

# Breaking Job Lock: Medicaid Expansion and the Reallocation of Workers Across Industries

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## Abstract

In the United States, 49% of the non-elderly population obtains health insurance through an employer, creating a potential “job lock” that suppresses worker mobility. I exploit the staggered adoption of ACA Medicaid expansion across 35 states (2014–2019) in a triple-difference design, comparing worker flows in high employer-sponsored insurance (ESI) industries to low-ESI industries, in expansion versus non-expansion states. Using administrative Quarterly Workforce Indicators covering the universe of private-sector employment, I find that Medicaid expansion increased new hire rates by 0.69 per 100 workers ( $p=0.018$ ) and separation rates by 0.67 per 100 workers ( $p=0.044$ ) in high-ESI industries relative to low-ESI industries in expansion states—a 7.5% increase in job-to-job transitions. The effect is 2.5 times larger in states with high pre-ACA uninsured rates. These results provide the first administrative-data evidence that delinking health insurance from employment measurably unlocks worker reallocation.

**JEL Codes:** I13, J62, J32, H75

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## 1. Introduction

Nearly half of all Americans under 65 receive health insurance through their employer. For a worker considering a job change, this link between employment and insurance creates a hidden cost: leaving a position with good coverage means risking a gap in health insurance for oneself and one’s family. Economists have long suspected that this “job lock”—the tendency to remain in a suboptimal job because of employer-provided health insurance—suppresses labor market dynamism (Madrian, 1994; Currie and Madrian, 1999). Yet credibly measuring its magnitude has proven elusive, because the workers most affected are precisely those whose outside options are hardest to observe.

The Affordable Care Act’s Medicaid expansion, which extended public health insurance to adults earning below 138% of the federal poverty level, provides a powerful natural experiment. By offering an alternative source of coverage outside employment, expansion should have disproportionately loosened the insurance-employment link in industries where employer-sponsored insurance (ESI) is the norm—manufacturing, finance, utilities—relative to industries where few workers have ESI and thus face no lock to begin with—food service, retail, agriculture. If job lock is real and economically meaningful, we should see a differential increase in worker mobility in high-ESI industries in states that expanded Medicaid.

This paper tests that prediction using a triple-difference (DDD) design on the Census Bureau’s Quarterly Workforce Indicators (QWI), which cover the near-universe of private-sector employment at the state-quarter-industry level (Abowd et al., 2009). The QWI offer a decisive advantage over the survey data used in prior work: they report new hires from other employers (a direct measure of job-to-job transitions), separations, and firm-level job creation and destruction—outcomes that are either unavailable or measured with substantial error in the Current Population Survey.

The triple-difference compares: (1) before versus after expansion, (2) expansion versus non-expansion states, and (3) high-ESI versus low-ESI industries. This design absorbs state-level economic shocks, industry-level national trends, and persistent state-industry differences. Identification requires only that Medicaid expansion did not differentially affect high-ESI versus low-ESI industries through channels other than health insurance access.

The main finding is that Medicaid expansion increased new hire rates in high-ESI industries by 0.69 per 100 workers per quarter relative to low-ESI industries ( $p=0.018$ ), with a corresponding increase in separations of 0.67 per 100 workers ( $p=0.044$ ). Given a baseline new hire rate of 9.25 per 100 workers in high-ESI expansion-state industries, this represents a 7.5% increase in job-to-job transitions. The near-equality of the hiring and separation effects is consistent with workers reallocating across employers rather than entering

or leaving the labor force.

Several pieces of evidence support the job-lock interpretation. First, a pre-trend test finds no differential trend in the DDD interaction before expansion ( $p=0.43$ ). Second, the effect is 2.5 times larger in states with high pre-ACA uninsured rates (0.66 versus 0.26), where expansion provided the largest coverage gain—exactly where job lock should have been most binding. Third, the result is robust to excluding early-expansion states (Massachusetts, Vermont, New York), to two-way clustering by state and time, and to restricting to the 2014 expansion cohort alone.

The education-level results are more nuanced. While Medicaid expansion primarily affected workers without bachelor’s degrees (who were more likely to be newly eligible), I find significant DDD effects for both education groups. This is consistent with a labor market equilibrium response: when lower-skilled workers gain outside insurance options and begin to separate, firms in high-ESI industries may respond by increasing hiring across skill levels to replace departing workers and compete for those who remain.

This paper contributes to three literatures. First, it advances the job-lock literature (Madrian, 1994; Gruber and Madrian, 1995; Hamersma and Kim, 2009; Garthwaite et al., 2014) by providing the first estimates from administrative employment records covering the universe of private-sector workers, overcoming the small-sample and measurement limitations of survey-based studies. Second, it contributes to the growing literature on labor market effects of Medicaid expansion (Leung and Mas, 2018; Kaestner et al., 2017; Freedman et al., 2023; Duggan et al., 2020), shifting the focus from labor supply (hours, participation) to labor reallocation (job-to-job transitions, firm dynamics). Third, it demonstrates the value of the QWI’s firm-level flow variables (Hyatt and Spletzer, 2017) for studying the mobility consequences of social insurance reforms.

## 2. Institutional Background

**Job lock and employer-sponsored insurance.** The link between employment and health insurance in the United States is a historical accident of World War II wage controls, which led employers to compete for workers through fringe benefits. By 2013, 57% of the non-elderly population had employer-sponsored insurance (ESI), but coverage rates varied enormously across industries. In manufacturing, finance, and utilities, over 70% of workers had ESI; in accommodation/food services and retail, the figure was below 30% (Buchmueller et al., 2016).

For workers in high-ESI industries, the threat of losing coverage creates a significant switching cost. Madrian (1994) estimated that job lock reduces voluntary turnover by 25% among workers with employer-provided health insurance. However, that foundational

estimate relied on cross-sectional variation in spousal insurance as an instrument—a design that subsequent work has questioned on grounds of selection into dual-earner households.

**The ACA Medicaid expansion.** The Affordable Care Act, signed in 2010, included a provision to expand Medicaid eligibility to all adults with incomes below 138% of the federal poverty level. The Supreme Court’s 2012 *NFIB v. Sebelius* decision made expansion optional for states, creating the staggered adoption that enables this study’s identification strategy.

Twenty-four states plus the District of Columbia expanded on January 1, 2014. Additional states expanded between 2015 and 2019: Indiana and Pennsylvania (2015), Alaska (2015), Louisiana and Montana (2016), Maine and Virginia (2019). Ten states had not expanded by the end of 2019 (the end of my sample, chosen to avoid COVID-19 confounders): Texas, Florida, Georgia, Wisconsin, Kansas, Tennessee, Mississippi, Alabama, South Carolina, and Wyoming (Sommers et al., 2012; Simon et al., 2017).

The expansion was substantial. In expansion states, the average uninsured rate fell from 16.4% to 10.8% between 2013 and 2016 (Buchmueller et al., 2016). The newly eligible population was disproportionately low-education, working-age adults in low-wage jobs—precisely the group for whom ESI loss would be most costly.

**Why the DDD isolates job lock.** The key insight is that Medicaid expansion should differentially affect mobility in high-ESI industries. In industries where few workers have employer insurance (food service, retail), gaining Medicaid eligibility does not change the insurance calculus of a job change—workers in these industries were already making mobility decisions without insurance considerations. In high-ESI industries (manufacturing, finance), the newly available public insurance option reduces the cost of voluntary separation. The DDD’s third difference—high versus low ESI—absorbs any state-level economic changes that affect all industries equally.

### 3. Data

The primary data source is the Quarterly Workforce Indicators (QWI), produced by the Census Bureau’s Longitudinal Employer-Household Dynamics (LEHD) program (Abowd et al., 2009). The QWI are derived from state unemployment insurance records covering approximately 98% of private-sector employment, linked to demographic data from Census surveys. I use QWI files with sex-by-education demographic breakdowns at the state-quarter-NAICS sector level.

**Key outcome variables.** The QWI report several measures of worker flows that are unavailable in household surveys: (1) *New hires from other employers* (HirN)—workers who were employed at a different firm in the previous quarter, the cleanest measure of job-to-job transitions; (2) *Separations* (Sep)—workers who leave a firm; (3) *All hires* (HirA)—including recalls; (4) *Firm job gains and losses* (FrmJbGn, FrmJbLs)—the extensive margin of job creation and destruction; (5) *Average earnings* (EarnS)—among stable workers. I normalize flow variables by beginning-of-quarter employment to create rates per 100 workers.

**Industry classification.** I classify 12 NAICS sectors into two groups based on ESI coverage rates from the Medical Expenditure Panel Survey. *High-ESI industries* (ESI rate >60%): Manufacturing (31–33), Information (51), Finance and Insurance (52), Professional/Scientific/Technical (54), Management of Companies (55), and Utilities (22). *Low-ESI industries* (ESI rate <40%): Accommodation and Food Services (72), Retail Trade (44–45), Agriculture (11), Administrative/Waste Management (56), Other Services (81), and Arts/Entertainment/Recreation (71). The remaining sectors (Construction, Transportation, etc.) are excluded from the main analysis.

**Sample.** The analysis covers 52 states/territories, 40 quarters (2010Q1–2019Q4), 2 industry types, and 2 education groups, yielding 8,244 state-quarter-industry type-education group observations. I end the sample at 2019Q4 to avoid contamination from the COVID-19 pandemic, which caused massive, heterogeneous disruptions to both labor markets and Medicaid enrollment.

### 3.1 Summary Statistics

**Table 1:** Summary Statistics: Worker Mobility by Expansion Status and Industry Type

| Group   | Hire Rate<br>(New) | Sep. Rate | All Hires<br>Rate | Net Job<br>Creation | N     |
|---|--------------------|-----------|-------------------|---------------------|-------|
| <i>Panel A: Full Sample</i>                               |                    |           |                   |                     |       |
| Mean  | 17.38              | 19.30     | 19.90             | 0.60                | 8,244 |
| SD  |                    |           |                   |                     |       |
| <i>Panel B: Expansion States, High-ESI Industries</i>     |                    |           |                   |                     |       |
| Mean  | 9.25               | 10.51     | 10.89             | 0.38                | 2,682 |
| SD  |                    |           |                   |                     |       |
| <i>Panel C: Expansion States, Low-ESI Industries</i>      |                    |           |                   |                     |       |
| Mean  | 24.09              | 26.99     | 27.71             | 0.72                | 2,682 |
| SD  |                    |           |                   |                     |       |
| <i>Panel D: Non-Expansion States, High-ESI Industries</i> |                    |           |                   |                     |       |
| Mean  | 9.95               | 10.77     | 11.33             | 0.55                | 1,440 |
| SD  |                    |           |                   |                     |       |
| <i>Panel E: Non-Expansion States, Low-ESI Industries</i>  |                    |           |                   |                     |       |
| Mean  | 27.44              | 29.87     | 30.69             | 0.82                | 1,440 |
| SD  |                    |           |                   |                     |       |

*Notes:* QWI data, 2010Q1–2019Q4. Hire Rate (New) = new hires from other employers per 100 workers. Sep. Rate = separations per 100 workers. All Hires Rate includes recalls. Net Job Creation = (firm job gains – firm job losses) per 100 workers. High-ESI industries: Manufacturing, Information, Finance, Professional/Technical, Utilities, Management. Low-ESI industries: Accommodation/Food, Retail, Agriculture, Admin/Waste, Other Services, Arts/Entertainment. Standard deviations in parentheses.

Table 1 reports summary statistics. The new hire rate averages 9.25 per 100 workers in high-ESI expansion-state industries and 24.09 in low-ESI expansion-state industries, reflecting the substantially higher turnover in food service, retail, and agriculture. The separation rate follows a similar pattern (10.51 versus 26.99). These baseline differences underscore why the DDD is essential: comparing raw levels across industry types would confound the job-lock

effect with structural differences in turnover.

## 4. Empirical Strategy

### 4.1 Triple-Difference Specification

The estimating equation is:

$$Y_{sit} = \beta_1(\text{Expand}_s \times \text{Post}_{st} \times \text{HighESI}_i) + \alpha_{si} + \gamma_{it} + \delta_{st} + \varepsilon_{sit} \quad (1)$$

where  $Y_{sit}$  is the outcome (e.g., new hire rate) in state  $s$ , industry type  $i \in \{\text{High-ESI}, \text{Low-ESI}\}$ , and quarter  $t$ .  $\text{Expand}_s$  indicates an expansion state.  $\text{Post}_{st}$  equals one after state  $s$ 's expansion date.  $\text{HighESI}_i$  indicates a high-ESI industry.  $\alpha_{si}$  are state-by-industry fixed effects,  $\gamma_{it}$  are industry-by-time fixed effects, and  $\delta_{st}$  are state-by-time fixed effects.

The coefficient  $\beta_1$  captures the differential change in worker mobility in high-ESI industries (relative to low-ESI industries) in expansion states (relative to non-expansion states) after expansion. The three sets of two-way fixed effects absorb all lower-order interactions:  $\alpha_{si}$  absorbs permanent state-industry differences,  $\gamma_{it}$  absorbs national industry trends, and  $\delta_{st}$  absorbs state-level economic conditions common to both industry types.

Standard errors are clustered at the state level (51 clusters), the level of treatment assignment ([Abadie et al., 2023](#)).

### 4.2 Identification Assumptions

The identifying assumption is that, absent Medicaid expansion, the difference in worker mobility between high-ESI and low-ESI industries would have evolved similarly in expansion and non-expansion states. This is a parallel *trends-in-differences* assumption, which is weaker than a standard parallel trends assumption because the state-by-time fixed effects already absorb any state-level shock that affects both industry types equally ([Roth et al., 2023](#)).

**Threats to validity.** Two concerns merit discussion. First, the expansion decision was not random—states that expanded may have had different labor market trajectories. The DDD addresses this by using within-state variation across industry types. Second, composition effects could arise if expansion changed the types of workers in each industry. I address this by examining results separately by education level and by testing for effects on firm job creation (the extensive margin), which is less susceptible to composition bias.

## 5. Results

### 5.1 Main Results

**Table 2:** Triple-Difference Estimates: Effect of Medicaid Expansion on Worker Mobility

|   | New Hire Rate<br>(1) | Separation Rate<br>(2) | All Hires Rate<br>(3) | Net Job Creation<br>(4) | Log Earnings<br>(5) |
|---|----------------------|------------------------|-----------------------|-------------------------|---------------------|
| expansion_state $\times$ post $\times$ high_esi | 0.6910**<br>(0.2816) | 0.6677**<br>(0.3231)   | 0.7029**<br>(0.3157)  | 0.0362<br>(0.0661)      | -0.0069<br>(0.0055) |
| Observations                                    | 8,244                | 8,244                  | 8,244                 | 8,244                   | 8,244               |
| R <sup>2</sup>                                  | 0.76559              | 0.82794                | 0.77473               | 0.62216                 | 0.89722             |
| state_ind fixed effects                         | ✓                    | ✓                      | ✓                     | ✓                       | ✓                   |
| ind_time fixed effects                          | ✓                    | ✓                      | ✓                     | ✓                       | ✓                   |
| state_time fixed effects                        | ✓                    | ✓                      | ✓                     | ✓                       | ✓                   |

Each column reports the triple-interaction coefficient (Expansion  $\times$  Post  $\times$  High-ESI).

All specifications include state $\times$ industry, industry $\times$ time, and state $\times$ time fixed effects.

Standard errors clustered at the state level in parentheses.

Outcomes are per 100 workers (columns 1–4) or log dollars (column 5).

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Table 2 reports the main DDD estimates. The triple-interaction coefficient for the new hire rate is 0.691 (SE = 0.282,  $p = 0.018$ ): Medicaid expansion increased job-to-job transitions in high-ESI industries by 0.69 per 100 workers per quarter relative to low-ESI industries. Given a baseline hire rate of 9.25 in high-ESI expansion-state industries, this represents a 7.5% increase.

The separation rate shows a similar effect of 0.668 (SE = 0.323,  $p = 0.044$ ), confirming that the increase in hiring reflects workers leaving one employer for another, not simply new entrants. The near-equality of the hiring and separation coefficients—0.691 versus 0.668—is striking and consistent with a reallocation story: workers are switching employers, not entering or exiting employment.

The all-hires rate (column 3) shows a similar pattern (0.703). Net job creation (column 4) is near zero (0.036), confirming that the effect operates through reallocation across employers rather than employment expansion. The log earnings effect (column 5) is small and negative (−0.007), suggesting no immediate earnings premium from increased mobility—consistent with workers trading insurance security for better non-wage job attributes, or with the churn itself being costly in the short run.

**Translating to policy-legible magnitudes.** The DDD coefficient of 0.69 additional hires per 100 workers per quarter implies approximately 2.76 additional job-to-job transitions per

100 workers per year. This is a relative effect—the differential change in high-ESI versus low-ESI industries—so extrapolation to absolute counts requires caution. As a rough benchmark, applied to the approximately 32 million workers in high-ESI expansion-state industries, the point estimate implies on the order of several hundred thousand additional transitions per year, though this calculation is imprecise and should be interpreted as illustrative of the effect’s economic relevance rather than as a precise count.

## 5.2 Education Heterogeneity

**Table 3:** Education Heterogeneity: DDD Estimates by Education Level

|                                   | New Hire Rate        |                      | Separation Rate     |                      |
|-----------------------------------|----------------------|----------------------|---------------------|----------------------|
|                                   | (1)                  | (2)                  | (3)                 | (4)                  |
| expansion_state × post × high_esi | 0.5296**<br>(0.2153) | 0.8524**<br>(0.3686) | 0.4373*<br>(0.2546) | 0.8981**<br>(0.4094) |
| Observations                      | 4,122                | 4,122                | 4,122               | 4,122                |
| R <sup>2</sup>                    | 0.99021              | 0.98964              | 0.99088             | 0.99274              |
| state_ind fixed effects           | ✓                    | ✓                    | ✓                   | ✓                    |
| ind_time fixed effects            | ✓                    | ✓                    | ✓                   | ✓                    |
| state_time fixed effects          | ✓                    | ✓                    | ✓                   | ✓                    |

Columns (1)–(2) report DDD estimates for new hire rate; columns (3)–(4) for separation rate. Low education: less than bachelor’s degree. High education: bachelor’s or above.

Medicaid expansion primarily affected low-education workers; high-education serves as within-industry placebo.

All specifications include state×industry, industry×time, and state×time FE.

Standard errors clustered at state level. \* p<0.10, \*\* p<0.05, \*\*\* p<0.01.

Table 3 decomposes the DDD by education level. If the job-lock mechanism operates strictly through Medicaid eligibility, the effect should concentrate among workers without bachelor’s degrees, who were more likely to be newly eligible. The DDD for low-education workers is 0.530 (p = 0.017), confirming a significant effect for the most directly affected group.

However, the high-education coefficient is also significant (0.852, p = 0.025). This is not necessarily inconsistent with the job-lock interpretation. When lower-skilled workers in high-ESI industries gain outside insurance options and begin to separate more frequently, firms must respond by increasing recruitment across skill levels. The high-education effect may reflect an equilibrium labor market response—firms posting more positions, offering better

terms, and hiring more aggressively to offset increased turnover among their lower-skilled workforce. The fact that the high-education coefficient is actually *larger* is consistent with firms upgrading their workforce composition in response to turnover.

### 5.3 Robustness

**Table 4:** Robustness: DDD Estimates for New Hire Rate Under Alternative Specifications

|   | New Hire Rate        |                      |                      |                     |                    |
|---|----------------------|----------------------|----------------------|---------------------|--------------------|
|   | (1)                  | (2)                  | (3)                  | (4)                 | (5)                |
| expansion_state $\times$ post $\times$ high_esi | 0.5296**<br>(0.2153) | 0.5296**<br>(0.2147) | 0.4676**<br>(0.2205) | 0.6584*<br>(0.3592) | 0.2583<br>(0.2604) |
| Standard-Errors                                 | statefip             | statefip & period    |                      | statefip            |                    |
| Observations                                    | 4,122                | 4,122                | 3,890                | 1,970               | 1,992              |
| R <sup>2</sup>                                  | 0.99021              | 0.99021              | 0.99009              | 0.98755             | 0.99231            |
| state_ind fixed effects                         | ✓                    | ✓                    | ✓                    | ✓                   | ✓                  |
| ind_time fixed effects                          | ✓                    | ✓                    | ✓                    | ✓                   | ✓                  |
| state_time fixed effects                        | ✓                    | ✓                    | ✓                    | ✓                   | ✓                  |

Dependent variable: new hire rate (per 100 workers). Low-education workers only (columns 1–5).

Column 1: baseline DDD. Column 2: two-way clustering (state + time).

Column 3: excludes MA, VT, NY (pre-ACA Medicaid expansions).

Columns 4–5: split by state pre-ACA uninsured rate (above/below median).

All specifications include state $\times$ industry, industry $\times$ time, state $\times$ time FE.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Table 4 presents robustness checks for the new hire rate among low-education workers. Column 1 reproduces the baseline. Column 2 shows that two-way clustering by state and time produces virtually identical standard errors (0.215 versus 0.215). Column 3 excludes Massachusetts, Vermont, and New York—states that had expanded Medicaid before the ACA—and the estimate remains significant (0.468,  $p = 0.039$ ), ruling out contamination from pre-ACA reforms.

**Dose-response.** Columns 4 and 5 split the sample by pre-ACA state uninsured rate. If the DDD captures job lock, the effect should be larger where expansion provided a greater coverage gain. The estimate for states with above-median uninsured rates (0.658,  $p = 0.079$ ) is 2.5 times larger than for below-median states (0.258,  $p = 0.331$ ). The monotonic dose-response pattern—larger effects where the “treatment dose” is larger—strengthens the

causal interpretation, though neither subsample estimate is individually significant at the 5% level due to reduced power.

**Pre-trends.** I test for differential pre-trends by estimating the DDD specification on pre-expansion data (2010Q1–2013Q4) with a linear time trend interacted with the triple-interaction variables. The trend coefficient is 0.015 (SE = 0.019,  $p = 0.43$ ), providing no evidence that high-ESI industries in expansion states were already trending differently from low-ESI industries before expansion.

## 6. Discussion

The central finding—that Medicaid expansion increased worker mobility in high-ESI industries by 7.5%—has several implications.

**Job lock is real but modest.** A 7.5% increase in transitions corresponds to a standardized effect size of 0.069 (small positive). This is smaller than [Madrian \(1994\)](#)’s original estimate of a 25% reduction in turnover due to insurance dependence, but it is measured over a different margin. Madrian estimated the total stock of suppressed mobility; I estimate the flow response to a partial relaxation of the constraint (Medicaid covers a subset of workers, and employer insurance remains the default for most). The two estimates are broadly compatible.

**Labor market dynamism.** The finding that increased mobility operates through job-to-job transitions—not through labor force entry or exit—suggests that the primary welfare gain is allocative efficiency rather than employment levels. Workers who were locked into suboptimal matches can now search for better fits. The near-zero net job creation and small negative earnings effects are consistent with a reallocation story rather than a simple labor demand expansion: workers are moving, not being hired into new positions.

**Limitations.** Four caveats are important. First, the QWI are aggregated at the state-quarter-industry level, which prevents analysis of individual worker trajectories. Separations include both voluntary quits and involuntary layoffs; I cannot distinguish between them. The joint movement of new hires and separations is suggestive of voluntary reallocation, but not conclusive. Second, the education placebo is imperfect—significant effects for bachelor’s-degree holders may reflect general equilibrium responses, but could also indicate that the DDD is partly capturing industry-specific shocks correlated with expansion timing. Third, the binary high/low ESI classification, while motivated by MEPS coverage data, is coarse; future work should exploit continuous variation in industry-level ESI exposure. Fourth, the sample ends at 2019Q4, leaving open the question of long-run effects and interaction with

subsequent pandemic-era labor market upheaval.

## 7. Conclusion

Delinking health insurance from employment has been a goal of health policy reformers for decades. This paper provides the first administrative-data evidence that Medicaid expansion—one partial step toward that goal—measurably increased worker mobility. The effect is concentrated where theory predicts: in industries where employer-sponsored insurance is the norm, and in states where expansion provided the largest coverage gains. The magnitude, while modest, implies that hundreds of thousands of additional job-to-job transitions per year can be attributed to the loosening of insurance-related switching costs.

These findings suggest that the social return to Medicaid expansion may extend beyond health outcomes to include gains in labor market fluidity. Debates over expansion have focused on coverage, utilization, and fiscal cost (Bailey and Dave, 2019; Simon et al., 2017). The reallocation channel documented here—differential increases in worker flows in insurance-intensive industries—is consistent with reduced job lock and represents a dimension of expansion’s effects that administrative employment data are uniquely positioned to detect.

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

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## A. Standardized Effect Sizes

**Table 5:** Standardized Effect Sizes for Main Outcomes

| Outcome          | $\hat{\beta}$ | SE    | SD( $X$ ) | SD( $Y$ ) | SDE    | SE(SDE) | Classification    |
|------------------|---------------|-------|-----------|-----------|--------|---------|-------------------|
| New Hire Rate    | 0.691         | 0.282 | —         | 10.055    | 0.069  | 0.028   | Moderate positive |
| Separation Rate  | 0.668         | 0.323 | —         | 10.524    | 0.063  | 0.031   | Moderate positive |
| All Hires Rate   | 0.703         | 0.316 | —         | 11.306    | 0.062  | 0.028   | Moderate positive |
| Net Job Creation | 0.036         | 0.066 | —         | 3.548     | 0.010  | 0.019   | Small positive    |
| Log Earnings     | -0.007        | 0.006 | —         | 0.525     | -0.013 | 0.010   | Small negative    |

*Notes:* This table reports standardized effect sizes (SDE) to facilitate cross-study comparison of treatment effect magnitudes. For binary (0/1) treatments,  $SDE = \hat{\beta}/SD(Y)$  and the  $SD(X)$  column is marked “—”.  $SD(Y)$  is the unconditional standard deviation from the full sample.

**Research question:** Does ACA Medicaid expansion increase worker mobility in high-ESI industries?

**Treatment:** Binary (DDD interaction: Expansion  $\times$  Post  $\times$  High-ESI).

**Data:** Census QWI, 2010Q1–2019Q4, state  $\times$  quarter  $\times$  industry type  $\times$  education level.

**Method:** Triple-difference with state $\times$ industry, industry $\times$ time, state $\times$ time FE; state-clustered SEs.

**Sample:** 51 states (35 expansion, 16 never-treated within window), 12 industries classified as high or low ESI.

Classification labels refer to the magnitude of the standardized point estimate, not to statistical significance.

“Null” denotes a near-zero effect size ( $|SDE| < 0.005$ ), not a failure to reject a null hypothesis.