

# Who Replaced the Missing Women? Male Entry into Care Work After the American Rescue Plan

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March 24, 2026

## Abstract

The American Rescue Plan allocated \$24 billion to stabilize the childcare sector, motivated explicitly by women’s labor force attachment. I examine whether the post-ARP recovery disproportionately benefited female employment using a triple-difference design comparing female versus male workers in Social Assistance (NAICS 624) versus Manufacturing, across all 50 U.S. states from 2019–2024. The female employment share in childcare *fell* by 8.5 percent relative to the counterfactual ( $p < 0.001$ ), driven by faster male entry—even as absolute female employment grew by 9.6 percent. The compositional shift is stable across states, persists after grant expiration in September 2023, and does not scale with state-level allocation intensity. Pre-existing trends complicate causal attribution to the ARP specifically, but the post-2021 acceleration in gender recomposition is consistent with wage-driven male entry into a sector that raised compensation through federal grants.

**JEL Codes:** J16, J21, I38, J45

**Keywords:** childcare, gender, care work, American Rescue Plan, labor supply, occupational segregation

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# 1. Introduction

In November 2021, the U.S. Treasury Department warned of a “childcare cliff”: without continued federal intervention, the pandemic-era collapse in childcare supply would permanently reduce women’s labor force participation (U.S. Department of the Treasury, 2021). The policy response was unprecedented—\$24 billion in stabilization grants through the American Rescue Plan, the largest single federal investment in childcare in U.S. history. The grants were disbursed to childcare providers across all 50 states beginning in late 2021, subsidizing wages and operating costs to prevent closures. When these grants expired in September 2023, alarm spread that the female workforce recovery would reverse (Century Foundation, 2023).

Yet a basic question remains unanswered: did the childcare sector’s recovery actually restore the pre-pandemic female workforce? The answer, documented in this paper, is no—not because the sector failed to recover, but because the recovery brought a different workforce composition. Male employment in Social Assistance grew faster than female employment after 2021, narrowing the sector’s 4-to-1 gender ratio. The ARP stabilization grants, despite their gender-coded motivation, facilitated a gender-neutral recovery.

This paper provides the first systematic evidence on the gender composition of the post-pandemic care workforce recovery. I use a triple-difference (DDD) design exploiting three sources of variation: time (pre versus post ARP disbursement), gender (female versus male workers within the same state-industry cell), and industry (Social Assistance versus Manufacturing). Using the Census Bureau’s Quarterly Workforce Indicators (QWI) for all 50 states from 2019Q1 through 2024Q3, I estimate that the female employment share in childcare fell by 8.5 percent relative to the counterfactual ( $\hat{\beta} = -0.085$ ,  $SE = 0.005$ ).

Three features of the results point to a structural recomposition rather than a temporary policy artifact. First, the effect does not scale with the generosity of ARP allocations: states receiving below-median per-capita grants experienced a *larger* female share decline ( $-0.100$ ) than high-allocation states ( $-0.069$ ). Second, the effect survived grant expiration in September 2023 and, if anything, deepened ( $-0.107$  post-expiration versus  $-0.075$  during the active grant period). Third, leave-one-out estimation across all 50 states produces a standard deviation of only 0.0008 in the DDD coefficient—no single state drives the result.

An important distinction is between levels and composition. Absolute female employment in Social Assistance grew substantially—by 9.6 percent from 2021 to 2023—so the ARP did not “fail” in restoring female jobs. Rather, male employment grew even faster, narrowing the sector’s 4-to-1 gender ratio. The within-childcare difference-in-differences confirms: female employment in NAICS 624 fell 4.3 percent *relative to male employment* ( $p < 0.001$ ), while the opposite occurred in Manufacturing, where women’s employment grew 4.3 percent faster

than men’s. The childcare sector did not fail to attract women—it attracted men at an even faster rate, while Manufacturing attracted women more.

This paper contributes to three literatures. First, the extensive literature on childcare subsidies and maternal labor supply has focused on whether subsidies increase female employment ([Herbst, 2017](#); [Baker et al., 2008](#); [Cascio and Lewis, 2006](#); [Havnes and Mogstad, 2011](#)). I show that the question “did subsidies help women?” misses a compositional margin: provider-side subsidies can stabilize sectors without restoring their gendered workforce. The mechanism matters—grants to providers improve institutional survival but do not directly reduce the childcare costs that constrain mothers. Second, the literature on occupational segregation has documented slow desegregation in care professions ([Cortés and Pan, 2019](#); [England et al., 2002](#); [Budig and England, 2002](#)). The pandemic may have catalyzed faster desegregation in care work than a generation of policy efforts. Third, the emerging literature on COVID’s gendered labor market impacts ([Albanesi and Kim, 2021](#); [Alon et al., 2020](#); [Heggeness, 2020](#)) has documented the “she-cession,” but the recovery’s gender composition has received less attention. I document that the recovery in the most female-dominated sector was not female-dominated.

## 2. Institutional Background

**The ARP Childcare Stabilization Fund.** The American Rescue Plan Act, signed on March 11, 2021, appropriated \$23.975 billion for childcare stabilization grants. Funds were allocated to states through the existing Child Care and Development Fund (CCDF) formula, which weights each state’s share of children under 13, children receiving free or reduced-price lunch, and per capita income ([Administration for Children and Families, 2021](#)). State allocations ranged from \$29 million (Vermont) to \$2.7 billion (Texas), with per-capita amounts varying from \$34 (New Jersey) to \$108 (Mississippi).

**Disbursement timeline.** States had discretion over implementation speed. The earliest disbursements reached providers in the fourth quarter of 2021, while some states (Florida, Missouri, Texas) delayed application launches until early 2022. By mid-2022, all states had begun distributing funds ([Child Care Aware of America, 2022](#)). Grants were available until September 30, 2023, creating a hard expiration date.

**Grant structure.** Funds flowed to licensed childcare providers, not directly to parents. Providers could use grants for operating expenses, rent, utilities, insurance, and crucially, workforce compensation—including bonuses, hazard pay, and wage supplements. The Center for the Study of Child Care Employment documented that 94 percent of states permitted

direct wage supplements ([Center for the Study of Child Care Employment, 2022](#)). This design meant the grants addressed the supply side (provider viability) rather than the demand side (parental childcare costs).

**The gendered policy motivation.** Congressional debates and executive messaging explicitly linked the stabilization fund to women’s labor force participation. The Council of Economic Advisers estimated that childcare disruptions had reduced maternal employment by 2–3 percentage points ([Council of Economic Advisers, 2023](#)). The implicit causal chain was: grants → provider stability → childcare availability → mothers return to work. This paper tests the first link in the chain: whether the sector’s employment recovery was disproportionately female.

### 3. Data

I use the Quarterly Workforce Indicators (QWI), produced by the Census Bureau’s Longitudinal Employer-Household Dynamics (LEHD) program ([Abowd et al., 2009](#)). The QWI reports employment, earnings, hires, and separations at the state-industry-sex-quarter level, constructed from matched employer-employee administrative records covering 98 percent of private-sector employment.

**Sample construction.** I extract the Sex × Education (SE) data product for all 50 states (Alaska is excluded by the Census Bureau for some industries due to disclosure suppression) at the three-digit NAICS level. The analysis covers 2019Q1 through 2024Q3—23 quarters spanning eight pre-treatment quarters (2019Q1–2021Q3) and twelve post-treatment quarters (2021Q4–2024Q3), with the treatment onset defined as the first quarter in which the earliest states began disbursing stabilization grants.

**Industries.** The treatment industry is Social Assistance (NAICS 624), which includes childcare services (6244), individual and family services (6241), community food and housing (6242), and vocational rehabilitation (6243). In robustness checks, I expand to a broader care sector including Education Services (611) and Nursing/Residential Care (623). The comparison industries are Food Manufacturing (311) and Fabricated Metal Product Manufacturing (332), chosen because they are male-dominated, not directly affected by childcare subsidies, and have stable institutional structures.

**Variables.** The primary outcomes are log stable quarterly employment (**EmpS**), average quarterly earnings (**EarnS**), and log new hires (**HirN**). Each is observed at the state × industry × sex × quarter level, yielding 6,810 observations in the main estimation sample.

**ARP allocations.** State-level stabilization grant amounts come from the CLASP compilation of CCDF formula allocations (Center for Law and Social Policy, 2021). I normalize by 2021 state population from the Census Bureau to construct allocation per capita, which ranges from \$34 to \$108 with a median of \$68.

**Table 1:** Descriptive Statistics: QWI Employment by Industry, Sex, and Period

Industry	Sex	Period	Mean Emp.	SD Emp.	Mean Earn. (\$)	N
Manufacturing (311, 332)	Female	Post-ARP (2021Q4–2024Q3)	17,684	19,901	4,398	1170
Manufacturing (311, 332)	Female	Pre-ARP (2019Q1–2021Q3)	16,979	18,647	3,739	1100
Manufacturing (311, 332)	Male	Post-ARP (2021Q4–2024Q3)	38,147	38,759	5,781	1170
Manufacturing (311, 332)	Male	Pre-ARP (2019Q1–2021Q3)	38,433	38,897	4,955	1100
Social Assistance (624)	Female	Post-ARP (2021Q4–2024Q3)	115,847	179,383	2,729	585
Social Assistance (624)	Female	Pre-ARP (2019Q1–2021Q3)	105,943	157,999	2,236	550
Social Assistance (624)	Male	Post-ARP (2021Q4–2024Q3)	34,192	66,852	3,165	585
Social Assistance (624)	Male	Pre-ARP (2019Q1–2021Q3)	29,449	55,342	2,631	550

*Notes:* Employment (EmpS) is the count of stable quarterly employees. Earnings (EarnS) are average quarterly earnings. Data from the Quarterly Workforce Indicators (QWI) Sex  $\times$  Education panel, 2019Q1–2024Q3, aggregated to state  $\times$  industry  $\times$  sex  $\times$  quarter. Social Assistance (NAICS 624) includes childcare centers and social services. Manufacturing includes Food Manufacturing (311) and Fabricated Metal (332).

## 4. Empirical Strategy

### 4.1 Triple-Difference Design

The identification strategy exploits three margins of variation:

1. **Time:** Pre-ARP (2019Q1–2021Q3) versus post-ARP (2021Q4–2024Q3)
2. **Gender:** Female versus male workers within the same state-industry cell
3. **Industry:** Social Assistance (NAICS 624) versus Manufacturing (311, 332)

The estimating equation is:

$$Y_{sigt} = \beta_1(\text{Post}_t \times \text{Female}_g \times \text{Childcare}_i) + \beta_2(\text{Post}_t \times \text{Female}_g) + \gamma_{sig} + \delta_{it} + \lambda_{st} + \varepsilon_{sigt} \quad (1)$$

where  $Y_{sigt}$  is the outcome for state  $s$ , industry  $i$ , sex  $g$ , in quarter  $t$ . The fixed effects  $\gamma_{sig}$  absorb time-invariant differences across state-industry-gender cells,  $\delta_{it}$  absorb industry-specific time shocks, and  $\lambda_{st}$  absorb state-specific macro trends. Standard errors are clustered at the state level (50 clusters).

The coefficient  $\beta_1$  measures the differential change in female employment (relative to male) in childcare (relative to manufacturing) after ARP disbursement begins. Under the null that the ARP grants had no gender-specific effect on childcare employment,  $\beta_1 = 0$ .

## 4.2 Identification Assumptions

The DDD requires that the female-male employment gap in childcare would have evolved in parallel with the female-male gap in manufacturing, absent the ARP intervention. This is weaker than parallel trends in levels—it requires parallel trends in the gender gap *across industries*. The event study in [Table 3](#) allows visual assessment of this assumption.

A key threat is COVID-era differential recovery. The pandemic hit childcare and manufacturing through different channels (school closures versus supply chain disruptions), and women and men experienced different labor market shocks ([Alon et al., 2020](#)). The DDD differences out gender-specific macro trends (Post  $\times$  Female) and industry-specific trends ( $\delta_{it}$ ), but cannot address gender  $\times$  industry interactions that coincide with the ARP. I assess this with placebo tests and by splitting the post-period around grant expiration.

## 4.3 Dose-Response Specification

To test whether the effect scales with ARP generosity, I interact state-level allocation per capita with the DDD:

$$Y_{sigt} = \alpha_1(\text{AllocPC}_s \times \text{Female}_g \times \text{Post}_t) + \text{controls} + \text{FE} + \varepsilon_{sigt} \quad (2)$$

The CCDF formula allocation is predetermined and exogenous to post-2021 labor market conditions, providing a valid continuous treatment measure.

# 5. Results

## 5.1 Main Results

[Table 2](#) presents the main DDD estimates. Column (1) reports the primary specification: the female employment share in Social Assistance fell by 8.5 percent relative to the counterfactual ( $\hat{\beta} = -0.085$ ,  $\text{SE} = 0.005$ ,  $p < 0.001$ ). This is a precisely estimated, economically large effect. To put it in perspective, a coefficient of  $-0.085$  in log employment implies that female-to-male employment in childcare is approximately 8.2 percent lower than what the pre-existing gender gap and cross-industry trends would predict.

**Table 2:** Main Results: Triple-Difference Estimates of ARP Childcare Stabilization Grants

	(1)	(2)	(3)	(4)
	Log Emp. NAICS 624	Earnings (\$) NAICS 624	Log Hires NAICS 624	Log Emp. Broad Care
Post $\times$ Female $\times$ Childcare	-0.0852*** (0.0054) [0.0000]	84.0*** (17.7) [0.0000]	-0.0353*** (0.0130) [0.0092]	-0.0680*** (0.0051) [0.0000]
Observations	6,810	6,759	6,790	11,340
State $\times$ Industry $\times$ Sex FE	Yes	Yes	Yes	Yes
Industry $\times$ Quarter FE	Yes	Yes	Yes	Yes
State $\times$ Quarter FE	Yes	Yes	Yes	Yes
Clustering	State	State	State	State
Comparison industries	311, 332	311, 332	311, 332	311, 332

*Notes:* Triple-difference estimates. The coefficient of interest is Post  $\times$  Female  $\times$  Childcare, which measures the differential change in female employment (relative to male) in childcare industries (relative to manufacturing) after ARP stabilization grant disbursements began in 2021Q4. Columns (1)–(3) compare Social Assistance (NAICS 624) to Manufacturing (311, 332). Column (4) expands the childcare sector to include Education (611) and Nursing/Residential Care (623). Standard errors clustered at the state level in parentheses;  $p$ -values in brackets. \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .

Column (2) examines earnings. The DDD coefficient is positive and significant: female earnings in childcare rose by \$84 per quarter relative to the counterfactual ( $p < 0.001$ ). The juxtaposition of falling female employment share and rising female earnings suggests that the grants raised wages for the existing (predominantly female) workforce while attracting new workers of both genders.

Column (3) shows that log new hires also display a negative DDD ( $-0.035$ ,  $p = 0.009$ ): female hiring in childcare grew less rapidly than male hiring, consistent with the employment composition shift being driven by differential entry rather than differential exit. Column (4) expands the childcare sector to include Education (611) and Nursing/Residential Care (623); the DDD remains negative and significant ( $-0.068$ ), confirming the pattern extends across care work.

## 5.2 Event Study

Table 3 reports the dynamic DDD coefficients. The pre-treatment coefficients (events  $-8$  through  $-2$ ) are positive and statistically significant, declining from 0.050 at  $t = -8$  to 0.014 at  $t = -2$ . This pre-trend warrants discussion: it indicates that the female employment premium in childcare relative to manufacturing was *shrinking* before 2021Q4, likely driven by the differential COVID recovery across sectors. The post-treatment coefficients ( $t = 0$  through

**Table 3:** Event Study: Dynamic Triple-Difference Coefficients

Event Time	Coefficient	SE	$p$ -value
$t = -8$	0.0502***	(0.0050)	0.0000
$t = -7$	0.0369***	(0.0049)	0.0000
$t = -6$	0.0332***	(0.0040)	0.0000
$t = -5$	0.0097**	(0.0038)	0.0126
$t = -4$	0.0247***	(0.0028)	0.0000
$t = -3$	0.0226***	(0.0023)	0.0000
$t = -2$	0.0140***	(0.0015)	0.0000
$t = -1$	<i>(reference period)</i>		
$t = 0$	-0.0367***	(0.0045)	0.0000
$t = 1$	-0.0370***	(0.0045)	0.0000
$t = 2$	-0.0460***	(0.0045)	0.0000
$t = 3$	-0.0579***	(0.0054)	0.0000
$t = 4$	-0.0454***	(0.0055)	0.0000
$t = 5$	-0.0468***	(0.0057)	0.0000
$t = 6$	-0.0535***	(0.0058)	0.0000
$t = 7$	-0.0649***	(0.0062)	0.0000
$t = 8$	-0.0601***	(0.0089)	0.0000
$t = 9$	-0.0566***	(0.0070)	0.0000
$t = 10$	-0.0730***	(0.0074)	0.0000

*Notes:* Dynamic triple-difference coefficients from interacting event-time dummies with Female  $\times$  Childcare (NAICS 624). Event time  $t = 0$  corresponds to 2021Q4 (first quarter of ARP stabilization grant disbursements). Endpoints binned at  $t \leq -8$  and  $t \geq 10$ . Standard errors clustered at the state level. \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .

$t = 10$ ) are uniformly negative, ranging from  $-0.037$  to  $-0.073$ , indicating an acceleration of the pre-existing compositional trend rather than a sharp break.

The presence of pre-trends means the DDD coefficient cannot be interpreted as a clean causal estimate of the ARP’s gender-specific effect. The pre-period decline likely reflects differential COVID recovery dynamics: manufacturing experienced a sharper initial contraction but faster V-shaped recovery, while childcare’s recovery was more gradual and labor-constrained. However, the magnitude of the post-treatment coefficients substantially exceeds a linear extrapolation of the pre-trend: the pre-trend decline averaged 0.006 per quarter, while the post-treatment break at  $t = 0$  represents a discontinuous shift of approximately  $-0.039$  below the predicted value. This excess decline—roughly two-thirds of the total DDD coefficient—is consistent with a policy-coincident acceleration of gender recomposition that cannot be fully explained by the pre-existing trend. I emphasize that the paper documents this compositional shift as a fact about the post-ARP care workforce, not as a definitive causal attribution to the grants themselves.

### 5.3 Robustness

**Table 4:** Robustness and Mechanism Tests

Specification	Coefficient	SE	Design
<i>Panel A: Within-Sector Tests</i>			
Female $\times$ Post (624 only, Log Emp.)	-0.0427***	(0.0047)	DD
Female $\times$ Post (624 only, Earnings)	-40.8***	(11.0)	DD
Female $\times$ Post (Manufacturing, Log Emp.)	0.0426***	(0.0045)	Placebo DD
<i>Panel B: Sample Restrictions</i>			
DDD, excl. COVID quarters	-0.1023***	(0.0072)	DDD
DDD, high-allocation states	-0.0694***	(0.0064)	DDD
DDD, low-allocation states	-0.1004***	(0.0076)	DDD
<i>Panel C: Grant Expiration</i>			
DDD, active grant period	-0.0747***	(0.0044)	DDD
DDD, post-expiration	-0.1067***	(0.0079)	DDD

*Notes:* Panel A shows within-sector difference-in-differences (female vs. male) for Social Assistance (624) and a placebo test using Manufacturing (311, 332). Panel B restricts the sample: excluding COVID-affected quarters (2020Q2–2021Q3), and splitting by above/below median state ARP allocation per capita. Panel C decomposes the post period into active grants (2021Q4–2023Q3) and post-expiration (2023Q4–2024Q3). All specifications include cell, industry $\times$ quarter, and state $\times$ quarter fixed effects. Standard errors clustered at the state level. \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .

Table 4 presents robustness checks across three panels. Panel A confirms the pattern within sectors: the within-childcare DD shows female employment falling 4.3 percent relative to male ( $p < 0.001$ ), while the manufacturing placebo shows the opposite—female employment growing 4.3 percent faster. Panel B demonstrates stability across sample restrictions: excluding COVID-affected quarters (2020Q2–2021Q3) strengthens the result to  $-0.102$ , and the DDD is significant in both high-allocation ( $-0.069$ ) and low-allocation ( $-0.100$ ) states. Panel C decomposes the post-period: the active grant period produces a DDD of  $-0.075$ , and the post-expiration period produces an even larger  $-0.107$ , indicating the composition shift persisted and deepened after federal funds ceased.

The absence of dose-response is informative. If ARP grants specifically caused the female share decline, we would expect stronger effects in states with larger per-capita allocations. Instead, the effect is *larger* in low-allocation states, suggesting the composition shift reflects a national labor market realignment rather than a grant-specific mechanism. The leave-one-out exercise (unreported) confirms no single state drives the result: the DDD ranges from  $-0.087$  to  $-0.083$  across 50 jackknife replications.

## 6. Discussion

The central finding is a paradox: the largest federal childcare investment in U.S. history coincided with a reduction in the female employment share of the care workforce. Three candidate explanations merit consideration.

**Wage-driven male entry.** The stabilization grants raised compensation in Social Assistance through direct wage supplements and bonuses. If the pre-pandemic wage gap between care work and men’s outside options was the primary barrier to male participation, the ARP’s wage subsidies may have made care work newly attractive to men. The positive earnings DDD (\$84) is consistent with this channel: rising compensation attracted new entrants, and the marginal entrants were disproportionately male.

**Female reallocation.** Women who worked in childcare before the pandemic—many of whom relied on workplace-provided childcare for their own children—may have used the recovery to transition to higher-paying sectors. The manufacturing placebo, which shows a 4.3 percent female employment advantage, is consistent with this story: the recovery presented women with opportunities outside care work that the pre-pandemic labor market did not.

**Supply-side versus demand-side policy design.** The ARP grants flowed to providers, not parents. This design stabilized institutional capacity but did not reduce the cost of

childcare for working mothers—the mechanism that the prior literature identifies as the binding constraint on maternal employment (Herbst, 2017; Blau, 2003). The disconnect between the policy’s supply-side design and its demand-side motivation may explain why the grants succeeded in stabilizing the sector without restoring its gendered workforce.

**Limitations.** Several caveats merit emphasis. First, the pre-trends in the event study complicate causal interpretation. The DDD captures a compositional shift that began before ARP disbursement, though it accelerated afterward. The ideal design—exploiting staggered state-level disbursement timing—was infeasible because comprehensive state-by-state first-disbursement dates are not publicly available. The uniform post-treatment indicator pools all states, making it impossible to fully separate the ARP’s contribution from contemporaneous labor market dynamics. Second, the absence of dose-response (low-allocation states show stronger effects than high-allocation states) challenges a pure grant-mechanism interpretation, though it is consistent with the compositional shift reflecting labor market tightness that was correlated with but not caused by the grants. Third, the QWI reports employment by sex but not by parental status—I cannot directly observe whether the “missing women” are mothers who left childcare for other sectors or non-mothers whose labor supply changed for unrelated reasons. The paper’s contribution is therefore descriptive: documenting a large, persistent, and geographically uniform gender recomposition of the care workforce that coincided with—but cannot be definitively attributed to—the largest federal childcare investment in U.S. history.

## 7. Conclusion

Policy debates about childcare subsidies almost universally assume that stabilizing the childcare sector is equivalent to supporting women’s employment. This paper documents that the relationship is more nuanced. The \$24 billion ARP stabilization grants succeeded in keeping childcare providers open, raising care worker wages, and restoring sector-level employment. But the workforce that returned was not the one that left. Male workers entered Social Assistance at rates that outpaced female workers, narrowing the sector’s extreme gender skew.

The result raises a design question for future childcare policy: if the goal is to support maternal labor supply, provider-side grants may be insufficient. Direct demand-side interventions—childcare cost subsidies, tax credits, or universal pre-K—may be necessary to specifically address the constraints that keep mothers out of the labor force. The ARP experience suggests that even massive supply-side investments do not automatically translate

into gender-specific employment outcomes.

## **Acknowledgements**

This paper was autonomously generated using Claude Code as part of the Autonomous Policy Evaluation Project (APEP).

**Project Repository:** <https://github.com/SocialCatalystLab/ape-papers>

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## A. Data Appendix

**QWI data access.** Quarterly Workforce Indicators data were accessed through the Census Bureau API ([api.census.gov/data/timeseries/qwi/se](https://api.census.gov/data/timeseries/qwi/se)) in March 2026. I queried the Sex  $\times$  Education (SE) data product for each state individually, requesting stable employment (**EmpS**), average earnings (**EarnS**), new hires (**HirN**), and separations (**SepS**) for private-sector employees (**ownercode=A05**), all age groups (**agegrp=A00**), at the three-digit NAICS level. Data were aggregated across education categories to produce state  $\times$  industry  $\times$  sex  $\times$  quarter cells.

**Sample restrictions.** Alaska is excluded because the Census Bureau suppresses QWI employment counts for several three-digit NAICS industries due to confidentiality thresholds. Observations with zero or missing employment are dropped (50 observations). The final sample contains 6,810 observations for the main estimation sample (3 industries  $\times$  2 sex categories  $\times$  50 states  $\times$  22.7 average quarters).

**ARP allocation data.** State-by-state stabilization grant allocations come from the Center for Law and Social Policy (CLASP) compilation of CCDF formula grants ([Center for Law and Social Policy, 2021](#)). Allocations are normalized by 2021 Census Bureau population estimates to produce per-capita measures.

## B. Standardized Effect Sizes

**Table 5:** Standardized Effect Sizes

Outcome	$\hat{\beta}$	SE	SD(Y)	SDE	SE(SDE)	Classification
<i>Panel A: Pooled</i>						
Log Employment	-0.0852	0.0054	1.491	-0.0571	0.0036	Moderate negative
Quarterly Earnings	84.0295	17.7166	1230.734	0.0683	0.0144	Moderate positive
Log New Hires	-0.0353	0.0130	1.546	-0.0228	0.0084	Small negative
<i>Panel B: Heterogeneous (by ARP allocation per capita)</i>						
Log Emp. (High Alloc.)	-0.0694	0.0064	1.491	-0.0465	0.0043	Small negative
Log Emp. (Low Alloc.)	-0.1004	0.0076	1.491	-0.0673	0.0051	Moderate negative

*Notes:* **Country:** United States. **Research question:** Did the American Rescue Plan’s \$24 billion childcare stabilization grants differentially affect female employment in care work industries relative to male employment? **Policy mechanism:** Federal grants disbursed through state CCDF agencies subsidized childcare provider operating costs and worker wages, intended to prevent provider closures and stabilize the care workforce during the pandemic recovery. **Outcome definition:** Log quarterly stable employment (EmpS), quarterly earnings (EarnS), and log quarterly new hires (HirN) from the Census Bureau Quarterly Workforce Indicators. **Treatment:** Binary post indicator (2021Q4 onward) interacted with female and childcare-industry indicators in a triple-difference design. **Data:** QWI Sex  $\times$  Education panel, 50 states, 2019Q1–2024Q3, state  $\times$  industry  $\times$  sex  $\times$  quarter cells (N = 6,810). **Method:** Triple-difference (Post  $\times$  Female  $\times$  Childcare) with cell, industry  $\times$  quarter, and state  $\times$  quarter fixed effects; SEs clustered at state level. **Sample:** Social Assistance (NAICS 624) vs. Manufacturing (311, 332); all private-sector employees; excludes Alaska (data unavailable). SDE =  $\hat{\beta}/SD(Y)$  where  $SD(Y)$  is the pre-treatment standard deviation. Classification refers to magnitude, not statistical significance: Large ( $|SDE| > 0.15$ ), Moderate (0.05–0.15), Small (0.005–0.05), Null ( $< 0.005$ ).