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Employment Impacts of the CHIPS Act

ABSTRACT The CHIPS and Science Act, enacted in August 2022, is a key element of the revival of US 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-differences designs, the first comparing counties with preexisting 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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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, signed into law 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-differences (DID) designs. In the first, we compare counties with preexisting semiconductor production facilities (which we refer to as “semiconductor counties”) to counties with preexisting 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 preexisting semiconductor fabrication facility (“fab counties”) to counties with semiconductor facilities but no fabrication facility (“fabless counties”).

From these county-level DID, 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 US defense spending (Ramey 2011a).

Second, we find significant short-term impacts of the act on semiconductor employment. Our preferred estimates using the semiconductor versus 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 percent on average for these counties (relative to pre-USICA means). Our preferred estimates using the fab versus fabless county design indicate impacts of 180 jobs in semiconductors per affected county (for the 83 fab counties)—an 11.8 percent increase on average for these counties.

Third, we find robust evidence of spillover effects on nonresidential 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 DID approaches estimate the *relative* impacts 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 DID 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 US 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 national security, and many policymakers viewed the latter justifications

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).

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 United States, 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 and others (2019), Freedman, Khanna, and Neumark (2023), and Lane (2025). Juhász, Lane, and Rodrik (2024) 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 2021; Goldberg and others 2024; Thurk 2024; Miao 2024; Bown and Wang 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, 2011b, 2019; Nakamura and Steinsson 2014; Ramey and Zubairy 2018; Chodorow-Reich 2019, 2020; Wolf 2023). Much of that literature has focused on the effects of defense spending. One contribution

2. On the theoretical justification for industrial policy interventions, see, for example, 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).

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 II describes the data used in the analysis. Section III presents our empirical strategy. Section IV presents the results, both the direct results in the semiconductor sector and indirect spillover results in related sectors and county-level aggregates. Section V discusses how to aggregate the county-level estimates to an overall national effect. Section VI discusses conceptual issues in the design of industrial policies raised by our analysis, and section VII concludes.

I. Background

I.A. 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 Mark Warner and John 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 USICA (S. 1260), which was filed by Senator Chuck 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 February 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 Joe Biden on August 9, 2022.⁴

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 of 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.

4. Records of legislations can be accessed at [Congress.gov](https://www.congress.gov/), <https://www.congress.gov/>, maintained by Library of Congress.

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 August 16, 2022. In addition, the \$1.2 trillion Infrastructure Investment and Jobs Act, also known as the Bipartisan Infrastructure Law, was signed on November 15, 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.

1.B. Details of the CHIPS Act

The CHIPS Act allocated funding for a range of semiconductor-related initiatives, building on authorizations provided by the National Defense Authorization Act of 2021, with appropriations detailed in online 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 research and development (R&D) through programs and institutes such as the National Semiconductor Technology Center 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, Grossman, and Sutter 2023).

Funding under the CHIPS Act is provided through grants, loans, loan guarantees, and tax credits, with disbursements tied to recipients' completion of specific project milestones (NIST 2023a; Department of Commerce Office of Inspector General 2025). Funding recipients are prohibited from engaging in certain transactions with foreign countries or entities of concern, notably the Chinese government, for ten years following an award. As of May 2025, NIST has issued eight notices of funding opportunities (NOFOs) across its CHIPS programs, awarding up to \$33.7 billion in direct funding and \$5.5 billion in loans through the CHIPS Program Office and nearly \$8.3 billion through the CHIPS Research and Development Office (Department of Commerce Office of Inspector General 2025).

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 CHIPS Program Office had 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 CHIPS Program Office had made nineteen awards under this NOFO, totaling \$30.7 billion in direct funding and \$5.5 billion in loans. The first major awards were finalized in November 2024 (Department of Commerce 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 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 Technology, Samsung, Texas Instruments, and GlobalFoundries (Department of Commerce Office of Inspector General 2025).

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 September 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 R&D activities (Department of Commerce Office of Inspector General 2025). The status of individual NOFOs is detailed in online appendix table A2.

The act also included the Advanced Manufacturing Investment Credit (AMIC), administered by the Internal Revenue Service, a tax credit equal to 25 percent 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 Donald Trump's One Big Beautiful Bill Act, signed in law on July 4, 2025, increased the AMIC rate from 25 percent to 35 percent, effective December 31, 2025.⁵

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.

5. For details, see Congress.gov, "H.R. 1—An Act to Provide for Reconciliation Pursuant to Title II of H. Con. Res. 14," <https://www.congress.gov/bill/119th-congress/house-bill/1/text>.

Applicants for CHIPS awards have to meet certain worker and community investment guidelines, which include paying prevailing wage rates to workers and working with regional entities to provide workforce training. These have been operationalized in a few ways; one is a requirement that the state and local jurisdictions where the project is located provide incentives, which are 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 2023a). 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 childcare. This requirement has arguably lowered barriers for women entering the workforce.⁶ 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 2023b).

As of this writing, other provisions of the CHIPS Act appear to remain in place and companies that received preliminary memoranda of terms 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).

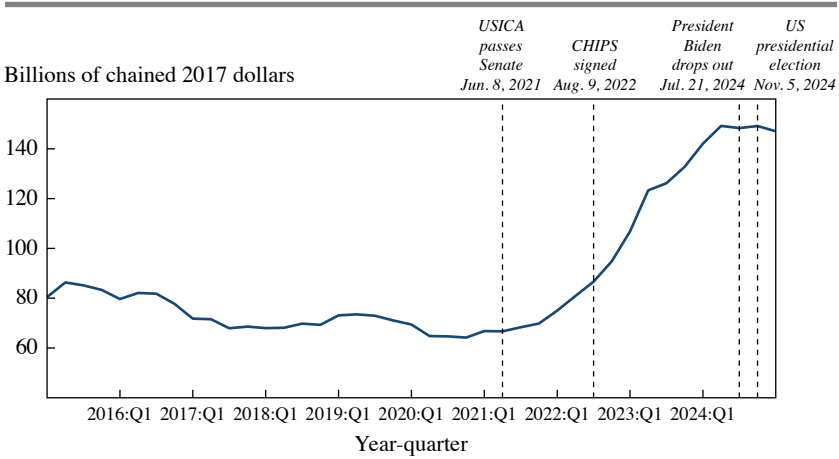
I.C. Trends in Investment, Employment, and Stock Prices

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 data is the US Bureau of Economic Analysis (BEA) series on real private fixed investment in nonresidential 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

6. 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.

Figure 1. Real Private Fixed Investment in Nonresidential Manufacturing Structures



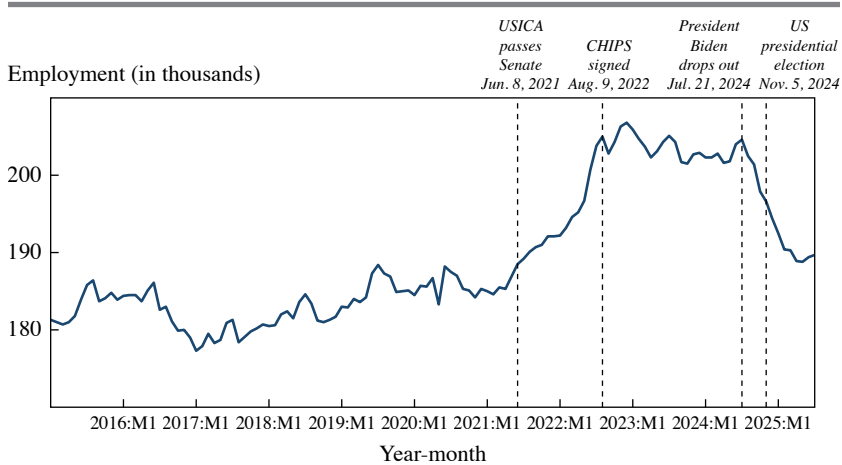
Source: BEA.

Note: National Income and Product Accounts, “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 vertical lines indicate (from left to right) 2021:Q2, when the USICA was passed; 2022:Q3, when the CHIPS Act and IRA were passed; 2024:Q3, when Biden dropped out of the presidential race; and 2024:Q4, when the presidential election occurred. Y-axis denotes investment per quarter.

from \$70 billion per year in 2021:Q2 to almost \$150 billion per year by mid-2024. Investment levels plateaued in 2024:Q2, at about the time President Biden abandoned his reelection bid. An obvious challenge in interpreting this figure is that the IRA and the Bipartisan Infrastructure Law were roughly contemporaneous with the CHIPS Act. Our DID 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.⁷ Online appendix figure A1 sums these reports for semiconductor firms and plots the total over the 2015–2024 period. There

7. 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, GlobalFoundries, Intel, Lattice Semiconductor, Littelfuse, Luminar, Marvell, Microchip, Micron, Nvidia, Onsemi, Qorvo, Qualcomm, Silicon Labs, SkyWater, Skyworks, Texas Instruments, Western Digital, and Wolfspeed.

Figure 2. Employment in Semiconductor Industry

Source: CES.

Note: Figure plots the total number of workers in the semiconductor industry (NAICS 334413) across the United States, as reported in the CES (National Series).

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 US Bureau of Labor Statistics (BLS) 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 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

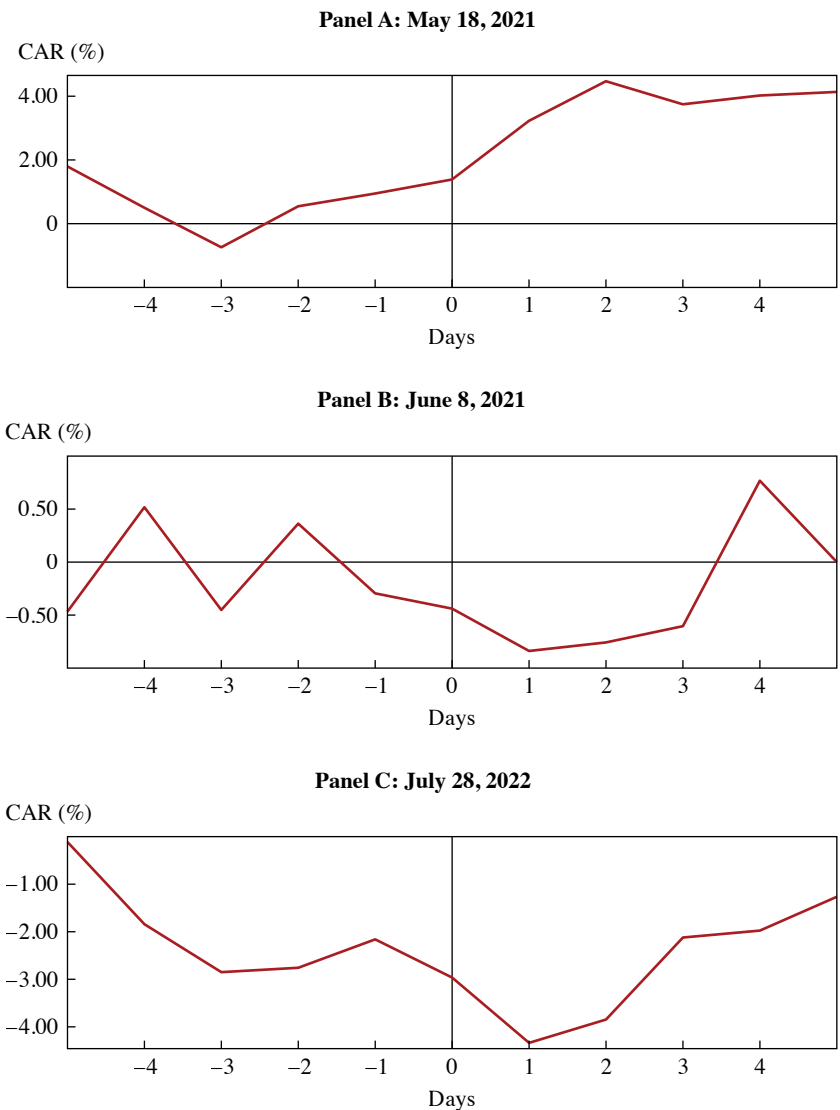
alone, given that the CES data are monthly (and the QCEW data used in our main analysis are quarterly).

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 Warner 2007). Figure 3 plots the cumulative average abnormal returns (CAARs) for semiconductor firms with production facilities in the United States for five-day windows around three key dates: May 18, 2021, the day Senator Schumer filed 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. Online 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 USICA's filing 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 at the time USICA was introduced.

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, CEO of GlobalFoundries, a leading producer, told Bloomberg Technology, "I think the important thing right now is, let's get that CHIPS bill funded so that we can accelerate manufacturing capacity in the US."⁸ 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 one thousand workers, and

8. Bloomberg Technology, "Biden's \$50 Billion Chips Bill Needs to Be Funded: GlobalFoundries CEO," interview, April 7, 2021, <https://www.youtube.com/watch?v=BeHMuyyxHtc>.

Figure 3. Cumulative Abnormal Returns (CARs) for Semiconductor Firms



Source: Yahoo Finance.

Note: 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 $AR_{it} = R_{it} - \hat{\gamma}_i R_{mt} - \hat{\alpha}_i$ 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 online appendix figure A1, excluding GlobalFoundries and SkyWater, which began trading on October 28, 2021, and April 21, 2021, respectively. See also online appendix table A3.

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.”⁹ 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 one to three years to get new greenfield facilities up and running, although there may be short-term increases in planning and design staff and construction-related employment.

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 November 3, 2021, are worth quoting at some length:

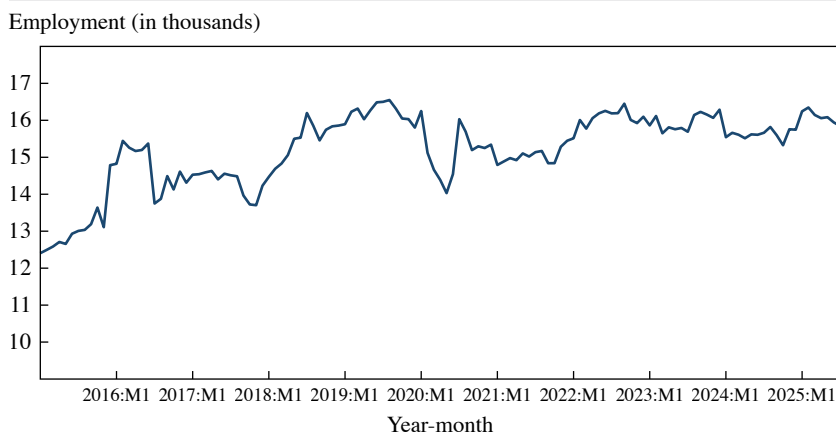
As the country is coalescing around the concept of semiconductor sovereignty, SkyWater plays an increasingly critical role in supporting the vision of reestablishing the U.S. as a technology manufacturing leader. . . . The CHIPS Act received bipartisan support in the Senate, and we remain confident that 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 a 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 you 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.¹⁰

At roughly the same time, the company added one hundred 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

9. CNBC Television, “‘It’s Better to Expand Facilities,’ Than Create New Chip Foundries, Says GlobalFoundries CEO,” interview, March 23, 2022, <https://www.youtube.com/watch?v=IETIGM4MG4>.

10. EarningsCall, “SkyWater Technology, Inc.” transcript, November 3, 2021, <https://earningscall.biz/e/nasdaq/s/skyt/y/2021/q/q3>.

Figure 4. Employment in Semiconductors and Related Industries: Canada

Source: Statistics Canada.

Note: Data are from the Survey of Employment, Payroll and Hours conducted by Statistics Canada, for Semiconductor and Other Electronic Component Manufacturing (NAICS 3344).

to August 2022. But the timing of the employment changes is 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 five-to-six-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.

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 United States 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 United States. 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 for Canada in Semiconductor 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 the shift in levels that we see in the United States in figure 2.

Another country that reports data for a reasonably comparable industry is Germany. Online 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 is the reason for the jumps in January 2020 and January 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 2023–2024 periods we see in figure 2 was not common across the board in industrialized countries.

II. Data

Our main source of employment and wage data is the QCEW, published by the BLS, which provides quarterly employment and wages by county and industry. The primary source for the QCEW is administrative data from state unemployment insurance systems; these are supplemented by responses to two BLS surveys, the Annual Refiling Survey and the Multiple Worksite Report. Employment and wage data are reported by six-digit NAICS (North American Industry Classification System) industries at various geographical levels, county level being the most disaggregated. We focus on QCEW data at the six-digit county-industry-quarter level, using employment reported in the first month of each quarter. We focus on the period from 2015:Q1 to 2025:Q1, 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 Machinery 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 county-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 US Census Bureau. The QWI data are only available at the four-digit NAICS level, rather than six-digit level, but they contain more information when there are small numbers of firms or individuals in a given cell.¹¹

To identify the location of semiconductor facilities by county, we use the Semiconductor Industry Association’s (SIA) US Semiconductor Ecosystem Map, which catalogs locations across the United States conducting research on, designing, and/or manufacturing semiconductors.¹² The SIA is the main trade association and lobbying group for the industry. The Ecosystem Map data are at the facility level, with details about each facility’s location and activity.

III. 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 IRA and the Bipartisan Infrastructure Law. As mentioned above, we address this challenge with two DID 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 “semiconductor counties”) to counties with at least one hundred employees in high-tech sectors but no semiconductor production facilities (“high-tech non-semiconductor counties,” or “non-semiconductor counties” for short).¹³ In the second, we compare counties with a preexisting semiconductor *fabrication* facility (“fab counties”—listed in the SIA data as having either a foundry or an

11. 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.

12. The SIA US Semiconductor Ecosystem Map is available at <https://www.semiconductors.org/ecosystem/>; accessed on June 4, 2025.

13. To define high-tech sectors, we use the following eleven four-digit NAICS sectors identified by the 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, Electro-medical, 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). Below we explore robustness to different definitions of high-tech counties, using high-tech employment cutoffs of zero, five hundred, or one thousand; we will see that the results are not sensitive to this definition.

integrated device manufacturer) 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 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 DID designs because they have different strengths and weaknesses. On the one hand, in the semiconductor versus 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.¹⁴ On the other hand, an advantage of the fab versus 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 Act funding was earmarked for fabrication facilities, it is plausible that the fab versus fabless design captures the most important 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 DID estimator and a synthetic one. In the simple DID approach, the specification is the following:

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

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 that

14. 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.

takes the value one for treated counties and zero 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 zero from 2015:Q1 to 2021:Q2, and one from 2021:Q3 to 2025:Q1. 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 zero from 2015:Q1 to 2021:Q2 and one from 2022:Q3 to 2025:Q1, and the quarters 2021:Q3–2022:Q2 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 DID, using the following specification:

$$(2) \quad Y_{it} = \mu + \alpha_i + \gamma_t + \sum_{\tau=2015:Q2}^{2025:Q1} \beta_{\tau} \cdot D_{it}^{\tau} + \varepsilon_{it},$$

where Y_{it} , α_i , and γ_t are defined as above and D_{it}^{τ} is an indicator that takes the value one if $t = \tau$ and county i is treated and zero otherwise. (We omit the indicator for 2015:Q1.) 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 DID 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-differences (SDID) estimator of Arkhangelsky and others (2021). The idea is that there may exist a weighted average of control counties that more closely mirrors the pretreatment 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 DID, such as invariance to additive unit-level shocks and valid inference in large panels.

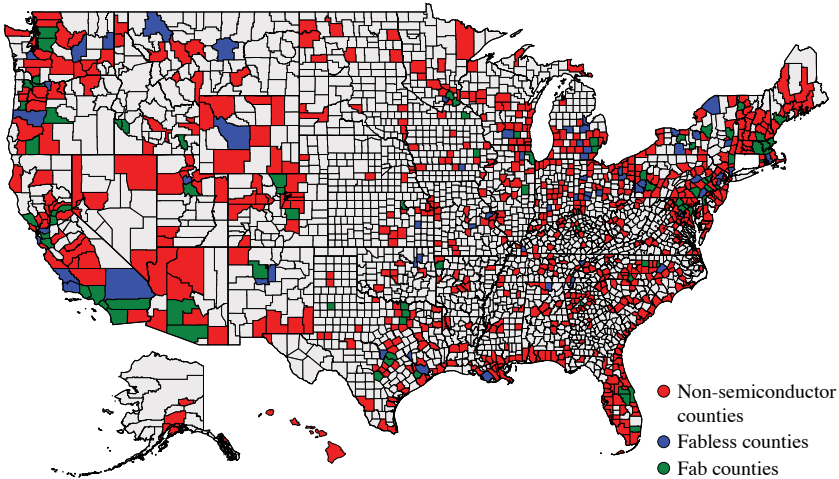
Unlike traditional synthetic control methods, which minimize differences in pretreatment *levels* (Abadie 2021), the SDID minimizes differences in pretreatment *trends*, which helps address bias concerns when pretreatment fit is imperfect and treatment is potentially correlated with unobserved confounders (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 and others 2021).

The SDID procedure solves the problem:

$$(3) \quad \left(\hat{\beta}, \hat{\mu}, \hat{\alpha}, \hat{\gamma} \right) \\ = \underset{\beta, \mu, \alpha, \gamma}{\operatorname{argmin}} \left\{ \sum_{i=1}^n \sum_{t=2015:Q1}^{2025:Q1} \left(Y_{it} - \mu - \alpha_i - \gamma_t - W_{it} \beta \right)^2 \hat{\omega}_i \hat{\lambda}_t \right\},$$

where W_{it} is an indicator of treatment, which takes the value of one for treated counties in the post period and zero 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, $\hat{\omega}_i$ and $\hat{\lambda}_t$, are chosen to minimize trend differences in the pretreatment 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 and others 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 and others (2024). Specifically, we compute the difference between treated and control groups in each period, relative to the average difference in the time-weighted pretreatment period, and again use a block bootstrap to construct confidence intervals. By optimally calculating weights to match pretreatment outcome trends more closely than in the simple DID, the SDID estimator reduces the risk of attributing spurious differences to treatment (Arkhangelsky and others 2021), and we prefer it for this reason. Below we start by reporting both the simple DID and the SDID but move to reporting just the SDID for secondary outcomes and robustness checks.

Figure 5. County Comparison Groups



Source: SIA US Semiconductor Ecosystem Map.

Note: “Non-semiconductor counties” are counties with employment greater than one hundred in eleven high-tech sectors, as defined by the Census Bureau (2024), but no private semiconductor production facility. “Fab counties” are counties with a semiconductor fabrication facility and “fabless counties” are counties with a semiconductor facility but no fabrication facility.

To illustrate our research design, figure 5 displays a map of US counties. The fab versus fabless design compares the counties with a semiconductor fabrication facility to those with a semiconductor facility but no fabrication facility. The semiconductor versus non-semiconductor design compares the non-semiconductor counties to the union of the fab and fabless counties. By the above definitions, there are 149 semiconductor counties and 752 high-tech non-semiconductor counties, and 83 fab and 66 fabless counties.¹⁵

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

15. 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.

embedded in local ecosystems of suppliers, skilled labor, and infrastructure (Goldberg and others 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 columns 5–8, 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 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 DID designs are important to highlight. First, our estimates will only capture impacts of the act in counties with preexisting semiconductor facilities (any semiconductor facility in the semiconductor versus non-semiconductor design, a fabrication facility in the fab versus fabless design). Greenfield investment in counties without an existing facility will not be reflected. In this sense, our estimates are likely to underestimate 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 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 2025:Q1. Another difficulty is that it is not yet clear whether the firms with preliminary memoranda of terms but not final awards as of the end of the Biden administration on January 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.

Table 1. Summary Statistics: Treated and Control Counties

| | <i>Semiconductor versus non-semiconductor</i> | | | | <i>Fab versus fabless</i> | | | |
|---|---|-----------|----------------|-----------|---------------------------|-----------|----------------|-----------|
| | <i>Control</i> | | <i>Treated</i> | | <i>Control</i> | | <i>Treated</i> | |
| | <i>Mean</i> | <i>SD</i> | <i>Mean</i> | <i>SD</i> | <i>Mean</i> | <i>SD</i> | <i>Mean</i> | <i>SD</i> |
| Panel A: General county characteristics | | | | | | | | |
| Total employment (in thousands) | 61.6 | 108.0 | 291.8 | 507.9 | 199.6 | 382.1 | 365.2 | 580.9 |
| Manufacturing (as % of total employment) | 3.2 | 4.9 | 4.2 | 3.9 | 4.1 | 4.5 | 4.3 | 3.4 |
| Employment in semiconductors | 3.4 | 43.1 | 850.1 | 3538.0 | 53.9 | 158.8 | 1483.1 | 4653.7 |
| Employment in semiconductor materials/equipment | 10.4 | 78.4 | 141.5 | 622.8 | 72.2 | 512.1 | 196.6 | 696.7 |
| Average 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 | | | | | | | | |
| 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 |
| 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 |
| Age (%) | | | | | | | | |
| Under 19 | 25.8 | 3.3 | 25.5 | 2.9 | 25.2 | 3.0 | 25.8 | 2.7 |
| 20 to 24 | 7.3 | 3.0 | 7.6 | 3.2 | 7.5 | 3.2 | 7.6 | 3.2 |
| 25 to 34 | 11.5 | 2.1 | 12.2 | 2.3 | 11.8 | 2.5 | 12.6 | 2.1 |
| 35 to 44 | 13.4 | 1.5 | 14.0 | 1.5 | 13.6 | 1.4 | 14.3 | 1.6 |
| 45 to 54 | 13.3 | 1.6 | 13.5 | 1.6 | 13.4 | 1.4 | 13.5 | 1.6 |
| 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 | |

Source: BLS; Census Bureau; National Cancer Institute; and authors' calculations.

Note: Comparison groups are defined in section III. Employment and wages are from the QCEW for 2015:Q1. Employment in semiconductors is for NAICS 334413. Employment in semiconductor materials/equipment is for NAICS 333242 (equipment) and NAICS 325120 and 325180 (material inputs). Unemployment data are from the BLS Local Area Unemployment Statistics for 2015. Rural share is from the Census Bureau Urban and Rural Geographic Area data for 2010. County demographic data are taken from SEER US County Population Data for 2010.

IV. Results

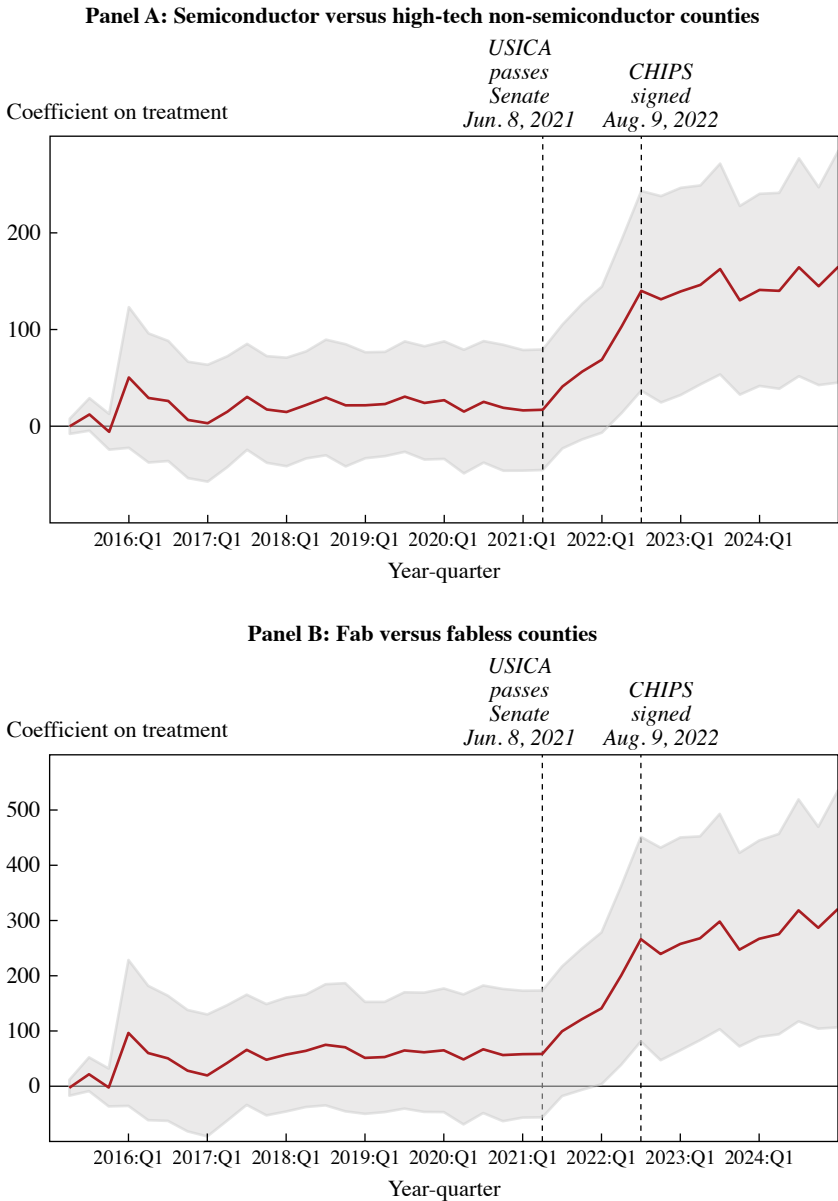
IV.A. *Employment Impacts in Semiconductors*

To illustrate the main empirical patterns, we begin with event study-type figures to show the evolution of impacts over time. Figure 6 plots the coefficient estimates from the event study version of the simple DID, equation (2), for employment in the core semiconductor sector (NAICS 334413) for the semiconductor versus non-semiconductor and fab versus 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 2021:Q3, 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 2022:Q3, about the time the CHIPS Act was signed.

Figure 7 plots the event study estimates from the 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 I.C, 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 differs between panels A and B in figure 6 and between the two panels of figure 7; the fab versus fabless design suggests impacts that are 50–80 percent 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 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 versus non-semiconductor comparison, and panel B the fab versus 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 estimate is larger: 191 jobs in semiconductors in fab counties (column 1), or 270 jobs if equipment or materials are included.

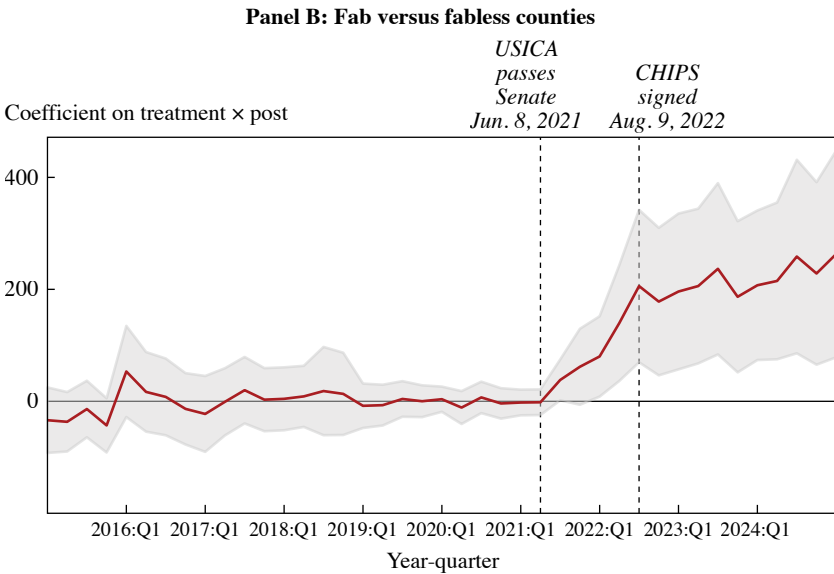
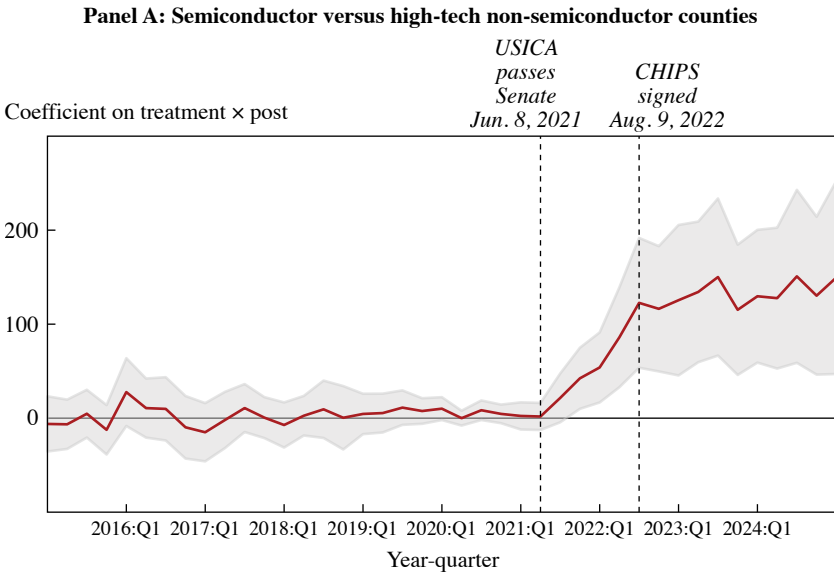
Figure 6. Employment in Semiconductors: Simple DID



Source: BLS and authors' calculations.

Note: Estimates are from event study specification of simple DID, equation (2) in text. Comparison groups are defined in section III. Outcome is the number of workers employed in the semiconductor sector (NAICS 334413). Source is QCEW six-digit data. Shaded area represents 95 percent confidence interval. Standard errors are clustered at the county level.

Figure 7. Employment in Semiconductors: SDID



Source: BLS and authors' calculations.

Note: Estimates are from SDID specification, equation (3) in text. Outcome is the number of workers employed in the semiconductor sector (NAICS 334413). Source is QCEW six-digit data. Comparison groups are defined in section III. Estimated treatment effects produced by implementing the event study estimator proposed by Clarke and others (2024). The shaded area represents the confidence interval at the 95 percent level.

Table 2. Employment in Semiconductors: Simple DID

| | <i>Semiconductor production employment (1)</i> | <i>Semiconductor equipment and materials employment (2)</i> | <i>Semiconductor production, equipment, and materials employment (3)</i> |
|---|--|---|--|
| Panel A: Semiconductor versus non-semiconductor counties | | | |
| Treated × post-USICA | 106.09*** (39.90) | 34.81** (16.82) | 140.90*** (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 versus fabless counties | | | |
| Treated × post-USICA | 191.35*** (70.80) | 78.53** (31.21) | 269.88*** (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 |

Source: Authors' calculations.

Note: Estimates are from simple DID specification, equation (2) in text. Comparison groups are defined in section III. Post-USICA indicator identifies quarters after USICA passed in the US Senate (2021:Q3 or later). Outcome in column 1 is the number of workers employed in the semiconductor sector (NAICS 334413). Outcome in column 2 is the number of workers employed in the manufacturing of equipment (NAICS 333242) or material inputs (NAICS 325120 and 325180) for semiconductors. Outcome in column 3 is the number of 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 2015:Q1–2021:Q2 period. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 3 shows average treatment effects using the SDID approach. For the reasons cited in section III 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 versus 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 percent and 12.0 percent, respectively, in treated counties. In panel B, using the fab versus 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 percent and 12.0 percent. We return in section V

Table 3. Employment in Semiconductors: SDID

| | <i>Semiconductor production employment (1)</i> | <i>Semiconductor equipment and materials employment (2)</i> | <i>Semiconductor production, equipment, and materials employment (3)</i> |
|---|--|---|--|
| Panel A: Semiconductor versus non-semiconductor counties | | | |
| Treated × post-USICA | 110.41*** (35.19) | 15.75 (12.00) | 124.08*** (38.53) |
| Observations | 36941 | 36941 | 36941 |
| Pre-USICA outcome mean (treated counties) | 868.7 | 165.3 | 1034.0 |
| Panel B: Fab versus fabless counties | | | |
| Treated × post-USICA | 180.13*** (52.48) | 27.27 (18.31) | 210.94*** (64.34) |
| Observations | 6109 | 6109 | 6109 |
| Pre-USICA outcome mean (treated counties) | 1523.6 | 239.4 | 1763.0 |

Source: Authors' calculations.

Note: Estimates are from SDID specification, equation (3) in text, using Stata SDID command. Comparison groups are defined in section III. Post-USICA indicator identifies quarters after USICA passed in the US Senate (2021:Q3 or later). Outcome in column 1 is the number of workers employed in the semiconductor sector (NAICS 334413). Outcome in column 2 is the number of workers employed in the manufacturing of equipment (NAICS 333242) or material inputs (NAICS 325120 and 325180) for semiconductors. Outcome in column 3 is the number of 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 2015:Q1–2021:Q2 period. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

below to the question of how to estimate national-level employment impacts of the CHIPS Act on the basis of these DID estimates.

Several robustness checks are reported in the online appendix. Online 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. Online 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 and 7. Online appendix table A7 reports results using the combined QCEW/QWI data at the four-digit level (described in section II); results are qualitatively similar to the baseline results. Online 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).

Online 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: expansion of production workforces driven by increases in output at existing facilities (as mentioned, for instance, in the quotes from the GlobalFoundries CEO in section I.C); and expansion 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.

IV.B. 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 versus 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.¹⁶ 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 versus 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 percent—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

16. 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 the quarter and by thirteen (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).

Table 4. Weekly Wages in Semiconductors

| | <i>Semiconductor wages (1)</i> | <i>Semiconductor equipment and materials wages (2)</i> | <i>Semiconductor production, equipment, and materials wages (3)</i> |
|---|--|--|---|
| Panel A: Semiconductor versus non-semiconductor counties, simple DID | | | |
| Treated × post-USICA | 254.23** (99.66) | 95.03** (38.29) | 268.96*** (99.65) |
| Observations | 36941 | 36941 | 36941 |
| Pre-USICA outcome mean (treated counties) | 829.2 | 411.0 | 931.0 |
| Panel B: Fab versus fabless counties, simple DID | | | |
| Treated × post-USICA | 239.90 (187.13) | 70.59 (73.44) | 269.65 (187.79) |
| Observations | 6109 | 6109 | 6109 |
| Pre-USICA outcome mean (treated counties) | 1085.7 | 535.7 | 1191.4 |
| Panel C: Semiconductor versus non-semiconductor counties, SDID | | | |
| Treated × post-USICA | 223.48** (91.05) | 95.39** (47.41) | 199.97** (79.84) |
| Observations | 36941 | 36941 | 36941 |
| Pre-USICA outcome mean (treated counties) | 829.2 | 411.0 | 931.0 |
| Panel D: Fab versus fabless counties, SDID | | | |
| Treated × post-USICA | 166.22 (144.59) | 77.75 (77.49) | 234.75* (140.20) |
| Observations | 6109 | 6109 | 6109 |
| Pre-USICA outcome mean (treated counties) | 1085.7 | 535.7 | 1191.4 |

Source: Authors' calculations.

Note: Estimates in panels A and B are of simple DID specification, equation (1) in text. Panels C and D are of SDID specification, equation (3) in text. Comparison groups are defined in section III. Post-USICA indicator identifies quarters after USICA passed in the US Senate (2021:Q3 or later). Outcome in column 1 is the average weekly wage for workers employed in the semiconductor sector (NAICS 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 and 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 2015:Q1–2021:Q2 period. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

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 versus 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.

IV.C. 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 the BEA input-output tables.¹⁷ 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 versus non-semiconductor design in panel A indicates a positive, statistically significant impact of approximately 54 jobs in these input sectors. But this effect is not robust to using the fab versus 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 nonresidential construction employment as the outcome. We see positive, statistically significant effects of 136 jobs per county using the semiconductor versus non-semiconductor design and 203 jobs

17. 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 334418), Bare Printed Circuit Board Manufacturing (NAICS 334412), Capacitor, Resistor, Coil, Transformer, and Other Inductor Manufacturing (NAICS 334416), Electronic Connector Manufacturing (NAICS 334417), Other Electronic Component Manufacturing (NAICS 334419), Plastics Packaging Film and Sheet (Including Laminated) Manufacturing (NAICS 326112), Unlaminated Plastics Film and Sheet (Except Packaging) Manufacturing (NAICS 326113), Computer Terminal and Other Computer Peripheral Equipment Manufacturing (NAICS 334118), 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 811310). While Semiconductor Machinery Manufacturing (NAICS 333242), Industrial Gas Manufacturing (NAICS 325120), and Other Basic Inorganic Chemical Manufacturing (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.

Table 5. Local Spillovers: SDID

| | <i>Semiconductor inputs employment (1)</i> | <i>Nonresidential construction employment (2)</i> | <i>Total county employment (3)</i> | <i>County GDP (00,000s USD) (4)</i> |
|---|--|---|--|---|
| Panel A: Semiconductor versus non-semiconductor counties | | | | |
| Treated \times post-USICA | 53.81** (25.69) | 135.78** (56.64) | -2246.02 (2643.47) | -4.59 (5.06) |
| Observations | 36941 | 36941 | 36941 | 7920 |
| Pre-USICA outcome mean (treated counties) | 1067.6 | 1800.1 | 307465.5 | 590.9 |
| Panel B: Fab versus fabless counties | | | | |
| Treated \times post-USICA | -48.10 (55.70) | 202.61** (101.87) | 8503.87* (5089.69) | 13.20 (8.49) |
| Observations | 6109 | 6109 | 6109 | 1314 |
| Pre-USICA outcome mean (treated counties) | 1516.4 | 2058.4 | 386371.7 | 706.2 |

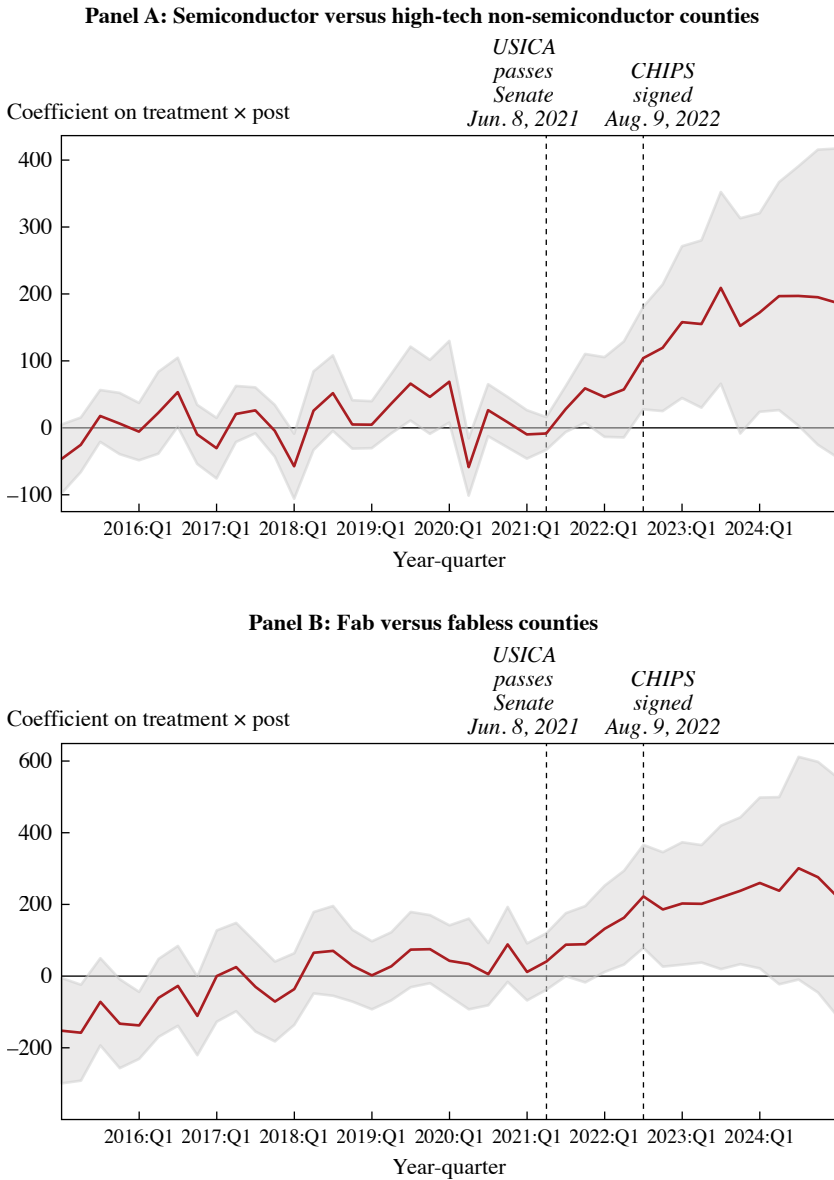
Source: Authors' calculations.

Note: Estimates are from SDID specification, equation (3) in text. Comparison groups are defined in section III. Post-USICA indicator identifies quarters after USICA passed in the US Senate (2021:Q3 or later). Outcome in column 1 is the aggregate number of workers employed in the input sectors for semiconductor (NAICS 331410, 334418, 334412, 334416, 334417, 334419, 326112, 326113, 334118, 334515, and 811310; see section IV.C for sector descriptions). Outcome in column 2 is the number of workers employed in nonresidential building construction (NAICS 236210 and 236220). Outcome in column 3 is the total county employment (all six-digit NAICS industries aggregated). The pre-USICA outcome mean is the outcome mean for treated counties for the 2015:Q1–2021:Q1 period. Outcome in column 4 is the yearly county GDP in hundred thousands of chained US dollars (from the BEA, available only through 2023). * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

per county using the fab versus fabless design. To get a better sense of the timing, figure 8 shows SDID event study graphs for nonresidential 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 nonresidential construction, which makes up a nontrivial 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 GDP. First consider total employment. Figure 9 presents event study SDID graphs for the two designs. In both cases, we see a relative decline

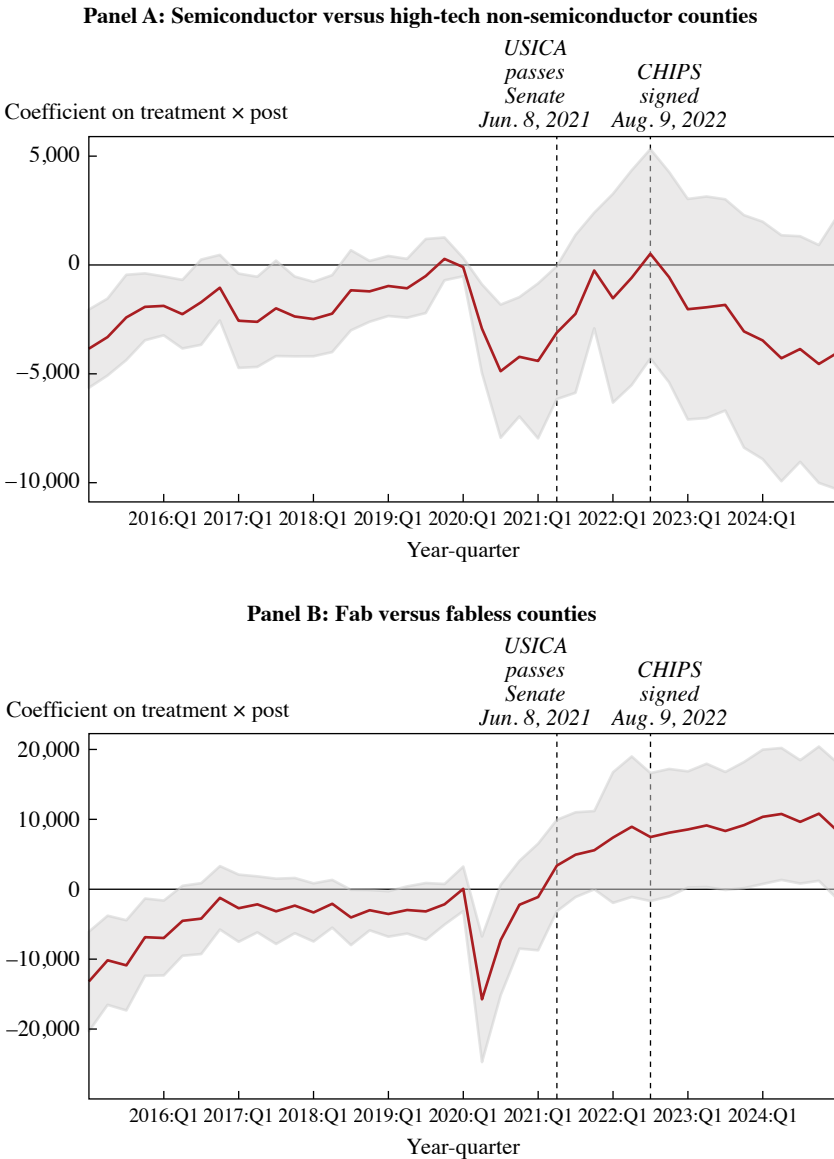
Figure 8. Nonresidential Construction Employment: SDID



Source: BLS and authors' calculations.

Note: Estimates are from 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 six-digit data. Comparison groups are defined in section III. Estimated treatment effects produced by implementing the event study estimator proposed by Clarke and others (2024). The shaded area represents the confidence interval at the 95 percent level.

Figure 9. Total County Employment: SDID



Source: BLS and authors' calculations.

Note: Estimates are from SDID specification, equation (3) in text. Outcome is the number of workers employed in all NAICS six-digit sectors. Source is QCEW six-digit data. The sample includes all counties with at least one hundred workers in the eleven high-tech sectors, as defined by the Census Bureau (2024) as of 2021:Q1. Comparison groups are defined in section III. Estimated treatment effects produced by implementing the event study estimator proposed by Clarke and others (2024). The shaded area represents the confidence interval at the 95 percent level.

in total employment in treated 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 versus non-semiconductor graph (panel A) shows that it took several quarters for total employment in 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 versus fabless graph (panel B) 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 versus non-semiconductor design is in fact negative, although not significant, but the estimate for the fab versus fabless design is positive and significant at the 90 percent level. The point estimate suggests an increase of 2.2 percent in total employment in fab counties (8,504/386,372). 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 percent 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 BEA, which publishes data annually but not quarterly. For this analysis, we extend the sample back to 2010, to have more data 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 versus 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.

V. Estimates of National Aggregate Effects

As noted above, our DID approaches estimate the *relative* impacts on treated versus control counties. Part of the *absolute* impacts 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 macroeconomy (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 DID 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—that is, there are violations of the stable unit treatment value assumption. 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 US 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 US 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 late 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 2011a; 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 in figure 2, based on unprocessed data from the 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 August 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 versus 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 versus 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 percent 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 effects of the act on related sectors, we include the impacts on employment in semiconductor equipment and materials manufacturing, in upstream inputs, and in nonresidential 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 versus non-semiconductor design ($16 + 54 + 136$) and 182 jobs per affected county in the fab versus 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 versus non-semiconductor and fab versus 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 2011b). 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.

VI. 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.¹⁸ 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 be desirable to use multiple instruments, including regulation, nonlinear taxes and subsidies, and targeted grants, in addition to, or in place of, Pigouvian subsidies; Stiglitz (2019) provides a discussion in the context of emissions regulation.

But the targeted grants approach also has some potential disadvantages. One is related to the fact that estimating the returns to investment is difficult and the approaches differ in who bears the burdens of mistakes. In the case of tax credits, a greater share of the costs of overestimates is 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

18. 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).

restriction to a rules-based allocation mechanism.¹⁹ 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 policy, 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 administration demanding 10 percent of the value of Intel in exchange for CHIPS Act subsidies (Grabenstein 2025). On one hand, such claims can help 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's 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 and 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 combining the experiment of a new industrial policy with a social policy experiment, showing the way for a new economic model that differs from one that would emerge from the market on its own. The other is that these provisions are part of the complex political process by which policies are set. One set of actors believes that all firms should be required to pay higher wages, but opposition means that legislation to that effect cannot be passed. Another set of actors is

19. 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.

concerned with the risks to the economy of excessive dependence on Taiwan for semiconductors. Politics is the art of compromise, and while 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 United States, 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.

VII. Conclusion

This paper has provided early empirical evidence on the labor market impacts of the CHIPS Act using two county-level DID 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 percent increases relative to the treated group pretreatment 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 nonresidential 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. By the time the CHIPS Act was signed in August 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 (2011a).

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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Comments and Discussion

COMMENT BY

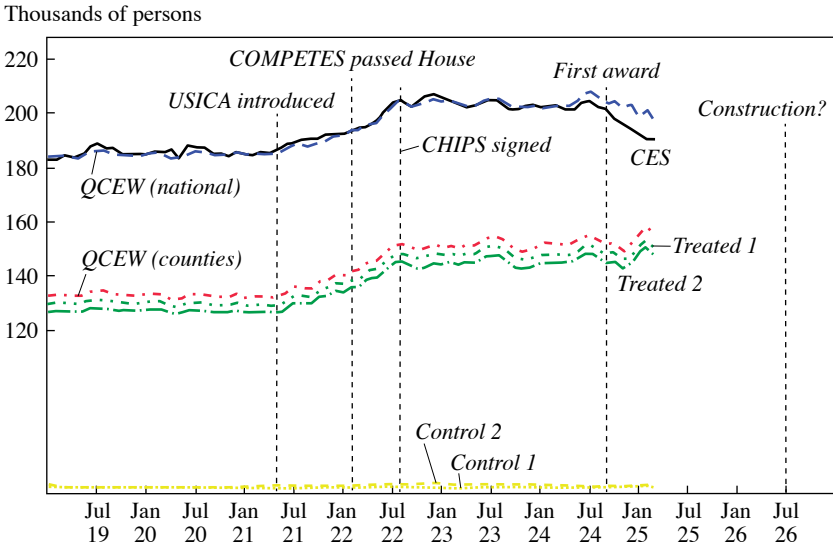
GABRIEL CHODOROW-REICH This paper by Erten, Stiglitz, and Verhoogen is a timely and ambitious empirical analysis of the near-term employment effects of the CHIPS Act. The paper is clearly written and makes use of the best available data. It also anticipates follow-up work using additional data and research designs, which I encourage the authors to pursue.

The present paper makes three main claims. First, a meaningful, albeit not primary, objective of the CHIPS Act was to create jobs. Second, the legislative run-up to the CHIPS Act coincided with an increase in national employment in semiconductor production. Third, semiconductor employment in counties with existing semiconductor activity grew faster than semiconductor employment in other counties, suggesting a causal effect of the CHIPS Act on semiconductor employment.

I will start my comment with a detailed discussion of the available data and the paper's research designs. While I will conclude that the cross-county comparison of semiconductor employment may not much improve on examining the national time series directly, I will also discuss other evidence suggesting that there was abnormally fast growth in the sector around the CHIPS Act. Next, I will discuss whether that growth should be attributed to the CHIPS Act or to something else, such as the contemporaneous semiconductor shortage. Finally, I will discuss the possible macroeconomic implications.

DID SEMICONDUCTOR EMPLOYMENT GROW ABNORMALLY FAST AROUND THE CHIPS ACT? Figure 1 shows semiconductor production employment

Figure 1. Employment in Semiconductor Production



Source: CES; QCEW; and author’s calculations.

Note: The line marked “CES” displays national employment in NAICS 334413 in the BLS CES. The line marked “QCEW (national)” displays national employment in NAICS 334413 in the BLS QCEW. The line marked “QCEW (counties)” displays the sum of employment in NAICS 334413 at the county level in the QCEW. The lines marked “Treated” display the sum of employment in NAICS 334413 in treated counties in the two research designs in the paper. The lines marked “Control” display the sum of employment in NAICS 334413 in control counties in the two research designs in the paper. The y-axis is distorted between zero and 120. The control lines never exceed 3,000 persons.

(NAICS 334413) for several different data sources and geographic aggregations. The “CES” line at the top of the figure shows national employment from the Bureau of Labor Statistics (BLS) Current Employment Statistics (CES). According to the authors, the first notable event signaling possible passage of the CHIPS Act occurred in May 2021 with the Senate’s consideration of the precursor bill titled United States Innovation and Competition Act (USICA). After remaining quite flat, including through the COVID shutdown period, national semiconductor employment rose by about 20,000 persons, or 10.6 percent, between the consideration of USICA and the end of 2022, after which it again flattened. The “QCEW (national)” line at the top of the figure shows national employment in semiconductor production as reported in the BLS Quarterly Census of Employment and Wages (QCEW). The QCEW aggregates directly from unemployment insurance (UI) tax records and hence contains a near-universe of private

sector employment. It also provides the benchmark for the CES program, so not surprisingly the CES and QCEW national employment totals closely track each other.

Because it builds from establishment-level UI reporting, the QCEW also contains information on semiconductor employment at the county level. However, in order to protect the confidentiality of individual establishments, the QCEW suppresses employment in counties with only a few establishments or highly concentrated employment in a sector. The “QCEW (counties)” line in the middle of the figure shows the sum of semiconductor employment as reported at the individual county level. Because semiconductor production tends to concentrate in large factories, the suppression of data is substantial. For example, in May 2021 more than 46,000 employees, or about 25 percent of total semiconductor employment, worked in counties with suppressed records. A county-level research design necessarily excludes these counties, despite several eventual CHIPS awards going to counties with suppressed semiconductor employment.

The authors’ cross-county research design, summarized in their figures 5–7, compares semiconductor employment in counties with semiconductor production to semiconductor employment in selected counties without semiconductor production. Their first design designates as treated any county with at least one semiconductor facility prior to 2021 and as control any county labeled as “high-technology” by the Census Bureau and not also treated. Their second design designates as treated any county with at least one semiconductor fabrication facility and as control counties with at least one semiconductor facility but no fabrication facility.

Figure 1 shows the time series of semiconductor employment summed over treated and control counties for both research designs. Two important features stand out. First, essentially all semiconductor employment is in counties designated as treated. This statement holds true using either research design. Second, and a corollary, there is essentially no semiconductor employment in the control counties. (For readability the *y*-axis on the figure is distorted—total employment in the control counties never exceeds 3,000 for either definition.) This fact should not surprise, since by construction the control counties do not have semiconductor production or fabrication facilities.

A consequence of designating a control group with essentially no employment is that the difference-in-differences estimator in fact just recovers the unweighted average employment change in the treated counties. This result obtains because the authors estimate their main difference-in-differences

specification with the level of semiconductor employment as the dependent variable:

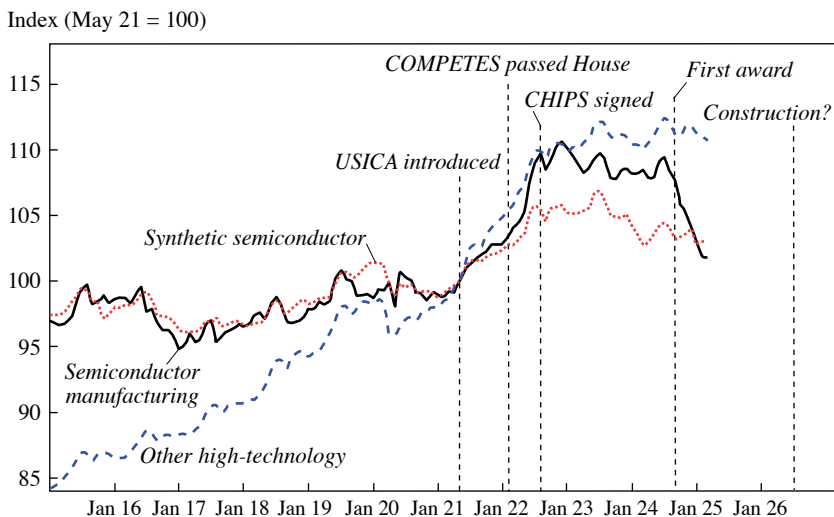
$$Y_{it} = \alpha_i + \gamma_t + \beta * \text{Treated}_i * \text{Post}_t + \epsilon_{it},$$

where Y_{it} denotes the level of semiconductor employment in county i at date t . The time fixed effect γ_t equals the average deviation of employment in each control county i from the county's sample mean. If control counties have very low semiconductor employment, then γ_t will be approximately zero in all months, leaving β as the difference in average employment in the treated counties before and after the treatment occurs.

The fact that the control counties do no “work” in the regression opens the question of whether the growth of semiconductor employment in this period actually was abnormal. Indeed, the USICA filing in May 2021 also coincided with the widespread availability of COVID vaccines and the full reopening of much of the US economy, which added 9.3 million jobs between May 2021 and December 2022 according to the CES. Could the increase shown in figure 1 simply reflect overall economic growth?

Figure 2 provides an alternative answer to that question by comparing national semiconductor employment to national employment in other high-technology sectors. The control group thus embodies the same idea as the first research design in the paper, but uses national employment in this group as the counterfactual for semiconductor employment. The solid line displays total semiconductor manufacturing employment and the dashed line total employment in other high-technology industries, both indexed to equal one hundred in May 2021. Immediately visible is much faster pre-2021 growth in the other high-technology sectors. To adjust for this difference, the dotted line displays the synthetic difference-in-differences counterfactual obtained by reweighting the other high-technology sectors using the method of Arkhangelsky and others (2021). A comparison of actual and synthetic semiconductor employment reveals faster growth in actual employment starting in May 2021 and persisting through 2022. If anything, this difference might understate the abnormal growth of semiconductor employment, because the synthetic counterfactual puts about half the weight on two sectors downstream from semiconductors—computer and peripheral equipment (NAICS 3341) and communications equipment (NAICS 3342).

Taking stock, it seems plausible that semiconductor employment after May 2021 grew faster than predicted by either its previous trend or employment growth in similar industries.

Figure 2. Employment in Semiconductor Production and Other High-Technology Sectors

Source: CES; QCEW; and author's calculations.

Note: The line marked "Semiconductor manufacturing" displays national employment in NAICS 334413 in the BLS CES. The line marked "Other high-technology" displays the sum of national employment in NAICS 3341, 3342, 3345, 3364, 5132, 5413, 5415, 5417, and 541713 in the BLS CES and NAICS 5182 in the BLS QCEW. The line marked "Synthetic semiconductor" applies the method of Arkhangelsky and others (2021).

WAS THE ABNORMAL GROWTH DUE TO THE CHIPS ACT? Assigning causality to the CHIPS Act requires additional argument. The timing itself offers *prima facie*, albeit not dispositive, reason for doubt. As described by the authors and illustrated in the figures in this comment, the timeline from filing of USICA to passage of the CHIPS Act to awarding of grants to construction of new facilities remains incomplete as of this writing. The period of rapid employment growth in semiconductor manufacturing concentrates between the filing of USICA in May 2021 and the signing of the final CHIPS bill in August 2022. Semiconductor employment remained essentially flat for more than a year after the signing of the CHIPS Act before falling starting in the latter part of 2024. Meanwhile, the first CHIPS awards were announced in late 2024, and these awards mostly anticipated construction starting in 2026 or later.¹ Thus, ascribing the employment growth from May 2021 to

1. Information on CHIPS awards can be found at National Institute of Standards and Technology, "CHIPS for America Awards," updated September 19, 2024, <https://www.nist.gov/chips/chips-america-awards>.

the end of 2022 to the CHIPS Act requires semiconductor firms to have ramped up employment in anticipation of possible passage of the act, with no certainty that they would be chosen as awardees, and years ahead of any new facilities funded by the act.

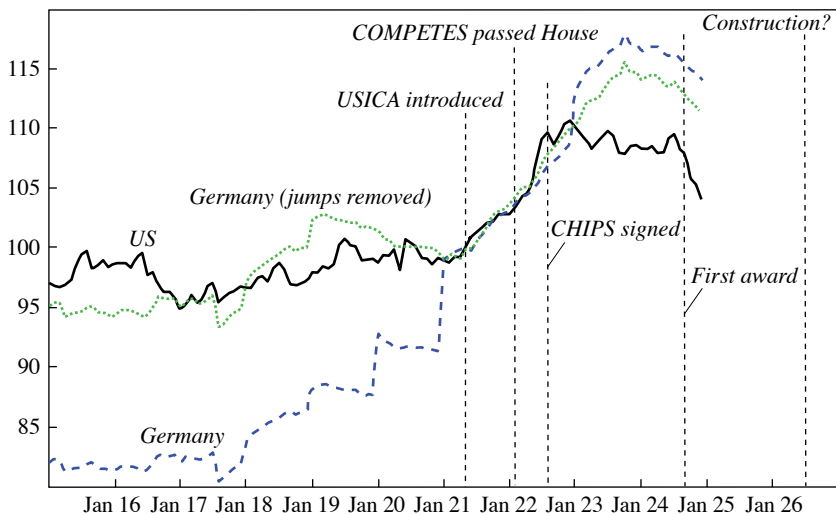
The authors discuss and dismiss a leading alternative explanation, the shortages of chips in early 2021. The case for this alternative emerges from news reports at the time. For example, a June 2021 *Wall Street Journal* article with the headline “Chip Shortages Are Starting to Hit Consumers. Higher Prices are Likely” describes the intersection of surging demand and strained supply (Fitch 2021). Or consider a January 2022 headline: “Chip Shortage Leaves U.S. Companies Dangerously Low on Semiconductors, Report Says” (Zumbrun and Leary 2022). The authors dismiss this alternative on two grounds: (1) The shortage already appeared before May 2021, but the employment growth coincided with the filing of USICA; and (2) semiconductor employment in Canada and Germany did not accelerate at the same time.

I find the international comparisons especially informative; however, to my eye, they do not clearly rule out a common cross-country factor. The sector in Canada employs less than 20,000 workers, or only about 10 percent of the US workforce (see figure 4 in the paper). The sector in Germany employs about 70,000 workers (see figure A2 in the paper’s online appendix). However, interpretation of the German case is complicated by periodic reclassifications of establishments. Figure 3 shows US semiconductor employment along with the German series without (as in the paper’s figure A2) and with the reclassification jumps removed. With the reclassification jumps removed, the employment trend in Germany looks very similar to the United States, with flat employment in 2019 and 2020, rising employment starting around the same time in the spring of 2021 and lasting through 2022, and a decline again in 2024. The German data therefore seem consistent with global demand for semiconductors affecting semiconductor employment during this period.²

2. Neither the authors nor I were able to fully discern whether the jumps should be removed. They arise due to the reclassification of activity at individual establishments. Typically, employment changes due to industry reclassification are removed from time series, as is done in the line labeled “Germany (jumps removed).” If one instead thinks the jumps should be “wedged” back into the preceding months, then the line labeled “Germany” appropriately characterizes the medium-term behavior of the series and the pre-May 2021 period looks very different from the United States. The case for wedging would appear to be that the reclassification of establishments captures the extensive margin of plant-level growth in semiconductor employment. However, it would seem economically surprising for the extensive margin to contribute positively to employment growth as in 2019 and 2020 at the same time that the intensive margin of employment changes at existing semiconductor plants was negative.

Figure 3. Semiconductor Employment in the United States and Germany

Index (May 21 = 100)



Source: CES and Statistisches Bundesamt (2021).

Note: The line marked “US” displays national US employment in NAICS 334413 in the BLS CES. The line marked “Germany” displays employment in 26.11 and 26.12 in the German monthly report for companies in the manufacturing sector. The line marked “Germany (jumps removed)” removes the January reclassification jumps in 2020, 2021, and 2023.

Global demand for semiconductors may also have spurred passage of the CHIPS Act. Indeed, concerns about fractured supply chains and shortages directly motivated the policy concern of increasing domestic manufacturing capacity. In this vein, the *Wall Street Journal* article reporting on the Commerce Department’s survey of chip inventories noted: “Commerce Secretary Gina Raimondo said the survey results show the urgency for Congress to approve the U.S. Innovation and Competition Act” (Zumbrun and Leary 2022). In this interpretation, semiconductor shortages caused both employment growth in semiconductor manufacturing and the passage of the CHIPS Act.

A third possibility is that a chips shortage and the promise of the CHIPS subsidies were both necessary conditions for semiconductor employment growth in 2021 and 2022. In this version, the shortage required additional investment and capacity expansion somewhere around the world, and the promise of CHIPS ensured that the expansion occurred in the United States. The quote from the CEO of SkyWater Technology in the paper supports this

interpretation, as it mentions both the near-term supply constraints and the long-term strategy tied to the CHIPS Act.

Taking stock, it is possible that the CHIPS Act mattered to employment in 2021 and 2022, prior to the actual passage. But the fact that the growth occurred prior to passage and years prior to construction, the coincidence with the global chips shortage, and the similarity of employment growth in Germany all suggest that at least some of the employment growth might have occurred without the act.

WHAT ABOUT AGGREGATE EMPLOYMENT? Suppose the additional semiconductor employment occurred due to the CHIPS Act. What were the macroeconomic consequences?

A first step in this analysis involves looking for local spillovers around semiconductor production. Figure 8 in the paper shows the difference-in-differences of nonresidential construction employment in counties with and without semiconductor production. Importantly, here the control counties do some “work,” since they also have substantial employment in nonresidential construction (although I would still prefer the estimation in logs than levels). The evidence suggests some spillovers to construction employment. On the other hand, total employment in treated and control counties does not evolve statistically differently after May 2021 and also reveals some pretreatment differences during the COVID shutdown period.

Determining the effect on aggregate employment requires also examining overall macroeconomic conditions. Figure 4 of this comment provides this context. The period of semiconductor employment growth after May 2021 coincided with the tightest labor market and highest inflation rate of the past forty years. By early 2022 the Federal Reserve had embarked on a historically rapid rate tightening cycle, with the express goal of cooling the labor market. In this context, no fiscal program could generate a large employment effect, both because of the limit of total workers and because any further tightening of the labor market would only lead to additional monetary policy action. The authors sidestep these considerations by pointing out that the employment effects were not large enough to arrive on the Federal Reserve’s radar. I am sympathetic to their argument and their framework, which closely follow Chodorow-Reich (2020). But it leaves the result that the macroeconomic employment consequences cannot have made much difference to the overall cost-benefit calculus of the CHIPS Act.

FINAL COMMENTS Outside of recessionary periods, “jobs created” provides an odd measure of macroeconomic success. An alternative focus of “good jobs” might emphasize the high wages directly associated with the project, the location of jobs in economically depressed areas, or the downstream

Fitch, Asa. 2021. “Chip Shortages Are Starting to Hit Consumers. Higher Prices Are Likely.” *Wall Street Journal*, June 21. <https://www.wsj.com/business/telecom/chip-shortages-are-starting-to-hit-consumers-higher-prices-are-likely-11624276801>.

Statistisches Bundesamt. 2021. *Monatsbericht für Betriebe des Verarbeitenden Gewerbes sowie des Bergbaus und der Gewinnung von Steinen und Erden: Qualitätsbericht* [Monthly Report for Companies in the Manufacturing Sector and in Mining and Quarrying: Quality Report]. Wiesbaden: Statistisches Bundesamt (Destatis).

Zumbrun, Josh, and Alex Leary. 2022. “Chip Shortage Leaves U.S. Companies Dangerously Low on Semiconductors, Report Says.” *Wall Street Journal*, January 25. <https://www.wsj.com/tech/u-s-companies-down-to-five-day-supply-of-key-chips-report-says-11643126434>.

COMMENT BY

PINELOPI K. GOLDBERG This paper by Erten, Stiglitz, and Verhoogen represents one of the first rigorous empirical attempts to assess the labor market effects of the CHIPS and Science Act of 2022—arguably the centerpiece of the recent revival of US industrial policy. Using county-level data from the Quarterly Census of Employment and Wages, the authors implement two difference-in-differences designs comparing counties with existing semiconductor facilities to otherwise similar high-tech counties without such facilities. The study yields three main sets of results:

1. There were large anticipation effects.
2. The policy had significant, positive short-run effects on employment in the semiconductor industry at the county level. There is some evidence of wage effects as well, but these are not robust. Given that these effects were obtained based on difference-in-differences designs, they are only relative effects, as the authors emphasize. Nevertheless, given the research design and the focus on the semiconductor industry, which is present only in a small set of counties, the authors make a convincing case that the results can be easily scaled up to the national level to yield the number of jobs added in the US semiconductor industry.
3. There are robust positive spillovers to employment in the local construction industry. The evidence on spillovers to upstream input sectors is mixed. There are no significant aggregate employment or wage gains at the county level.

The paper also provides a useful chronology of the legislation and a wealth of factual information on the semiconductor industry that will be valuable to future researchers.

Overall, this is an ongoing and promising research program. The authors are up-front about the limitations of their analysis, which stem primarily from the lack of data at the time of the study. My comments will focus on the interpretation of the results and on what they imply—and do not imply—for assessing the effectiveness of the CHIPS Act.

INTERPRETING THE RESULTS: ANTICIPATION EFFECTS ARE NOT PERMANENT EMPLOYMENT GAINS At this stage, the paper credibly documents anticipation effects rather than the impacts of actual disbursements. This is due to the fact that the authors do not have firm-level data; hence, they are not comparing firms that received awards to similar firms that did not. Instead, as noted earlier, they rely on two difference-in-differences designs that involve comparisons of counties. In the first design, they compare counties with preexisting semiconductor facilities to counties with a high-tech sector but no semiconductor facilities. In the second, they compare counties with preexisting semiconductor fabrication facilities to counties with semiconductor industry but no preexisting semiconductor fabrication facilities. In both cases, almost the entire employment gains indicated by the estimates occur between June 2021 and August 2022 (see figures 6 and 7 in the paper).

However, most of the major CHIPS awards were made after the November 2024 elections; by January 2025 the Department of Commerce had announced over \$30 billion in awards, many finalized in the two months preceding the change in administration (Moore 2025). Hence, the employment increases captured in the authors' preferred specifications most likely reflect firms' anticipation of increases in capacity rather than realized investments.

This naturally raises the question of why the anticipation effects were so large. One plausible interpretation is that the act signaled the US government's commitment to supporting the semiconductor sector. Absent such government backing, the goal of reviving US chip manufacturing had little prospect of success, as the domestic industry was no longer competitive by international standards—precisely the reason semiconductor fabrication had shifted almost entirely to East Asia. Another explanation is that existing producers may have responded by scaling up employment to demonstrate capacity and strengthen their bids for subsequent awards. Consistent with this view, employment levels off—and even declines—after late 2024, as shown in figure 2 of the paper.

WHAT THE RESULTS DO AND DO NOT SHOW Figure 2, which shows the evolution of aggregate employment in the US semiconductor sector, is a problem for the authors' statement in the conclusion that "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 figure shows that the employment gains were almost entirely reversed by February 2025. This reversal coincides with layoffs at Intel due to changing market conditions (Ortutay 2024). While the layoffs were not related to the CHIPS Act, Intel was among the primary beneficiaries of the act, and the firm's troubles underscore the challenge inherent in government efforts to pick "winners." In the context of the paper's message, the figure highlights the distinction between short-lived anticipatory hiring and the creation of durable, long-term employment.

A second issue with the interpretation of the findings is that the paper finds positive effects *only within the semiconductor sector*. There is no evidence of aggregate employment or wage gains at the county level. A plausible explanation is that any increases in semiconductor jobs were offset by reductions in other sectors within the same localities. This lack of evidence of any county-level employment gains further limits the scope for interpreting the results as evidence that the CHIPS Act produced substantial short-term job creation.

CHIPS ACT AND EMPLOYMENT One might argue that the CHIPS Act was never primarily about employment. Its stated objectives were to bolster national security and supply chain resilience and to reduce dependence on geopolitically sensitive regions. The key design questions therefore centered on issues such as: What types of chips should be produced—legacy and mainstream chips or cutting-edge technologies? Would it be feasible to leap directly into advanced chip production without first rebuilding capabilities in earlier stages of the value chain? And so on.

That said, I agree with the authors that political economy considerations inevitably put employment effects at the forefront as well. Employment arguments were politically expedient—and may well have been necessary to secure bipartisan support. Still, they are not the appropriate metric for evaluating the policy. Ultimately, the success of the CHIPS Act will be judged based on answers to questions such as: Are US-based fabrication facilities actually producing chips? If so, of what generation and technological sophistication? And at what cost?

If one nevertheless focuses on employment, two dimensions merit particular attention: spatial distribution and job quality.

CHIPS ACT, SPATIAL INEQUALITY, AND “GOOD JOBS” In the aftermath of the COVID-19 pandemic, the US economy moved rapidly from COVID-induced unemployment to nearly full employment and eventually to labor shortages. By the time the CHIPS Act was enacted, aggregate employment was not a pressing concern, and while the industrial policies pursued by the Biden administration had multiple objectives, they were never intended to function as a form of fiscal stimulus. Nevertheless, employment considerations remained relevant in two distinct contexts.

Spatial inequality. Industrial policy under the Biden administration was at times framed as a form of place-based policy aimed at revitalizing communities that had been “left behind,” thereby reducing spatial inequality. The relevant question in this context is whether the CHIPS Act generated jobs specifically in such communities. As a side note, if this is the question of interest, then the difference-in-differences strategy the authors employ is exactly the right one. Difference-in-differences can identify only relative effects, but inequality is—by definition—a relative concept. Throughout the paper, the authors seem somewhat defensive about their use of difference-in-differences, but to the extent the goal is to speak to spatial inequality, they should not be.

From the perspective of spatial inequality, the paper indicates that the CHIPS Act was irrelevant for reducing spatial inequality. Table 1, which contains summary statistics, shows that both treatment and control groups consist of high-tech counties, which are among the most prosperous in the country. The treated counties in particular (the ones with existing semiconductor fabrication facilities) are on average larger, more urban, and better paid than the controls. The result, if anything, could be a modest increase in spatial inequality—though the absence of aggregate employment effects makes that unlikely.

“Good jobs.” While there was no pressure to increase aggregate employment in the post-COVID era, there remained great demand for “good jobs”—that is, jobs with benefits, stability, offering not only good pay but also a promising career trajectory. Jobs in the semiconductor industry generally fit this description: They tend to be stable, high-skilled, and well compensated. Therefore, to the extent that the CHIPS Act led to an increase in employment, two important questions arise: First, who filled these new positions? Engineers, technicians, lawyers, accountants? Or lower-skilled service workers associated with construction and facility operations? Second, where did the additional employees come from? Possible sources include other high-tech sectors within the same county, other US regions, or international labor flows, such as movements from

Taiwan Semiconductor Manufacturing Company (TSMC) in Taiwan to TSMC Arizona—presumably small in number but significant for the most skilled employees. Ideally, the additional employment would come from people who were nonemployed, or high-skilled workers who were underemployed, or fresh college graduates who might have chosen a different path.

The good news is that the authors are well positioned to address these questions in future work using micro employer-employee matched data. In the meantime, the focus on semiconductor employment as the dependent variable in the empirical specifications limits the relevance of the results for policy analysis. One could instead consider employment in high-tech sectors more broadly or employment of high-skilled workers, in order to capture potential negative spillovers on other high-tech activities within the same county. In the short run, it is not obvious how the CHIPS Act could have increased employment of engineers and other high-skilled professionals without crowding out similar workers in other sectors. Of course, in the longer run, the act may well create the incentives needed to expand the supply of relevant skills and specialties.

In sum, to the extent that the employment effects of the CHIPS Act are of interest, the success of the policy will be judged based on two questions: (a) Where did the additional employment come from? And (b) were the additional jobs “good jobs”? These are questions that can be addressed with appropriate micro data that will be available in the future.

CONCLUDING THOUGHTS To summarize, the paper convincingly shows a short-term increase in semiconductor employment following the passage of the CHIPS Act’s precursor legislation, driven largely by anticipation effects. These gains are confined to the semiconductor industry, with no detectable spillovers to aggregate employment or wages, and are almost entirely reversed by February 2025. Hence, the main value of the analysis and results is in highlighting the signaling role of policy. Conditional on an employment-oriented perspective, the natural next step is to extend the analysis to more recent years to assess whether any long-run, durable employment gains materialized and, if so, to determine what kinds of jobs were created and who holds them. Linking the CHIPS program to micro data could provide valuable insights along these dimensions.

Ultimately, the key question is not how many jobs the CHIPS Act created, but whether the act achieved its strategic goals: Are the new or expanded facilities producing chips? What type—legacy, mainstream, or leading-edge? At what cost, and with what implications for US competitiveness and resilience? Answering these questions will require time and detailed firm-level data. In the meantime, the authors’ careful empirical work and evidence

provide an important early snapshot of market reactions to the policy signal and lay a good foundation for future research.

I look forward to seeing subsequent papers that exploit micro-level data to explore the persistence and composition of employment changes—and, ultimately, to evaluate whether the CHIPS Act has succeeded in achieving its main objectives.

REFERENCES FOR THE GOLDBERG COMMENT

- Moore, Samuel K. 2025. “What the CHIPS Act Looks Like Now.” *IEEE Spectrum*, July 28. <https://spectrum.ieee.org/chips-act-map>.
- Ortutay, Barbara. 2024. “Chipmaker Intel to Cut 15,000 Jobs as Tries to Revive Its Business and Compete with Rivals.” Associated Press, August 1. <https://apnews.com/article/intel-chip-ai-job-cuts-layoffs-loss-e61781e9364b69af63481c34ca5dcd67>.

GENERAL DISCUSSION Offering a direction for future analysis, John Haltiwanger mentioned that the latest Business Dynamics Statistics data through 2023 provide information on job creation, job destruction, and business entry and exit at the industry level. On a preliminary review of the data, he noticed that the increase in employment observed by the authors was very much associated with a decline in establishment exits and a decline in job destruction for continuing establishments. Since poorly performing establishments tend to exit the market, Haltiwanger wondered whether the CHIPS Act has simply been propping up businesses that would have exited otherwise.

Katharine Abraham raised concerns about the confounding effects on total employment at the county level, particularly other factors that might have affected employment in the control group. For instance, she noted, the Inflation Reduction Act that provided subsidies for clean energy and advanced manufacturing, was signed into law about the same time as the CHIPS Act. Abraham posited that if other high-tech non-semiconductor counties were also experiencing a shock that affected their total employment, then the authors’ analysis comparing semiconductor counties with non-semiconductor counties would not be picking up the impact of the CHIPS Act specifically.

Justin Wolfers commented that what macroeconomists call an anticipation effect—when the measured effect of a policy predates the policy, which is the focus of the paper—would be considered a failure of robustness test by the applied microeconomists. Wolfers acknowledged the difficulty in

determining when the effects of a policy take place, but he emphasized the importance of recognizing hypothesis testing in the research, in which case Bonferroni correction should be applied. In addition, referencing discussant Gabriel Chodorow-Reich's remarks, Wolfers noted that the authors use semiconductor employment in counties without semiconductor facilities as their control group, which is nearly zero by nature; hence the authors' difference-in-differences estimate is merely an unweighted difference. Wolfers pointed out that the point of a control group is not to find a group that is unaffected by a policy, but a group that otherwise would have followed the same path. Lastly, Wolfers wondered in the authors' analysis, what set of coefficients on employment effects would lead one to consider the CHIPS Act a failed policy.

David Romer thought that one possible effect of the CHIPS Act would be to move workers from lower- to higher-quality jobs, but this effect seems small. Instead, he proposed two alternative mechanisms through which the act might have influenced workers: first, by incentivizing capital investment that enhances worker productivity and wages; and second, by fostering research and development as well as learning by doing within the semiconductor industry, which similarly increases labor productivity. Romer argued that these productivity-related impacts were more likely to be sources of benefits for workers than movements to higher-quality jobs.

Tristan Reed noticed that the wage effects in the authors' findings seem very large, which could indicate an inelastic labor supply and motivate discussant Pinelopi Goldberg's suggestion to examine the possibilities of crowding out and decline in employment in other related industries.

Considering the current events, Yuanchen Yang questioned the scalability of the act and whether counties would quickly hit labor supply bottlenecks given recent restrictions on the issuance of H-1B visas targeting high-skilled workers.¹ Tarek Hassan pondered to what extent the CHIPS Act subsidy would be undone by the tariffs on the machines needed to produce chips. Gerald Cohen asked what the authors' results would have been had their analysis been conducted after recent cuts to the CHIPS awards.² More broadly, Cohen wondered what the best way would be to measure the impact of policies that are time inconsistent.

1. White House, "Restriction on Entry of Certain Nonimmigrant Workers," proclamation, September 19, 2025, <https://www.whitehouse.gov/presidential-actions/2025/09/restriction-on-entry-of-certain-nonimmigrant-workers/>.

2. Samuel K. Moore, "The U.S. CHIPS Act Takes Another Hit: SMART USA, a \$285 Million Center Devoted to Digital Twins, Loses Funding," *IEEE Spectrum*, December 18, 2025, <https://spectrum.ieee.org/semiconductor-digital-twins-funding>.

Assuming the main objective of the CHIPS Act is to create semiconductor jobs in the United States, John Sabelhaus asked if there is any evidence of the act reducing the number of chips jobs overseas or impacting the stock prices of foreign chip manufacturers.

In response, Eric Verhoogen acknowledged that difference-in-differences analysis always has issues where group-specific phenomena can give rise to effects. Verhoogen noted that the authors have considered several factors that might have affected their control group: For example, the boom of generative AI created demand for chips, but it started after the CHIPS Act was passed. The chip shortage during the COVID-19 pandemic could have also played a role, but the drastic increase in wait time for chips started around January 2021, about five months before the spike in semiconductor employment in June 2021 (see figures 6 and 7 in the paper).³ Verhoogen added that the authors have also done difference-in-differences analysis comparing counties with preexisting semiconductor fabrication facilities to those with preexisting semiconductor production facilities but no fabrication facilities, which shows similar results. He also noted that international comparisons could be useful. Bilge Erten shared that, additionally, the authors did an exercise comparing counties with semiconductor facilities that received awards later to those that didn't receive awards as well, since the award process took several months. Even in this more conservative exercise, there is still an increase in employment, albeit a smaller one than what is presented in the paper.

In regards to Reed's question about the wage effect, Verhoogen clarified that their estimates particularly in the synthetic difference-in-differences analysis are less robust. Since they did not attempt to control for workforce composition, he suggested, the large wage effects could be attributed to companies hiring a greater share of high-skilled, high-wage workers.

Responding to the discussion on anticipation effect, Verhoogen explained that the authors had first observed such effect starting around June 2021—when the United States Innovation and Competition Act (USICA) was passed in the Senate—and subsequently confirmed this in the stock market response. Joseph Stiglitz elaborated that the large wage increases observed in their results suggest crowding out and provide an explanation for the anticipation effect: If the labor market is tight and firms anticipate an award from

3. Ian King, Debby Wu, and Demetrios Pogkas, "How a Chip Shortage Snarled Everything From Phones to Cars," Bloomberg, March 29, 2021, <https://www.bloomberg.com/graphics/2021-semiconductors-chips-shortage/>.

the government, they will begin hiring in anticipation knowing that there is a shadow price on labor higher than the market price. Alluding to Romer's comment, Stiglitz noted that learning by doing is an important aspect of industrial policy; and when firms rationally expect future opportunities for learning by doing, it creates an anticipation effect on firms' labor demand that includes incremental benefits from learning. On the other hand, Stiglitz suggested that the possibility of repealing the CHIPS Act and terminating finalized awards would lead to a negative anticipation effect: Firms that have hired labor in anticipation of awards may proceed to fire unnecessary workers.

Stiglitz agreed that the primary goal of the CHIPS Act is to build supply chain resilience and reduce reliance on other countries such as Taiwan for semiconductor chips. However, he highlighted, in a period of unemployment, there is a shadow price in employment that reduces the net cost of resilience. Therefore, quantifying the employment consequences of the CHIPS Act is an important step in calculating the broader social welfare impact of the policy.

Stiglitz further commented on whether the act could be partly motivated by a shortage of capital or the need to subsidize industries where doing so may create greater social value. In his opinion, Intel's extensive investment in semiconductor production before the CHIPS Act undermines the capital shortage argument and instead suggests an incentive effect.⁴ On the other hand, because the act's incentives are applied discretionarily, there is a complex differential effect that cannot be parsed by the authors' analysis.

On the issue of spatial inequality, Stiglitz suggested that politics could have affected the location and timing of funding allocation, which remains a persistent issue in the design of industrial policy. In addition, Erten highlighted that the authors' preliminary analysis of the Quarterly Workforce Indicators data, which is not included in their conference draft, shows that most wage increases occurred for workers who are more likely to be college educated, male, and white. This suggests that the act's goal of reducing inequality has not yet been achieved.

4. Intel, "Intel CEO Pat Gelsinger Announces 'IDM 2.0' Strategy for Manufacturing, Innovation and Product Leadership," press release, March 23, 2021, <https://www.intel.com/news-events/press-releases/detail/1451/intel-ceo-pat-gelsinger-announces-idm-2-0-strategy>.

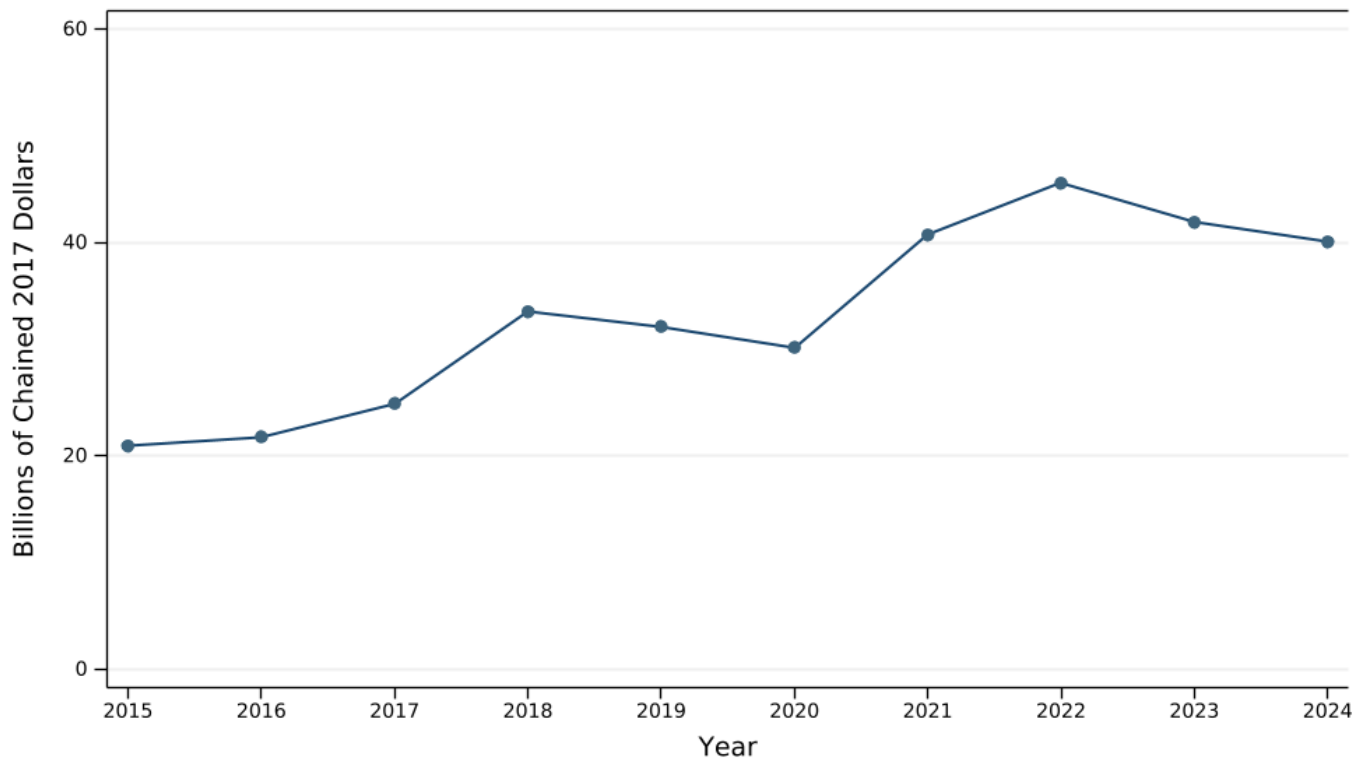
Employment Impacts of the CHIPS Act

Bilge Erten
Joseph E. Stiglitz
Eric Verhoogen

Nov. 2025

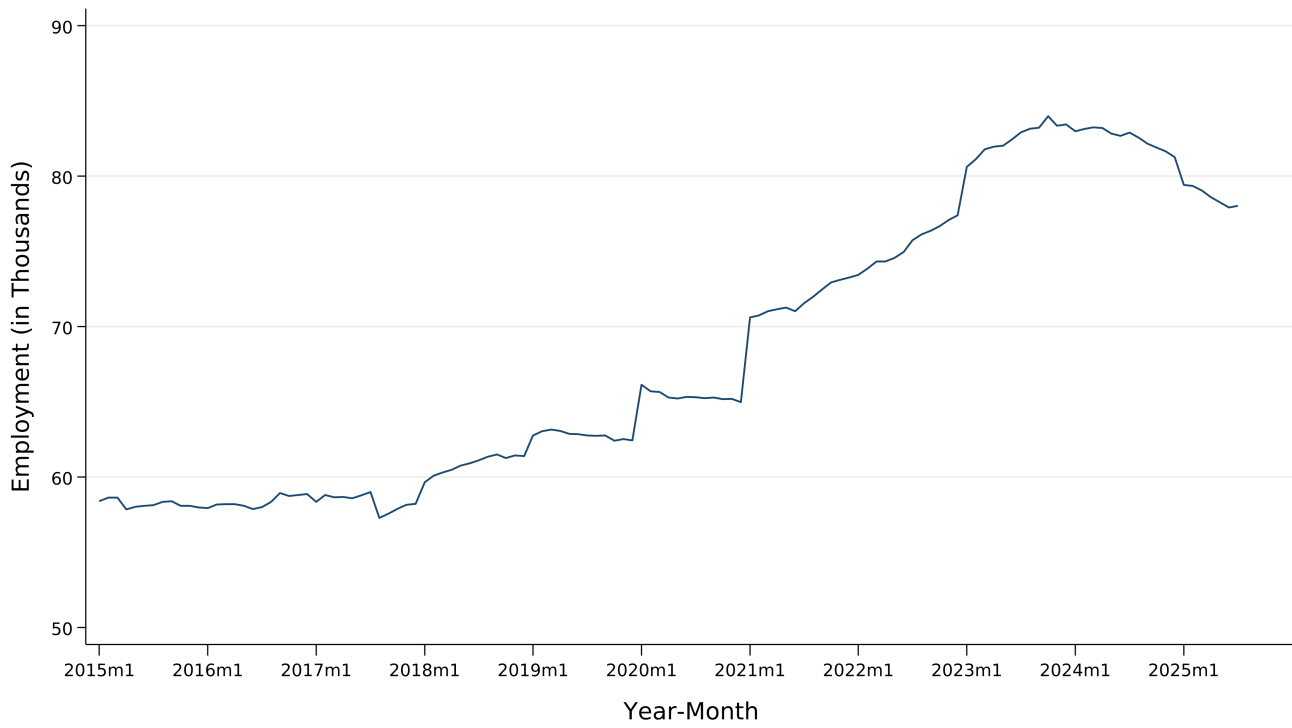
ONLINE APPENDIX

FIGURE A1: REAL PURCHASES OF PROPERTY, PLANT AND EQUIPMENT BY SEMICONDUCTOR FIRMS



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

FIGURE A2: EMPLOYMENT IN ELECTRONIC COMPONENTS: GERMANY



Notes: Source is Monthly Report on Manufacturing, generated by the Federal Statistical Office of Germany (Statistisches Bundesamt), for industry WZ 261: Manufacture of Electronic Components and Boards (equivalent of ISIC rev 4 industry 2610). Data can be accessed at <https://www-genesis.destatis.de/datenbank/online/url/937eb0e8>.

TABLE A1: CHIPS ACT APPROPRIATION BY FUND

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

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

TABLE A2: NOTICE OF FUNDING OPPORTUNITIES FOR THE CHIPS ACT

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

Notes: The table describes all Notice of Funding Opportunities (NOFOs) released by the National Institute of Standards and Technology (NIST) relating to the CHIPS Act programs. Information taken from Department of Commerce Office of Inspector General (2025) and is updated as of May 14, 2025.

TABLE A3: CUMULATIVE ABNORMAL RETURNS

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

Notes: Cumulative Average Abnormal Returns (CAARs) around major semiconductor policy events are calculated as follows (using the Stata `estudy` command). We first calculate Abnormal Returns (ARs) by estimating the regression $R_{it} = \gamma_i R_{mt} + \alpha_i + \varepsilon_{it}$, where R_{it} is firm i 's return and R_{mt} is the S&P 500's return, over the period 250 days to 30 days before the event, and then defining $AR_{it} = R_{it} - \hat{\gamma}_i R_{mt} - \hat{\alpha}_i$ for the indicated event window. The ARs are averaged across firms and then summed across the event window to get CAARs. Inference is based on the Boehmer–Musumeci–Poulsen (BMP) test. Windows are indicated in days. The sample is the set of firms included in Figure A1, excluding Global Foundries and Skywater, who began trading on October 28, 2021 and April 21, 2021, respectively. *p < 0.10; **p < 0.05; ***p < 0.01. See also Fig. 3.

TABLE A4: EMPLOYMENT IN SEMICONDUCTORS: SIMPLE DID, NO IMPUTATION

| | Semiconductor production employment (1) | Semiconductor equipment & materials employment (2) | Semiconductor production, equipment & materials employment (3) |
|--|--|--|---|
| Panel A: Semiconductor vs. Non-Semiconductor Counties | | | |
| Treated x Post-USICA | 176.68** (75.98) | 68.04** (33.37) | 244.72** (97.15) |
| Observations | 27157 | 27157 | 27157 |
| Pre-USICA outcome mean (treated counties) | 1596.5 | 287.8 | 1884.3 |
| County FE | Y | Y | Y |
| Year-Quarter FE | Y | Y | Y |
| Panel B: Fab vs. Fabless Counties | | | |
| Treated x Post-USICA | 374.80** (157.47) | 190.15*** (66.03) | 564.95*** (196.92) |
| Observations | 3314 | 3314 | 3314 |
| Pre-USICA outcome mean (treated counties) | 3161.4 | 471.8 | 3633.2 |
| 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. County-industry-quarters with data suppressed for confidentiality are omitted from regressions. *p <0.10; **p <0.05; ***p <0.01.

TABLE A5: EMPLOYMENT IN SEMICONDUCTORS: SIMPLE DID, ALTERNATIVE DEFINITION OF POST

| | Semiconductor production employment (1) | Semiconductor equipment & materials employment (2) | Semiconductor production, equipment & materials employment (3) |
|--|--|--|---|
| Panel A: Semiconductor vs. Non-Semiconductor Counties | | | |
| Treated x Post-CHIPS | 127.54*** (46.91) | 36.09** (18.25) | 163.63*** (58.00) |
| Observations | 31535 | 31535 | 31535 |
| 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-CHIPS | 229.12*** (83.15) | 82.93** (34.25) | 312.05*** (102.71) |
| Observations | 5215 | 5215 | 5215 |
| 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-CHIPS indicator identifies quarters after CHIPS Act was signed (2022Q4 or later). Quarters from 2021Q3-2022Q3 are omitted. 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 A6: EMPLOYMENT IN SEMICONDUCTORS: SYNTHETIC DID, ALTERNATIVE DEFINITION OF POST

| | Semiconductor production employment (1) | Semiconductor equipment & materials employment (2) | Semiconductor production, equipment & materials employment (3) |
|--|--|--|---|
| Panel A: Semiconductor vs. Non-Semiconductor Counties | | | |
| Treated x Post-CHIPS | 133.06*** (43.52) | 13.84 (15.05) | 142.39*** (48.34) |
| Observations | 31535 | 31535 | 31535 |
| Pre-USICA outcome mean (treated counties) | 868.8 | 164.5 | 1033.3 |
| Panel B: Fab vs. Fabless Counties | | | |
| Treated x Post-CHIPS | 217.93*** (62.16) | 28.45 (20.64) | 252.68*** (76.55) |
| Observations | 5215 | 5215 | 5215 |
| Pre-USICA outcome mean (treated counties) | 1523.5 | 238.1 | 1761.6 |

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-CHIPS indicator identifies quarters after CHIPS Act was signed (2022Q4 or later). Quarters from 2021Q3-2022Q3 are omitted. 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 A7: EMPLOYMENT IN SEMICONDUCTORS: ROBUSTNESS USING QWI/QCEW 4-DIGIT DATA

| | Semiconductor production employment (1) | Semiconductor equipment & materials employment (2) | Semiconductor production, equipment & materials employment (3) |
|---|--|--|---|
| Panel A: Semiconductor vs. Non-Semiconductor Counties, Simple DID | | | |
| Treated x Post-USICA | 89.73** (45.23) | 86.71*** (25.58) | 176.43*** (62.11) |
| Observations | 36040 | 36040 | 36040 |
| Pre-USICA outcome mean (treated counties) | 1717.3 | 551.3 | 2268.5 |
| County FE | Y | Y | Y |
| Year-Quarter FE | Y | Y | Y |
| Panel B: Fab vs. Fabless Counties, Simple DID | | | |
| Treated x Post-USICA | 178.69** (79.44) | 115.15** (46.08) | 293.84*** (109.48) |
| Observations | 5960 | 5960 | 5960 |
| Pre-USICA outcome mean (treated counties) | 2893.0 | 643.9 | 3536.9 |
| County FE | Y | Y | Y |
| Year-Quarter FE | Y | Y | Y |
| Panel C: Semiconductor vs. Non-Semiconductor Counties, Synthetic DID | | | |
| Treated x Post-USICA | 104.38** (44.72) | 59.95*** (17.18) | 173.38*** (52.18) |
| Observations | 36040 | 36040 | 36040 |
| Pre-USICA outcome mean (treated counties) | 1716.4 | 552.6 | 2269 |
| Panel D: Fab vs. Fabless Counties, Synthetic DID | | | |
| Treated x Post-USICA | 177.37*** (54.15) | 86.18*** (31.39) | 262.07*** (75.80) |
| Observations | 5960 | 5960 | 5960 |
| Pre-USICA outcome mean (treated counties) | 2892 | 646.3 | 3538.3 |

Notes: Data are from QWI/QCEW combined data at 4-digit level. 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 number of workers employed in the semiconductor sector (NAICS industry code 3344). Outcome in Column 2 is the number of workers employed the manufacturing of equipment (NAICS 3332) or material inputs (NAICS 3251) for semiconductors. Outcome in Column 3 is the number of workers employed in either the semiconductor industry or the manufacturing of equipment (NAICS 3332) or material inputs (NAICS 3251) for semiconductors. The pre-USICA outcome mean is the outcome mean for treated counties for the 2015Q1-2021Q1 period. The standard errors included in parentheses are clustered at the county level. *p < 0.10; **p < 0.05; ***p < 0.01.

TABLE A8: ROBUSTNESS: INCLUDING ADDITIONAL CONTROLS

| | Semiconductor production employment (1) | Semiconductor equipment & materials employment (2) | Semiconductor production, equipment & materials employment (3) |
|--|--|--|---|
| Panel A: Including Demographic Controls | | | |
| i. Semiconductor vs. Non-Semiconductor | | | |
| Treated x Post-USICA | 110.31*** (40.58) | 15.55 (14.02) | 123.91*** (43.64) |
| Observations | 36900 | 36900 | 36900 |
| Pre-USICA outcome mean (treated counties) | 868.7 | 165.3 | 1034.0 |
| ii. Fab vs. Fabless | | | |
| Treated x Post-USICA | 179.83*** (52.48) | 25.19 (16.82) | 209.79*** (63.11) |
| Observations | 6109 | 6109 | 6109 |
| Pre-USICA outcome mean (treated counties) | 1523.6 | 239.4 | 1763.0 |
| Panel B: Including 2010 Rural Share Interaction | | | |
| i. Semiconductor vs. Non-Semiconductor | | | |
| Treated x Post-USICA | 96.65*** (34.76) | 38.64*** (13.10) | 140.97*** (42.03) |
| Observations | 36941 | 36941 | 36941 |
| Pre-USICA outcome mean (treated counties) | 868.7 | 165.3 | 1034.0 |
| ii. Fab vs. Fabless | | | |
| Treated x Post-USICA | 236.30*** (61.95) | 34.87 (22.02) | 197.35*** (72.97) |
| Observations | 6109 | 6109 | 6109 |
| Pre-USICA outcome mean (treated counties) | 1523.6 | 239.4 | 1763.0 |

Notes: Regressions are similar to those in Table 3 but with additional controls. In Panel A, the demographic controls include percent of county population that is female, white, black, asian, hispanic, younger than 19, between ages 20 to 24, 25 to 34, 35 to 44, 45 to 54, and 55 to 64. County demographic data from SEER U.S. County Population Data, 1969-2023 (<https://seer.cancer.gov/popdata/download.html>). In Panel B, rural share was controlled for by interacting the rural share for a county in 2010 with county FIPS code. Initial rural share for each county in 2010 data taken from the Census Bureau Urban and Rural Geographic Area data, found at <https://www.census.gov/programs-surveys/geography/guidance/geo-areas/urban-rural.html> *p <0.10; **p <0.05; ***p <0.01.

TABLE A9: ROBUSTNESS: ALTERNATIVE CUTOFFS FOR HIGH-TECH EMPLOYMENT

| | Semiconductor production employment (1) | Semiconductor equipment & materials employment (2) | Semiconductor production, equipment & materials employment (3) |
|--|--|--|---|
| Panel A: High Tech Employment > 0 | | | |
| Treated x Post-USICA | 110.67*** (34.66) | 14.35 (12.63) | 122.05*** (38.54) |
| Observations | 70807 | 70807 | 70807 |
| Pre-USICA outcome mean (treated counties) | 868.7 | 165.3 | 1034.0 |
| Panel B: High Tech Employment > 500 | | | |
| Treated x Post-USICA | 110.06*** (40.20) | 15.51 (15.08) | 124.36*** (46.92) |
| Observations | 21566 | 21566 | 21566 |
| Pre-USICA outcome mean (treated counties) | 868.7 | 165.3 | 1034.0 |
| Panel C: High Tech Employment > 1000 | | | |
| Treated x Post-USICA | 109.88*** (36.02) | 13.13 (12.33) | 118.63*** (39.16) |
| Observations | 16810 | 16810 | 16810 |
| Pre-USICA outcome mean (treated counties) | 868.7 | 165.3 | 1034.0 |

Notes: Regressions are similar to those in Table 3 Panel A, but use different values of the cutoff for a country to be a high-tech county (and hence included in the control group if it does not have a semiconductor facility). *p < 0.10; **p < 0.05; ***p < 0.01.

TABLE A10: LOCAL SPILLOVERS: SYNTHETIC DID, ALTERNATIVE DEFINITION OF POST

| | Semiconductor inputs employment (1) | Non-residential construction employment (2) | Total county employment (3) | County GDP (00,000s USD) (4) |
|--|--|--|-----------------------------------|------------------------------------|
| Panel A: Semiconductor vs. Non-Semiconductor Counties | | | | |
| Treated x Post-CHIPS | 59.48* (34.65) | 159.82** (78.21) | -3238.83 (3155.70) | -5.38 (5.95) |
| Observations | 31535 | 31535 | 31535 | 7040 |
| Pre-USICA outcome mean (treated counties) | 1069.3 | 1800.3 | 307456.4 | 590.9 |
| Panel B: Fab vs. Fabless Counties | | | | |
| Treated x Post-CHIPS | -56.56 (63.85) | 250.03* (138.99) | 11471.05* (6709.18) | 12.98 (9.93) |
| Observations | 5215 | 5215 | 5215 | 1168 |
| Pre-USICA outcome mean (treated counties) | 1519.2 | 2056.8 | 386279.3 | 706.2 |

Notes: Estimates are from synthetic difference-in-difference (SDID) specification, equation (3) in text. Comparison groups are defined in Section 4. Post-CHIPS indicator identifies quarters after after CHIPS Act was signed (2022Q4 or later). Quarters from 2021Q3-2022Q3 are omitted. 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). *p <0.10; **p <0.05; ***p <0.01.