHS	HS	EHS	HS	EHS	HS	EHS	
MI	54	54	53	51	51	50	47	50	410
MN	25	24	25	23	25	23	25	23	193
MO	28	33	26	31	26	31	24	25	224
MS	21	25	21	26	22	27	22	27	191
MT	13	6	13	6	13	7	13	7	78
NC	46	45	46	41	46	43	45	43	355
ND	10	7	9	7	9	7	9	7	65
NE	15	17	15	16	15	17	15	16	126
NH	5	2	5	3	5	3	5	3	31
NJ	25	30	24	29	23	29	23	28	211
NM	13	16	13	16	13	16	13	16	116
NV	4	6	4	6	4	6	4	6	40
NY	164	115	161	113	156	115	155	118	1097
OH	56	54	57	58	57	58	57	56	453
OK	21	25	20	24	20	24	21	23	178
OR	21	19	21	19	21	17	22	18	158
PA	56	77	54	77	54	77	53	72	520
RI	6	7	6	7	6	7	6	8	53
SC	16	24	16	23	15	23	17	23	157
SD	8	6	8	6	8	6	8	5	55
TN	24	24	24	23	24	23	25	22	189
TX	93	98	89	90	89	87	90	84	720

Table C.1 – Continued

State	2022		2023		2024		2025		Total
	HS	EHS	HS	EHS	HS	EHS	HS	EHS	
UT	9	13	9	12	10	13	10	13	89
VA	50	37	49	36	47	33	43	31	326
VT	7	6	7	6	7	7	7	6	53
WA	28	27	27	27	26	25	26	24	210
WI	28	26	28	26	29	27	28	29	221
WV	21	13	21	12	21	12	21	11	132
WY	7	5	7	5	7	5	8	6	50
Total	1526	1522	1498	1477	1485	1461	1471	1429	11869

APPENDIX D

RESEARCH QUESTION ONE TO FOUR FULL STATE-LEVEL ANALYSIS RESULTS

Table D.1
DiD Results Full-State: Impact on Classroom Teachers' Turnover Rates Across States (Equation 3.5) in RQ1

State	**β**	***SE***	***p***	**n**	***p*(Bonf)**	***p*(FDR BH)**
AK	-0.83	3.18	.806	36	1.000	.879
AL	-9.08	4.97	.077.	176	1.000	.439
AR	-0.67	6.51	.919	186	1.000	.938
AZ	7.93	8.59	.374	77	1.000	.797
CA	-1.08	1.79	.547	954	1.000	.812
CO	3.44	4.55	.452	303	1.000	.812
CT	-11.09	6.44	.100	132	1.000	.439
DE	-23.01	15.53	.199	28	1.000	.541
FL	-2.78	2.12	.195	490	1.000	.541
GA	-3.63	5.74	.531	248	1.000	.812
HI	-5.65	2.63	.069.	38	1.000	.439
IA	-13.14	6.32	.050*	143	1.000	.439
ID	32.06	15.67	.075.	52	1.000	.439
IL	-2.47	3.93	.532	675	1.000	.812
IN	-7.82	6.34	.225	263	1.000	.580
KS	-8.03	9.66	.413	168	1.000	.812
KY	-7.92	4.77	.106	249	1.000	.439
LA	-1.11	4.20	.792	315	1.000	.879
MA	-1.66	4.20	.696	190	1.000	.879
MD	-1.38	8.47	.872	215	1.000	.909
ME	-6.06	3.34	.095.	91	1.000	.439

Table D.1 – Continued

State	β	*SE*	*p*	n	*p*(Bonf)	*p*(FDR BH)
MI	-7.16	3.14	.027*	403	1.000	.439
MN	-5.69	5.91	.344	192	1.000	.766
MO	8.12	5.59	.158	220	1.000	.516
MS	-1.46	3.77	.702	189	1.000	.879
MT	-9.91	12.45	.436	76	1.000	.812
NC	-6.95	4.80	.153	348	1.000	.516
ND	2.25	9.32	.814	63	1.000	.879
NE	-0.33	4.94	.947	123	1.000	.947
NH	3.26	5.70	.598	31	1.000	.862
NJ	-4.18	3.14	.193	203	1.000	.541
NM	5.71	5.11	.276	112	1.000	.676
NV	-24.60	15.04	.153	38	1.000	.516
NY	-1.18	3.21	.714	1003	1.000	.879
OH	-1.17	3.55	.742	451	1.000	.879
OK	1.30	3.62	.722	172	1.000	.879
OR	-6.84	7.01	.339	158	1.000	.766
PA	-1.15	3.00	.703	510	1.000	.879
RI	15.06	7.39	.076.	53	1.000	.439
SC	1.41	5.74	.808	151	1.000	.879
SD	-49.60	21.92	.045*	54	1.000	.439
TN	-2.82	5.83	.632	187	1.000	.879
TX	-5.52	3.40	.108	706	1.000	.439
UT	-4.24	6.82	.544	86	1.000	.812

Table D.1 – Continued

State	β	***SE***	***p***	**n**	***p*(Bonf)**	***p*(FDR BH)**
VA	-0.80	3.61	.826	319	1.000	.879
WA	-3.90	5.51	.484	209	1.000	.812
WI	-6.61	3.66	.081.	220	1.000	.439
WV	6.29	9.53	.515	125	1.000	.812
WY	-12.57	18.28	.506	50	1.000	.812

Note: Standard errors are clustered at the grantee-level.

Table D.2
DiD Results Full-State: Impact on Classroom Teachers' Real Wage Growth Across States (Equation 3.11) in RQ2

State	β	***SE***	***p***	**n**	***p*(Bonf)**	***p*(FDR BH)**
AK	-1.27	1.73	.468	36	1.000	.698
AL	-1.35	0.54	.014	183	0.674	.064
AR	-0.09	0.57	.869	191	1.000	.892
AZ	-0.33	0.81	.681	78	1.000	.812
CA	0.10	0.16	.526	970	1.000	.749
CO	-0.29	1.05	.785	323	1.000	.892
CT	-0.88	0.98	.372	135	1.000	.587
DE	7.68	3.54	.040	29	1.000	.123
FL	-0.86	0.15	.000	513	0.000	.000
GA	-1.63	0.42	.000	252	0.006	.001
HI	-0.61	0.98	.535	39	1.000	.749
IA	-1.72	0.72	.018	145	0.864	.072
ID	-2.43	1.67	.151	52	1.000	.308
IL	-0.17	0.12	.147	690	1.000	.308
IN	0.94	0.31	.003	268	0.146	.021
KS	-1.93	1.05	.068	169	1.000	.167
KY	0.08	0.39	.837	257	1.000	.892
LA	0.33	0.32	.297	329	1.000	.502
MA	0.10	0.23	.677	195	1.000	.812
MD	0.31	2.30	.892	223	1.000	.892
ME	-1.39	0.48	.005	91	0.252	.031

Table D.2 – Continued

State	β	*SE*	*p*	n	*p*(Bonf)	*p*(FDR BH)
MI	0.57	0.23	.014	410	0.673	.064
MN	-0.10	0.59	.863	193	1.000	.892
MO	0.08	0.52	.874	224	1.000	.892
MS	0.81	0.42	.055	191	1.000	.142
MT	-3.05	2.52	.231	78	1.000	.420
NC	-0.39	0.28	.167	355	1.000	.327
ND	1.84	1.16	.125	32	1.000	.278
NE	-2.09	1.06	.051	126	1.000	.139
NH	1.34	2.85	.643	31	1.000	.812
NJ	-1.70	0.47	.000	211	0.021	.003
NM	1.19	0.93	.203	116	1.000	.383
NV	5.16	2.28	.030	40	1.000	.104
NY	-0.32	0.16	.047	1097	1.000	.135
OH	-0.75	0.32	.021	453	1.000	.077
OK	0.20	0.38	.602	178	1.000	.797
OR	-0.59	0.62	.343	158	1.000	.560
PA	-2.29	0.51	.000	520	0.000	.000
RI	6.34	3.54	.080	53	1.000	.186
SC	0.56	0.77	.470	157	1.000	.698
SD	-0.42	1.07	.696	55	1.000	.812
TN	-1.87	0.76	.014	189	0.701	.064
TX	-1.04	0.15	.000	720	0.000	.000
UT	1.57	2.77	.572	89	1.000	.779

Table D.2 – Continued

State	β	***SE***	***p***	**n**	***p*(Bonf)**	***p*(FDR BH)**
VA	0.71	0.61	.244	326	1.000	.428
WA	-0.16	0.38	.669	210	1.000	.812
WI	0.10	0.57	.860	221	1.000	.892
WV	-1.59	0.37	.000	132	0.001	.000
WY	-5.27	2.40	.033	50	1.000	.108

Note: Standard errors are clustered at the grantee-level.

Table D.3
DiD Results Full-State: Impact on Classroom Teachers' Real Wage Growth Across States (Equation 3.11) Placebo Test in RQ2

State	β	*SE*	*p*	n	*p*(Bonf)	*p*(FDR BH)
AK	.128	4.209	.976	18	1.000	.976
AL	2.139	.648	.001	92	.068	.009
AR	1.442	.498	.005	97	.232	.019
AZ	-.454	.684	.511	40	1.000	.659
CA	.190	.203	.350	502	1.000	.520
CO	.101	.550	.855	156	1.000	.911
CT	2.404	.517	.000	71	.001	.000
DE	1.899	2.578	.475	15	1.000	.647
FL	-2.830	.618	.000	264	.000	.000
GA	-.588	.585	.317	129	1.000	.502
HI	4.128	3.396	.241	20	1.000	.449
IA	5.634	1.060	.000	72	.000	.000
ID	-2.549	3.628	.489	26	1.000	.648
IL	-.059	.189	.755	356	1.000	.826
IN	.725	.847	.394	136	1.000	.551
KS	.044	.879	.960	85	1.000	.976
KY	1.315	1.214	.281	127	1.000	.459
LA	.057	.115	.618	168	1.000	.738
MA	.116	.374	.757	97	1.000	.826
MD	-3.044	1.808	.095	114	1.000	.203
ME	4.107	1.237	.002	46	.090	.009

Table D.3 – Continued

State	β	*SE*	*p*	n	*p*(Bonf)	*p*(FDR BH)
MI	-1.935	.608	.002	212	.083	.009
MN	-.433	.131	.001	97	.063	.009
MO	.767	.402	.059	118	1.000	.144
MS	-1.986	.852	.022	93	1.000	.072
MT	-2.890	3.334	.392	38	1.000	.551
NC	.332	.223	.139	178	1.000	.284
ND	-4.443	1.847	.031	16	1.000	.094
NE	2.336	.965	.019	63	.907	.065
NH	-2.114	1.168	.095	15	1.000	.203
NJ	1.645	.838	.052	108	1.000	.135
NM	-6.506	2.546	.013	58	.656	.050
NV	-.848	2.716	.759	20	1.000	.826
NY	.055	.158	.727	553	1.000	.826
OH	.175	.287	.542	225	1.000	.680
OK	-.386	.213	.074	90	1.000	.172
OR	-.192	2.391	.936	80	1.000	.976
PA	2.640	.519	.000	264	.000	.000
RI	1.491	1.102	.189	26	1.000	.371
SC	-.929	1.629	.570	79	1.000	.698
SD	-.414	.350	.247	28	1.000	.449
TN	2.261	1.120	.046	95	1.000	.127
TX	1.262	.228	.000	370	.000	.000
UT	-1.939	1.976	.332	43	1.000	.509

Table D.3 – Continued

State	β	***SE***	***p***	**n**	***p*(Bonf)**	***p*(FDR BH)**
VA	-.757	.375	.045	172	1.000	.127
WA	-.470	.413	.257	109	1.000	.450
WI	-.656	.589	.267	108	1.000	.452
WV	1.740	.493	.001	67	.038	.006
WY	8.074	2.326	.002	24	.112	.010

Note: Standard errors are clustered at the grantee-level.

Table D.4

DiD Results Full-State: Impact on Classroom Teachers' Classroom Teachers' Raw Wages Across States (Equation 3.17) in RQ3

State	β	***SE***	***p***	**n**	***p*(Bonf)**	***p*(FDR BH)**
AK	-72.557	3733.562	.985	36	1.000	.985
AL	3904.967	1136.409	.001	183	.036	.002
AR	1120.309	864.045	.196	191	1.000	.258
AZ	-188.321	1296.615	.885	78	1.000	.912
CA	149.369	339.950	.660	970	1.000	.768
CO	-584.788	1651.529	.724	323	1.000	.788
CT	-733.775	2328.185	.753	135	1.000	.802
DE	4417.667	1536.608	.008	29	.408	.016
FL	4351.064	752.816	.000	513	.000	.000
GA	3266.730	838.800	.000	252	.006	.000
HI	3277.195	1631.837	.053	39	1.000	.083
IA	3988.572	1006.226	.000	145	.006	.000
ID	268.782	625.921	.670	52	1.000	.768
IL	2283.033	591.972	.000	690	.006	.000
IN	1323.251	617.038	.033	268	1.000	.054
KS	3468.969	1978.816	.081	169	1.000	.121
KY	2025.363	1118.645	.071	257	1.000	.109
LA	3434.125	706.247	.000	329	.000	.000
MA	2828.598	760.880	.000	195	.013	.001
MD	7718.505	2701.286	.005	223	.230	.011
ME	2561.214	503.738	.000	91	.000	.000

Table D.4 – Continued

State	*β*	*SE*	*p*	n	*p*(Bonf)	*p*(FDR BH)
MI	1793.823	648.956	.006	410	.292	.013
MN	-146.785	348.069	.674	193	1.000	.768
MO	862.882	745.961	.249	224	1.000	.312
MS	1701.246	474.580	.000	191	.021	.001
MT	2512.127	902.120	.007	78	.334	.014
NC	2648.552	532.598	.000	355	.000	.000
ND	4931.033	1515.542	.002	65	.092	.005
NE	-2090.849	1621.626	.200	126	1.000	.258
NH	-241.316	1790.279	.894	31	1.000	.912
NJ	10669.100	1992.058	.000	211	.000	.000
NM	2707.887	1655.890	.105	116	1.000	.151
NV	3929.167	1659.835	.024	40	1.000	.040
NY	3328.327	845.901	.000	1097	.004	.000
OH	1508.818	611.585	.014	453	.686	.026
OK	4192.165	1159.427	.000	178	.019	.001
OR	-1781.225	1307.173	.175	158	1.000	.245
PA	3305.727	663.555	.000	520	.000	.000
RI	6509.366	1835.703	.001	53	.043	.002
SC	3058.113	623.878	.000	157	.000	.000
SD	590.098	1484.980	.693	55	1.000	.772
TN	2730.990	1160.479	.020	189	.963	.036
TX	6602.473	866.304	.000	720	.000	.000
UT	3360.991	1457.242	.024	89	1.000	.040

Table D.4 – Continued

State	β	***SE***	***p***	**n**	***p*(Bonf)**	***p*(FDR BH)**
VA	1795.280	1391.501	.198	326	1.000	.258
WA	325.795	696.561	.640	210	1.000	.768
WI	2697.424	969.217	.006	221	.287	.013
WV	7454.878	2335.982	.002	132	.087	.005
WY	5754.019	1031.128	.000	50	.000	.000

Note: Standard errors are clustered at the grantee-level.

Table D.5
DiD Results Full-State: Impact on Classroom Teachers' Classroom Teachers' Raw Wages Across States (Equation 3.17) Placebo Test in RQ3

State	β	***SE***	***p***	**n**	***p*(Bonf)**	***p*(FDR BH)**
AK	-2114.583	4345.363	.634	18	1.000	.675
AL	6473.050	1722.374	.000	92	.015	.003
AR	2433.936	866.236	.006	97	.296	.017
AZ	1445.495	1673.186	.393	40	1.000	.507
CA	267.396	444.121	.547	502	1.000	.622
CO	2498.366	1606.368	.122	156	1.000	.206
CT	-170.779	1389.135	.903	71	1.000	.921
DE	2099.813	1300.418	.132	15	1.000	.211
FL	4297.666	1070.248	.000	264	.004	.001
GA	4238.875	1204.656	.001	129	.030	.004
HI	7440.583	2862.942	.019	20	.917	.046
IA	5428.467	1556.209	.001	72	.042	.005
ID	5.369	792.902	.995	26	1.000	.995
IL	2173.714	729.795	.003	356	.152	.010
IN	2249.008	664.595	.001	136	.046	.005
KS	2828.649	2456.417	.253	85	1.000	.354
KY	880.064	1500.986	.559	127	1.000	.622
LA	1935.549	911.391	.035	168	1.000	.078
MA	2104.211	649.251	.002	97	.081	.007
MD	4038.617	1915.623	.037	114	1.000	.079
ME	3258.816	918.328	.001	46	.047	.005

Table D.5 – Continued

State	β	*SE*	*p*	n	*p*(Bonf)	*p*(FDR BH)
MI	896.168	841.650	.288	212	1.000	.392
MN	421.469	511.639	.412	97	1.000	.518
MO	1480.531	854.744	.086	118	1.000	.168
MS	395.697	537.978	.464	93	1.000	.554
MT	-1187.654	1951.689	.547	38	1.000	.622
NC	2468.699	780.271	.002	178	.090	.007
ND	3023.393	1989.763	.139	33	1.000	.213
NE	535.538	1033.920	.606	63	1.000	.660
NH	-3997.333	2309.113	.109	15	1.000	.191
NJ	11830.854	2536.661	.000	108	.000	.000
NM	1474.240	1945.976	.452	58	1.000	.554
NV	2224.071	1499.553	.156	20	1.000	.225
NY	1477.388	1019.525	.148	553	1.000	.220
OH	2370.184	812.590	.004	225	.191	.012
OK	4063.796	1552.245	.010	90	.511	.028
OR	-431.182	1587.123	.787	80	1.000	.820
PA	4503.796	893.468	.000	264	.000	.000
RI	2329.833	1200.411	.065	26	1.000	.132
SC	1311.511	865.300	.134	79	1.000	.211
SD	2218.250	1301.152	.101	28	1.000	.183
TN	4795.207	1308.740	.000	95	.020	.003
TX	7005.068	1180.804	.000	370	.000	.000
UT	1142.005	515.120	.032	43	1.000	.076

Table D.5 – Continued

State	β	*SE*	*p*	n	*p*(Bonf)	*p*(FDR BH)
VA	2728.096	1621.175	.094	172	1.000	.178
WA	2728.646	854.770	.002	109	.091	.007
WI	1226.277	1263.834	.334	108	1.000	.443
WV	8369.405	3465.959	.019	67	.912	.046
WY	9082.400	2431.623	.001	24	.060	.005

Note: Standard errors are clustered at the grantee-level.

Table D.6
MLM Results Full-State: Between Classroom Teachers' Turnover Rates and Pre- and Post- Policy (Equation 3.28) in RQ4

State	β	*SE*	*p*	*p* (Bonf)	*p* (FDR BH)
AK	-2.656	6.117	.667	1.000	.787
AL	-7.156	3.817	.063	1.000	.285
AR	1.233	4.393	.779	1.000	.812
AZ	1.104	4.568	.810	1.000	.826
CA	-1.407	1.134	.215	1.000	.375
CO	-8.940	2.742	.001	.062	.012
CT	-5.309	2.929	.072	1.000	.301
DE	-3.681	6.351	.567	1.000	.754
FL	-.863	1.530	.573	1.000	.754
GA	-7.708	2.628	.004	.185	.028
HI	-11.080	6.138	.079	1.000	.303
IA	1.190	2.832	.675	1.000	.787
ID	4.119	8.296	.622	1.000	.787
IL	-1.882	2.342	.422	1.000	.620
IN	-2.715	3.134	.387	1.000	.587
KS	-18.935	5.290	.000	.023	.008
KY	-1.690	2.648	.524	1.000	.728
LA	-2.229	1.800	.217	1.000	.375
MA	-1.650	1.880	.381	1.000	.587
MD	-11.803	2.982	.000	.005	.003
ME	-2.333	3.266	.477	1.000	.681

Table D.6 – Continued

State	β	*SE*	*p*	*p* (Bonf)	*p* (FDR BH)
MI	-3.222	1.958	.101	1.000	.328
MN	-3.214	2.494	.199	1.000	.375
MO	-4.364	3.223	.177	1.000	.375
MS	-6.040	2.706	.027	1.000	.135
MT	7.512	8.370	.373	1.000	.587
NC	-.841	2.153	.697	1.000	.787
ND	2.005	6.916	.774	1.000	.812
NE	-4.686	3.376	.169	1.000	.375
NH	-5.279	4.188	.217	1.000	.375
NJ	-3.484	2.168	.110	1.000	.328
NM	.706	3.519	.841	1.000	.841
NV	1.754	5.463	.750	1.000	.812
NY	-7.548	1.707	.000	.001	.001
OH	-1.786	2.062	.387	1.000	.587
OK	-3.656	2.200	.099	1.000	.328
OR	3.500	2.602	.181	1.000	.375
PA	-3.651	1.633	.026	1.000	.135
RI	-9.249	3.591	.013	.665	.083
SC	-10.437	3.073	.001	.044	.011
SD	3.600	8.506	.674	1.000	.787
TN	-2.727	2.202	.217	1.000	.375
TX	-2.029	1.474	.169	1.000	.375
UT	6.405	4.647	.172	1.000	.375

Table D.6 – Continued

State	β	***SE***	***p***	***p* (Bonf)**	***p* (FDR BH)**
VA	-3.317	2.116	.118	1.000	.328
VT	-11.761	7.371	.117	1.000	.328
WA	1.570	4.193	.708	1.000	.787
WI	-.979	2.556	.702	1.000	.787
WV	-9.764	3.320	.004	.198	.028
WY	-6.541	4.740	.177	1.000	.375

Table D.7

MLM Results Full-State: Between Classroom Teachers' Turnover Rates and Classroom Teachers' Real Wage Growth (Equation 3.28) in RQ4

State	β	*SE*	*p*	*p*(Bonf)	*p*(FDR BH)
AK	-.146	.209	.489	1.000	.815
AL	-.303	.621	.626	1.000	.874
AR	-.768	.334	.023	1.000	.278
AZ	.125	.271	.647	1.000	.874
CA	.004	.110	.968	1.000	.985
CO	-.325	.348	.351	1.000	.701
CT	-.701	.315	.028	1.000	.278
DE	.080	.447	.859	1.000	.942
FL	-.279	.169	.100	1.000	.384
GA	.058	.205	.777	1.000	.917
HI	.238	.651	.717	1.000	.888
IA	.395	.263	.136	1.000	.454
ID	.194	.719	.789	1.000	.917
IL	.287	.525	.585	1.000	.861
IN	-.495	.418	.237	1.000	.564
KS	1.111	.462	.017	.869	.278
KY	-.337	.245	.170	1.000	.468
LA	.114	.139	.414	1.000	.759
MA	.034	.284	.904	1.000	.942
MD	.168	.187	.371	1.000	.714
ME	.128	.272	.640	1.000	.874

Table D.7 – Continued

State	β	*SE*	*p*	*p*(Bonf)	*p*(FDR BH)
MI	-.308	.185	.098	1.000	.384
MN	-.031	.213	.885	1.000	.942
MO	-.762	.337	.025	1.000	.278
MS	-.435	.300	.149	1.000	.462
MT	.442	.713	.537	1.000	.861
NC	.039	.223	.860	1.000	.942
ND	.509	.670	.454	1.000	.782
NE	-.127	.342	.710	1.000	.888
NH	.420	.432	.339	1.000	.701
NJ	.328	.243	.178	1.000	.468
NM	.143	.255	.574	1.000	.861
NV	-.756	.386	.058	1.000	.349
NY	.764	.498	.125	1.000	.447
OH	-.373	.290	.200	1.000	.499
OK	.107	.256	.676	1.000	.888
OR	.012	.099	.905	1.000	.942
PA	-.437	.120	.000	.015	.015
RI	-.246	.306	.425	1.000	.759
SC	.522	.252	.040	1.000	.335
SD	.497	1.420	.728	1.000	.888
TN	-.226	.200	.259	1.000	.565
TX	-.370	.202	.068	1.000	.349
UT	-.218	.192	.260	1.000	.565

Table D.7 – Continued

State	β	*SE*	*p*	*p*(Bonf)	*p*(FDR BH)
VA	.322	.166	.053	1.000	.349
VT	-.470	.791	.555	1.000	.861
WA	.668	.392	.090	1.000	.384
WI	.253	.178	.157	1.000	.462
WV	.855	.467	.070	1.000	.349
WY	-.003	.135	.985	1.000	.985

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