Where the CHIPS Fall: Local Labor Market Impacts of Semiconductor Mega-Investments in Maricopa County, Arizona

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Abstract

This paper examines the local labor market effects of mega-scale semiconductor investment, using Maricopa County, Arizona, as a case study. The county has received about $300 billion in commitments through the 2030s under the CHIPS and Science Act of 2022, the largest place-based industrial investment in recent US history. Using synthetic difference-in-differences, we find large employment gains, but few of these gains occur within the manufacturing sector. Semiconductor manufacturing shows no measurable net change, as hiring at new facilities offsets reductions at existing ones. The gains instead concentrate in construction—13 to 33 percent above the synthetic counterfactual—and in supply chain sectors—5 to 46 percent above—which together represent about 9,700 and 7,100 jobs, respectively. More than 80 percent of the latter fall into wholesale trade and technical services rather than manufacturing. We attribute this composition to the high capital-to-labor ratio of semiconductor fabrication and to a scale threshold in supplier relocation.

JEL Classifications: R11, R58, L63

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1 Introduction

This paper examines the local labor market effects of mega-scale semiconductor investment, using Maricopa County, Arizona, as a case study. In the United States, dependence on foreign semiconductor supply has become a critical national security concern. To strengthen domestic competitiveness and supply chain resilience, Congress enacted the CHIPS and Science Act in August 2022, allocating $52.7 billion in direct federal funding alongside an estimated $24 billion in tax provisions for semiconductor manufacturing facilities, research and development, and workforce training (Congressional Budget Office, 2022).[1] Beyond addressing supply chain security, the act reflects a broader federal effort to improve employment opportunities through manufacturing reshoring, creating sustainable pathways to middle-skill, high-wage manufacturing jobs (Muro and Yang, 2023). The legislation culminated years of effort, building on earlier initiatives introduced in 2020 and 2021, during which federal officials also negotiated directly with major chip manufacturers to encourage domestic production (Congressional Research Service, 2023; The New York Times, 2019).

These policy initiatives have spurred large capital commitments. Since 2020, major domestic and foreign semiconductor manufacturers have announced multibillion-dollar investment plans, with individual commitments reaching $265 billion across multiple years (Table A1). This scale substantially exceeds typical manufacturing benchmarks. Indeed, a single commitment of $265 billion surpasses the entire US manufacturing sector's annual capital expenditure, which averaged $174 billion annually during the 2018–2021 period.[2] Two factors account for the magnitude of these commitments. First, the semiconductor industry is inherently capital intensive and highly concentrated, with advanced manufacturing dominated by a handful of global firms. Second, the CHIPS and Science Act provides large financial incentives: $39 billion in direct grants and loans for facility construction and equipment, complemented by a 35 percent (up from 25 percent) Advanced Manufacturing Investment Tax Credit on qualified capital expenditures (Congressional Research Service, 2023; U.S. Code, 2025).

Despite the unprecedented scale of these commitments, there is limited empirical understanding of their impact on local labor markets. Erten et al. (2026) examine labor market impacts across the full set of counties potentially affected by the CHIPS and Science Act, estimating gains per affected county of 110 to 180 jobs in the core semiconductor sector and 140 to 200 jobs in nonresidential construction. The effects of individual mega-scale investments—those exceeding tens of billions of dollars, which are the legislation's primary beneficiaries— remain understudied.

[1]"CHIPS" stands for *Creating Helpful Incentives to Produce Semiconductors*.

[2]Source: US Census Bureau Annual Survey of Manufactures and authors' calculations.

We address this gap in the literature by analyzing Maricopa County, Arizona, which offers two advantages. First, the county has received an extraordinary concentration of semiconductor investment: Taiwan Semiconductor Manufacturing Company (TSMC) is establishing new fabrication facilities (or ”fabs”), and Intel is expanding existing operations. The combined commitments total about $300 billion through the 2030s. This is the largest place-based industrial investment in recent US history and a policy-significant case in its own right. Second, implementation has progressed further in Maricopa County than elsewhere. The new fabs of TSMC and Intel began large-volume production in the fourth quarters of 2024 and 2025, respectively; most of the other announced facilities are still under construction. This advanced timeline allows us to observe labor market adjustments as mega-scale semiconductor investment moves beyond the construction phase.

Our synthetic difference-in-differences (SDID) estimates show substantial employment gains, but few of these gains occur within the manufacturing sector. Nonresidential building construction employment averaged 33 percent above its synthetic counterfactual over the post-treatment period, and building equipment contractors were 13 percent above. Together, they represented about 9,700 additional jobs. Across the eight supply chain sectors we examine, gains range from 5 to 46 percent, totaling about 7,100 jobs. More than 80 percent of the supply chain jobs are in wholesale trade and technical services. Yet semiconductor manufacturing employment shows no measurable net change over the study period, and gains in supply chain manufacturing are small in absolute terms. These effects grew over the post-treatment period as construction advanced and the facilities moved toward production. The implied total employment gains averaged about 16,800 jobs over the post-treatment period (2021:Q2 through 2025:Q4) and reached 26,500 during the final four quarters of the study period (2025:Q1 through 2025:Q4).

Two features of the semiconductor industry account for much of this pattern. Semiconductor fabrication is highly capital intensive, with capital expenditure per worker six times the manufacturing average; thus, a given volume of investment generates few production jobs. The industry also depends on highly specialized suppliers that relocate production only after local operating scale justifies the fixed costs. As a result, the indirect employment the fabs generate takes the form of sales, technical support, and engineering services rather than manufacturing production. A third dynamic is specific to counties with a substantial existing semiconductor presence. TSMC reports employing more than 3,000 workers at its Arizona fab as of early 2025, while Intel reduced its workforce through company-wide restructuring, and our estimate nets the two. The absence of a net effect is therefore specific to counties with a contracting incumbent producer.

Relative to the public funds committed, these employment gains are modest. The federal grants committed to these investments imply a cost of about $550,000 per job as of the 2025:Q1–2025:Q4 period, or close to $1 million once tax credits are included. Both figures are several times the

$22,000–$125,000 range that earlier studies of fiscal stimulus find (Chodorow-Reich et al., 2012; Shoag, 2013; Chodorow-Reich, 2019). Because our estimates cover less than one-quarter of the announced commitment, they describe the construction phase and earliest production rather than the long-run effects of the full investment. The cost per job should therefore decline as production progresses, though it will likely remain above the benchmarks.

Beyond the direct effects, we find suggestive evidence of general equilibrium local multiplier effects (Moretti, 2010, 2011). Employment in three nontradable service sectors—retail trade, accommodation and food services, and other services—rose 3 to 8 percent relative to synthetic controls, while effects in tradable sectors were neutral to modestly negative. Consumer prices and housing prices in Maricopa County grew 4 to 5 percentage points above the synthetic counterfactual. We interpret these patterns as descriptive rather than causal, since some of these sectors were also subject to pandemic-related shocks that we cannot fully distinguish from the investment effects.

This paper contributes to the empirical research on the CHIPS and Science Act's employment effects. Erten et al. (2026) is the only other relevant study to our knowledge. However, our estimates differ in both composition and magnitude from the county-average effects reported in that study. We find no measurable change in semiconductor manufacturing employment, and we find construction gains that are many times larger than the per-county averages in Erten et al. (2026). The scale of investments accounts for much of the difference, suggesting that averaging across recipient counties obscures the effects on the act's primary beneficiaries. The paper also relates to a broader literature evaluating local labor market effects of industrial policy and large public subsidies using quasi-experimental methods (Kline and Moretti, 2014; Criscuolo et al., 2019; Freedman et al., 2023; Hanson and Rohlin, 2024; Garin and Rothbaum, 2025) and to a closely related literature on fiscal multipliers and the employment returns to public spending (Wilson, 2012; Chodorow-Reich et al., 2012; Shoag, 2013; Suárez Serrato and Wingender, 2016; Chodorow-Reich, 2019; Popp et al., 2022).

The remainder of the paper proceeds as follows. Section 2 describes our data and empirical strategy. Section 3 presents the main results and discusses their implications. Section 4 concludes.

2 Method

2.1 Data

We use quarterly employment and wage data from the Bureau of Labor Statistics (BLS) Quarterly Census of Employment and Wages (QCEW), spanning 2015:Q1 through 2025:Q4. The QCEW is an administrative data set derived from unemployment insurance (UI) tax records and covers approximately 95 percent of US employment. It reports employment counts and total quarterly wages at the county-industry-quarter level, with industry classifications detailed to the six-digit North American Industry Classification System (NAICS) code.[3]

Our primary analysis examines 11 sectors across private-sector establishments. Three sectors are directly affected by semiconductor investment: semiconductor and related device manufacturing (NAICS 334413), nonresidential building construction (NAICS 2362), and building equipment contractors (NAICS 2382). Eight sectors are indirectly affected through supply chain relationships: basic chemical manufacturing (NAICS 3251), other chemical product and preparation manufacturing (NAICS 3259), industrial machinery manufacturing (NAICS 3332), architectural and structural metals manufacturing (NAICS 3323), professional and commercial equipment and supplies merchant wholesalers (NAICS 4234), machinery, equipment, and supplies merchant wholesalers (NAICS 4238), chemical and allied products merchant wholesalers (NAICS 4246), and architectural, engineering, and related services (NAICS 5413).

We construct two outcome measures. Average quarterly employment is the mean of monthly employment across the three months of each quarter. Average weekly wages equal total quarterly wages divided by average quarterly employment, then divided by 13 weeks. Both measures are log-transformed and indexed to 2015:Q1: $\tilde{y}_{it} = \ln(Y_{it}) - \ln(Y_{i,2015Q1})$. This indexation does not affect the estimated treatment effects, but it allows clearer visual assessment of the parallel pre-trends assumption.

The BLS suppresses data when publication could reveal information about individual establishments. Suppression is more prevalent at detailed NAICS levels and in smaller counties. We set suppressed values to missing and apply linear interpolation to fill gaps of one to three consecutive quarters, provided the total missing quarters do not exceed seven across the full sample period. This threshold retains counties with sporadic suppression while excluding those with persistent data quality issues. We interpolate about 0.2 percent of county-quarter-industry observations in our sample.

2.2 Empirical Strategy

We estimate the sector-level effects of semiconductor investment on the Maricopa County labor market using the synthetic difference-in-differences estimator of Arkhangelsky et al. (2021). SDID constructs a synthetic control group from a weighted combination of unaffected donor counties $i = 1, \ldots, N_0$, combining the parallel trends framework of difference-in-differences with the optimal weighting of synthetic control methods.

[3]The QCEW excludes self-employed workers, proprietors, and unpaid family workers.

2.2.1 Investment Timeline

The treated unit is Maricopa County, Arizona. Treatment begins in 2021:Q2, corresponding to TSMC's April 2021 groundbreaking of its first fab (Fab 21), which followed the May 2020 investment announcement.[4] This yields $T_0 = 25$ pre-treatment quarters (2015:Q1 through 2021:Q1) and $T_1 = 19$ post-treatment quarters (2021:Q2 through 2025:Q4).

Our post-treatment window captures construction activity from TSMC beginning in 2021:Q2 and from Intel beginning in 2021:Q3, following Intel's March 2021 announcement of Fab 52 and Fab 62. It also captures early-stage production from TSMC's Fab 21 (commencing 2024:Q4) and Intel's Fab 52 (commencing 2025:Q4). It does not, however, capture the remainder of committed investments. TSMC's and Intel's combined investment plans include six fabs and two advanced packaging facilities in Maricopa County through the 2030s (TSMC, 2025, 2024; Intel, 2021a). Our estimates therefore reflect near-term labor market effects during the construction-intensive phase and initial operations rather than long-run effects of the full investment plan.

2.2.2 Donor Pool Construction

We construct the donor pool through a three-stage process. First, we apply geographic and treatment contamination exclusions: (1) Maricopa County's six neighboring Arizona counties (Yavapai, La Paz, Yuma, Pima, Pinal, and Gila), to avoid spillover effects and (2) counties receiving semiconductor investments exceeding $10 billion during the 2020–2025 period, as identified from public announcements in Table A1.

Second, we impose data quality restrictions. Counties must have average employment of at least 100 jobs in the examined sector during the pre–COVID-19 period of 2015 through 2019 to ensure meaningful sectoral activity and no more than seven quarters of suppressed data over the study period to ensure sufficient observations for reliable comparisons.

Third, from the counties satisfying these criteria, we select the 40 donors most similar to Maricopa County in absolute distance in log average employment during the 2015–2019 period in the relevant sector. This matching ensures that donors have comparable sectoral employment scales and limits the overfitting associated with excessively large donor pools.

[4]We define treatment as construction start (2021:Q2) rather than announcement date (2020:Q2). This choice places the pandemic onset and early recovery within the pre-treatment period, enabling the SDID weights to adjust for differential pandemic exposure across counties. To the extent that labor markets responded to the investment announcement prior to construction, our estimates represent a conservative lower bound on the total causal effect.

2.2.3 Estimation Procedure

Following Arkhangelsky et al. (2021), the SDID estimator constructs a synthetic control using two sets of weights. Unit weights $\hat{\omega} = (\hat{\omega}_1, \ldots, \hat{\omega}_{N_0})$ determine the contribution of each donor county, selected to minimize pre-treatment prediction error while encouraging dispersion across donors through L2 regularization. Time weights $\hat{\lambda} = (\hat{\lambda}_1, \ldots, \hat{\lambda}_{T_0})$ identify the pre-treatment periods most predictive of post-treatment outcomes for control units, down-weighting less informative periods. Together, these weights produce a weighted two-way fixed effects difference-in-differences estimator under which parallel trends are more plausible than in standard difference-in-differences.

The estimated average treatment effect on the treated (ATT) is

$$\hat{\tau} = \left(\frac{1}{T_1} \sum_{t=T_0+1}^{T} Y_{\text{Maricopa},t} - \sum_{t=1}^{T_0} \hat{\lambda}_t Y_{\text{Maricopa},t} \right) - \sum_{i=1}^{N_0} \hat{\omega}_i \left(\frac{1}{T_1} \sum_{t=T_0+1}^{T} Y_{it} - \sum_{t=1}^{T_0} \hat{\lambda}_t Y_{it} \right), \tag{1}$$

which measures the difference between Maricopa County and its synthetic counterfactual in average post-treatment growth relative to a time-weighted pre-treatment baseline. We report $\hat{\tau}$ for each of the 11 sectors examined in Section 3.

To assess whether treatment effects evolve over time, we also report the treatment effect averaged over the final four quarters:

$$\hat{\tau}^{\text{final}} = \left(\frac{1}{4} \sum_{t=T-3}^{T} Y_{\text{Maricopa},t} - \sum_{t=1}^{T_0} \hat{\lambda}_t Y_{\text{Maricopa},t} \right) - \sum_{i=1}^{N_0} \hat{\omega}_i \left(\frac{1}{4} \sum_{t=T-3}^{T} Y_{it} - \sum_{t=1}^{T_0} \hat{\lambda}_t Y_{it} \right). \tag{2}$$

Comparing $\hat{\tau}^{\text{final}}$ with $\hat{\tau}$ indicates whether impacts are growing, stable, or declining as the investment progresses.

Because both estimates are expressed in log points, we convert them to employment levels for interpretation. We refer to

$$\bar{Y}_{\text{Maricopa}} = \exp\left(\sum_{t=1}^{T_0} \hat{\lambda}_t \ln Y_{\text{Maricopa},t} \right) \tag{3}$$

as baseline employment: Maricopa County's pre-treatment employment, averaged using the same time weights that the estimator applies. The implied level effect is $\bar{Y}_{\text{Maricopa}} (\exp(\hat{\tau}) - 1)$ and analogously for $\hat{\tau}^{\text{final}}$. Using the estimator's own time weights keeps the level conversion consistent with the ATT. Baseline employment also serves as the weight when we aggregate four-digit sector estimates to the two-digit level in Section 3.

2.2.4 Inference

With a single treated unit, resampling-based inference methods such as bootstrap and jackknife are not applicable, as they require variation across multiple treated units. We therefore construct 95 percent confidence intervals using the placebo-based method of Arkhangelsky et al. (2021), which assumes homoskedasticity across counties. The procedure reassigns treatment at $T_0 + 1$ to each donor county in turn, re-estimates the SDID effect under that placebo assignment, and takes the dispersion of the resulting estimates,

$$\hat{V}_\tau = \frac{1}{N_0} \sum_{i=1}^{N_0} \left(\hat{\tau}_i^{\text{placebo}} - \bar{\tau}^{\text{placebo}} \right)^2, \tag{4}$$

where $\hat{\tau}_i^{\text{placebo}}$ is the estimate obtained when donor i is assigned treatment and $\bar{\tau}^{\text{placebo}}$ is the mean across donors. This yields the interval $\hat{\tau} \pm 1.96\sqrt{\hat{V}_\tau}$.

However, this procedure also imposes normality on the placebo distribution, which a Shapiro–Wilk test rejects in seven of 11 sectors. We therefore report alongside each estimate the permutation p-value of Abadie et al. (2010), which uses only the rank of $\hat{\tau}$ within the placebo distribution. Appendix B reports both, each as one- and two-sided tests; the one-sided tests are against the signed alternative $H_1 : \tau > 0$.

2.2.5 Identifying Assumptions

The key identifying assumption is the absence of time-varying unit-specific confounders: Maricopa County must not experience time-varying shocks during the post-treatment period that (1) are correlated with the semiconductor investment timing, (2) affect labor market outcomes, and (3) cannot be represented as a reweighted combination of shocks experienced by donor counties. SDID removes bias from time-invariant unit-specific factors, such as industrial composition and geographic advantages, and from common time-varying shocks affecting all counties. It cannot, however, adjust for Maricopa County–specific time-varying confounders that diverge from the county's historical relationship with donor counties precisely when treatment begins.

Several features of our setting support this assumption. TSMC's and Intel's investment locations and timing choices appear driven by factors orthogonal to contemporaneous labor market shocks: proximity to existing semiconductor ecosystem partners, availability of large tracts of undeveloped land, and federal policy incentives from the CHIPS and Science Act and its antecedents (Brennan, 2024). Consistent with these factors driving investment choice, pre-treatment trends in the majority of the 11 sectors we examine track the weighted synthetic control closely in the years immediately preceding treatment (see Figures 2–**??**).

The primary threat to identification is COVID-19 pandemic confounding. TSMC began construction in April 2021, coinciding with the pandemic recovery. If Maricopa County's recovery differed systematically from that of donor counties for reasons unrelated to semiconductor investment, such as differential remote-work adoption or pandemic-related migration, our estimates would conflate the investment's causal effect with these confounders.

We conduct two robustness checks to assess COVID-19 confounding. First, we examine whether remote-work adoption systematically affected post-treatment employment growth in the 11 sectors we examine.[5] Using county-level data for areas unaffected by major semiconductor investments, we find no association between remote-work adoption rates and employment recovery in nearly all these sectors. In the isolated exception, the implied bias runs against the effect we estimate rather than generating it. Remote work is therefore unlikely to confound our main estimates. Remote-work adoption does correlate negatively with employment in the broader two-digit professional services sector, in which Maricopa County's higher adoption rates make it difficult to attribute employment patterns to semiconductor spillovers (discussed in Section 3.3).

Second, we test whether differential population growth confounds our employment results. Faster post-pandemic population growth could mechanically increase employment in certain sectors independent of semiconductor investment. Using county-level data for areas unaffected by major semiconductor investments, we estimate the association between the change in net population growth rates and sectoral employment growth.[6] We find associations in a subset of the 11 sectors, but Maricopa County's post-treatment population growth deviated only slightly and insignificantly from its synthetic control—too little to bias the estimates in either direction. Population dynamics therefore do not credibly account for our findings.

These diagnostics cannot rule out confounding, but they narrow the range of alternative explanations. We interpret our estimates as the causal effect of semiconductor investment, conditional on the assumption that no time-varying unobservables specific to Maricopa County emerge at the treatment date beyond what the synthetic counterfactual captures.

3 Results

We organize the results into three categories. We first examine direct employment effects in semiconductor manufacturing and construction sectors, then focus on supply chain effects in manufacturing and service industries. We then present suggestive evidence of general equilibrium spillover effects.

[5]Results are reported in Appendix C.1.

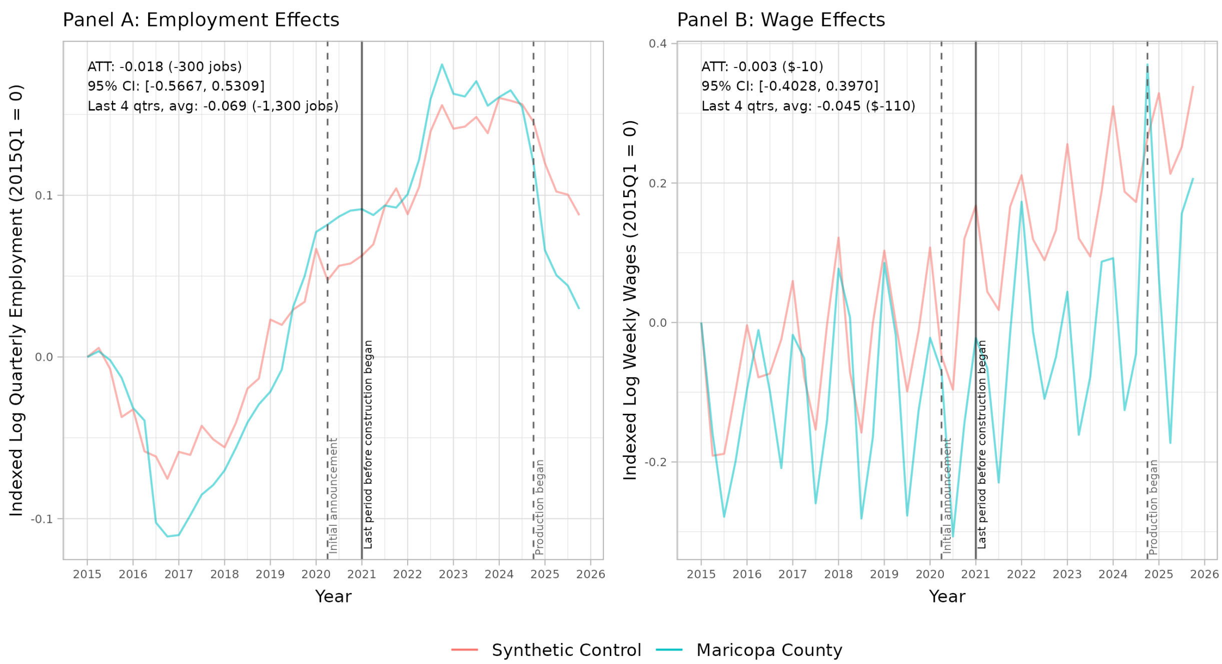
[6]Results are reported in Appendix C.2.

3.1 Direct Effects

Figures 1 and 2 present synthetic difference-in-differences estimates for sectors affected directly by semiconductor investments. Each figure shows log employment and wage trajectories for Maricopa County (blue) versus its synthetic control (red), indexed to 2015:Q1 = 0. We report two treatment effect estimates: the average over the entire post-treatment period ($\hat{\tau}$) and the average over the final four quarters ($\hat{\tau}^{\text{final}}$).

3.1.1 Semiconductor Manufacturing

Figure 1: Estimates for Semiconductor and Related Device Manufacturing



Note(s): This figure shows the employment (Panel A) and wage (Panel B) trajectories for NAICS 334413 from 2015:Q1 through 2025:Q4 for Maricopa County (blue) and its synthetic control (red), constructed via the synthetic difference-in-differences method. The vertical lines indicate key events in the semiconductor investment timeline. From left to right: The leftmost dashed line (2020:Q2) marks the initial investment announcement, the solid line (2021:Q1) represents the final pre-treatment period, and the rightmost dashed line (2024:Q4) marks the start of chip production at the first new fab.
Source(s): QCEW and authors' calculations.

Figure 1 presents results for semiconductor manufacturing (NAICS 334413). Employment in Maricopa County shows no significant divergence from its synthetic control, averaging −0.018 log points (2 percent below counterfactual) over the post-treatment period. By the 2025:Q1–2025:Q4 period, observed employment had fallen 0.069 log points (7 percent) below the synthetic control, corresponding to about 1,300 fewer jobs than the counterfactual predicts. Wage effects mirror this pattern. Average weekly wages showed little divergence from the synthetic counterfactual, at −0.003 log points (less than 1 percent below), though wages in Maricopa County exhibited greater volatility.

Two explanations are consistent with the absence of measurable employment or wage gains: the sector's capital intensity and offsetting dynamics within the local industry. Semiconductor manufacturing creates few jobs per dollar invested. The 2022 US Economic Census puts capital expenditure in the industry at $100,000 per employee compared with $16,000 across all manufacturing. This ratio describes existing operations rather than the marginal effect of new investment, but a gap of that size indicates how little labor semiconductor fabrication requires relative to equipment.

The aggregate effect also masks opposing movements within the county's semiconductor sector. TSMC reported employing more than 3,000 workers at its Arizona fab as of early 2025 (TSMC, 2025), while Intel's Arizona workforce declined from 2024 to 2025 (Intel, 2024a, 2025a; AZ Job Connection, 2025). The estimate nets hiring at the new facilities against contraction at the incumbent. Donor counties followed a similar path over these quarters, with semiconductor employment expanding from 2021:Q2 to 2024:Q2 and then declining through 2025:Q4, so industry conditions likely contributed to the restructuring. Yet our design cannot establish whether the new domestic capacity added under the CHIPS and Science Act contributed to those conditions.

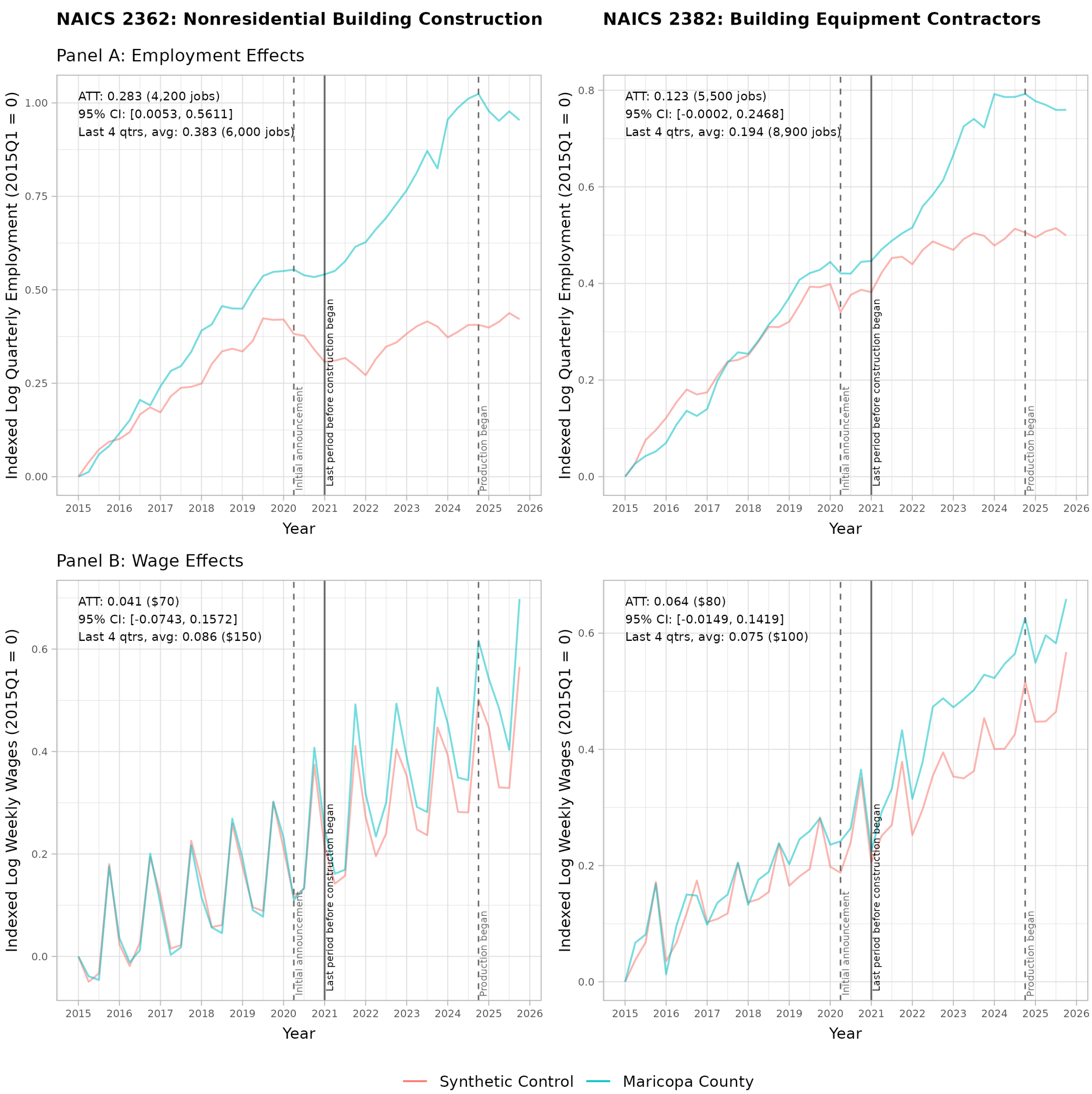
3.1.2 Construction

Although semiconductor manufacturing itself exhibited no net employment change during the study period, the extended construction phase of the fabs generated substantial employment in the construction sector. Figure 2 presents results for the two construction subsectors directly involved in building them: nonresidential building construction (NAICS 2362) and building equipment contractors (NAICS 2382), which install essential systems, including electrical, plumbing, and HVAC infrastructure.

Nonresidential building construction employment in Maricopa County exceeded its synthetic counterfactual by 0.283 log points (33 percent) on average over the post-treatment period, with the effect expanding to 0.383 log points (47 percent) by the 2025:Q1–2025:Q4 period.[7] In levels, these gains correspond to about 4,200 jobs on average and 6,000 jobs in the final quarters. Building equipment contractors exhibited a similar pattern, with employment 0.123 log points (13 percent) above the counterfactual on average and 0.194 log points (21 percent) above in the final period, corresponding to 5,500 and 8,900 additional jobs, respectively. Consistent with rising labor demand, weekly wages in both sectors exhibited stronger growth throughout the post-treatment period, though at

[7]Construction employment gains are not unique to Maricopa County. We apply the same method to five other counties that received semiconductor investments during this period and find positive ATT estimates on nonresidential building construction in all five, though these sites remain in the construction phase and their shorter post-treatment windows yield wide confidence intervals. See Appendix Table A4.

Figure 2: Estimates for Construction Sectors



Note(s): This figure shows the employment (Panel A) and wage (Panel B) trajectories for NAICS 2362 and 2382 from 2015:Q1 through 2025:Q4 for Maricopa County (blue) and its synthetic control (red), constructed via the SDID method. The vertical lines indicate key events in the semiconductor investment timeline. From left to right: The leftmost dashed line (2020:Q2) marks the initial investment announcement, the solid line (2021:Q1) represents the final pre-treatment period, and the rightmost dashed line (2024:Q4) marks the start of chip production at the first new fab.
Source(s): QCEW and authors' calculations.

magnitudes much smaller than the employment effects.

The pre-treatment trajectories for nonresidential building construction warrant comment. The gap between Maricopa County and the synthetic control widened in 2017, before any investment activity, and then remained stable through 2020. The estimated time weights concentrate on 2017 and later, so this earlier shift largely does not affect the comparison baseline. The gap widened again following the initial investment announcements and before groundbreaking. Employment responses may therefore have begun during the planning and permitting stages, in which case our estimates represent a conservative lower bound on the total construction employment impact.

3.2 Supply Chain Effects

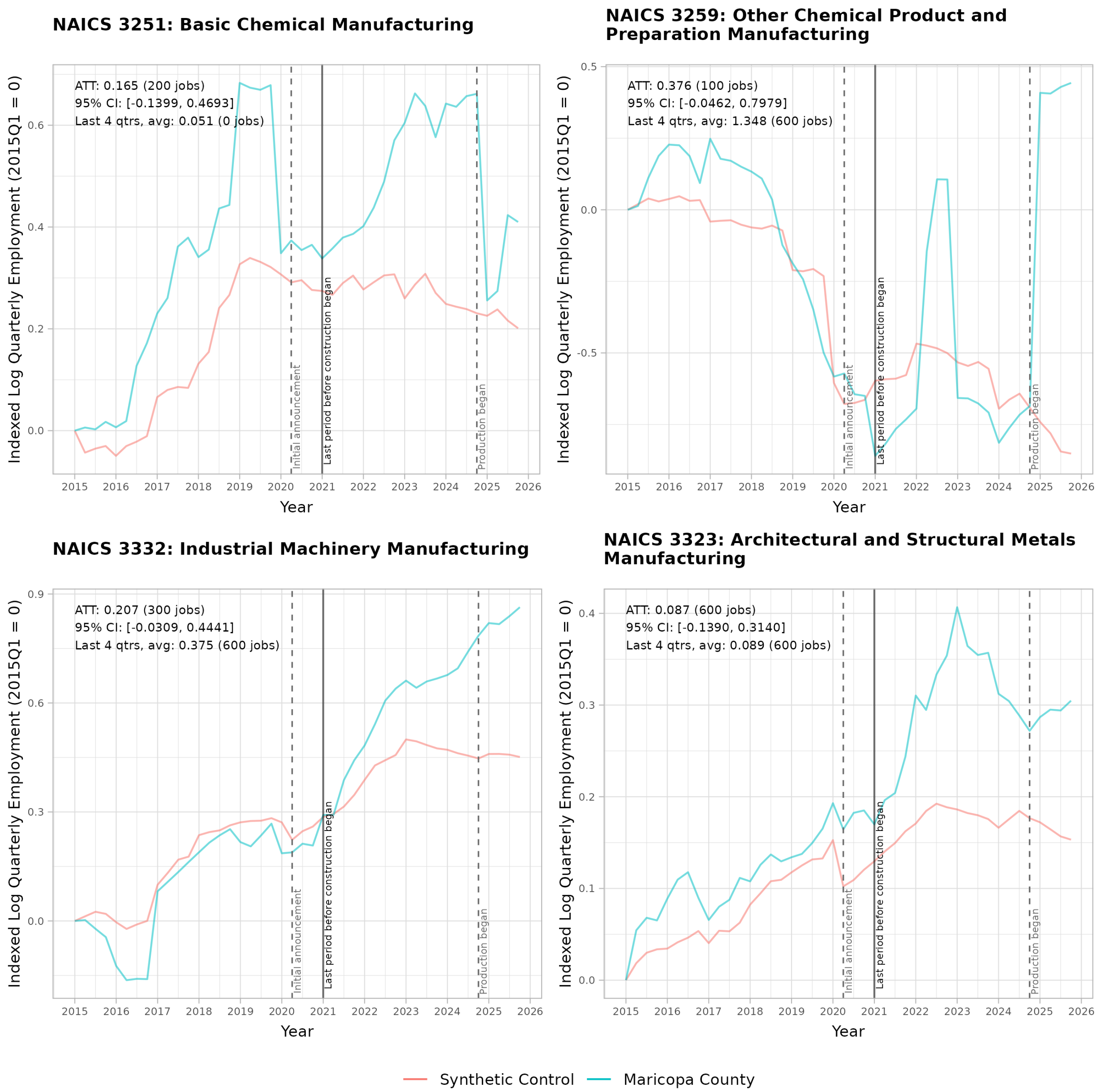
Beyond creating semiconductor manufacturing and construction jobs, establishing fabs requires specialized materials and equipment that may generate demand in local supply chains. Materials and equipment produced locally create employment in the county's manufacturing sector, while those sourced from domestic or international suppliers generate positions in sales and technical services.

To assess these supply chain effects, Figures 3 and 4 present SDID estimates for eight sectors that serve semiconductor manufacturing demand. These sectors span both manufacturing and non-manufacturing industries, with employment outcomes shown for Maricopa County (blue) versus its synthetic control (red).

The estimated employment effects are positive in all eight sectors, consistent with expanding construction and operational activity. Figure 3 shows the four manufacturing sectors: basic chemical manufacturing (NAICS 3251), other chemical product and preparation manufacturing (NAICS 3259), industrial machinery manufacturing (NAICS 3332), and architectural and structural metals manufacturing (NAICS 3323). Figure 4 presents the four non-manufacturing sectors: professional and commercial equipment and supplies merchant wholesalers (NAICS 4234), machinery, equipment, and supplies merchant wholesalers (NAICS 4238), chemical and allied products merchant wholesalers (NAICS 4246), and architectural, engineering, and related services (NAICS 5413).

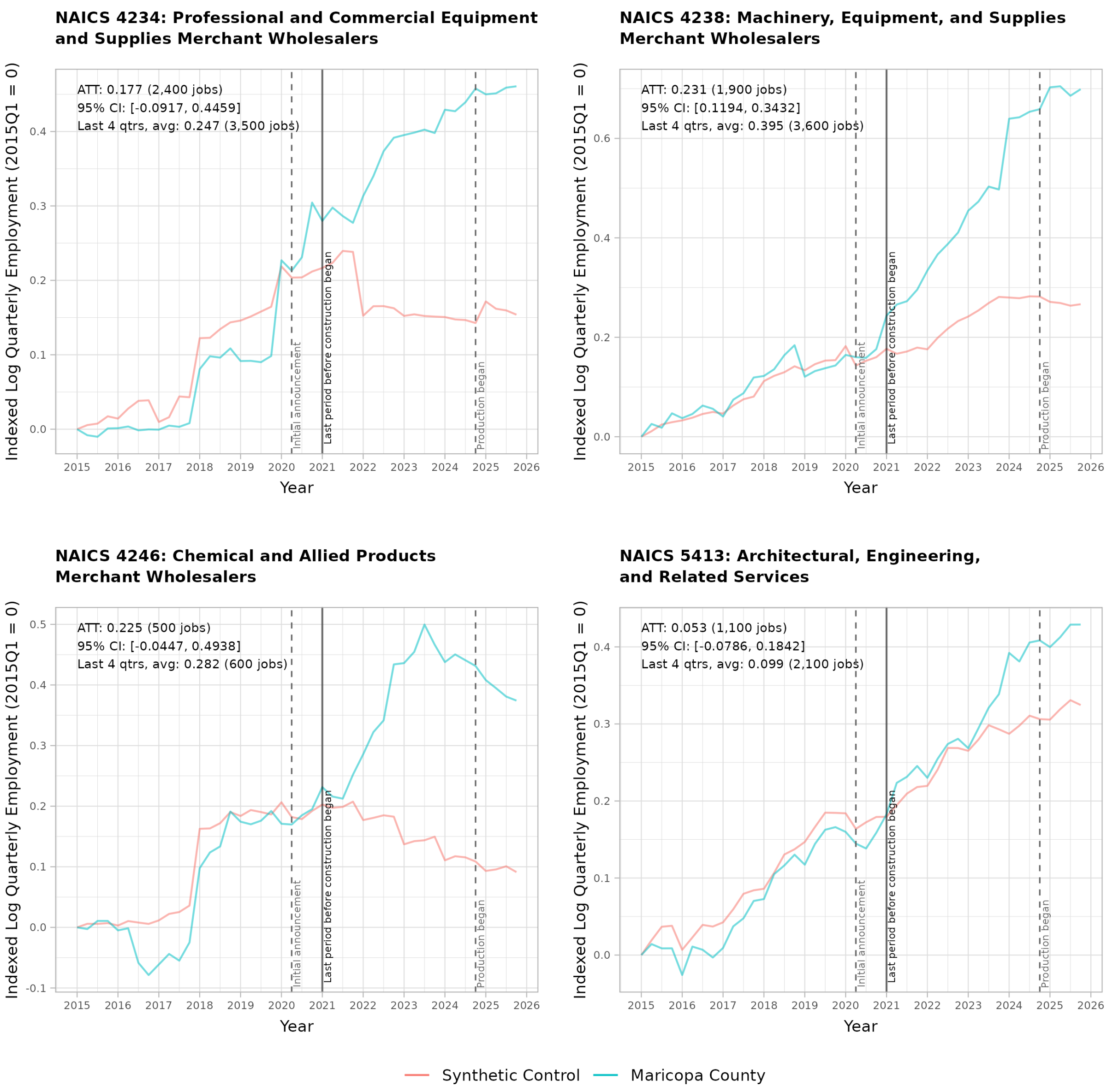
While the estimated effects are of comparable magnitude in log terms across supply chain manufacturing and service sectors, the absolute employment gains are concentrated in service industries due to their larger baseline employment levels. Employment in the four manufacturing sectors increased by 0.087 to 0.376 log points (9 to 46 percent) relative to the synthetic counterfactual in the post-treatment period, corresponding to 100 to 600 jobs per sector. Employment in the four non-manufacturing sectors grew by 0.053 to 0.231 log points (5 to 26 percent), corresponding to larger absolute gains of 500 to 2,400 jobs per sector. Statistical precision varies across these

Figure 3: Estimates for Manufacturing Supply Chain Sectors



Note(s): This figure shows employment trajectories for NAICS 3251, 3259, 3332, and 3323 from 2015:Q1 through 2025:Q4 for Maricopa County (blue) and its synthetic control (red), constructed via the SDID method. The vertical lines indicate key events in the semiconductor investment timeline. The leftmost dashed line (2020:Q2) marks the initial investment announcement, the solid line (2021:Q1) represents the final pre-treatment period, and the rightmost dashed line (2024:Q4) marks the start of chip production at the first new fab.
Source(s): QCEW and authors' calculations.

Figure 4: Estimates for Non-manufacturing Supply Chain Sectors



Note(s): This figure shows employment trajectories for NAICS 4234, 4238, 4246, and 5413 from 2015:Q1 through 2025:Q4 for Maricopa County (blue) and its synthetic control (red), constructed via the SDID method. The vertical lines indicate key events in the semiconductor investment timeline. The leftmost dashed line (2020:Q2) marks the initial investment announcement, the solid line (2021:Q1) represents the final pre-treatment period, and the rightmost dashed line (2024:Q4) marks the start of chip production at the first new fab.
Source(s): QCEW and authors' calculations.

sectors and depends on the inference method. The permutation test rejects the null of no effect against the predicted positive direction in four of the eight sectors, while the more conservative normal-approximation intervals annotated on the figure panels exclude zero in one. Appendix B reports both for each sector.

Trade data support this service-intensive supply chain structure. Arizona's imports from Taiwan in three broad manufacturing categories—chemicals (NAICS 325), fabricated metal products (NAICS 332), and machinery (NAICS 333)—rose relative to other US states following the 2021 investment, reflecting TSMC's established supplier relationships in Taiwan (see Appendix D for import comparisons across states). Imports from a single trading partner capture only a portion of the inputs sourced for the two investments, so we treat this as partial evidence. The pattern is nonetheless consistent with the absolute employment gains accruing predominantly to wholesale distribution and technical services rather than to local manufacturing production. One explanation lies in the industry's supplier structure: Semiconductor fabrication depends on highly specialized suppliers whose relocation requires local operating scale sufficient to justify the high fixed costs of moving production. Until that scale is reached, inputs are imported, and the associated employment accrues to distribution and technical services rather than to local manufacturing.

3.3 General Equilibrium Spillover Effects: Suggestive Evidence

The preceding estimates imply employment gains from fab construction and operation that grew over the post-treatment period. On average, these effects amount to about 9,700 jobs across construction sectors and 7,100 jobs across supply chain sectors, reaching 14,900 and 11,600 jobs, respectively, by the 2025:Q1–2025:Q4 period. These gains represent 1.0 to 1.5 percent of pre-treatment total employment in Maricopa County.

A general equilibrium framework predicts that employment shocks of this magnitude propagate through the local economy along two channels (Moretti, 2010, 2011). Consumption from newly added, higher-paying jobs raises demand for local nontradable services, which generates additional employment. At the same time, higher demand for labor and land raises local costs, which can crowd out employment in tradable sectors without direct investment linkages, since these firms face nationally determined output prices and cannot pass through higher input costs.

Identifying spillover effects on broader sectors, however, presents challenges distinct from those in the preceding analysis. While our diagnostics find no evidence that COVID-19–related confounding biases the construction and specialized supply chain estimates upward (see Appendix C), selected service sectors experienced concurrent post-pandemic shocks that confound identification. Remote-work adoption is one such shock. Maricopa County demonstrated above-average remote-work adoption during the post-pandemic period, and our auxiliary analysis finds that counties with higher remote-work shares experienced slower local employment growth in information (NAICS 51), finance (NAICS 52), and professional services (NAICS 54), sectors in which remote arrangements are more feasible and in which workers face demand competition from high-wage remote employers. Because finance and professional services carry much of the evidence for the crowding-out channel, their negative trajectories in Maricopa County cannot be credibly attributed to semiconductor-related crowding out alone. We read the spillover estimates, particularly those for the crowding-out channel, as suggestive.

Table 1: Employment Effects by Two-digit NAICS Sector (Excluding Semiconductor-related Employment)

Sector (NAICS code)	Weighted ATT
Non-tradable:	
Retail Trade (44–45)	0.052
Accommodation and Food Services (72)	0.032
Other Services (81)	0.073
Tradable:	
Manufacturing (31-33)	0.021
Wholesale Trade (42)	0.044
Information (51)	0.007
Finance and Insurance (52)	-0.038
Professional, Scientific, and Technical Services (54)	-0.058

Note(s): Two-digit NAICS sectors exclude semiconductor-related employment (3344, 2362, 2382, 3251, 3259, 3323, 3332, 4234, 4238, 4246, 5413). For manufacturing (31-33), wholesale (42), finance (52), professional services (54), accommodation/food (72), and other services (81), we report weighted averages of four-digit sector effects. For retail trade (44-45) and information (51), we report direct two-digit estimates.

Table 1 reports treatment effects on employment for major two-digit NAICS sectors. These estimates are weighted averages of SDID effects across four-digit subsectors within each sector, in which weights correspond to pre-treatment baseline employment levels.[8] We exclude subsectors affected directly by semiconductor investment or its supply chain linkages to isolate spillover effects.

Employment effects are positive in the locally oriented nontradable service sectors. Retail trade employment increased 0.052 log points (5 percent) above the synthetic control, while accommodation and food services grew 0.032 log points (3 percent) and other services increased 0.073 log points (8 percent). By contrast, tradable sectors generally exhibited comparable or modestly slower growth relative to the counterfactual, with most effects ranging from −0.058 to 0.021 log points (–6 to 2 percent) across the post-treatment period.

[8]For the retail trade sector (NAICS 44–45) and information sector (NAICS 51), the estimates represent SDID effects estimated directly at the two-digit level, as changes in four-digit classification schemes over time prevent subsector-level analysis.

Wholesale trade is an exception, with employment growth 0.044 log points (4 percent) above the synthetic control. The positive contributions come from subsectors serving local demand: household appliances and electronics wholesalers (NAICS 4236); hardware, plumbing, and heating equipment wholesalers (NAICS 4237); furniture and home furnishings wholesalers (NAICS 4232); and grocery and related products wholesalers (NAICS 4244). Hence, the difference primarily reflects the sector's more localized market orientation.

This divergence between nontradable and tradable sectors is consistent with the two-channel prediction outlined earlier, and local price indexes provide corroborating evidence. As shown in Appendix E, Maricopa County's indexed consumer price level (CPI-U) increased about 5 percentage points above the synthetic control during the post-treatment period, while the FHFA house price index rose 4 percentage points more. Although these price increases cannot be attributed exclusively to semiconductor investment, they are consistent with theoretical predictions that positive labor demand shocks elevate local prices. Such cost increases may erode Maricopa County's historical cost advantages, offering one explanation for the flat to negative tradable-sector estimates reported earlier.

3.4 Discussion

The employment gains from semiconductor investment in Maricopa County fell largely outside manufacturing, and they arrived in sequence. Construction employment rose first and accounts for the largest share of the total. Supply chain employment followed as the facilities began operations, concentrated in wholesale trade and technical services. Direct semiconductor manufacturing employment showed no net change over the period we observe.

3.4.1 Investment Scale and Time Horizon

Our estimates capture only part of Maricopa County's commitment, since two of six committed fabs had begun production by the end of our sample, and direct employment should rise as the others enter production. The operating scale we observe is nonetheless comparable to that of most other semiconductor investments announced in the United States. Because construction employment is temporary, the total gain at a project of this scale should decline once building is complete. The manufacturing employment that remains is limited by the industry's capital intensity, and when a county has an existing semiconductor presence, the net effect also depends on developments at those establishments.

Maricopa County is an exception to that pattern. Its $300 billion commitment exceeds any comparable US project, and less than one-quarter of it has been realized, so construction employment should remain elevated longer than it does at projects of typical size. Local operating scale may also pass the threshold at which specialized suppliers relocate production. The Arizona Commerce Authority, the state's economic development agency, has announced several semiconductor suppliers committing to production facilities in the Greater Phoenix area during our sample period (Arizona Commerce Authority, 2024a, 2026, 2024b, 2025), though these remained at early stages through 2025:Q4 and are too small to register in our estimates. Both the magnitude and the composition of the effects may therefore evolve once the investment is complete.

3.4.2 Fiscal Cost per Job

These employment gains are substantial in absolute terms yet small relative to the public funds committed to these investments. Recent US-based research on fiscal spending multipliers estimates the cost per job created at about \$22,000 to \$125,000 (Chodorow-Reich et al., 2012; Shoag, 2013; Chodorow-Reich, 2019). The US federal government committed \$14.5 billion in direct grants and about \$11.2 billion in tax credits to Intel's and TSMC's Arizona investments through CHIPS and Science Act provisions.[9] Against our estimates, this implies about \$550,000 per job counting grants alone and close to \$1 million counting both. This ratio should decline as investment progresses, but it will likely remain above the benchmarks. These magnitudes reflect the CHIPS and Sciene Act's policy priorities, which center on national security and supply chain resilience rather than employment generation, with job creation representing a co-benefit rather than the principal objective.

4 Conclusion

This paper estimates the local labor market effects of mega-scale semiconductor investment, using Maricopa County, Arizona, as a case study. Applying the synthetic difference-in-differences method, we find that employment gains concentrated outside manufacturing. Semiconductor manufacturing employment shows no measurable change. Construction employment exceeds its synthetic counterfactual by 13 to 33 percent over the post-treatment period, and gains across supply chain sectors range from 5 to 46 percent. Most of the supply chain gains are concentrated in wholesale trade and technical services, while supply chain manufacturing gains are modest in absolute terms. Summed across sectors, the estimates imply about 16,800 additional jobs on average over the post-treatment period, rising to 26,500 by the 2025:Q1–2025:Q4 period.

[9]This tax credit calculation is based on the 35 percent Advanced Manufacturing Investment Tax Credit applied to the first-fab capital expenditures: TSMC's Fab 21 (\$12 billion announced in 2020) and Intel's Fab 52 and Fab 62 (\$20 billion announced in 2021).

Two features of the industry account for much of this composition. Semiconductor fabrication requires little labor relative to capital, which limits direct employment per dollar invested. The industry also depends on highly specialized suppliers that relocate production only when local operating scale justifies the fixed costs, which slows the development of a local manufacturing supply chain. A third dynamic is specific to counties with a substantial existing semiconductor presence. The new facilities hired while Intel reduced its workforce through company-wide restructuring over the same period, and our estimate nets the two.

Our estimates cover less than one-quarter of the announced semiconductor investment and therefore describe the construction phase and early operations rather than the long-run effects of the full commitment. Manufacturing employment should rise as the remaining facilities enter production, both through direct hiring at the fabs and through the supplier relocation that greater local operating scale makes viable. Even so, the committed federal funds per additional job would likely remain high relative to benchmarks from the fiscal stimulus literature. This high cost reflects the CHIPS and Science Act's primary objectives, which center on supply chain resilience rather than job creation. For communities and policymakers evaluating similar investments, the paper's estimates help calibrate expectations for how much direct manufacturing employment such projects will generate and how long those gains will take to appear.

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Appendix

A Major Semiconductor Investment Announcements since 2020

Table A1: Major Semiconductor Manufacturing Investments in the United States

Company	County	State	Initial Amount	Current Amount	CHIPS Grants	Construction Start
TSMC	Maricopa	AZ	$12B (2020)	$265B (2026)	$6.6B	2021Q2
Intel	Maricopa	AZ	$20B (2021)	$32B (2024)	$7.86B	2021Q3
	Franklin	OH	$20B (2022)	$28B (2024)		2022Q3
Samsung	Williamson	TX	$17B (2021)	$40B* (2024)	$4.745B	2022Q1
Micron	Onondaga	NY	$20B (2022)	$250B** (2026)	$6.44B	2026Q1
	Ada	ID	$15B (2022)	$250B** (2026)		2022Q3
Texas Instruments	Grayson	TX	$30B (2021)	$40B (2025)	$1.61B	2022Q2
	Utah	UT	$11B (2023)	$11B (2023)		2023Q4
GlobalFoundries	Saratoga	NY	$11.6B (2024)	$16B (2025)	$1.50B	2025

Note(s): Data compiled from public announcements and CHIPS Act awards. Initial Amount reflects the first publicly announced investment amount; Current Amount shows the commitment to date, including revisions over time. Investment announcements, CHIPS grants and loans, and construction start sources: TSMC (TSMC, 2020; U.S. Department of Commerce, 2026; NIST, 2026e; TSMC, 2026). Intel (Intel, 2021b, 2025b; Intel, 2022; Intel, 2024b, 2022; NIST, 2026a); Samsung (Office of the Texas Governor, 2021a; US Department of Commerce, 2024; NIST, 2026c; Samsung, 2026); Micron (Micron, 2022; Micron, 2026a,b; Idaho Commerce, 2024; Micron, 2022; NIST, 2026b); Texas Instruments (Office of the Texas Governor, 2021b; Texas Instruments, 2022, 2025, 2026, 2023; NIST, 2026d); GlobalFoundries (Office of the New York Governor, 2024; GlobalFoundries, 2025a, 2024, 2025b). CHIPS grants and loans represent federal funding allocated under the CHIPS and Science Act of 2022. *$40 billion allocated to the construction of a new semiconductor site in Williamson with an unspecified portion allocated to the expansion of Samsung's Austin, Texas Fab (US Department of Commerce, 2024). **$250 billion will be distributed across Micron's semiconductors sites in currently unspecified shares.

B Alternative Placebo-based Inference

Table A2 reports inference under two treatments of the same placebo distribution. The first refers $\hat{\tau}/\sqrt{\hat{V}_\tau}$ to the standard normal, following Arkhangelsky et al. (2021); this underlies the confidence intervals annotated on the figure panels in the main text. The second is a permutation p-value similar to Abadie et al. (2010), computed from the rank of $\hat{\tau}$ within the placebo distribution. This statistic cannot fall below $1/(N_0+1)$, or 0.024 with 40 donors, a limit that binds in four sectors on the one-sided test.

The methods diverge because the placebo distributions are non-normal, rejected by a Shapiro–Wilk test in seven of 11 sectors. Six of those seven are left-skewed, with the placebo estimates furthest from the mean belonging to donor counties with pronounced employment declines. Because $\hat{V}_\tau$ weights deviations without regard to sign, these counties widen the interval on both sides, including against a positive estimated effect. The one-sided permutation p-value avoids this because it counts only placebo estimates above $\hat{\tau}$. The two-sided version counts any placebo estimate as far from zero as $\hat{\tau}$, so a large decline in a donor county counts the same as a large increase. In nonresidential building construction, no placebo estimate exceeds $\hat{\tau}$ but two fall below $-\hat{\tau}$, which raises the p-value from 0.024 to 0.073. The skew also widens the normal interval because the standard error is built from squared deviations that the sharply declining donor counties inflate. The normal interval is accordingly wider than the central 95 percent of the placebo distribution in nine of 11 sectors, making the normal approximation the more conservative of the two methods.

This skew leaves inference stable for most sectors but method-dependent at the margin. At the 5 percent level, machinery and equipment merchant wholesalers rejects the null under all four columns, while six sectors, among them semiconductor and related device manufacturing, reject under none. The four remaining sectors are sensitive to the choice of method. Nonresidential building construction and building equipment contractors reject under every column except the two-sided permutation test. Professional and commercial equipment wholesalers and chemical and allied products merchant wholesalers reject only on the one-sided permutation test.

Table A2: Placebo-Based Inference for Sectoral Employment Effects

NAICS	Sector	$\hat{\tau}$	$\sqrt{\hat{V}_\tau}$	95% CI	Normal p-value 2-sided	Normal p-value 1-sided	Permutation p-value 2-sided	Permutation p-value 1-sided
Panel A: Semiconductor and construction sectors								
334413	Semiconductor & related device mfg.	−0.018	0.280	[−0.5667, 0.5309]	0.949	0.525	0.838	0.649
2362	Nonresidential building construction	0.283	0.142	[0.0053, 0.5611]	0.046	0.023	0.073	0.024
2382	Building equipment contractors	0.123	0.063	[−0.0002, 0.2468]	0.050	0.025	0.098	0.024
Panel B: Supply chain sectors								
3251	Basic chemical mfg.	0.165	0.155	[−0.1399, 0.4693]	0.289	0.145	0.146	0.073
3259	Other chemical product mfg.	0.376	0.215	[−0.0462, 0.7979]	0.081	0.040	0.098	0.049
3323	Architectural & structural metals mfg.	0.087	0.116	[−0.1390, 0.3140]	0.449	0.225	0.390	0.220
3332	Industrial machinery mfg.	0.207	0.121	[−0.0309, 0.4441]	0.088	0.044	0.073	0.073
4234	Prof. & commercial equip. whlsl.	0.177	0.137	[−0.0917, 0.4459]	0.197	0.098	0.122	0.049
4238	Machinery & equip. whlsl.	0.231	0.057	[0.1194, 0.3432]	<0.001	<0.001	0.024	0.024
4246	Chemical & allied products whlsl.	0.225	0.137	[−0.0447, 0.4938]	0.102	0.051	0.122	0.024
5413	Architectural & engineering services	0.053	0.067	[−0.0786, 0.1842]	0.431	0.215	0.488	0.317

Note(s): The outcome is log average quarterly employment, with treatment beginning in 2021:Q2. Both methods use the same placebo estimates, obtained by reassigning treatment to each donor county in turn and re-estimating. The donor pool comprises $N_0 = 40$ counties in all sectors except NAICS 334413, in which data quality restrictions yield $N_0 = 36$.

C COVID-19 Confounding: Remote Work and Population Growth

Table A3 presents regression results testing whether differential remote-work adoption or population growth during the post-treatment period confounds our main employment estimates. Both regression samples exclude counties that received major semiconductor investments (those exceeding \$10 billion during the 2020–2025 period) and Maricopa County's six neighboring counties (Yavapai, La Paz, Yuma, Pima, Pinal, and Gila), and each imposes a further restriction on county size described later. We regress quarterly changes in log employment on the interaction between the post-treatment period (2021:Q2 onward) and either (i) the average remote-work adoption rate during the 2022–2025 period or (ii) the change in the county's average net population growth rate between the pre-treatment (2015–2020) and post-treatment (2021–2025) periods.

The regression specification takes the form

$$\Delta \ln(\text{employment})_{it} = \alpha_i + \gamma_t + \beta_1 \text{Confounder}_i + \beta_2 \text{Post}_t + \beta_3 (\text{Confounder}_i \times \text{Post}_t) + \epsilon_{it} \quad \text{(A1)}$$

where α_i and γ_t are county and time fixed effects, respectively. The interaction coefficient β_3 measures whether counties with higher remote-work adoption or a larger change in population growth experienced systematically different employment trajectories in the post-treatment period. A significant coefficient would suggest that Maricopa County's observed employment patterns could reflect these confounders rather than semiconductor investment effects.

Results are reported separately for two sample restrictions: counties with 2015–2019 average population exceeding 200,000 (Sample 1) and the 40 counties closest to Maricopa County by log population distance, mirroring our SDID donor pool construction (Sample 2). Remote-work adoption rates are measured using the Current Population Survey, calculated as the share of workers reporting 35 or more hours of telework per week during October 2022 through December 2025. The population growth confounder is the change in each county's average net population growth rate, computed from the US Census Bureau's annual county population estimates, between the 2015–2020 and 2021–2025 periods.

C.1 Remote-work Adoption and Employment Growth

The remote-work results (columns 1–2) indicate minimal association between remote-work adoption and employment growth in the 11 sectors examined in our main analysis. Ten of the 11 show no statistically significant interaction in either sample. The exception is machinery and equipment wholesalers (NAICS 4238), in which the interaction is negative and significant in both samples, with coefficients of −0.048 and −0.120. Because Maricopa County's remote-work adoption rate exceeds that of comparable counties by about 2 percentage points, a negative interaction implies

Table A3: COVID-19 Confounding: Remote Work and Population Growth Robustness Checks

	Remote-Work Adoption		Population Growth	
NAICS Sector	Sample 1	Sample 2	Sample 1	Sample 2
Panel A: Semiconductor and Construction Sectors				
Semiconductor Mfg (334413)	0.105	−0.085	−0.823	−0.311
	(0.202)	(0.200)	(0.979)	(0.606)
Nonres. Construction (2362)	−0.077	−0.105	0.968*	2.362*
	(0.054)	(0.068)	(0.430)	(1.096)
Building Equipment (2382)	−0.026	−0.043	0.341*	1.038*
	(0.023)	(0.034)	(0.154)	(0.433)
Panel B: Supply Chain Sectors				
Basic Chemicals (3251)	−0.151	−0.348	0.836**	2.500**
	(0.119)	(0.351)	(0.301)	(0.799)
Other Chemicals (3259)	0.015	0.154	1.192	−0.132
	(0.206)	(0.155)	(0.925)	(0.842)
Industrial Machinery (3332)	−0.144	−0.292	1.279*	1.768*
	(0.133)	(0.168)	(0.541)	(0.785)
Struct. Metals (3323)	−0.008	0.009	0.456	0.947
	(0.041)	(0.087)	(0.291)	(0.806)
Prof. Equipment Whls (4234)	−0.038	0.020	−0.242	−0.880
	(0.042)	(0.090)	(0.320)	(0.643)
Machinery Whls (4238)	−0.048*	−0.120**	0.521*	0.979
	(0.022)	(0.037)	(0.204)	(0.551)
Chemical Whls (4246)	−0.061	−0.017	−0.181	0.345
	(0.041)	(0.049)	(0.353)	(0.616)
Arch. & Engineering (5413)	0.000	0.009	0.310	0.508
	(0.028)	(0.039)	(0.185)	(0.547)
Panel C: Selected Two-Digit NAICS Service Sectors				
Wholesale Trade (42)	−0.028**	−0.043***	0.095	0.091
	(0.011)	(0.012)	(0.080)	(0.181)
Retail Trade (44-45)	−0.082	−0.199	0.321	0.779
	(0.065)	(0.117)	(0.172)	(0.552)
Information (51)	−0.183***	−0.180**	1.180***	1.707***
	(0.033)	(0.057)	(0.239)	(0.480)
Finance (52)	−0.050*	−0.068	0.247	0.371
	(0.021)	(0.044)	(0.137)	(0.302)
Professional Services (54)	−0.085***	−0.121***	0.235	0.033
	(0.016)	(0.036)	(0.123)	(0.341)
Accommodation & Food (72)	0.164***	0.061	−1.213***	−1.163**
	(0.046)	(0.060)	(0.205)	(0.418)
Other Services (81)	−0.050	−0.047	−0.401**	−0.942***
	(0.030)	(0.032)	(0.126)	(0.268)

Note(s): This table reports coefficients on the interaction term between post-treatment period (2021:Q2 onward) and the confounding variable, with standard errors in parentheses. The confounder is either the average remote-work adoption rate (columns 1–2) or the change in the county's average net population growth rate between the 2015–2020 and 2021–2025 periods (columns 3–4). Sample 1 includes counties with average 2015–2019 population ≥ 200,000; Sample 2 includes the 40 counties closest to Maricopa County by log population distance. All regressions include county and time fixed effects, are weighted by pre-2020 average sectoral employment, and cluster standard errors at the county level. Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Source(s): Quarterly Census of Employment and Wages (QCEW); Current Population Survey (CPS); U.S. Census Bureau County Population Estimates; and authors' calculations.

that remote work restrained employment growth in this sector rather than raising it, biasing our estimated treatment effect downward. Differential remote-work adoption is therefore unlikely to account for the effects we estimate.

By contrast, several two-digit NAICS sectors exhibit significant negative associations between remote work and employment growth, particularly information (NAICS 51), professional services (NAICS 54), and finance (NAICS 52). For these sectors, Maricopa County's above-average remote-work adoption may have constrained local employment growth independent of semiconductor investment. We therefore interpret the employment results for these sectors with caution and do not attribute the observed patterns solely to semiconductor spillover effects.

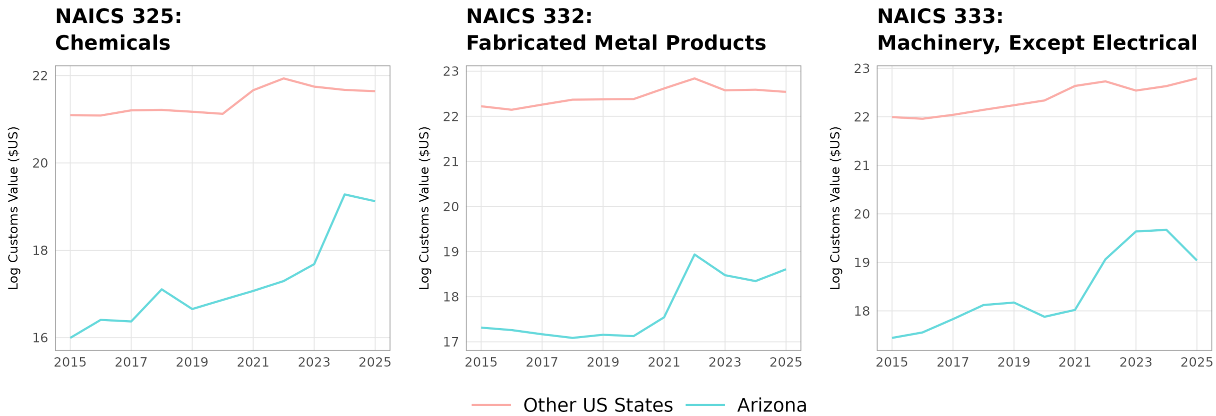
C.2 Population Growth and Employment Growth

The population growth results (columns 3–4) associate faster relative post-pandemic population growth with higher employment gains in construction (NAICS 2362, 2382), basic chemical manufacturing (NAICS 3251), industrial machinery (NAICS 3332), and information (NAICS 51). Accommodation and food services (NAICS 72) and other services (NAICS 81) are the only sectors with a significant negative association, and semiconductor and related device manufacturing (NAICS 334413) shows none. Maricopa County's net population growth slowed relative to its synthetic control over the post-treatment period, but the gap is small. An SDID analysis using the net population growth rate as the outcome returns an ATT of -0.35 percentage points in annual net population growth rate, which cannot be distinguished from zero.[10] Such a small gap can bias the employment estimates by little either way, and in the positively associated construction and supply-chain sectors, it would push them down, not up. Population dynamics are unlikely to account for the employment effects we estimate.

[10]The analysis uses the same donor pool construction as the employment estimates, so the ATT is Maricopa County's post-treatment deviation in the growth rate relative to its synthetic control. The estimate is -0.0035 (SE = 0.0033), not statistically significant.

D Arizona Imports from Taiwan Comparison

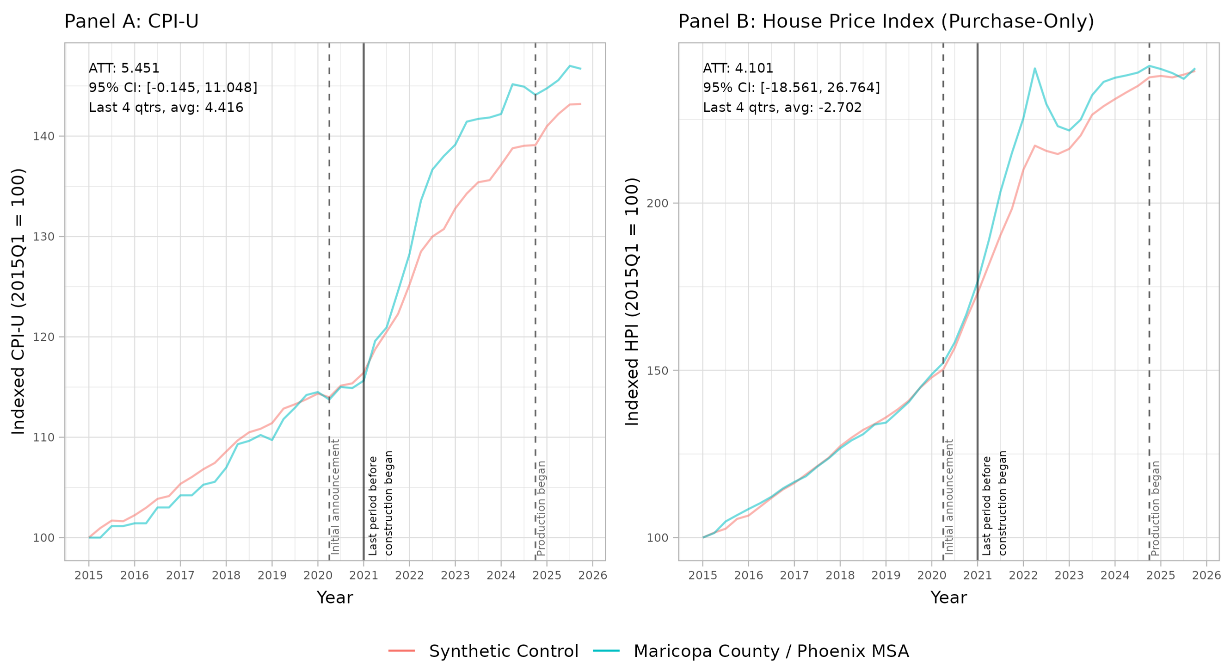
Figure A1: Arizona Imports from Taiwan by Manufacturing Category



Note(s): This figure shows Arizona's imports from Taiwan in three broad manufacturing categories—chemicals (NAICS 325), fabricated metal products (NAICS 332), and machinery (NAICS 333)—relative to other US states following the 2021 semiconductor investment.
Source(s): USA Trade Online and authors' calculations.

E Consumer Price and Housing Cost Dynamics

Figure A2: SDID Estimates for Local Price Indexes



Note(s): This figure shows the trajectories for the Consumer Price Index for All Urban Consumers (Panel A) and the FHFA Purchase-only House Price Index (Panel B) from 2015:Q1 to 2025:Q4 for Maricopa County or the Phoenix-Mesa-Scottsdale metropolitan statistical area (blue) and its synthetic control (red), constructed via the SDID method. The vertical lines indicate key events in the semiconductor investment timeline. From left to right: The leftmost dashed line (2020:Q2) marks the initial investment announcement, the solid line (2021:Q1) represents the final pre-treatment period, and the rightmost dashed line (2024:Q4) marks the start of chip production at the first new fab.
Source(s): US Bureau of Labor Statistics (BLS) Consumer Price Index and Federal Housing Finance Agency (FHFA) Purchase-only House Price Index for metropolitan areas, and authors' calculations.

F Labor Market Impacts in Other Counties Receiving Mega Investments

Table A4 reports SDID estimates for five other counties that received semiconductor investments exceeding $10 billion during the 2020–2025 period. We apply the same estimator and donor pool construction described in Section 2, treating each county as the treated unit and setting the treatment date to the quarter when construction began. Estimates are reported for nonresidential building construction (NAICS 2362), building equipment contractors (NAICS 2382), and semiconductor manufacturing (NAICS 3344), the three NAICS four-digit sectors directly influenced by semiconductor investments.

Construction of the fabs remains underway at all five sites, and, to our understanding, none has begun production during the time examined. The estimates therefore speak to the construction phase alone and are not comparable to our findings for semiconductor manufacturing or the operational supply chain in Maricopa County. Post-treatment windows are also short, between two and four years, which widens the confidence intervals relative to those in the main analysis.

Table A4: Employment ATT and 95 percent Confidence Interval by NAICS Code and County

	Nonres. Construction (2362)	Building Equipment (2382)	Semiconductor Mfg (3344)
Franklin County, OH	0.084 [-0.120, 0.288]	0.027 [-0.097, 0.151]	0.048 [-0.377, 0.473]
Utah County, UT	0.210 [-0.101, 0.522]	-0.076 [-0.265, 0.113]	–
Grayson County, TX	0.236 [-0.094, 0.567]	-0.142 [-0.376, 0.091]	–
Ada County, ID	0.178 [-0.051, 0.407]	0.097 [-0.009, 0.204]	-0.036 [-0.241, 0.167]
Williamson County, TX	0.400 [0.154, 0.645]	0.090 [-0.008, 0.188]	0.099 [-0.284, 0.481]

Note(s): The average treatment effect in log points is shown in the first row for each county; the 95 percent confidence interval is shown in the second row. – indicates that the NAICS code was not analyzed for that county. Treatment start: Franklin County (2022:Q3), Ada County (2022:Q3), Grayson County (2022:Q2), Utah County (2023:Q4), Williamson County (2022:Q1). Saratoga County and Onondaga County are not included due to their construction beginning in early 2025 and 2026:Q1, respectively.