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Abstract

Child care and early childhood education (CCEE) educators are among the lowest-paid workers in the United States and earn substantially less than similarly qualified educators in public schools. Washington, DC's Early Childhood Educator Pay Equity Fund (PEF) is the nation's first dedicated public funding stream designed to address pay disparities between the CCEE and public school sectors. Launched in 2022, the PEF delivered direct payments of $10,000 to $14,000 annually to more than 4,000 educators over its first two years before shifting to a facility payment model that integrated compensation into employer payroll. Using quarterly labor market data and multiple-outcome synthetic control methods, we estimated program impacts on CCEE sector outcomes. Through three years, the PEF had statistically significant positive impacts on CCEE employment, with effects emerging shortly after the launch of the program and growing to reach 341 additional educators, or about 11 percent relative to baseline. Impacts on average employer-reported wages remained close to zero when payments were delivered directly to educators but became positive and statistically significant following the shift to the facility payment model, reaching $179 per week (about $9,300 annually). Impacts on the number of CCEE establishments were not statistically significant but negative, suggesting that workforce growth occurred primarily within existing establishments and the program may have reduced incentives to open new ones. Findings are robust to alternative samples, designs, and specifications. We discuss how these results have informed decisions about the future of the PEF in Washington, DC, and the design of compensation initiatives in other states and localities.

Introduction

Compensation for child care and early education (CCEE) educators is a policy challenge with far-reaching implications for the CCEE sector and the children and families who rely on it. Decades of research demonstrate the essential role that CCEE educators play in shaping children's development during the formative early years (Hamre et al., 2014; Mashburn et al., 2008; Peisner-Feinberg et al., 2001; Phillips et al., 2016). Yet, CCEE educators are among the lowest-paid workers in the United States, particularly those employed outside of school-based settings, who comprise the majority of the workforce. In May 2024, the median hourly wage for child care educators was $15.41—more than 50 percent below that of preschool teachers in school-based settings, and 39 percent below the median hourly wage across all occupations (U.S. Bureau of Labor Statistics [BLS], 2025).

Low wages have negative consequences for CCEE educators themselves, the facilities where they work, and the children and families they serve. Many CCEE educators live in poverty and rely on public assistance benefits (Center for the Study of Child Care Employment [CSCCE], 2024; Gould, 2015). Inadequate compensation is linked to poor mental health and reduced personal well-being (Morrissey & Bowman, 2024). Low pay also hinders educators' professional growth and contributes to workforce instability. Lower compensation is associated with higher rates of absenteeism in general (Pfeifer, 2010) and among educators specifically (O'Sullivan, 2022), resulting in additional wage losses for educators employed in the roughly half of CCEE facilities nationwide that do not offer paid time off (National Survey of Early Care and Education Project Team, 2023). Low wages further increase the risk that educators leave their jobs or exit the CCEE field entirely (Bassok et al., 2021; Bellows et al., 2022), forfeiting opportunities to invest in human capital skills that can help advance their careers (Belfield & Schochet, 2024).

High turnover and absenteeism, in turn, undermine the operational efficiency of CCEE facilities. Estimates suggest that 25 to 40 percent of CCEE educators leave their employer

within a year—more than double the turnover rate observed among K–12 teachers (Bryant et al., 2023; Caven et al., 2021; Doromal et al., 2022). As educators leave, facilities must divert scarce resources towards recruiting, onboarding, and training new staff (Doromal et al., 2022; Whitebook & Sakai, 2003), while also losing valuable site-specific capital, including institutional knowledge and relationships with families and colleagues. Unfilled staffing vacancies may increase workloads for remaining staff, further disrupting workplace climate and staff relationships. Higher rates of absenteeism among poorly compensated educators who remain employed also require administrators to devote time and resources to securing substitutes and floaters (McCormick et al., 2021; Roberts et al., 2019).

Instability in the CCEE workforce also has direct consequences for children and families. Persistent challenges retaining staff and filling vacancies contribute to widespread CCEE labor supply shortages, limiting families' access to services (CSCCE, 2024; Grunewald et al., 2022). These challenges were further exacerbated by the COVID-19 pandemic, which triggered nationwide staffing shortages from which the CCEE sector has yet to fully recover (Crouse et al., 2023; Weiland et al., 2021). High turnover further undermines service quality by disrupting the stable, responsive relationships between children and caregivers that are foundational to high-quality CCEE (Hamre et al., 2014; Markowitz, 2024; Phillips et al., 2016). Frequent staff exits also undermine facilities' investments in professional development and continuous quality improvement as experienced educators leave and new hires must be recruited and trained (Hale-Jinks et al., 2006; Hall et al., 2024; Whitebook & Sakai, 2003).

There is growing recognition that increasing CCEE educator compensation requires a dedicated source of public funding to supplement existing revenue streams (Davis & Sojourner, 2021; Showers et al., 2025). Community-based CCEE operates largely as a market-based system that relies on private tuition paid by families; according to national data, most young children who participate in CCEE do not have publicly funded arrangements (Kabourek, 2024). Public investment in CCEE remains modest relative to K-12 education: across federal, state, and local funding streams, public spending averages approximately

$2,800 per child for children age three to five and $1,300 per child for children under age three, compared to roughly $13,000 per school-age child (based on 2021 data analyzed by Hawley et al., 2024). Absent additional public investment, CCEE facilities have limited options to increase revenues. Strict staff-child ratios—particularly to serve infants and toddlers—constrain opportunities to increase enrollment to generate additional revenue, while tuition rates are already unaffordable for many families, such that raising tuition further to finance pay increases risks suppressing demand for care (Child Care Aware, 2019; Gould & Cooke, 2015; Hotz & Wiswall, 2019; Morrissey, 2017).

Washington, DC's Early Childhood Educator Pay Equity Fund (PEF) represents the nation's first dedicated public funding stream designed to sustain meaningful increases in CCEE educator compensation at scale. Launched in fall 2022, the PEF seeks to address the earnings disparity between CCEE educators and public school teachers, primarily by supplementing educator wages (DC Office of the State Superintendent of Education [OSSE] n.d.-a). The program is financed through a dedicated tax on DC residents with annual incomes above $250,000 (DC Official Code § 1-325.431). Across fiscal years (FYs) 2022 and 2023, the PEF delivered direct supplement payments to more than 4,000 educators employed in licensed CCEE facilities, increasing annual wages by $10,000 for full-time assistant teachers and $14,000 for full-time teachers. In FY 2024, the program began distributing payments through facilities, with payroll funding awards calculated using a formula designed to align average current and target salaries stratified by educator role, credentials, and experience. This transition integrated program participation with facility operations and leveraged information from facilities to estimate pay gaps between facility staff and DC Public Schools (DCPS) teachers. In 2023, the PEF also began providing access to subsidized health insurance through the HealthCare4ChildCare (HC4CC) initiative.

Research studying the implementation of the PEF found that it was favorably experienced by participants. Educators reported that receiving higher wages improved their personal, professional, and financial well-being and strengthened their intentions to remain with

their employer (Doromal, Greenberg, et al., 2024; Mefferd, Doromal, et al., 2025; Sandstrom et al., 2024). Directors of center-based facilities also described how offering higher wages supported staff retention, recruitment, and professional development (Doromal, Nikolopoulos, et al., 2025; Doromal, Lamb, et al., 2025; Nikolopoulos et al., 2024). Yet, given the novelty of the PEF, its scale, and its reliance on sustained public investment, it is important to complement evidence on the perceived value of the program with rigorous estimates of program effectiveness. In this study, we examine the impacts of the PEF on the CCEE sector, including employment levels and labor supply, average wages, and the number of employers. We use quasi-experimental synthetic control methods and federal labor market data to estimate impacts through three years of the program.

Background and Literature Review

Prior Research on Publicly Funded CCEE Educator Compensation Initiatives

Though the PEF is distinctive in its scale and design, other states and localities have pursued a range of publicly funded efforts to address low CCEE educator pay. These efforts vary widely in their funding sources, scale, duration, and delivery mechanisms—such as one-time bonuses, incentives tied to retention or credential attainment, incremental changes to subsidy reimbursement rates, tax credits, or scholarship stipends. In this section, we review prior CCEE educator compensation initiatives and the existing evidence on their effectiveness.

Many compensation initiatives have relied on funding provided to states and localities through federal grants, such as the Preschool Development Grant Birth through Five (PDG B-5) program and the Child Care and Development Block Grant (CCDBG) (CSCCE, n.d). For instance, several states have used CCDBG to fund incremental changes in compensation by raising Child Care and Development Fund (CCDF) subsidy reimbursement rates (Lovejoy, 2024). During the COVID-19 pandemic, states and localities also used federal emergency relief funds to increase educator compensation (CSCCE, 2024). The American

Rescue Plan Act (ARPA), for instance, included $24 billion in stabilization funds for the child care industry and an additional $15 billion in supplemental CCDF discretionary funds through the CCDBG, which some state CCDF lead agencies used to increase educator wages and provide recruitment and retention bonuses (CSCCE, n.d.; Sun et al., 2024). Federally funded initiatives have typically been modest in scope. For example, initiatives funded via pandemic relief dollars often included one-time payments of $500 to $2,000 per individual (CSCCE, n.d.).

Evidence on the effectiveness of federally funded compensation initiatives is limited to research on two wage supplement pilots.[1] In 2021, the Virginia Department of Education implemented the Teacher Recognition Program (TRP) using federal PDG B-5 funds. The TRP provided eligible educators with a wage supplement of $1,500 if they remained in the same facility for eight months. Bassok et al. (2021) conducted an experimental evaluation of the TRP and found that by the end of the study period, CCEE educators in the TRP group were 11 percentage points more likely to have remained at their facility. Second, using funds allocated by the 2014 reauthorization of the CCDBG, Texas's CCDF lead agency regional boards increased child care subsidy reimbursement rates to supplement annual wages by amounts ranging from $120 to $3,900 across regions. Using administrative data and a structural labor supply model, Cunha and Lee (2023) simulated the effects of wage increases of this magnitude and found that incremental compensation gains had limited impacts on recruitment and retention, suggesting a need for more ambitious strategies to permanently raise educator wages.

States and localities may also fund CCEE educator compensation initiatives with state and local revenues. State and local revenues can come from a variety of funding mechanisms beyond general appropriations, such as earmarking portions of revenues from general

[1]To our knowledge, no evidence on the efficacy of initiatives funded by federal pandemic relief dollars exists. Research from Louisiana suggests that center-based facilities with higher wages reported fewer staffing challenges during the pandemic (Hall et al., 2024), and descriptive research suggests the end of relief funding exacerbated challenges related to staff burnout and staff shortages, increased operating costs for programs, and led to program closures (Sun et al., 2024).

sales and excise taxes, gambling revenues, public settlement agreements and revenues from progressive taxes such as capital gains taxes and income taxes on high earners (Showers et al., 2025). Most CCEE educator compensation initiatives funded by states and localities offer temporary financial relief or modest workforce retention incentives (CSCCE, n.d.). These may include cash bonuses, tax credits, and scholarship stipends for educators pursuing additional education or professional development (Prenatal-to-3 Policy Impact Center, 2025). To our knowledge, no effectiveness studies have evaluated the impact of these initiatives.[2]

Collectively, the evidence base on publicly funded CCEE compensation initiatives is concentrated in a very small number of studies examining relatively modest or time-limited strategies; there is no prior evidence on the effectiveness of dedicated public investments to sustain sector-level wage growth large enough to functionally narrow pay gaps with educators in public schools. This limitation reflects both the scale of prior initiatives—often one-time bonuses or incremental subsidy reimbursement rate increases—and reliance on temporary funding streams. For instance, Virginia's TRP relied on federal PDG B-5 funds which have expired, leaving the program without dedicated funding (Virginia Department of Education, n.d.). Similarly, few states were able to make the significant investments necessary—either through committing their own funds or repurposing federal funds like CCDF and PDG B-5 grants—to continue funding educator compensative initiatives once the ARPA expired (CSCCE, 2024; Sun et al., 2024).

The PEF represents the first effort in the nation to pair a dedicated local revenue source with a policy commitment to deliver sustainable wage increases large enough to align CCEE educator pay with that of public school teachers. As a result, the PEF provides an opportunity to examine the effectiveness of this novel and important strategy. In the next section, we review the history and implementation of the PEF, highlighting the policy and design features that differentiate it from prior publicly funded CCEE educator compensation

[2]In a nonexperimental study of Missouri's Workforce INcentive Project, Gable et al. (2007) found that among center-based educators with lower wages and a high school education, those who received bi-annual cash incentives were more likely to be retained over a 20-month period compared to those who did not, but that the incentives had no relationship with turnover among educators in the full sample.

initiatives.

Washington, DC's 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), the city began offering publicly funded, full-day preschool through DCPS and select public charter schools and community-based organizations to 3- and 4-year-olds. The Pre-K Act established OSSE's role in managing DC's universal preschool system. In the 2020-2021 school year, 74 percent of DC's 17,386 three- and four-year-olds were enrolled in this system (DC OSSE, 2022a). Preschool teachers employed by DCPS are paid on the same salary scale as their K-12 counterparts.

In 2018, the DC Council passed the Birth-to-Three for All DC Act, which expanded the District's investment in CCEE to also focus on infants and toddlers. OSSE was given administrative oversight for licensed CCEE facilities not already affiliated with the universal preschool program which 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 facilities, targeting 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 late fall 2022 (Figure 1). 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 of 2022, the Task Force released its initial 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 each role (Early Childhood Educa-

Figure 1. Timeline of key events related to the Early Childhood Educator Pay Equity Fund

Source: Greenberg and colleagues (2023), DC OSSE (n.d.-a), and Schochet (2024).

tor Equitable Compensation Task Force, 2022a). All center-based educators (teachers and assistant teachers) and home-based providers[3] in facilities licensed by OSSE were eligible for the payments, with limited exceptions related to the District's universal pre-K system (DC OSSE, 2022b).[4] Educators who met these criteria were eligible without regard to whether their program received other sources of public funding (such as from CCDF subsidies or the federal Head Start program). Directors of center-based facilities and other staff (for example, aides, substitutes, cooks, bus drivers, janitorial staff) were ineligible. In March 2022, the Task Force published its 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 recommendations for designing a CCEE salary scale to establish target compensation levels based on educator roles and qualifications.

[3]Licensed home-based proprietors were eligible to participate as the primary caregiver, alongside associate caregivers employed in larger home-based facilities.

[4]Washington, DC's universal pre-K system uses a mixed-delivery model. Most universal pre-K classrooms operate in DCPS and public charter schools, which are not licensed by OSSE as CCEE facilities. A smaller number operate in community-based facilities through the Pre-K Enhancement and Expansion Program (PKEEP). Assistant teachers in PKEEP classrooms were eligible to participate, though lead teachers were not.

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 (Fiscal Year 2023 Budget Support Act of 2022) payments. In May 2022, OSSE partnered with AidKit, an organization assisting public and private entities with cash assistance distribution. Using OSSE's Division of Early Learning Licensing Tool (DELLT) database, OSSE and AidKit identified approximately 3,200 eligible educators employed as of May 2022 who were invited to apply for the initial PEF payments (DC OSSE, 2023a). The application window opened in August 2022 and closed the following month, after which the first payments began to be distributed. Over 90 percent of eligible CCEE educators applied for the FY 2022 payments (DC OSSE, 2022c). In total, the PEF disbursed about $38.4 million to 3,217 CCEE educators in FY 2022 (DC OSSE, 2023a). In FY 2023, the fund made quarterly payments totaling about $41.9 million to 4,085 educators (DC OSSE, 2024).

In FY 2024, the PEF shifted from a direct educator payment model to a facility payment model that implemented a salary scale for eligible educators and required participating facilities to use program awards to meet the salary targets. To determine facility awards, OSSE developed a payroll funding formula as the sum of three components (DC OSSE, n.d.-b). The first component was a base award, calculated as the incremental difference between *current salaries* and *minimum salaries* by educator role and credential. *Current salaries* were based on average salary estimates from OSSE's child care cost estimation model, updated annually (DC OSSE, n.d.-c),[5] whereas *minimum salaries* were based on the DCPS salary scale at the time, reflecting program goals to achieve pay parity with public school teachers (DC OSSE, n.d.-d). The second component was an administrative enhancement to account for expenses incurred by participating facilities (including increased payroll taxes), and the third was an adjustment that gave additional funds to facilities that enrolled a greater share

[5]FY 2024 current average salaries were drawn from OSSE's 2023 child care cost estimation model (DC OSSE, 2023b). The salaries used in the 2023 model reflected salary data reported by facilities that responded to the 2022 DC Child Care Provider Survey.

of children whose care was subsidized by CCDF.

Facilities employing educators who would have previously been eligible for the direct payments could opt into the program if they agreed to use the funds calculated by the payroll funding formula, once awarded, to meet or exceed the minimum salaries that had been established for those educators. Facilities still without sufficient revenue to meet the minimum salary requirements (predominantly those offering wages below the average current salary estimates used to calculate base awards; Gunderson, 2023) could apply for a waiver from those requirements. In FY 2024, to further assist participating facilities in meeting minimum salary requirements, OSSE provided an additional supplement equal to 30 percent of the base award (DC OSSE, 2025a).[6] In FY 2024, OSSE ultimately distributed $67.3 million in PEF awards to 365 facilities, raising wages for more than 4,000 educators (DC OSSE, 2025a). About 75% of operating facilities employing educators eligible for the direct payments in prior years received a facility award in FY 2024 (Doromal, Jimenez-Parra, et al., 2025).

The PEF also funds HC4CC, which, in January 2023, began providing access to free or lower-premium health insurance to CCEE staff and their families through the DC Health Benefits Exchange (Kasselman, 2025). One justification for including HC4CC was to ensure that educators who lost Medicaid eligibility after receiving PEF payments remained insured (Doromal & Greenberg, 2025). HC4CC group coverage provides free or lower premium health insurance to CCEE staff—including those ineligible for PEF payments—and their dependents, provided they are employed by eligible facilities (small businesses with 100 or fewer staff) that enroll in the program. DC residents employed by facilities that do not enroll in group coverage (including larger, ineligible facilities) may also enroll in HC4CC directly as individuals or families (non-DC residents can only qualify for HC4CC through

[6]Beginning in FY 2025, these funds were repurposed into additional adjustments to the CDF payroll formula, including larger payments for serving infants and toddlers as well as for home-based providers (DC OSSE, 2025b). In the spirit of the temporary supplement, these adjustments were also intended to help facilities with relatively larger gaps in actual and current average compensation levels meet minimum salary requirements.

their employer). Enrollment for HC4CC occurs on a rolling basis and is not tied to DC's fiscal year (which operates October to September). HC4CC guarantees subsidized health insurance premiums for 12 months after enrollment. At the end of 2024, 1,607 CCEE employees and 360 dependents were covered through HC4CC, and 220 (out of 351 eligible) facilities were enrolled in HC4CC group coverage (DC Health Benefit Exchange Authority, 2025).

The Current Study

Descriptive and qualitative findings from an ongoing implementation study of the PEF suggest that participating CCEE educators and center-based facility directors reported positive experiences with the program. In surveys conducted with educators, about two in three agreed that they planned to continue working in DC child care longer than previously expected both as a result of the direct payments distributed in FYs 2022 and 2023 (Doromal, Greenberg, et al., 2024), and, separately, their employers' participation in FY 2024 (Nikolopoulos et al., 2025). In FY 2024, center-based facility directors also reported that the competitive wages afforded by PEF participation strengthened their capacity to retain existing staff and recruit new employees, particularly those with better skills and qualifications (Doromal, Lamb, et al., 2025; Doromal, Nikolopoulos, et al., 2025), and created pathways for educators to pursue additional education and training (Nikolopoulos et al., 2024).

The current study complements these descriptive findings and builds on the limited research on the effectiveness of prior CCEE educator compensation initiatives by providing the first evidence about the impacts of the PEF on CCEE supply and labor market outcomes.[7] We draw on data from the Quarterly Census of Employment and Wages (QCEW) collected by the BLS to evaluate the PEF's impact through three years of the program,

[7]Though not measures of program effectiveness, the ongoing implementation study has also described differences in selected outcomes between eligible facilities in DC that did and did not choose to participate in the PEF in FY 2024. For instance, educators whose facilities opted in reported better financial well-being and mental health outcomes than those whose facilities did not (Mefferd, Doromal, Sandstrom, et al., 2025). Analysis of administrative data also found variability in associations between participation status and educator turnover by whether center-based facilities accepted CCDF subsidies (Doromal, Lamb, et al., 2025).

capturing the effects of both the direct educator payments in FYs 2022 and 2023 and the facility payment model in FY 2024. We use multiple-outcome synthetic control methods to compare trends in CCEE employment, wages, and provider supply in Washington, DC, with a synthetic Washington, DC, comprised of a weighted combination of counties selected to approximate CCEE sector outcomes in the District without the PEF.[8]

Our findings show that the PEF had sustained impacts on the CCEE labor market. Through three years, the PEF had statistically significant positive impacts on CCEE employment levels, consistent with program goals to support educator retention and recruitment. Positive employment effects emerged shortly after the launch of the program and grew in magnitude over time. The effects of the PEF on educators' average weekly employer payroll wages remained close to zero when payments were delivered directly to educators but emerged as positive and statistically significant following the shift to the facility payment model. Impacts on the number of CCEE establishments were not statistically significant but negative, suggesting that the program increased the size of the workforce in existing establishments though may have disincentivized new establishments. We conclude with a discussion of how this evidence has influenced decisions to sustain the PEF in DC and how it offers insights for designing and implementing CCEE educator compensation initiatives in other states and localities.

Methods

Data Source and Sample

The Quarterly Census of Employment and Wages

The current study used data from the QCEW, a quarterly count of employment and wages reported by employers covering more than 95 percent of industries and all geographic

[8]The current study presents findings from Mathematica's Early Childhood Educator Pay Equity Fund Impact and Cost Effectiveness Study. Prior study products include reported program impacts on CCEE sector outcomes through FY 2022 and FY 2023 (Schochet, 2023, 2024). The current study presents the full timeline of impact findings through three years of the program, incorporating estimates from FY 2024.

counties in the United States (U.S. BLS, n.d.-a). Employers report on 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 survey data from the BLS Annual Refiling Survey and its Multiple Worksite Report.

The QCEW produces counts of the number of reporting employers (or establishments) each calendar quarter; the number of filled jobs reported by employers, whether full or part time, and whether temporary or permanent, in each month of the quarter; and the total compensation paid over the quarter, including labor and other earnings, such as bonuses, and employer contributions to certain deferred compensation plans. Counts are aggregated by selected characteristics of employers, including their industry, geographic location (county), and ownership type (whether private sector or federal, state, or local government employment). Industry classification is applied to each employer on the basis of its primary economic activity using the North American Industry Classification System (NAICS).

We constructed key CCEE supply and labor market measures using information reported by employers with NAICS 624410, Child Care Services (U.S. BLS, n.d.-b). This industry comprises establishments primarily engaged in providing CCEE services for children from birth through school age and may also offer pre-K or before- or after-school programs. NAICS 624410 encompasses all reporting CCEE facilities not located in school-based settings, therefore excluding virtually all facilities and affiliated educators ineligible to participate in the PEF (specifically DCPS and public charter school programs providing universal pre-K, categorized under NAICS 611110, Elementary and Secondary Schools). Yet at the same time, the data may also exclude or undercount some facilities that are eligible for the program. First, employers that operate multiple facilities could appear either as multiple establishments or a smaller number of consolidated establishments, depending on whether they respond to the Multiple Worksite Report supplement that breaks out employment and wages by worksites. Estimates from OSSE administrative data (Doromal, Bassok, et al.,

2024) suggest that during the first program year, about 320 individual facilities employed educators who were eligible for PEF payments, with about 270 unique directors overseeing these facilities (we also find about 270 establishments providing child care services in Washington, DC, when the program began; see Table 1). Second, home-based providers are included in NAICS 624410 only if they operate with payroll employees; homes that are sole proprietors or self-employed fall outside the scope of the QCEW. Finally, a small number of school-based Montessori programs deliver CCEE services and employ educators eligible for PEF payments yet are likely categorized under NAICS 611110.

The QCEW measures employment and wages for all UI-covered payroll jobs reported by NAICS 624410 establishments. These jobs are predominantly held by teaching staff who are eligible for PEF payments but also include smaller shares of staff in ineligible positions (such as center-based facility directors, administrative assistants, and other support staff on regular payroll). Substitutes, floaters, aides, and other intermittent, on-call, or temporary positions are excluded from the employment and wage totals. Taken together, we find that Washington, DC, CCEE employment levels across NAICS 624410 establishments in the QCEW align with the number of educators who were eligible to participate in the PEF. In May 2022, the QCEW recorded 3,282 workers in NAICS 624410 establishments, while OSSE identified approximately 3,200 educators who were eligible to apply for the initial, lump-sum FY 2022 payment. In December 2022, 3,497 workers were reported by NAICS 624410 establishments, while 3,470 educators received the first FY 2023 quarterly payment (DC OSSE, 2024).

Within each geographic county, we constructed repeated quarterly measures of the number of NAICS 624410 establishments (herein referred to as CCEE establishments), the total number of workers employed across those establishments (herein referred to as CCEE educators), and the average weekly wages paid to those workers. We also constructed these measures across all industries to include additional variables for matching Washington, DC, with other counties in the donor pool. The number of CCEE educators in each quarter was

Table 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: Analysis of the Quarterly Census of Employment and Wages (QCEW) data.

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 making up the synthetic Washington, DC. Standardized percent bias measures the difference between the averages for Washington, DC, and each comparison group, standardized by the comparison group mean.

constructed as the average of the three monthly employment levels. Average weekly wages were calculated by dividing total quarterly wages paid 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.[9] Outlier values were top-coded, and each variable

[9]In the quarter prior to the launch of the PEF, just three CCEE establishments in Washington, DC, were publicly owned, all by the federal government. CCEE educators employed by federally owned establishments (such as agency-affiliated child care for federal employees) are eligible for PEF payments if they meet other program eligibility criteria. School-based public pre-K programs under state/local government ownership in Washington, DC, are excluded from NAICS 624410, as previously described.

was smoothed to adjust for short-term fluctuations.[10]

Description of Study Counties

We initially limited the study sample to counties with information on educators, wages, and establishments both in the CCEE sector and across QCEW industries in all quarters over a five-year period. In total, we included 24 quarters from the first quarter (Q1) of 2019 through the fourth quarter (Q4) of 2024. Quarters were distributed around the introduction of the PEF, with 13 quarters in the pre-treatment period and 10 quarters in the post-treatment period; we defined Q2 2022, the last full quarter before eligible educators were invited to apply for the initial PEF payments, as the baseline reference period. We analyzed an extended pre-treatment period 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, as previously described, the influx of federal relief funds that many states and territories allocated to support educator retention, including temporary investments in educator compensation (CSCCE, n.d.).

Over this period, 3,142 unique counties appeared in the QCEW data, of which 1,233 had non-missing information on constructed CCEE sector measures in all quarters.[11] 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 was comprised of 145 counties (including Washington, DC) that were in the top half of the distribution of employment levels, average wages, and

[10] 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.

[11] QCEW county-by-industry series are usually blank when a county has no UI-covered employment in that industry and/or when values are suppressed for confidentiality in very small cells. As a result, most excluded counties had missing CCEE sector data across many quarters (with about half missing data in all quarters) and tended to have very low levels of CCEE employment and establishments when observed. Only 8 counties with intermittent missingness would otherwise have met the eligibility criteria to be included in the donor pool; we did not impute their sector outcomes given tradeoffs between a small marginal gain in sample size and both the additional assumptions introduced through multiple imputation and challenges implementing the analytic approach with multiple imputed datasets.

establishments, both within the CCEE sector and across occupations. Figure 2 visualizes the CCEE sector outcomes over time for all counties in the analysis. 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 at the 95th percentile for average wages.

Multiple-Outcome Synthetic Control Method

To estimate the effects of the PEF on CCEE sector 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

Figure 2. CCEE labor market outcomes for Washington, DC, and donor counties

Source: Analysis of the Quarterly Census of Employment and Wages (QCEW) data.

is denoted as follows:

$$\tau_{1t,k} = Y^1_{1t,k} - Y^0_{1t,k}, t > T_0, k \in \{1, ..., K\},$$

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

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

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

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

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

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.

Forming 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), our benchmark analyses 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 SCM framework, where the relative positions of the units may vary across different

outcomes.[12] Following Sun and colleagues (2023), we denoted $\overline{Y}_{i.k} = \frac{1}{T_0}\sum_{t=1}^{T_0} Y_{it,k}$ as the pre-treatment average for a given unit and outcome, and $\dot{Y}_{it,k} = Y_{it,k} - \overline{Y}_{i.k}$ as the demeaned outcome.

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 $Y^0_{1t,k}$ is as follows:

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

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

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

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).

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 related 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,

[12] As previously discussed, the relative position of Washington, DC, among the study counties varies across the three outcomes (Figure 2), highlighting the utility of adjusting for the differences in the level of the outcomes through demeaning.

then we lose the benefits of matching on multiple related outcomes.[13] 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 $L_{2t,k}, ..., L_{Nt,k}$ 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 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:[14]

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

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:

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

[13]The number of CCEE educators and establishments and average weekly wages reflect related aspects of local child care markets and are plausibly influenced by similar underlying factors including local demand for paid care and cost conditions (U.S. Department of the Treasury, 2021; Hotz & Xiao, 2011).

[14]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.

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

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.

Because of limited prior evidence on the effectiveness of CCEE educator compensation initiatives, we implemented a more conservative two-sided inference procedure that ranks the absolute value of the post- to pre-treatment RMSE ratios, which departs from the one-sided procedure implemented by Abadie (2021) and Tian and colleagues (2023), who tested directional hypotheses. Specifically, 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. We focus on estimates with p-values below 0.10 as statistically significant; this threshold reflects a ranking of 14 or better out of the 145 counties in the analytic sample.

Robustness Checks

We conducted two robustness checks to test the sensitivity of the benchmark findings to alternative samples and designs. First, we conducted a leave-one-out re-analysis to check whether the main results were robust to the exclusion of any county that received positive weights from the construction of the synthetic Washington, DC. Second, we backdated treatment to Q4 2021 to ensure the treatment date used in the benchmark analysis—the quarter before the start of the application window for the initial PEF payments (Q2 2022, as previously described)—did not attenuate impacts, which could have happened if participants

anticipated receiving payments before they were allowed to apply.[15][16]

We also re-estimated impacts to better understand the consequences of selecting the benchmark SCM estimators. First, instead of matching on multiple related outcomes simultaneously, we matched on single outcomes to construct different synthetic control units (i.e., different weighted combinations of donor counties) for each study outcome. Second, we obtained impact estimates without demeaning outcomes to account for differences in their relative levels. It is more difficult to obtain a good pre-treatment fit in outcomes between the treated and synthetic control units when using non-demeaned outcomes, particularly when the treated unit is closer to the top (or bottom) of the sample distribution as well as when matching on multiple outcomes.

Results

In this section, we first describe the synthetic Washington, DC, which we constructed using the full donor pool of comparison group counties and by matching on multiple outcomes that were demeaned with respect to their averages in the pre-treatment period (Q1 2019 through Q2 2022). Next, we present impacts on CCEE sector outcomes defined as the differences between Washington, DC, and the synthetic Washington, DC, in the number of educators, average weekly wages, and the number of establishments after the launch of the PEF. We focus both on the magnitude of these differences and their statistical significance in each post-treatment period and overall. We conclude with findings from the leave-one-out, backdated treatment, single outcome, and no demeaning robustness checks.

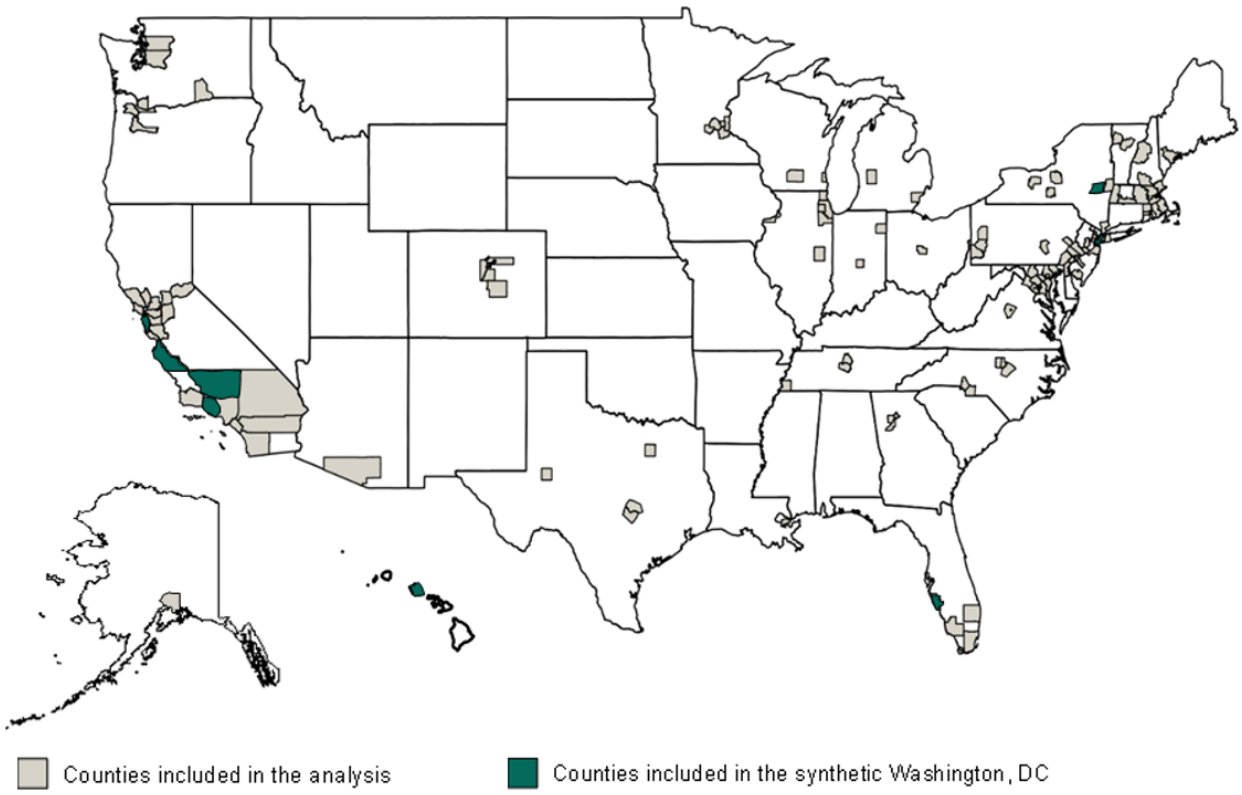
[15] As mentioned earlier, during Q1 2022, the PEF Task Force published its initial report with recommendations for the implementation of the PEF. This was the first public information about the PEF payments.

[16] 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.

The Synthetic Washington, DC

Figure 3 shows the 145 counties (including Washington, DC) that were included in the donor pool as well as the 9 donor counties assigned a positive weight in the construction of the synthetic Washington, DC: 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).

Figure 3. Donor counties included in the analysis and the synthetic Washington, DC



Source: Analysis of the Quarterly Census of Employment and Wages (QCEW) data.

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), California (San Francisco, Ventura, Monterey, and Kern), Hawaii (Honolulu), and Florida (Sarasota). Table B.1 presents the optimal weights for these counties from the benchmark analysis.

This combination of weighted counties was selected because it most closely resembled Washington, DC, in the pre-treatment periods in terms of the CCEE sector 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 1. We also present the standardized percent bias for Washington, DC, compared to the synthetic Washington, DC and the simple average of donor counties. The standardized percent bias is calculated as the simple difference in means between Washington, DC, and each control group, then divided by the relevant control group mean. Washington, DC, differs significantly from the average county in the donor pool, as indicated by the larger percent bias values for that comparison. Conversely, Washington, DC, and the synthetic control group are well balanced in the pre-treatment periods in terms of CCEE sector outcomes and covariates.

Impacts of the Pay Equity Fund

We present impact findings from the benchmark analysis on the number of CCEE educators, the average CCEE weekly wage, and the number of CCEE establishments. Table 2 presents all point estimates underlying these findings, including outcome estimates for Washington, DC, and the synthetic control group, and corresponding impacts and p-values from permutation tests, by post-treatment quarter and on average across post-treatment quarters. Figure 4 displays trends in each outcome for both Washington, DC, and its synthetic control over time, including prior to the PEF, when educators received payments directly, and after the PEF shifted to the facility payment model. We present additional details about the statistical significance testing in Appendix A.[17]

[17]Figure A.1 displays standardized gaps between each county and its synthetic counterpart from the permutation test by CCEE outcome, whereas Figure A.2 presents the rankings of the post- to pre-treatment RMSE ratios for each CCEE outcome across the post-treatment quarters.

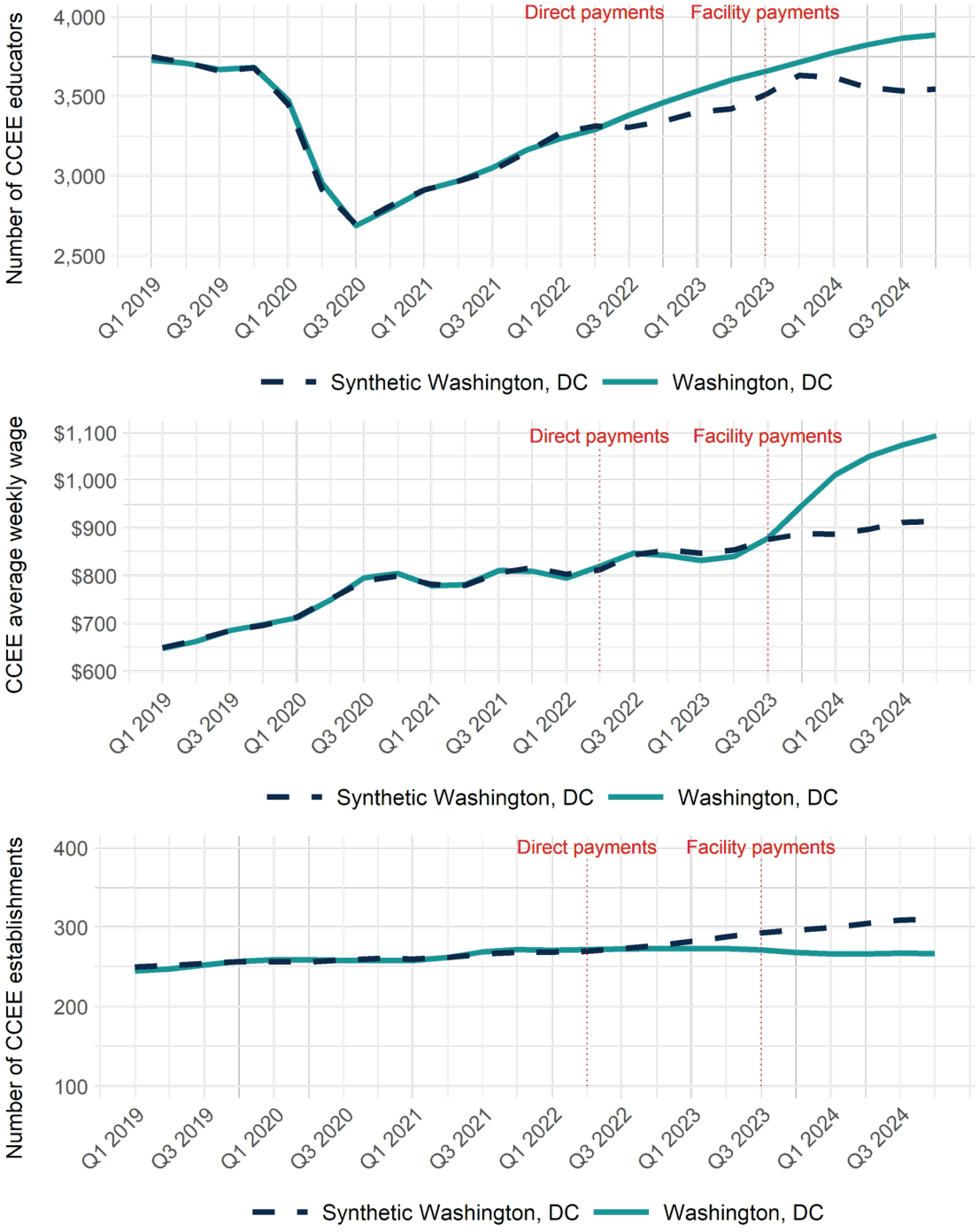
Table 2. Point estimates for the effects of the Pay Equity Fund on CCEE labor market outcomes, overall and by post-treatment quarter

	Washington, DC	Synthetic Washington, DC	Impact	p-value
Number of CCEE educators				
Average estimates across post-treatment quarters	3,670	3,487	184	0.055
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	3,657	3,509	147	0.076
Q4 2023	3,716	3,632	84	0.166
Q1 2024	3,775	3,619	156	0.097
Q2 2024	3,825	3,556	268	0.034
Q3 2024	3,865	3,534	331	0.014
Q4 2024	3,887	3,545	341	0.021
CCEE average weekly wage				
Average estimates across post-treatment quarters	$942	$877	$65	0.110
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	$879	$876	$3	0.938
Q4 2023	$947	$888	$59	0.193
Q1 2024	$1,012	$887	$125	0.103
Q2 2024	$1,050	$898	$153	0.076
Q3 2024	$1,074	$912	$163	0.083
Q4 2024	$1,093	$914	$179	0.090
Number of CCEE establishments				
Average estimates across post-treatment quarters	270	293	-23	0.166
Estimates by post-treatment quarter				
Q3 2022	273	273	0	0.972
Q4 2022	273	277	-3	0.800
Q1 2023	273	282	-9	0.483
Q2 2023	273	288	-15	0.352
Q3 2023	272	293	-22	0.241
Q4 2023	268	296	-28	0.214
Q1 2024	267	299	-33	0.179
Q2 2024	267	305	-38	0.145
Q3 2024	268	309	-41	0.124
Q4 2024	267	310	-43	0.145

Source: Analysis of the Quarterly Census of Employment and Wages (QCEW).

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.

Figure 4. 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.

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

Number of CCEE Educators

Benchmark results show that the PEF had a positive impact on the number of CCEE educators in Washington, DC. Statistically significant impacts emerged almost immediately following the launch of the PEF. Although generally increasing over time, the magnitudes of these impacts fluctuated in concert with changes to program design and implementation and the broader CCEE policy and funding context.

Consistent with the findings presented in Table 1, trends in the number of CCEE educators were nearly identical between Washington, DC, and its synthetic control prior to the PEF. Following the launch of the PEF, Washington, DC, immediately started to accumulate a greater number of CCEE educators than the synthetic Washington, DC, such that the estimated impact of the program was 119 additional educators by the end of 2022. Although the size of the CCEE workforce increased in both Washington, DC, and the synthetic DC, by the end of FY 2023, Washington, DC had accumulated an additional 147 educators relative to the synthetic DC.[18]

While positive throughout, the gap between Washington, DC, and the synthetic Washington, DC, did narrow to 87 educators in the first quarter of FY 2024 (Q4 2023), a period characterized by the transition from the direct educator payment to the facility payment model in the District, as well as the end of emergency COVID-19 pandemic funding across the nation (we further explore the relationships between these factors, outcome trends, and program impacts in the Discussion section). Nevertheless, positive impacts decreased only briefly, before again continuing to grow thereafter, from 156 educators in Q1 2024 to 341 educators in the most recently observed quarter (Q4 2024); the Q4 2024 impact represents about an 11 percent increase in the size of the CCEE workforce, relative to control group levels at baseline. When averaged across the post-treatment quarters, the findings indicate an overall effect of 184 educators through three years of the PEF. Notably, the cumulative effect of

[18]Estimates through Q3 2023 were first published in Schochet (2024), as previously noted. Findings were identical, apart from Q3 2023 estimates, which, due to smoothing of the panel, are now influenced by Q4 2023 records. In Schochet (2024), we estimated a Q3 2023 impact of 219 additional educators.

the program enabled Washington, DC, to recover and ultimately exceed employment levels relative to the start of the COVID-19 pandemic, whereas the number of educators in the counterfactual remained below pre-pandemic levels, with labor supply stagnating following the Q4 2023 deadline for spending ARPA stabilization grants. We return to the potential role of the PEF in stabilizing the CCEE workforce following the expiration of pandemic relief funding in the Discussion.

As described above, we determined statistical significance of program impacts by permuting treatment status among the donor counties. At each of the 10 post-treatment quarters and overall across these quarters, we generated p-values by ranking Washington, DC's, position in the distribution of the absolute pre- to post-treatment RMSE ratios. Out of the 145 total counties, Washington, DC, had the 8th largest overall post- to pre-treatment RMSE ratio, such that its standardized impact was larger than that found in about 95 percent of all counties across post-treatment periods ($p = 0.055$; also see Figure A.2). The overall effect was attenuated by the reduction in the workforce gap in Q4 2023, which was the only post-treatment quarter without a statistically significant effect. Impacts in Q3 2023 and Q1 2024, both attenuated by the Q4 2023 effect, were significant at the 10 percent level, whereas impacts for all other post-treatment periods were statistically significant at the 5 percent level or below. In the last quarter of FY 2024 (Q3 2024), the standardized employment effect in Washington, DC, was larger than all but 2 of the 145 donor counties ($p = .014$; also see Figure A.1).

CCEE Average Weekly Wages

Benchmark findings on the impacts of the PEF on educators' average weekly wages reflect patterns in how educator payments were distributed and recorded and increase confidence in the validity of the QCEW for capturing outcomes of program participation. During the first two program years, when payments were delivered directly to educators, we estimated near-zero impacts on educator wages reported from employer payrolls. Positive and

statistically significant wage effects only emerged in the third year of the program, shortly after the PEF began routing educator payments through facility payrolls.

Trends in average CCEE weekly wages were similar between Washington, DC, and its synthetic control both prior to the launch of the PEF, and from baseline through the end of FY 2023. Estimated impacts from Q3 2022 to Q3 2023 ranged from $3 (Q3 2023) to -$16 (Q1 2023), and results of the permutation tests described above indicated that none of the differences in these time periods were statistically significant. These null findings are consistent with the expectation that payments delivered outside of employer payrolls would have no effect on wages collected by the QCEW based on employer reports.

Beginning in FY 2024, predicted post-treatment trends for Washington, DC, began to diverge from the synthetic Washington, DC. This shift coincided with the program's transition from the direct payment model to the facility payment model, as previously noted. In Q4 2023, educators in Washington, DC, earned $59 more per week, on average, and by Q4 2024, this impact increased to $179 per week. Annually, this represents a wage increase of approximately $9,300 per educator. Directly prior to the launch of the program, the CCEE workforce in Washington, DC, and the synthetic control group earned $808 on average per week (Table 1), or approximately $40,000 per year; in Q4 2024, educators in Washington, DC, earned $1,093 per week, or about $57,000 per year. Permutation test findings suggested that following the shift to the FY 2024 facility payment model, the estimated impacts on average weekly wages were statistically significant at the 10 percent level in most post-treatment periods. By the end of third program year, the standardized wage effect in Washington, DC, was larger than that estimated in about 92 percent of counties across the nation (Figure A.1).

Number of CCEE Establishments

Despite the positive impacts of the PEF on the size of Washington, DC's CCEE workforce, benchmark findings do not indicate a corresponding increase in the number of CCEE

establishments. Instead, the estimates suggest that establishment counts in Washington, DC, remained relatively flat over the post-treatment period while the number of establishments in the synthetic Washington, DC, continued to grow.

Following the launch of the PEF, the two series began to diverge. The number of CCEE establishments in Washington, DC, changed little over time, declining only slightly from 273 in Q3 2022 to 267 in Q4 2024. In contrast, the number of establishments in the synthetic Washington, DC, increased steadily over this same period, from 273 to 310. As a result, the estimated impact on the number of CCEE establishments became increasingly negative over time, growing from essentially zero in Q3 2022 to -43 establishments by Q4 2024. Averaged across post-treatment quarters, Washington, DC, had 23 fewer CCEE establishments than its synthetic control, an overall effect equal to about 8 percent of the synthetic control's baseline level.

Results from the permutation tests indicated that neither the overall effect nor the quarter-specific effects on the number of CCEE establishments were statistically significant. *P*-values declined over time and were smallest in FY 2024 but remained above the 10 percent level of statistical significance. We therefore cannot rule out the possibility that these differences were due to chance. At the same time, the estimates provide no evidence that the PEF increased establishment counts. Rather, taken together with the positive employment findings, these results suggest that increased CCEE labor supply attributed to the PEF occurred within existing reporting establishments.[19]

Robustness Checks

We conducted several robustness checks to assess the sensitivity of our results to changes in the design of the study. As previously described, these changes included leaving

[19]Because QCEW establishment counts for multi-site employers depend in part on worksite-level reporting through the Multiple Worksite Report, as previously discussed, it is important not to interpret these findings literally as evidence about the number of CCEE facilities (sites). If the PEF led some multi-site providers to add physical sites, the additional sites would only be reflected in the establishment counts among employers that completed the Multiple Worksite Report.

out each donor county included in the benchmark analysis, backdating the treatment so that we could be confident that the outcomes observed before this date were not influenced by the treatment, matching on single outcomes rather than multiple related outcomes, and using original rather than demeaned outcomes. These results are presented in Appendix B. Tables B.1 and B.2 provide the county weights used to construct the alternative synthetic control groups and Table B.3 presents point estimates for the treatment effects from robustness checks.

Leave-one-out. First, to check whether the results were sensitive to the choice of counties in constructing the synthetic Washington, DC, we conducted a leave-one-out re-analysis, where we repeated the estimation procedure, iteratively excluding each key donor county at a time. We found that the benchmark impacts were tightly bound by the range of leave-one-out estimates across study outcomes and post-treatment periods. In other words, the outcome trends for the benchmark synthetic control unit aligned with those for the synthetic control units constructed from the different pools of donor counties (see Figure B.1). In Q4 2024, leave-one-out impact estimates ranged from 237 to 394 additional educators, average weekly wage increases of $171 to $208, and from 49 to 30 fewer establishments.

Backdated Treatment. In the main analysis, we selected Q2 2022, the quarter before the start of the application window for the initial PEF payments, as the treatment date. To rule out anticipatory effects if participants were influenced by knowledge of the PEF before they were invited to apply, we re-estimated impacts using Q4 2021, a period before the public had any information about the PEF. Findings suggested that the synthetic Washington, DC, closely tracked outcome trends in Washington, DC, before not only the backdated treatment date, but also the benchmark treatment date (see Figure B.2). For instance, the Q2 2022 gap was just -19 educators, -$3 per week, and 2 establishments. These results both support our benchmark treatment definition and demonstrate that the synthetic Washington, DC, reproduces the untreated potential outcomes in the counterfactual.

Single Outcome. We examined whether estimates were sensitive to altering our

SCM approach to match on single outcomes instead of multiple related outcomes simultaneously. Single-outcome SCM estimates may be reliable when the number of pre-treatment periods is large, as in the current study, although 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). Results indicated that estimates from the single-outcome approach have an upward bias but lead to the same conclusions (see Figure B.3). For instance, in Q4 2024, single outcome impacts suggested an additional 361 educators, $202 more per week, and 19 fewer establishments.

No Demeaning. The benchmark estimates were 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 good fit on multiple outcomes simultaneously. When using the original, non-demeaned outcomes, results suggested poorer pre-treatment fit, which comes at a cost for accurately tracking the dynamics of the treated unit over time (see Figure B.4). Nevertheless, the post-treatment effects estimates are somewhat consistent with the benchmark results, suggesting, for example, 345 additional educators, $200 more per week, and 3 fewer establishments in Q4 2024.

Discussion

This study provides the first rigorous evidence on the labor market impacts of a large-scale, dedicated public funding stream designed to sustain increased compensation for CCEE educators. Across three years of implementation, the PEF increased the number of CCEE educators in Washington, DC, and, once payments were routed through employer payrolls, increased average weekly wages reported in federal labor market data. These findings emerge in a policy context where most prior compensation initiatives have been modest, temporary, or both (e.g., Bassok et al., 2021; Cunha & Lee, 2023; Herbst, 2018; Showers et al., 2025).

The PEF therefore offers unusually strong evidence that public financing and sustained compensation policies can alter labor market conditions in a sector long characterized by low wages, staffing instability, and labor supply shortages.

Interpreting the Impacts of the Pay Equity Fund

Employment Levels

We found that positive effects on the size of the CCEE workforce emerged quickly and then grew over time, reaching an estimated 341 additional educators by Q4 2024, or roughly 11 percent relative to the synthetic control at baseline. That pattern is consistent with the PEF's theory of change: sufficiently large and credible compensation increases can help stabilize the existing workforce while also making CCEE employment more attractive to prospective workers. A subset of educators—about one in three participants in FYs 2023 and 2024—also received subsidized health insurance through HC4CC. Subsidized health insurance may have further supported educator retention and entry, contributing to the observed employment effects alongside the wage payments.[20] Although the QCEW cannot separately identify retention and recruitment, these estimates complement implementation evidence that the program changed incentives facing both workers and employers. Educators reported that the PEF increased their intention to remain in their current jobs and in the DC child care sector, while center-based facility directors reported improved recruitment and retention under the program (Nikolopoulos et al., 2024; Nikolopoulos et al., 2025; Sandstrom et al., 2024).

Increased CCEE labor supply supports several of the program's theorized benefits for educators, facilities, and families. Most directly, a larger workforce increases the system's

[20]HC4CC may influence labor supply through two channels. First, viewing health insurance subsidies (about $5,200 per HC4CC participant; Schochet & Gonzalez, 2026) as indirect income, reductions in health insurance spending would influence labor supply through the same mediating pathways as direct wage increases (the income elasticity of health insurance spending could be assumed to be unitary, though alternative elasticity values are also plausible; Belfield & Schochet, 2024). Second, health insurance also directly conveys benefits that mediate employment effects (Belfield & Schochet, 2024), such as health status gains (Barker & Li, 2020; Finkelstein et al., 2012) and reductions in medical debt (ASPE, 2022; Hu et al., 2018).

capacity to serve families. Using a conservative assumption that each additional educator attributable to the program could serve five additional children (see Belfield & Schochet, 2024), the estimated increase in the workforce by the end of 2024 implies capacity for roughly 1,700 additional children. Greater workforce stability also implies more accumulated work experience for educators who remain in the field, lower recruitment and onboarding costs for facilities, fewer disruptions associated with staffing vacancies and turnover, and more stable caregiver-child relationships that support service quality. Analysis of program economic returns calculated that increased access attributable to labor supply growth accounted for about one-third of the total value of PEF benefits, while returns to work experience, recruitment savings, and gains in service quality accounted for much of the remainder (Belfield & Schochet, 2024; Schochet & Gonzalez, 2026).

Though positive throughout the post-treatment period, the employment gap between Washington, DC, and its synthetic control narrowed briefly in late 2023, just as the PEF was transitioning from direct educator payments to the facility payment model. The shift in program model may have temporarily attenuated employment effects if employment decisions were responsive to the size, structure, or certainty of wage support. About one in four facilities employing educators who had previously received direct payments did not participate in the program in FY 2024, and staff-record analyses indicate that educators who changed employers between FY 2023 and FY 2024 were substantially more likely to move to a participating facility (Doromal, Nikolopoulos, et al., 2025; Doromal, Lamb, et al., 2025). The smaller impact in the quarter following the change in program design is consistent with temporary employment gaps as some educators searched for and transitioned into positions at participating facilities.

After this point, workforce trajectories diverged: Washington, DC, continued to add educators through the end of 2024, whereas employment in the synthetic control flattened. Washington, DC's positive employment trend throughout the third program year is consistent with higher per-educator spending on wage subsidies under the facility payment model

(about $15,000, compared with roughly $10,000 per year under the direct payment model; Belfield & Schochet, 2024; Schochet & Gonzalez, 2026). Multiple years of permanent wage increases may also generate extra-proportional labor market benefits over the direct educator payments, which were intended as a temporary payment mechanism until the program could implement the salary scale. Sustained wage increases may accelerate the accumulation of educator skills and productivity and enhance the applicant pool for jobs in the CCEE sector. For example, analysis of staff records found that new educators beginning jobs during the third program year were more likely to join participating facilities (Doromal, Nikolopoulos, et al., 2025).

The divergence in employment trends between Washington, DC, and the synthetic control also coincided with the expiration of more than $52 billion in federal pandemic-era stabilization funds that many states used to support educator compensation and provider operations (Government Accountability Office, 2023). By the end of 2024, employment in the synthetic control group remained below pre-pandemic levels and was also lower than one year earlier, a pattern consistent with national survey evidence documenting renewed staffing shortages and operating pressures following the expiration of ARPA stabilization funding (National Association for the Education of Young Children, 2024). Although only suggestive of mechanism, the relationship between the employment findings and public funding conditions in the counterfactual is consistent with the broader hypothesis that sustained compensation policies can stabilize labor supply after temporary emergency relief ends.

Average Wage Effects

The wage results support the validity of the QCEW for capturing anticipated wage effects of the PEF. We found that the wage series shifted at the point when the programmatic mechanism changed in a way that should have made wage gains visible in employer-reported payroll data. During the first two program years, when funds were paid directly to educators outside employer payroll, estimated impacts on weekly wages remained close to zero. Once

the program shifted to the facility payment model tied to employer payroll, positive wage effects emerged quickly and became statistically significant. By Q4 2024, the estimated wage effect had reached $179 per week—about $9,300 per year, or 22 percent of baseline wages. Adjusting this estimate for the share of non-educator payroll staff also included in the data and for incomplete facility participation yields a per-participant wage increase consistent with independent estimates under the facility payment model.[21] To this end, the wage results function partly as a validation exercise for the data source and design.

Estimated impacts on average weekly wages also reflect the successful translation of direct one-time or quarterly payments into more complex employer payroll compensation. The PEF facility payment model established a CCEE salary schedule and embedded minimum required compensation increases into payroll systems to move closer toward parity with public-school teachers. The evidence here suggests that this shift altered measured wage levels in the sector. From a policy design standpoint, engaging facilities in the program helps ensure minimum salary requirements are met and allows wage subsidies to interact with other elements of employer compensation systems, including retirement contributions, unemployment insurance coverage, and other benefits tied to employee wages and employer payroll. Receiving increased salaries regularly through employer payrolls could also be more likely than ad hoc payments to affect workers' expectations about the reliability of compensation over time, and to support professional identity and investments in job skills, themes that appear in the program implementation study (Nikolopoulos et al., 2025; Sandstrom et al., 2024).

[21] Based on OSSE administrative records and nationally representative CCEE provider survey data, Belfield and Schochet (2024) calculated that 80% of facility staff were in PEF-eligible roles, on average. Doromal and colleagues (2025c) reported that about 75% of operating facilities participated in the program in FY 2024 based on analysis of program administrative records. The estimated Q4 2024 impact would therefore suggest that each program participant received an average wage increase of about $15,500. Using information reported by OSSE on total facility award expenditures, award allocations, and participant cohorts, Schochet and Gonzalez (2026) estimated an average salary increase of about $15,200 in FY 2024.

Establishment Counts

We do not find evidence that the PEF increased the number of reporting CCEE establishments in Washington, DC. Point estimates instead suggest that establishment counts remained roughly stable while those in the synthetic control increased, yielding increasingly negative—but never statistically significant—gaps over time. Establishment trends therefore suggested that workforce growth associated with the PEF occurred within a relatively stable number of reporting establishments rather than through a detectable increase in the establishment count. This interpretation is compatible with the employment findings. If the program increased labor supply to relax staffing constraints, existing facilities may have first filled vacancies, stabilized classrooms, or expanded staffing before the CCEE sector grew through additional establishments.

Why might CCEE establishment growth lag increases in labor supply? One possibility is that the program compressed wage differences between center-based classroom staff and facility leadership, particularly under the facility payment model where educator wage gains were largest. About one-quarter of directors reported that, because of the new minimum salary requirements, most teachers at their facilities earned more than they did (Jimenez Parra et al., 2025). Directors also reported wage compression due to the direct educator payments, with nearly one in three indicating that they had considered returning to the classroom to become eligible for the PEF payments (Nikolopoulos et al., 2024). In related qualitative analysis, some directors argued that wage compression dynamics could weaken the leadership pipeline and create management challenges, suggesting that future iterations of the program also consider administrator pay (Jimenez Parra et al., 2025). If becoming or remaining an administrator becomes financially less attractive relative to staying in a teaching role, that could decrease incentives to move into administration, assume leadership responsibilities, or open and operate new facilities.

Another consideration is that, as noted earlier, QCEW establishment counts are not a one-to-one measure of physical worksites. Establishment data for multi-site employers

depend in part on the Multiple Worksite Report, which distributes employment and wages across worksites. If a multi-site employer fails to submit the report, BLS may keep the firm recorded as a single establishment or prorate employment and wages across a previously known number of sites. Accordingly, if the PEF was especially effective at increasing the number of facilities among multi-site providers, incomplete worksite-level reporting could cause the establishment series to understate program impacts on facility counts. This bias would need to be substantial to overturn the finding of fewer establishments relative to the synthetic control, but it does mean these results should be interpreted as evidence about reporting establishments rather than a definitive count of operating facilities.

Policy Implications

The study findings have implications for policymaking in Washington, DC, and beyond. Impact evidence from the first two years of the program was cited by the Washington, DC, Council in its FY 2025 budget recommendations as justification for restoring $70 million in funding for the program after an earlier budget proposal had it eliminated (DC Council Committee of the Whole, 2024). At the federal level, the introduction of the Child Care Workforce Act—bipartisan legislation in the Senate proposing a competitive grant program with evaluation requirements for states and localities seeking to adopt or expand CCEE educator compensation initiatives—cited the PEF as a model program and referenced the study's findings on worker supply along with evidence on turnover, financial well-being, and job satisfaction among participants (U.S. Senator Tim Kaine, 2024; U.S. Senator Katie Britt, 2025). These are unusual instances in which impact evidence from ongoing research shaped live budgetary and legislative debates.

The success of the PEF has also helped motivate publicly funded compensation initiatives emerging in other jurisdictions. In early 2025, the Child Care Boost Initiative, a wage enhancement pilot in Contra Costa County, CA, began providing $1,000 per month to about 120 educators for 18 months; the program design framework discussed the earlier

PEF employment findings (Powell et al., 2024). Also launched in 2025, King County, Washington's Best Start for Kids Wage Boost Pilot provided about 850 CCEE educators up to $8,320 in additional pay in its first year and is similarly framed around workforce stability, continuity of care, and labor supply (Mefferd, Doromal, Miles, et al., 2025). Connecticut has planned a staged compensation agenda in its Early Childhood Education Endowment, pointing to evidence of short-run labor supply growth in Washington, DC, in support of including wage supplements as part of its broader reform policies (Connecticut Blue Ribbon Panel on Child Care, 2023; Connecticut Office of Early Childhood, 2025). Vermont and New Mexico, though pursuing strategies centered on universal CCEE access and affordability, have also moved toward larger-scale public financing models designed to support educator compensation, sector capacity, or both (New Mexico Early Childhood Education & Care Department, n.d.; Richards et al., 2025).

Limitations and Future Research

Several limitations should shape interpretation of the study findings. First, the QCEW captures UI-covered payroll employment, not the full universe of educators and facilities potentially affected by the PEF. This is a strength in terms of data coverage and consistency, but it excludes some eligible educators and settings, specifically home-based providers operating as sole proprietors without payroll employees. These providers represent both educators and establishments, reflecting just one percent of eligible educators but about 15 percent of their facilities at study baseline (Doromal, Bassok, et al., 2024). On the one hand, compensation policies may be particularly effective for these smaller home-based providers that operate on tighter margins and have more volatile entry and exit from the regulated market (Bromer et al., 2021). On the other hand, this population may need greater support to meet salary minimums and may have difficulty complying with program administrative requirements without other staff to support them (Porter et al., 2024). Regardless, the estimates reported here pertain most directly to the formal payroll segment of

the community-based CCEE sector.

Second, QCEW employment and wage measures include all regular payroll staff employed by NAICS 624410 establishments, not only teachers and assistant teachers directly eligible for higher wages through the PEF. In one sense, this likely makes the unadjusted sector estimates conservative with respect to the focal population. Yet it also raises the possibility that the PEF awards generated spillover benefits for the broader workforce and facility operations that contributed to the study findings under the facility payment model. Provided they met minimum educator salary requirements, facility administrators were given flexibility in allocating award funds, and the implementation study found that nearly half of directors reported using funds to also raise compensation for noneducator roles (Jimenez-Parra et al., 2025). In most cases, these allocations reflected additional administrative time to implement the program, but some directors reported using portions of their awards to hire additional support staff or address pay disparities for other staff that were ineligible for the program. Better understanding of these non-salary award allocations is important for documenting the full extent of the program's labor market impacts and economic returns.

Third, the aggregate nature of the data limits what can be learned about mechanisms and impact heterogeneity. We cannot distinguish entry from retention, employer-to-employer mobility from sector exit or unemployment, or changes in workforce hours from changes in headcount. Nor can we estimate exploratory impacts on a wider range of theorized benefits, including those related to service quality such as educator competencies, credentials, or facility quality ratings. Another important next step is determining how effects vary across policy-relevant subpopulations—such as by setting type, age group served, subsidy participation, quality rating, or worker role—and across program exposure, including the duration of participation. Our forthcoming analyses linking PEF payment records with longitudinal workforce registry data from Washington, DC, and several comparison jurisdictions are better suited to address these questions.

Conclusion

The PEF represents the first large-scale publicly financed effort in the United States to raise compensation for community-based CCEE educators through sustained wage subsidies. Using administrative labor market data and a synthetic control design, this study finds that the program increased the size of the CCEE workforce and, once compensation was routed through employer payroll, raised measured wages in the sector. The results therefore provide evidence that sustained compensation policies can influence labor supply in a sector long characterized by low wages and persistent staffing shortages. At the same time, findings suggest that workforce growth occurred primarily within existing establishments rather than through the creation of new ones, both reflecting facility priorities to fill vacancies and strengthen staffing as well as potential wage compression between educators and administrators that weakens incentives to assume leadership roles or open new facilities. Together, these findings suggest that sufficiently large and sustained compensation increases can affect labor market outcomes in the CCEE sector and represent an important component of broader strategies to strengthen the workforce and expand the supply of CCEE services.

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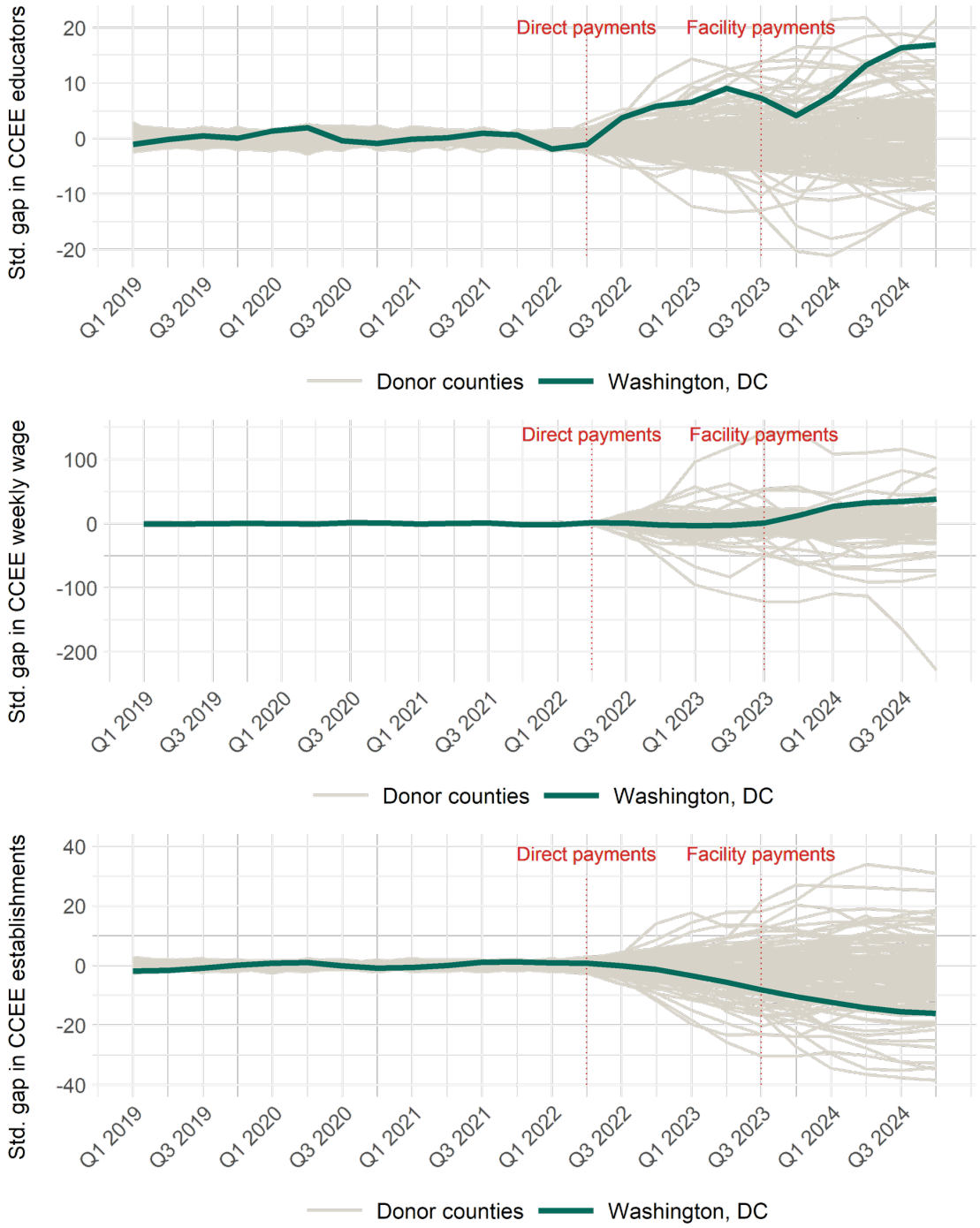
Appendix A

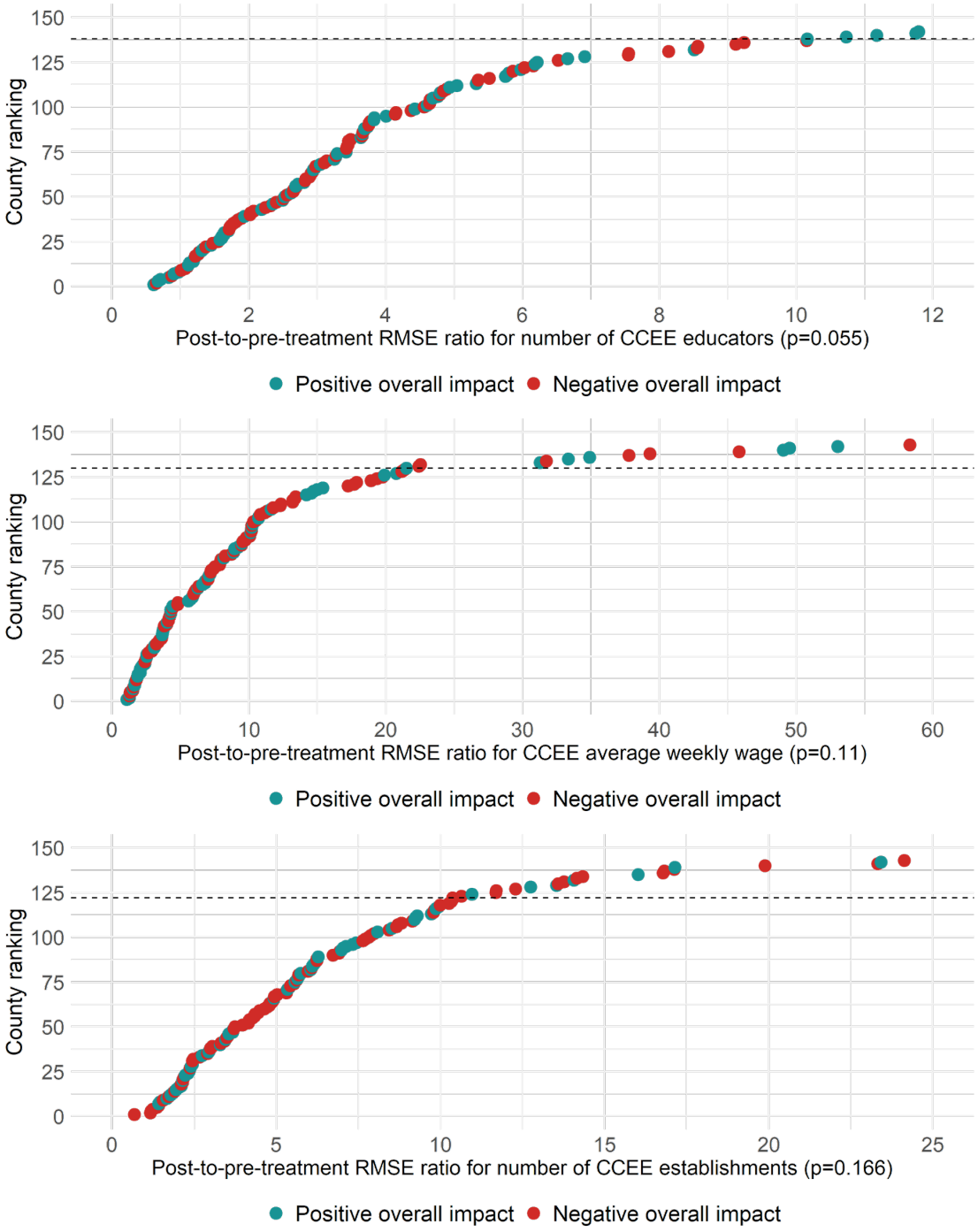
Figure A1. Placebo gaps in CCEE labor market outcomes for donor counties



Source: Author's analysis of the Quarterly Census of Employment and Wages (QCEW) data.

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 A2. 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.

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.

Appendix B

Table B1. Optimal county weights for the construction of the synthetic Washington, DC, in the benchmark analysis and leave-one-out robustness checks

	Benchmark	Leave-one-out, excluding:								
County		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1. New York County, New York	22%	-	20%	24%	19%	27%	21%	24%	22%	22%
2. San Francisco County, California	19%	0%	-	22%	14%	13%	26%	17%	18%	20%
3. Ventura County, California	18%	34%	25%	-	23%	10%	19%	18%	21%	18%
4. Monterey County, California	12%	0%	5%	15%	-	0%	12%	13%	11%	12%
5. Albany County, New York	10%	16%	9%	6%	10%	-	12%	9%	11%	10%
6. Richmond County, New York	7%	15%	22%	8%	11%	8%	-	8%	8%	7%
7. Honolulu County, Hawaii	6%	1%	2%	6%	4%	0%	7%	-	6%	6%
8. Kern County, California	5%	0%	0%	12%	4%	13%	5%	5%	-	5%
9. Sarasota County, Florida	1%	0%	6%	0%	7%	0%	0%	3%	3%	-
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: Analysis of the Quarterly Census of Employment and Wages (QCEW) data.

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 B2. 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 CCEE outcome			No demeaning
			Educators	Wages	Establishments	
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: Analysis of the Quarterly Census of Employment and Wages (QCEW) data.

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 B3. Effects of the Pay Equity Fund on CCEE labor market outcomes from the benchmark analysis and robustness checks

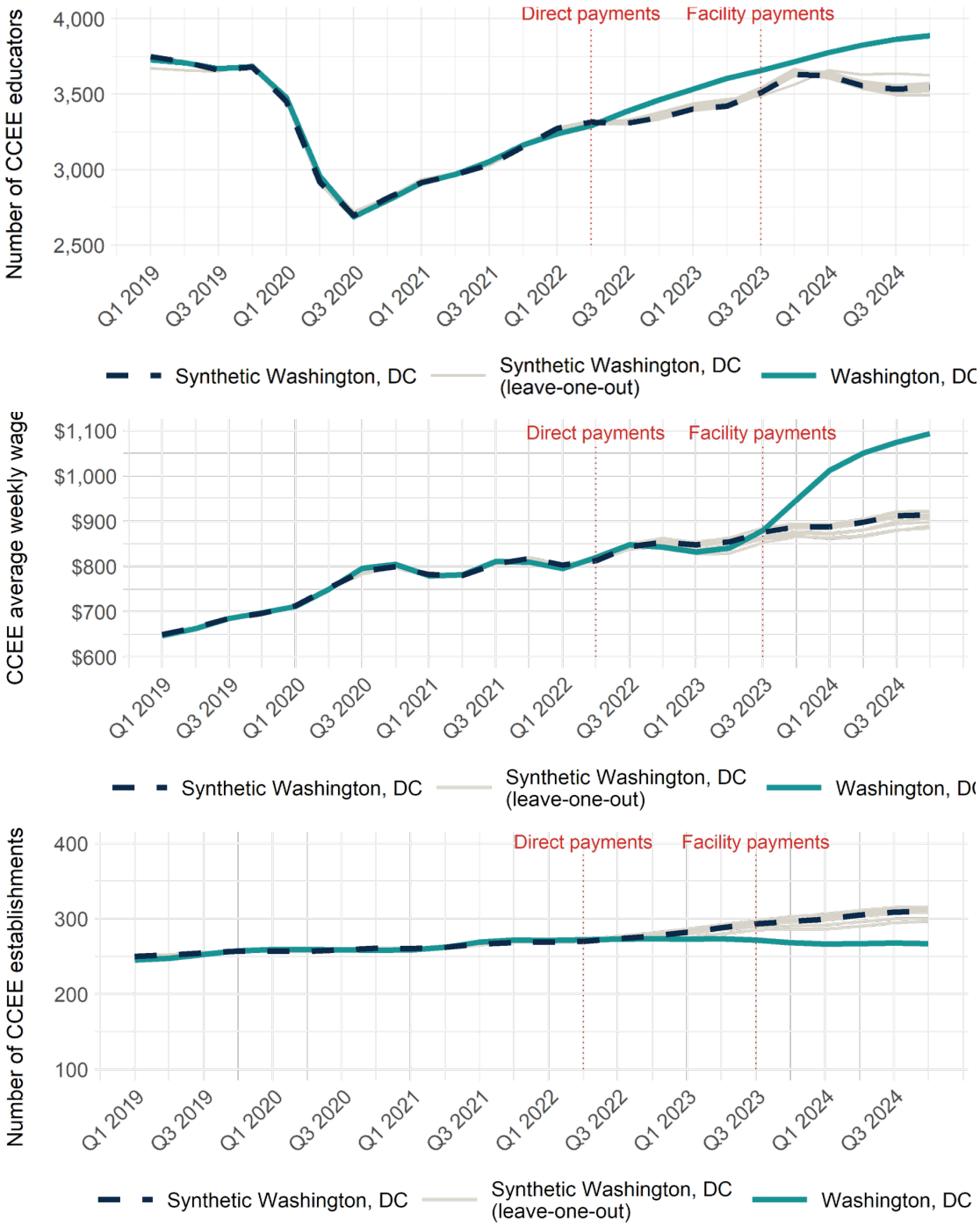
	Impact from:				
	Benchmark	Leave-one-out (min, max)	Backdated treatment	Single outcome	No demeaning
Number of CCEE educators					
Average estimates across pre-treatment quarters	0	0	0	0	38
Average estimates across post-treatment quarters	184	(146, 192)	150	186	131
Estimates by post-treatment quarter					
Q1 2022	-	-	-25	-	-
Q2 2022	-	-	-19	-	-
Q3 2022	76	(53, 83)	69	45	61
Q4 2022	119	(83, 130)	105	67	40
Q1 2023	133	(95, 142)	119	83	18
Q2 2023	183	(138, 192)	166	140	90
Q3 2023	147	(113, 170)	118	148	78
Q4 2023	84	(48, 153)	46	186	4
Q1 2024	156	(116, 168)	112	254	85
Q2 2024	268	(185, 290)	222	311	245
Q3 2024	331	(231, 371)	285	353	343
Q4 2024	341	(237, 394)	297	361	345
CCEE average weekly wage					
Average estimates across pre-treatment quarters	$0	$0	$0	$0	$2
Average estimates across post-treatment quarters	$65	($58, $86)	$76	$83	$81
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, $5)	-$3	$16	-$3
Q2 2023	-$14	(-$23, -$11)	-$5	$28	$5
Q3 2023	$3	(-$6, $27)	$11	$35	$27
Q4 2023	$59	($52, $81)	$67	$75	$81
Q1 2024	$125	($119, $151)	$135	$135	$143
Q2 2024	$153	($145, $185)	$165	$168	$171
Q3 2024	$163	($154, $195)	$176	$179	$182
Q4 2024	$179	($171, $208)	$193	$202	$200
Number of CCEE establishments					
Average estimates across pre-treatment quarters	0	0	0	0	-2
Average estimates across post-treatment quarters	-23	(-28, -14)	-22	-15	-1
Estimates by post-treatment quarter					
Q1 2022	-	-	2	-	-
Q2 2022	-	-	3	-	-
Q3 2022	0	(-4, 2)	0	-3	5
Q4 2022	-3	(-8, 1)	-3	-7	4

	Impact from:				
	Benchmark	Leave-one-out (min, max)	Backdated treatment	Single outcome	No demeaning
Q1 2023	-9	(-13, -2)	-9	-13	2
Q2 2023	-15	(-18, -6)	-14	-19	0
Q3 2023	-22	(-26, -13)	-21	-24	-3
Q4 2023	-28	(-35, -18)	-27	-21	-5
Q1 2024	-33	(-40, -20)	-31	-12	-4
Q2 2024	-38	(-44, -23)	-35	-12	-4
Q3 2024	-41	(-47, -27)	-39	-17	-3
Q4 2024	-43	(-49, -30)	-41	-19	-3

Source: Analysis of the Quarterly Census of Employment and Wages (QCEW) data.

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. The backdated treatment analysis excludes Q1 2022 and Q2 2022 from the average estimates across post-treatment quarters.

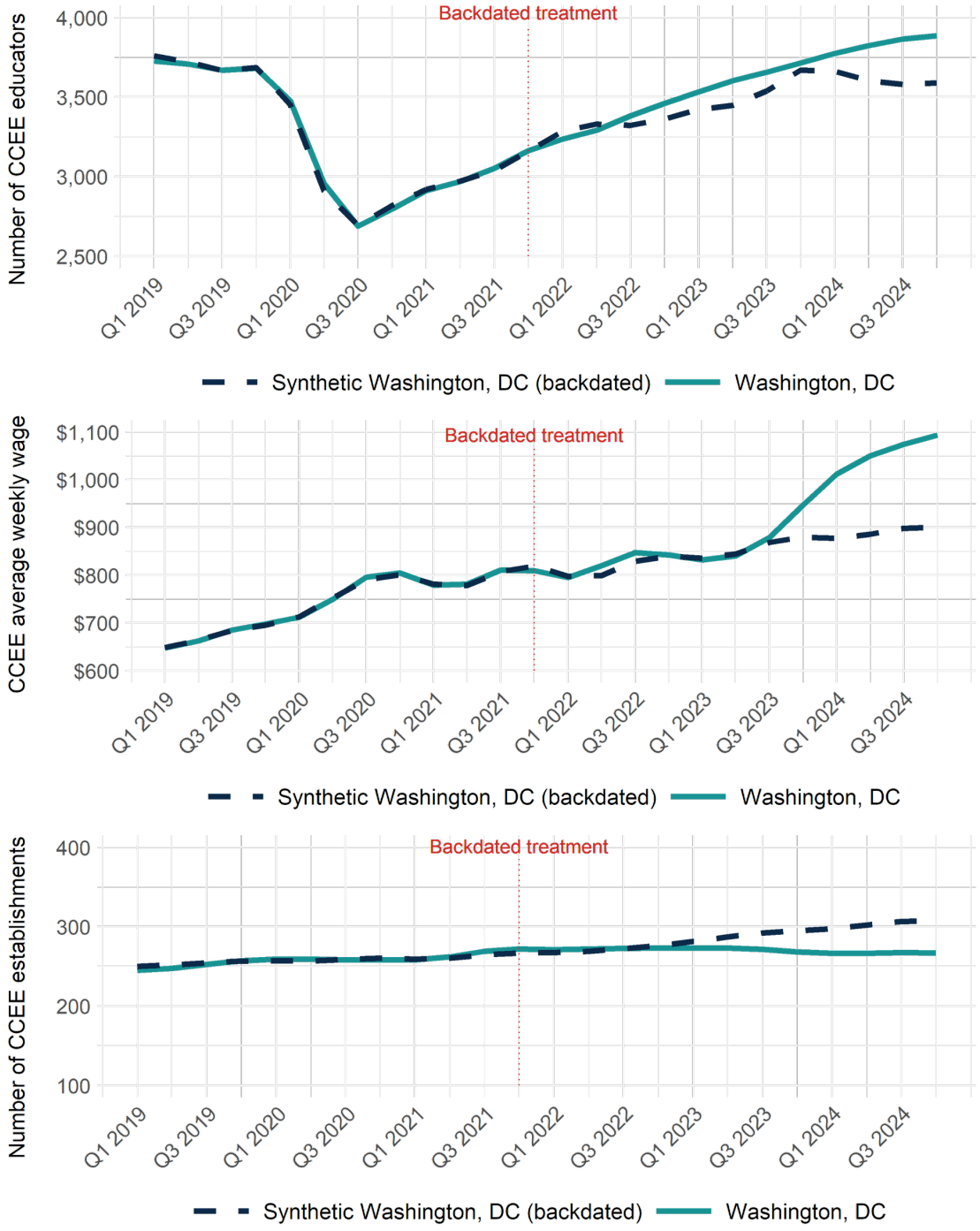
Figure B1. CCEE labor market outcomes for Washington, DC, and its synthetic control: Leave-one-out robustness check



Source: Author's analysis of the Quarterly Census of Employment and Wages (QCEW) data.

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

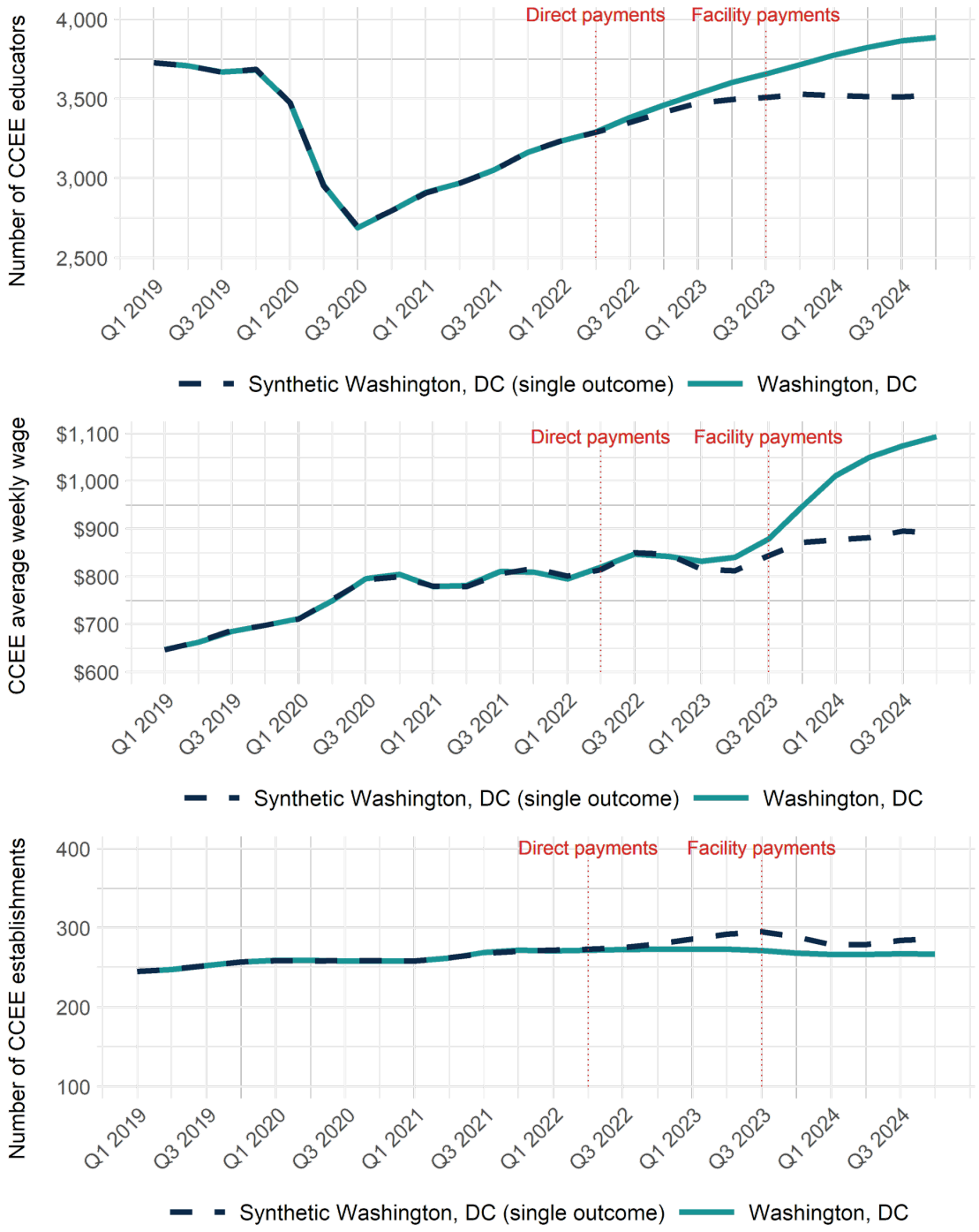
Figure B2. CCEE labor market outcomes for Washington, DC, and its synthetic control: Backdated treatment robustness check



Source: Author's analysis of the Quarterly Census of Employment and Wages (QCEW) data.

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 those used in the benchmark specification.

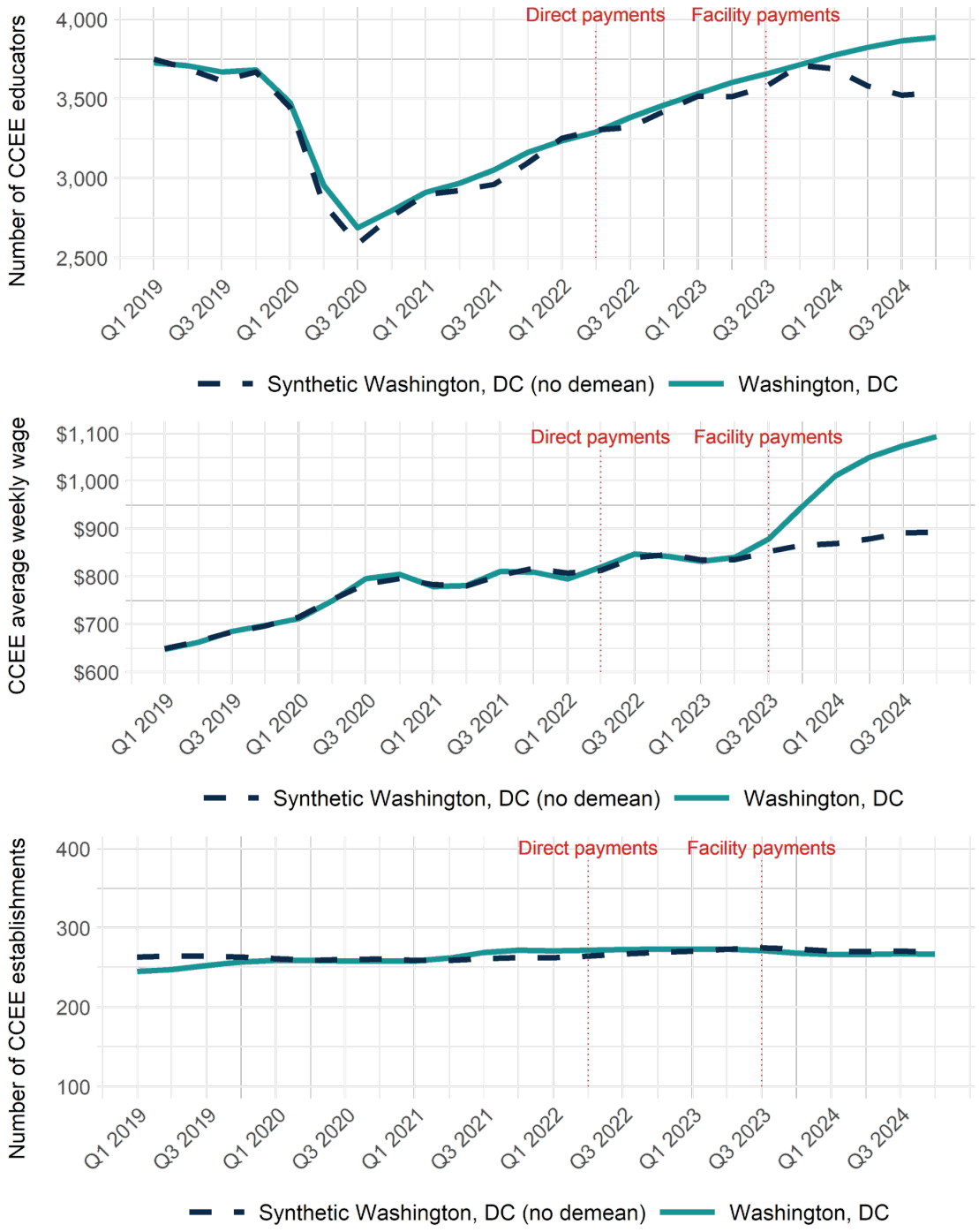
Figure B3. CCEE labor market outcomes for Washington, DC, and its synthetic control: Single outcome robustness check



Source: Author's analysis of the Quarterly Census of Employment and Wages (QCEW) data.

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 those used in the benchmark specification.

Figure B4. CCEE labor market outcomes for Washington, DC, and its synthetic control: No demeaning robustness check



Source: Author's analysis of the Quarterly Census of Employment and Wages (QCEW) data.

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