Employment Impacts of the CHIPS Act *

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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. Drawing on quarterly industry-by-county data from the Quarterly Census of Employment and Wages (QCEW), we implement two county-level difference-in-difference designs, the first comparing counties with pre-existing semiconductor facilities to other counties with high-tech industries and the second comparing counties with semiconductor fabrication facilities (which were targeted for the bulk of the CHIPS funding) to counties with non-fabrication semiconductor facilities. Using both approaches, we find robust, positive employment impacts in affected counties. The effects began at the time of the passage in the Senate of a precursor bill, in anticipation of the signing of the CHIPS Act. Our preferred estimates suggest an increase of 110 jobs per affected county in the first design and 180 jobs per affected county in the second design. We also find robust positive impacts on local construction employment. Evidence on total employment and GDP at the county level, as well as on employment in upstream input sectors, is mixed. Simple back-of-the-envelope calculations (which come with caveats) suggest national direct employment effects of approximately 15,000-16,000 jobs in the core semiconductor sector and indirect effects of 15,000-30,000 jobs in related sectors.

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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 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.

Data constraints are a key challenge: micro-data on individual firms or plants are not yet available for years following the Act's passage. Our approach is to focus on outcomes at the county level, using the Quarterly Census of Employment and Wages (QCEW), and to implement two difference-in-difference designs. In the first, we compare counties with pre-existing semiconductor production facilities (which we refer to as "semiconductor counties") to counties with pre-existing high-tech employment but no semiconductor producers ("high-tech non-semiconductor counties," or "non-semiconductor" counties for short). In the second, we compare counties with a pre-existing semiconductor fabrication facility ("fab counties") to counties with semiconductor facilities but no fabrication facility ("fabless counties").

From these county-level difference-in-differences, we are able to draw three conclusions about the short-term consequences of the Act. First, there were significant anticipation effects. The employment response appears to have begun with the introduction of a precursor act, the United States Innovation and Competition Act (USICA), which passed in the Senate in June 2021. It appears that the industry concluded quickly that final passage of a semiconductor-support law was 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. Our preferred estimates using the semiconductor vs. non-semiconductor county design indicate direct impacts of 110 jobs in the core semiconductor sector per affected county (for the 149 semiconductor counties). This represents an increase of 12.7% on average for these counties (relative to pre-USICA means). Our preferred estimates using the fab vs. fabless county design indicate impacts of 180 jobs per affected county (for the 83 fab counties) — an 11.8% increase on average for these counties.

Third, we find robust evidence of spillover effects on non-residential construction employment in affected counties. Our preferred estimates for the two designs suggest that the act generated 136 and 203 construction jobs per affected county, respectively. We also investigate the impacts of the Act on wages in semiconductors, on employment in upstream input sectors, and on total employment and GDP at the county level. Although the estimates for these outcomes are mostly positive, they are generally not statistically significantly different from zero.

It is important to note that our difference-in-difference approach estimates the *relative* impact on "treated" versus "control" counties (semiconductor versus non-semiconductor counties in the first design, fab versus fabless counties in the second). 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-difference estimates — an issue 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. Multiplying the estimates mentioned above by the number of affected counties in each design, we arrive at direct employment effects of approximately 15,000-16,000 in the core semiconductor sector and indirect effects of approximately 15,000-30,000 in related sectors.

A natural question in this context is whether the employment impacts that we estimate should be considered large or small. On the one hand, given the amounts of money slated to be spent under the Act ($52.7 billion appropriated), the employment effects seem modest.[1] On the other hand, given the highly capital-intensive nature of semiconductor production — it is among the most capital-intensive in U.S. manufacturing — one would not have expected enormous employment effects. 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

[1]Our direct estimate of 15,000-16,000 jobs is below the May 2021 forecast of 42,000 new jobs in the industry by the main industry association (Semiconductor Industry Association and Oxford Economics, 2021).

national security, and many policy-makers viewed the latter justifications as primary. From this perspective, the employment gains seem larger than many expected.

Another question one might reasonably ask is: if the key goal was to foster a resilient semiconductor supply chain within the U.S., why focus just on employment impacts? One answer is simply that employment data become available more quickly than the data that would be required to characterize the full supply-chain impacts of the Act. But beyond that simple answer, we would emphasize that employment impacts are an important input into any calculation of the net cost of resilience. Increases in employment generate additional tax revenue, reducing the net fiscal cost of the policy. They also reduce public spending on unemployment benefits, further mitigating the burden on government budgets. To the extent that they generate learning-by-doing or other forms of productivity gains, those gains should also be included in a net cost of resilience calculation. For all of these reasons, we view rigorous estimates of the employment impacts of the Act as a crucial first step in evaluating the success of the policy.

Our analysis also raises the question of 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. Below 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 on 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

[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).

contribution of the current study is to show that a sector-focused industrial policy can also boost employment in the targeted industry.

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. Section 5 presents the results, both the "direct" results on the semiconductor sector and "indirect" spillover results in related sectors and county-level aggregates. Section 6 discusses how to aggregate the county-level estimates to an overall, national effect. Section 7 discusses conceptual issues in the design of industrial policies raised by our analysis and Section 8 concludes.

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. 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.

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, 2023; 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 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. The CHIPS Program Office required applicants to demonstrate support from state and local governments, which proved to be a binding constraint for some applicants (Keller, 2025). 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 major 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 Act," passed on July 4, 2025, increased the AMIC rate from 25% to 35%, effective December 31, 2025.[4]

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 have to meet certain worker and community investment guidelines, which include paying prevailing wage rates to workers and

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

working with regional entities to provide workforce training. These have operationalized in a few ways; one is 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 has come with requirements for programs to reach economically disadvantaged individuals through workforce development and regional partnerships (NIST, 2023). For example, many of the workforce training programs have been encouraged to provide some form of childcare and projects that have applied for more than $150 million in direct funding have had to have a plan to provide facility and construction workers with access to child care. This requirement has arguably lowered barriers for women entering the workforce.[5] 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).

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 IRA

[5]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.

and the Bipartisan Infrastructure Law were roughly contemporaneous with the CHIPS Act. Our difference-in-difference strategies, 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, plant and equipment reported in semiconductor companies' Securities and Exchange Commission (SEC) 10-K filings, which are available annually.[6] Appendix Figure A1 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.

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 2 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 August 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 2, 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

[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.

Warner, 2007). Figure 3 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 Senator 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 to the signing of the CHIPS Act on August 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 use quarterly data and the precise timing of reactions to news about the bill does not play an important role. The key point to take away from the abnormal returns is that the market appears to have formed expectations of forthcoming government support for the industry in 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 Senator 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 2. 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.

[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`.

Several companies explicitly discussed their optimism about forthcoming government support, soon after the passage of USICA, well before the House passed its version of the bill. The comments of Thomas Sonderman, CEO of SkyWater Technology, a Minnesota-based foundry, on the company's 2021 Q3 earnings call on Nov. 3, 2021, are worth quoting at some length:[9]

> "As the country is coalescing around the concept of semiconductor sovereignty, SkyWater plays an increasingly critical role in supporting the vision of reestablishing the U.S. as a technology manufacturing leader... The CHIPS Act received bipartisan support in the Senate, and we remain confident that it will ultimately become law... [A] lot of the mechanics of what the CHIPS Act will actually look like are yet to be defined. There's USICA, which is the broader component tied to innovation investment in addition to manufacturing investment... Skywater will make a lot of money off the mere fact that there's going to be more innovation, more investment going into R&D... [W]e're talking with the state of Minnesota, both the executive branch as well as the senators and representatives from the U.S. government in terms of how we can accelerate adding capacity into our Minnesota fab so that [we] can resolve some of these near-term supply constraints. So I believe that we have a great long-term strategy tied to CHIPS, tied to USICA."

At roughly the same time, the company added 100 jobs at its Bloomington, Minnesota site (Hauser, 2021).

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 August 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 and 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.

[9] Source: https://earningscall.biz/e/nasdaq/s/skyt/y/2021/q/q3.

Another way to get at the question of whether chips shortages were driving the increase from May-June 2021 to August 2022 is to compare semiconductor employment in the U.S. to semiconductor employment in other countries. Such comparisons are made difficult by the fact that countries use different classification systems and often do not report employment at as disaggregated a level as the U.S. But one natural comparison is Canada, which has a small semiconductor sector and uses the same industrial classification system. Figure 4 plots employment over the study period Canada in Semiconductors and Other Electronic Component Manufacturing (NAICS 3344), the most disaggregated data publicly available. There was a dip in employment due to Covid-19 in early 2021 and by mid-2022 employment had just recovered to its pre-Covid level; we do not see a shift in levels that we see in the U.S. in Figure 2. Another country that reports data for a reasonably comparable industry is Germany. Appendix Figure A2 plots employment for industry WZ 261, Manufacture of Electronic Components and Boards (which corresponds to ISIC rev 4 industry 2610) from a monthly survey of establishments. The interpretation of this figure is complicated by the fact that the German statistical agency periodically changes the assignment of establishments to industries; this the reason for the jumps in Jan. 2020 and Jan. 2021 (Statistisches Bundesamt, 2021). Although the story is clearer for Canada than for Germany, we interpret the international evidence as suggesting that the level shift in semiconductor employment between the pre-2021 and 2023-24 periods we see in Figure 2 was not common across the board in industrialized countries.

3 Data

Our main source of employment and wage data is the Quarterly Census of Employment and Wages (QCEW), published by the U.S. Bureau of Labor Statistics (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 NAICS (North American Industry Classification System) 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. We focus on the period from 2015Q1 to 2025Q1, the most recent quarter available as of this writing. Semiconductor production is NAICS 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 include producers of inputs not dedicated to semiconductor production. The QCEW suppresses information in many country-industry-quarter cells for confidentiality reasons (when information about particular companies might be revealed). In our baseline results, we impute zeros for these suppressed observations. To check robustness, we will also report results when these observations are simply dropped. In another set of 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 of firms or individuals in a given cell.[10]

To identify the location of semiconductor facilities by county, we use the Semiconductor Industry Association's (SIA) U.S. Semiconductor Ecosystem Map, which catalogs locations across the U.S. conducting research on, designing, and/or manufacturing semiconductors.[11] 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 and activity.

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 Inflation Reduction Act (IRA) and the Bipartisan Infrastructure Law. As mentioned above, we address this challenge with two difference-in-difference designs. In the first, we compare counties with at least one semiconductor facility in the SIA Ecosystem Map data as of the date of passage of USICA (which we label "semiconduc-

[10]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.

[11]The SIA U.S. Semiconductor Ecosystem Map is available at `https://www.semiconductors.org/ecosystem/`. Accessed on June 4, 2025.

tor counties") to counties with at least 100 employees in high-tech sectors but no semiconductor production facilities ("high-tech non-semiconductor counties," or "non-semiconductor counties" for short).[12] In the second, we compare counties with a pre-existing semiconductor *fabrication* facility ("fab counties" – listed in the SIA data as having either a foundry or Integrated Device Manufacturer (IDM)) to counties with at least one semiconductor facility but no fabrication facility ("fabless counties"). In both cases, the key assumption for this approach to be valid is that the "treated" and "control" counties would have had parallel trends in the absence of the CHIPS Act. Under this assumption, deviations in trends in treated counties from trends in control counties can be attributed to the causal effect of the CHIPS Act. Both designs arguably allow us to identify the effects of the CHIPS Act separately from the IRA, Bipartisan Infrastructure Law, and other macroeconomic changes. The assumption is that the these other changes had similar effects on the treated and control counties, and hence will be absorbed by time effects in the regressions below.

We present both difference-in-difference designs because they have different strengths and weaknesses. On one hand, in the semiconductor vs. non-semiconductor county design, we can be reasonably confident that the control group experienced few direct effects of the CHIPS Act. Fabless counties, by contrast, may have been directly affected by the CHIPS Act provisions for funding of R&D and manufacturing of semiconductor equipment and materials, as well as the AMIC investment tax credit.[13] On the other hand, an advantage of the fab vs. fabless design is that the treatment and control counties may be more comparable, and the control counties may provide a more plausible counterfactual for what would have happened in the treated counties in the absence of the Act. Given that the great majority of the CHIPS funding was earmarked for fabrication facilities, it is plausible that the fab vs. fabless design captures the most important

[12]To define high-tech sectors, we use the following 11 four-digit NAICS sectors identified by Census Bureau (2024) as high-tech: Computer and Peripheral Equipment Manufacturing (3341), Communications Equipment Manufacturing (3342), Semiconductor and Other Electronic 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). We use data from 2021Q1 to define this variable. Below we explore robustness to different definitions of high-tech counties, using high-tech employment cutoffs of 0, 500, or 1000; we will see that the results are not sensitive to this definition.

[13]While pre-USICA employment in high-tech non-semiconductor counties is by construction very low, we note that nothing prevents semiconductor employment from rising in these counties, for instance due to greenfield investment, in the post-USICA period. The fact that semiconductor employment in these counties is initially low, in other words, does not in itself invalidate their use as a comparison group.

effects of the Act. In interpreting the results, we will emphasize findings that are robust across the two designs.

Within each design, we implement two econometric estimators, a simple difference-in-difference (DID) estimator and a synthetic difference-in-difference (SDID) estimator. In the simple DID approach, the specification is the following:

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

where Y_{it} denotes the outcome of interest (e.g., the level of semiconductor employment) in county i and year-quarter t. Treated$_i$ is an indicator which takes the value 1 for treated counties and 0 for control counties. The α_i and γ_t are county and year-quarter fixed effects, which absorb all time-invariant county-specific 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 2021Q2, and 1 from 2021Q3 to 2025Q1. We also explore robustness to an alternative specification in which the post-period is defined as post-CHIPS, rather than post-USICA; in this specification, Post$_t$ takes the value 0 from 2015Q1 to 2021Q2 and 1 from 2022Q3 to 2025Q1, 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:

$$Y_{it} = \mu + \alpha_i + \gamma_t + \sum_{\tau=2015q2}^{2025q1} \beta_\tau \cdot D_{i,t}^{\tau} + \varepsilon_{it} \quad (2)$$

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 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 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 treated and control counties. To address this concern, we implement the synthetic difference-in-difference (SDID) estimator of Arkhangelsky, Athey, Hirshberg, Imbens, and Wager (2021). The idea is that there may exist a weighted average of control counties that more closely mirrors the pre-treatment outcome trajectory of treated counties and hence more accurately represents the trend that would have been observed in the treated 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 pre-treatment *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 using post-CHIPS as the post-period. The weights, $\hat{\omega}_{ij}$ and $\hat{\lambda}_t$, are chosen 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 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.

To illustrate our research design, Figure 5 displays a map of U.S. counties. High-tech non-semiconductor counties are indicated in red. Fabless counties (counties with at least one semiconductor facility but no fab) are in blue. Fab counties are in green. The semiconductor vs. non-semiconductor design compares the red counties to the union of the green and blue counties. The fab vs. fabless design compares the green counties to the blue counties. By the above definitions, there are 149 semiconductor counties and 752 high-tech non-semiconductor counties, and 83 fab and 66 fabless counties.[14]

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 two sets of treated and control counties. In the first four columns, we see that, 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 than the non-semiconductor counties. In the fifth through eighth columns, we see that the fab counties again tend to have higher total employment and be less rural than the fabless counties, but the manufacturing shares of the two sets of counties are comparable. On the various demographic dimensions reported in Panel B, the sets of

[14]Inconveniently, Connecticut changed from using nine counties to eight planning regions for statistical purposes in 2024; because of the difficulties in tracking outcomes over time, we drop Connecticut from the sample.

counties are reasonably similar. 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 designs 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 will examine pre-trends below.

Two features of both of our difference-in-difference designs are important to highlight. First, our estimates will only capture impacts of the Act in counties with pre-existing semiconductor facilities (any seminconductor facility in the semiconductor vs. non-semiconductor design, a fabrication facility in the fab vs. fabless design). Greenfield investment in counties without an existing facility will not be reflected. In this sense, our estimates are likely to under-estimate the true impacts of the Act. Second, our analysis does not use information on actual grants under the CHIPS Act; our estimates are based on firms' reactions to the expectation of funding 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 to counties with firms 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 approval. The main difficulty with this alternative strategy is timing, given current data constraints. The first major CHIPS awards were not finalized until November 2024 and, as explained above, the QCEW data currently end in 2025Q1. 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. While this alternative strategy is not currently feasible, it remains a promising potential 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. Figures 6a and 6b plot 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) for the semiconductor vs. non-semiconductor and fab vs. fabless designs, respectively. In both designs, there is little evidence of differential pre-trends between the treated and control counties prior to 2021, which is reassuring about the parallel trends assumption. Beginning in 2021Q3, when USICA passed the Senate, we see a relative increase in semiconductor employment for five quarters in treated counties in both figures. Semiconductor employment stabilized in 2022Q3, about the time the CHIPS Act was signed.

Figures 7a and 7b plot the event-study estimates from the synthetic difference-in-difference (SDID) specification (equation (3)) for the two designs. The SDID evidence is even stronger than the simple DID: again, there are no differential pre-trends and the increases beginning with the passage of USICA are clear. Consistent with the descriptive evidence in Section 2.3, all four event-study specifications 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. Note that the scale of the y-axes differ between Figures 6a and 6b and between Figures 7a and 7b; the fab vs. fabless design suggests impacts that are 50-80% larger in levels, consistent with the idea that the fab counties saw the largest impacts among the semiconductor counties. But the time-pattern of changes is quite similar across the designs and specifications.

Table 2 reports estimates of average treatment effects from the simple difference-in-difference (DID) specification in equation (1), which constrains the post-treatment employment effect to be constant across quarters. The Column 1 outcome is the level of employment in semiconductor production; the Column 2 outcome is the level of employment in semiconductor equipment and materials (pooled); and the Column 3 outcome is employment in production, equipment and materials combined. Panel A reports the semiconductor vs. non-semiconductor comparison, and Panel B the fab vs. fabless comparison. The Panel A estimate of the impact of CHIPS on semiconductor employment in semiconductor counties is 106 jobs (Column 1), or 141 jobs if employment in semiconductor equipment and materials is included (Column 3). The Panel B estimates are larger: 191 jobs in semiconductors in fab counties (Column 1), or 270 jobs if equipment or materials are included.

Table 3 shows average treatment effects using the synthetic difference-in-difference (SDID) approach. For the reasons cited in Section 4 above, the SDID estimates are our preferred estimates. The organization of the table is similar to Table 2. The results are also similar. In Panel A, using the semiconductor vs. non-semiconductor comparison, we estimate treatment effects of 110 jobs per county in semiconductor production alone and 124 if we include semiconductor equipment and materials. Relative to the pre-USICA mean employment numbers for semiconductor counties, these represent increases of 12.7% and 12.0%, respectively, in treated counties. In Panel B, using the fab vs. fabless comparison, the corresponding numbers are 180 and 211. Relative to the pre-USICA mean employment for fab counties, these represent increases of 11.8% and 12.0%. We return in Section 6 below to the question of how to estimate national-level employment impacts of the CHIPS Act on the basis of these difference-in-difference estimates.

Several robustness checks are reported in the appendix. Appendix Table A4 reports results similar to Table 2 but dropping the observations with suppressed data. The results are qualitatively similar to those in Table 2 but of larger magnitude; in this sense, our baseline approach of imputing zeros is conservative. Appendix Tables A5 and A6 report results analogous to Tables 2 and 3 but using post-CHIPS as the post-period. The results are again similar with larger magnitudes — unsurprisingly given the visual evidence in Figures 6, 6a-6b, and 7a-7b. Appendix Table A7 reports results using the combined QCEW/QWI data at the 4-digit level (described in Section 3); results are qualitatively similar to the baseline results. Appendix Table A8 explores the robustness of our findings to the inclusion of time-varying county demographics (Panel A) and to allowing for differential trends associated by 2010 rural share (Panel B). Appendix Table A9 checks robustness to using different cutoffs for high-tech employment in the definition of high-tech non-semiconductor counties. Overall, the employment results are quite robust to the choice of specification, data processing, and comparison group definitions.

In our view, the employment increases most likely reflected two changes: expansions of production workforces driven by increases in output at existing facilities (as mentioned for instance in the quotes from GlobalFoundries' CEO in Section 2.3 above); and expansions of planning staff to design and in other ways prepare for the construction of new facilities. It is also possible that firms hired even before either type of expansion, in order to be prepared to expand when (or if) CHIPS funding was approved. The overall increase in employment in the industry, and the presumably tight labor market for employees with specialized skills needed by the industry, may have accentuated this latter motive. It is difficult to distinguish between these mechanisms in existing data; more light will be able to be shed once more detailed information on output and skill composition at semiconductor facilities becomes available.

5.2 Wage Impacts in Semiconductors

We next examine the effects on real average weekly wages per worker in the semiconductor sector. Given that semiconductor employment is very low in the high-tech non-semiconductor counties, the fab vs. fabless comparison is the more natural one for examining wage effects, but we report the results from both designs for completeness. Table 4 reports wage estimates for the DID and SDID estimators for each design.[15] The outcomes are average weekly wages in semiconductors (Column 1), average weekly wages in semiconductor equipment and materials (Column 2), and average weekly wages combining semiconductors and semiconductor equipment and materials (Column 3). The point estimate for the SDID in the fab vs. fabless design, our preferred specification, indicates a positive effect on average weekly wages of $166, on a pre-USICA mean of $1,086 — an increase of 15.3% — but this estimate is not statistically significant at conventional levels of confidence, and caution is warranted in interpreting it. In addition to the lack of statistical significance, we note that average weekly wages at the county-industry level may reflect changes in the composition of the workforce, as well as wage changes for continuing workers. Although there is stronger evidence of positive wage effects using the semiconductor vs. non-semiconductor county design, overall we would characterize the evidence on wage effects as no stronger than suggestive. It is worth noting that if the supply of labor is very elastic, for instance because workers are very willing to move across counties or across industries within affected counties to take up semiconductor jobs, then a positive employment demand shock, of the sort that the CHIPS Act appears to have generated, would not be expected to generate large positive wage effects.

5.3 Local Spillover Effects

In this section, we examine the local spillover effects of the CHIPS Act on related sectors in the same county as well as on total county employment and county GDP. First consider the effects on upstream input suppliers. Semiconductor production facilities are often 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. To determine the list of sectors that supply material inputs to semiconductor production, we use

[15] Average weekly wages in the QCEW are calculated as total quarterly wage bill in the county-industry-quarter divided by employment in first month of quarter and by 13 (the number of weeks per quarter). To adjust for seasonality, we then calculate a moving average of the wage bill over the current quarter and the three preceding quarters (quarters t-3 through t).

the Bureau of Economic Analysis (BEA) input-output tables.[16] Column 1 of Table 5 reports results from the SDID specification with the sum of employment in input sectors as the outcome. The estimate from the semiconductor vs. non-semiconductor design in Panel A indicates a positive, statistically significant impact of approximate 54 jobs in these input sectors. But this effect is not robust to using the fab vs. fabless design. The estimate from the latter design is negative but not statistically significant. The results for upstream input sectors are thus mixed and we do not draw strong conclusions from them.

A clearer message emerges about the impact of the CHIPS Act on another related sector: construction. Column 2 of Table 5 reports SDID estimates with non-residential construction employment as the outcome. We see positive, statistically significant effects of 136 jobs per county using the semiconductor vs. non-semiconductor design and 203 jobs per county using the fab vs. fabless design. To get a better sense of the timing, Figure 8 shows SDID event-study graphs for non-residential construction employment. We see a significant rise following the passage of USICA, with the upward trend continuing after the CHIPS Act was enacted. An important qualification is that these construction jobs may be temporary jobs, lasting only as long as the construction projects stimulated by the Act, but they nonetheless contribute toward the job-creation goals of the Act. Given the necessarily local nature of construction spillovers, it is perhaps not surprising that the results for construction are more robust than for upstream inputs, but we view it as quite reassuring about our research designs that non-residential construction, which makes up a non-trivial share of employment in both treatment and control counties in both designs, responded as expected to the positive shock generated by the Act.

We also examine two county-level aggregates: total employment and county Gross Domestic Product (GDP). First consider total employment. Figures 9a and 9b present event-study SDID graphs for the two designs. In both cases, we see a relative decline in total employment in treated

[16] In particular, we use the BEA "Use" table available at `https://apps.bea.gov/industry/Release/XLSX/IOUse_After_Redefinitions_PRO_Detail.xlsx`. The input sectors we consider are the following: nonferrous metal (except aluminum) smelting and refining (NAICS 331410), printed circuit assembly (electronic assembly) manufacturing (NAICS 334118), 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 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.

counties in the second quarter of 2020 due 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 hence were more affected by high infection rates and the ensuing lockdowns. Following the pandemic, the two graphs tell somewhat different stories. The semiconductor vs. non-semiconductor graph (Figure 9a) shows that it took several quarters for total employment semiconductor counties to recover relative to non-semiconductor counties, and there is no apparent effect of the CHIPS Act in the longer term. The fab vs. fabless graph (Figure 9b) indicates that employment in fab counties recovered quickly in relative terms and rose relative to fabless counties in the longer term. Column 3 of Table 5 reports the corresponding SDID results. The estimate for the semiconductor vs. non-semiconductor design is in fact negative, although not significant, but the estimate for the fab vs. fabless design is positive and significant at the 90% level. The point estimate suggests an increase of 2.2% in total employment in fab counties (8,503/386,371). We consider this to be suggestive evidence that the Act was able to move total employment in fab counties, but the fact that the estimate is significant only at the 90% level and the lack of robustness across designs warrant caution.

For county-level GDP, the results are easily summarized: we find little evidence of an effect of the Act. The available county-level GDP numbers are from the Bureau of Economic Analysis, which publishes data annually but not quarterly. For this analysis, we extend the sample back to 2010, to have more data in which to match pre-trends. Column 4 of Table 5 presents the results. The point estimates have the same signs as those for total employment, and the positive estimate for the fab vs. fabless design is consistent with the hypothesis that the Act has a positive aggregate effect particularly for fab counties, but the estimates are imprecise and not statistically significant. Our interpretation is that the CHIPS Act was not large enough to have detectable effects on GDP at the county level, at least over the short-term time horizon we are able to focus on.

6 Estimates of National Aggregate Effects

As noted above, our difference-in-difference approaches estimate the *relative* impact on treated vs. control counties. Part of the *absolute* impact of the CHIPS Act on national aggregate employment in semiconductors 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 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-difference 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., 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 argue that the differences between these effects are likely to be small in our context, and that the aggregate direct and indirect effects on employment 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. 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 low semiconductor employment in the control counties in our two designs, particularly in the high-tech non-semiconductor counties (refer to Table 1), means that the scope for within-sector factor mobility from untreated to treated counties is limited and suggests that the difference between β^{DID} and β^{micro} is not likely to be large 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, 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, $\beta^{\text{all regions}}$. It is plausible that this argument applies in our setting. It is also worth noting that we do not detect effects on 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 time-series variation we observe in aggregate semiconductor employment we observe in Figure 2, based on unprocessed data from the Current Employment Statistics (CES). 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 arrive at numbers similar to this time-series estimate. In the semiconductor vs. non-semiconductor design, we have 149 treated semiconductor counties. Simply multiplying our preferred per-county estimate of 110 additional semiconductor jobs (Column 1 of Table 3 Panel A) by the number of treated counties, we get an estimate of 16,390 jobs nationally. In the fab vs. fabless design, we have 83 treated fab counties. Multiplying by our preferred estimate of 180 jobs (Column 1 of

Table 3 Panel B), we get 14,940 jobs. The time-series estimate of 18,000 jobs is well within the intervals that would be generated by scaling up the 95% confidence intervals by the number of treated counties. This supports our argument that both the "micro" (between particular counties) and "macro" (from one county to the 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.

The calculations above refer to direct effects on employment in the core semiconductor industry (NAICS 334413). To derive an estimate of the indirect effect of the Act on related sectors, we include the impacts on employment in semiconductor equipment and materials manufacturing, in upstream inputs, and in non-residential construction in the affected counties. Although many of these coefficients are not statistically significant, as discussed above, they still represent our best estimates of the indirect employment impacts of the Act. Using our preferred SDID estimates from Tables 3 and 5, we have an effect on related sectors of 206 jobs per affected county in the semiconductor vs. non-semiconductor design (16 + 54 + 136) and 182 jobs per affected county in the fab vs. fabless design (27 - 48 + 203). Scaling these up by the number of affected counties, we arrive at national indirect impacts of 30,694 jobs (206 * 149) and 15,106 jobs (182 * 83) for the semiconductor vs. non-semiconductor and fab vs. fabless designs, respectively.

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 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 find 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 area of industrial policy.

7 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 about 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.[17] Arguably, another 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

[17] Initial estimates indicated that the IRA would include approximately $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).

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.[18] 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 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 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; the discretion associated with the Trump Administration stake in Intel, but not other companies receiving CHIPS subsidies, provides 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

[18] 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.

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 we should 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.

8 Conclusion

This paper has provided early empirical evidence on the labor market impacts of the CHIPS Act using two county-level difference-in-difference designs, one comparing counties with semiconductor facilities to counties with high-tech employment but no semiconductor facilities and the other comparing counties with a semiconductor-fabrication facility to counties with at least one semiconductor facility but not a fabrication plant. Our preferred estimates indicate direct impacts on employment in the core semiconductor sector of 110 jobs per affected county in the former design and 180 jobs per affected county in the latter design — approximately 12% increases relative to the treated group pre-treatment means in both cases. Aggregating to the national level, which comes with caveats as discussed above, we estimate a total direct impact of roughly 15,000-16,000 jobs in both designs. Our best estimates of the indirect employment impacts, on employment in semiconductor equipment and materials manufacturing, in manufacturing of upstream inputs, and in non-residential construction are roughly 15,000-30,000 jobs. Combining the direct and indirect impacts, we arrive at total impacts of roughly 30,000-45,000 jobs that can be attributed to the CHIPS Act.

One key message of our study is that industrial policies can deliver measurable employment benefits in targeted strategic sectors, even in the short run. The results speak not only to the question of whether the Act generated employment, a widely cited and politically salient policy objective, but are also potentially useful as an input into the "net cost of resilience," which should take into account the additional tax revenue and lower spending on unemployment benefits that the additional employment generates.

Another key message is that there were important anticipation effects. We find that the employment increases began at the time of passage of a precursor act (USICA) in the Senate in June, 2021. But the time the CHIPS Act was signed in Aug. 2022, the employment increases that we argue were due to the Act had already largely occurred. The argument that the market anticipated the effects of the Act is supported by evidence from stock-market returns as well as contemporary press accounts and corporate earnings calls. This finding reinforces earlier work on anticipation effects, for instance by Ramey (2011b).

One argument that we are not making is that estimating short-term employment impacts is the only or even the best way to evaluate the overall success of an industrial policy such as the CHIPS Act. The extent to which the Act has increased investment in the sector and generated learning-by-doing within subsidized firms and learning spillovers to other firms may well be more important for growth and hence worker welfare in the long run than short-term job creation. We view this paper as a first step in understanding the consequences of the Act. We hope that it will be followed by many more analyses of other impacts, including on capital deepening and productivity improvements, as well as on employment and wages in the longer term, once the necessary data become available.

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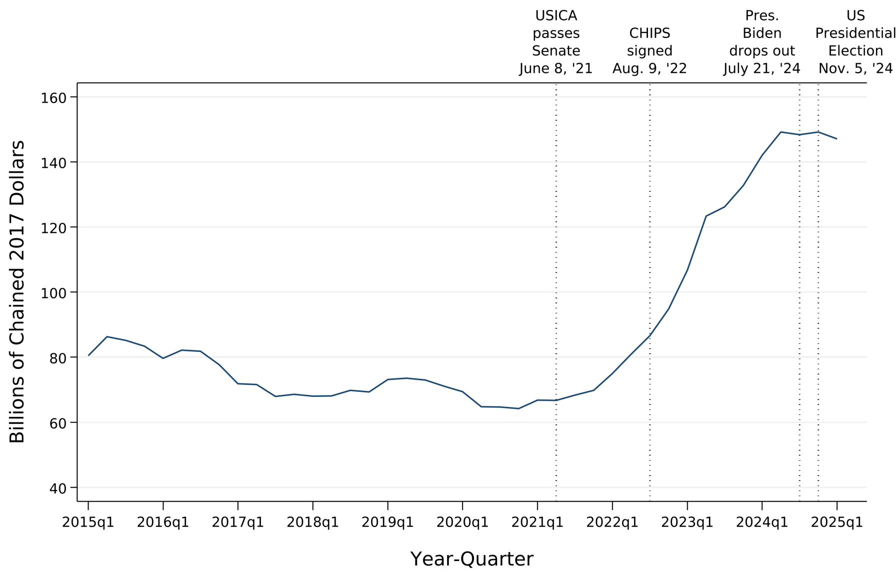
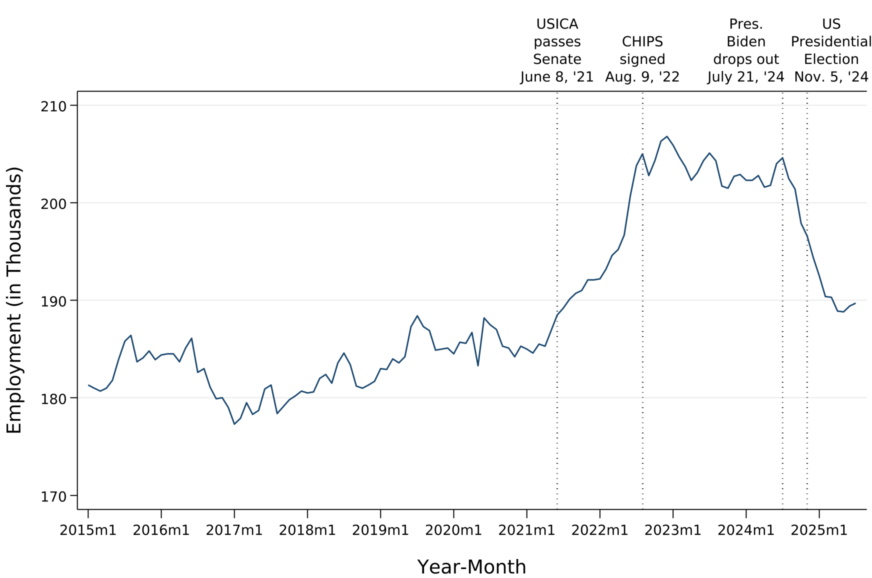
FIGURE 1: REAL PRIVATE FIXED INVESTMENT IN NONRESIDENTIAL MANUFACTURING STRUCTURES



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). The dotted vertical lines indicate (from left to right) Q2 of 2022, when the USICA was passed; Q3 of 2022 when the CHIPS Act and Inflation Reduction Act (IRA) were passed; Q3 of 2024, when Biden dropped out of the presidential race; and Q4 of 2024 when the presidential election occurred. Y-axis is investment per quarter. Data can be accessed at `https://apps.bea.gov/iTable/?isuri=1&reqid=19&step=4&categories=flatfiles&nipa_table_list=1`.

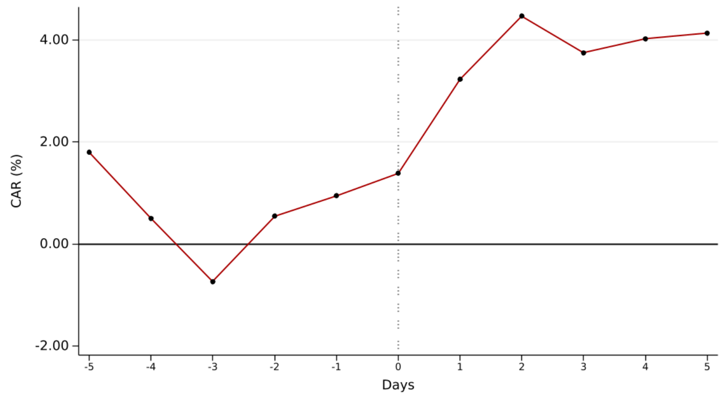
FIGURE 2: EMPLOYMENT IN SEMICONDUCTOR INDUSTRY



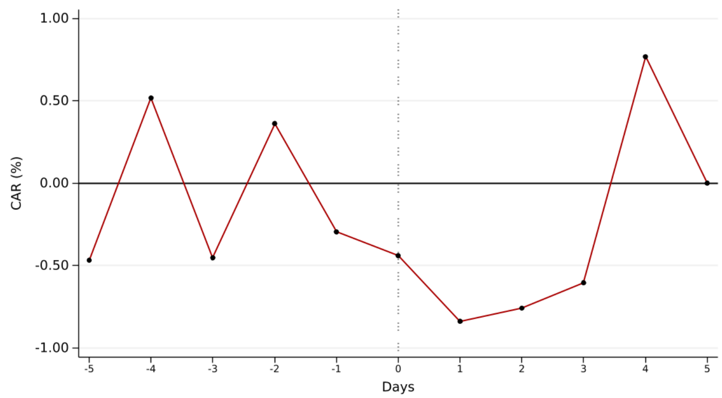
Notes: Figure plots the total number of workers in the semiconductor industry (NAICS 334413) across the United States, as reported in the Current Employment Statistics (National Series). Data can be accessed at `https://download.bls.gov/pub/time.series/ce/ce.data.0.AllCESSeries`.

Figure 3: Cumulative Abnormal Returns for Semiconductor Firms

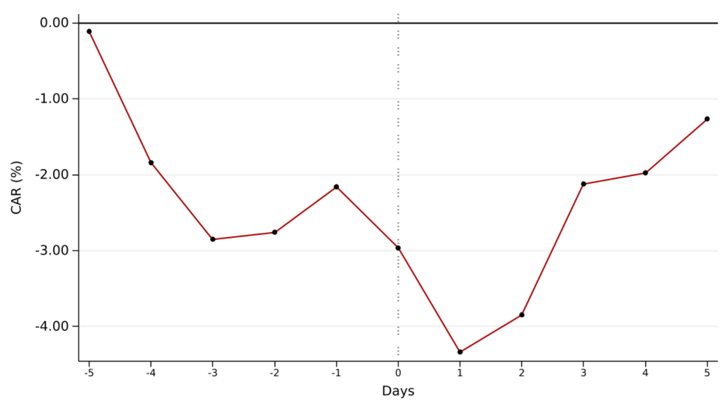
A. May 18, 2021



B. June 8, 2021

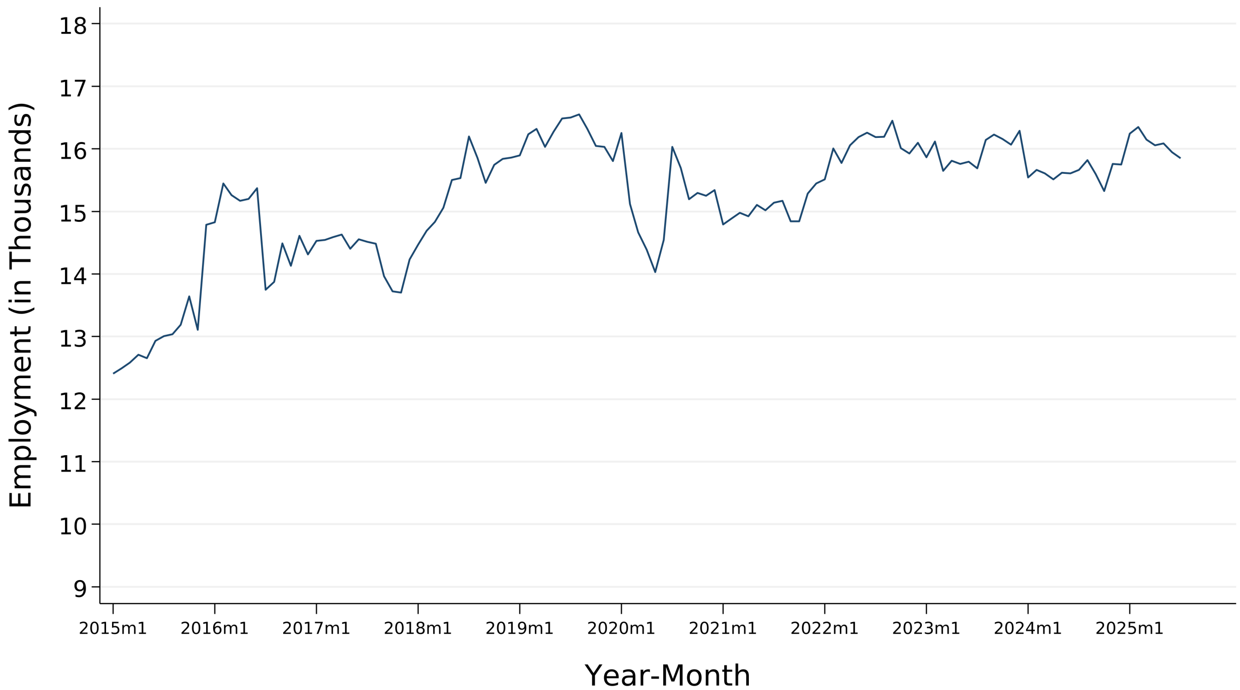


C. July 28, 2022



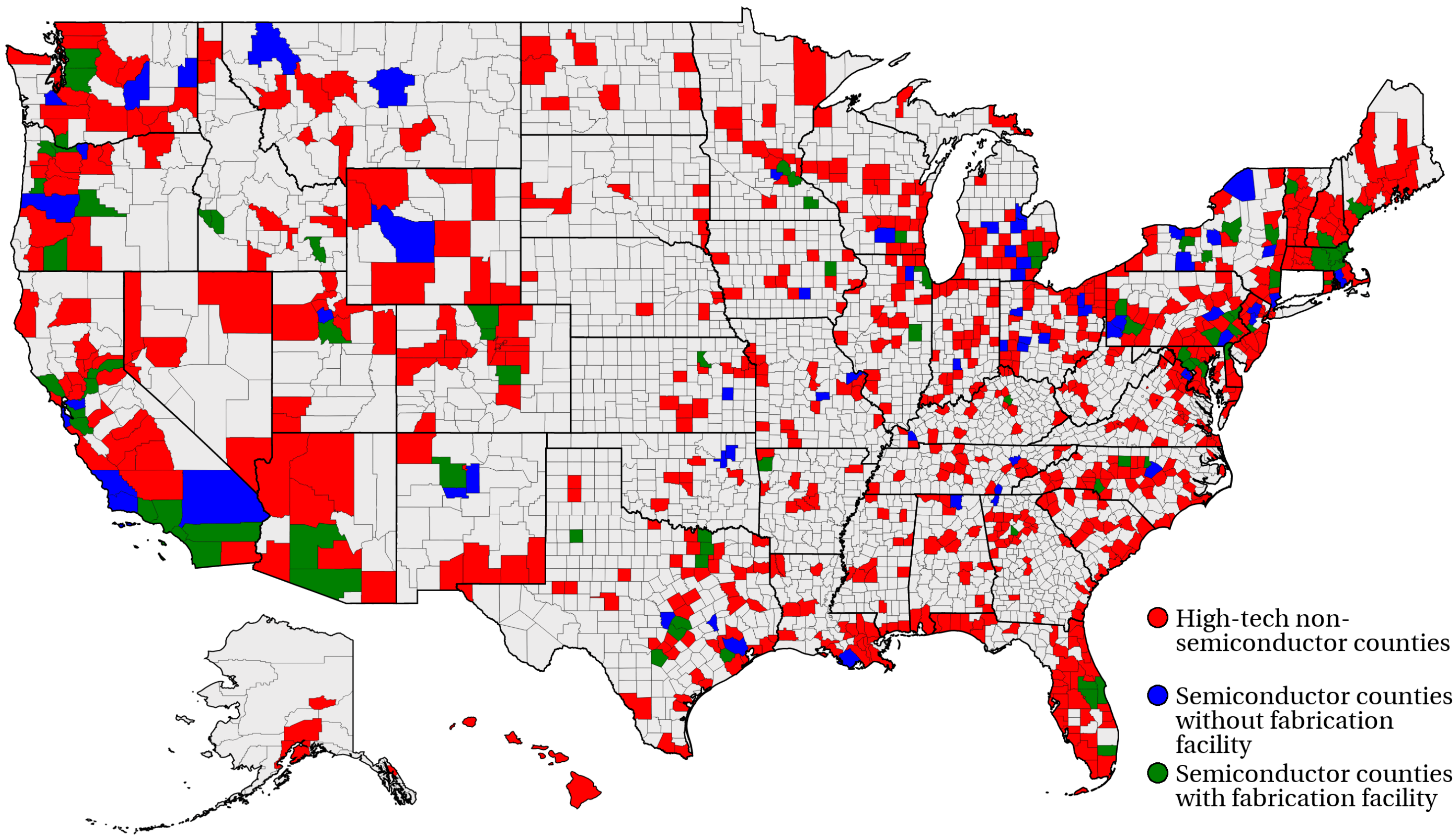
Notes: Cumulative Average Abnormal Returns (CAARs) around major semiconductor policy events are calculated as follows (using the Stata estudy command). We first calculate Abnormal Returns (ARs) by estimating the regression $R_{it} = \gamma_i R_{mt} + \alpha_i + \varepsilon_{it}$, where R_{it} is firm 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. The sample is the set of firms included in Figure A1, excluding Global Foundries and Skywater, who began trading on October 28, 2021 and April 21, 2021, respectively. See also Appendix Table A3. Data for historical stock prices taken from `https://finance.yahoo.com/`.

FIGURE 4: EMPLOYMENT IN SEMICONDUCTORS AND AND OTHER ELECTRONIC COMPONENT MANUFACTURING: CANADA



Notes: Source is Survey of Employment, Payroll and Hours (SEPH) conducted by Statistics Canada, for semiconductor and other electronic component manufacturing (NAICS 3344). Data can be accessed at `https://www150.statcan.gc.ca/t1/tbl1/en/cv.action?pid=1410020101`

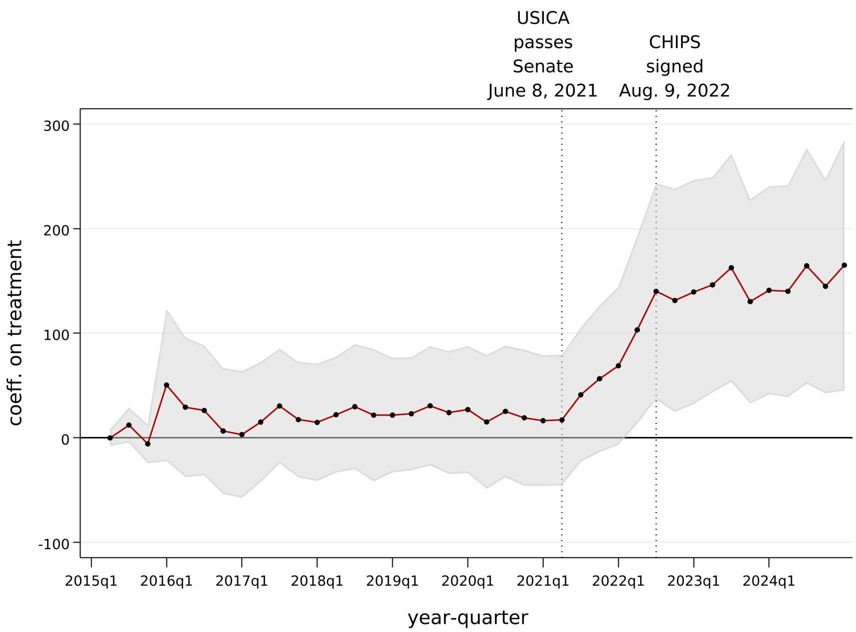
FIGURE 5: COUNTY COMPARISON GROUPS



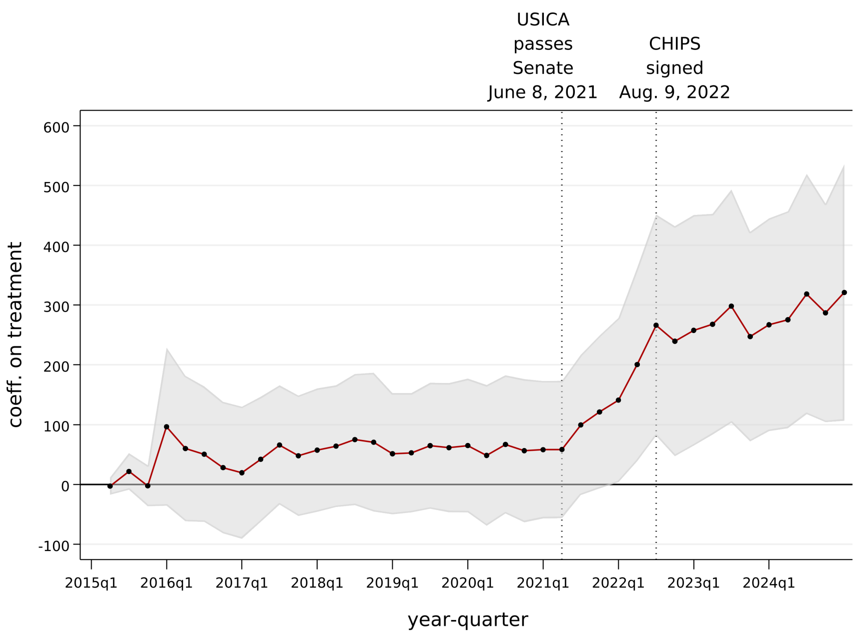
Notes: The data are from the Semiconductor Industry Association's (SIA) U.S. Semiconductor Ecosystem Map. Counties with employment >100 in 11 high-tech sectors (defined by Census Bureau (2024)) but no private semiconductor production facility ("non-semiconductor counties") are marked in red. Counties with a semiconductor fabrication facility ("fab counties") are marked in green. Counties with a semiconductor facility but no fabrication facility ("fabless counties") are marked in blue.

FIGURE 6: EMPLOYMENT IN SEMICONDUCTORS: SIMPLE DID

A. Semiconductor vs. High-Tech Non-Semiconductor Counties



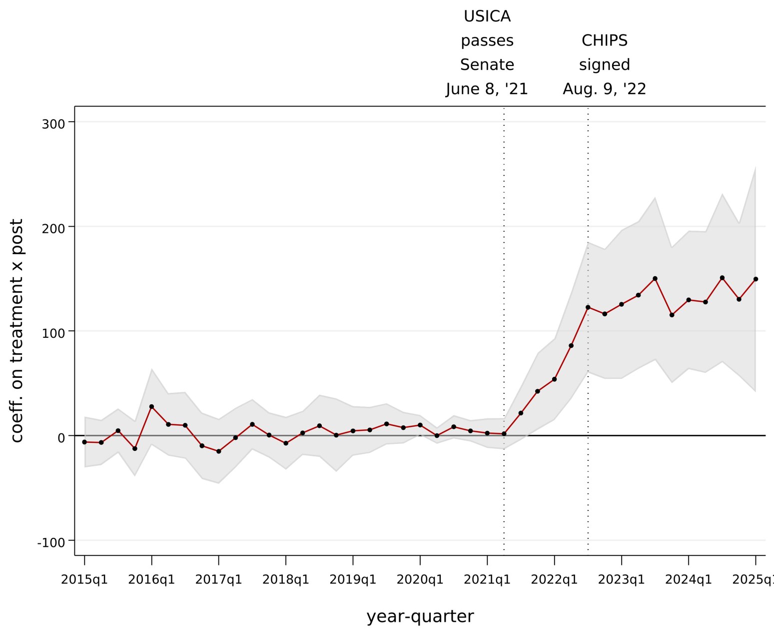
B. Fab vs. Fabless Counties



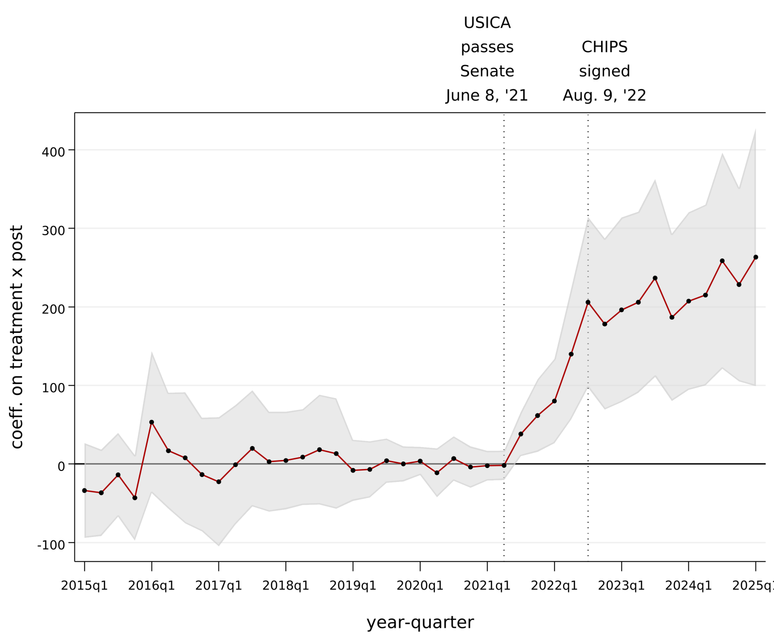
Notes: Estimates are from event-study specification of simple difference-in-differences, equation (2) in text. Comparison groups are defined in Section 4. Outcome is the number of workers employed in the semiconductor sector (NAICS industry code 334413). Source is QCEW 6-digit data. Sample includes all counties with at least 100 workers in 11 high-tech sectors, as defined in Census Bureau (2024), as of 2021Q1. Shaded area represents 95% confidence interval. Standard errors are clustered at the county level.

FIGURE 7: EMPLOYMENT IN SEMICONDUCTORS: SYNTHETIC DID

A. Semiconductor vs. High-Tech Non-Semiconductor Counties



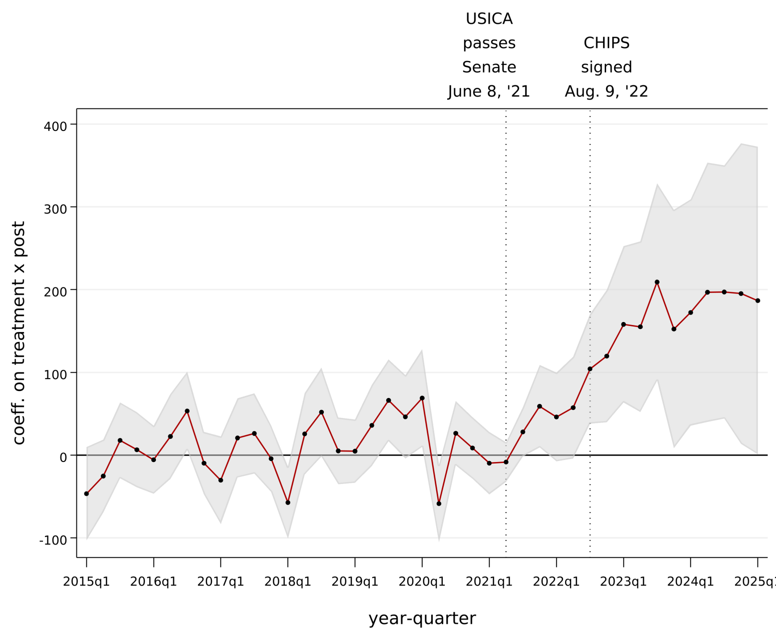
B. Fab vs. Fabless Counties



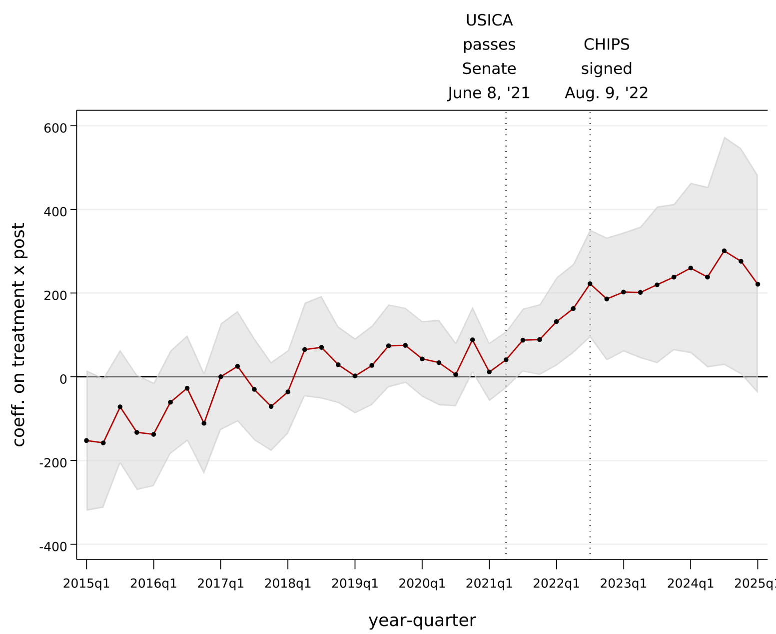
Notes: Estimates are from synthetic difference-in-difference (SDID) specification, equation (3) in text. Outcome is the number of workers employed in the semiconductor sector (NAICS industry code 334413). Source is QCEW 6-digit data. Comparison groups are defined in Section 4. Estimated treatment effects 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.

FIGURE 8: NON-RESIDENTIAL CONSTRUCTION EMPLOYMENT: SYNTHETIC DID

A. Semiconductor vs. High-Tech Non-Semiconductor Counties



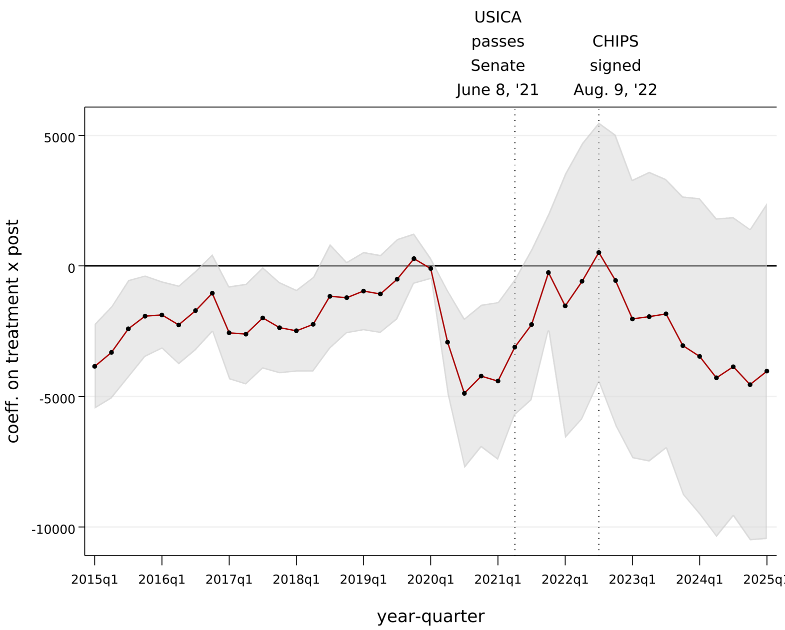
B. Fab vs. Fabless Counties



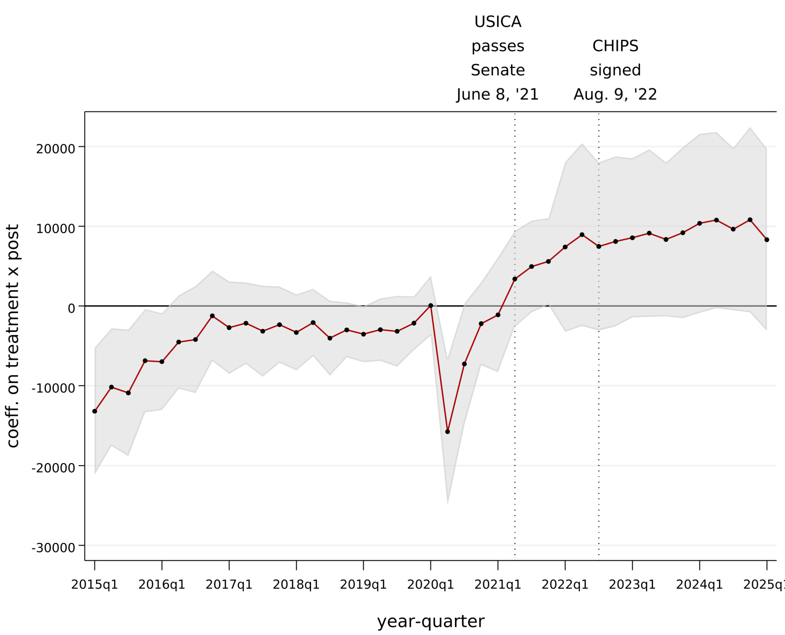
Notes: Estimates are from synthetic difference-in-difference (SDID) specification, equation (3) in text. Outcome is the number of workers employed in either industrial building construction (NAICS 236210) or commercial and institutional building construction (NAICS 236220). Source is QCEW 6-digit data. Comparison groups are defined in Section 4. 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.

Figure 9: Total County Employment: Synthetic DID

A. Semiconductor vs. High-Tech Non-Semiconductor Counties



B. Fab vs. Fabless Counties



Notes: Estimates are from synthetic difference-in-difference (SDID) specification, equation (3) in text. 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. Comparison groups are defined in Section 4. 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 1: SUMMARY STATISTICS: TREATED AND CONTROL COUNTIES

	Semiconductor vs. Non-Semiconductor				Fab vs. Fabless			
	Control		Treated		Control		Treated	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Panel A: General County Characteristics								
Total Empl. (in thousands)	61.6	108.0	291.8	507.9	199.6	382.1	365.2	580.9
Manufacturing, as % of total emp	3.2	4.9	4.2	3.9	4.1	4.5	4.3	3.4
Empl. in Semiconductors	3.4	43.1	850.1	3538.0	53.9	158.8	1483.1	4653.7
Empl. in Semi. Materials/Equip.	10.4	78.4	141.5	622.8	72.2	512.1	196.6	696.7
Avg. Weekly Wage, all Industries	734.6	179.1	909.7	300.4	876.5	346.3	936.1	257.4
Unemployment Rate	5.8	1.9	5.3	1.2	5.6	1.3	5.1	1.1
Rural %	28.2	20.5	17.3	19.4	24.5	24.2	11.5	11.7
Panel B: Demographics								
Panel B.1: Gender								
Male %	49.6	1.4	49.5	0.9	49.6	0.9	49.4	0.8
Female %	50.4	1.4	50.5	0.9	50.4	0.9	50.6	0.8
Panel B.2: Race/Ethnicity								
White %	83.8	14.1	82.7	11.9	85.1	10.3	80.8	12.7
Black %	11.7	13.1	9.4	9.2	7.9	6.8	10.6	10.6
Asian %	3.2	5.5	6.4	6.6	5.2	6.7	7.4	6.5
Hispanic %	10.6	12.6	14.8	13.4	12.6	13.6	16.6	13.0
Panel B.3: Age								
Ages under 19 %	25.8	3.3	25.5	2.9	25.2	3.0	25.8	2.7
Ages 20 to 24 %	7.3	3.0	7.6	3.2	7.5	3.2	7.6	3.2
Ages 25 to 34 %	11.5	2.1	12.2	2.3	11.8	2.5	12.6	2.1
Ages 35 to 44 %	13.4	1.5	14.0	1.5	13.6	1.4	14.3	1.6
Ages 45 to 54 %	13.3	1.6	13.5	1.6	13.4	1.4	13.5	1.6
Ages 55 to 64 %	13.2	2.0	12.8	1.7	13.2	1.7	12.5	1.7
Number of counties	752		149		66		83	

Notes: Comparison groups are defined in Section 4. Employment and wages are from the QCEW for 2015Q1. Employment in semiconductors for NAICS industry code 334413. Employment in semiconductor materials/equipment is for NAICS 333242 (equipment) and NAICS 325120, 325180 (material inputs). 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	Semiconductor equipment & materials employment	Semiconductor production, equipment & materials employment
	(1)	(2)	(3)
Panel A: Semiconductor vs. Non-Semiconductor Counties			
Treated x Post-USICA	106.09***	34.81**	140.90***
	(39.90)	(16.82)	(50.17)
Observations	36941	36941	36941
Pre-USICA outcome mean (treated counties)	868.7	165.3	1034.0
County FE	Y	Y	Y
Year-Quarter FE	Y	Y	Y
Panel B: Fab vs. Fabless Counties			
Treated x Post-USICA	191.35***	78.53**	269.88***
	(70.80)	(31.21)	(88.81)
Observations	6109	6109	6109
Pre-USICA outcome mean (treated counties)	1523.6	239.4	1763.0
County FE	Y	Y	Y
Year-Quarter FE	Y	Y	Y

Notes: Estimates are from simple difference-in-difference (DID) specification, equation (2) in text. Comparison groups are defined in Section 4. Post-USICA indicator identifies quarters after USICA passed in the U.S. Senate (2021Q3 or later). 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 2015Q1-2021Q2 period. *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: Semiconductor vs. Non-Semiconductor Counties			
Treated x Post-USICA	110.41***	15.75	124.08***
	(35.19)	(12.00)	(38.53)
Observations	36941	36941	36941
Pre-USICA outcome mean (treated counties)	868.7	165.3	1034.0
Panel B: Fab vs. Fabless Counties			
Treated x Post-USICA	180.13***	27.27	210.94***
	(52.48)	(18.31)	(64.34)
Observations	6109	6109	6109
Pre-USICA outcome mean (treated counties)	1523.6	239.4	1763.0

Notes: Estimates are from synthetic difference-in-difference (SDID) specification, equation (3) in text, using Stata sdid command. Comparison groups are defined in Section 4. Post-USICA indicator identifies quarters after USICA passed in the U.S. Senate (2021Q3 or later). 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 2015Q1-2021Q2 period. *p <0.10; **p <0.05; ***p <0.01.

TABLE 4: WEEKLY WAGES IN SEMICONDUCTORS

	Semiconductor wages	Semiconductor equipment & materials wages	Semiconductor production, equipment & materials wages
	(1)	(2)	(3)
Panel A: Semiconductor vs. Non-Semiconductor Counties, Simple DID			
Treated x Post-USICA	254.23**	95.03**	268.96***
	(99.66)	(38.29)	(99.65)
Observations	36941	36941	36941
Pre-USICA outcome mean (treated counties)	829.2	411.0	931.0
Panel B: Fab vs. Fabless Counties, Simple DID			
Treated x Post-USICA	239.90	70.59	269.65
	(187.13)	(73.44)	(187.79)
Observations	6109	6109	6109
Pre-USICA outcome mean (treated counties)	1085.7	535.7	1191.4
Panel C: Semiconductor vs. Non-Semiconductor Counties, Synthetic DID			
Treated x Post-USICA	223.48**	95.39**	199.97**
	(91.05)	(47.41)	(79.84)
Observations	36941	36941	36941
Pre-USICA outcome mean (treated counties)	829.2	411.0	931.0
Panel D: Fab vs. Fabless Counties, Synthetic DID			
Treated x Post-USICA	166.22	77.75	234.75*
	(144.59)	(77.49)	(140.20)
Observations	6109	6109	6109
Pre-USICA outcome mean (treated counties)	1085.7	535.7	1191.4

Notes: Estimates in Panels A & B are of simple difference-in-difference (DID) specification, equation (1) in text. Panels C & D are of synthetic difference-in-difference (SDID) specification, equation (3) in text. Comparison groups are defined in Section 4. Post-USICA indicator identifies quarters after USICA passed in the U.S. Senate (2021Q3 or later). 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 2015Q1-2021Q2 period. *p <0.10; **p <0.05; ***p <0.01.

TABLE 5: LOCAL SPILLOVERS: SYNTHETIC DID

	Semiconductor inputs employment	Non-residential construction employment	Total county employment	County GDP (00,000s USD)
	(1)	(2)	(3)	(4)
Panel A: Semiconductor vs. Non-Semiconductor Counties				
Treated x Post-USICA	53.81**	135.78**	-2246.02	-4.59
	(25.69)	(56.64)	(2643.47)	(5.06)
Observations	36941	36941	36941	7920
Pre-USICA outcome mean (treated counties)	1067.6	1800.1	307465.5	590.9
Panel B: Fab vs. Fabless Counties				
Treated x Post-USICA	-48.10	202.61**	8503.87*	13.20
	(55.70)	(101.87)	(5089.69)	(8.49)
Observations	6109	6109	6109	1314
Pre-USICA outcome mean (treated counties)	1516.4	2058.4	386371.7	706.2

Notes: Notes: Estimates are from synthetic difference-in-difference (SDID) specification, equation (3) in text. Comparison groups are defined in Section 4. Post-USICA indicator identifies quarters after USICA passed in the U.S. Senate (2021Q3 or later). 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 5.3 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. Outcome in Column 4 is the yearly county GDP in hundred thousands of chained US dollars (from the Bureau of Economic Analysis, available only through 2023; data can be accessed at `https://apps.bea.gov/regional/downloadzip.htm`). *p <0.10; **p <0.05; ***p <0.01.