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Jobs in the Balance: The Two-Year Labor Market Impacts of Washington, DC's Early Childhood Educator Pay Equity Fund

Final Report

May 2024

Owen Schochet

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May 28, 2024

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Abstract

This report evaluates the labor market impacts of Washington, DC's Early Childhood Educator Pay Equity Fund (PEF), a pioneering initiative to address pay disparities between child care and early childhood education (CCEE) educators and K–12 teachers. In its first two years, the PEF has delivered supplement payments ranging from $10,000 to $14,000 per year to more than 4,000 CCEE educators in licensed settings. Using data from the Quarterly Census of Employment and Wages and a multiple-outcome synthetic control method, we found that after two years, the PEF had increased CCEE employment in Washington, DC, by 219 educators, or about 7 percent relative to employment estimates in the absence of the PEF. We did not estimate significant impacts on the number of CCEE establishments, suggesting the PEF enabled existing establishments to increase staffing amidst documented staffing shortages in the sector. Near-zero effects on employer-reported wages were expected in the first two years of the program during which payments were disbursed directly to educators. We assess the robustness of these findings to several changes in the study design and technical approach.

Key words: Early Childhood Educator Pay Equity Fund (PEF), child care and early childhood education (CCEE), early care and education (ECE), wage supplements, teacher turnover, teacher retention, synthetic control method, compensation strategies, Washington, DC, labor market outcomes, earnings, labor force participation, establishments, Quarterly Census of Employment and Wages (QCEW)

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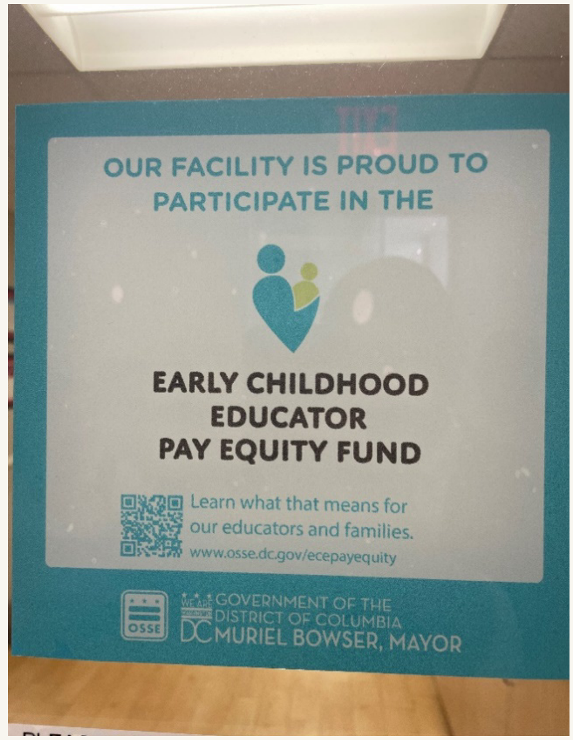
Executive Summary



Washington, DC's Early Childhood Educator Pay Equity Fund (PEF) was created to address the significant pay disparity between child care and early childhood education (CCEE) educators and K–12 teachers. Through the PEF, Washington, DC, is the first jurisdiction in the nation to use local tax revenue as a dedicated source of public funding to supplement CCEE educator wages. In its first two years of operation, the PEF has delivered payments ranging from $10,000 to $14,000 per year to more than 4,000 CCEE educators in licensed centers and home-based programs in Washington, DC.

This report is part of a study sponsored by the Bezos Family Foundation and DC Action to contribute evidence on the impacts of the PEF on the CCEE sector in Washington, DC. A previous report (Schochet 2023) explored the initial impacts of the PEF during the first year of the program. The primary focus of this report is the effectiveness of the PEF on CCEE labor market outcomes through the program's second year of operation.

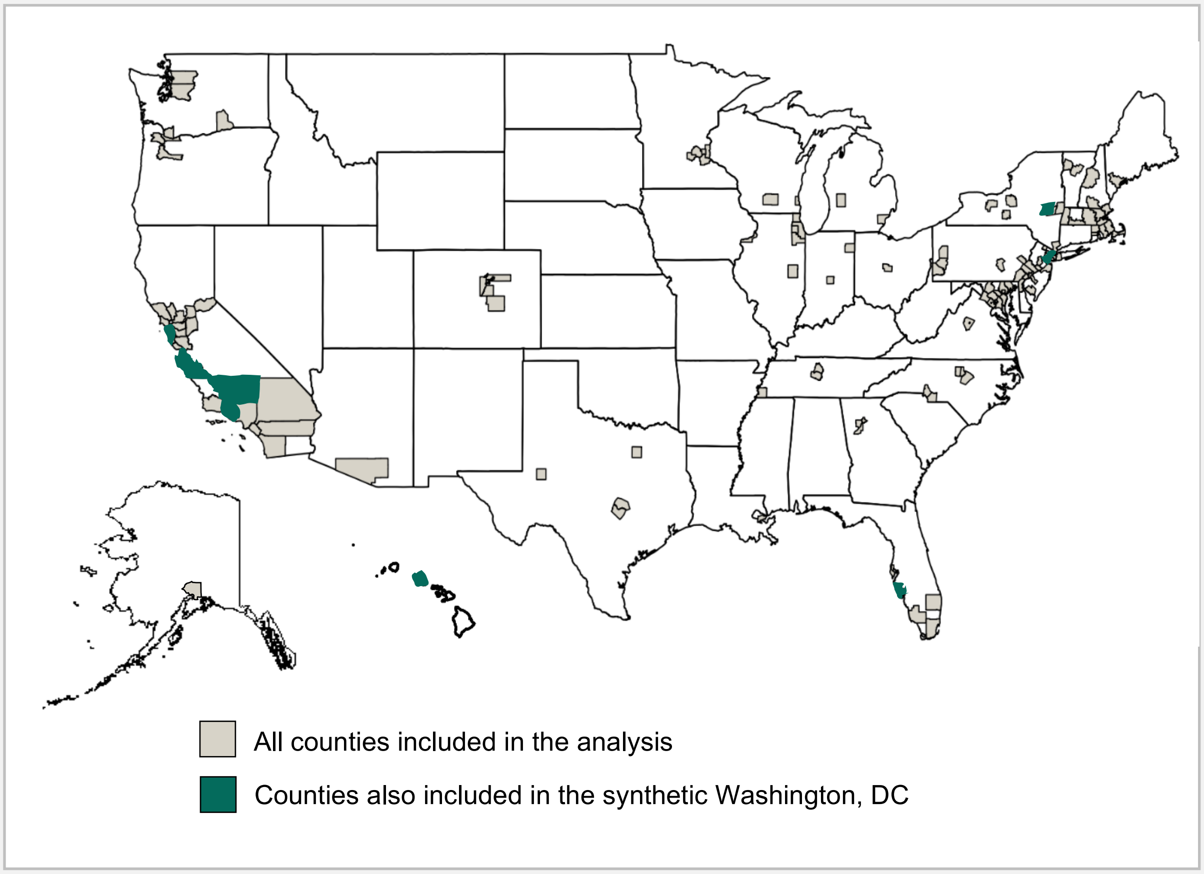
A. Research design

The launch of the PEF offered an opportunity to examine whether and how increased educator compensation affects the CCEE labor market. We focused this analysis on three CCEE outcomes:

1. **Employment levels**. The PEF payments provided immediate financial relief to potentially reduce economic stress, boost morale, and anchor CCEE educators in their roles. The payments also may have supported the hiring of new educators to fill staffing vacancies.
2. **Average weekly wages**. Although we could not rule out the potential for unintended wage effects, in its first two years, the PEF would not be expected to influence CCEE wages from employer payrolls because payments were delivered directly to educators, outside of their regular wages.
3. **Number of establishments**. Our analysis of the number of CCEE establishments was exploratory; although administrators did not receive payments, the PEF could help to stabilize existing establishments that would have otherwise closed due to staffing shortages.

Our analysis relied on data from the Quarterly Census of Employment and Wages (QCEW), a quarterly count of employment, wages, and establishments across industries and counties in the United States. The analysis included 19 quarters of data—from 2019 to 2023—and 145 counties (including Washington, DC) that were in the top half of the national distribution of employment levels, wages, and number of establishments, both within the CCEE sector and across all occupations (Figure ES.1).

Figure ES.1. Counties included in the analysis and the synthetic Washington, DC



Source: Author's analysis of the Quarterly Census of Employment and Wages (QCEW) data (https://www.bls.gov/cew/downloadable-data-files.htm).

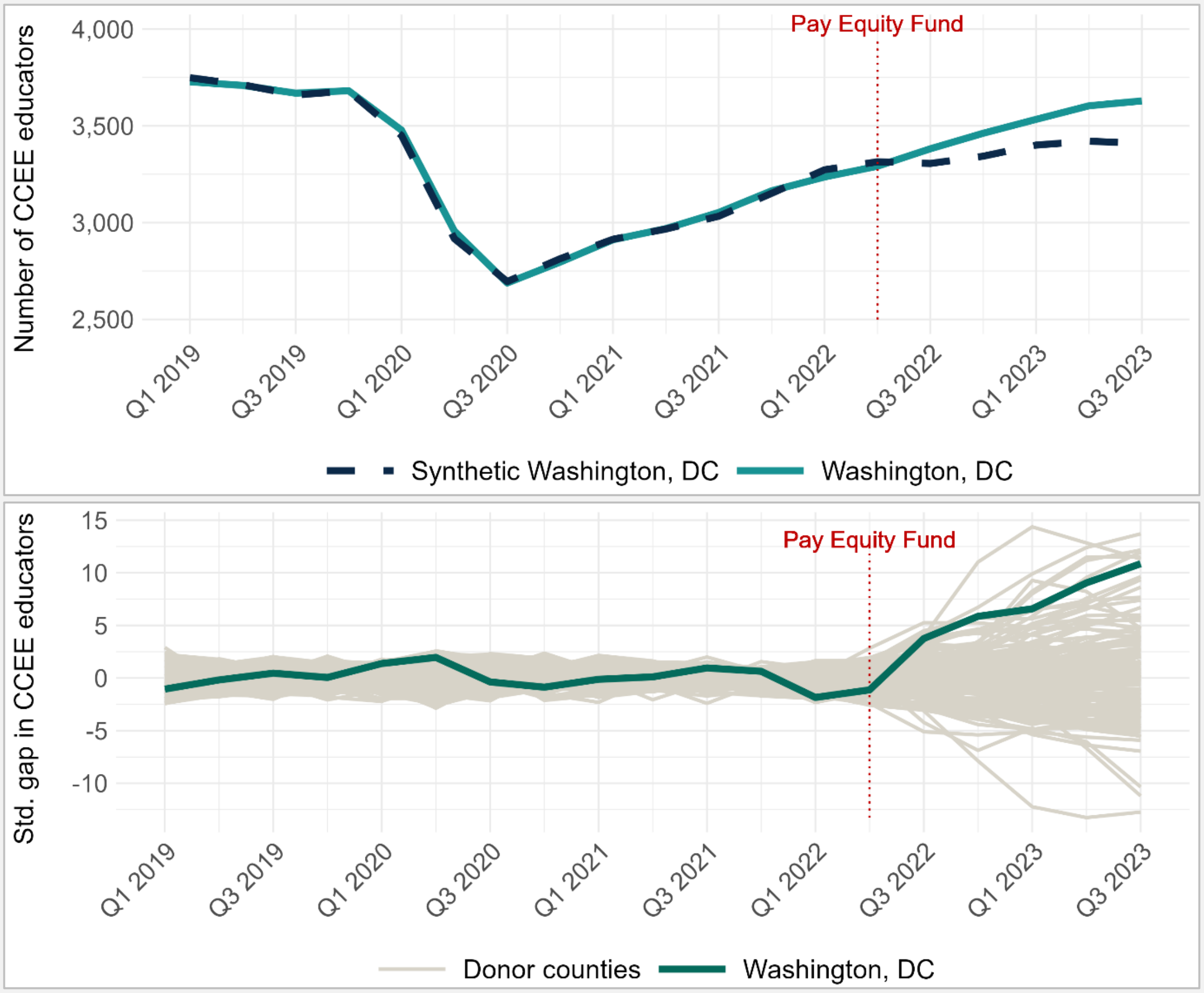
Note: The CCEE labor market outcomes for Washington, DC, are best approximated by a combination of nine counties in New York (New York, Albany, and Richmond Counties), California (San Francisco, Ventura, Monterey, and Kern Counties), Hawaii (Honolulu County), and Florida (Sarasota County).

To estimate the effects of the PEF on CCEE labor market outcomes, we used a multiple-outcome synthetic control method (SCM) to construct a synthetic Washington, DC, using a convex combination of donor counties in the comparison group that did not implement such a program. This weighted combination of nine chosen counties approximated the CCEE labor market trends that Washington, DC, would have experienced in the absence of the PEF (Figure ES.1).

B. Summary of findings

The PEF had a statistically significant positive impact on the number of CCEE educators in Washington, DC. We estimated that by the third quarter of 2023, the PEF resulted in an additional 219 CCEE educators, representing about a 7 percent increase relative to estimated CCEE employment levels in the counterfactual (Figure ES.2). The treatment effects on CCEE employment were statistically significant overall and across all post-treatment quarters, suggesting that the PEF effectively supported the hiring and retention of educators in Washington, DC, through its first two years of operation.

Figure ES.2. CCEE employment levels and impacts for Washington, DC



Source: Author's analysis of the Quarterly Census of Employment and Wages (QCEW) data (https://www.bls.gov/cew/downloadable-data-files.htm).

Note: The benchmark analysis includes all donor counties in the comparison group, uses information from Q1 2019 through Q2 2022, matches on multiple outcomes simultaneously, and obtains estimates using demeaned outcomes. Gaps reflect the difference between each county and its synthetic counterpart, estimated using the benchmark approach. Gaps are standardized by the pre-treatment root mean squared percent error. Std. = standardized.

The PEF had no statistically significant impact on average weekly wages for CCEE educators. The treatment effects on wages remained close to zero throughout the post-treatment period, consistent with the expectation that PEF payments delivered outside of employer payrolls would not be captured in the QCEW data. We did not find evidence for other wage effects, such as those that could result from changes in the CCEE labor supply.

The PEF had a modest negative impact on the number of CCEE establishments, although this finding was not statistically significant. On average, Washington, DC, had 10 fewer CCEE establishments compared to the synthetic control group, with impacts ranging from 0 to 14 fewer establishments in individual post-treatment quarters. These impacts were not statistically significant, however, suggesting the observed increase in the CCEE workforce was driven by the PEF's positive impacts on staffing in existing establishments.

We conducted several robustness checks to ensure our findings were reliable. The benchmark findings were robust to the exclusion of any particular county in constructing the synthetic control group, whereas a backdated treatment exercise found no evidence of anticipatory effects. Alternative specifications also highlighted the importance of matching on multiple outcomes to improve balance in latent factors shared across similar outcomes and using demeaned outcomes to improve the pre-treatment fit.

I. Introduction

The economic stability and professional well-being of child care and early education (CCEE) educators are critical issues that have significant implications for the CCEE sector. Despite the essential role they play in the formative years of children's development, CCEE educators are among the lowest-paid workers in the United States. This disparity in compensation not only undermines the quality of CCEE services but also exacerbates the challenges of recruitment and retention in the CCEE workforce.

Washington, DC's Early Childhood Educator Pay Equity Fund (herein referred to as the PEF) represents a pioneering effort to address these challenges by providing substantial, publicly funded wage supplements to CCEE educators. By examining the impacts of the PEF on CCEE labor market outcomes, this report aims to contribute evidence on how increased compensation can influence the CCEE sector. This report is part of a larger study made possible through a partnership with the Bezos Family Foundation and DC Action. Using federal labor market data from the Quarterly Census of Employment and Wages (QCEW) and rigorous multiple-outcome synthetic control methods, this study leverages the opportunity presented by the launch of the PEF to evaluate its effectiveness through the second year of the program.[1]

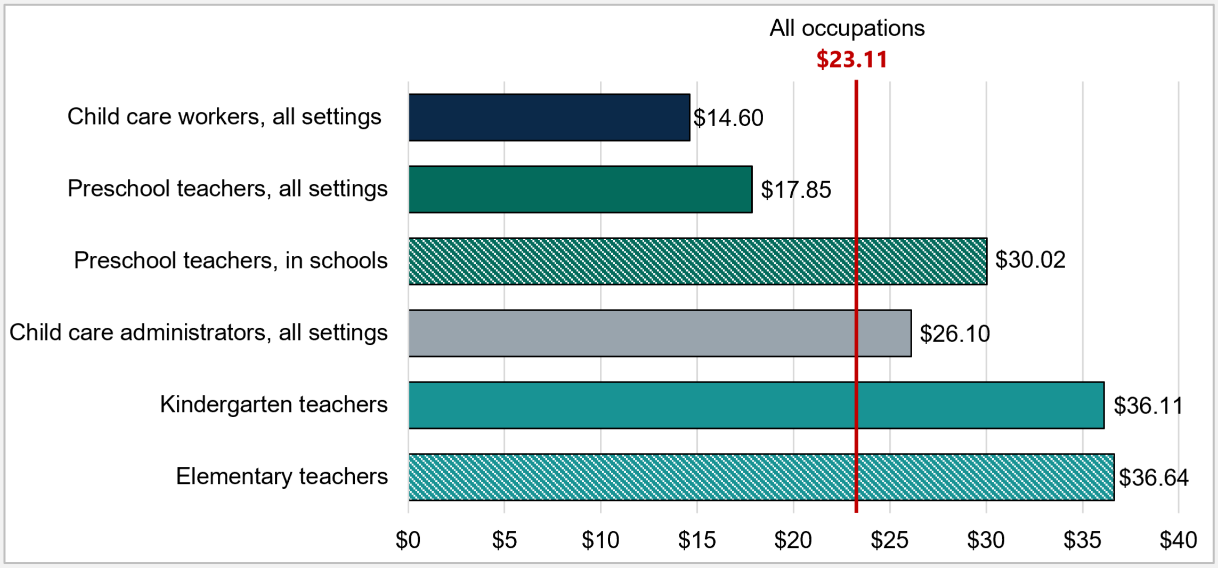
A. Background and policy context

Despite the contributions of their work to the learning and development of young children, CCEE educators are among the lowest-paid workers in the United States. CCEE educators, who are predominantly female and are disproportionately women of color, earn less than other employees in a range of similar roles requiring comparable skills and qualifications. In May 2023, the median hourly wage for CCEE educators who operated outside of school-based settings was $14.60, more than 50 percent below the $30.02 median hourly wage for preschool teachers in schools, and 37 percent below the $23.11 median hourly wage across all occupations (Figure I.1; BLS 2024). A significant number of CCEE educators live in poverty and rely on public assistance benefits (Gould 2015). In 2020, CCEE educators were almost eight times as likely to live in poverty compared to K–8 educators (McLean et al. 2021). Wages for CCEE educators working with infants and toddlers tend to be lower than the wages of those working with preschool-age children.

As with any profession, adequate compensation is necessary to attract and retain the best employees, and recruiting and retaining educators has been a longstanding issue for the CCEE field. Estimates suggest that as many as 25 to 40 percent of CCEE educators left their employer within a year, which is more than double the turnover rate for K–12 teachers (Caven et al. 2021; Doromal et al. 2022a; Bryant et al. 2023). Several studies show that educator wages are negatively associated with turnover rates (Caven et al. 2021; Grunewald et al. 2022; Johnson et al. 2020; Whitebook et al. 2014). Turnover rates are particularly high among teachers working with infants and toddlers; one study reported annual turnover rates of nearly 50 percent for this population (Bassok et al. 2021). CCEE educators who work in center-based settings with lower compensation (Bellows et al. 2021), who identify as racial minorities, who have lower levels of education, and who have lower household incomes (Schochet and Caronongan 2022) are also more likely to leave their jobs.

[1] A previous research brief (Schochet 2023) focused on evaluating the immediate effects of the initial PEF wage supplement payments on employment outcomes in the CCEE sector during the first year of the program.

Figure I.1. Median hourly wages for CCEE educators and other similar occupations in May 2023



Source: Occupational Employment Statistics (OES) Survey, Bureau of Labor Statistics, U.S. Department of Labor (http://stats.bls.gov/oes) and the Early Childhood Workforce Index 2020, Figure 2.1 (https://cscce.berkeley.edu/workforce-index-2020/report-pdf).

Note: All teacher estimates exclude special education teachers. Hourly wages for preschool teachers in schools and kindergarten and elementary teachers were calculated by dividing the median annual salary by 40 hours per week, 10 months per year, to reflect a standard school-year schedule.

High turnover of CCEE educators has negative consequences for staff, programs, and children. It can lead to negative effects on children by disrupting the continuity of care and bonding with an educator (Bratsch-Hines et al. 2020; Markowitz 2019; Phillips et al. 2016; Hamre et al. 2014). High turnover may also require administrators and staff to reallocate their attention away from quality improvement efforts and toward recruiting new staff or filling in for their colleagues who left (Doromal et al. 2022b). High turnover as a result of low compensation may also contribute to lack of educator well-being and low morale. Low educator retention and recruitment may also have detrimental effects on the broader CCEE sector as it experiences educator shortages if qualified educators leave the profession for better prospects in other fields or with other employers, such as public schools, that reward higher levels of education and experience (Hogan 2021; Markowitz 2019).

High turnover and its negative consequences underscore the need for focused efforts to mitigate the considerable compensation disparities across the CCEE sector. Particular attention should be given to supporting CCEE educators who operate outside of school-based settings and who serve younger children, because they tend to be the most poorly compensated and the hardest to retain. In a pioneering effort, Washington, DC, has launched the nation's first large-scale, publicly funded program to supplement the wages of CCEE educators in this population. The PEF was created to achieve compensation equity with Washington, DC, Public Schools (DCPS) teachers (Greenberg et al. 2023). In its first two years of operation, this initiative, launched in fall 2022, has delivered supplemental payments ranging from $10,000 to $14,000 per year to more than 4,000 CCEE educators in licensed centers and home-based programs. This report examines the impacts of these payments on CCEE employment levels, wages, and the number of CCEE establishments in Washington, DC, through the PEF's second year of operation.

B. The Early Childhood Educator Pay Equity Fund

Washington, DC, has a history of innovative investment in CCEE. Following the unanimous passage of the Pre-K Enhancement and Expansion Act of 2008 (Pre-K Act 2008), the city began offering publicly funded, full-day preschool through DCPS and select public charter schools and community-based organizations to children ages 3 and 4. The Pre-K Act established the role of the DC Office of the State Superintendent of Education (OSSE) in managing DC's universal preschool system. In the 2020–2021 school year, 74 percent of DC's 17,386 children ages 3 and 4 were enrolled in this system (DC OSSE 2022a). CCEE educators employed by DCPS are already paid on the same salary scale as K–12 educators.

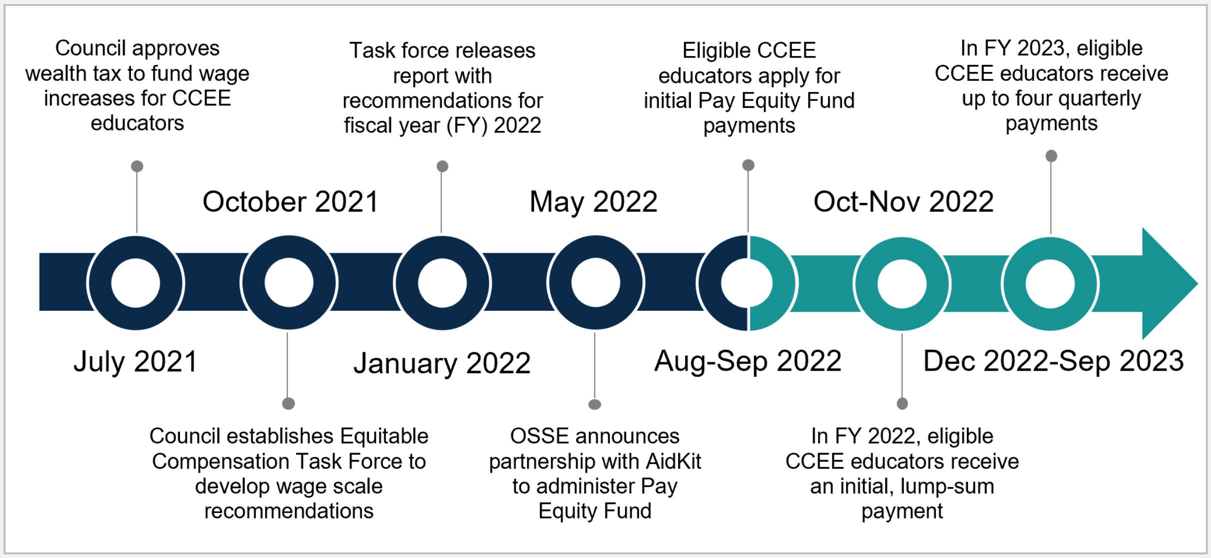
In 2018, the DC Council passed the Birth-to-Three for All DC Act (2018), which expanded the District's investment in CCEE to focus on infants and toddlers. OSSE was given administrative oversight for licensed CCEE settings that were not already affiliated with the universal preschool program and mostly operated through DCPS. The Birth-to-Three Act stipulated the creation of a competitive compensation scale for lead teachers and teaching assistants in these licensed CCEE settings, aiming for pay equity with DCPS educators.

Several key events following the passage of the Birth-to-Three Act led to the distribution of the first PEF payments to CCEE educators in fall 2022 (Figure I.2). In July 2021, the DC Council voted to raise taxes on individuals earning more than $250,000 a year and allocated a portion of the revenue to supplement CCEE educator wages, totaling $54 million in the first year (FY 2022; Early Childhood Educator Equitable Compensation Task Force 2022a). In October 2021, the DC Early Childhood Educator Equitable Compensation Task Force was established to develop innovative strategies to distribute these funds.

In January 2022, the Task Force released a report recommending immediate lump-sum payments of $14,000 to full-time teachers, $10,000 to full-time assistant teachers, and half of these amounts to part-time staff in these positions, to be distributed in fiscal year (FY) 2022 (Early Childhood Educator Equitable Compensation Task Force 2022a). The Task Force recommended that all licensed center-based educators (teachers and assistant teachers) and home-based providers operating outside of the District's universal pre-K system (including DCPS and public charter schools) were to be eligible for the payments (DC OSSE 2022b). Educators who met these criteria were to be eligible regardless of whether their program accepted child care subsidies or were Head Start or Early Head Start. Center directors and other program staff (such as cooks, bus drivers, and janitorial staff) were ineligible. In March 2022, the Task Force published a final report outlining the FY 2023 strategy for delivering payments to educators on a quarterly basis (Early Childhood Educator Equitable Compensation Task Force 2022b). The final report also provided additional recommendations regarding target compensation levels for CCEE educators based on roles and qualifications.

In its first two years of operation, the Early Childhood Educator Pay Equity Fund has delivered supplement payments ranging from $10,000 to $14,000 per year to more than 4,000 CCEE educators in licensed centers and home-based programs.

Figure I.2. Timeline of key events related to the Early Childhood Educator Pay Equity Fund



Source: Toward Pay Equity: A Case Study of Washington, DC's Wage Boost for Early Childhood Educators, Box 2. (https://www.urban.org/sites/default/files/2023-06/Toward%20Pay%20Equity.pdf) and the Early Childhood Pay Equity Fund: Timeline and History (https://osse.dc.gov/ecepayequity).

Following the recommendations of the Task Force, the DC Council formally authorized OSSE to disburse the FY 2022 (The Early Childhood Educator Equitable Compensation Task Force Temporary Amendment Act of 2022) and FY 2023 payments (Fiscal Year 2023 Budget Support Act of 2022). In May 2022, OSSE partnered with a third-party vendor, AidKit, to begin the distribution of the FY 2022 payments. Using the Division of Early Learning Licensing Tool (DELLT) database, OSSE and AidKit identified approximately 3,200 eligible educators employed as of May 2022, before the launch of the PEF (DC OSSE 2023). The application window opened in August 2022 and closed the following month. More than 90 percent of eligible CCEE educators applied for the payments, which were distributed between September and November 2022 (DC OSSE 2022c). In FY 2022, the fund disbursed about $38.4 million to 3,217 CCEE educators who received a one-time payment. As of December 2023, in FY 2023, the fund had paid about $41.8 million to 4,061 educators who received quarterly payments (Urban Institute 2024). Taxes were not withheld from the FY 2022 lump-sum payments in order to expedite distribution of funds, though taxes were withheld from the FY 2023 quarterly payments. The PEF also supports HealthCare4ChildCare, which began providing access to free or lower-premium health insurance to CCEE staff and their families in FY 2023.

C. Prior research on CCEE educator wage boost initiatives

Addressing low CCEE educator pay requires a dedicated source of additional public funding to supplement existing revenue. Community-based CCEE is a market-based system that primarily relies on private tuition paid by families. Although K–12 schools, for instance, benefit from public investment and in-kind support to reduce their non-labor expenses (such as facilities), these costs consume a larger share of operating budgets in CCEE settings. Indeed, data suggest that about 80 percent of public-school costs are allocated to labor, compared to approximately 60 percent of costs in CCEE settings (Center for American Progress 2018; National Center for Education Statistics 2020; Neelan and Caronongan 2022). In addition, CCEE settings must operate on tighter margins because, due to health and safety regulations, they are required to employ a greater number of staff relative to the number of children served (CSCCE 2021). This is particularly true of settings serving infants and toddlers, where child–staff ratios are lowest.

Few policy strategies in CCEE focus on generating the public funding needed for long-term, sustainable wage improvement. Substantial funding that helped many CCEE employers sustain operations and provide wage boosts to CCEE educators during the COVID-19 pandemic was temporary and short term. Several states have experimented with raising subsidy reimbursement rates for providers whose care is funded through child care subsidies (Center for American Progress 2024), although these strategies are targeted and represent more incremental changes in CCEE educator compensation. A recent study examining the effects of one such initiative in Texas shows that incremental changes in compensation had a limited impact on recruitment and retention over time (Cunha and Lee 2023), suggesting that more ambitious strategies to permanently raise wages are needed.

One study using experimental methods found that larger financial bonuses reduced staff turnover (Bassok et al. 2021). In 2021, the Virginia Department of Education implemented the Teacher Recognition Program (TRP). Funded through a federal Preschool Development Birth to Five grant (PDG), this program provided eligible educators with a wage supplement of $1,500 if they remained in the same site for eight months. CCEE educators at the PDG sites were randomly selected to a program group that received an invitation to participate in the TRP or a control group that did not receive an invitation to participate. This enabled evaluators to estimate causal impacts of the TRP on turnover rates. By the end of the study period, CCEE educators in the program group were 11 percentage points more likely to have remained at their site. Descriptive findings from a follow-up survey of study participants suggested that the financial incentives increased morale and job satisfaction, helped educators meet their financial needs, and reduced stress.

Through the PEF, Washington, DC, is the first jurisdiction in the nation to use local tax revenue as a dedicated source of public funding with the goal of permanently increasing the wages of all eligible CCEE educators irrespective of other conditions, such as whether educators continue in their role or accept funding from subsidies. The PEF payments—representing a 40 percent annual wage boost for the average CCEE educator in Washington, DC—are also larger than wage supplements provided by other compensation strategies or initiatives. The only rigorous evidence on the efficacy of the PEF comes from this study's initial analysis (Schochet 2023). The analysis examined whether the initial, lump-sum PEF payments disbursed in FY 2022 influenced the number of CCEE educators in Washington, DC, in the first two quarters after the launch of the program. Findings suggested that by the fourth quarter of 2022, the initial payments had increased CCEE employment levels in Washington, DC, by about 100 additional educators, or about 3 percent. Additional analysis led to the conclusion that this positive early-term impact was unlikely to be due to chance.

These findings also affirmed self-reports from CCEE educators who received PEF payments and their employers. Nearly two in three DC educators agreed or strongly agreed that, as a result of the PEF payments, they now planned to continue working in DC CCEE longer than previously expected (Doromal et al. 2024). Many center directors (61 percent) also said that the payments had made it easier to retain their "best" educators, and most directors (70 percent) said the PEF had influenced their educators' decisions to continue working at their setting (Nikolopoulos et al. 2024). Many directors (59 percent) also agreed that the PEF had influenced new educators' decisions to start working at their setting.

D. Road map for the rest of this report

This report focuses on the effectiveness of the PEF on CCEE labor market outcomes. We leveraged the launch of the PEF as a natural experiment to estimate the impacts of the program on the CCEE workforce levels, sector wages, and the number of CCEE establishments, using a multiple-outcome synthetic control method (SCM). To examine the dynamics of the PEF's impacts over time, we estimated the treatment effects through the program's second year of operation (FY 2023), drawing on the most recently available federal employment data from the QCEW at the time of this report for all counties in the United States.

The main text of the report proceeds as follows:

/ Chapter II discusses the data used for the study, describes the analysis sample, and reviews the theoretical framework for and application of the multiple-outcome SCM.

/ Chapter III presents the results from our benchmark SCM analysis of the effectiveness of the PEF on CCEE labor market outcomes. This analysis measures impacts on the number of CCEE educators, CCEE average weekly wages, and the number of CCEE establishments.

/ Chapter VI presents the results for several robustness checks. These exercises assess the sensitivity of the benchmark findings to changes in the design of the study, analysis sample, and technical approach.

/ Chapter V provides additional discussion of our main findings and concluding remarks.

In addition, Appendix A includes tables of detailed results for readers who would like to dive more deeply into the statistical estimates discussed in this report.

II. Data Source and Research Methods

To answer the study research questions, we used data from the QCEW to evaluate CCEE employment, wages, and establishments in Washington, DC, and all other counties in the United States between 2019 and 2023. We identified a weighted combination of counties, referred to as the synthetic Washington, DC, to approximate the CCEE labor market trends that Washington, DC, would have experienced in the absence of the PEF. Our approach generalizes the synthetic control method to a multiple-outcome framework to improve the reliability of treatment effect estimation. This chapter provides an overview of the contents and structure of the QCEW and describes the theoretical framework for the multiple-outcome SCM. To provide additional context for the analysis, this section also describes Washington, DC, and how it compares to the nation as a whole in terms of key measures of the CCEE labor market.

A. The Quarterly Census of Employment and Wages

The QCEW program publishes a quarterly count of employment and wages, reported by employers, covering more than 95 percent of industries across all counties in the United States (BLS n.d.[a]). For each industry and county, the QCEW produces comprehensive data on the number of establishments, monthly employment, and quarterly wages for workers covered by state unemployment insurance (UI) laws and federal workers covered by the Unemployment Compensation for Federal Employees (UCFE) program. The primary source for the QCEW is administrative data from state UI programs, which are supplemented by data from two Bureau of Labor Statistics (BLS) surveys: the Annual Refiling Survey and the Multiple Worksite Report.

The QCEW provides several key variables used in the analysis:

/ **Industry** classification is applied to each establishment on the basis of its primary economic activity. The QCEW uses the North American Industry Classification System (NAICS) for industry detail.

/ **County** is determined as the primary local geographic designation for an establishment. It is assigned based on the establishment's physical location.

/ **Ownership** distinguishes between private sector and public sector employment. Public sector employment includes federal, state, and local government employment.

/ **Establishment count** aggregates the number of establishments in a given county, in a given industry, and/or with a given ownership status by calendar quarter.

/ **Employment count** aggregates the number of filled jobs, whether full or part time, and whether temporary or permanent, across establishments by county, industry, and ownership status. The quarterly reports include employment levels for each month in that quarter.

/ **Wages** reflect the total compensation paid, including labor and other earnings, such as bonuses, tips and other gratuities, and, in some states, employer contributions to certain deferred compensation plans, by county, industry, and ownership status.

The analysis includes QCEW data for the nearly four-year period before the PEF through the most recent available quarter; in total, 19 quarters from 2019 through the third quarter of 2023 were selected. We analyzed the extended pre-treatment period prior to the PEF to ensure representation of quarters both before and after the start of the COVID-19 pandemic in 2020, which led to sharp job losses among CCEE educators (CSCCE 2023) and an influx of temporary federal relief funds that many states and territories allocated to support them (CSCCE n.d.).

We constructed CCEE employment, wages, and establishments using Industry 624410, Child Care Services (BLS n.d.[b]). This industry comprises establishments primarily engaged in providing CCEE for children from birth through school age and may also offer pre-K or before- or after-school programs. Child Care Services encompasses all CCEE establishments not located in school-based settings. Notably, it excludes DCPS and public charter school programs in Washington, DC, and the CCEE educators employed by these settings who are ineligible for PEF payments. In May 2022, OSSE identified approximately 3,200 educators eligible for the PEF, whereas in December 2022, this number was anticipated to be about 3,500. In the QCEW, 3,282 CCEE educators were employed in May 2022, whereas 3,497 educators were employed in December 2022. This suggests that these data align with the population of educators eligible for the PEF.

B. Description of the study counties and measures

The QCEW includes data for 3,142 unique counties over the study period, of which 1,233 had valid information on CCEE employment, wages, and establishments in all quarters. We further restricted the analytic sample to exclude many counties with smaller populations and lower costs of living on the basis that these counties would be implausible matches for Washington, DC. The final analysis sample included Washington, DC, and 144 other counties in the top half of the distribution of employment levels, wages, and establishment levels, both within the CCEE sector and across all occupations.[2]

Labor market outcomes included in the analysis

The following quarterly CCEE labor market outcomes were included in the analysis: (1) the number of educators, (2) average weekly wages, and (3) the number of establishments. Employment counts, wages, and establishment counts across all occupations were also included as variables to match Washington, DC, with the donor counties. The number of educators in each quarter was constructed as the average of the three monthly employment levels. Average weekly wages were calculated by dividing total quarterly wages by the average of the three monthly employment levels and then dividing the result by the 13 weeks in the quarter. Each measure was aggregated across ownership groups.[3] Outlier values were top-coded, and each variable was smoothed to adjust for short-term fluctuations.[4] ◢

Figure II.1 visualizes the CCEE outcomes over time for all counties in the analysis, with an emphasis on the outcome trajectories for Washington, DC. The vertical dotted lines are positioned to separate the pre-treatment and post-treatment periods. On average across the pre-treatment period, Washington, DC, falls at about the 75th percentile of the distributions of the number of CCEE educators and establishments, and

[2] The comparison group in Schochet (2023) included 105 potential donor counties that were in the top third of the distribution of these variables. This study did not analyze the number of CCEE establishments.

[3] In the second quarter of 2022, just three CCEE establishments in Washington, DC, were publicly owned (by the federal government). CCEE educators employed by publicly owned establishments (such as Head Start) are eligible for PEF payments as long as they meet other program eligibility criteria.

[4] Outliers were defined as greater than three standard deviations above the outcome mean. Measures were smoothed using a weighted average, where each value was weighted twice as heavily as the value that came before and after.

Figure II.1. CCEE labor market outcomes for Washington, DC, and donor counties

Source: Author's analysis of the Quarterly Census of Employment and Wages (QCEW) data (https://www.bls.gov/cew/downloadable-data-files.htm).

at the 95th percentile for average CCEE weekly wages.[5] The number of CCEE educators was adversely impacted by the COVID-19 pandemic in the first quarter of 2020, before partially recovering in the later quarters.

C. Multiple-outcome synthetic control framework

To estimate the effects of the PEF on CCEE labor market outcomes, we used a multiple-outcome SCM to construct a synthetic Washington, DC, using a convex combination of donor counties in the comparison group that did not implement such a program. This weighted combination of chosen counties closely approximates the dynamics of the outcomes and selected covariates in Washington, DC, in the approximately four-year period before the PEF, thereby providing a counterfactual for estimating treatment effects.

Theoretical framework

The SCM (see Abadie and Gardeazabal 2003; Abadie et al. 2010, 2015) constructs a synthetic control unit as a convex combination of control units, minimizing the difference between the treated unit's outcome and the synthetic unit's outcome before treatment. This method then estimates treatment effects by comparing the treated unit's observed outcome with the synthetic control's counterfactual outcome post treatment. This analysis generalizes the conventional single-outcome SCM to a multiple-outcome framework that simultaneously incorporates numerous pre-treatment outcomes as matching variables (see Tian et al. 2023; Sun et al. 2023).

Let $Y_{it,k}$ represent the outcome k for unit i at time t. Suppose we observe K outcomes for $J+1$ units over T time periods. Without loss of generality, assume unit $i=1$ is treated from period T_0+1 onward, and the remaining J units are untreated throughout the observation period. The treatment effect for the treated unit on outcome k after treatment is denoted as follows:

$$\tau_{1t,k} = Y_{1t,k}^1 - Y_{1t,k}^0, t > T_0, k \in \{1, \dots, K\},$$

where $Y_{1t,k}^1$ and $Y_{1t,k}^0$ are the potential outcomes with and without treatment, respectively. The observed outcome is as follows:

$$Y_{1t,k} = D_{1t}Y_{1t,k}^1 + (1 - D_{1t})Y_{1t,k}^0,$$

with D_{it} indicating the treatment status. Because $Y_{1t,k}^0$ is unobserved for the treated unit post treatment, it is estimated using a convex combination of control units.

Assume the untreated potential outcome $Y_{1t,k}^0$ follows an interactive fixed effects model (Athey et al. 2021):

$$Y_{1t,k}^0 = \alpha_{ik} + \beta_{tk} + L_{it,k} + \epsilon_{it,k},$$

where α_{ik} and β_{tk} are unit and time fixed effects specific to outcome k, $L_{it,k}$ is a latent term assumed to be common across outcomes, and $\epsilon_{it,k}$is the idiosyncratic error. As we discuss next, outcome-specific unit fixed effects result from the application of demeaned outcomes.

[5] The variability in the relative position of Washington, DC, across outcomes highlights the utility of adjusting for the differences in the level of the outcomes through demeaning, as discussed in the next section.

Formation of the synthetic control unit

To estimate the untreated potential outcomes, we constructed a synthetic control unit that closely approximated the treated unit's pre-treatment characteristics.

As suggested by Doudchenko and Imbens (2017) and Ferman and Pinto (2021), we primarily used demeaned outcomes (that is, outcomes in differences with respect to their pre-treatment averages) to improve the pre-treatment fit. This may be especially helpful in the multiple-outcome framework, where the relative positions of the units may vary across different outcomes. Following Sun and colleagues (2023), we denoted $\bar{Y}_{i.k} = \frac{1}{T_0}\sum_{t=1}^{T_0} Y_{it,k}$ as the pre-treatment average for a given unit and outcome, and $\dot{Y}_{it,k} = Y_{it,k} - \bar{Y}_{i.k}$ as the demeaned outcome.

The single-outcome case. Under the conventional, single-outcome approach, a synthetic control is constructed with weights chosen to optimize the pre-treatment fit for a single outcome. The single-outcome SCM estimator for the counterfactual outcome $Y_{1t,k}^0$ is as follows:

$$\hat{Y}_{1t,k}^0 = \bar{Y}_{i.k} + \sum_{i=2}^{N} \gamma_i \dot{Y}_{it,k},$$

where γ is the set of synthetic control weights chosen to minimize the pre-treatment fit for the demeaned outcome:

$$\hat{\gamma}_k = \arg min_{\gamma \epsilon \Delta N0} \sqrt{\frac{1}{T_0}\sum_{t=1}^{T_0}(\dot{Y}_{it,k} - \sum_{i=2}^{N} \gamma_i \dot{Y}_{it,k})^2}$$

and where $\Delta N0$ is the simplex constraint ensuring the weights are non-negative and sum to one (see Sun et al. 2023 for additional technical details).

Leveraging multiple outcomes. The multiple-outcome synthetic control approach extends the single-outcome approach by considering multiple related outcomes within the same domain. This method leverages information across outcomes to identify a single set of weights to minimize the distance between the synthetic control and the treated unit across all outcomes simultaneously.

Sun and colleagues (2023) describe two related assumptions for applying a multiple-outcome model. Both involve the latent component ($L_{it,k}$) of the interactive fixed effects model described above. First, as previously discussed, these unobserved factors must be common across outcomes. If the outcomes depend on different sets of unobserved predictors, then we lose the benefits of matching on multiple related outcomes.[6] Second, we assume a low number of common factors underlying related variables. This low-rank assumption is plausible when the number of outcomes K is relatively small or when there is a high degree of shared information across outcomes.

In principle, we would like to find multiple-outcome SCM weights that can recover $L_{1t,k}$ from a weighted average of $L_{2t,k}, \dots, L_{Nt,k}$ for all k. Because the underlying model components are unobserved, we must instead use observed outcomes Y to construct feasible balance measures. To leverage the common factor

[6] The number of CCEE educators, CCEE average weekly wages, and the number of CCEE establishments are likely to be influenced by similar underlying factors.

structure across outcomes, we considered an alternative balance measure—concatenated weights—that uses information from multiple-outcome series.

The multiple-outcome weights simply concatenate the different outcome series together to assess the pre-treatment fit achieved across all outcomes and pre-treatment time periods simultaneously:[7]

$$\hat{\gamma}_k = \arg min_{\gamma \epsilon \Delta N0} \sqrt{\frac{1}{T_0}\frac{1}{K}\sum_{k=1}^{K}\sum_{t=1}^{T_0}(\dot{Y}_{it,k} - \sum_{i=2}^{N}\gamma_i \dot{Y}_{it,k})^2}$$

Inference

Inference for the multiple-outcome SCM follows the permutation-based approach suggested by Abadie (2021). This involves permuting the treatment status among all units and calculating the pre-treatment and post-treatment root mean squared prediction error (RMSE) for each unit and outcome:

$$R_{pre,i,k} = \sqrt{\frac{1}{\#_{pre,k}}\sum_{t=1}^{T_0}(\hat{Y}_{it,k} - Y_{it,k})^2},$$

$$R_{post,i,k} = \sqrt{\frac{1}{\#_{post,k}}\sum_{t=T_0+1}^{T}(\hat{Y}_{it,k} - Y_{it,k})^2}.$$

The post-treatment to pre-treatment RMSE ratio is $r_{i,k} = R_{post,i,k}/R_{pre,i,k}$. The *p*-value for the treatment effect is computed based on the ranking of $r_{i,k}$ among all units. *P*-values for individual post-treatment periods are computed based on the ranking of the ratio of each period-specific treatment effect (that is, the gap between each unit and its synthetic control) and the pre-treatment RMSE. We implemented a two-sided inference procedure that ranks the absolute value of the ratios, which departs from the one-sided procedure implemented by Abadie (2021) and Tian and colleagues (2023), who tested directional hypotheses.

Robustness checks

We conducted several robustness checks to test the sensitivity of the benchmark findings to alternative samples, designs, and SCM estimators:

/ **Leave-one-out.** To check whether the results are sensitive to the choice of counties in constructing the synthetic Washington, DC, we conducted a leave-one-out re-analysis, where we iterated the estimation procedure, excluding one of the counties that received positive weights from the construction of the synthetic Washington, DC, at a time. This check tests whether the main results are robust to the exclusion of any particular county.

/ **Backdated treatment.** In the benchmark analysis, we selected the second quarter of 2022—the quarter before the start of the application window for the initial PEF payments—as the treatment date. This choice could lead to attenuated estimates of treatment effects if the outcomes were affected before this period because educators or administrators had anticipated the implementation of the PEF before they

[7] We also included the total number of workers, average weekly wages, and total number of establishments across all sectors as additional covariates. See Botosaru and Ferman (2019) for a discussion on the role of covariates in SCM.

were allowed to apply.[8] We backdated the treatment to the fourth quarter of 2021 to see whether we obtained results similar to those in the benchmark specification.[9]

- **Single outcome.** Instead of matching on multiple related outcomes simultaneously, we could construct the synthetic controls by matching on each outcome separately. The single-outcome SCM estimates a different weighted combination of donor counties for each outcome analyzed.
- **No demeaning.** The estimates in the benchmark specification were obtained using demeaned outcomes to account for the differences in the levels of the outcomes. As previously discussed, the values for CCEE labor market outcomes, and average weekly wages in particular, are extreme for Washington, DC, in which case the SCM using the original outcomes may not be able to provide credible estimates of treatment effects due to poor pre-treatment fits. Matching on multiple outcomes may worsen the problem, as it is more difficult to obtain a good fit on multiple outcomes. Bearing this in mind, we checked whether the results produced by matching on the original outcomes differ from the benchmark results.

[8] As mentioned earlier, during the first quarter of 2022, the PEF Task Force published its initial report with recommendations for the implementation of the PEF. This was the first public information about the PEF payments.

[9] The backdating exercise is also useful for evaluating the credibility of the SCM estimator by assessing whether the synthetic Washington, DC, can reproduce the outcomes of the actual Washington, DC, in the absence of the treatment.

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III. Findings from the Benchmark Analysis

The launch of the PEF offered an opportunity to examine whether increased educator compensation affects outcomes in the CCEE sector. The PEF payments provided immediate financial relief to potentially reduce economic stress, boost morale, and anchor educators in their roles. The payments also may have supported the hiring of new educators to fill staffing vacancies. The FY 2022 and FY 2023 payments evaluated in this study would not be expected to influence wages from employer payrolls because they were delivered directly to educators, outside of their regular wages. Analysis of the number of CCEE establishments is exploratory; although administrators did not receive payments and the direct educator payments would not be expected to provide incentive for new establishments, the payments could help stabilize existing establishments by reducing closures due to staffing shortages.

In this chapter, we describe findings from the benchmark SCM analysis, focusing on treatment effects on the number of CCEE educators, average weekly wages in the sector, and the number of CCEE establishments. As previously discussed, the benchmark analysis included all donor counties in the comparison group, used information from the first quarter of 2019 through the second quarter of 2022 to define the pre-treatment period, matched on multiple outcomes simultaneously, and obtained estimates using demeaned outcomes. We provide an overview of how the synthetic Washington, DC, was constructed, present descriptive comparisons between Washington, DC, and its synthetic control, and summarize the statistical significance in each period *t* and in the post-treatment periods overall.

A. The synthetic Washington, DC

Figure III.1 shows the weights assigned to the donor counties in the comparison group that were selected for constructing the synthetic Washington, DC. We see that the CCEE labor market outcomes for Washington, DC, are best approximated by a combination of New York County, New York (22 percent); San Francisco County, California (19 percent); Ventura County, California (18 percent); Monterey County, California (12 percent); Albany County, New York (10 percent); Richmond County, New York (7 percent); Honolulu County, Hawaii (6 percent); Kern County, California (5 percent); and Sarasota County, Florida (1 percent).

This combination of weighted counties was selected because it most closely resembled Washington, DC, in the pre-treatment periods in terms of the CCEE labor market outcomes and additional covariates. The list of outcomes averaged over each pre-treatment year and additional covariates averaged over the full pre-treatment period, as well as their values for Washington, DC, the synthetic Washington, DC, and the simple average of all donor counties in the comparison group are summarized in Table III.1. We see that, compared with the simple average of the other counties in the sample, the nine counties averaged together in this specific combination to form the synthetic control are much closer to Washington, DC, in terms of employment levels, average wages, and establishment counts, both in the CCEE sector and across all occupations. The standardized percent bias quantifies the degree of imbalance or discrepancy between Washington, DC, and each control group. This measure is the simple difference in means between Washington, DC, and each control group, then divided by the control group mean. Larger percent bias values indicate that Washington, DC, differs significantly from the average county in the donor pool. Smaller values indicate that Washington, DC, and the synthetic control group are well balanced in the pre-treatment periods.

Figure III.1. Optimal county weights for the construction of the synthetic Washington, DC

Source: Author's analysis of the Quarterly Census of Employment and Wages (QCEW) data (https://www.bls.gov/cew/downloadable-data-files.htm).

Table III.1. Balance on CCEE labor market outcomes averaged over the pre-treatment quarters

	Washington, DC (1)	Synthetic Washington, DC (2)	Donor county average (3)	Standardized percent bias (1–2)	Standardized percent bias (1–3)
CCEE labor market outcomes					
Number of CCEE educators					
Q1 2019 to Q4 2019	3,697	3,700	2,696	0%	37%
Q1 2020 to Q4 2020	2,980	2,969	2,199	0%	36%
Q1 2021 to Q4 2021	3,024	3,016	2,330	0%	30%
Q1 2022 to Q2 2022	3,264	3,294	2,538	-1%	29%
CCEE average weekly wage					
Q1 2019 to Q4 2019	$673	$674	$523	0%	29%
Q1 2020 to Q4 2020	$765	$763	$572	0%	34%
Q1 2021 to Q4 2021	$795	$796	$611	0%	30%
Q1 2022 to Q2 2022	$808	$808	$642	0%	26%
Number of CCEE establishments					
Q1 2019 to Q4 2019	251	253	214	-1%	17%
Q1 2020 to Q4 2020	259	258	214	0%	21%
Q1 2021 to Q4 2021	265	264	216	0%	23%
Q1 2022 to Q2 2022	272	269	220	1%	24%
Additional covariates					
Total number of workers	743,115	776,378	401,318	-4%	85%
Average weekly wage	$2,053	$1,992	$1,340	3%	53%
Total number of establishments	43,272	45,288	29,116	-4%	49%

Source: Author's analysis of the Quarterly Census of Employment and Wages (QCEW) data (https://www.bls.gov/cew/downloadable-data-files.htm).

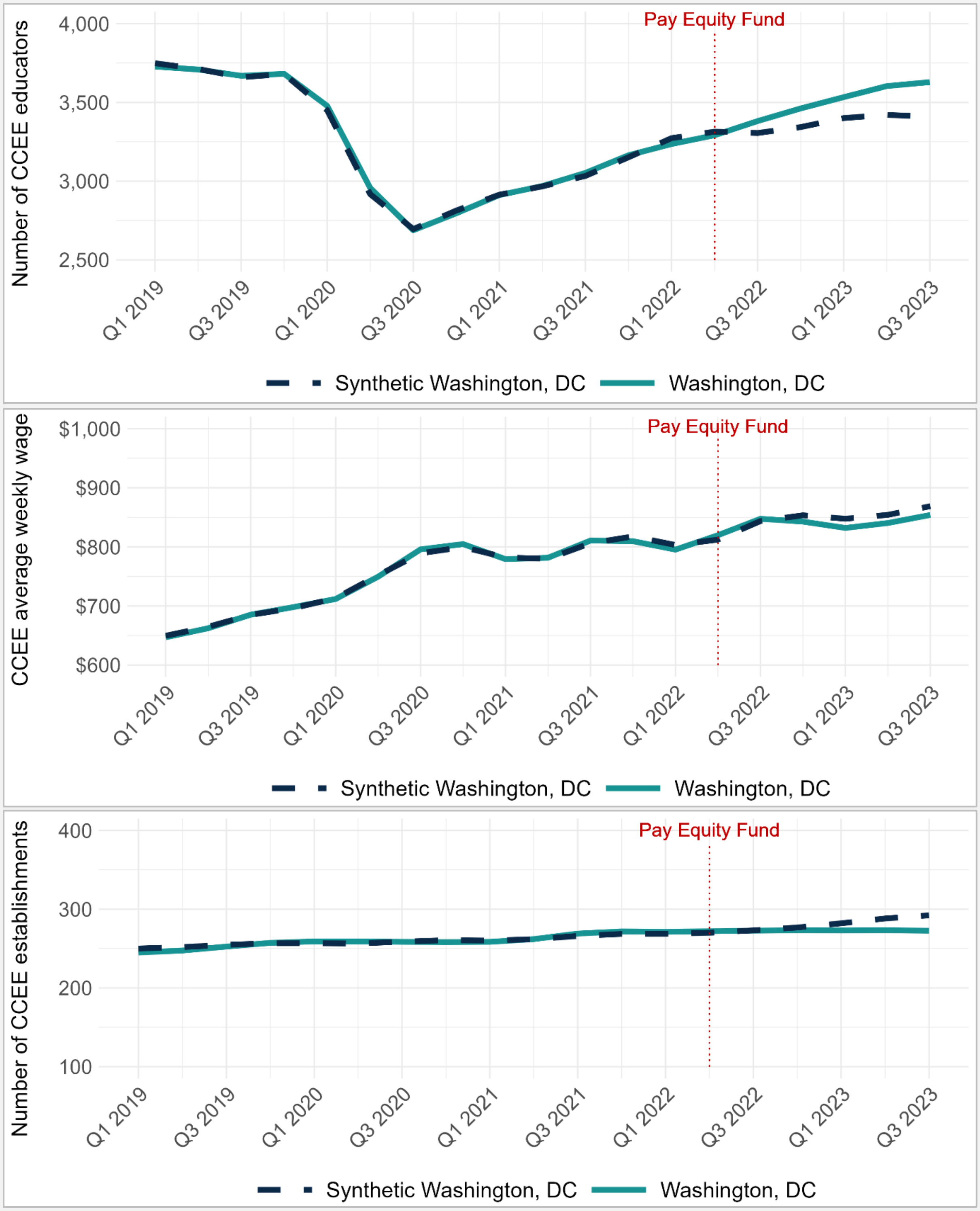
Note: This table compares the list of CCEE labor market outcomes averaged over the pre-treatment quarters by calendar year and additional covariates averaged over all pre-treatment quarters for Washington, DC; the synthetic Washington, DC, constructed using the listed outcomes and covariates; and the simple average of the donor counties in the comparison group. Standardized percent bias measures the difference between the averages for Washington, DC, and each comparison group, standardized by the comparison group mean.

B. Differences between Washington, DC, and its synthetic control

Figure III.2 compares the trajectories of each CCEE outcome for Washington, DC, and the synthetic Washington, DC.[10] In the top panel, the actual Washington, DC, immediately starts to accumulate a greater number of CCEE educators than the synthetic Washington, DC, following the launch of the PEF. The gaps between the two continue to widen thereafter, with the largest treatment effects in the most recently observed quarter. The predicted post-treatment trend for the synthetic control group—shown as the dashed line—suggests that without the PEF, the number of CCEE educators would have increased by 95 workers by the third quarter of 2023. With the PEF, Washington, DC, increased its CCEE workforce by

[10] Table A.1 presents CCEE outcome levels for Washington, DC, and point estimates for the synthetic Washington, DC, and the treatment effects in the post-treatment quarters.

Figure III.2. CCEE labor market outcomes for Washington, DC, and its synthetic control



Source: Author's analysis of the Quarterly Census of Employment and Wages (QCEW) data (https://www.bls.gov/cew/downloadable-data-files.htm).

Note: The benchmark analysis includes all donor counties in the comparison group, uses information from Q1 2019 through Q2 2022, matches on multiple outcomes simultaneously, and obtains estimates using demeaned outcomes.

314 educators over this period, reflecting a cumulative treatment effect of 219 educators, or nearly 7 percent, relative to the total number of CCEE educators in the control group in the second quarter of 2022. This effect is nearly twice the magnitude of the impact observed in the fourth quarter of 2022 (119 educators). Across the post-treatment quarters, the findings indicate an overall effect of 146 educators.

The effects of the PEF on CCEE average weekly wages remained close to zero throughout the post-treatment period. Across the post-treatment quarters, CCEE educators in Washington, DC, earned an average weekly wage of $843, compared with $854 earned by educators in the synthetic control group. This reflected an overall treatment effect of just –$10, or about 1 percent of control group average wages at study baseline. Impacts for individual post-treatment quarters similarly ranged from $4 (third quarter of 2022) to –$16 (first quarter of 2023). These findings were consistent with the expectation that payments delivered outside of employer payrolls would have no effect on wages collected by the QCEW because they are not reported to UI agencies.

As for the number of CCEE establishments, we found that the PEF led to a modest decrease in its second year of operation. On average across the post-treatment quarters, Washington, DC, had 10 fewer CCEE establishments compared to the benchmark synthetic control group (273 versus 282 establishments), with impacts ranging from 0 (third quarter of 2022) to –14 (third quarter of 2023) establishments in the individual post-treatment quarters. The overall effect represents about a 4 percent decrease in terms of the number of CCEE establishments estimated for the synthetic Washington, DC, at study baseline. We contextualize this effect in relation to the distribution of placebo effects in the next section.

C. Statistical significance of treatment effects

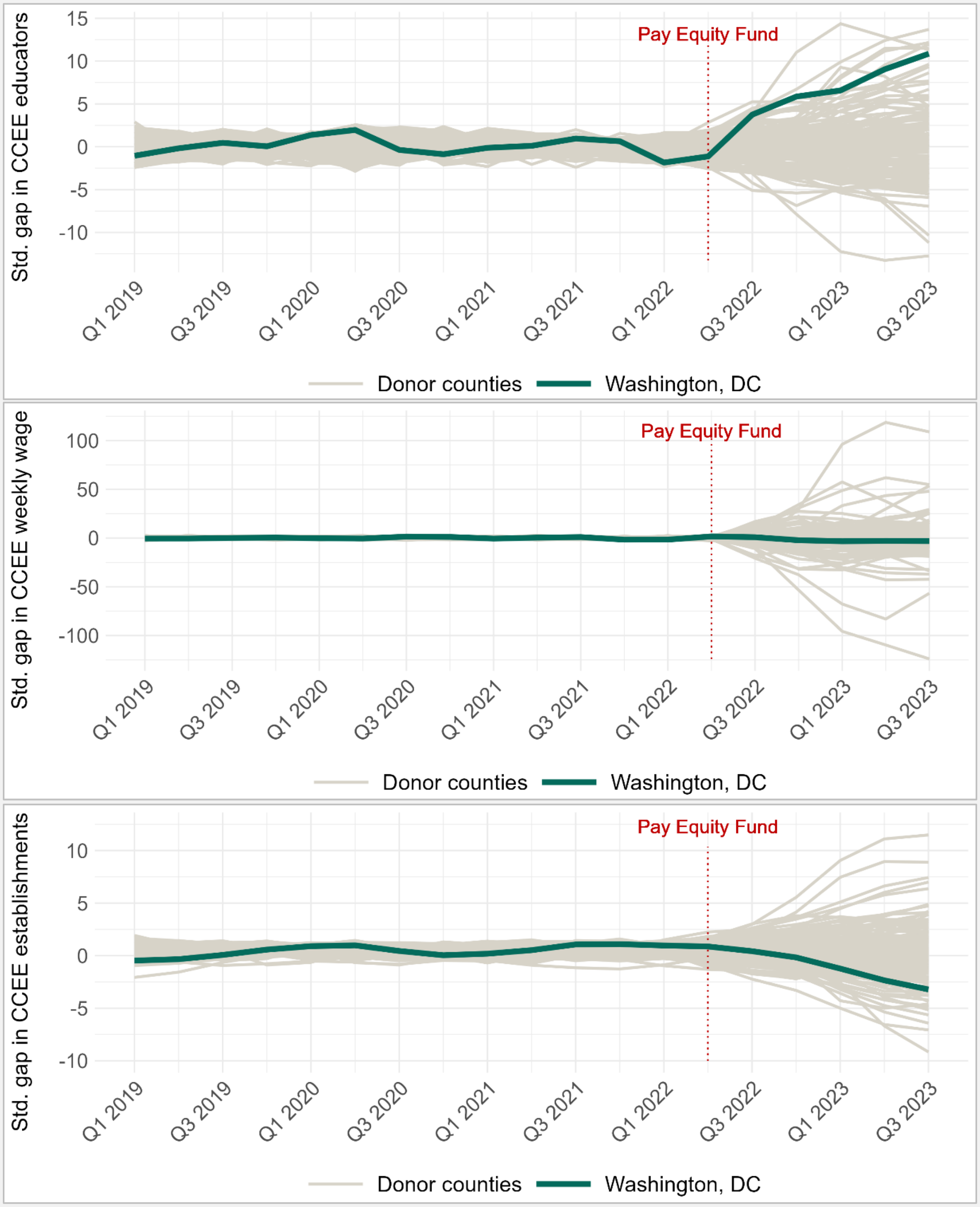
Because of limited prior evidence on the effects of implementing CCEE educator wage boost initiatives, we tested the null hypothesis for outcome k at $t > T_0$, $H_0 : \tau_{1t,k} = 0$, against the alternative hypothesis, H_1 : $\tau_{1t,k} != 0$, so that if the null hypothesis is rejected, then we can conclude that the implementation of the PEF would have a statistically significant absolute effect on outcome k for Washington, DC, at time t. As previously discussed, we generated per-period p-values by first computing—and then ranking —the ratios of treatment effects in each post-treatment period and the pre-treatment RMSE. Similarly, p-values for the post-treatment periods overall were based on the ranking of the post- to pre-treatment RMSE ratio.

Detailed graphs showing the standardized gaps between each county and its synthetic counterpart in the permutation test (that is, the ratio of each county's gap and its pre-treatment RMSE) are shown in Figure III.3. The rankings of the post- to pre-treatment RMSE ratios for each CCEE outcome across the post-treatment quarters are shown in Figure III.4, with the horizontal dashed line indicating the position of Washington, DC. Figure III.5 shows the per-period p-values for each outcome, with the p-values in the post-treatment periods overall reported in parentheses. The horizontal dashed line represents the significance level at α = 0.10. *P*-values that fall below this threshold reflect a ranking of 14 or better out of the 145 counties in the analytic sample.

The effects of the PEF on the number of CCEE educators were statistically significant overall and at each post-treatment quarter. Out of the 145 total counties, Washington, DC, had the sixth largest overall impact (Figure III.4). The post- to pre-treatment RMSE ratio of Washington, DC, was larger than that found in about 96 percent of all counties. This suggests that this impact is statistically significant at the 4 percent level, which enables us to confidently rule out the possibility that the PEF had no impact on CCEE employment in Washington, DC. The significance levels for the impacts at the five individual PEF quarters ranged from 2 percent to 5 percent (Figure III.5), suggesting that the rank order of Washington, DC, in the distribution of estimates from the permutation tests tended to be similar over time (Figure III.3).

The effects of the PEF on CCEE average weekly wages and on the number of CCEE establishments were not statistically significant. As shown in Figure III.3, the standardized gap in wages between Washington, DC, and its synthetic counterpart remained close to zero both before and after the study baseline. Overall, Washington, DC, ranked 106th out of the 145 counties in the analysis in terms of its post- to pre-treatment RMSE ratio for wage effects (Figure III.4), and the per-period *p*-values in Figure III.5 further indicate that the observed changes in CCEE average weekly wages cannot be confidently attributed to the PEF in any quarter. Similarly, although the descriptive findings suggested that the PEF resulted in fewer CCEE establishments, Washington, DC, also ranked in the middle range of the distribution overall and in the individual quarters; we cannot reject the null hypotheses that the PEF had no effect on the number of CCEE establishments in the first five quarters following the launch of the program.

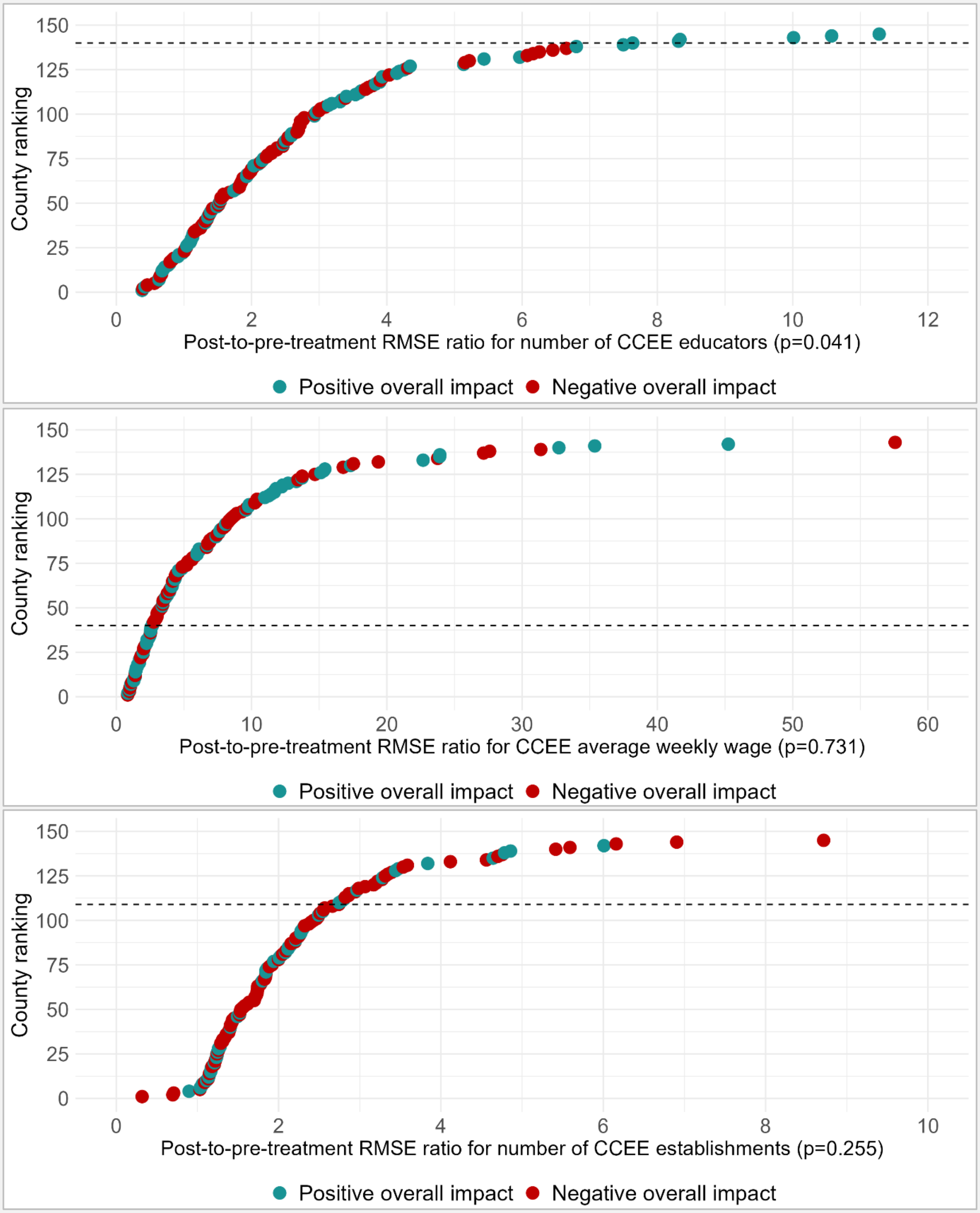
Figure III.3. Placebo gaps in CCEE labor market outcomes for donor counties



Source: Author's analysis of the Quarterly Census of Employment and Wages (QCEW) data (https://www.bls.gov/cew/downloadable-data-files.htm).

Note: Gaps reflect the difference between each county and its synthetic counterpart, estimated using the benchmark approach. Gaps are standardized by the pre-treatment root mean squared percent error. Std. = standardized.

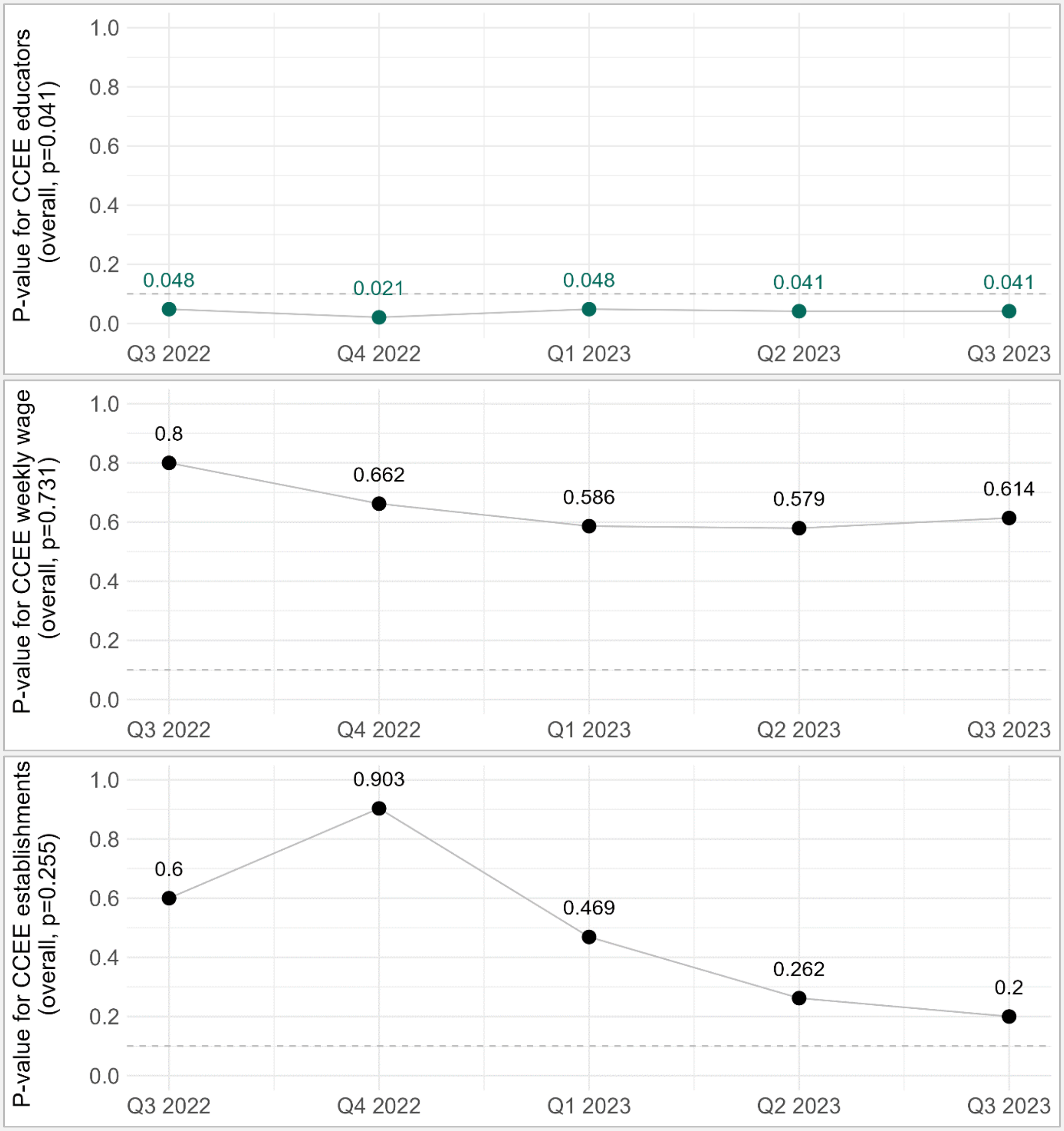
Figure III.4. Post-treatment to pre-treatment RMSE ratios for CCEE labor market outcomes



Source: Author's analysis of the Quarterly Census of Employment and Wages (QCEW) data (https://www.bls.gov/cew/downloadable-data-files.htm).

Note: Each county is ranked according to its post- to pre-treatment root mean squared percent error (RMSE) ratio. The horizontal dashed line reflects the ranking of Washington, DC, used to compute the *p*-value in the post-treatment quarters overall reported in parentheses.

Figure III.5. *P*-values of the two-sided tests of H_0: The Pay Equity Fund had no effect on CCEE labor market outcomes at the corresponding post-treatment quarter



Source: Author's analysis of the Quarterly Census of Employment and Wages (QCEW) data (https://www.bls.gov/cew/downloadable-data-files.htm).

Note: The figure presents the per-quarter *p*-values for each outcome, with the *p*-values in the post-treatment quarters overall reported in parentheses. The horizontal dashed line represents the significant level at α = 0.10. *P*-values were estimated using two-sided tests that rank the absolute value of the standardized gaps.

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IV. Findings from the Robustness Checks

We conducted several robustness checks to assess the sensitivity of our results to changes in the design of the study. These changes included leaving out any particular county; backdating the treatment so that we could be confident that the outcomes observed before this date were by no means contaminated; matching on single outcomes rather than multiple related outcomes; and using the original outcomes rather than the demeaned outcomes. In this chapter, we present the results of these exercises, which are similar to the benchmark results. The county weights used to construct the synthetic control groups for the robustness checks are provided in Table A.2 and Table A.3. Table A.4 presents point estimates for the treatment effects from these additional analyses.

A. Leave-one-out

To check whether the results are sensitive to the choice of counties in constructing the synthetic Washington, DC, we conducted a leave-one-out re-analysis. In this procedure, we iterated the estimation, each time excluding one of the nine counties that received positive weights in the construction of the synthetic Washington, DC.

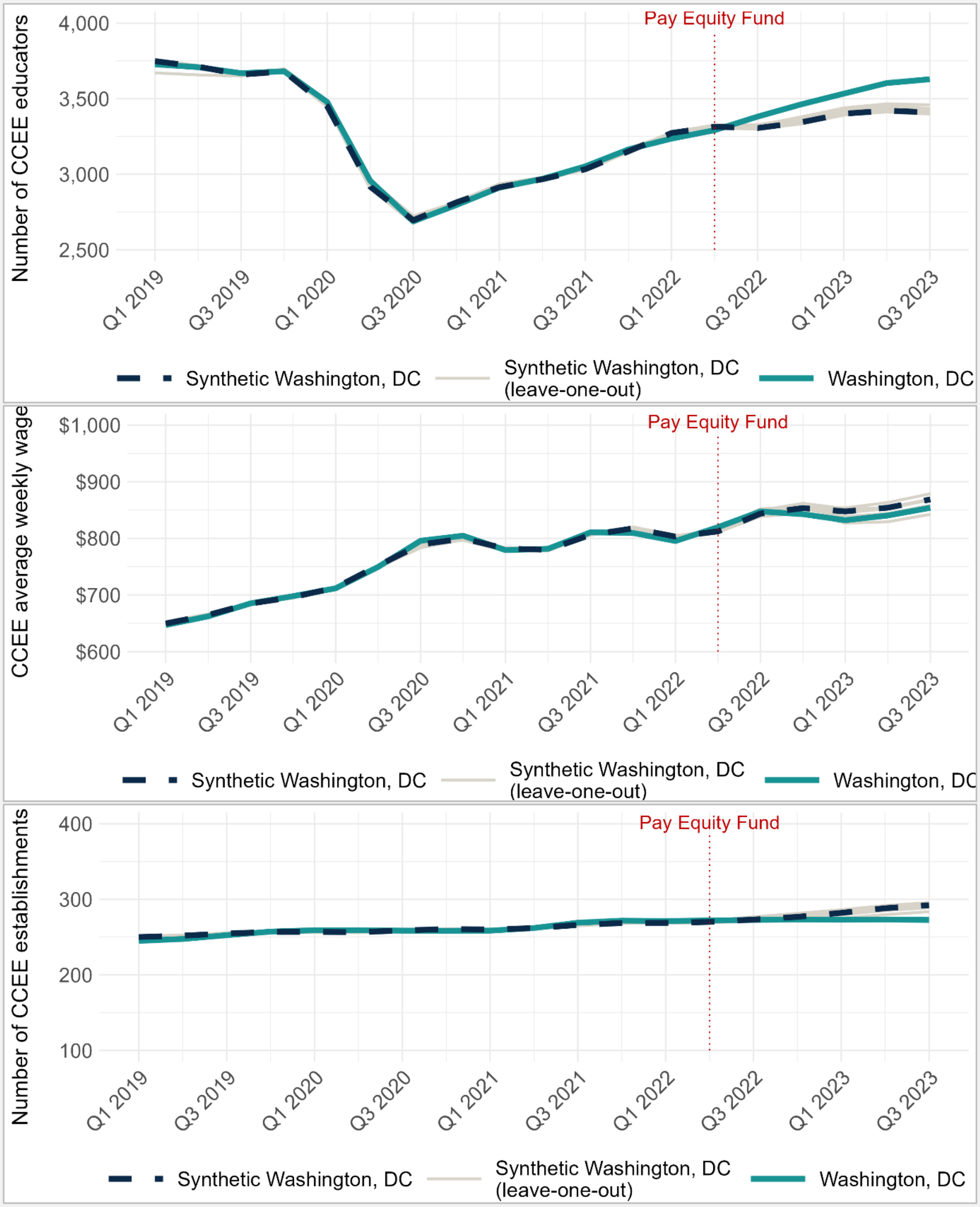
The results, presented in Figure IV.1, show that the leave-one-out estimates, illustrated by the thin grey lines, are closely centered around the benchmark estimates represented by the dashed lines. For all three outcomes—CCEE educators, CCEE average weekly wages, and the number of CCEE establishments—the benchmark estimates consistently fall within the range of the leave-one-out estimates. For instance, considering the overall results averaged across the post-treatment periods, the benchmark estimate for the number of CCEE educators was 146, whereas the leave-one-out estimates ranged from 108 to 155; the benchmark estimate for CCEE average weekly wages was –\$10, with leave-one-out estimates ranging from –\$19 to \$4; and the benchmark estimate for the number of CCEE establishments was –8, with leave-one-out estimates ranging from –12 to –3 (Table A.4). These findings demonstrate that the benchmark results are robust to the exclusion of any particular county.

B. Backdated treatment

In the benchmark analysis, the treatment date was conservatively set to the second quarter of 2022, the quarter before the period when CCEE educators were first invited to apply for the PEF payments, as previously discussed. However, to ensure the robustness of the benchmark findings and rule out any anticipatory effects, we conducted a backdated treatment exercise. Here, we backdated the treatment to the fourth quarter of 2021, a period before any public information about the PEF's planned operations could have been known to educators.

The results of this backdated treatment analysis are detailed in Figure IV.2 and show that the synthetic Washington, DC, closely tracks the actual outcomes, not only before the fourth quarter of 2021 but also after this placebo treatment and before the benchmark treatment date in the second quarter of 2022. For instance, the overall backdated treatment estimates for the three CCEE labor market outcomes were 130 educators, \$1, and –7 establishments, all similar to the benchmark estimates for these outcomes (Table A.4). The absence of estimated effects in the first two quarters of 2022 (that is, before the benchmark treatment date) also indicates that the synthetic Washington, DC, can reliably reproduce the untreated potential outcomes in the counterfactual.

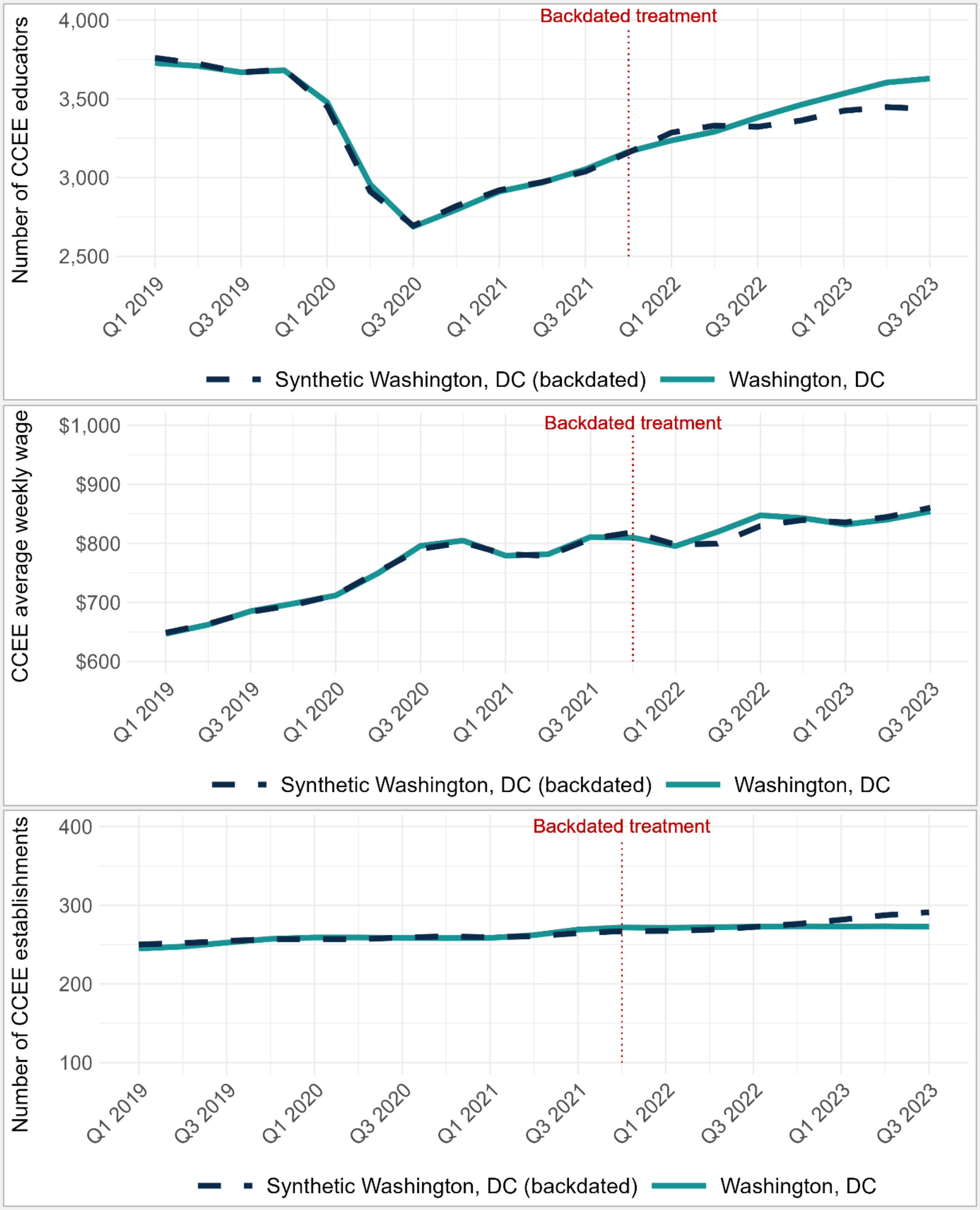
Figure IV.1. CCEE labor market outcomes for Washington, DC, and its synthetic control (leave-one-out)



Source: Author's analysis of the Quarterly Census of Employment and Wages (QCEW) data (https://www.bls.gov/cew/downloadable-data-files.htm).

Note: The leave-one-out robustness check excludes one of the counties that received positive weights from the construction of the benchmark synthetic Washington, DC, at a time. Other methods align with the benchmark specification.

Figure IV.2. CCEE labor market outcomes for Washington, DC, and its synthetic control (backdated treatment)



Source: Author's analysis of the Quarterly Census of Employment and Wages (QCEW) data (https://www.bls.gov/cew/downloadable-data-files.htm).

Note: The backdated treatment robustness check uses information from Q1 2019 through Q4 2021, rather than Q2 2022, to construct the synthetic Washington, DC. Other methods align with the benchmark specification.

C. Single outcome

Instead of matching on multiple related outcomes simultaneously, we can construct the synthetic controls by matching on each outcome separately. Single-outcome SCM estimates may be fairly reliable because the number of pre-treatment periods in this study is large, although they are susceptible to bias due to overfitting to noise. Single-outcome weights do not effectively minimize imbalance in the latent factors shared across multiple outcomes in the same domain (see Kellogg et al. 2021; Sun et al. 2023).

The results are presented in Figure IV.3, which shows that despite small changes in the magnitudes, constructing the synthetic controls by matching on single outcomes does not fundamentally change the benchmark conclusions. Once again using the overall estimates averaged across the post-treatment period as illustrative, the single-outcome approach produces treatment effect estimates that, relative to the benchmark analysis, suggest a negative bias for the number of CCEE educators (100 versus 146 educators) and the number of CCEE establishments (–11 versus –8 establishments), and a positive bias for CCEE average weekly wages ($12 versus –$10; Table A.4).[11]

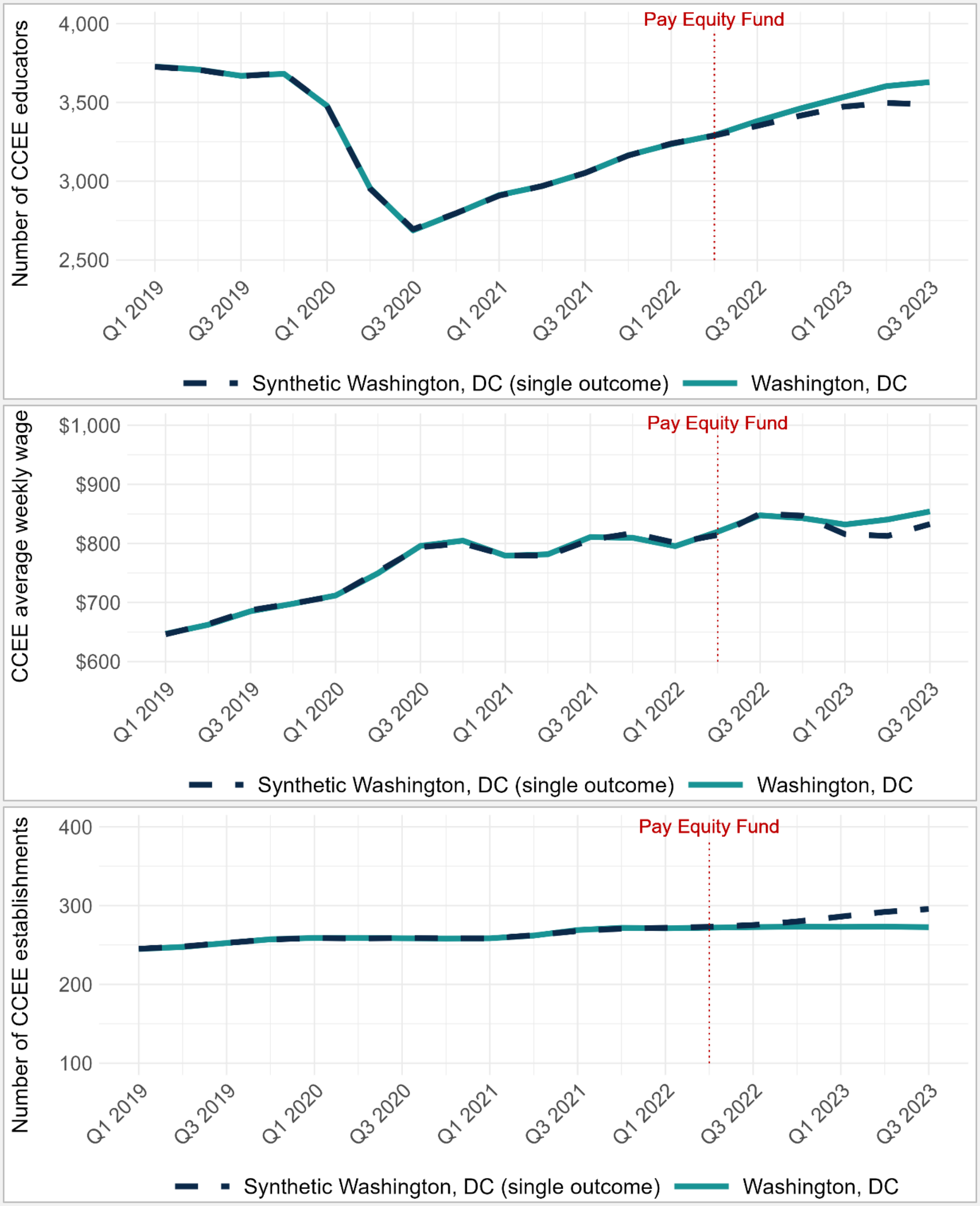
D. No demeaning

The benchmark estimates are obtained using demeaned outcomes to account for the differences in the level of the outcomes. This approach reduces bias in the treatment effects by improving the pre-treatment fit, particularly when intending to obtain a good fit on multiple outcomes simultaneously. To examine whether the benchmark results are robust to this methodological choice, we conducted a robustness check using the original, non-demeaned outcomes. The results are presented graphically in Figure IV.4, and point estimates compared to the benchmark analysis are shown in Table A.4.

The no demeaning results show a slightly worse pre-treatment fit, as expected, which can introduce bias in the estimates. Specifically, the average gaps across the full pre-treatment period are no longer zero, unlike in the benchmark analysis and the other robustness checks. Despite this, the post-treatment effects estimates are generally consistent with the benchmark results, although with some larger differences in magnitude. Specifically, the overall no demeaning impact estimates were 74 educators, $3, and 2 establishments. These results suggest that while the no demeaning approach leads to the same overall conclusions as the benchmark analysis (that is, positive impacts on the number of educators and impacts on wages and the number of establishments that are closer to zero), the worse pre-treatment fit comes at a cost for accurately tracking the dynamics of the treated unit over time.

[11] Larger relative changes in treatment effect magnitudes for wages are likely to result from an outsized contribution of a single donor unit; New York County contributed 61 percent of the single-outcome wage estimates (Table A.3). New York, like Washington, DC, ranks on the extreme upper tail of the county distribution of CCEE wages, so its contribution effectively minimized bias due to imperfect pre-treatment fit in wages. However, New York County also has a much larger number of CCEE educators and establishments because it is more populous than Washington, DC. Because these outcomes are unobserved in the single-outcome framework, New York County's outsized contribution leads to noisy realizations of these latent factors. As previously described, one advantage of the multiple-outcome approach in the benchmark analysis is that it seeks to minimize imbalance in the latent factors themselves.

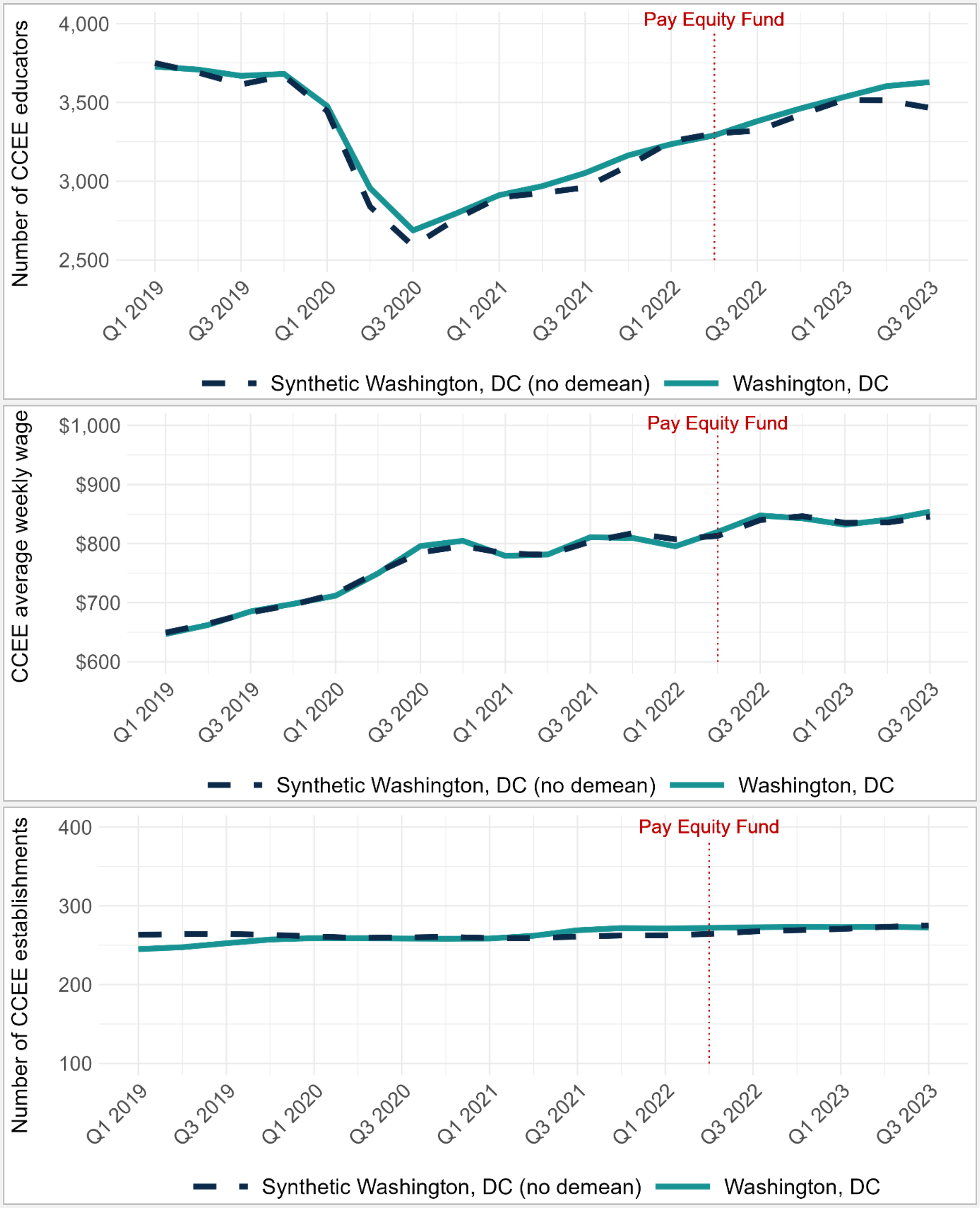
Figure IV.3. CCEE labor market outcomes for Washington, DC, and its synthetic control (single outcome)



Source: Author's analysis of the Quarterly Census of Employment and Wages (QCEW) data (https://www.bls.gov/cew/downloadable-data-files.htm).

Note: The single outcome robustness check constructs the synthetic Washington, DC, by matching on each outcome separately rather than on multiple outcomes simultaneously. Other methods align with the benchmark specification.

Figure IV.4. CCEE labor market outcomes for Washington, DC, and its synthetic control (no demeaning)



Source: Author's analysis of the Quarterly Census of Employment and Wages (QCEW) data (https://www.bls.gov/cew/downloadable-data-files.htm).

Note: The no demeaning robustness check constructs the synthetic Washington, DC, using the original outcomes without demeaning. Other methods align with the benchmark specification.

V. Conclusions

The PEF in Washington, DC, represents a pioneering initiative aimed at addressing the significant compensation disparities that CCEE educators face. Launched in fall 2022, the PEF seeks to achieve pay equity with DCPS teachers by providing substantial, publicly funded wage supplements to CCEE educators. This report evaluates the PEF's impacts on the CCEE labor market over its first two years of operation, focusing on employment levels, wages, and the number of establishments. Our findings, based on a multiple-outcome SCM and data from the QCEW, offer valuable insights into the program's effectiveness and inform future policy directions.

A. Key findings

CCEE employment levels

The PEF had a statistically significant positive impact on the number of CCEE educators in Washington, DC. By the third quarter of 2023, the benchmark SCM analysis estimated a positive impact of the PEF of 219 additional CCEE educators, or nearly a 7 percent increase relative to the control group. The PEF was also found to be correlated with an overall treatment effect of 146 educators, on average. The treatment effects on CCEE employment were statistically significant overall and across all post-treatment quarters, suggesting that the PEF has effectively supported the hiring and retention of educators in Washington, DC, through its first two years of operation.

These findings underscore the importance of adequate compensation in retaining and attracting qualified educators. In a survey of CCEE educators in Washington, DC, 70 percent at least somewhat agreed that because of the PEF payments, they were now being compensated fairly for the credentials they held (Doromal et al. 2024), despite 35 percent reporting dissatisfaction with their current compensation from their employer. Higher compensation through the PEF may help anchor educators in their roles by relieving financial stress. Nearly all educators surveyed reported that the PEF payments helped them pay for basic needs, and many noted that the payments enabled them to pay off debts and cover emergency expenses (Mefferd et al. 2024). The wage supplements also may have improved retention by boosting morale and promoting feelings of professionalism and recognition (Nikolopoulos et al. 2024).

CCEE average weekly wages

The analysis found no statistically significant effects of the PEF on average weekly wages for CCEE educators. Treatment effects were consistently near zero throughout the post-treatment period. These findings were expected. The FY 2022 and FY 2023 PEF payments were delivered directly to educators, so they were not reported by employers to state UI agencies or measured by the QCEW as a result. However, it is important for future analyses using the QCEW to monitor whether FY 2024 operational changes to the PEF do influence wages. Notably, the new program rules disburse funds to facilities based on the number of eligible educators they employ and an estimate of average salaries by role (DC OSSE n.d.). Employers are then required to use these payments to supplement educator salaries so that they meet the target salaries established by the program.

Beyond registering in the QCEW specifically, the FY 2024 payments may have additional implications for future wage effects. First, the new structure sets higher minimum salaries based on educators' credentials. This guarantee of higher wages could induce educators to increase their human capital. In a survey of center directors in Washington, DC, 68 percent indicated that the PEF impacts teachers' ability to pursue additional education, training, or other professional development activities (Nikolopoulos et al. 2024). Second, attention should be paid to ensure the new funding formula does not penalize CCEE employers that have already increased compensation, or otherwise encourage higher-paying employers to adjust their existing compensation so that educators benefit from the wage subsidies. These potential outcomes warrant careful monitoring, as they could counteract the intended effects of the PEF by creating a wage floor that might lead to reduced wage growth in more generous settings.

Number of CCEE establishments

The impact of the PEF on the number of CCEE establishments was not statistically significant, suggesting the observed increase in the CCEE workforce was driven by the PEF's positive impacts on staffing in existing establishments. This explanation is reinforced by the modest negative trend that emerged in the program's second year. On average, there were 10 fewer CCEE establishments in Washington, DC, compared to the synthetic control group, and 14 fewer in the most recent quarter. Because these estimates were within the range of other counties based on the results of the permutation tests, we should be cautious in attributing them to the PEF. However, any continued decline into the third year of the program should not be ignored. A theoretical unintended consequence of the PEF is wage compression for center administrators who are ineligible for the payments. In the survey of center directors, 25 percent reported that most of their teachers now earned more than they did, and 31 percent indicated that they had considered changing their role to become eligible for the PEF payments (Nikolopoulos et al. 2024). Wage compression could potentially slow the growth of new establishments or lead to closures if administrators transition back to teaching roles for higher pay.

B. Robustness checks

The robustness checks, including the leave-one-out analysis, backdated treatment, single outcome matching, and no demeaning approaches, generally corroborated the benchmark findings. The leave-one-out results demonstrated that the benchmark estimates were not sensitive to the exclusion of any particular county, whereas the backdated treatment exercise did not find evidence for the existence of anticipatory effects. Single outcome matching highlighted the importance of matching on multiple related outcomes to minimize imbalance in the latent factors shared across those outcomes, whereas the no demeaning analysis demonstrated the usefulness of using demeaned, rather than original, outcomes for better pre-treatment fit, particularly in a multiple-outcome SCM framework.

C. Implications and future directions

The PEF represents a groundbreaking effort to address compensation inequity between CCEE educators and public-school teachers. The positive impacts of the PEF on CCEE employment levels in the first two years of the program are promising because they suggest that substantial wage supplements can improve workforce retention and stability in a setting as large and diverse as Washington, DC. Future research should continue to evaluate the PEF's long-term impacts, including analysis of the PEF's impacts on educator qualifications and CCEE quality, and the consequences of the adjustments to its implementation and funding in FY 2024. It also remains unclear whether the PEF will continue to receive sufficient public funding to sustain these achievements. Funding for the PEF is not currently committed beyond FY 2024.

The PEF marks a shift in CCEE funding in the United States through its broad-scale alignment of educator compensation with that of public-school teachers. As the nation's first publicly funded CCEE educator wage supplement, the PEF represents a significant step toward addressing compensation inequities in the CCEE sector. The findings from this study highlight its potential as a tool for supporting the CCEE workforce in Washington, DC, and invite questions about the replicability and sustainability of such an initiative in other contexts, as well as how best to design and implement similar programs. As other areas consider similar initiatives, they will need to navigate their unique fiscal, policy, and programmatic landscapes. In Washington, DC, as policymakers and community leaders continue to navigate the future of the PEF, they may consider this evidence to make informed decisions in pursuit of fair and equitable pay for CCEE educators.

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Appendix A
Tables of Results from Statistical Analyses

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Table A.1. Point estimates for the effects of the Pay Equity Fund on CCEE labor market outcomes, overall and by post-treatment quarter

	Washington, DC	Synthetic Washington, DC	Impact	*p*-value
Number of CCEE educators				
Average estimates across post-treatment quarters	3,522	3,376	146	0.041
Estimates by post-treatment quarter				
Q3 2022	3,381	3,306	76	0.048
Q4 2022	3,462	3,343	119	0.021
Q1 2023	3,533	3,400	133	0.048
Q2 2023	3,604	3,421	183	0.041
Q3 2023	3,629	3,409	219	0.041
CCEE average weekly wage				
Average estimates across post-treatment quarters	$843	$854	-$10	0.731
Estimates by post-treatment quarter				
Q3 2022	$847	$844	$4	0.800
Q4 2022	$843	$853	-$11	0.662
Q1 2023	$832	$848	-$16	0.586
Q2 2023	$840	$854	-$14	0.579
Q3 2023	$854	$869	-$15	0.614
Number of CCEE establishments				
Average estimates across post-treatment quarters	273	282	-10	0.255
Estimates by post-treatment quarter				
Q3 2022	273	273	0	0.600
Q4 2022	273	277	-4	0.903
Q1 2023	273	282	-9	0.469
Q2 2023	273	288	-11	0.262
Q3 2023	273	292	-14	0.200

Source: Author's analysis of the Quarterly Census of Employment and Wages (QCEW) data (https://www.bls.gov/cew/downloadable-data-files.htm).

Note: This table presents CCEE labor market outcomes for Washington, DC, and the benchmark synthetic Washington, DC, in the quarters following the launch of the Pay Equity Fund. *P*-values were estimated using two-sided tests that rank the absolute value of the standardized gaps.

Table A.2. Optimal county weights for the construction of the synthetic Washington, DC, in the benchmark analysis and leave-one-out robustness checks

		Leave-one-out, excluding:								
County	**Benchmark**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
1. New York County, New York	22%	NA	20%	24%	19%	27%	21%	24%	22%	22%
2. San Francisco County, California	19%	0%	NA	22%	14%	13%	26%	17%	18%	20%
3. Ventura County, California	18%	34%	25%	NA	23%	10%	19%	18%	21%	18%
4. Monterey County, California	12%	0%	5%	15%	NA	0%	12%	13%	11%	12%
5. Albany County, New York	10%	16%	9%	6%	10%	NA	12%	9%	11%	10%
6. Richmond County, New York	7%	15%	22%	8%	11%	8%	NA	8%	8%	7%
7. Honolulu County, Hawaii	6%	1%	2%	6%	4%	0%	7%	NA	6%	6%
8. Kern County, California	5%	0%	0%	12%	4%	13%	5%	5%	NA	5%
9. Sarasota County, Florida	1%	0%	6%	0%	7%	0%	0%	3%	3%	NA
Montgomery County, Maryland	0%	26%	8%	0%	5%	0%	0%	0%	0%	0%
El Dorado County, California	0%	0%	0%	0%	0%	28%	0%	0%	0%	0%
Santa Clara County, California	0%	8%	0%	0%	0%	0%	0%	0%	0%	0%
Washington County, Vermont	0%	0%	0%	7%	0%	0%	0%	0%	0%	0%
Bronx County, New York	0%	1%	0%	0%	3%	0%	0%	2%	0%	0%

Source: Author's analysis of the Quarterly Census of Employment and Wages (QCEW) data (https://www.bls.gov/cew/ downloadable-data-files.htm).

Note: This table presents optimal county weights from the benchmark analysis and leave-one-out robustness checks. Numbered counties were assigned weights in the benchmark analysis. Other counties are sorted according to their average weight across the presented robustness checks.

Table A.3. Optimal county weights for the construction of the synthetic Washington, DC, in the benchmark analysis and backdated treatment, single outcome, and no demeaning robustness checks

County	Benchmark	Backdated treatment	Single outcome for CCEE outcome: Educators	Weekly wages	Establishments	No demeaning
1. New York County, New York	22%	23%	0%	61%	8%	23%
2. San Francisco County, California	19%	18%	0%	6%	0%	0%
3. Ventura County, California	18%	23%	0%	7%	0%	0%
4. Monterey County, California	12%	7%	0%	0%	0%	0%
5. Albany County, New York	10%	16%	0%	0%	0%	8%
6. Richmond County, New York	7%	0%	0%	12%	0%	15%
7. Honolulu County, Hawaii	6%	0%	17%	0%	0%	0%
8. Kern County, California	5%	7%	0%	0%	0%	0%
9. Sarasota County, Florida	1%	0%	2%	0%	0%	0%
Montgomery County, Maryland	0%	0%	32%	0%	10%	0%
Barnstable County, Massachusetts	0%	0%	31%	0%	0%	0%
Alameda County, California	0%	0%	0%	0%	28%	0%
Marin County, California	0%	0%	0%	6%	0%	15%
San Mateo County, California	0%	2%	0%	0%	0%	17%
Santa Clara County, California	0%	0%	0%	0%	17%	0%
Hartford County, Connecticut	0%	0%	0%	0%	14%	0%
Santa Cruz County, California	0%	0%	0%	0%	13%	0%
Essex County, New Jersey	0%	0%	0%	0%	0%	12%
Philadelphia County, Pennsylvania	0%	3%	0%	0%	10%	0%
Sonoma County, California	0%	0%	0%	9%	0%	0%
Shelby County, Tennessee	0%	0%	8%	0%	0%	0%
Suffolk County, Massachusetts	0%	0%	0%	0%	0%	6%
Queens County, New York	0%	0%	4%	0%	1%	0%
Hillsborough County, New Hampshire	0%	0%	0%	0%	0%	4%
Fairfield County, Connecticut	0%	0%	3%	0%	0%	0%

Source: Author's analysis of the Quarterly Census of Employment and Wages (QCEW) data (https://www.bls.gov/cew/ downloadable-data-files.htm).

Note: This table presents optimal county weights from the benchmark analysis and backdated treatment, single outcome, and no demeaning robustness checks. Numbered counties were assigned weights in the benchmark analysis. Other counties are sorted according to their average weight across the presented robustness checks.

Table A.4. Effects of the Pay Equity Fund on CCEE labor market outcomes from the benchmark analysis and robustness checks

	Impact from:				
	Benchmark analysis	**Leave-one-out (min, max)**	**Backdated treatment**	**Single outcome**	**No demeaning**
Number of CCEE educators					
Average estimates across pre-treatment quarters	0	0	0	0	38
Average estimates across post-treatment quarters	146	(108, 155)	130	100	74
Estimates by post-treatment quarter					
Q1 2022	-	-	-35	-	-
Q2 2022	-	-	-29	-	-
Q3 2022	76	(53, 83)	69	45	61
Q4 2022	119	(83, 130)	105	67	40
Q1 2023	133	(94, 142)	119	83	18
Q2 2023	183	(138, 192)	166	140	90
Q3 2023	219	(170, 230)	193	164	163
CCEE average weekly wage					
Average estimates across pre-treatment quarters	$0	$0	$0	$0	$4
Average estimates across post-treatment quarters	-$10	(-$19, $4)	$1	$12	$3
Estimates by post-treatment quarter					
Q1 2022	-	-	-$3	-	-
Q2 2022	-	-	$20	-	-
Q3 2022	$4	(-$5, $8)	$18	-$3	$8
Q4 2022	-$11	(-$19, -$1)	$3	-$4	-$4
Q1 2023	-$16	(-$22, -$8)	-$3	$16	-$3
Q2 2023	-$14	(-$23, -$11)	-$5	$28	$5
Q3 2023	-$15	(-$25, -$12)	-$6	$21	$8
Number of CCEE establishments					
Average estimates across pre-treatment quarters	0	0	0	0	-2
Average estimates across post-treatment quarters	-8	(-12, -3)	-7	-11	2
Estimates by post-treatment quarter					
Q1 2022	-	-	2	-	-
Q2 2022	-	-	3	-	-
Q3 2022	0	(-4, 2)	0	-3	5
Q4 2022	-4	(-8, 1)	-3	-7	4
Q1 2023	-9	(-13, -2)	-9	-13	2
Q2 2023	-11	(-15, -6)	-11	-16	0

	Impact from:				
	Benchmark analysis	Leave-one-out (min, max)	Backdated treatment	Single outcome	No demeaning
Q3 2023	-14	(-20, -10)	-13	-17	-2

Source: Author's analysis of the Quarterly Census of Employment and Wages (QCEW) data (https://www.bls.gov/cew/downloadable-data-files.htm).

Note: This table presents CCEE labor market outcomes for Washington, DC, and the synthetic Washington, DC, constructed in the benchmark analysis and in the leave-one-out, backdated treatment, single outcome, and no demeaning robustness checks. Average estimates across pre-treatment quarters are defined as zero in the demeaned specifications. Average estimates across post-treatment quarters exclude Q1 2022 and Q2 2022 in the backdated treatment analysis.