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Employment Impacts of the CHIPS Act

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PRELIMINARY

Abstract

The CHIPS and Science Act, enacted in August 2022, is a key element of the revival of U.S. industrial policy. We examine the short-term employment effects of the act. Using quarterly industry-by-county data from the Quarterly Census of Employment and Wages (QCEW), we implement a difference-in-differences design, comparing counties with pre-existing semiconductor facilities to other counties with high-tech industries. We find that counties with pre-existing facilities experienced significant employment gains in the semiconductor sector relative to other counties with high-tech employment. The effects began at the time of the introduction and passage in the Senate of a precursor bill, in anticipation of the signing of the CHIPS Act. The estimates suggest an increase of approximately 100-140 semiconductor jobs and a $206-232 rise in average weekly wages in the sector in affected counties. We also find positive spillovers on employment in upstream input sectors and non-residential construction, representing an additional 185-225 jobs per county, but limited broader effects on total county employment or county-level GDP. Simple back-of-the-envelope calculations (which come with caveats) suggest total direct employment effects in the semiconductor sector of 14,900-20,860 jobs and total indirect employment effects in related sectors of 27,565-33,525 jobs.

JEL Codes: E24, H25, O25

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1 Introduction

Under the Biden administration, industrial policy underwent a revival in the United States. One of the key elements was the Creating Helpful Incentives to Produce Semiconductors (CHIPS) and Science Act, passed in August 2022, through which the federal government committed tens of billions of dollars to revitalize the domestic semiconductor industry. A main selling point of the act — and, arguably, a key basis of its (once and future) political viability — was that it would create jobs. Has it? How many? In this paper, we provide some of the first empirical evidence on the short-term labor-market impacts of the CHIPS Act. We also examine spillover effects on employment in related sectors and on GDP at the local level.

To examine these effects, we draw primarily on quarterly industry-by-county employment and wage data from the Quarterly Census of Employment and Wages (QCEW), together with information on the locations of semiconductor facilities from the Semiconductor Industry Association (SIA). We compare counties with pre-existing semiconductor production facilities to counties with pre-existing high-tech employment but no semiconductor producers, in a difference-in-differences approach. Our analysis is constrained by data availability: micro-data on individual firms or plants are not yet available for years following passage of the act; the outcomes that we are able to track at a detailed industry-by-county level after the passage of the act are limited; and our main QCEW series currently ends in the fourth quarter of 2024.

Despite the data constraints, it is possible to draw three conclusions about the short-term consequences of the act. First, there were significant anticipation effects. The employment response to the CHIPS Act appears to have begun with the introduction of a precursor act, the United States Innovation and Competition Act (USICA), which first filed in the Senate on May 18, 2021 and passed by a vote of 68-32 on June 8, 2021, with 19 Republican votes. It appears that the industry concluded very quickly that final passage of a semiconductor-support law was very likely and began making employment decisions accordingly. This finding is consistent with previous work on anticipatory responses to increases in U.S. defense spending (Ramey, 2011b).

Second, we find significant short-term impacts of the act on semiconductor employment, with gains in the core semiconductor-production sector and in semiconductor equipment and material manufacturing. Our preferred estimates suggest an increase of 100-140 semiconductor jobs per affected county, depending on the specification, representing a 10-14% increase over baseline semiconductor employment. For wages, we find an average weekly wage increase in the sector of $206-232 in constant 2017 USD terms depending on the specification, over a baseline average of $823 per week in treated counties, representing a 25-28% increase.

Third, we find evidence of spillover effects in sectors that supply material inputs to semiconductor producers as well as in non-residential construction in affected counties. Our preferred estimates suggest that the act generated 53-60 jobs in upstream material-input suppliers and 132-155 jobs in non-residential construction per county. At the same time, it appears that the Act was not large enough to generate detectable aggregate impacts at the county level; we do not find statistically significant county-level effects on total employment or GDP.

It is important to note that our difference-in-difference approach estimates the *relative* impact on counties with pre-existing semiconductor employment compared to counties with high-tech employment but no pre-existing semiconductor presence. Any impact that is common across both treated and control counties is absorbed in the intercept term in our regressions and is not reflected in the difference-in-differences estimate. This is often referred to as the "missing intercept" problem. There is little consensus in the academic literature about how to deal with this issue; the most common approach is to structurally estimate a fully specified macroeconomic model, which is beyond the scope of the current paper. But below we argue, drawing on insights from Chodorow-Reich (2020), that in our setting the spillovers to other counties and to the macroeconomy as a whole are likely to be small and that the aggregate impacts of the Act are reasonably well approximated by simply scaling up the per-county effects. Given that 149 counties are "treated" under our definitions, our per-county estimates suggest total "direct" employment effects of 14,900-20,860 jobs in the semiconductor sector and total "indirect" effects of 27,565-33,525 in related sectors.

A natural question in this context is whether the employment impacts that we estimate should be considered large or small. Summing the "direct" and "indirect" employment impacts, we estimate a total employment effect of 42,465-54,385 jobs. On one hand, given the amounts of money slated to be spent under the Act ($52.7 billion appropriated), this effect seems modest.[1] On the other hand, given the highly capital-intensive nature of semiconductor, one would not have expected enormous employment effects. The sector is among the most capital-intensive in U.S.

[1]Our direct estimate of 14,900-20,860 jobs is below the May 2021 forecast of 42,000 new jobs in the industry of the main industry association (Semiconductor Industry Association and Oxford Economics, 2021).

manufacturing; it relies heavily on extremely sophisticated machinery, clean-room facilities, and advanced automation. It is also worth emphasizing that generating employment was just one of several justifications offered for the Act, along with boosting supply chain resilience and strengthening national security. From this perspective, the employment gains seem larger than many expected.

Another question that our analysis raises is whether the CHIPS Act was designed in the best way to achieve its various objectives. The design issues are complex, and the policy process is subject to many constraints. In Section 8, we raise several conceptual issues that we see as salient, with a view toward improving the design of similar interventions in the future.

Our paper contributes to several strands of literature. First, it adds to a small but growing literature using quasi-experimental approaches to evaluate industrial-policy interventions, which includes Kline and Moretti (2014), Criscuolo, Martin, Overman, and Van Reenen (2019), Freedman, Khanna, and Neumark (2023), and Lane (2025). Juhász, Lane, and Rodrik (2023) provide a recent review.[2] Second, it relates to the expanding body of empirical research on the semiconductor industry, a sector that is widely regarded as strategic (Flamm, 2019; Goldberg, Juhász, Lane, Lo Forte, and Thurk, 2024; Thurk, 2022; Miao, 2024). We are not aware of other academic studies of the regional or employment impacts of the CHIPS Act.[3] Finally, our findings intersect with the broader literature on the local effects of government spending and fiscal multipliers (Ramey, 2011a,b, 2019; Nakamura and Steinsson, 2014; Ramey and Zubairy, 2018; Chodorow-Reich, 2019, 2020; Wolf, 2023). Much of that literature has focused on the effects of defense spending. One contribution of the current study is to show that a sector-focused industrial policy can also boost employment in the targeted industry and related sectors.

The next section provides background on the CHIPS Act and broad trends. Section 3 describes the data used in the analysis. Section 4 presents our empirical strategy, and Section 5 presents the main "direct" results on employment and wages. Section 6 presents "indirect" spillover results in related sectors, and on total employment and GDP at the county level. Section 7 discusses how to aggregate the county-level estimates to an overall, national effect. Section 8 discusses conceptual issues in the design of industrial policies raised by out analysis and Section 9 concludes.

[2] On the theoretical justification for industrial-policy interventions, see e.g. Eaton and Grossman (1986), Harrison and Rodríguez-Clare (2010), Stiglitz and Greenwald (2014), and Liu (2019).

[3] The closest work we are aware of is a lengthy blog post by Politano (2024).

2 Background

2.1 Legislative History

The CHIPS Act had several precursors. The Endless Frontiers Act, a bicameral bill introduced in May 2020 (S. 3832/H.R. 6978), sought to boost investment in high-tech research. In June 2020, Senators Warner and Cornyn introduced the CHIPS for America Act (S. 3933), which proposed $52 billion in direct support for semiconductor investment and manufacturing. These bills were combined into the United States Innovation and Competition Act (USICA), which was introduced by Senator Schumer on May 18, 2021 and passed the Senate by a vote of 68-32 on June 8, 2021. The House version of the Bill, the America COMPETES Act (H.R. 4521), passed on Feb. 4, 2022. The final, amended legislation, named the CHIPS and Science Act, passed the Senate and House on July 27-28, 2022 (by votes of 64-33 and 243-187-1, respectively), and was signed into law by President Biden on August 9, 2022.

From the earliest stages, the Act had bipartisan support. Nineteen Republicans, including Minority Leader Mitch McConnell, voted for USICA in the Senate in June, 2021. The New York Times article on the bill the day after passage described the vote as "lopsided" and "overwhelming" (Edmondson, 2021). One reason was that the Covid-19 pandemic, and related chip shortages, had raised awareness of the need to bolster supply-chain resilience. Another was that both main parties shared concerns regarding Chinese competition in the industry. Press accounts suggested that the bipartisan support for USICA led many observers to have high expectations that a semiconductor-support bill would be passed in some form.

The passage of the CHIPS Act was nearly contemporaneous with the passage of the much larger and more sprawling Inflation Reduction Act (IRA), which aimed to promote investment in clean energy and green technologies and was signed on Aug. 21, 2022. In addition, the $1.2 trillion Infrastructure Investment and Jobs Act (IIJA), also known as the Bipartisan Infrastructure Law (BIL), was signed on Nov. 21, 2021. Distinguishing the employment effects of CHIPS from the effects of these other large spending commitments requires some care; we will return to this issue below.

While the main motivations for the CHIPS Act regarded security and supply chain resilience, various employment-related requirements were included and were widely seen as important to the passage of the legislation. Applicants for CHIPS awards had to meet certain worker and community investment guidelines, which included paying prevailing wage rates to workers and working with regional entities to provide workforce training. These were operationalized in a few ways; one was a requirement that the state and local jurisdictions where the project was located provide incentives, which were considered a signal of local buy-in. Similarly, almost all funding came with requirements for programs to reach economically disadvantaged individuals through workforce development and regional partnerships (NIST, 2023a). For example, many of the workforce training programs were encouraged to provide some form of childcare and projects that applied for more than $150 million in direct funding had to have a plan to provide facility and construction workers with access to child care. This requirement lowered barriers for women entering the workforce.[4] Other requirements of workforce development plans included commitments to skills-based hiring, robust outreach and recruitment plans to ensure a diversity of talent, and sectoral partnerships for skills development (NIST, 2023).

2.2 Details of CHIPS Act

The CHIPS Act allocated funding for a range of semiconductor-related initiatives, building on authorizations provided by the National Defense Authorization Act (NDAA) of 2021, with appropriations detailed in Appendix Table A1. The bulk of the funding, $50 billion, has been channeled through the Department of Commerce, including $39 billion in incentives to support the financing, expansion, and modernization of semiconductor manufacturing facilities, and $11 billion for R&D through programs and institutes such as the National Semiconductor Technology Center (NSTC) and the National Institute of Standards and Technology (NIST). In addition, the Act granted the Department of Commerce up to $75 billion in loan authority. An additional $2 billion was allocated to the Department of Defense to establish a Microelectronics Commons, aimed at advancing microelectronics innovation and leadership in the United States (Blevins, Sutter, and Grossman, 2023).

Funding under the CHIPS Act is provided through grants, loans, loan guarantees, and tax credits, with disbursements tied to recipients' completion of specific project milestones (NIST, 2023a; Department of Commerce Office of Inspector General, 2025). Funding recipients are prohibited from engaging in certain transactions with "foreign countries or entities of concern," notably the

[4]Recent research has found that a 10 percent decrease in the cost of childcare leads to a 0.5 to 2.5 percent increase in maternal employment, which is even higher for low-income mothers; Morrissey (2017) provides a review.

Chinese government, for 10 years following an award. To date, the Department of Commerce's National Institute of Standards and Technology (NIST) has issued eight Notices of Funding Opportunities (NOFOs) across its CHIPS programs, awarding $33.7 billion in direct funding and $5.5 billion in loans through the CHIPS Program Office (CPO) and nearly $8.3 billion through the CHIPS Research and Development Office (CRDO).

The largest NOFO by total award size, the Commercial Fabrication Facilities NOFO, was issued on February 28, 2023, to support the construction, expansion, and modernization of facilities for semiconductor fabrication, wafer manufacturing, and materials production. By the June 18, 2024, application deadline, the CPO received 692 statements of intent, 167 pre-applications, and 92 full applications. As of January 31, 2025, the CPO had made 19 awards under this NOFO, totaling $30.7 billion in direct funding and $5.5 billion in loans. The first awards were finalized in Nov. 2024. Notable awards include $7.9 billion in direct funding to Intel for facility construction and modernization in Arizona, Oregon, and Ohio (the largest direct funding award), and $6.6 billion in direct funding plus $5 billion in loans to Taiwan Semiconductor Manufacturing Corporation (TSMC) for the construction of three advanced chip fabrication facilities in Arizona (the largest combined federal investment). Other recipients of awards exceeding $1 billion include Micron, Samsung, Texas Instruments, and GlobalFoundries.

The CHIPS Act also envisioned support for the manufacturing of semiconductor equipment and materials used in semiconductor production. A NOFO covering these activities was issued on Sept. 29, 2023, and applications were accepted through July 1, 2024. To date, there have been no awards finalized under this NOFO and the status of the submitted applications is unclear. The other six NOFOs issued to date cover various aspects of research and development (R&D) activities. The status of individual NOFOs is detailed in Appendix Table A2.

The Act also included the Advanced Manufacturing Investment Credit (AMIC), administered by the IRS, a tax credit equal to 25% of qualified investments in facilities primarily engaged in the production of semiconductors or semiconductor equipment. The credit applies to projects that begin construction between January 1, 2023, and December 31, 2026, regardless of whether the project receives CHIPS award funding. President Trump's so-called "One Big Beautiful Bill," passed on July 4, 2025, increased the AMIC rate from 25% to 35%, effective December 31, 2025.[5]

[5] For details, see `https://www.congress.gov/bill/119th-congress/house-bill/1/text`

As of this writing, other provisions of the CHIPS Act appear to remain in place and companies that received Preliminary Memoranda of Terms (PMTs) with the CHIPS Program Office appear to remain eligible for finalized awards (Department of Commerce Office of Inspector General, 2025), although it has been reported that the Trump administration is reviewing existing awards and the CHIPS Program Office has seen significant staff cuts (Reuters, 2025; Stone, Potkin, and Lee, 2025).

2.3 Trends in Investment, Employment, and Stock Prices

In this section, before turning to our main estimation strategy, we present a descriptive analysis of the evolution of investment, employment, and stock prices over the study period.

The standard source for manufacturing investment is the U.S. Bureau of Economic Analysis (BEA) series on real private fixed investment in non-residential manufacturing structures. This series is not available at the sector or county level but illustrates broader trends. Figure 1 plots this series over time, by quarter, with the dates of various key events indicated by vertical lines. Private manufacturing investment began rising in mid-2021, at roughly the time that USICA was introduced in the Senate. It rose from \$70 billion per year in 2021Q2 to almost\$150 billion per year by mid-2024. Investment levels plateaued in 2024Q2, at about the time President Biden abandoned his re-election bid. An obvious challenge in interpreting this figure is that the bipartisan infrastructure bill and the IRA were roughly contemporaneous with the CHIPS Act. Our difference-in-differences strategy, explained below, will help to separate the effects of the CHIPS Act from these other laws.

Another way to get a sense of investment trends is to examine reports of purchases of property, plants and equipment reported in semiconductor companies' Securities and Exchange Commission (SEC) 10-K filings, which are available annually.[6] Figure 2 sums these reports for semiconductor firms and plots the total over the 2015-2024 period. There appears to have been an increase in investment in the semiconductor industry starting in 2021 and continuing in 2022. (Note that the 10-K filings cover calendar years, so approximately half of the totals reported for 2021 follow the Senate passage of USICA.) Investment was then relatively flat in 2023 and 2024.

[6]We are grateful to Greg LaRocca of the Semiconductor Industry Association (SIA) for sharing the SIA's collation of these data (which are publicly available). Following the SIA, we include data for the following companies: Akoustis, AMD, Analog Devices, Broadcom, Cirrus Logic, Global Foundaries, Intel, Lattice Semiconductor, Littelfuse, Luminar, Marvell, Microchip, Micron, Nvidia, ONSEMI, Qorvo, Qualcomm, Silicon Labs, Skywater, SkyWorks, Texas Instruments, Western Digital, and Wolfspeed.

Turning to employment, we focus first on the monthly data from the Census Bureau's Current Employment Statistics (CES). The disadvantage of these data, relative to the QCEW data used in the main analysis below, is that they are based on a survey of establishments rather than a census and are noisier (and less suited to the comparison at the county level we conduct below). But the advantages are that they are available on a monthly basis and are available for a more recent period than the QCEW. Figure 3 plots national employment in the semiconductor industry from these data. We see that employment in the sector rose sharply around the time that the USICA passed the Senate in June 2021 and continued to increase until the final signing of the law in Aug. 2022. It then flattened and remained roughly steady until approximately the time President Biden withdrew from the presidential race in July 2024, and declined sharply thereafter.

From Figure 3, it appears that the increase in employment may have begun in May 2021, rather than June, the month the bill was passed. We are not able to make precise statements on the basis of employment data alone, given that the CES data are monthly (and the QCEW data used in our main analysis are quarterly). To get a better sense of the precise timing, we consider the stock market valuation of semiconductor firms, in particular semiconductor firms with production facilities, which stood to benefit from the support envisioned in USICA. The standard way of gauging the stock market reaction is to examine Cumulative Abnormal Returns (CARs) for particular stocks or sets of stocks, in excess of average returns for the broader market (Kothari and Warner, 2007). Figure 4 plots the average cumulative abnormal returns for semiconductor firms with production facilities in the U.S. for 5-day windows around three key dates: May 18, 2021, the day Sen. Schumer introduced USICA in the Senate (late in the day); June 8, 2021, the day USICA passed the Senate; and July 28, 2022, the day the final version of the CHIPS Act passed the House. Appendix Table A3 presents corresponding regression estimates and reports standard errors. There is a clear increase in abnormal returns for semiconductor firms on May 19, 2021. There is little evidence of a stock-market reaction either to the actual passage of USICA on June 8, 2021, or the signing of the CHIPS Act on Aug. 9, 2022. Our interpretation of these patterns is that it was likely already clear on the day of the USICA's introduction that there would be bipartisan support for some form of a law to support the semiconductor industry. In our main analysis below, we will be using quarterly data and the precise timing of reactions to news about the bill will not play an important role. The key point is that the market appears to have formed expectations of forthcoming government support for the industry in roughly this period.

Contemporary press accounts reinforce the view that the early progress toward the CHIPS Act influenced firms' expectations and employment decisions. For instance, in April 2021, Thomas Caulfield, the CEO of GlobalFoundries, a leading producer, told Bloomberg News, "I think the important thing right now is let's get that chips bill funded so that we can accelerate manufacturing capacity in the U.S."[7] Then on July 19, 2021, he held a press conference with Sen. Schumer and Commerce Secretary Gina Raimondo to announce both that the company would expand production at one of its existing facilities in Malta, New York, investing $1 billion and expanding employment by approximately 1,000 workers, and that the company was planning a new fabrication plant at the same site (Moore, 2021). Notably, the company reported that it prioritized building capacity at existing facilities over greenfield investments; Caulfield later told CNBC, "We believe that for economies of scale and the ability to bring capacity online quicker it's better to expand existing facilities."[8] This emphasis on expansion of existing facilities may help to explain the sharp increase in employment beginning in May-June 2021 evident in Figure 3. By contrast, it can take 1-3 years to get new greenfield facilities up and running, although there may be short-term increases in planning/design staff and construction-related employment.

It is worth noting that persistent shortages of chips, especially specialized chips tailored for use in particular products, were part of the motivation for the CHIPS Act and reactions to the shortages could conceivably explain the increase in employment in the industry from May-June 2021 to Aug. 2022. But the timing of the employment changes are difficult to explain by reference to the shortages alone. Acute shortages of chips were already evident by late 2020 (King, Wu, and Pogkas, 2021). It is not clear why companies would have reacted to the shortages by increasing employment only with a 5-6 month lag. In our view, the sharpness of the trend break in May-June 2021, as well as the jump in stock market returns on May 19, 2021, point to the expectation of government support for the industry as the more likely explanation.

3 Data

In our main analysis, we use data from the U.S. Bureau of Labor Statistics (BLS), the U.S. Census Bureau, and the Semiconductor Industry Association (SIA). We focus on the period from 2015Q1 to 2024Q4.

[7]Bloomberg News interview, April 7, 2021, `https://www.youtube.com/watch?v=BeHMuypxHtc`.

[8]CNBC interview, March 23, 2022, `https://www.youtube.com/watch?v=lEETIGM4MG4`.

Our main source of employment and wage data is the Quarterly Census of Employment and Wages (QCEW), published by the BLS, which provides quarterly employment and wages by county and industry. The primary source for the QCEW is administrative data from state unemployment-insurance systems; these are supplemented by responses to two BLS surveys, the Annual Refiling Survey and the Multiple Worksite Report. Employment and wage data are reported by 6-digit North American Industry Classification System (NAICS) industries at various geographical levels, county being the most disaggregated. We focus on QCEW data at the 6-digit industry/county/quarter level, using employment reported in the first month of each quarter. Semiconductor production falls under six-digit category 334413 ("Semiconductor and Related Device Manufacturing"); the corresponding four-digit category (3344) is "Semiconductor and Other Electronic Component Manufacturing." Manufacturers of semiconductor equipment are typically classified under NAICS 333242 ("Semiconductor Equipment Manufacturing") and manufacturers of materials for semiconductors under NAICS 325120 ("Industrial Gas Manufacturing") and 325180 ("Other Basic Inorganic Chemical Manufacturing"), although the latter two clearly include producers of inputs not dedicated to semiconductor production. In some robustness checks, we supplement the QCEW data with information from the Quarterly Workforce Indicators (QWI), published by the U.S. Census Bureau. The QWI data are only available at the 4-digit NAICS level, rather than 6-digit, but contain more information when there are small numbers in a given cell.[9]

The Semiconductor Industry Association's (SIA) U.S. Semiconductor Ecosystem Map catalogs locations across the U.S. conducting research on, designing, and/or manufacturing semiconductors.[10] The SIA is the main trade association and lobbying group for the industry; it represents 99% of the U.S. semiconductor industry by revenue. The Ecosystem Map data are at the facility level, with details about each facility's location, industry segment, activity, and whether or not additional investment has been announced. Facilities are classified by industry segment: manufacturing, chip design, intellectual property (IP) & electronic design automation (EDA), and Research & Development.

[9]When the number of firms in a given cell is small, the QCEW typically suppresses the information and reports a missing value, while the QWI includes "fuzzed" values, with imputed noise. When not suppressed, the QCEW data are thus more accurate (i.e. we know there is no imputed noise) but the QWI data provide information when the QCEW values are suppressed.

[10]The SIA U.S. Semiconductor Ecosystem Map is available at `https://www.semiconductors.org/ecosystem/`. The map was launched in March 2023, and was last updated on March 28, 2024. Accessed on June 4, 2025.

4 Empirical Strategy

A key empirical challenge is to estimate the effects of the CHIPS Act separately from other changes that occurred at roughly the same time, notably the Infrastructure Investment and Jobs Act (IIJA), the Inflation Reduction Act (IRA), and lingering macroeconomic effects of the covid-19 pandemic. Our strategy to address this challenge is a difference-in-differences design, in which we compare counties with a pre-existing semiconductor facility at the time of passage of USICA to those with pre-existing high-tech employment but no semiconductor facility. We refer to the former group as "semiconductor counties" and the latter as "high-tech non-semiconductor counties." The key assumption for this approach to be valid is that the two sets of counties would have had parallel trends in the absence of the CHIPS Act. Under this assumption, deviations in trends in "treated" counties (i.e. semiconductor counties, which presumably stood to benefit from CHIPS funding) from trends in "control" counties (i.e. high-tech non-semiconductor counties) can be attributed to the causal effect of the CHIPS Act.

We implement this strategy in two ways, a simple difference-in-differences and a synthetic difference-in-differences. In the simple approach, we effectively compare unweighted means of the treated and control counties. The specification is the following:

$$Y_{it} = \mu + \alpha_i + \gamma_t + \beta \cdot \text{Treated}_i \cdot \text{Post}_t + \varepsilon_{it} \tag{1}$$

where Y_{it} denotes the outcome of interest (e.g., the level of employment or average wages in semiconductors) in county i and year-quarter t. Treated_i is an indicator equal to 1 for counties with an existing semiconductor facility. The α_i and γ_t are county and year-quarter fixed effects, which absorb all time-invariant county-specific confounding factors and all common temporal shocks, respectively. We cluster standard errors at the county level to adjust for potential serial correlation of outcomes within counties.

We face an important choice in how to define the pre-CHIPS and post-CHIPS periods, embodied in the Post_t variable. Our preferred specification uses the date of passage of USICA, June, 8, 2021, to define pre and post; in this specification, Post_t takes the value 0 from 2015Q1 to 2021Q1, and 1 from 2021Q2 to 2024Q4. We also explore robustness to an alternative specification in which we define the pre-period as pre-USICA and the post-period as post-CHIPS; in this specification,

Post_t takes the value 0 from 2015Q1 to 2021Q2, and 1 from 2022Q3 to 2024Q4, and the quarters 2021Q3-2022Q2 are dropped. Given the likelihood of positive anticipation effects, our preferred definition is the more conservative one. We will see that the results are robust to this choice.

To get a better sense of the timing, we also estimate an "event study" version of the simple difference-in-differences, using the following specification:

$$Y_{it} = \mu + \alpha_i + \gamma_t + \sum_{\tau=2015q2}^{2024q4} \beta_\tau \cdot D_{i,t}^{\tau} + \varepsilon_{it} \tag{2}$$

where Y_{it}, α_i, and γ_t are defined as above and $D_{i,t}^{\tau}$ is an indicator that takes the value 1 if $t = \tau$ and county i has a pre-existing semiconductor facility (i.e. is treated) and 0 otherwise. (We omit the indicator for 2015Q1.) We recover the coefficient estimates β_τ and plot them over time. We would expect the estimates of β_τ corresponding to periods before the Senate passage of USICA to be zero; this is a way to check the parallel trends assumption. An advantage of the event-study-type specification is that it allows us to avoid taking a stand on the definition of pre and post. As in equation (1), we cluster standard errors at the county level.

While the simple difference-in-differences has the virtues of transparency and simplicity, one may be concerned about the assumption of parallel trends between semiconductor and high-tech non-semiconductor counties. To address this concern, we implement a synthetic difference-in-differences (SDID) design (Arkhangelsky, Athey, Hirshberg, Imbens, and Wager, 2021). The idea is that there may exist a weighted average of high-tech non-semiconductor counties that more closely mirrors the pre-treatment outcome trajectory of semiconductor counties and hence more accurately represents the trend that would have been observed in the semiconductor counties post-CHIPS in the absence of the Act. The method retains key advantages of the simple difference-in-differences, such as invariance to additive unit-level shocks and valid inference in large panels. Unlike traditional synthetic-control methods, which minimize differences in pre-treatment levels (Abadie, 2021), the synthetic difference-in-differences minimizes differences in trends, which helps address bias concerns when pre-treatment fit is imperfect and treatment is potentially correlated with unobserved confounders (Ferman and Pinto, 2021). Importantly, both unit and time weights are derived solely from the outcome data, minimizing researcher discretion. Arguably, this design strengthens statistical power while better satisfying the assumption of parallel trends, without requiring subjective decisions about which units or covariates to include (Arkhangelsky et al, 2021).

The SDID procedure solves the problem:

$$\left(\hat{\beta}, \hat{\mu}, \hat{\alpha}, \hat{\gamma}\right) = \underset{\beta,\mu,\alpha,\gamma}{\arg\min} \left\{ \sum_{i=1}^{n} \sum_{t=2015q1}^{2024q4} \left(Y_{it} - \mu - \alpha_i - \gamma_t - W_{it}\beta\right)^2 \hat{\omega}_i \hat{\lambda}_t \right\} \tag{3}$$

where W_{it} is an indicator of treatment, which takes the value of 1 for treated counties in the post-period and 0 otherwise. As above, our preferred definition of post-period is post-USICA, but we explore robustness to different definitions. The weights, $\hat{\omega}_{ij}$ and $\hat{\lambda}_t$, are chosen optimally to minimize trend differences in the pre-treatment periods. The optimal unit-specific weights $\hat{\omega}_i$ (but not the time-specific weights $\hat{\lambda}_t$) are subject to a regularization penalty, which prevents overfitting while increasing the variance and uniqueness of the weights. These features improve the robustness and precision of the SDID estimator (Arkhangelsky et al, 2021). For statistical inference, we rely on a block bootstrap and cluster standard errors at the county level, using the Stata sdid command (Clarke, Pailañir, Athey, and Imbens, 2024). Using the weights from the SDID procedure, we also estimate event-study coefficients with confidence intervals, following Clarke, Pailañir, Athey, and Imbens (2024). Specifically, we compute the difference between treated and control groups in each period, relative to the average difference in the time-weighted pre-treatment period, and again use a block bootstrap to construct confidence intervals. By optimally calculating weights to match pre-treatment outcome trends more closely than in the simple DID, the SDID estimator reduces the risk of attributing spurious differences to treatment (Arkhangelsky et al, 2021) and we prefer it for this reason. Below we start by reporting both the simple DID and the SDID but move to just reporting the SDID for secondary outcomes and robustness checks.

We construct the sets of treatment and control counties as follows. As treatment counties, we select counties that had an existing, private, semiconductor production facility as of the passage of USICA in June, 2021, according to the SIA Ecosystem Map data. We only include counties with production of semiconductors; we exclude counties with facilities identified by SIA as "fabless" or having only R&D activities. As control counties, we select counties with at least 100 employees in high-tech industries, using the list of 11 four-digit NAICS sectors identified as high-tech by the U.S. Census Bureau, and then exclude treatment counties.[11] Below we explore robustness

[11]The four-digit sectors identified by the Census Bureau as high-tech are: Computer and Peripheral Equipment Manufacturing (3341), Communications Equipment Manufacturing (3342), Semiconductor and Other Elec-

to different definitions of high-tech counties, using high-tech employment cutoffs of 0, 1000, or 2000; we will see that the results are not sensitive to this definition.

To illustrate our research design, Figure 5 displays a map of the U.S. with semiconductor and high-tech non-semiconductor counties indicated. By the above definitions, there are 149 semiconductor counties and 796 high-tech non-semiconductor counties. Inconveniently, Connecticut changed from using nine counties to using eight planning regions for statistical purposes in 2024; because of the difficulties in following outcomes over time, we drop Connecticut from the sample. The map highlights the pronounced spatial inequality in the distribution of semiconductor production facilities across the United States. A relatively small number of counties host large-scale fabrication facilities, while most high-tech counties have no semiconductor presence at all. This pattern reflects the industry's tendency toward geographic clustering, where production is embedded in local ecosystems of suppliers, skilled labor, and infrastructure (Goldberg, Juhász, Lane, Lo Forte, and Thurk, 2024).

Table 1 presents summary statistics for the semiconductor (treated) and high-tech non-semiconductor (control) counties. Compared to the high-tech non-semiconductor counties, the semiconductor counties tend to be larger in terms of total employment, to have a higher manufacturing share of employment, and to be less rural. We emphasize again that any time-invariant differences across counties will be captured by the county fixed effects and any common trends over time will be captured by the year-quarter effects. The key question for our design is whether the treated and control counties would have had parallel trends in the absence of the CHIPS Act; to shed light on this question, we examine pre-trends below.

It is worth noting that our difference-in-difference estimates in this paper do not use information on actual grants under the CHIPS Act; they are based on firms' responses to the presumed expectation that they would benefit from financial support under the Act. A reasonable alternative strategy would be to compare counties with firms whose CHIPS awards were finalized and disbursed to counties with semiconductor facilities that did not receive awards — perhaps in particular those counties that received Preliminary Memoranda of Terms (PMTs) from the CHIPS Program Office, a key formal step in the process of receiving awards, but did not receive final ap-

tronic Component Manufacturing (3344) Navigational, Measuring, Electromedical, and Control Instruments Manufacturing (3345), Aerospace Product and Parts Manufacturing (3364), Software Publishers (5112), Data Processing, Hosting and Related Services (5182), Other Information Services (5191), Architectural, Engineering and Related Services (5413), Computer Systems Design and Related Services (5415), and Scientific Research and Development Services (5417). See `https://www.census.gov/programs-surveys/ces/data/public-use-data/experimental-bds/bds-high-tech/methodology.html`; accessed June 30, 2025.

proval. The main difficulty with this alternative strategy is timing, given current data constraints. The first CHIPS awards were not finalized until Nov. 2024 and, as explained above, our current QCEW data end in 2024Q4. Another difficulty is that it is not yet clear whether the firms with PMTs but not final awards as of the end of the Biden administration on Jan. 20, 2025 are still being considered for a final award.[12] While this alternative strategy is not yet feasible, it remains a promising avenue for future research.

5 Results

5.1 Employment Impacts in Semiconductors

To illustrate the main empirical patterns, we begin with event-study-type figures to show the evolution of impacts over time. Figure 6 plots the coefficient estimates from the event-study version of the simple difference-in-differences (equation (2)) for employment in the core semiconductor sector (NAICS 334413), using the QCEW data at the 6-digit level. We see that there is little evidence of differential pre-trends between the treatment (semiconductor) and control (high-tech non-semiconductor) counties prior to 2021, which is reassuring about the parallel trends assumption. Beginning in 2021Q2, when the USICA bill passed the Senate, we see a relative increase in semiconductor employment for five quarters in treated counties, suggesting that semiconductor firms anticipated government funding for domestic semiconductor production. After the CHIPS Act was signed on August 9, 2022, semiconductor employment stabilized. Figure 7 plots the event-study estimates from the synthetic difference-in-differences specification (equation (3)). Again, there are no differential pre-trends and the employment effects with the passage of USICA are clear. The SDID evidence is even stronger than the simple DID. Both specification suggest that the eventual passage of government support for the semiconductor industry was anticipated already in mid-2021, at the time of Senate passage of the precursor USICA bill.

As noted in Section 2.2 above, the CHIPS Act included support for manufacturing of equipment and materials used in the production of semiconductors. Although no awards have yet been issued in these sectors, it is possible that firms anticipated support and expanded employment accordingly. Appendix Figures A1 and A2 plot estimates similar to Figures 6 and 7 for semi-

[12]A third difficulty is that the CHIPS Act provided for tax credits that are not limited to firms approved for awards under the Act, and it may be challenging to distinguish the effects of these credits from the effects of raised expectations of firm-specific awards.

conductor equipment (NAICS industry 333242) and materials (NAICS industries 325120, 325180). There is suggestive evidence of a very short-term impact on employment in these sectors in the SDID, but we cannot reject a zero effect in most quarters.

Table 2 reports estimates of average treatment effects from the simple difference-in-differences specification in equation (1). This specification constrains the post-treatment employment effect to be constant across quarters. In Panel A, pre-period is defined as pre-USICA and post-period as post-USICA. In Column 1, the outcome is the level of employment in semiconductor production; in Column 2, the outcome is the level of employment in semiconductor equipment and materials (pooled); and in Column 3, the outcome is employment in production, equipment and materials combined. Panel B uses the alternative definition of pre- and post-periods as pre-USICA and post-CHIPS. Panel A indicates that semiconductor employment in semiconductor counties increased by 103 workers on average after the USICA was passed (Column 1), or by 139 workers if employment in semiconductor equipment and materials is included (Column 3). The estimates in Panel B are a bit larger (125 and 163, respectively) — perhaps unsurprisingly, given the visual evidence in Figure 6.

Table 3 shows average treatment effects using the synthetic DID approach. The organization of the table is similar to Table 2. The results are also similar. In Panel A, we estimate treatment effects of 108 jobs per county in semiconductor production alone and 123 if we include equipment and materials. In Panel B, excluding the period between USICA and CHIPS, the corresponding numbers are 131 and 142.

Excluding the Table 2 Panel B estimate, which is a bit of an outlier, and including equipment and materials and doing some rounding, the employment results indicate increases of 100-140 jobs per semiconductor county. Relative to the mean employment of approximately 1,000 semiconductor employees (including equipment and materials) per county in treated counties (see Table 1), the job gains represent an increase of 10-14% in semiconductor employment in those counties.

5.2 Wage Impacts in Semiconductors

We next examine the effects on real average weekly wages per worker in the semiconductor sector. The results for wages are not as clear as for employment, but there is suggestive evidence of an impact of CHIPS on this dimension as well. Figures 8 and 9 plot the event-study coefficients for the simple difference-in-differences and the synthetic difference-in-differences, similar to Figures 6 and 7. There is some evidence of differential pre-trends in the simple DID in Figure 6. But once we move to the preferred SDID specification, there is no longer evidence of differential pre-trends and we see a clear relative increase in wages at roughly the time of passage of USICA. Wages remained elevated for most of the post-CHIPS period. Tables 4 and 5 show the average treatment effects using simple DID and SDID approaches, respectively. We focus on the SDID approach, which are our preferred estimates. The point estimates in Panel A of Table 5 (which are more conservative as discussed in Section 4) imply that semiconductor weekly wages increased by \$232 on average after the USICA was passed, or by \$206 if semiconductor equipment and materials sectors are included (Columns 1 and 3). (Comparing the period after the CHIPS Act to pre-USICA, Panel B estimates indicate an average wage increase of \$257 per week in the semiconductor sector, or \$232 including equipment and materials in semiconductors.) Relative to the pre-USICA mean of \$823 per week in semiconductors, these wage changes represent an increase of 25-28% in semiconductor counties.

5.3 Robustness

We assess the robustness of our findings to alternative sample definitions, time-varying county demographics, and allowing for differential trends associated with rural share of population at the county level. Panel A of Appendix Table A4 shows that the average treatment effects on semiconductor employment for the post-CHIPS period remain consistent when controlling for time-varying county gender, race/ethnicity, and age composition, including the share of county population that is female, White, Black, Asian, Hispanic, and ages 0-19, 20-24, 25-34, 35-44, 45-54, and 55-64. Panel B indicates that the estimates are robust to restricting the sample to counties with at least 1, 500, or 1,000 high-tech employees in 2015, instead of the 100-worker threshold used in the baseline specification. Panel C controls for the 2010 rural share of county population interacted with period fixed effects to account for potential differential effects in employment trends associated with baseline rural composition. The results remain consistent. Appendix Table A5 conducts the same robustness checks for real weekly wages per worker in the semiconductor sector. The results remain robust to these alternative specifications. In Appendix Figures A3-A4 and Appendix

Tables A6-A7, we report results similar to Figures 6-7 and Tables 2-3 at the 4-digit level, using a combination of QCEW and QWI data. (As noted in Section 3 above, the QWI has fewer cells with missing values, which could conceivably affect the results.) The results are broadly consistent with the results for the 6-digit QCEW data above.

6 Local Spillover Effects

In this section, we examine the local spillover effects of the CHIPS Act on related sectors as well as on total county employment and county GDP. We focus on upstream suppliers in the same county as semiconductor production facilities. Semiconductor production facilities are typically embedded within regional ecosystems that include suppliers of components such as printed circuit boards, electronic connectors, capacitors and resistors, plastics films, industrial gases and nonferrous metals. These inputs are often highly customized for chip production, and the need for just-in-time delivery and close coordination encourages suppliers to co-locate with the fabrication facilities. SIA's Ecosytem Map (described above), U.S. government program documents (NIST, 2023b), and industry and consultant accounts (Semiconductor Industry Association and Boston Consulting Group, 2021; McKinsey & Company, 2025) all indicate that such co-location is common.[13]

To determine the list of sectors that supply material inputs to semiconductor production, we use the Bureau of Economic Analysis (BEA) input-output tables.[14] The input sectors we consider are the following: nonferrous metal (except aluminum) smelting and refining (NAICS 331410), printed circuit assembly (electronic assembly) manufacturing (NAICS 334418), bare printed circuit board manufacturing (NAICS 334412), capacitor, resistor, coil, transformer, and other inductor manufacturing (NAICS 334416), electronic connector manufacturing (NAICS 334417), other electronic component manufacturing (NAICS 334419), plastics packaging film and sheet (including laminated) manufacturing (NAICS 326112), unlaminated plastics film and sheet (except packaging) manufacturing (NAICS 326113), computer terminal and other computer peripheral

[13]For example, industrial bulk gases such as nitrogen, hydrogen, CO2, and helium or argon are typically piped directly from nearby gas producers to the fabrication facilities (McKinsey & Company, 2025). While some inputs are sourced from further away, we do not have access to data on the geographic origins of inputs, and we are not able to estimate non-local spillover effects using our difference-in-differences strategy. Given that our estimates do not take into account spillovers at longer distances, they are likely to be underestimates of the total spillover effects on upstream suppliers.

[14]In particular, we use the BEA "Use" table available at `https://apps.bea.gov/industry/Release/XLSX/IOUse_After_Redefinitions_PRO_Detail.xlsx`.

equipment manufacturing (NAICS 334418), instrument manufacturing for measuring and testing electricity and electrical signals (NAICS 334515), and commercial and industrial machinery and equipment (except automotive and electronic) repair and maintenance (NAICS 831100). While manufacturing of semiconductor equipment (NAICS 333242), industrial gases (NAICS 325120) and other basic inorganic chemicals (NAICS 325180) may also have been affected by spillovers from semiconductor production, they were also in part targeted directly by the CHIPS Act as part of the semiconductor supply chain; for this reason, we do not include them in the set of "spillover" sectors.

In Figure 10, we sum employment in the material-input sectors and estimate an event-study version of the synthetic difference-in-differences, similar to Figure 7 above. There is more cause for concern here about pre-trends than for the semiconductor sector in Figure 7. In particular, there was an increase in employment in these related sectors in semiconductor counties in 2018Q1 which persisted until the start of the covid pandemic in 2020Q2. But the figure is certainly suggestive of a post-USICA effect on employment in these sectors. When we constrain the treatment effect to be constant in the post-period in Column 1 of Table 6 we see a significant effect on employment (marginally significant in Panel B) in these input sectors.

Another local industry that may be affected by greater demand from the semiconductor sector is construction. Figure 11 shows SDID estimates for employment in non-residential construction. Here we also see a significant rise following the passage of USICA, with the upward trend continuing after the CHIPS Act was enacted. Columns 2 and 3 of Table 6, constraining the post-treatment effect to be constant, are consistent with the figures and show a highly statistically significant effect.

Despite these notable increases in employment in material-input sectors and non-residential construction, we are not able to detect an effect of CHIPS on overall employment or GDP in treated counties. As shown in Figure 12, there is no evidence of a significant relative increase in total county employment following the passage of either USICA or CHIPS. We see a relative decline in total employment in semiconductor counties in the second quarter of 2020, which persists for several quarters and appears to be related to the covid-19 pandemic. It is possible that the pandemic had a greater negative effect on employment in the treated counties because they are more urban (refer to Table 1) and were more affected by high infection rates and the ensuing lockdowns. Whatever the effect of covid-19 may have been, Figure 12 does not support the hypothesis of a county-level employment effect of CHIPS. Column 3 of Table 6 presents the corresponding regression estimates. The point estimate is negative. The effect is imprecisely estimated and the 95% confidence interval (in the Panel A specification) includes positive employment effects as large as approximately 3,000 jobs per county (on a baseline mean of approximately 300,000 jobs per county — i.e. a 1% effect). But overall we interpret the results as suggesting that the CHIPS Act subsidies were not large enough to have an economically significant impact at the county-aggregate level.

For county-level GDP, we find a similar non-result. The available county-level GDP numbers are from the BEA, which publishes data annually but not quarterly. For this analysis, we extend the sample back to 2010, in order to have more data in which to match pre-trends. As shown in Figure 13, the event-study estimates reveal no evidence of significant changes in total county GDP. The corresponding regression estimates are in Column 4 of Table 6 likewise show no significant effects. Like for county employment, we interpret the results as suggesting that the CHIPS Act was not large enough to have meaningful effects on aggregate economic activity at the county level, at least over the short-term time horizon we are able to focus on.

7 Estimates of Aggregate Effects

As noted above, our difference-in-difference approach estimates the *relative* impact on counties with pre-existing semiconductor employment compared to counties with high-tech employment but no pre-existing semiconductor presence. Part of the *absolute* impact of the CHIPS Act on aggregate employment in the entire sample of counties may be absorbed in the intercept term in our regressions. This is often referred to as the "missing intercept" problem. There is an ongoing debate in the academic literature about what can be inferred about aggregate impacts from relative impacts in such approaches. See, for example, Nakamura and Steinsson (2014), Ramey (2019), Chodorow-Reich (2019, 2020), Wolf (2023), and Moll and Hanney (2025). The most widely accepted strategy for characterizing aggregate impacts is to write down and structurally estimate a fully specified model of the macro-economy (as for instance in Nakamura and Steinsson (2014)), which is beyond the scope of the current paper. Nonetheless, it is possible to draw some tentative conclusions based on the reduced-form evidence we have presented.

Chodorow-Reich (2020) very usefully draws a distinction between several causal effects that one may want to estimate: the difference-in-differences effect, which he calls β^{DID}; the true effect of a program on a treated region only, β^{micro}; the economy-wide impact of a local shock, $\beta^{\text{all regions}}$; and the aggregate impact of an aggregate shock, β^{agg}. Differences between β^{DID} and β^{micro} arise if there are spillovers between treated and control regions (counties in our application) — in technical terms, if assignment of one county to treatment affects the potential outcomes under treatment and control of other counties, i.e., if there are violations of the Stable Unit Treatment Values Assumption (SUTVA). Differences between β^{micro} and $\beta^{\text{all regions}}$ arise if spillovers between regions aggregate to a substantial shock, even if spillovers between particular regions are small on average. Differences between $\beta^{\text{all regions}}$ and β^{agg} arise if other aggregate variables (including monetary policy) respond to the shock.

Following arguments in Chodorow-Reich (2020), we contend that the differences between these effects are likely to be small in our context, and that the aggregate direct and indirect effects on employment in our context can be plausibly summarized by simply multiplying our per-county estimates by the number of treated counties. First consider spillovers between treated and untreated areas, in our case between semiconductor and non-semiconductor counties. Chodorow-Reich (2020) argues that in settings with geographical units the size of U.S. states or smaller and demand shocks that do not induce factor mobility, the difference between β^{DID} and β^{micro} can usually be safely ignored. Although we do not directly observe migration flows, the very limited semiconductor employment in untreated counties (refer to Table 1) and hence the limited potential for within-sector factor mobility from untreated to treated counties, as well as the limited effects we estimate on total employment at the county level, all suggest that this argument applies in our setting.

Next, consider the aggregate effects of treatment of one county, which may give rise to a difference between β^{micro} and $\beta^{\text{all regions}}$ even if between-county spillovers are small on average. Chodorow-Reich (2020) argues that if factors do not move in response to the program, as we have asserted above, then the demand spillover effects of a program or shock are unambiguously positive and the county-specific estimate, β^{micro}, provides a lower bound on the aggregate effect, $\beta^{\text{all regions}}$. Again, this argument appears to apply in our setting. It is also worth noting that we do not detect effects on total employment or GDP at the county level. This suggests that the aggregate effects of the program are probably very limited and hence that β^{micro} is quite close to $\beta^{\text{all regions}}$, not just that the former provides a lower bound for the latter.

Turning to the difference between $\beta^{\text{all regions}}$ and β^{agg}, we note that the CHIPS Act expenditures were quite small relative to the size of the U.S. economy and hence seem unlikely to have induced changes in monetary policy or other macroeconomic variables. The $52.7 billion in funding appropriated for spending under the Act, which did not start flowing until Nov. 2024, well after the employment increases we observe, pales in comparison to the spending forecasted under the IRA or the defense spending that has been the focus of much of the related academic literature (Ramey, 2011b; Nakamura and Steinsson, 2014). This suggests that there is unlikely to be a large difference between $\beta^{\text{all regions}}$ and β^{agg} in our setting.

A final piece of evidence comes from the times-series variation we observe in aggregate semiconductor employment we observe in Figure 3, based on unprocessed data from the Current Employment Survey (CES).[15] Estimating level effects from a single time series is often challenging, but in this case it is evident that total employment was relatively flat, at approximately 185,000, in the two years before the USICA introduction in May 2021 and then relatively flat again, at approximately 203,000, in the two years after the final signing of the CHIPS Act in Aug. 2022. This suggests an impact of the CHIPS Act on aggregate semiconductor employment of approximately 18,000 jobs.

When we scale up our county-specific employment impacts to the national level, we get a range of estimates very similar to this time-series estimate. We have 149 treated semiconductor counties. Simply multiplying out per-county estimate of 100-140 semiconductor jobs by the number of treated counties, we get a range of 14,900-20,860 jobs. It is striking that the time-series estimate falls very near the middle of this estimated range. This supports our argument that both the “micro” (between particular counties) and “macro” (from one county to macroeconomy) spillovers appear to be small in this setting. We make no claim that this is generally true for government spending — the current setting is special in that we focus on a single, small (relative to the size of the county economies) spending program in a particular industry — but it does suggest that in our case the simple approach of multiplying the per-county effect by the number of treated counties gives a reasonable estimate of the aggregate employment effect.

[15]We focus on the CES data because it is available at monthly frequency and covers a more recent period than the QCEW, the patterns in the two datasets are similar.

The range calculated above, 14,900-20,860, refers to what we call the direct effect of the CHIPS Act on aggregate employment in the semiconductor industry. To derive an estimate of the indirect effect of the Act on related sectors, we simply multiply the per-county indirect effect range estimated above, 185-225 per county, by the number of treated counties (149) to get a range of 27,565-33,525 jobs. Summing the direct and indirect ranges, we get a range of 42,465-54,385 jobs in total.

While we do not observe actual CHIPS spending (on which we have incomplete data as explained above) and therefore cannot compute a traditional fiscal multiplier, our findings of significant employment gains in semiconductor-intensive counties align with the broader literature showing that targeted public investment can stimulate local labor markets (Ramey, 2011a). Our findings complement earlier work such as Nakamura and Steinsson (2014), who estimate large regional multipliers using variation in military spending, and Chodorow-Reich (2019), who synthesizes cross-sectional and panel estimates of local multipliers, highlighting the importance of labor market slack, industrial structure, and labor mobility. Our results support the notion that well-targeted federal investments — particularly in high-tech tradable sectors — can generate positive employment effects, extending the multiplier logic to the arena of industrial policy.

8 Design Issues

A natural question that our analysis raises is whether the CHIPS Act was well designed, given its various objectives. Would the impacts on employment have been larger if it had been designed differently? One could pose a similar question for output and, more broadly, economic efficiency and welfare, which (in part because of data constraints) have not been our focus here. How could the provisions of the Act be modified to improve these outcomes, and how should similar interventions be designed in the future? To address these questions, we need to step briefly out of the realm of quasi-experimental policy evaluation to consider some theoretical issues.

One important design issue is whether to use Pigouvian subsidies (which incentivize investment by any firm that chooses to undertake it) or targeted grants (for particular, selected firms). Although the CHIPS Act included a provision for investment tax credits, a form of Pigouvian subsidy, the majority of the funds were earmarked for direct grants, for which firms had to apply and be approved by the CHIPS Program Office. On this dimension, there is a contrast in the design of the CHIPS and IRA programs, with the latter largely based on tax benefits.

The targeted-grants approach has several advantages relative to the tax-credit approach. One is less uncertainty about the fiscal burden. As the IRA has demonstrated, even though the expansion of renewable energy that these credits induced may well be socially desirable, uncapped tax credits create substantial fiscal uncertainty.[16] Another arguable advantage of the targeted-grants approach is that it is more transparent; it is often difficult to ascertain which firms are benefiting from the tax credits. In addition, tax credits are often ill-suited to supporting new entrants with little taxable income; the ability to support new entrants is another potential advantage of the targeted-grants approach. Finally, it can be shown theoretically that when redistribution is a social goal and there are multiple market failures and the government has limited instruments for redistribution, it may desirable to use multiple instruments, including regulation, non-linear taxes and subsidies, and targeted grants, in addition to, or in place of, Pigouvian subsidies; (Stiglitz, 2019) provides a discussion in the context of emissions regulation.

But the targeted-grants approach also has some potential disadvantages. One is related to the fact that estimating the returns to investment is difficult and the approaches differ in who bears the burdens of mistakes. In the case of tax credits, a greater share of the costs of overestimates are typically borne by the investors, rather than the public. A second disadvantage of targeted grants is that the discretion associated with the evaluation of projects opens up the possibility of political capture. This is the standard argument for a restriction to a rules-based allocation mechanism.[17] Of course, a country with good governance can construct administrative procedures that reduce the likelihood of abuse, and in a country with poor governance, a government unconstrained by democratic norms will find some way of abusing not just industrial policies, but virtually any other policy, including bank regulation and monetary policy. Nevertheless, it is important to recognize that political capture is a real concern.

A second important design issue is whether and how the government should claim a share of the upside potential of incentivized investments, an issue that is front-and-center of policy

[16]Initial estimates indicated that the IRA would include approxiately $369 billion in spending on climate- and energy-related funding (Dennis, 2022), but subsequent analyses suggested that spending could rise to $1.2 trillion or more (Della Vigna and others, 2023).

[17]There is, of course, discretion in the choice of rules and their interpretation and enforcement. A thoroughly corrupt administration can abuse both systems with perhaps equal ease. Rules-based systems are, however, more constraining for normal governments complying with democratic norms.

debates in light of the Trump demanding 10% of the value of Intel in exchange for CHIPS Act subsidies. On one hand, such claims can help to defray the costs to taxpayers and insisting on participating in the upside potential may also deter unbridled rent seeking. On the other hand, there is again a conflict here between rules-based systems and discretion, with the discretion associated with the Trump Administration stake in Intel, but not other companies receiving CHIPS subsidies, providing a notable recent example. If market investors behave in a risk averse manner in areas subject to industrial policy, then loans combined with warrants (i.e. options to purchase at a set price at a later date) may be a superior way for government to share in the risk than taking an ownership share, and may avoid some of the problematic issues arising out of government control/ownership.

A third important design issue is the extent to which social policy should be embedded in industrial policy. The CHIPS Act carried a number of requirements for provision of childcare, paying of prevailing wages, and provision of workforce training. Are these sorts of provisions appropriate to include in a law like the CHIPS Act? In our view, there are two ways of looking at these requirements. One is to see them as an "experiment," combining the experiment of a new industrial policy with that of a social policy experiment, showing the way for a new economic model that differs from that which would emerge from the market on its own. The other is that these provisions are part of the complex political process by which policies are set. One set of actors believes that all firms should be required to pay higher wages, but opposition means that legislation to that effect cannot be passed. Another set of actors is concerned with the risks to the economy of excessive dependence on Taiwan for semiconductors. Politics is the art of compromise, and while the embedding social goals in industrial policy might admittedly pose problems for intellectual consistency — if we really believe it is desirable to have childcare, it is not clear why should we limit the requirement to just the semiconductor industry —– the compromise is pragmatic and necessary, especially so given legitimate sensitivities among some quarters about government subsidizing firms that do not engage in good labor market practices.

The CHIPS Act is not the only model for industrial policy, nor would we argue that it got every design feature exactly right. There are many issues (e.g. the role of procurement policies) that we have not touched on here. There remains much to be learned and, more than in many other policy arenas, the devil is in the details. But we do believe that the short-term impacts we have presented provide some grounds for optimism about the longer-term impacts of the CHIPS Act and of other industrial policies. We note that among the countries that have been most successful in development, industrial policies have often been central. The hope is that the US, which has not openly engaged in industrial policies in the past (though it has effectively had such policies, typically buried in the defense or energy departments) can learn from both the successes and failures elsewhere to design an efficient and effective strategy.

9 Conclusion

This paper provides early empirical evidence on the labor market impacts of the CHIPS Act, focusing on semiconductor-producing counties in the United States. Our estimates suggest an increase of approximately 100-140 semiconductor jobs per county in counties with existing semiconductor production facilities compared to those with high-tech sector employment but no such facilities. We also find an increase of a \$206–232 in average weekly wages in the semiconductor sector in affected counties, In addition, we estimate indirect employment gains in upstream input sectors and non-residential construction of 185-225 jobs per affected county. Back-of-the-envelope calculations, which come with caveats as discussed above, suggest that the CHIPS Act directly created to 14,900-20,860 semiconductor jobs in treated counties and indirectly created 27,565-33,525 jobs in related sectors in the same counties. At the same time, there is limited evidence of impacts on total county employment or GDP.

Our findings suggest that industrial policies can deliver measurable employment benefits in targeted strategic sectors, even in the short run. Yet the extent of these benefits is shaped by the structure of the industry and its supply chain. The capital intensity and automation of semiconductor manufacturing imply that job creation may be more limited than anticipated, and the diffusion of benefits beyond directly affected sectors remains modest. These results underscore the importance of maintaining realistic expectations about the labor market returns from industrial-policy efforts, particularly in capital-intensive sectors.

It will be important to conduct longer-term evaluations of the CHIPS Act and other components of the revival of U.S. industrial policy, in particular the IRA. CHIPS-funded programs remain active and continue to influence private investment decisions, even as the political environment evolves and debates over the scope of industrial policy continue. The long-term employment impacts may be very different from the short-term, and it will also be important to evaluate the impacts on other outcomes which, due to data constraints, we have not been able to focus on here, including innovation, productivity, and regional economic resilience.

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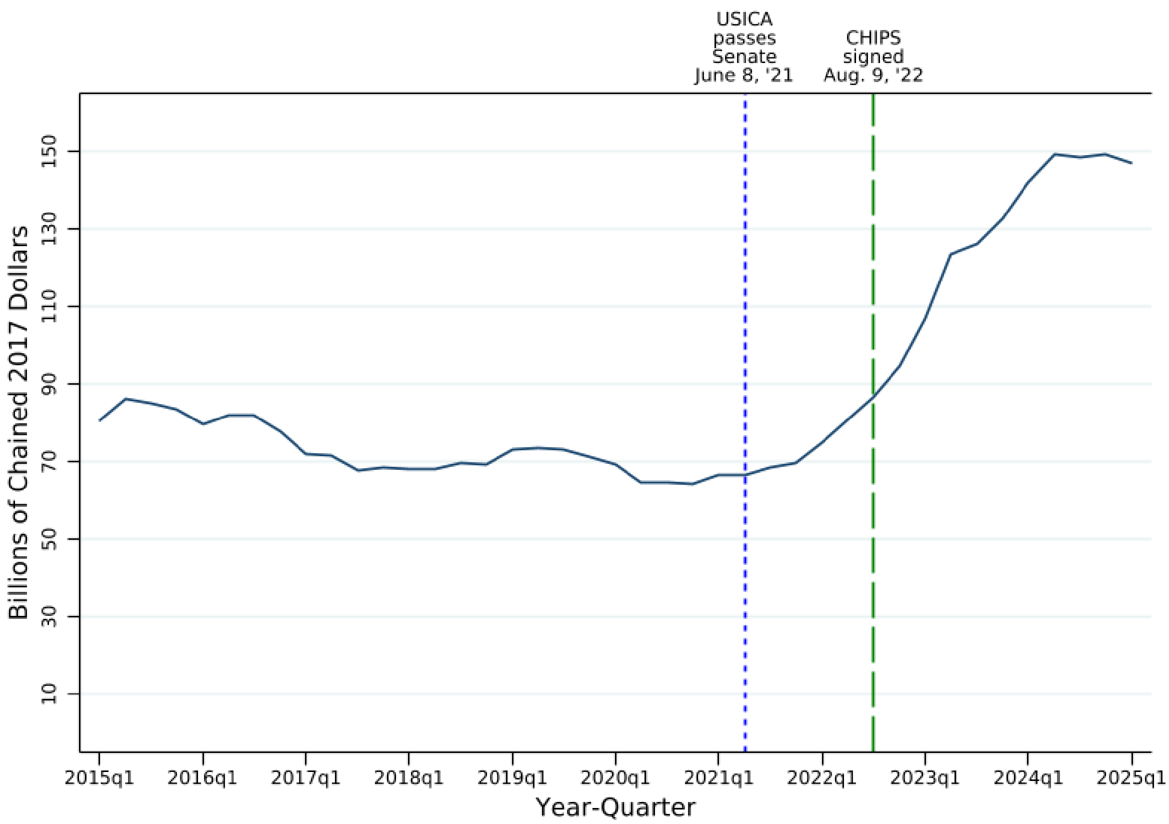
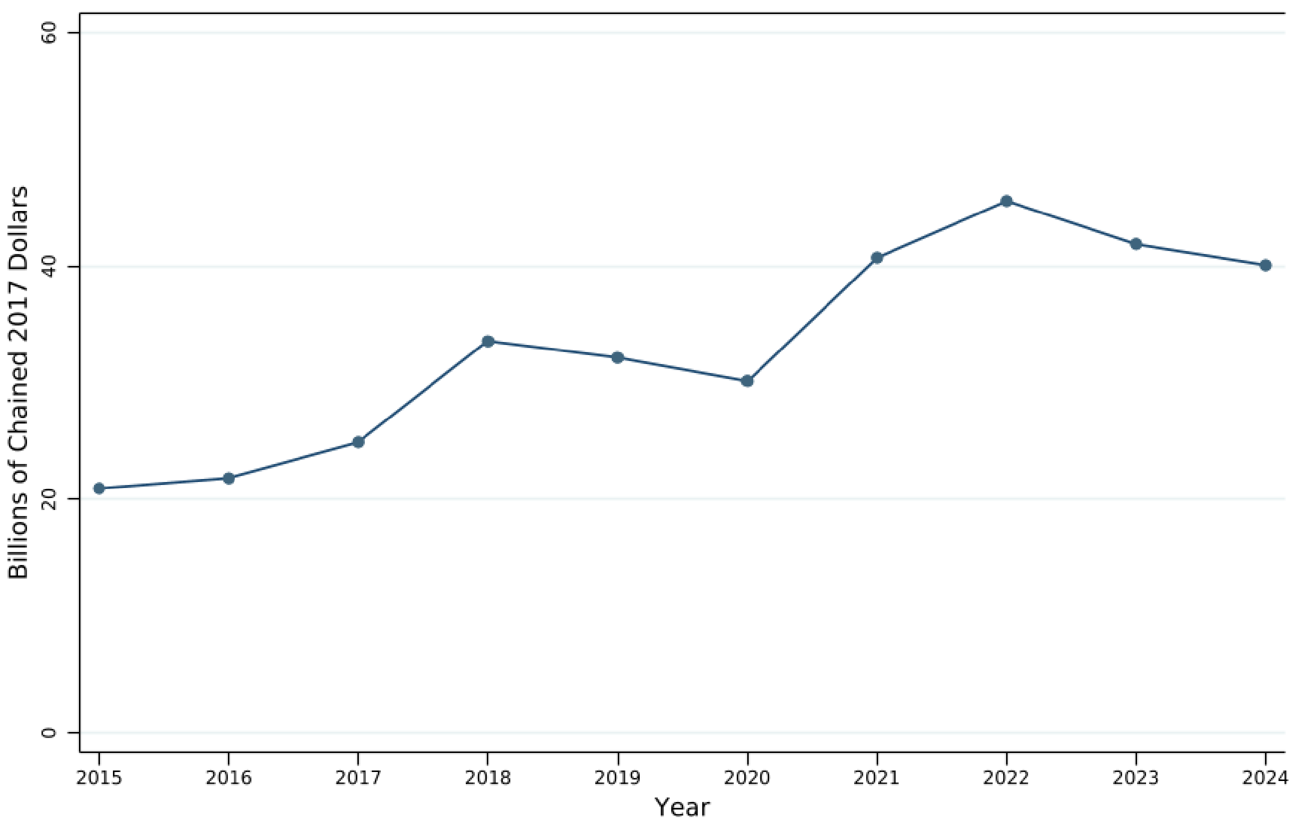
Figures and Tables

FIGURE 1: REAL PRIVATE FIXED INVESTMENT IN NONRESIDENTIAL MANUFACTURING STRUCTURES



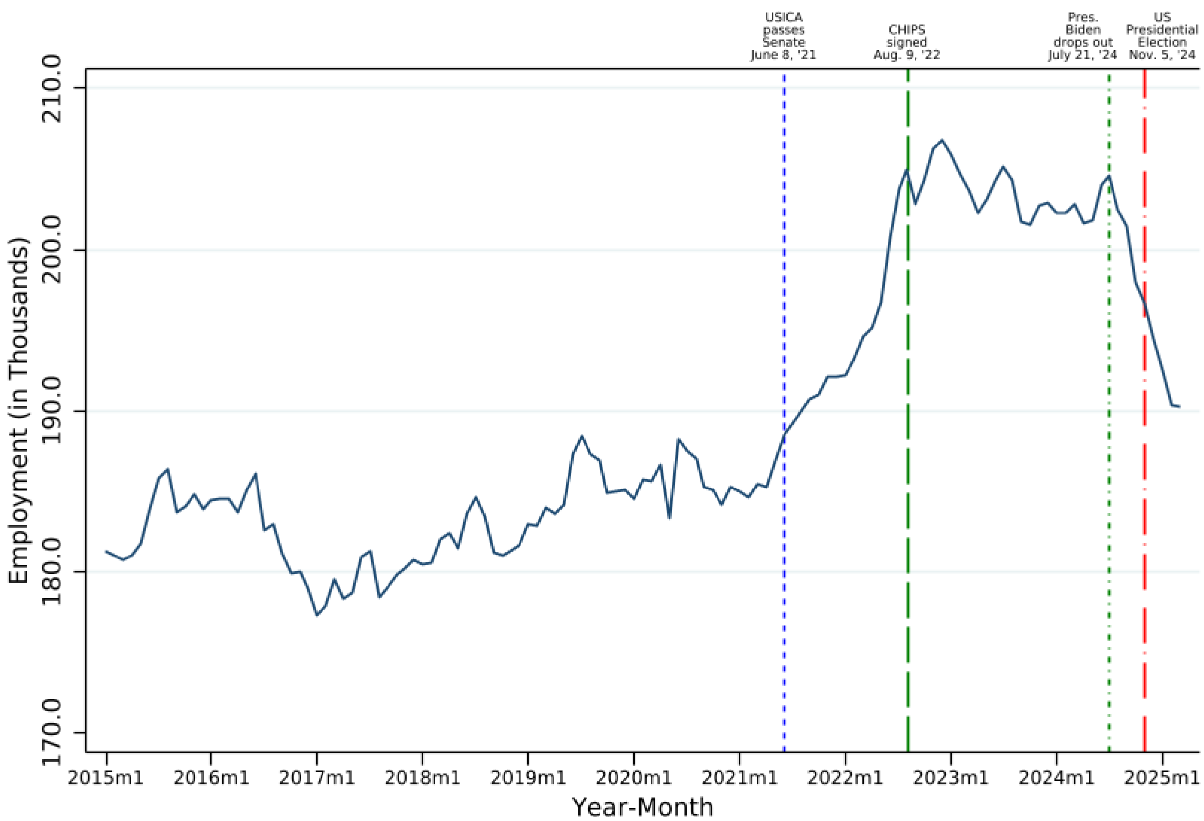
Notes: Source is U.S. Bureau of Economic Analysis, Gross Private Domestic Investment and Capital Transfers: Private Fixed Investment in Structures by Type, Chained dollars: Manufacturing. Data are seasonally adjusted and annualized (by BEA). Dotted blue line indicates Q2 of 2022, when the USICA was passed and the dotted green line indicates Q3 of 2022 when the CHIPS Act and Inflation Reduction Act (IRA) were passed. Y-axis is investment per quarter.

FIGURE 2: REAL PURCHASES OF PROPERTY, PLANT AND EQUIPMENT BY SEMICONDUCTOR FIRMS



Notes: Source is Security and Exchange Commission Form 10-K filings by semiconductor firms. Following the Semiconductor Industry Association, the following firms are included: Akoustis, AMD, Analog Devices, Broadcom, Cirrus Logic, Global Foundaries, Intel, Lattice Semiconductor, Littelfuse, Luminar, Marvell, Microchip, Micron, Nvidia, ONSEMI, Qorvo, Qualcomm, Silicon Labs, Skywater, SkyWorks, Texas Instruments, Western Digital, and Wolfspeed. The y-axis variable is total purchases of property, plant and equipment for the above firms in billions of 2017 dollars. The 10-K forms report purchases for entire calendar year; 2021 thus includes more than six months following the Senate passage of USICA on June 8, 2021.

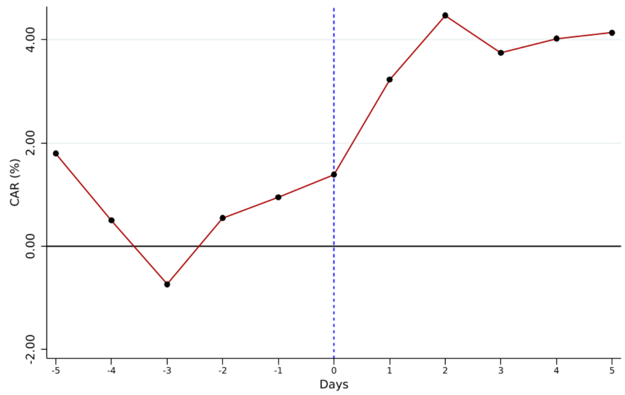
FIGURE 3: EMPLOYMENT IN SEMICONDUCTOR INDUSTRY



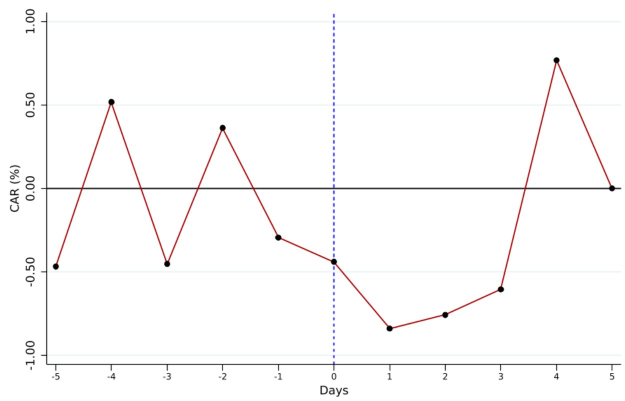
Notes: This figure plots the total number of workers in the semiconductor industry (NAICS 334413) across the United States, as reported in the Current Employment Statistics (National Series).

FIGURE 4: CUMULATIVE ABNORMAL RETURNS FOR SEMICONDUCTOR FIRMS

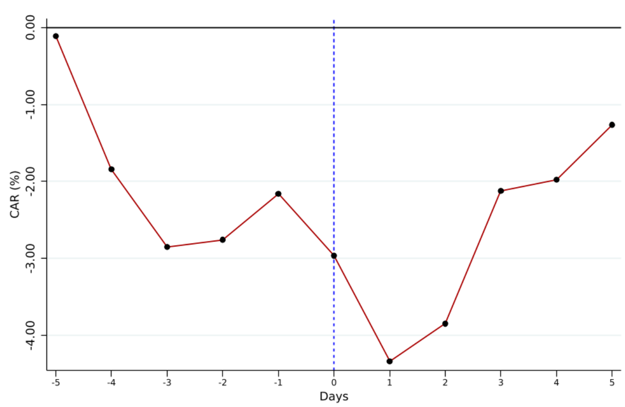
A. May 18, 2021



B. June 8, 2021

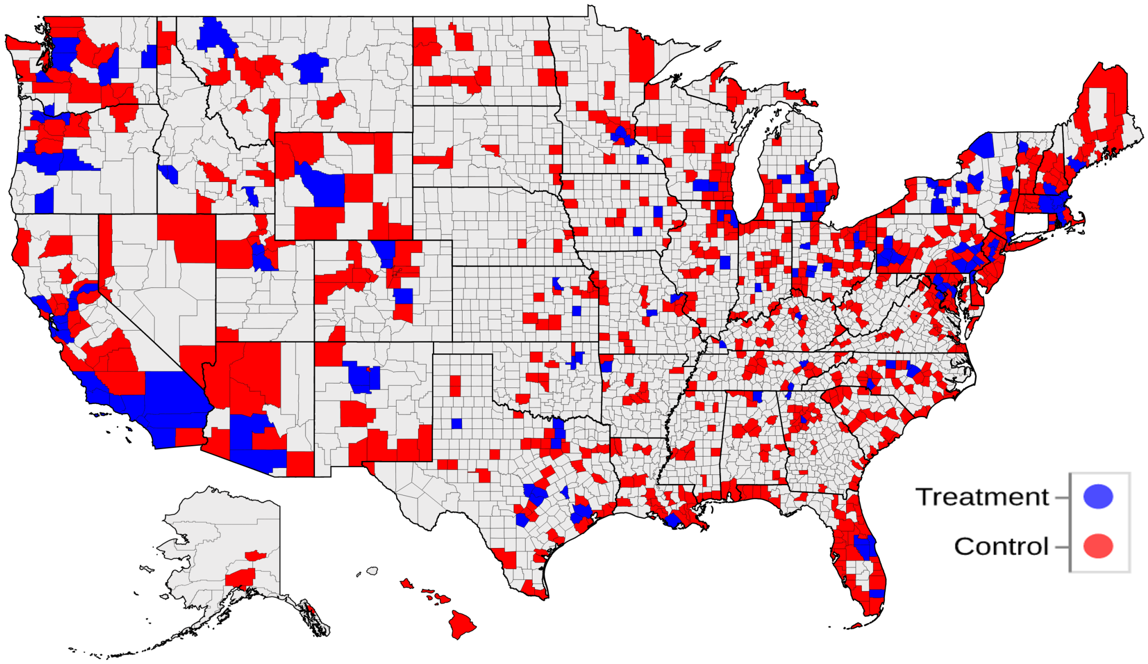


C. July 28, 2022



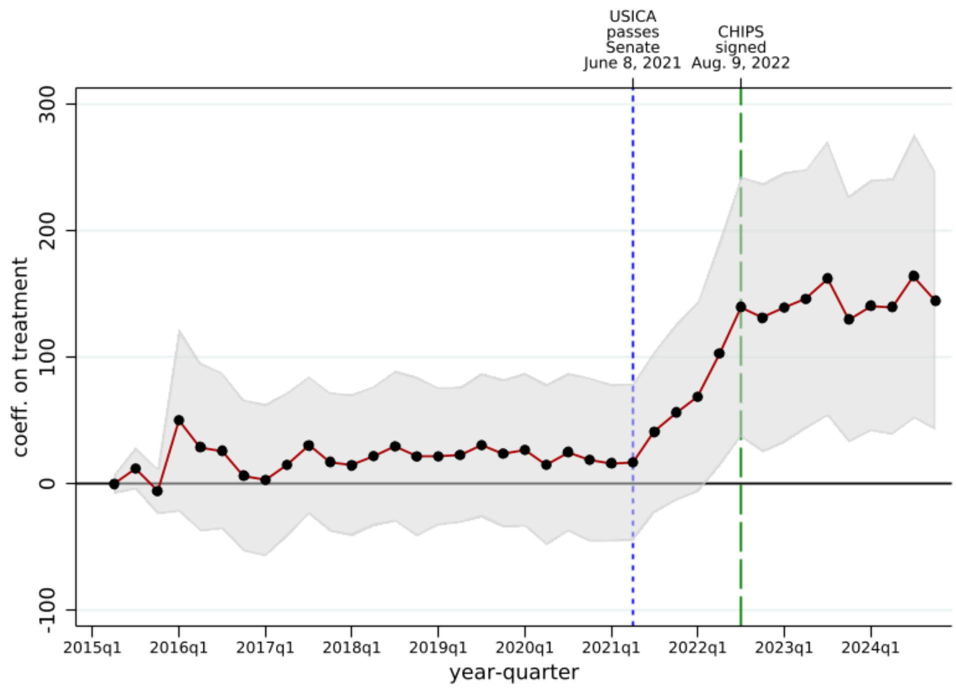
Cumulative Average Abnormal Returns (CAARs) around major semiconductor policy events are calculated as follows (using the Stata estudy command). We first calculate Abnormal Returns (ARs) by estimating the regression $R_{it} = \gamma_i R_{mt} + \alpha_i + \varepsilon_{it}$, where R_{it} is firm i's return and R_{mt} is the S&P 500's return, over the period 250 days to 30 days before the event, and then defining $AR_{it} = R_{it} - \widehat{\gamma}_i R_{mt} - \widehat{\alpha}_i$ for the indicated event window. The ARs are averaged across firms and then summed across the event window to get CAARs. The sample is the set of firms included in Figure 2, excluding Global Foundries and Skywater, who began trading on October 28, 2021 and April 21, 2021, respectively. See also Appendix Table A3.

FIGURE 5: COUNTIES WITH SEMICONDUCTOR FACILITIES AND OTHER HIGH-TECH SECTORS



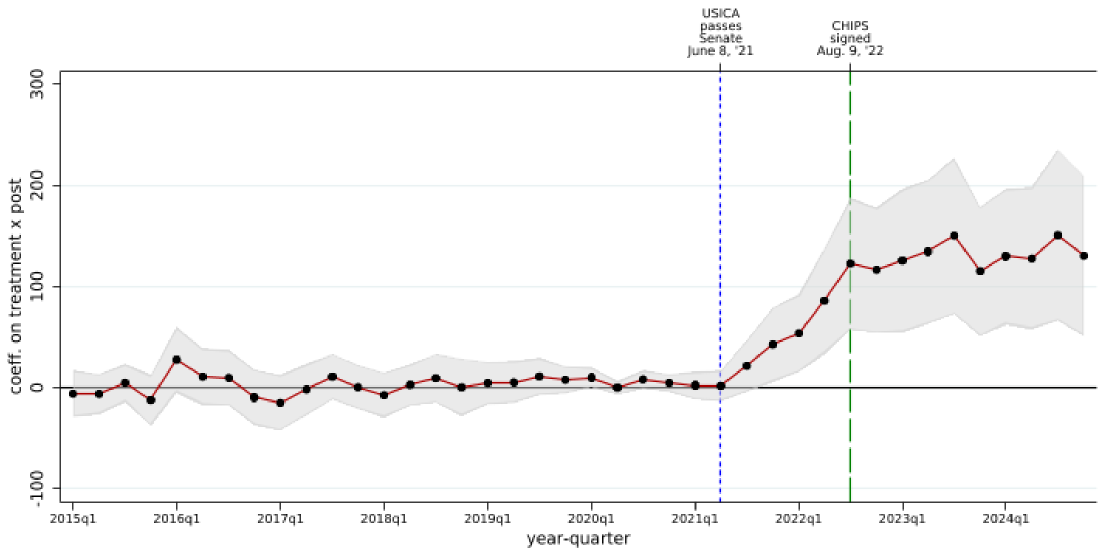
Notes: The data comes from the Semiconductor Industry Association's (SIA) U.S. Semiconductor Ecosystem Map. Counties with a pre-existing, private semiconductor production facility are marked with blue. Counties with employment >100 in 11 high-tech sectors (defined by Census Bureau) but no pre-existing, private semiconductor production facility marked with red.

FIGURE 6: EMPLOYMENT IN SEMICONDUCTORS: SIMPLE DID



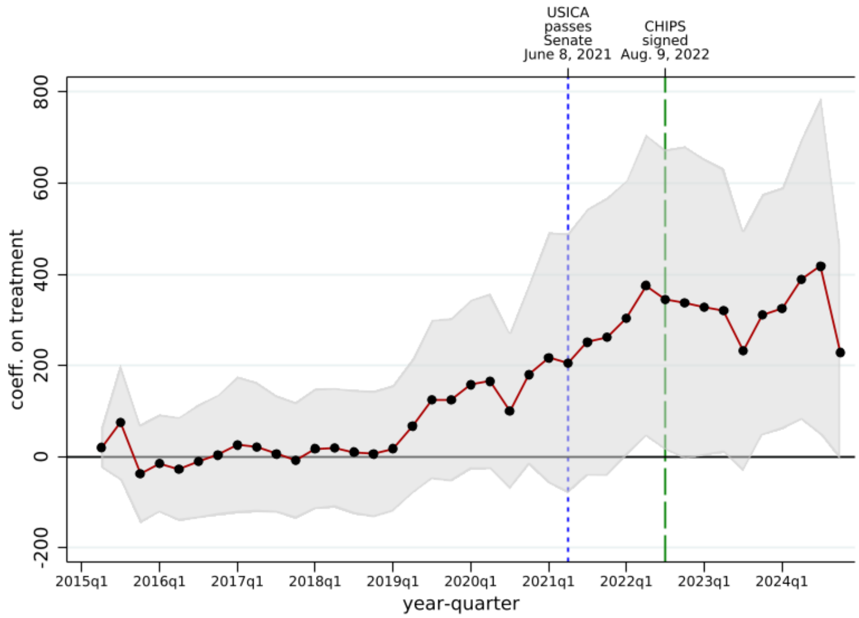
Notes: Estimates are from event-study specification of simple difference-in-differences, equation (2) in text. Outcome is the number of workers employed in the semiconductor sector (NAICS industry code 334413). Source is QCEW 6-digit data. Sample includes all counties with at least 100 workers in 11 high-tech sectors, as defined in Census Bureau (2024), as of 2021Q1. Treatment indicator identifies counties with an existing private semiconductor production facility as listed by the SIA Ecosystem data. Shaded area represents 95% confidence interval. Standard errors are clustered at the county level.

FIGURE 7: EMPLOYMENT IN SEMICONDUCTORS: SYNTHETIC DID



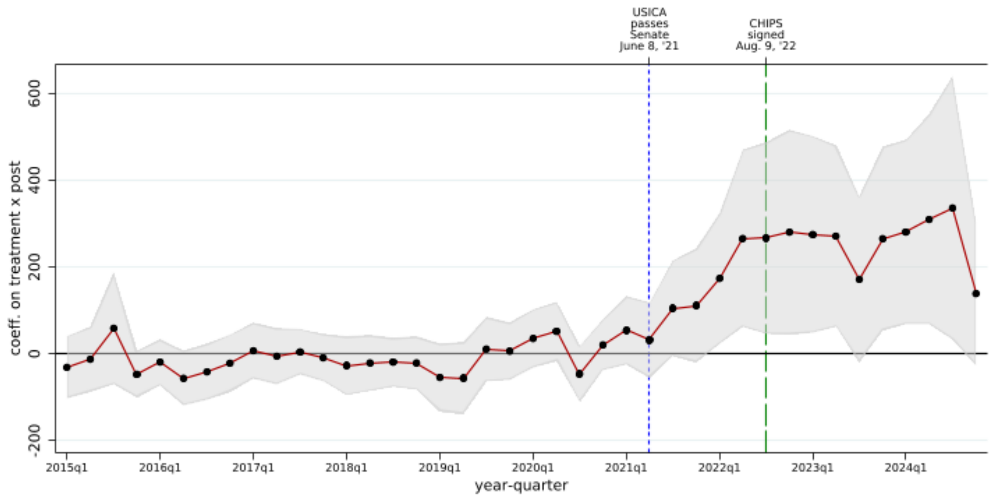
Notes: Outcome is the number of workers employed in the semiconductor sector (NAICS industry code 334413). Source is QCEW 6-digit data. The sample includes all counties with at least 100 workers in the 11 high-tech sectors, as defined in Census Bureau (2024) as of 2021Q1. The "Treatment" indicator identifies counties with an existing private (not a University or an R&D partner) semiconductor facility as listed by the Semiconductor Industry Association. The "Post" indicator identifies quarters after USICA passed in the U.S. Senate. Estimated treatment effects produced by implementing the event-study estimator proposed by Clarke, Pailañir, Athey, and Imbens (2024). The shaded area represents the confidence interval at the 95% level. The employment numbers are obtained from the BLS Quarterly Census of Employment and Wages.

FIGURE 8: WAGES PER WORKER IN SEMICONDUCTORS: SIMPLE DID



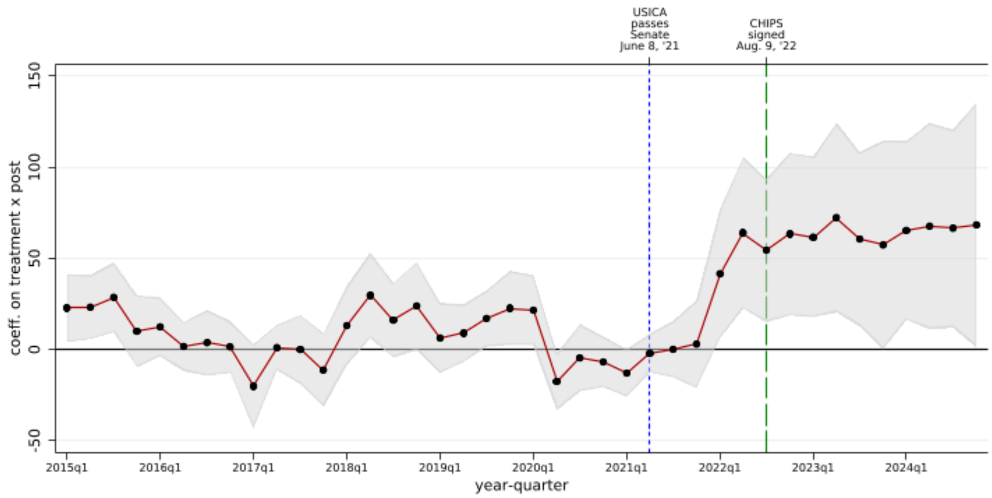
Notes: Outcome is the average weekly wage per worker in the county employed in the semiconductor sector (NAICS industry code 334413), deflated to 2017 dollars. Source is QCEW 6-digit data. The sample includes all counties with at least 100 workers in the 11 high-tech sectors, as defined in Census Bureau (2024) as of 2021Q1. The “Treatment“ indicator identifies counties with an existing private (not a University or an R&D partner) semiconductor facility as listed by the Semiconductor Industry Association. The shaded area represents the confidence interval at the 95% level, the standard errors are clustered at the county level. The wage numbers are obtained from the BLS Quarterly Census of Employment and Wages.

FIGURE 9: AVERAGE WEEKLY WAGES IN SEMICONDUCTORS: SYNTHETIC DID



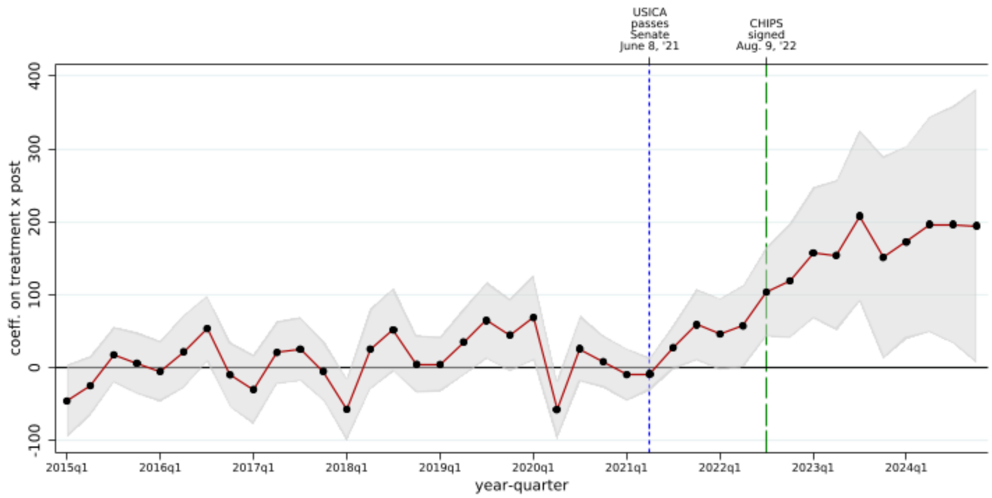
Notes: Outcome is the average weekly wage per worker in the county employed in the semiconductor sector (NAICS industry code 334413), deflated to 2017 dollars. Source is QCEW 6-digit data. The sample includes all counties with at least 100 workers in the 11 high-tech sectors, as defined in Census Bureau (2024) as of 2021Q1. The "Treatment" indicator identifies counties with an existing private (not a University or an R&D partner) semiconductor facility as listed by the Semiconductor Industry Association. The "Post" indicator identifies quarters after USICA passed in the U.S. Senate. Estimated treatment effects produced by implementing the event-study estimator proposed by Clarke, Pailañir, Athey, and Imbens (2024). The shaded area represents the confidence interval at the 95% level. The wage numbers are obtained from the BLS Quarterly Census of Employment and Wages.

FIGURE 10: EMPLOYMENT IN INPUT SECTORS FOR SEMICONDUCTORS: SYNTHETIC DID



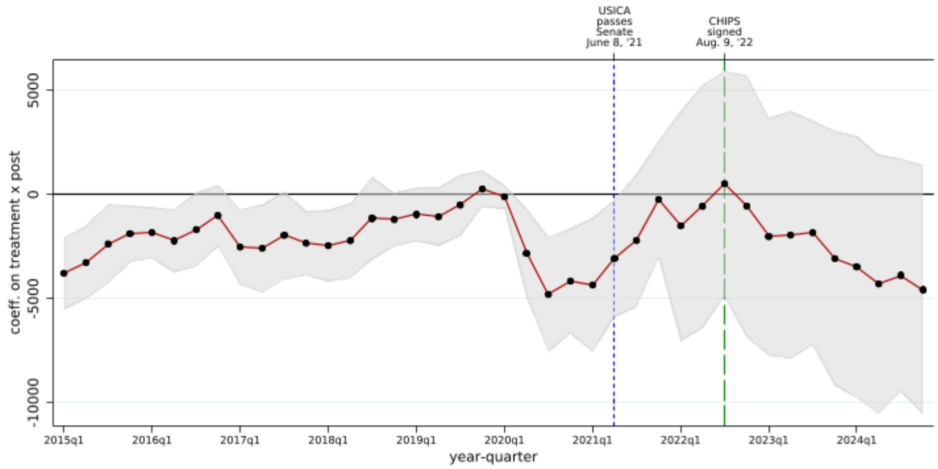
Notes: Outcome is the aggregate number of workers employed in the following input sectors for semiconductors: 331410, 334418, 334412, 334416, 334417, 334419, 326112, 326113, 334118, 334515, 811310. (See Section 6 for sector descriptions.) Source is QCEW 6-digit data. The sample includes all counties with at least 100 workers in the 11 high-tech sectors, as defined in Census Bureau (2024) as of 2021Q1. The "Treatment" indicator identifies counties with an existing private (not a University or an R&D partner) semiconductor facility as listed by the Semiconductor Industry Association. The "Post" indicator identifies quarters after USICA passed in the U.S. Senate. Estimated treatment effects produced by implementing the event-study estimator proposed by Clarke, Pailañir, Athey, and Imbens (2024). The shaded area represents the confidence interval at the 95% level. The employment numbers are obtained from the BLS Quarterly Census of Employment and Wages.

FIGURE 11: NON-RESIDENTIAL CONSTRUCTION EMPLOYMENT: SYNTHETIC DID



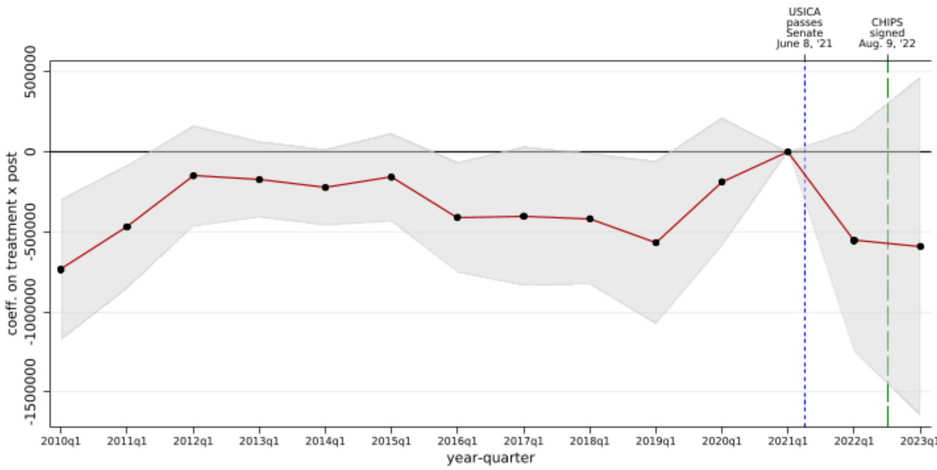
Notes: Outcome is the number of workers employed in either industrial building construction (NAICS 236210) or commercial and institutional building construction (NAICS 236220). Source is QCEW 6-digit data. The sample includes all counties with at least 100 workers in the 11 high-tech sectors, as defined in Census Bureau (2024) as of 2021Q1. The "Treatment" indicator identifies counties with an existing private (not a University or an R&D partner) semiconductor facility as listed by the Semiconductor Industry Association. The "Post" indicator identifies quarters after USICA passed in the U.S. Senate. Estimated treatment effects produced by implementing the event-study estimator proposed by Clarke, Pailañir, Athey, and Imbens (2024). The shaded area represents the confidence interval at the 95% level. The employment numbers are obtained from the BLS Quarterly Census of Employment and Wages.

FIGURE 12: TOTAL COUNTY EMPLOYMENT: SYNTHETIC DID



Notes: Outcome is the number of workers employed in all NAICS 6-digit sectors. Source is QCEW 6-digit data. The sample includes all counties with at least 100 workers in the 11 high-tech sectors, as defined in Census Bureau (2024) as of 2021Q1. The "Treatment" indicator identifies counties with an existing private (not a University or an R&D partner) semiconductor facility as listed by the Semiconductor Industry Association. The "Post" indicator identifies quarters after USICA passed in the U.S. Senate. Estimated treatment effects produced by implementing the event-study estimator proposed by Clarke, Pailañir, Athey, and Imbens (2024). The shaded area represents the confidence interval at the 95% level. The employment numbers are obtained from the BLS Quarterly Census of Employment and Wages.

FIGURE 13: COUNTY GDP: SYNTHETIC DID



Notes: Outcome is the annual county GDP from the Bureau of Economic Analysis. The sample includes all counties with at least 100 workers in the 11 high-tech sectors, as defined in Census Bureau (2024) as of 2021Q1. The "Treatment" indicator identifies counties with an existing private (not a University or an R&D partner) semiconductor facility as listed by the Semiconductor Industry Association. The "Post" indicator identifies quarters after USICA passed in the U.S. Senate. Estimated treatment effects produced by implementing the event-study estimator proposed by Clarke, Pailañir, Athey, and Imbens (2024). The shaded area represents the confidence interval at the 95% level.

TABLE 1: SUMMARY STATISTICS – TREATED AND CONTROL COUNTIES

	Control		Treated	
	Mean	S.D.	Mean	S.D.
Panel A: General County Characteristics				
Total Empl. (in thousands)	61.6	108.0	314.7	521.1
Manufacturing, as % of total emp	3.2	4.9	4.1	3.3
Empl. in Semiconductors	3.4	43.1	917.8	3668.8
Empl. in Semi. Materials/Equip.	10.4	78.4	152.8	646.0
Avg. Weekly Wage, all Industries	734.6	179.1	933.1	297.3
Unemployment Rate	5.8	1.9	5.3	1.2
Rural %	28.2	20.5	13.7	13.9
Panel B: Demographics				
Panel B.1: Gender				
Male %	49.6	1.4	49.4	0.8
Female %	50.4	1.4	50.6	0.8
Panel B.2: Race/Ethnicity				
White %	83.8	14.1	81.8	11.7
Black %	11.7	13.1	10.0	9.3
Asian %	3.2	5.5	6.9	6.7
Hispanic %	10.6	12.6	15.7	13.5
Panel B.3: Age				
Ages under 19 %	25.8	3.3	25.5	2.9
Ages 20 to 24 %	7.3	3.0	7.7	3.3
Ages 25 to 34 %	11.5	2.1	12.4	2.3
Ages 35 to 44 %	13.4	1.5	14.1	1.6
Ages 45 to 54 %	13.3	1.6	13.5	1.6
Ages 55 to 64 %	13.2	2.0	12.7	1.7
Number of counties	752		149	

Notes: The “Treated“ indicator identifies counties with an existing private (not a University or an R&D partner) semiconductor facility as listed by the Semiconductor Industry Association. The “Control” indicator identifies counties with at least 100 workers in the 11 high-tech sectors, as defined in Census Bureau (2024) as of 2021Q1, that do not have an existing private semiconductor facility. The employment and wage numbers are from the QCEW 6-digit sample for 2015Q1. “Employment in Semiconductors“ is the number of workers employed in the semiconductor sector (NAICS industry code 334413). “Empl. in Semi. Materials/Equip.“ is the number of workers employed in the manufacturing of equipment (NAICS 333242) or material inputs (NAICS 325120, 325180) for semiconductors. Unemployment data are from the BLS Local Area Unemployment Statistics (`https://www.bls.gov/lau/`) for 2015. Rural share is from the Census Bureau Urban and Rural Geographic Area data (`https://www.census.gov/programs-surveys/geography/guidance/geo-areas/urban-rural.html`) for 2010. County demographic data taken from SEER U.S. County Population Data (`https://seer.cancer.gov/popdata/download.html#19`) for 2010.

TABLE 2: EMPLOYMENT IN SEMICONDUCTORS: SIMPLE DID

	Semiconductor production employment	Semconductor equipment & materials employment	Semiconductor production, equipment & materials employment
	(1)	(2)	(3)
Panel A: Treatment effect post-USICA			
Treated x Post-USICA	103.226**	35.722**	138.947***
	(40.609)	(16.907)	(50.788)
Observations	36040	36040	36040
Pre-USICA outcome mean (treated counties)	868.808	164.518	1033.326
County FE	Y	Y	Y
Year-Quarter FE	Y	Y	Y
Panel B: Treatment effect post-CHIPS, omitting 2021Q2-2022Q3			
Treated x Post-CHIPS	125.484***	37.567**	163.051***
	(48.480)	(18.445)	(59.512)
Observations	30634	30634	30634
Pre-USICA outcome mean (treated counties)	868.808	164.518	1033.326
County FE	Y	Y	Y
Year-Quarter FE	Y	Y	Y

Notes: The sample includes all counties with at least 100 workers in the 11 high-tech sectors, as defined in Census Bureau (2024) as of 2021Q1. The "Treatment" indicator identifies counties with an existing private (not a University or an R&D partner) semiconductor facility as listed by the Semiconductor Industry Association. In Panel A, the "Post" indicator identifies quarters after USICA passed in the U.S. Senate. In Panel B, the "Post" indicator identifies quarters after the CHIPS Act was signed into law. Panel B omits the time period from USICA until CHIPS Act for comparing outcomes after CHIPS Act to those prior to the precursor of CHIPS, the USICA. Outcome in Column 1 is the number of workers employed in the semiconductor sector (NAICS industry code 334413). Outcome in Column 2 is the number of workers employed in the manufacturing of equipment (NAICS 333242) or material inputs (NAICS 325120, 325180) for semiconductors. Outcome in Column 3 is the number of workers employed in either the semiconductor industry or the manufacturing of equipment (NAICS 333242) or material inputs (NAICS 325120, 325180) for semiconductors. The pre-USICA outcome mean is the outcome mean for treated counties for the 2015Q1-2021Q1 period. The employment numbers are obtained from the BLS Quarterly Census of Employment and Wages. The standard errors included in parentheses are clustered at the county level. *p <0.10; **p <0.05; ***p <0.01.

TABLE 3: EMPLOYMENT IN SEMICONDUCTORS: SYNTHETIC DID

	Semiconductor production employment	Semiconductor equipment & materials employment	Semiconductor production, equipment & materials employment
	(1)	(2)	(3)
Panel A: Treatment effect post-USICA			
Treated x Post-USICA	107.627***	17.362	122.810***
	(34.381)	(11.901)	(37.560)
Observations	36040	36040	36040
Pre-USICA outcome mean (treated counties)	868.808	164.518	1033.326
Panel B: Treatment effect post-CHIPS, omitting 2021Q2-2022Q3			
Treated x Post-CHIPS	131.302***	15.702	142.487***
	(43.113)	(14.868)	(47.467)
Observations	30634	30634	30634
Pre-USICA outcome mean (treated counties)	868.808	164.518	1033.326

Notes: The sample includes all counties with at least 100 workers in the 11 high-tech sectors, as defined in Census Bureau (2024) as of 2021Q1. The "Treatment" indicator identifies counties with an existing private (not a University or an R&D partner) semiconductor facility as listed by the Semiconductor Industry Association. In Panel A, the "Post" indicator identifies quarters after USICA passed in the U.S. Senate. In Panel B, the "Post" indicator identifies quarters after the CHIPS Act was signed into law. Panel B omits the time period from USICA until CHIPS Act for comparing outcomes after CHIPS Act to those prior to the precursor of CHIPS, the USICA. Outcome in Column 1 is the number of workers employed in the semiconductor sector (NAICS industry code 334413). Outcome in Column 2 is the number of workers employed in the manufacturing of equipment (NAICS 333242) or material inputs (NAICS 325120, 325180) for semiconductors. Outcome in Column 3 is the number of workers employed in either the semiconductor industry or the manufacturing of equipment (NAICS 333242) or material inputs (NAICS 325120, 325180) for semiconductors. The pre-USICA outcome mean is the outcome mean for treated counties for the 2015Q1-2021Q1 period. The employment numbers are obtained from the BLS Quarterly Census of Employment and Wages. Estimated treatment effects produced by implementing the event-study estimator proposed by Clarke, Pailañir, Athey, and Imbens (2024). *p <0.10; **p <0.05; ***p <0.01.

TABLE 4: WEEKLY WAGES IN SEMICONDUCTORS: SIMPLE DID

	Semiconductor wages	Semiconductor equipment & materials wages	Semiconductor production, equipment & materials wages
	(1)	(2)	(3)
Panel A: Treatment effect post-USICA			
Treated x Post-USICA	259.961**	94.111**	276.679***
	(104.379)	(37.844)	(104.568)
Constant	183.957***	143.349***	264.180***
	(6.041)	(2.190)	(6.052)
Observations	36040	36040	36040
Pre-USICA outcome mean (treated counties)	822.832	409.242	923.515
Panel B: Treatment effect post-CHIPS, omitting 2021Q2-2022Q3			
Treated x Post-CHIPS	270.747**	107.766**	284.796***
	(108.443)	(45.752)	(108.249)
Constant	182.046***	142.769***	261.532***
	(4.747)	(2.003)	(4.739)
Observations	30634	30634	30634
Pre-USICA outcome mean (treated counties)	822.832	409.242	923.515

Notes: The sample includes all counties with at least 1000 workers as of 2015Q1 in the 11 high-tech sectors, as defined in Census Bureau (2024) as of 2015Q1. The "Treatment" indicator identifies counties with an existing private (not a University or an R&D partner) semiconductor facility as listed by the Semiconductor Industry Association. In Panel A, the "Post" indicator identifies quarters after USICA passed in the U.S. Senate. In Panel B, the "Post" indicator identifies quarters after the CHIPS Act was signed into law. Panel B omits the time period from USICA until CHIPS Act for comparing outcomes after CHIPS Act to those prior to the precursor of CHIPS, the USICA. Outcome in Column 1 is the average weekly wage for workers employed in the semiconductor sector (NAICS industry code 334413). Outcome in Column 2 is the average weekly wage for workers employed in either the manufacturing of equipment (NAICS 333242) or material inputs (NAICS 325120, 325180) for semiconductors. Outcome in Column 3 is the average weekly wage for workers employed in either the semiconductor industry or the manufacturing of equipment or material inputs for semiconductors. The wage numbers are obtained from the BLS Quarterly Census of Employment and Wages. The standard errors included in parentheses are clustered at the county level. The wage figures are deflated to 2017 USD. *p <0.10; **p <0.05; ***p <0.01.

TABLE 5: WEEKLY WAGES IN SEMICONDUCTORS: SYNTHETIC DID

	Semiconductor wages	Semiconductor equipment & materials wages	Semiconductor production, equipment & materials wages
	(1)	(2)	(3)
Panel A: Treatment effect post-USICA			
Treated x Post-USICA	232.180**	94.283**	206.345**
	(97.053)	(47.310)	(84.234)
Observations	36040	36040	36040
Pre-USICA outcome mean (treated counties)	822.832	409.242	923.515
Panel B: Treatment effect post-CHIPS, omitting 2021Q2-2022Q3			
Treated x Post-CHIPS	256.627**	114.879*	231.962**
	(119.415)	(59.814)	(102.007)
Observations	30634	30634	30634
Pre-USICA outcome mean (treated counties)	822.832	409.242	923.515

Notes: The sample includes all counties with at least 100 workers in the 11 high-tech sectors, as defined in Census Bureau (2024) as of 2021Q1. The "Treatment" indicator identifies counties with an existing private (not a University or an R&D partner) semiconductor facility as listed by the Semiconductor Industry Association. In Panel A, the "Post" indicator identifies quarters after USICA passed in the U.S. Senate. In Panel B, the "Post" indicator identifies quarters after the CHIPS Act was signed into law. Panel B omits the time period from USICA until CHIPS Act for comparing outcomes after CHIPS Act to those prior to the precursor of CHIPS, the USICA. Outcome in Column 1 is the average weekly wage for workers employed in the semiconductor sector (NAICS industry code 334413). Outcome in Column 2 is the average weekly wage for workers employed in either the manufacturing of equipment (NAICS 333242) or material inputs (NAICS 325120, 325180) for semiconductors. Outcome in Column 3 is the average weekly wage for workers employed in either the semiconductor industry or the manufacturing of equipment or material inputs for semiconductors. The pre-USICA outcome mean is the outcome mean for treated counties for the 2015Q1-2021Q1 period. The wage figures are deflated to 2017 USD. *p <0.10; **p <0.05; ***p <0.01.

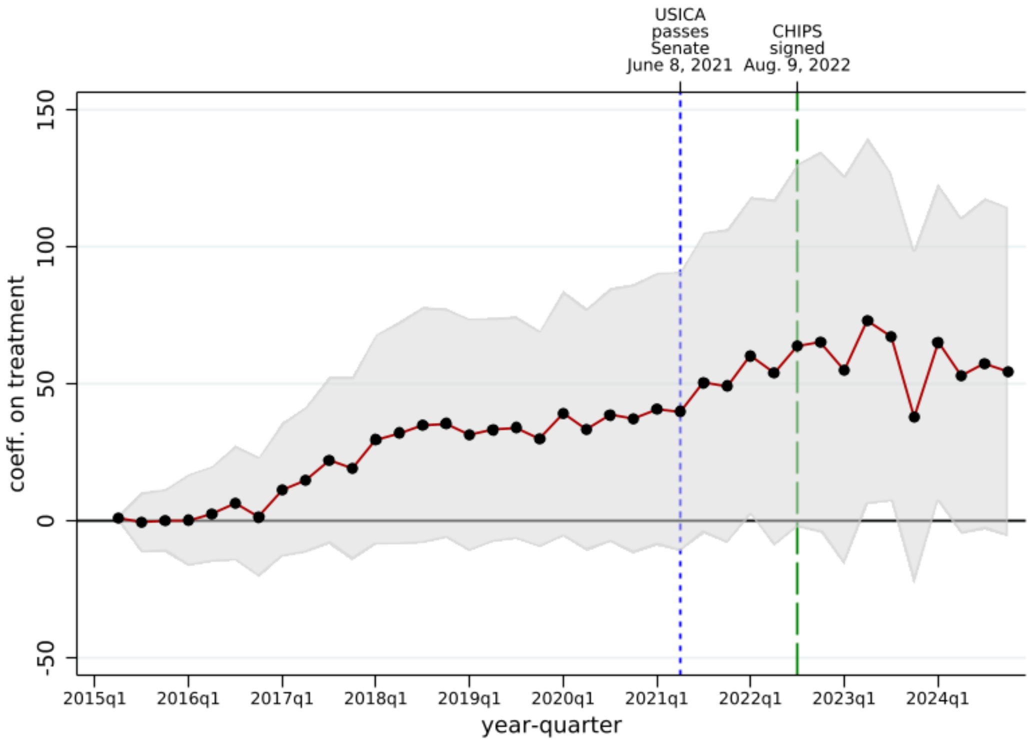
TABLE 6: LOCAL SPILLOVERS: SYNTHETIC DID

	Semiconductor inputs employment	Non-residential building construction employment	Total county employment	County GDP (00,000s USD)
	(1)	(2)	(3)	(4)
Panel A: Treatment effect post-USICA				
Treated x Post-USICA	53.320**	131.661**	-2119.145	-4.590
	(24.200)	(53.701)	(2600.231)	(5.061)
Observations	36040	36040	36040	7920
Pre-USICA outcome mean (treated counties)	1069.256	1800.271	307456.376	590.851
Panel B: Treatment effect post-CHIPS, omitting 2021Q2-2022Q3				
Treated x Post-CHIPS	59.779*	155.014**	-3160.585	-5.378
	(33.047)	(75.955)	(3116.770)	(5.947)
Observations	30634	30634	30634	7040
Pre-USICA outcome mean (treated counties)	1069.256	1800.271	307456.376	590.851

Notes: The sample includes all counties with at least 100 workers in the 11 high-tech sectors, as defined in Census Bureau (2024) as of 2021Q1. The "Treatment" indicator identifies counties with an existing private (not a University or an R&D partner) semiconductor facility as listed by the Semiconductor Industry Association. In Panel A, the "Post" indicator identifies quarters after USICA passed in the U.S. Senate. In Panel B, the "Post" indicator identifies quarters after the CHIPS Act was signed into law. Panel B omits the time period from USICA until CHIPS Act for comparing outcomes after CHIPS Act to those prior to the precursor of CHIPS, the USICA. Outcome in Column 1 is the aggregate number of workers employed in the input sectors for semiconductors (NAICS codes 331410, 334418, 334412, 334416, 334417, 334419, 326112, 326113, 334118, 334515 and 811310; see Section 6 for sector descriptions.). Outcome in Column 2 is the number of workers employed in non-residential construction building construction (NAICS 541713 and 541715). Outcome in Column 3 is the total county employment (All 6-digit NAICS industries aggregated). The pre-USICA outcome mean is the outcome mean for treated counties for the 2015Q1-2021Q1 period. The employment numbers are obtained from the BLS Quarterly Census of Employment and Wages. Outcome in Column 4 is the yearly county GDP in hundred thousands of chained US dollars. County level GDP numbers are only available on the year level until 2023 and are obtained from Bureau of Economic Analysis. *p <0.10; **p <0.05; ***p <0.01.

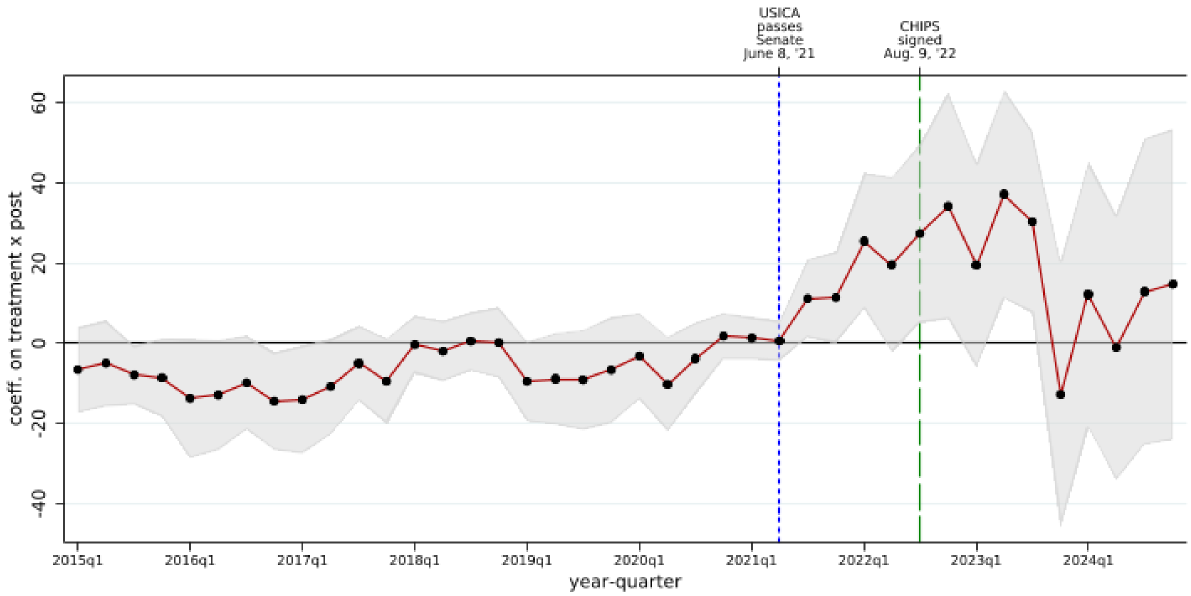
A Additional Figures and Tables

FIGURE A1: EMPLOYMENT IN EQUIPMENT/MATERIALS: SIMPLE DID



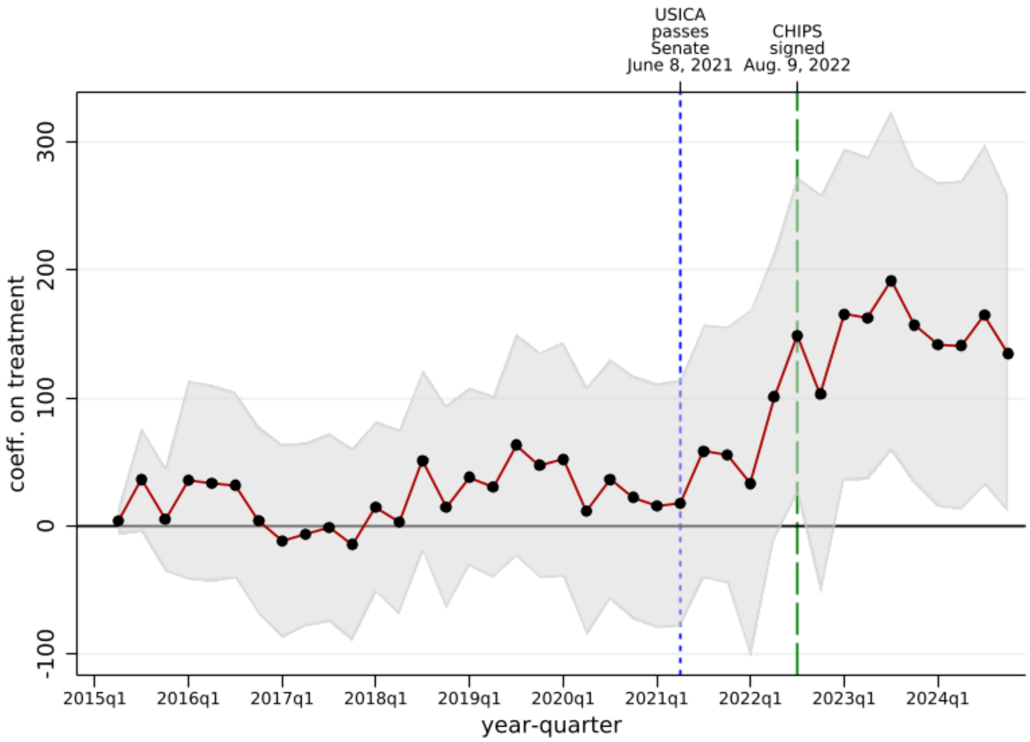
Notes: Estimates are from event-study specification of simple difference-in-differences, equation (2) in text. Outcome is the number of workers employed in the manufacturing of equipment (NAICS 333242) or material inputs (NAICS 325120, 325180) for semiconductors. Source is QCEW 6-digit data. Sample includes all counties with at least 100 workers in 11 high-tech sectors, as defined in Census Bureau (2024), as of 2021Q1. Treatment indicator identifies counties with an existing private semiconductor production facility as listed by the SIA Ecosystem data. Shaded area represents 95% confidence interval. Standard errors are clustered at the county level.

FIGURE A2: EMPLOYMENT IN EQUIPMENT/MATERIALS: SYNTHETIC DID



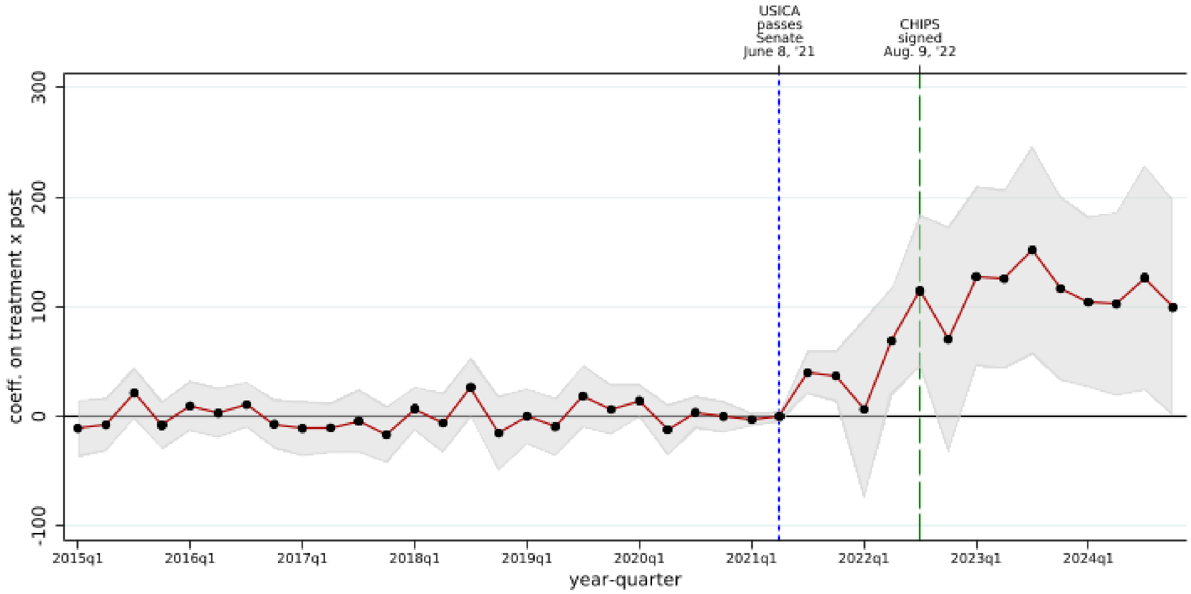
Notes: Outcome is the number of workers employed in the manufacturing of equipment (NAICS 333242) or material inputs (NAICS 325120, 325180) for semiconductors. The sample includes all counties with at least 100 workers in the 11 high-tech sectors, as defined in Census Bureau (2024) as of 2021Q1. The "Treatment" indicator identifies counties with an existing private (not a University or an R&D partner) semiconductor facility as listed by the Semiconductor Industry Association. The "Post" indicator identifies quarters after USICA passed in the U.S. Senate. Estimated treatment effects produced by implementing the event-study estimator proposed by Clarke, Pailañir, Athey, and Imbens (2024). The shaded area represents the confidence interval at the 95% level. The employment numbers are obtained from the BLS Quarterly Census of Employment and Wages.

FIGURE A3: EMPLOYMENT IN SEMICONDUCTORS: SIMPLE DID USING QWI/QCEW 4-DIGIT DATA



Notes: Outcome is the number of workers employed in the semiconductor sector (NAICS industry code 3344). The sample includes all counties with at least 100 workers in the 11 high-tech sectors, as defined in Census Bureau (2024) as of 2021Q1. The "Treatment" indicator identifies counties with an existing private (not a University or an R&D partner) semiconductor facility as listed by the Semiconductor Industry Association. The shaded area represents the confidence interval at the 95% level. The standard errors are clustered at the county level. The employment numbers are obtained from the BLS Quarterly Census of Employment and Wages and the Census Quarterly Workforce Indicator, wherever available.

FIGURE A4: EMPLOYMENT IN SEMICONDUCTORS: SYNTHETIC DID USING QWI/QCEW



Notes: Outcome is the number of workers employed in the semiconductor sector (NAICS industry code 3344). The sample includes all counties with at least 100 workers in the 11 high-tech sectors, as defined in Census Bureau (2024) as of 2021Q1. The "Treatment" indicator identifies counties with an existing private (not a University or an R&D partner) semiconductor facility as listed by the Semiconductor Industry Association. The "Post" indicator identifies quarters after USICA passed in the U.S. Senate. Estimated treatment effects produced by implementing the event-study estimator proposed by Clarke, Pailañir, Athey, and Imbens (2024). The shaded area represents the confidence interval at the 95% level. The employment numbers are obtained from the BLS Quarterly Census of Employment and Wages.

TABLE A1: CHIPS ACT APPROPRIATION BY FUND

Fund	Appropriation	Agency	Description
CHIPS for America Fund	\$50 billion	Department of Commerce	Incentives to develop domestic manufacturing capacity, R&D, and workforce development.
CHIPS for America Defense Fund	\$2 billion	Department of Defense	Establishes a Microelectronics Commons, an onshore network of university based research institutions.
CHIPS for America International Technology Security and Innovation Fund	\$500 million	Department of State	Coordination with foreign government partners to support international security and supply chain activities.
CHIPS for America Workforce and Education Fund	\$200 million	National Science Foundation	Promote growth of semiconductor workforce.

Notes: The funding descriptions and amounts come from Blevins, Sutter, and Grossman (2023).

Table A2: Notice of Funding Opportunities for the CHIPS Act

NOFO Name	Agency	Funding Amount	Date of Release	Description	Award Status
Commercial Fabrication Facilities NOFO	CHIPS Program Office	$38.2 billion in direct funding $75 billion in direct loans or loan guarantees	February 28, 2023	Awards funding for projects related to the construction, expansion, or modernization of commercial facilities for fabrication, wafer manufacturing, and materials used to manufacture semiconductors.	19 awards up to $30.7 billion in direct funding and $5.5 billion in loans. 15 non-binding PMTs totaling up to $1.9 billion in direct funding and $350 million in loans.
Facilities for Semiconductor Materials and Manufacturing Equipment NOFO	CHIPS Program Office	$500 million in direct funding through grants, cooperative agreements, and other transactional agreements (OTAs)	September 29, 2023	Awards funding for projects for the construction, expansion, or modernization for commercial facilities for semiconductor materials and manufacturing equipment with capital investments of less than $300 million.	No awards have been made yet, applications were accepted until July 1, 2024.
National Advanced Packaging Manufacturing Program (NAPMP) Materials and Substrates NOFO	CHIPS R&D Office	$300 million in funding	February 28, 2024	Awards funding for projects that establish and accelerate domestic R&D for advanced packaging substrates and substrate materials. Substrates are the foundation on which elements of a semiconductor are attached.	3 awards totaling $300 million in direct funding.
NAPMP Advanced Packaging Research and Development NOFO	CHIPS R&D Office	$1.5 billion in OTAs with individual awards up to $150 million	October 18, 2024	Awards funding for projects accelerating R&D in equipment integration, power delivery, connector technology, chiplets ecosystem, and co-design automation.	No awards have been made yet, concept papers were due on December 20, 2024.
CHIPS Manufacturing USA Institute Competition NOFO	CHIPS R&D Office	$285 million in funding	May 6, 2024	Awards to establish and operate a CHIPS Manufacturing USA Institute to join the existing network of 17 institutes to strengthen national manufacturing competitiveness and R&D infrastructure.	The Semiconductor Research Corporation Manufacturing Consortium Corporation was awarded $285 million to establish an institute known as SMART USA on January 3, 2025.
Measurement Science and Engineering Research Grant Program NOFO	CHIPS R&D Office	Expected 300 awards between $5,000 to $250,000 per year, with performance periods of up to 5 years	May 14, 2025	Offers financial assistance within multiple National Institute of Standards and Technology (NIST) programs including CHIPS. Support is provided for programs focusing on conducting metrology critical to semiconductor R&D.	8 awards as of January 31, 2025, totaling $1.1 million.
Small Business Innovation Research Program NOFO	CHIPS R&D Office	Expected 24 awards in two phases. Phase I with individual awards up to $283,500 and phase II with individual awards up to $1.9 million through cooperative agreements.	April 16, 2024	Awards eligible small businesses that want to explore the technical merit or feasibility of an innovative technology with the goal of developing a viable product for the commercial microelectronic marketplace.	17 awards in Phase I totaling to $4.8 million. Progress reports are required within 4 and 7 months, and projects with commercial viability will be developed into Phase II.
CHIPS AI-Powered AE for Rapid, Industry-Informed Sustainable Semiconductor Materials and Processes Competition NOFO	CHIPS R&D Office	$100 million through OTAs. Multiple awards ranging from $20-$40 million with a 5 year performance period.	October 30, 2024	Seeks to fund research into sustainable materials and processes for semiconductor through the application of artificial intelligence (AI) and autonomous experimentation (AE).	No awards have been made yet, concept papers were due January 13, 2025.

Notes: The table describes all Notice of Funding Opportunities (NOFOs) released by the National Institute of Standards and Technology (NIST) relating to the CHIPS Act programs. Information taken from Department of Commerce Office of Inspector General (2025) and is updated as of January 31, 2025.

TABLE A3: CUMULATIVE ABNORMAL RETURNS

	Event Window								
	(-1,1)			(-3,3)			(-5,5)		
	CAAR	SE	p-val	CAAR	SE	p-val	CAAR	SE	p-val
Panel A: USICA Introduction (May 18, 2021)									
	0.0273***	0.4848	0.0000	0.0338***	0.4002	0.0000	0.0430***	0.4698	0.0000
Panel B: USICA Senate Passage (June 8, 2021)									
	-0.0117***	0.5856	0.0070	-0.0105	0.6266	0.1440	0.0014	0.6169	0.5490
Panel C: CHIPS Senate Passage (July 28, 2022)									
	-0.0152	1.5295	0.1580	-0.0016	0.9623	0.6600	-0.0107	0.9821	0.3940

Notes: Cumulative Average Abnormal Returns (CAARs) around major semiconductor policy events are calculated as follows (using the Stata estudy command). We first calculate Abnormal Returns (ARs) by estimating the regression $R_{it} = \gamma_i R_{mt} + \alpha_i + \varepsilon_{it}$, where R_{it} is firm i's return and R_{mt} is the S&P 500's return, over the period 250 days to 30 days before the event, and then defining $AR_{it} = R_{it} - \widehat{\gamma}_i R_{mt} - \widehat{\alpha}_i$ for the indicated event window. The ARs are averaged across firms and then summed across the event window to get CAARs. Inference is based on the Boehmer–Musumeci–Poulsen (BMP) test. Windows are indicated in days. The sample is the set of firms included in Figure 2, excluding Global Foundries and Skywater, who began trading on October 28, 2021 and April 21, 2021, respectively. *p <0.10; **p <0.05; ***p <0.01. See also Fig. 4.

TABLE A4: ROBUSTNESS CHECKS: EMPLOYMENT (SYNTHETIC DID)

	Semiconductor employment	Equipment or materials employment	Semiconductor equipment or materials employment
	(1)	(2)	(3)
Panel A: Treatment effect post-CHIPS, omitting 2021Q2-2022Q3, with demographic controls			
Treated x Post-CHIPS	131.074***	15.622	142.350***
	(50.261)	(17.882)	(52.700)
Observations	30600	30600	30600
Pre-USICA outcome mean (treated counties)	868.808	164.518	1033.326
Panel B: Treatment effect post-CHIPS, omitting 2021Q2-2022Q3, varying control group definition			
a. High Tech Employment > 0			
Treated x Post-CHIPS	131.717***	13.311	139.101***
	(42.795)	(15.919)	(47.405)
Observations	58718	58718	58718
Outcome Mean	868.808	164.518	1033.326
b. High Tech Employment > 500			
Treated x Post-CHIPS	130.624**	16.561	144.823**
	(51.699)	(18.267)	(58.957)
Observations	17884	17884	17884
Outcome Mean	868.808	164.518	1033.326
c. High Tech Employment > 1000			
Treated x Post-CHIPS	130.251***	11.959	136.978***
	(44.910)	(15.993)	(49.017)
Observations	13940	13940	13940
Outcome Mean	868.808	164.518	1033.326
Panel C: Treatment effect post-CHIPS, omitting 2021Q2-2022Q3, with 2010 rural share interaction			
Treated x Post-CHIPS	115.435**	35.275**	148.657***
	(49.562)	(16.519)	(56.175)
Observations	30600	30600	30600
Pre-USICA outcome mean (treated counties)	868.808	164.518	1033.326

Notes: Demographic controls include percent of county population that is: Female, White, Black, Asian, Hispanic, younger than 19, between ages 20 to 24, between ages 25 to 34, between ages 35 to 44, between ages 45 to 54, and between ages 55 to 64. The percentage of a county's population containing each demographic was added as a covariate to our SDID estimation. County demographic data from SEER U.S. County Population Data, 1969-2023 (`https://seer.cancer.gov/popdata/download.html#19`). Different sample definitions were tested by adjusting the cutoff used for high-tech county employment. Seasonality was controlled for by interacting county FIPS code on year-quarter. Rural share was controlled for by interacting the rural share for a county in 2010 with county FIPS code. Initial rural share for each county in 2010 data taken from the Census Bureau Urban and Rural Geographic Area data, found at `https://www.census.gov/programs-surveys/geography/guidance/geo-areas/urban-rural.html` *p <0.10; **p <0.05; ***p <0.01.

TABLE A5: ROBUSTNESS CHECKS: WAGES (SYNTHETIC DID)

	Semiconductor wages	Equipment or materials wages	Semiconductor equipment or materials wages
	(1)	(2)	(3)
Panel A: Treatment effect post-CHIPS, omitting 2021Q2-2022Q3, with demographic controls			
Treated x Post-CHIPS	251.880**	115.367**	230.186**
	(108.176)	(52.102)	(104.120)
Observations	30600	30600	30600
Pre-USICA outcome mean (treated counties)	822.832	409.242	923.515
Panel B: Treatment effect post-CHIPS, omitting 2021Q2-2022Q3, varying control group definition			
a. High Tech Employment > 0			
Treated x Post-CHIPS	269.214**	122.655***	236.347**
	(107.028)	(46.500)	(91.937)
Observations	58718	58718	58718
Outcome Mean	822.832	409.242	923.515
b. High Tech Employment > 500			
Treated x Post-CHIPS	237.464**	102.658*	224.018**
	(109.891)	(60.918)	(111.735)
Observations	17884	17884	17884
Outcome Mean	822.832	409.242	923.515
c. High Tech Employment > 1000			
Treated x Post-CHIPS	226.292*	96.719*	214.264*
	(127.256)	(58.000)	(117.253)
Observations	13940	13940	13940
Outcome Mean	822.832	409.242	923.515
Panel C: Treatment effect post-CHIPS, omitting 2021Q2-2022Q3, with rural share interaction			
Treated x Post-CHIPS	249.457**	131.537**	240.665**
	(104.989)	(56.946)	(105.086)
Observations	30600	30600	30600
Pre-USICA outcome mean (treated counties)	822.832	409.242	923.515

Notes: Demographic controls include percent of county population that is: Female, White, Black, Asian, Hispanic, younger than 19, between ages 20 to 24, between ages 25 to 34, between ages 35 to 44, between ages 45 to 54, and between ages 55 to 64. The percentage of a county's population containing each demographic was added as a covariate to our SDID estimation. County demographic data taken from SEER U.S. County Population Data - 1969-2023, found at `https://seer.cancer.gov/popdata/download.html#19`. Different sample definitions were tested by adjusting the cutoff used for high-tech county employment. Seasonality was controlled for by interacting county FIPS code on year-quarter. Rural share was controlled for by interacting the rural share for a county in 2010 with county FIPS code. Initial rural share for each county in 2010 data taken from the Census Bureau Urban and Rural Geographic Area data, found at `https://www.census.gov/programs-surveys/geography/guidance/geo-areas/urban-rural.html` *p <0.10; **p <0.05; ***p <0.01.

TABLE A6: EMPLOYMENT IN SEMICONDUCTORS: SIMPLE DID USING QWI/QCEW 4-DIGIT DATA

	Semiconductor employment (1)	Equipment or materials employment (2)	Semiconductor equipment or materials employment (3)
Panel A: Treatment effect post-USICA			
Treated x Post-USICA	104.980**	74.995***	179.975***
	(49.435)	(25.962)	(65.750)
Observations	42680	42680	42680
Pre-USICA outcome mean (treated counties)	1605.080	508.060	2113.140
County FE	Y	Y	Y
Year-Quarter FE	Y	Y	Y
Panel B: Treatment effect post-CHIPS, omitting 2021Q2-2022Q3			
Treated x Post-CHIPS	130.575**	85.977***	216.552***
	(57.571)	(30.107)	(77.244)
Observations	36278	36278	36278
Pre-USICA outcome mean (treated counties)	1605.080	508.060	2113.140
County FE	Y	Y	Y
Year-Quarter FE	Y	Y	Y

Notes: Data are from QWI/QCEW combined data at 4-digit level. The sample includes all counties with at least 100 workers in the 11 high-tech sectors, as defined in Census Bureau (2024) as of 2021Q1. The “Treatment“ indicator identifies counties with an existing private (not a University or an R&D partner) semiconductor facility as listed by the Semiconductor Industry Association. In Panel A, the “Post” indicator identifies quarters after USICA passed in the U.S. Senate. In Panel B, the “Post” indicator identifies quarters after the CHIPS Act was signed into law. Panel B omits the time period from USICA until CHIPS Act for comparing outcomes after CHIPS Act to those prior to the precursor of CHIPS, the USICA. Outcome in Column 1 is the number of workers employed in the semiconductor sector (NAICS industry code 3344). Outcome in Column 2 is the number of workers employed the manufacturing of equipment (NAICS 3332) or material inputs (NAICS 3251) for semiconductors. Outcome in Column 3 is the number of workers employed in either the semiconductor industry or the manufacturing of equipment (NAICS 3332) or material inputs (NAICS 3251) for semiconductors. The pre-USICA outcome mean is the outcome mean for treated counties for the 2015Q1-2021Q1 period. The employment numbers are obtained from the BLS Quarterly Census of Employment and Wages and the Census Quarterly Workforce Indicator, wherever available. The standard errors included in parentheses are clustered at the county level. *p <0.10; **p <0.05; ***p <0.01.

TABLE A7: EMPLOYMENT IN SEMICONDUCTORS: SYNTHETIC DID USING QWI/QCEW 4-DIGIT DATA

	Semiconductor employment	Equipment or materials employment	Semiconductor equipment or materials employment
	(1)	(2)	(3)
Panel A: Treatment effect post-USICA			
Treated x Post-USICA	92.209**	48.080***	148.626***
	(38.527)	(17.041)	(49.931)
Observations	42680	42680	42680
Pre-USICA outcome mean (treated counties)	1605.080	508.060	2113.140
Panel B: Treatment effect post-CHIPS, omitting 2021Q2-2022Q3			
Treated x Post-CHIPS	116.043**	60.239***	183.431***
	(49.428)	(22.264)	(64.436)
Observations	36278	36278	36278
Pre-USICA outcome mean (treated counties)	1605.230	507.071	2112.301

Notes: Data are from QWI/QCEW combined data at 4-digit level. The sample includes all counties with at least 100 workers in the 11 high-tech sectors, as defined in Census Bureau (2024) as of 2051Q1. The "Treatment" indicator identifies counties with an existing private (not a University or an R&D partner) semiconductor facility as listed by the Semiconductor Industry Association. In Panel A, the "Post" indicator identifies quarters after USICA passed in the U.S. Senate. In Panel B, the "Post" indicator identifies quarters after the CHIPS Act was signed into law. Panel B omits the time period from USICA until CHIPS Act for comparing outcomes after CHIPS Act to those prior to the precursor of CHIPS, the USICA. Outcome in Column 1 is the number of workers employed in the semiconductor sector (NAICS industry code 3344). Outcome in Column 2 is the number of workers employed the manufacturing of equipment (NAICS 3332) or material inputs (NAICS 3251) for semiconductors. Outcome in Column 3 is the number of workers employed in either the semiconductor industry or the manufacturing of equipment (NAICS 3332) or material inputs (NAICS 3251) for semiconductors. The pre-USICA outcome mean is the outcome mean for treated counties for the 2015Q1-2021Q1 period. The employment numbers are obtained from the BLS Quarterly Census of Employment and Wages and the Census Quarterly Workforce Indicator, wherever available. The standard errors included in parentheses are clustered at the county level. *p <0.10; **p <0.05; ***p <0.01.