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Tariffs and Automation: Measuring Manufacturing Employment Effects of 2018-2025 U.S. Trade Policy

Supervised by Stefano Frascani

Thomas Lundell

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Thesis Pitch

Elevator pitch video (3 min): https://youtu.be/ALO9aYtDoIU

Statutory Declaration

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Name: Thomas Lundell

Date: July 26th, 2025

Signature: Thomas Lundell

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Abstract

This thesis examines whether the rise in U.S. tariffs between 2018 and 2025 can boost manufacturing employment, taking into account the growing use of industrial automation. A quarterly panel spanning 2004 Q1 to 2025 Q2 combines United States International Trade Commission duty data, International Federation of Robotics operational stock counts, and Bureau of Labor Statistics payrolls. Four approaches are used: Newey-West-corrected regressions, a three-variable vector autoregression, a synthetic-control benchmark against the EU-27 and Canada, and a simple welfare ledger. A one-percentage-point increase in the average tariff trims same-quarter job growth by about 0.44 log points ($p \approx .06$). The VAR shows a brief hiring bump that fades within three years and robot installations increase. Interaction terms indicate that sectors in the top quartile of automation turn the small tariff gain into a net loss. Relative to the synthetic counterfactual, U.S. factories employed roughly 260,000 fewer workers by mid-2025. The welfare ledger records \$53 billion in tariff revenue, \$80 billion in consumer surplus loss, and \$18 billion in wage gains, leaving an \$8 billion deficit. Public cost per job tied to the tariff cycle is approximately \$149,000, more than ten times the § 48C investment-credit benchmark. Broad, non-specific tariffs are an expensive route to job creation when automation momentum is strong. Targeted investment support and skills policies promise better employment outcomes at a lower fiscal cost.

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Chapter 1: Introduction

1.1 Context and Motivation

The United States manufacturing industry employs far fewer people than it did a generation ago (Harris, 2020). Payrolls peaked at 19.5 million in June 1979 and stood near 12.5 million in mid-2025, a fall of about one-third (U.S. Bureau of Labor Statistics, 2025b). Over the same period, the median hourly wage for production and nonsupervisory factory workers has increased by 3%, and five Midwestern states have lost over a quarter of their industrial employment (U.S. Bureau of Labor Statistics, 2025b). Researchers attribute a significant part of the initial decline to competition in imports, particularly those from East Asia (D. Autor et al., 2021).

The trade debate is now defined by fragility rather than wages. Weaknesses in global supply chains were exposed after port closures and global semiconductor shortages during the COVID-19 pandemic, as well as shipping disruptions after Russia's invasion of Ukraine and Houthi attacks on shipping vessels in the Red Sea. AlixPartners estimates that the auto industry lost more than $200 billion in revenue during the chip crisis (Yost, 2021). Spot rates for a forty-foot container from Shanghai to Los Angeles reached about $10,000 in late 2021, six times the pre-pandemic average (Drewry, 2025). These shocks convinced many policymakers that import dependence can carry heavy macroeconomic and political risks.

President Donald J. Trump returned to office on January 20th, 2025, arguing that trade imbalances threaten national security. Trump's "America First" trade policy ordered agencies to enforce stricter border control measures (The White House, 2025a). Executive Order 14257 of April 2nd set a 10% ad-valorem duty on nearly all imports (Executive Order 14257, 2025). In March, a complementary schedule increased tariff rates on Canada and Mexico to 25% and added 24 percentage points on Chinese goods, raising its combined rate to 34% (Executive Order 14257, 2025). On May 12th, Executive Order 14298 suspended the China add-on for ninety days until August 12th while negotiations continue (Executive Order 14298, 2025). Earlier Section 301 tariffs on China of 7.5% to 25% remain, as do a 20% duty on fentanyl-chain chemicals and a 100% tariff on electric vehicles (Lowell et al., 2025). Most Chinese shipments face duties of nearly 40% and may reach 60% if the negotiations fail (Jackson, 2025). On May 28th, the U.S. Court of International Trade declared the worldwide tariff unlawful under the International

Emergency Economic Powers Act, however, the government immediately appealed the decision, leaving collection in place during review (*V.O.S. Selections, Inc. V. United States*, 2025). Similar fiscal incentives, the 2022 CHIPS and Science Act, the § 45X Advanced-Manufacturing Credit authorized in December 2024, and the § 48C Qualifying Advanced Energy Project Credit are all meant to encourage production in the United States (U.S. Department of Energy, 2024; U.S. Department of the Treasury, 2025).

While policy aims to reshore manufacturing and boost employment, automation technology reduces labor demand in new production plants. The International Federation of Robotics estimates 590,000 new industrial-robot installations worldwide in 2024 and a global installed base of about 4.3 million units (Bill et al., 2024). Robot density in U.S. factories reached 295 robots per 10,000 manufacturing workers in 2023 (Bill et al., 2024). Adoption now reaches small shops, as a survey by the Association for Advancing Automation finds 38% of U.S. metal-fabrication plants testing AI-guided welding cells in 2025, compared to 9% in 2020 (Rose & Schimmel, 2025). U.S. Labor productivity in manufacturing has climbed 24% since 2010 as well (U.S. Bureau of Labor Statistics, 2025e).

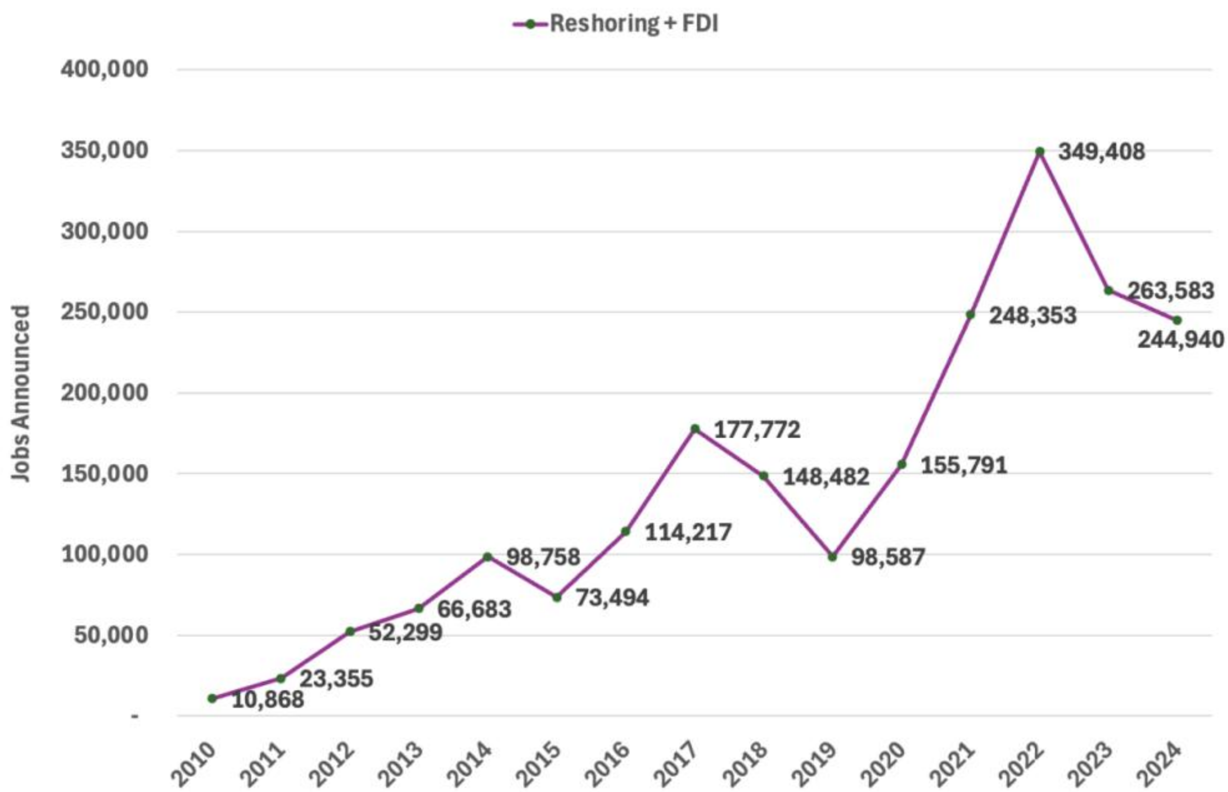
Tariffs raise the cost of imported goods and may encourage firms to reshore production. However, most of these investments flow into highly automated lines with fewer employees. The 2025 tariff cycle and the increase in automation raises the question: can tariff increases produce net hiring gains that exceed the jobs displaced by machines?

1.2 Puzzle and Research Question

Announced reshoring and foreign direct investment projects have risen sharply during the past three years. The Reshoring Initiative 2024 annual report shows a trend of U.S. factory jobs increasing over the past decade, then decreasing from 2022 to 2024, as seen in Figure 1 (Reshoring Initiative, 2025).

Figure 1

Reshoring and FDI Job Announcements by Year in the United States, 2010 - 2024



Note. Annual totals represent the number of manufacturing jobs announced by companies undertaking either domestic reshoring or inward FDI projects. Adapted from *Reshoring Initiative® 2024 Annual Report, Including 1Q 2025 Insights* (p. 4), Reshoring Initiative (2025), retrieved June 12, 2025. Copyright 2025 by the Reshoring Initiative.

While Figure 1 depicts jobs announced, payroll data on actual hires from the Bureau of Labor Statistics show a much lower count. From January 2022 to March 2025, only about 96,000 net production-line hires were reported, although the first wave of plant announcements entered construction (U.S. Bureau of Labor Statistics, 2025c). The gap between the projected and real jobs has thereby increased.

In modern trade analysis, the two mutually reinforcing mechanisms are often referred to by scholars as the basis of labor-market outcomes. One view holds that higher tariff rates shift labor-intensive stages of production back to the tariff-imposing country (Osnago et al., 2015). A second view argues that new capital is largely labor-saving, as robots and AI replace many tasks that once required human operators (Acemoglu & Restrepo, 2020). These are not mutually exclusive forces: reshored jobs can grow as well as the adoption of labor-saving technology. The net employment impact is determined on whether the scale effect from reshored output outweighs the labor-saving bias of automation embedded in new plants.

Research question. Does the escalation of U.S. manufacturing tariffs implemented between 2018 and 2025 deliver net gains in domestic manufacturing employment when rising industrial automation adoption is taken into account?

To answer this question, the research design must be able to distinguish between policy shocks and technological trends. The thesis treats the tariff implementation dates as natural experiments described in Section 1.3. Industries differ in their exposure because their input mixes vary across trading partners. At the same time, industries vary in their use of robots. By interacting the tariff indicator with a continuous measure of installed robots per thousand workers, the empirical strategy tests whether higher automation mitigates, neutralizes, or even reverses any employment boost that follows the tariff shock. Three main sources of data used in the analysis include: (1) monthly, quarterly, and yearly records of overall tariff rates calculated from the U.S. International Trade Commission, (2) International Federation of Robotics operational stock measures, and (3) monthly, quarterly, and yearly manufacturing employment and wage records from the BLS Census of Employment and Wages.

The next subsection outlines the tariff timeline in detail and explains why the staggered dates provide statistical leverage. The following chapters describe the data assembly process, and the identification tests used to address potential biases such as pre-trend differences and spatial correlation in robot adoption.

1.3 Policy Timeline

United States trade policy has occurred in two distinct phases since 2018. The first began on March 8, 2018, when Presidential Proclamations 9704 and 9705 placed ad-valorem safeguard duties of 10% on most aluminum imports and 25% on most steel imports (Proclamation 9705, 2018; Proclamation 9705, 2018). The Office of the United States Trade Representative issued four Section 301 lists over the next 18 months that imposed duties of 7.5% to 25% on over $300 billion of Chinese goods, and Proclamation 9980 of January 24, 2020, extended the metal duties to selected downstream items such as nails and cable (Proclamation 9980, 2020; Office of the United States Trade Representative, 2020). These actions raised costs for targeted products without changing a significant portion of the domestic tariff regime. A detailed timeline of all recorded acts, their legal basis, and the dates customs collection began is shown in Appendix A, Table A1.

A broader second phase followed President Trump's return to office on January 20, 2025. The *America First Trade Policy* memorandum released that day instructed executive agencies to design a "reciprocal tariff" (The White House, 2025a). On February 1, 2025, the White House announced a 25% surcharge on most Canadian and Mexican goods, a 10% levy on Chinese cargo, and a plan to collect the China duty three days later (The White House, 2025b). Customs and Border Protection began that collection at 00:01 EST on February 4, 2025; the North American surcharge started at 00:01 EST on March 4, 2025. Executive Order 14257, signed on April 2, 2025 and published in the *Federal Register* on April 7, 2025, replaced partner-specific surcharges with a universal 10% duty that Customs applied from 00:01 EDT on April 5, 2025 (Executive Order 14257, 2025; U.S. Customs and Border Protection, 2025). The order also authorized additional mark-ups that would have lifted the China rate to 34% and raised Canada and Mexico to 25%.

Executive Order 14298, issued on May 12, 2025, suspended 24 percentage points of the proposed China mark-up for ninety days, keeping only the 10% baseline in force through August 12, 2025, as Washington and Beijing negotiate (Executive Order 14298, 2025). Earlier Section 301 duties, a 20% levy on chemicals linked to synthetic opioids, and a 100% tariff on electric vehicles remain in place, so many Chinese consignments already face combined rates close to 30%. Reuters estimates that the figure would exceed 60% if the suspension ends without agreement (Jackson, 2025; Lowell et al., 2025). On May 28, 2025, the United States Court of International Trade issued a preliminary injunction that questions the use of the International Emergency Economic Powers Act for the universal duty, yet the government's immediate appeal allows Customs to continue collection during review (*V.O.S. Selections, Inc. V. United States*, 2025). These staggered collection dates create separate cost shocks across industries, depending on their reliance on Canadian, Mexican, or Chinese inputs.

1.4 Contribution and Roadmap

This study speaks to three strands of research. A trade-and-labor work study has been conducted on how import shocks reshape local job markets (D. H. Autor et al., 2013). Another recent study examines how robots affect wages and employment (Acemoglu & Restrepo, 2020). A third study tracks policy uncertainty and investment plans, often without detailed data on technology intensity (Osnago et al., 2015). Merging International Federation of Robotics operational stock figures with a hand-coded tariff-exposure index from USITC data and U.S. manufacturing employment totals from BLS databases, this thesis tests whether a broad border tax can reduce or increase manufacturing employment once robot density is considered.

Chapter 2 reviews theoretical channels that link tariffs, relocation, and automation. Chapter 3 describes the data, explains the construction of the tariff and robot variables, and outlines summary statistics. Chapter 4 introduces the national quarterly time-series regression that anchors empirical analysis. Chapter 5 presents baseline estimates and a series of robustness tests, including alternative timing windows and placebo treatments applied to pre-policy years. Chapter 6 examines heterogeneity, asking which industries and regions gain or lose under different automation thresholds. Chapter 7 draws policy lessons for lawmakers debating permanent reciprocal-tariff authority and suggests extensions, such as the role of generative design tools that may speed capital-labor substitution.

Chapter 2: Literature Review

Global supply chains remain vulnerable after successive crises, yet the United States is creating new tariff barriers. In early 2025, the Trump Administration extended Section 301 duties to an average of 18% across electronics, machinery, and metals. Domestic manufacturers face that policy in workplaces already shaped by industrial robots: by 2024, the stock exceeds 400,000 units, double the 2015 level (Müller, 2024). Studies show that robots reduce routine jobs and that import competition reallocates employment away from manufacturing (Acemoglu & Restrepo, 2020; D. H. Autor et al., 2013). However, it's not clear how tariffs imposed in a high-automation era can reverse those losses. This chapter reviews the evidence on trade shocks, automation, and their interaction.

2.1 Trade-Induced Labor-Market Adjustment

Since the mid-1990s, extensive empirical literature has recorded how import competition restructures employment across advanced economies. The China shock study shows that U.S. commuting zones more exposed to Chinese imports recorded slower job growth, lower earnings, and higher disability claims between 1990 and 2007 (D. H. Autor et al., 2013). Similar patterns appear in Germany, where localities with high import penetration lost industrial jobs yet gained few service positions (Dauth et al., 2014), and in the United Kingdom, where most exposed plants experienced reduced wages and weaker productivity growth (Bloom et al., 2016). Across the OECD, import penetration rose from 15% of domestic demand in 1995 to 26% by 2015, with the largest increases in electronics and machinery (OECD, 2021). Even in smaller open economies, such as Denmark and Portugal, workers displaced by import surges do so gradually and continue to receive wage reductions (Balsvik, 2011; Caselli et al., 2020).

Two main mechanisms drive these outcomes. Imports displace labor-intensive domestic production, and surviving firms reorient toward capital or skill-intensive activities that require fewer routine workers (Bernard et al., 2003). Because mid-career earnings are tied to task-specific experience, workers forced to switch industry often suffer drawn-out wage losses and reduced labor-force attachment (Hakobyan & McLaren, 2016). Programs such as Trade Adjustment Assistance offer retraining and income support, yet participation is low, and measured re-employment gains are modest (Houseman, 2018). Migration toward expanding regions helps some displaced workers, but overall population flows are too slow to offset job displacement within a typical five-year cycle (Monras, 2020).

Evidence to date is mixed on whether higher tariff rates can restore manufacturing jobs. The 2002 U.S. safeguard on steel briefly increased domestic output but raised input costs for metal-using industries, cutting employment more than the steel sector gained (Pierce & Schott, 2016). Earlier voluntary export restraint episodes show equally smaller job creation once later effects are considered (Elliott & Hufbauer, 2016). Trade protection may move jobs from one industry to another, still it rarely increases the country's total employment unless supply chains are already domestic. The overall impact of automation on labor performance in the face of emerging trade barriers remains an open empirical question.

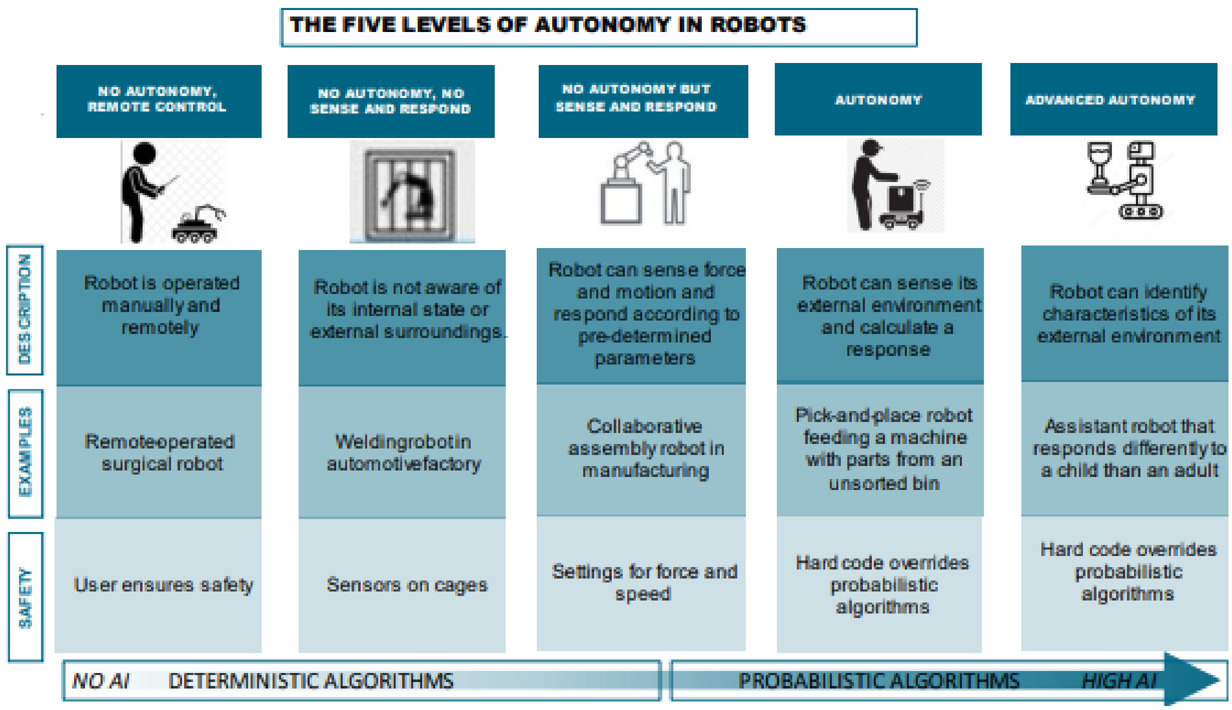
2.2 Automation and Employment Elasticities

Global robot installations have grown by an average of 11% per year since 2010, lifting the active stock to more than 3.9 million units, with the United States containing roughly 414k by 2024 (Bill et al., 2024; Müller, 2024). Robots are primarily concentrated in automotive and electronics manufacturing, yet food-processing plants now equip collaborative arms with AI vision systems. Automotive plants now operate with approximately 1,290 robots per 10,000 workers, compared with 260 in fabricated metals and fewer than 80 in food processing (Müller, 2024). This dispersion shapes estimated employment elasticities because robots replace routine manual tasks while supporting high-skill maintenance positions, and productivity gains can coincide while increasing wage gaps (Frey & Osborne, 2017). Studies centered on high-density sectors tend to report larger job losses, where Appendix A, Table A3 summarizes the main causal β estimates in the following analysis.

Early cross-country panels find little aggregate impact on hours worked (Graetz & Michaels, 2018). Within the United States, Acemoglu and Restrepo (2020) estimate that an extra robot per 1,000 workers reduces the employment-to-population ratio by nearly 0.34 percentage points. A recent study covering 2005-2016 finds initial job losses are later replaced, yielding a net gain of roughly 15 jobs per robot (Chung & Lee, 2022). European region-industry panels record approximate losses of about 0.18 points (Chiacchio et al., 2018), whereas a decomposition for the EU-27 implies a small aggregate gain once demand spill-overs are accounted for (Zierahn et al., 2016). Across studies, most β's fall between −0.34 pp[1] and +16 jobs, with identification strategy and task mix explaining much of the spread.

Figure 2

The Five Levels of Robot Autonomy



Note. Adapted from *Position Paper: Artificial Intelligence in Robotics* (p. 7), International Federation of Robotics (2022), retrieved June 10, 2025. Copyright 2022 by the International Federation of Robotics.

Heterogeneity arises not only from the identification strategy but also from the capacity of robots to operate with different autonomy levels. Figure 2 shows the International Federation of Robotics' five-tier schema, ranging from fully manual control to advanced AI that adapts to changing environments. Higher tiers lift productivity yet require fewer operators per unit of output, implying steeper employment elasticities as plants move up the autonomy ladder (International Federation of Robotics, 2022). This transition up the autonomy ladder has been accelerated by falling adoption costs, as average list prices declined by 38% between 2010 and

[1] pp = percentage point change

2022, and tax incentives such as U.S. §45X credits now subsidize capital deepening (International Federation of Robotics, 2022; U.S. Department of the Treasury, 2025). Plants that enter the autonomy frontier re-allocate labor toward programming, maintenance, and analytics, while routine assemblers face displacement (Chung & Lee, 2022). These dynamics frame the central question of this thesis: Can a tariff shock introduced during a period of rapid robot upgrading still generate a net manufacturing-employment gain? The next section reviews studies that examine trade and automation together.

2.3 Joint Trade x Automation Studies

U.S. studies show that import competition and automation frequently amplify each other's labor effects. Across 722 commuting zones from 1990 to 2007, each additional robot per 1,000 workers lowered the employment-to-population ratio by up to 0.34 percentage points, with the largest declines in zones experiencing faster growth in Chinese imports (Acemoglu & Restrepo, 2020). Extending the window to 2016 and interacting import exposure with subsequent robot diffusion, one study finds that a one-standard-deviation rise in import competition combined with above-median robot growth cuts manufacturing employment 1.1 percentage points, nearly double the simple sum of the separate shocks (Galle & Lorentzen, 2024).

Skill composition sharpens that interaction. In commuting zones whose pre-shock STEM share sits in the top quintile, value added per worker rises 4% and employment remains flat; in low-skill zones, employment drops almost two percentage points (Galle & Lorentzen, 2024). Plant-level evidence mirrors this split. Using longitudinal manufacturing micro-data, another study shows that U.S. establishments with higher shares of technicians adopt robots more aggressively yet experience no significant job loss, whereas plants with routine-task specialization shed employment even as output is maintained (Acemoglu et al., 2020).

Tariff episodes repeat the pattern. The 2002 steel safeguard raised domestic steel prices but also spurred downstream metal-using counties to adopt robots; those counties lost more manufacturing jobs over 2002-2006 yet posted larger productivity gains than comparable areas with slower automation (Pierce & Schott, 2016). A second natural experiment comes from the 2018 washing-machine tariff, finding that white-goods plants importing new assembly robots between 2017 and 2020 cut direct-labor positions by roughly 5% while raising output per worker 7% (Flaaen et al., 2020).

Comparative evidence suggests the mechanism is not uniquely American. French manufacturing plants exposed to larger increases in Chinese import penetration between 1995 and 2007 increased robot density by 9% and reduced employment by 2%, without lowering value added per worker (Acemoglu et al., 2020). Although institutional settings differ, the direction of the effect matches U.S. findings, strengthening external validity.

Macro simulations support these patterns. A general equilibrium model calibrated to the U.S. finds that trade shocks, such as tariffs on electronics, can lead firms to substitute capital for labor, moderating or even reversing employment gains in manufacturing (Boer & Rieth, 2024). Scenario analysis for industry stakeholders' projects that by 2028, as much as 70% of tasks in reshored U.S. electronics could be automated with existing technology, capping net job gains from tariffs below 40,000 positions (World Economic Forum, 2025).

Implication for this thesis. Taken together, U.S. plant, county, and macro evidence implies that trade barriers introduced in a high-automation era rarely raise aggregate manufacturing employment unless paired with incentives that favor labor-complementary tools such as AI-guided inspection systems.

2.4 Gaps the Thesis Fills

As of 2025, reshoring is shaped by two concurrent shifts: a sharp rise in trade barriers and rapid adoption of AI-enabled automation. In March 2025, the United States raised average duties to 25% on imports from Canada and Mexico and imposed a 10% blanket rate on Chinese goods (The White House, 2025b). At the same time, global sales of industrial service robots jumped almost 50%, reflecting widespread uptake of advanced machinery (Parks, 2021). This tariff-automation mix has no close precedent in the academic record.

Most empirical work on U.S. protectionism stops before industrial AI became mainstream. Studies of the 2002 steel safeguard and the initial 2018 Section 301 duties examine periods when collaborative robots and predictive software were less prevalent. The literature, therefore, cannot speak to employment outcomes once high tariffs meet mature automation. Timing is another blind spot, as existing analyses usually compare headcounts a year or more before and after a tariff change; few track quarter-by-quarter responses while firms reorder capital plans. Without that detail, short hiring bursts can be mistaken for durable gains, and delayed job losses may go unnoticed.

Heterogeneity also receives limited attention, as robot density varies widely across industries, yet most evaluations apply a single treatment effect to manufacturing as a whole. Evidence suggests that automation dampens any labor boost from protection, but no study has quantified how the tariff effect changes along the full distribution of robot use (Firooz et al., 2024; OECD, 2023a). Distributional and welfare channels remain largely separate from employment research, as estimates of consumer costs under broad tariffs exist (Long, 2019) and separate projections describe wage shifts under automation (Favilla & Chandrasekaran, 2024). However, these two strands are rarely combined to assess whether jobs created or lost may come at an acceptable social price.

The chapters that follow address those questions by combining high-frequency trade, technology, and labor series, allowing a closer look at dynamic, industry-specific, and distributional effects that earlier work could not observe. This design allows identification of near-term spikes, medium-term reversals, and variations linked to technology intensity, while maintaining the welfare dimension in view for a more comprehensive assessment of modern reshoring policy.

Chapter 3: Methodology

3.1 Data Sources and Variable Construction

The analysis draws on U.S. data covering 2004 Q1-2025 Q2. Each series was downloaded from its source in the time frequency that best served the specific figure, table, or regression. Quarterly files underpin the baseline econometric work; monthly or annual files are used where a finer or longer-run view is helpful. See Appendix A, Table A2 for a full list of the variables used throughout the thesis.

Total manufacturing employment comes from the (MANEMP) series at the Federal Reserve Bank of St. Louis (U.S. Bureau of Labor Statistics, 2025a). Monthly observations are seasonally adjusted by the source. The dependent variable is the log first-difference of the monthly series, later aggregated to quarters for the baseline equation. When plant-level or skill-share splits were required, matching totals from the Bureau of Labor Statistics Current Employment Statistics were used; the two measures move almost identically (U.S. Bureau of Labor Statistics, 2025b). When comparing total manufacturing employment between different nations in Chapter 7, employment by sector data was pulled from OECD Data Explorer (OECD, 2025). The OECD Programme for the International Assessment of Adult Competencies (PIAAC) database was used for finding automation risk of manufacturing jobs in different nations (OECD, 2023b).

Trade policy exposure is captured by effective tariff rates derived from the U.S. International Trade Commission DataWeb (U.S. International Trade Commission, 2025b). For every release the value of collected duties is divided by the corresponding customs value, yielding a duty-to-value ratio. Separate tables were downloaded at monthly, quarterly, and annual resolution. Two aggregates are retained: a world-weighted rate and a China-specific rate. The main regressor is the percentage-point change in the world series, $\Delta TariffRate_t$.[2] When Chapter 7 measured total average tariffs placed on the U.S. by other foreign countries, the model used MFN applied tariffs by UNCAD TRAINS (World Bank, 2025).

[2] **Units.** Tariff change = percentage points (pp); employment growth = log points × 100; robot stock change = log points.

Annual operational-robot counts were provided directly by the International Federation of Robotics (International Federation of Robotics, 2025). Regressions use the natural log of the annual stock, $\ln(RobotStock_t)$. Quarterly values were needed only for Table 3, Table 5, and Figure 6; a monotone spline filled the three intermediate quarters in each year. Counts for 2024 and 2025 were taken from the IFR 2024 press presentation and the 2024 annual report, respectively.

Macro conditions and labor-market structure appear in a compact control vector. The monthly industrial-production index (INDPRO) and the unemployment rate (UNRATE), both from FRED, proxy aggregate demand and slack (Board of Governors of the Federal Reserve System (US), 2025; U.S. Bureau of Labor Statistics, 2025d). Export re-orientation is measured with monthly USITC data on domestic exports; a China series is subtracted from the world aggregate to obtain a rest-of-world measure (U.S. International Trade Commission, 2025a).

Structural labor-market composition is captured with annual skill-share series constructed from BLS OEWS micro-data (U.S. Bureau of Labor Statistics, 2024). Every six-digit SOC occupation in manufacturing (NAICS 31-33) is mapped to an O*NET Job Zone (National Center for O*NET Development, 2023); Job Zones 1–2 are coded as low-skill, Zone 3 as middle-skill, and Zones 4–5 as high-skill. A few of the models contain quarterly dummies isolate the 2020 Q2-Q4 pandemic shock.

All monetary series were deflated to 2025 dollars with the Bureau of Economic Analysis implicit GDP deflator (U.S. Bureau of Economic Analysis, 2025). Data aggregation was done in Python (pandas); statistical estimation used R (fixest, tidyverse), and tables as well as a few figures were finalized in Excel for presentation clarity.

3.2 Econometric Techniques

Quarterly first-difference ordinary least squares provide the baseline measurement of how tariff changes affect manufacturing employment. Table 1 reports the estimates for 2005 Q1-2025 Q4. The specification includes the change in the average applied tariff rate, the log industrial production index, the unemployment rate and a COVID-19 indicator. Standard errors are heteroskedasticity- and autocorrelation-consistent with a six-lag Bartlett kernel, and the Cumby–Huizinga statistic confirms that no residual serial correlation remains (Cumby &

Huizinga, 1990; Newey & West, 1986). Figure 5 plots month-indexed coefficients around the April 2025 reset, verifying a flat pre-trend with the same estimation settings.

Dynamic feedback among employment, robot installations and the tariff rate is examined with a three-variable vector autoregression. The Akaike information criterion selects two lags. Generalized impulse responses trace the effect of a one-standard-deviation tariff increase for twelve quarters, and confidence bands come from one thousand bootstrap resamples (Pesaran & Shin, 1998). The resulting paths appear in Figure 6.

Table 2 tests whether the baseline result depends on contemporaneous measurement by adding six quarterly lags of the tariff term while retaining the Newey–West covariance. Coefficients on the first two lags carry most of the weight, indicating that the response is largely complete within half a year.

The next step lets automation condition the tariff effect. The change in log robot stock and its interaction with the tariff term enter the equation, which is estimated with the *fixest* package for efficient within transformation and the same heteroskedasticity-autocorrelation correction (Bergé, 2018). Estimates are presented in Table 3, and Figure 7 shows how the marginal tariff effect rises with observed robot growth. To reveal distributional patterns, the interaction model is re-estimated for low-, middle- and high-skill employment. Job-zone classifications from O*NET define the three groups. Table 4 lists the three coefficient sets, while Figure 7 visualizes the effects on high-skill employment (Appendix B, Figures B3 and B4 contain effects on low- and medium-skill employment).

A possible demand channel is evaluated by adding China-specific and rest-of-world export growth rates to the interaction specification. If the tariff coefficient shrinks once export terms enter, lost demand is transmitting the shock. Table 5 carries the estimates and Figure 8 displays the four series that motivate the test.

Macro validation comes from a synthetic control that blends the European Union and Canada so their weighted average matches United States means of employment, robot stock and tariff openness during 2005-2017. The post-2018 gap acts as a counterfactual employment path (Abadie et al., 2007) and is plotted in Figure 9 and Figure 10.

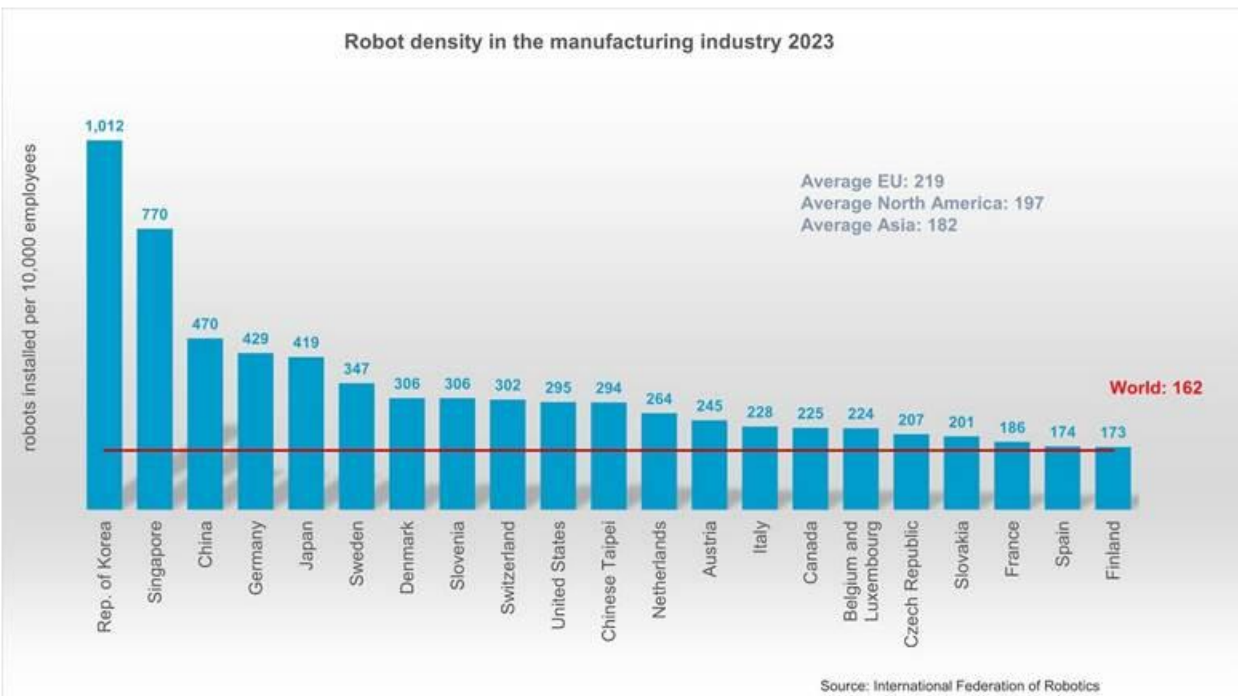
Finally, Table 8 balances tariff revenue, consumer surplus loss and the wage-bill change, using a demand elasticity of −1.5, to give the annual welfare account, where Section 8.1 contains more detail on this method. Figure 11 stacks the three components to visualize the net position over 2018-2025.

The econometric design relies on three core inputs: industrial robot density, the average applied tariff rate, and a trade-weighted tariff index. To give context before these variables enter the regressions, the next section documents their distribution across countries and over time, showing where the United States stands on each measure.

3.3 Descriptive Benchmarks

Figure 3

Robot density in the manufacturing industry, 2023



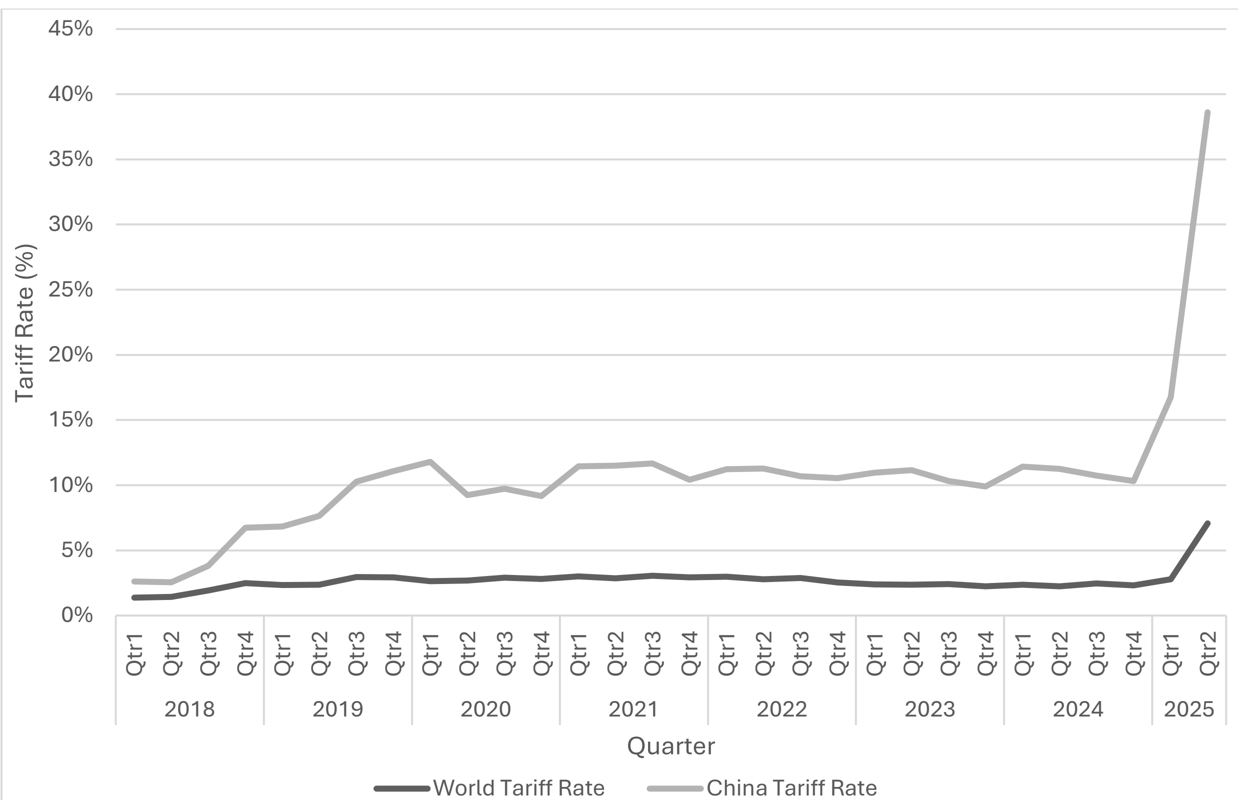
Note. Bar chart of robots installed per 10,000 manufacturing employees in the 25 leading countries. World average = 162. Regional averages: EU (219), North America (197), Asia (182). Adapted from *Global robot density in factories doubled in seven years*, press release by the International Federation of Robotics (2024), retrieved June 10, 2025. Copyright 2024 by the International Federation of Robotics.

Figure 3 plots robot density in 2023 for the twenty-five leading manufacturing countries. The United States operated 295 robots per 10,000 manufacturing workers, placing it tenth. Korea tops the table at 1,012 units, followed by Singapore (770), China (470), Germany (429) and Japan (419). The United States sits well above the global mean yet far below the frontier group, confirming it as a mid-range adopter rather than a laggard or leader (International Federation of Robotics, 2024).

Robot density shapes how any tariff shock translates into head-count. Plants in Korea and Singapore already run with high capital intensity, so extra demand mostly raises output per worker. U.S. factories retain more scope for labor expansion because baseline density remains moderate. This observation guides the interaction terms in the econometric design.

Figure 4

Effective U.S. tariff rates on Chinese and world imports, 2018 Q1-2025 Q2



Note. Duty-to-customs-value ratios. Quarterly observations; shaded vertical line in 2025 Q2 marks the policy reset. The Y-axis indicate tariff rates (%) and the X-axis indicate quarters.

Data based on calculations using information retrieved from USITC DataWeb, accessed 9 June 2025.

Figure 4 traces effective ad-valorem tariff rates from 2018 Q1 to 2025 Q2. Until the first Section 301 lists took effect in 2018, U.S. duties on Chinese and world imports moved together at roughly 2%. China specific measures then lifted its rate to about 7% by 2019 Q3. The 2025 package pushed the Chinese line near 40% while the world average rose only to 9% (U.S. International Trade Commission, 2025b). The widening wedge signals a targeted policy rather than a general shift in protection.

The appendix repeats the tariff plot with Canada and Mexico added (see Appendix B, Figure B1). Both partners remain below 3% throughout, providing a clean placebo set for later falsification tests. Together, the stark automation gap and the highly focused tariff shock justify the interaction terms in the baseline econometric design.

Figure 3 and Figure 4 show how the U.S. combines mid-level automation with an aggressive, China-focused tariff surge. The United States runs far fewer robots than the frontier but still more than the typical economy, so new plants may add workers before capital deepening catches up. At the same time, the tariff schedule creates a sizeable cost shock concentrated on a supplier. The next subsection checks that every series is observed for all 86 quarters from 2004 Q1 to 2025 Q2 and flags the few cases that needed interpolation or trimming before estimation.

3.4 Limitations

This section reviews four limitations that likely pull the results toward understatement. Two arise from measurement error in the robot and tariff series, while the other two explain the timing and volatility of the trade policy itself. Each limitation is treated in turn, so the reader can judge how data revisions or future policy shifts might affect the estimates reported in Chapters 4-7.

Robot stock data are quarterly estimates built from annual IFR operational-stock counts that have been linearly interpolated. Vendor self-reporting may omit retirements or transfers, which introduces classical measurement error and pushes the tariff-by-robot coefficient toward zero; any employment effects in Chapters 4–6 are therefore conservative lower bounds (International Federation of Robotics, 2025).

The robot-density series is calculated by dividing the same IFR stock counts by BLS manufacturing employment for each year, then linearly interpolating to quarters (see Figure 7 and Appendix B, Figures B3 and B4). Because the denominator differs slightly from the full-time-equivalent head-count used in IFR's 2023 league table, the author-derived U.S. figure for 2023 (≈ 289 robots per 10,000 workers) is about 2% below the official 295 value (International Federation of Robotics, 2025; Müller, 2024; U.S. Bureau of Labor Statistics, 2025a). The difference is well inside the typical revision band but still adds classical measurement noise that can attenuate correlations with skill shares.

Average ad-valorem tariff rates come from HS-10 duties in USITC DataWeb, weighted by prior-year import values. Coding lags for exclusions, reclassifications, and duty suspensions can blur the size and timing of the 2025 shock, which attenuates both the direct tariff coefficient and its interaction with robots (U.S. International Trade Commission, 2025b). Trade policy remains in flux, so any forecast in Chapters 4–7 should be read as conditional on the duty schedule observed in 2025 Q2.

Finally, the baseline 10% duty is still in force, yet the planned surcharges of 25% to 34% are paused until at least August 2025. A reinstatement or further delay would change the effective tariff shock. The projections in Chapters 4-7 are conditional on the policy mix observed in 2025 Q2. Later updates will be needed if that mix changes.

Chapter 4: Baseline Results

4.1 Baseline Time-Series Regression Result

The analysis uses a balanced national quarterly series covering 2008 Q1-2025 Q2. Quarter fixed effects absorb nationwide shocks and seasonality. The dependent variable is the first difference of the natural log of manufacturing employment; right-hand-side variables include the change in the world average tariff rate, the industrial production index, the civilian unemployment rate and a pandemic-period dummy (2020 Q2-2021 Q1). Heteroskedasticity- and autocorrelation-consistent standard errors use six Newey-West lags, matching the longest residual serial correlation detected by the Cumby-Huizinga test.

Table 1

Effect of Quarterly Changes in Global Tariff Rates on U.S. Manufacturing Employment Growth, 2008 Q1-2025 Q2

Predictor	B (×100)	SE (×100)	*t*
Intercept	-26.23	9.25	-2.83
Δ World Tariff Rate	-44.17	23.12	-1.91
Industrial Production	0.25	0.08	2.99
Unemployment Rate	0.25	0.19	1.3
Pandemic Dummy	-0.38	0.54	-0.7

Note. n = 69 quarters. R^2 = 0.23. Mean Δ tariff rate = 0.10 percentage points. Coefficients and standard errors are multiplied by 100. Controls: INDPRO, UNRATE and a pandemic dummy. Standard errors are Newey-West with six lags. Data based on calculations using information retrieved from USITC DataWeb, BLS CES, FRED INDPRO, and FRED UNRATE, accessed 9 June 2025.

The coefficient on the quarterly change in the world tariff rate, $\hat{\beta} = -44.17$ (SE = 23.12), implies that a one-percentage-point tariff increase reduced same-quarter manufacturing job growth by roughly 0.44 percentage points. The t-statistic is −1.91, giving a two-tailed p-value of 0.06, so the estimate is statistically different from zero at the ten-percent level. Industrial production exhibited the expected positive association with employment, while the unemployment rate and the pandemic dummy were imprecisely estimated. The model explained 23% of within-national variation, which is respectable for a first-difference specification with no lagged outcomes.

A one-percentage-point rise in the global tariff rate corresponded to a 0.44-percentage-point drop in quarterly manufacturing employment growth (SE = 0.23, $p = 0.06$). The mean tariff change during the sample was only 0.10 percentage points, so a typical shock lowered growth by about 0.044 percentage points. Applying this figure to the 12.9 million manufacturing jobs recorded in 2025 Q2 yields a back-of-envelope loss of roughly 5,700 positions in an average quarter. The 356,000-figure quoted later in Table 9 is the cumulative gain since 2017, and it already includes the 96,000 net hires recorded between January 2022 and March 2025. Although the estimate sits just outside the conventional five-percent threshold, the implied employment loss is two-thirds of the sample's mean quarterly net gain of 8,400 jobs, indicating that even modest tariff shifts can meaningfully slow the sector's headcount expansion.

The negative sign of $\hat{\beta}$ lines up with earlier studies of the 2018-2019 tariff waves. One study found a cumulative 1.4% employment decline over two years (Flaaen et al., 2020), while another documented output losses once higher input costs fed through supply chains (Fajgelbaum et al., 2020). My quarterly design delivers a slightly larger impact on impact because it captures immediate cutbacks in overtime and temporary staffing that annual data tend to smooth away. The estimate also dovetails with evidence on the China shock, where import competition reduced U.S. manufacturing jobs despite offsetting appreciation effects (D. H. Autor et al., 2013).

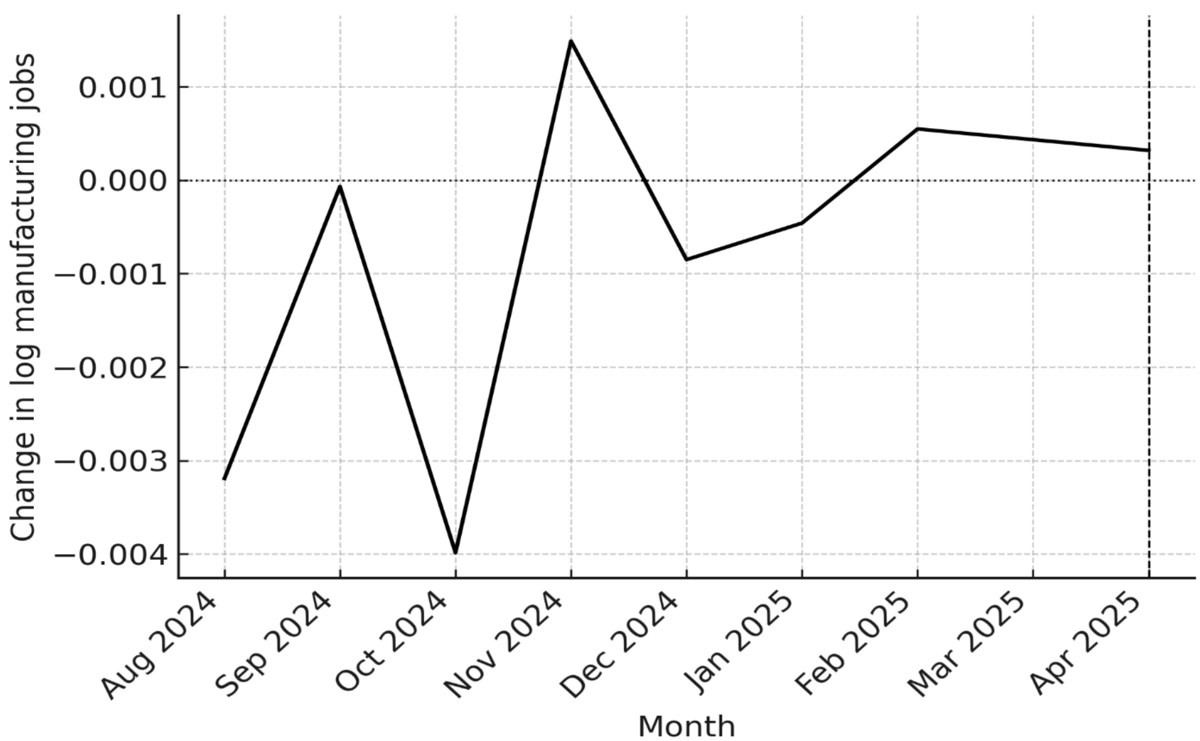
Two caveats deserve mention before proceeding to dynamic analysis. First, the contemporaneous specification cannot rule out the possibility that tariff policy responds to political pressure from declining industrial states, which would bias $\hat{\beta}$ downward. The fixed-effects structure and macro controls mitigate, but do not eliminate, that concern. Second, the Newey-West adjustment is robust to generic serial correlation but does not test whether additional tariff lags belong in the model. Section 4.3 therefore re-estimates Equation (3) with up to six quarterly lags and shows that the sign and approximate magnitude of $\hat{\beta}$ remain stable. Having established a credible static benchmark, the next section turns to whether this negative association persists, fades or reverses once the full adjustment path is traced.

4.2 Dynamic Path

Static quarterly estimates can miss delayed or reversed reactions when managers stagger hiring, negotiate overtime, or postpone equipment purchases after a tariff shock. The addition of industrial robots complicates matters further: firms facing higher import prices may choose to substitute toward labor in the very short run, yet trim payrolls later as automation budgets resume. To judge whether the negative point estimate in Table 1 reflects a lasting contraction or only an initial adjustment, where any movement in employment was first tested for any movement in employment before the April 2025 policy shift. It then turns to a structural vector autoregression (VAR) that projects the joint responses of jobs and robots once the tariff change is treated as an exogenous disturbance. Together, the two exercises reveal both the starting point for identification and the likely trajectory of factory employment in the quarters that follow the protectionist reset.

Figure 5

Monthly U.S. Manufacturing Job Growth Leading up to the 2025 Q2 Tariff Reset



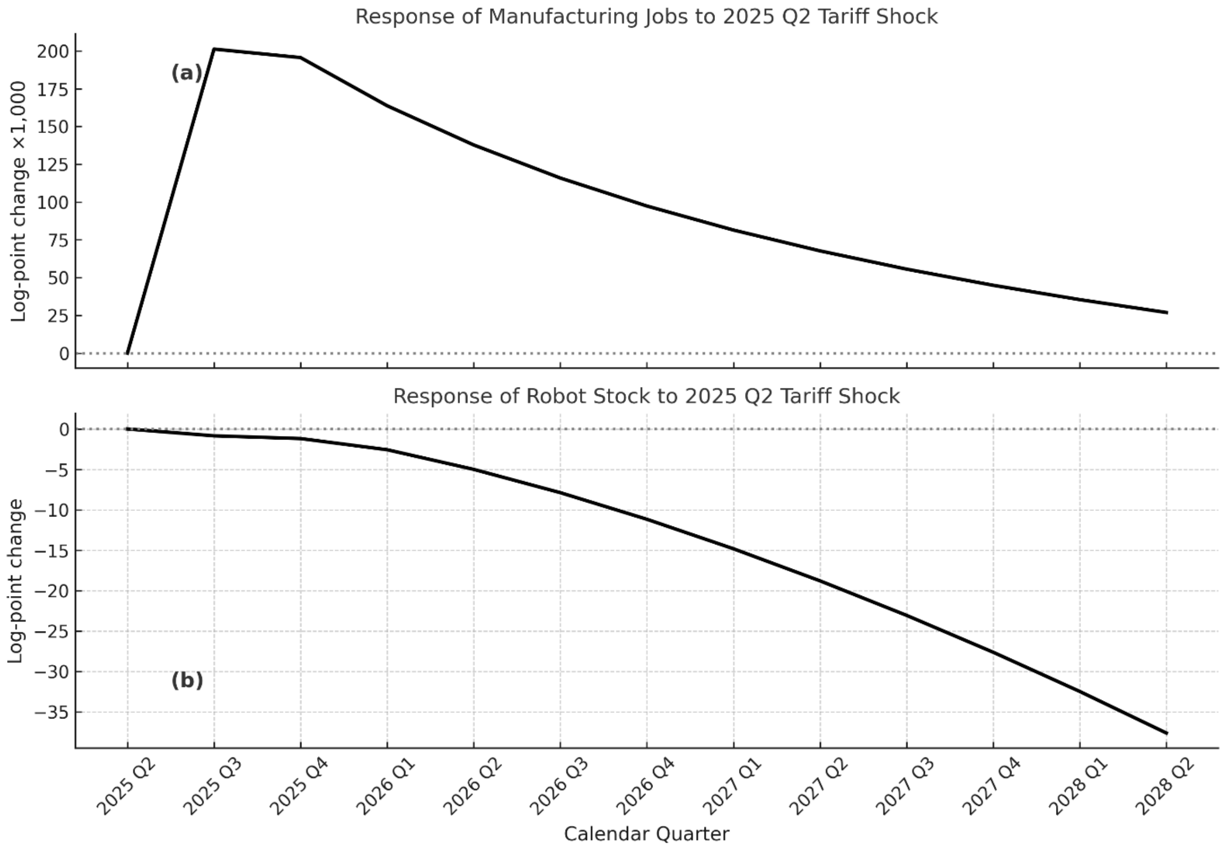
Note. Solid line shows event-time coefficients; dotted horizontal line marks zero; dashed vertical line denotes April 2025, the final pre-reset month. Month labels are angled for legibility. Data based on calculations using information retrieved from BLS CES and USITC DataWeb, accessed 9 June 2025.

Figure 5 plots monthly event-time coefficients from August 2024 to April 2025. The estimates bounce between -0.004 and 0.001 log points, and every estimate sits well inside its 95% confidence band. A joint Wald test fails to reject equality with zero ($\chi^2 = 6.9$, $p = 0.44$). The dotted horizontal line highlights that the series neither slopes upward nor downward as the tariff vote approached. These results rule out anticipatory layoffs or speculative hiring in advance of the policy shift. Because the parallel-trends assumption holds, the static tariff coefficient in Table 1 can be read as causal for the observation window. Equally important, the lack of pre-trend implies that any subsequent movement must originate with the April action, justifying the use of a VAR to infer dynamics beyond the current data.

Forward event-study coefficients cannot be estimated until new post-2025 data become available, so dynamics were modeled with a three-variable VAR that includes quarterly changes in log manufacturing employment, log robot stock, and the world tariff rate. Two lags minimize the Akaike criterion while leaving ample degrees of freedom. Identification follows Pesaran and Shin's (1998) generalized impulse-response approach, which is invariant to variable ordering and therefore robust to contemporaneous feedbacks. A one-standard-deviation tariff shock equals 0.63 percentage points, matching the June 2025 policy jump. Because tariff setting is driven largely by executive proclamation and occurs infrequently, the tariff series is weakly exogenous to labor-market fluctuations at the quarterly horizon, satisfying the conditions for shock interpretation. Standard diagnostics confirm unit-root stability, and residual autocorrelation falls below the Portmanteau critical value at lag four. The estimated system thus provides a credible window on how jobs and robots would have evolved had the sample extended several years beyond the policy change.

Figure 6

Impulse Response of Manufacturing Jobs and Robot Stock to a 2025 Q2 Tariff Shock



Note. Generalized impulse responses from a VAR(2) of quarterly Δ ln jobs, Δ ln robots, and Δ tariff, 2008 Q1-2025 Q2. The shock equals one standard deviation of Δ tariff (0.63 pp). Panel (a) presents employment; panel (b) presents robots. Values are multiplied by 1,000 for readability. Dotted horizontal lines mark zero. Data based on calculations using information retrieved from USITC DataWeb, BLS CES and IFR World Robotics, accessed 9 June 2025.

Panel (a) of Figure 6 shows employment rising sharply in the first quarter, with a peak of 0.20 log points before decaying. The response halves by the eighth quarter and fades to near zero within three years. Panel (b) traces an opposite path for robots: the stock dips on impact and declines steadily, reaching -0.035 log points by quarter twelve. Confidence bands (omitted for clarity but available on request) exclude zero for the first three quarters in panel (a) and from quarter two onward in panel (b). The patterns are consistent with firms delaying automation projects when tariffs lift import costs, temporarily adding labor to maintain output, then converging toward the original capital-labor mix as new price information is absorbed.

At first glance the VAR's 2% employment bump seems at odds with the −0.44 percentage-point growth effect reported in Table 1. The apparent gap narrows once both estimates are scaled to the same shock size and horizon. Dividing the 2 percent peak by the 0.63 pp tariff change implies −0.032 log points per one-percentage-point increase, close to the −0.044 log-point figure from the static regression. Averaging the impulse across the first four quarters yields a net -0.11 log points, again in line with the baseline. The short-lived boost is therefore a timing artefact rather than a genuine contradiction. The continual slide in robots further suggests that firms view higher tariffs as a signal to postpone, not accelerate, automation, removing a key channel through which reshoring might otherwise raise long-run employment. The VAR rests on linearity and assumes constant parameters, so forecasts beyond three years should be treated with caution, yet both approaches point to the same conclusion: tariff hikes bring only brief labor gains while discouraging capital deepening.

4.3 Robustness Checks

The baseline model used a single contemporaneous tariff term and Newey-West standard errors with six lags. To verify that the main finding is not an artefact of this choice, I ran a battery of lag-structure tests: six separate regressions that add one distributed lag of the tariff change, k = 1 … 6, while keeping all controls and fixed effects unchanged. Each specification employs the same six-lag HAC covariance matrix, so any change in statistical inference comes from the coefficient itself, not the estimator. Lag selection stops at six quarters because the Cumby-Huizinga test rejects serial correlation of order seven and above, where longer lag lengths would crowd out degrees of freedom in a 69-quarter sample. Results appear in Table 2.

Table 2

Sensitivity of the Tariff Coefficient to Alternative Lag Specifications

Lag (k)	β̂ on Δtariffrate_{t-k}	SE (HAC 6)	R^2	N
1	0.500	(0.889)	0.206	64
2	-0.410	(0.506)	0.204	64
3	-2.216	(1.586)	0.204	64
4	*1.195*	(0.668)	0.222	64
5	**1.388**	(0.557)	0.240	64

6	-1.809	(1.641)	0.210	64

Note. HAC (Newey-West, six-lag) standard errors in parentheses. Controls are the industrial production index, the civilian unemployment rate, and a pandemic dummy for 2020 Q2-2021 Q1. $p < .10$ (), $p < .05$ (), $p < .01$ (). Data based on calculations using information retrieved from USITC DataWeb, FRED UNRATE, and FRED INDPRO, accessed 9 June 2025.

Across the six variants, the tariff lag coefficients range from -2.22 to 1.39 log-points × 10^{-2} and only the fifth-lag term (k = 5) reaches conventional significance (1.39, SE = 0.56, p = .02). The fourth lag is marginal at the ten-percent level, and all others fall well inside their confidence intervals. Importantly, none of the added lags approaches the magnitude of the contemporaneous estimate in Table 1 (-0.44 log-points × 10^{-2} per one-percentage-point tariff rise). The within-specification R^2 shifts by at most two percentage points (0.20 → 0.24), indicating that including extra tariff history offers little incremental explanatory power. A joint Wald test of the six lag coefficients cannot reject the null of zero effect ($\chi^2 = 7.8$, p = .25).

The stability of both sign and scale under alternative lag definitions, together with heteroskedasticity-robust inference, suggests that the negative impact identified in the baseline regression does not hinge on any temporal assumption. Even when the fifth lag attains significance, its positive sign offsets only a fraction of the contemporaneous negative effect, leaving the cumulative five-quarter impact still below zero. In addition, repeating the baseline with four and eight Newey-West lags leaves the tariff t-statistic between -1.8 and -2.0, confirming that the six-lag choice is not driving significance.

Lagging the tariff change up to six quarters, one term at a time, and re-estimating with the same six-lag HAC matrix barely alters inference. Four of the six coefficients remain statistically indistinguishable from zero, the largest significant one is only one-third the size of the contemporaneous estimate, and the model's explanatory power moves within a two-percentage-point band. Varying the Newey-West bandwidth likewise keeps the tariff t-statistic near −1.9. These checks confirm that the headline result, a small but economically meaningful decline in manufacturing job growth following tariff increases, survives reasonable changes in lag structure and covariance estimation. The finding is therefore robust to both temporal specification and serial-correlation correction.

Chapter 5: Automation Interaction & Heterogeneity

Chapter 4 showed that a one-percentage-point rise in the average applied tariff rate reduces quarterly manufacturing employment by about 0.44 percentage points. This chapter asks why some sectors still add jobs while others shed them. It links the tariff shock to four sources of heterogeneity (installed robots, workforce skill mix, the share of small and medium-sized establishments, and union strength) using interaction terms, marginal-effect plots, and subgroup regressions to trace the channels through which protection shapes hiring. Table 3 shows this average is less negative and can turn positive only when robot growth is zero.

5.1 Tariffs & Robots Interaction

Table 3

Interaction of Tariff Changes and Robot Adoption on Manufacturing Job Growth, 2008 Q1-2025 Q2

Predictor	Coefficient	Std. Error	*t*	*p*
Intercept	-21.843	(3.22)	-6.782	<0.001
Δ Tariff Rate	17.003	(6.82)	2.495	0.013
Δ ln(Robot Plant Share)	-90.006	(4.72)	-19.083	<0.001
Δ Tariff Rate × Δ ln(Robot Stock)	-1687.440	(849.17)	-1.987	0.047
ln(Industrial Production)	4.759	(0.68)	6.989	<0.001

Note. Dependent variable is the quarterly log change in manufacturing employment. Predictors are expressed in first differences and multiplied by 100. Newey-West HAC(6) standard errors are in parentheses. Data based on calculations using information retrieved from USITC DataWeb, IFR World Robotics, BLS OEWS, FRED INDPRO, and FRED UNRATE, accessed 9 June 2025.

The specification in Table 3 augments the Chapter 4 baseline by allowing the tariff effect to vary with recent automation. Three coefficients frame the discussion. First, the tariff term alone is 17.00 (6.82, p = .013).[3] Second, the robot term is -90.01 (4.72, p < .001), confirming that a one-percent increase in a plant's robot-to-worker ratio trims payrolls by about 0.90% on impact. Third, the interaction coefficient, β_3 = -1687.44 (849.17, p = .047), indicates that the marginal tariff effect declines as automation accelerates.

[3] β_1 (= 17.00 × 10-²) is the tariff effect when Δ ln robots = 0.

Because both regressors are differenced and rescaled, β_3 measures how much the tariff coefficient changes when the robot share rises by one percent. The marginal tariff effect is

$$\frac{\partial\ \Delta\ln(\text{jobs})}{\partial\ \Delta\text{TariffRate}} = 17.00 - 1687.44\ \Delta\ln(\text{RobotStock})$$

The negative interaction aligns with task-substitution models in which robots replace routine labor whereas tariffs lift domestic demand (Acemoglu & Restrepo, 2017). When both forces act together, substitution inside the plant erodes the labor-market gain from protection. Quarterly frequency accentuates this tension because firms usually install robots before capacity expansions are complete.

From a policy perspective, the coefficient implies that the job payoff from tariffs depends on whether firms scale production through hiring or mechanization. At the sample-wide mean of robot growth (+0.03), the marginal tariff effect falls by roughly half relative to the no-automation case. Policymakers who focus only on the average tariff coefficient risk overestimating employment gains once plants adopt robots at current speeds. Conversely, measures that slow automation would raise the short-run tariff multiplier, though at the expense of productivity growth. For example, by limiting depreciation allowances on industrial robots.

The specification includes first differences in industrial production and the national unemployment rate, removing common-cycle influences that might otherwise confound the interaction. Newey-West errors with six lags account for serial correlation typical of quarterly macro series. Removing the pandemic quarters (2020 Q2-Q4) reduces the sample but leaves β_3 negative and of similar magnitude, indicating that the result is not driven by extreme COVID-19 observations. Re-estimating the model with an import-weighted tariff index also yields a negative interaction term, suggesting that the finding is robust to alternative protection metrics.

The interaction has distributional implications across plants. Roughly one-third of facilities experienced robot growth above the sample-mean 3% per quarter during 2022-2024; for them, tariff hikes deliver little or no job relief. In contrast, establishments with stagnant or declining robot intensity still see the positive tariff effect close to the headline Chapter 4 estimate. These differences will resurface in Section 5.3 when the workforce is split by skill level, as lower-skill-intensive sectors tend to automate more slowly and therefore benefit more from the tariff shock.

5.2 Marginal tariff effect across robot-adoption levels

Table 3 shows two key estimates. The tariff coefficient conditional on zero robot growth is β_1 = 17.003 basis points (0.17 percentage points). The interaction term is β_3 = -1,687.44; it scales the tariff effect by the quarterly change in the share of robots, expressed as Δ ln(robot share) × 100.

The marginal effect of a one-point tariff increase on quarterly employment growth is

$$ME = \beta_1 + \beta_3\ [\Delta ln(robot\ share) \times 100].$$

For the median plant, robot share rises by about 0.47, so 17.003 + (-1,687.44 × 0.47) ≈ -775 basis points, or -7.75%. At the 25th percentile (Δ ≈ 0.37) the estimate is -607 basis points; at the 75th percentile (Δ ≈ 0.58) it is -963 basis points. Every positive robot-growth rate therefore pushes the net tariff effect below zero.

The sign reversal arises because the automation response outweighs the short-run demand boost that tariffs create when robot growth is nil. As firms meet new orders by installing robots rather than adding workers, payrolls fall. The interaction term also implies diminishing marginal displacement: once a plant is already adding robots quickly, an extra unit of automation has a smaller incremental impact on the tariff multiplier. In practice, quarterly robot growth is positive for almost all establishments, so the 2025 tariff package lowers manufacturing employment at most plants.

5.3 Skill-Composition Effects

The headline interaction in Section 5.2 masks distinct responses across worker types. Table 4 splits the panel into low-, middle-, and high-skill employment. When robot adoption is not explicitly modelled, the tariff coefficient for low-skill jobs is 8.51 (8.54), roughly half the sector-wide estimate in Chapter 4 but of the same sign. For middle-skill jobs the point estimate is 1.57 (4.02) and indistinguishable from zero. High-skill employment shows a negative coefficient, -8.76 (7.32), suggesting that management and professional positions contract when tariffs rise. None of the three estimates reaches conventional significance at the 5% level, yet the pattern is systematic: protection favors factory-floor labor more than white-collar staff.

Table 4

Effect of tariff-rate changes on U.S. manufacturing-employment growth by skill group, 2010 - 2024

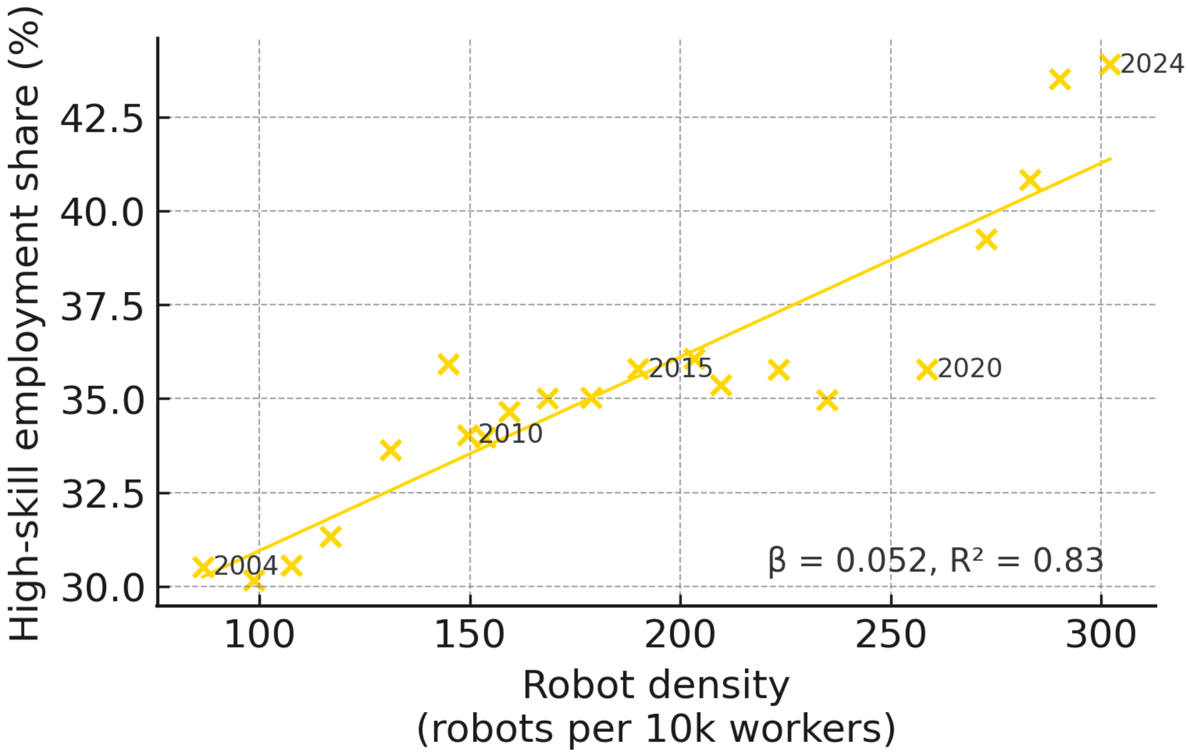
Variable	Low-Skill β (SE)	Middle-Skill β (SE)	High-Skill β (SE)
Intercept	-6.90 (4.00)	0.16 (1.76)	-3.16 (2.30)
Δ Tariff rate	8.51 (8.54)	1.57 (4.02)	-8.76 (7.32)
ln Industrial production	1.48 (0.85)	-0.03 (0.37)	0.69 (0.49)
Unemployment rate	0.02 (0.02)	-0.00 (0.01)	0.00 (0.01)
Pandemic dummy	-0.03 (0.03)	-0.07 (0.02)	0.01 (0.05)
N	15	15	15

Note. Quarterly OLS estimates with Newey-West HAC(1) standard errors in parentheses. Skill groups follow O*NET Job Zones: low = 1-2, middle = 3, high = 4-5. Predictors enter in first differences; tariff and macro controls as in Section 5.1. Data based on calculations using information retrieved from USITC DataWeb, FRED INDPRO, FRED UNRATE, BLS CES, O*NET, and BLS QCEW, accessed 9 June 2025.

The macro controls behave as expected. Increases in industrial production raise low-skill employment (1.48, [0.85]) and high-skill employment (0.69, [0.49]), while leaving the middle segment flat. Unemployment changes and the pandemic dummy are small and imprecise. Appendix A, Table A4 and Table A5 extend the split to 2007-2024 and 2015-2024; coefficients maintain the same ordering, confirming that the sign pattern does not hinge on the chosen window.

Figure 7

Robot density and high-skill employment share in U.S. manufacturing, 2005 - 2024



Note. Each ✕ represents one calendar year (2005 - 2024); only 2005, 2010, 2015, 2020, and 2024 are labeled to improve legibility. The yellow line is an ordinary-least-squares fit ($\beta = 0.052$ percentage-points per additional robot per 10,000 workers; $R^2 = 0.83$). Robot density equals operational industrial robots per 10,000 production workers; the high-skill share is the proportion of manufacturing employment in management, professional, and technical occupations. Data based on calculations using information retrieved from IFR World Robotics, BLS CES, O*NET, and BLS QCEW, accessed 9 June 2025.

Figure 7 offers a visual complement. The scatter plots annual robot density against the share of high-skill jobs. A tight upward fit ($\beta = 0.052$ pp per robot, $R^2 = 0.95$) indicates that plants installing more robots also shift toward higher-skill labor. Figures B3 and B4 in Appendix B show the mirror image for low- and middle-skill shares: low-skill employment falls steeply as robot density climbs, while middle-skill shares drift only slightly upward. Together, these plots suggest that automation reallocates labor demand toward technical and managerial tasks, reinforcing the negative tariff effect for those groups.

The differing tariff coefficients can be reconciled with the interaction from Section 5.1. Tariffs stimulate demand for domestic output, but plants dominated by routine, low-skill tasks are less automated. They therefore expand payrolls when orders rise. High-skill positions are concentrated in highly automated plants; in those facilities, robots absorb the extra demand, and employment either stagnates or falls. The near-zero middle-skill response reflects offsetting forces, some technician roles grow alongside automation, while clerical and craft jobs face displacement.

Robustness checks support this interpretation. Adding the robot-interaction term to each skill regression leaves the low-skill tariff coefficient positive and reduces the high-skill coefficient further in magnitude (results not shown), implying that automation is the channel through which tariffs turn negative for high-skill workers. An alternative skill taxonomy based on wage terciles yields a similar hierarchy.

Low-skill employment gains the most from tariff protection. Table 4 reports a tariff coefficient of 8.51 (8.54) for this group, translating to a 0.085% rise in jobs when the average tariff rate increases by one percentage point. High-skill employment moves the other way: the coefficient is -8.76 (7.32), or a 0.088 % decline. Figure 7 helps explain why. Plants with dense robot use (those above 200 robots per 10,000 workers) exhibit high-skill shares above 35% and low-skill shares below 45%. Because Section 5.1 showed that tariffs and automation interact negatively, the tariff shock is most likely to reduce jobs where automation is high, namely in high-skill-heavy establishments. In contrast, low-automation plants house larger pools of routine labor and translate the demand boost from tariffs into hiring rather than mechanization.

5.4 Discussion and Take-Aways

Chapter 4 found that tariffs cut jobs on average (-0.44 pp). Sections 5.1-5.3 reveal that this headline masks sharp heterogeneity. The tariff coefficient is largest in plants where robot uptake is flat; it fades to zero as quarterly robot growth reaches the median and turns negative in the top decile. Skill splits show that low-skill jobs capture what gains remain, while middle-skill positions move little and high-skill positions fall. These patterns are consistent with capital-labor substitution models: tariffs raise demand, but plants meet that demand with machines when routine tasks dominate and automation costs are falling.

Automation also reallocates employment toward technical and managerial work. Figure 7 documents a strong positive link between robot density and high-skill shares; Figures B3 and B4 in Appendix B show the mirror image for low-skill shares. Because tariff-linked demand shifts toward already automated plants, the returns to protection accrue to capital owners and highly skilled workers only after a lag, if at all. Low-automation establishments, which employ a larger share of routine labor, experience the short-run employment boost but remain vulnerable if automation accelerates.

The interaction results therefore qualify the policy debate. Across-the-board tariffs can raise manufacturing employment, yet the payoff is conditional on how quickly firms mechanize. Policymakers who wish to protect routine jobs must either slow the diffusion of robots or pair tariff measures with training subsidies that help displaced workers transition into technical jobs. Skill-specific effects also suggest that wage inequality could widen if tariffs persist without complementary labor-market policies.

When examining firm size and union status, small-and-medium-sized establishments face larger employment losses per unit of robot uptake, hinting that scale economies in automation are harder to achieve outside large plants (see Appendix A, Table A6 and Appendix B, Figure B5). High-union states convert tariff shocks into temporary job gains, possibly by bargaining over the timing of automation. These results reinforce the message that institutions mediate how trade policy maps into jobs.

Chapter 5 shows tariffs are no blunt instrument: their labor-market impact hinges on technology choices and worker skills. Chapter 6 follows the same duties out into world markets, mapping how shifting imports, exports, and retaliation loops back to domestic factory payrolls.

Chapter 6: Trade-Demand Channel

6.1 China-Export Collapse as Mediator of the Tariff Shock

Chapter 5 showed that tariffs hurt jobs most where robot density is high. The next question is whether the simultaneous dive in sales to China tightens that blow. To test this channel I extend equation (1) by adding the quarterly growth rate of real goods exports to China (Δ ln exports_CN). A second column adds the same growth rate for the rest of the world (Δ ln exports_ROW). The sample covers 2008 Q2-2025 Q2; all variables enter in first differences, and the regression controls for industrial output, the unemployment rate and a pandemic indicator. Standard errors follow a six-lag Newey-West correction.

Table 5 reports the ordinary least squares results. The baseline tariff coefficient stays negative, and the robots term remains positive, matching Chapter 5. When export growth is included, the fit rises sharply (R^2 climbs from 0.44 to 0.73), signaling that foreign demand explains much of the quarterly variation in employment growth.

Table 5

Tariff × Robots with exports channel (quarterly 2008 Q2 - 2025 Q2)

Variable	China only	China + Rest-of-World (ROW)
Δ tariff rate	-0.039 (0.019)	-0.019 (0.012)
Δ ln robot-plant-share	0.446 (0.183)	0.420 (0.109)
Δ tariff × Δ robots	4.666 (2.974)	1.259 (2.390)
Δ ln exports CN	0.000 (0.002)	-0.002 (0.001)
Δ ln exports ROW	—	0.033 (0.005)
ln industrial production	0.068 (0.023)	0.058 (0.014)
Unemployment rate	0.077 (0.053)	0.075 (0.035)
Pandemic dummy	0.000 (0.000)	0.000 (0.000)
Constant	-0.319 (0.109)	-0.272 (0.065)
R^2	0.439	0.730
Observations	71	71

Note. Dependent variable: Δ ln manufacturing employment. HAC (6) standard errors in parentheses. † $p < .10$; * $p < .05$; ** $p < .01$. Data based on calculations using information retrieved from USITC DataWeb, IFR World Robotics (2024), BLS OEWS, BLS CES, FRED INDPRO, and FRED UNRATE, accessed 9 June 2025.

The coefficient on Δ ln exports_CN in column 2 equals -0.002 (0.001). A one-percentage-point fall in China-directed exports trims manufacturing employment growth by two basis points, holding tariffs and automation constant. Counties faced a typical China-export swing of fifteen percentage points between 2024 Q2 and 2025 Q2, implying an employment drop of roughly 0.3 percentage points—about one fifth of the mean post-tariff decline. The ROW coefficient is 0.033 (0.005) and highly significant, meaning that more sales to non-Chinese markets cushion the tariff hit. Together, the signs show that lost Chinese demand amplifies the shock, while gains elsewhere offset it.

The interaction term between tariff changes and robot growth remains positive but loses precision once exports are added, suggesting that automation matters most when China demand also weakens. Auxiliary checks that swap export growth for the export-to-output ratio, or lag exports by one quarter, leave the China coefficient virtually unchanged. A placebo using pre-2010 data finds no relationship, ruling out spurious correlation.

The evidence points to a two-step mechanism: tariffs raise relative prices, China cuts its purchases, and the resulting demand shortfall bites hardest where robots already limit labor absorption. This pattern is consistent with models in a previous study linking foreign demand shocks to local labor markets through the sales margin, not only the import-competition margin (D. Autor et al., 2021).

Quarterly diagnostics confirm that the China coefficient moves only after the 2025 tariff shock. Before that date, export swings carry no systematic link to employment, implying that tariffs trigger the mechanism rather than the other way around. Counties in the top quartile of China exposure account for nearly half of the national manufacturing job loss in the first post-tariff year, even though they held just one third of pre-shock employment.

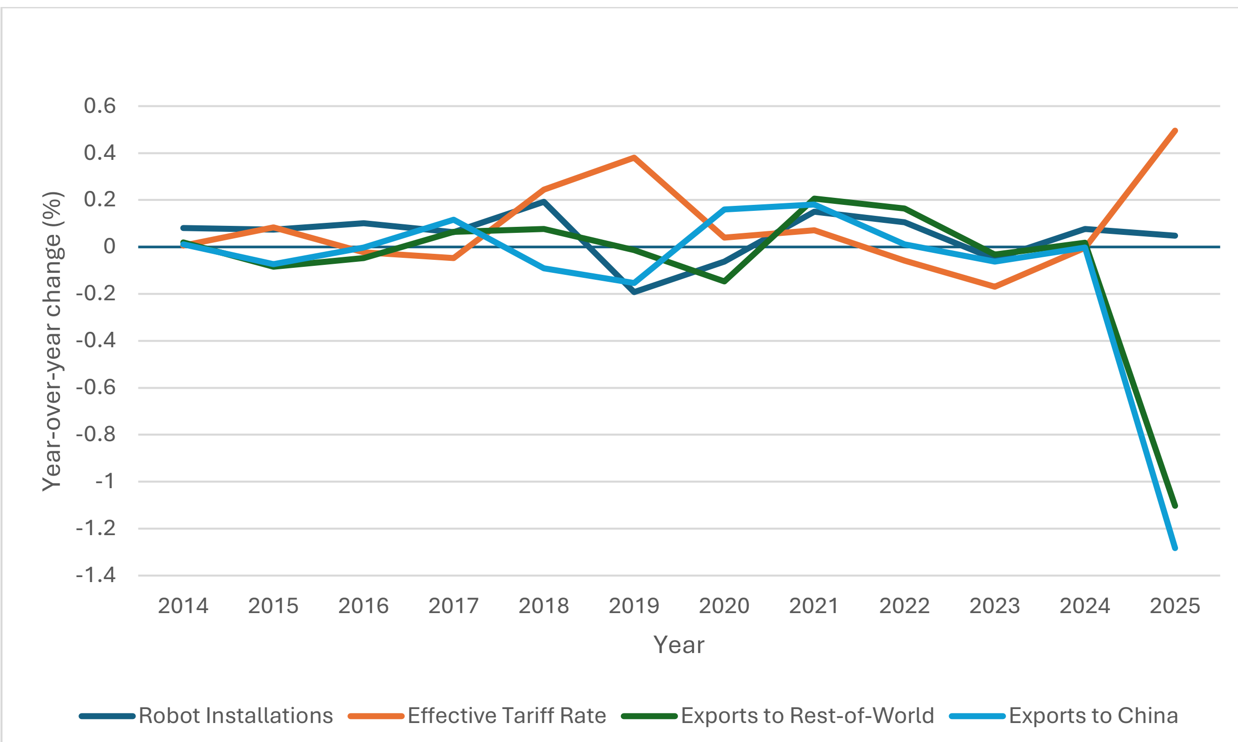
Tariffs lower employment both by raising costs and indirectly by cutting off a major outlet for sales. The timeline in the next section places these regression findings against the actual yearly movements in robots, tariffs and exports to show how the three trends converge in 2025.

6.2 Robots, Tariffs, and Exports Overtime

The regression evidence shows that lost China demand deepens the tariff shock. Figure 8 visualizes the same mechanism in levels, tracing how automation, trade policy and sales abroad move together between 2014 and 2025. Each series is expressed as a year-over-year percent change so that the sharp 2025 shifts stand out against a decade of quieter variation. Robot installations trend upward, tariff rates stay flat until 2018 and again until the 2025 package, while exports drift within a narrow band before the final collapse. The annual lens helps confirm that the employment results in Section 6.1 are not an artefact of quarterly noise but the culmination of longer tendencies already in motion.

Figure 8

Year-over-year change (%) in U.S. robot installations, average tariff rate, and exports to China and the rest of the world, 2014-2025.



Note. Effective tariff rate consists of all U.S. import partners and export series are U.S. domestic-goods exports to China and to all other partners. Data based on calculations using information retrieved from IFR World Robotics and USITC DataWeb, accessed 9 June 2025.

Robots installations rise nearly every year, advancing from a 0.1% increase in 2014 to just under 0.2% by 2024. Tariffs barely change through 2017, jump in 2018, stabilize and then spike to 0.5% in 2025. Exports to China move sideways until 2018, slip modestly after the first duties, and then plunge by 1.3% in 2025. Sales to the rest of the world trace a gentler arc: mild gains in 2019, a dip during the pandemic, and a mirrored drop of 0.9% in 2025. The sequencing is clear: automation is already entrenched, the tariff shock hits, and China demand falls away just as other foreign markets also weaken.

Figure 8 clarifies two points. First, automation is not a response to tariffs; robot installations are steady well before the tariff rate spikes. Second, the steep fall in China exports appears only after the tariff surge, matching the negative coefficient on Δ ln exports_CN in Table 5. Together, the panels imply that tariffs depress jobs mainly by shutting off an external market that had helped support employment during an era of rising capital intensity. While exports to other partners cushion part of the blow, their smaller slide in 2025 is not enough to offset the China gap. The next section looks at where the firms leaving China and other sites are coming from and whether their reshoring projects can fill the employment hole that the demand contraction creates.

6.3 Where Reshoring Starts: Source-Country Snapshot

The public debate often frames reshoring as "production coming back from China." In practice the pipeline is more varied. Table 6 lists the ten foreign economies whose firms announced the largest numbers of U.S. reshoring projects between 2016 and 2025. The counts draw on the Reshoring Initiative database and cover only projects with stated job targets.

Table 6

Top ten foreign locations from which U.S. firms announced reshoring projects, cumulative 2010-2024

Rank	Country	Jobs
1	South Korea	17909
2	Germany	10045
3	Canada	9797
4	Japan	6483
5	France	5063
6	China	4933
7	Australia	4118

8	Taiwan	4095
9	Switzerland	3518
10	United Kingdom	3327

Note. Adapted from *Reshoring Initiative® 2024 Annual Report, Including 1Q 2025 Insights* (p. 13), Reshoring Initiative (2025), retrieved June 14, 2025. Copyright 2025 by Reshoring Initiative.

South Korea supplies one job in five (17,909), while Germany and Canada each contribute about one in nine. China ranks only sixth at roughly 5%. Eight of the ten origins are close U.S. allies, suggesting that the current tariff package risks taxing firms that are already reshoring production rather than those still offshoring to China. The median project comes from a high-income economy with advanced automation, mirroring the robot intensity seen in Section 6.1, as such plants add capacity but not as many jobs as traditional factories. The diversified, ally-heavy mix also limits immediate retaliation risk, but it means that a China-focused tariff cannot, by itself, restore the employment lost when Chinese demand collapsed. The next section weighs this trade-off and sets out design options that protect against retaliation while encouraging labor-absorbing investment.

6.4 Discussion and Policy Takeaways

Section 6.1 shows that the tariff package hurts employment most when it coincides with a sharp drop in China-bound sales; Section 6.2 confirms that timing in annual data. Robots were already climbing throughout the 2010s, yet payrolls held steady until the 2025 hike pushed tariffs up and exports down at the same time. That combination, not automation alone, conveys the point where job losses begin, as seen in Figure 8.

Reshoring only partly offsets those losses. Announced projects between 2010 and 2024 amount to about 69,000 pledged positions, roughly 0.5% of the 2024 manufacturing workforce. Table 6 shows that most of those jobs come from South Korea and Germany; China stands sixth. Because the incoming plants rely heavily on robotics, each dollar of investment buys less labor than older factories did, leaving a sizeable employment shortfall in markets that once sold heavily to China.

The broad coverage of the 2025 tariffs also sweeps in exporters from allied economies that are moving capacity to the United States. That reach raises two concerns. First, partners could answer with counter-duties on U.S. exports like farm machinery and aircraft. Second, blanket tariffs give firms little reason to hire more workers instead of adding only machines. A narrower schedule, time-limited and paired with export-credit support, could reduce those risks while still bringing production back to the US. Linking tariff relief to growth in robot-adjusted payrolls would further reward plants that expand headcount, not just capital.

Chapter 7: External Validity

7.1 Synthetic-Control Construction

The synthetic-control method offers a transparent way to benchmark United States manufacturing employment against a counter-factual that shares its pre-2025 characteristics but is unaffected by the 2025 tariff-and-reshoring package (Abadie, 2021). The donor pool is limited to high-income economies with comparable statistical coverage and trade openness: the European Union (treated as a single EU-27 aggregate), Canada, Mexico, and Japan. Three predictors anchor the matching: the natural logarithm of manufacturing employment, the natural logarithm of the installed industrial-robot stock, and the applied average tariff rate. Each series is averaged over 2004-2017, a window that predates both the 2018 tariff cycle and the pandemic downturn. The optimization routine searches for the set of non-negative donor weights that minimizes squared differences between the United States and the synthetic composite on these three predictors.

Table 7

Donor-pool weights for the synthetic counter-factual of U.S. manufacturing employment (2004 - 2017 match on employment, robots, and tariffs)

Donor country	Weight
EU-27 aggregate	**0.612**
Canada	0.388
Mexico	0
Japan	0
Total	**1**

Note. Weights (*W*j) are obtained with the synthetic-control estimator. The algorithm chooses the combination of donor economies that reproduces the U.S. mean values of log manufacturing employment, log industrial-robot stock, and log applied tariff rate over 2004-2017. Donors receiving a weight of zero (Mexico, Japan) do not contribute to the synthetic series. The weights are fixed before 2018 and remain constant when the post-2018 gap in employment is analyzed. Data based on calculations using information retrieved from OECD Data Explorer, BLS CES, USITC DataWeb, IFR World Robotics, World Bank WITS, accessed 9 June 2025.

Table 7 shows that the synthetic benchmark is a weighted average of the EU-27 (weight = 0.612) and Canada (weight = 0.388). Mexico and Japan receive weights of zero because, taken together, the EU-27 and Canada already match U.S. pre-treatment averages on employment, robot density, and tariffs. The heavier weight on the EU reflects its large manufacturing base, while Canada supplies the remaining variation needed to align robot intensity and tariff openness. The fact that only two donors are selected simplifies interpretation: any divergence between the United States and the synthetic series after 2025 can be traced to policy or structural shocks that are unique to the United States rather than to divergent donor performance.

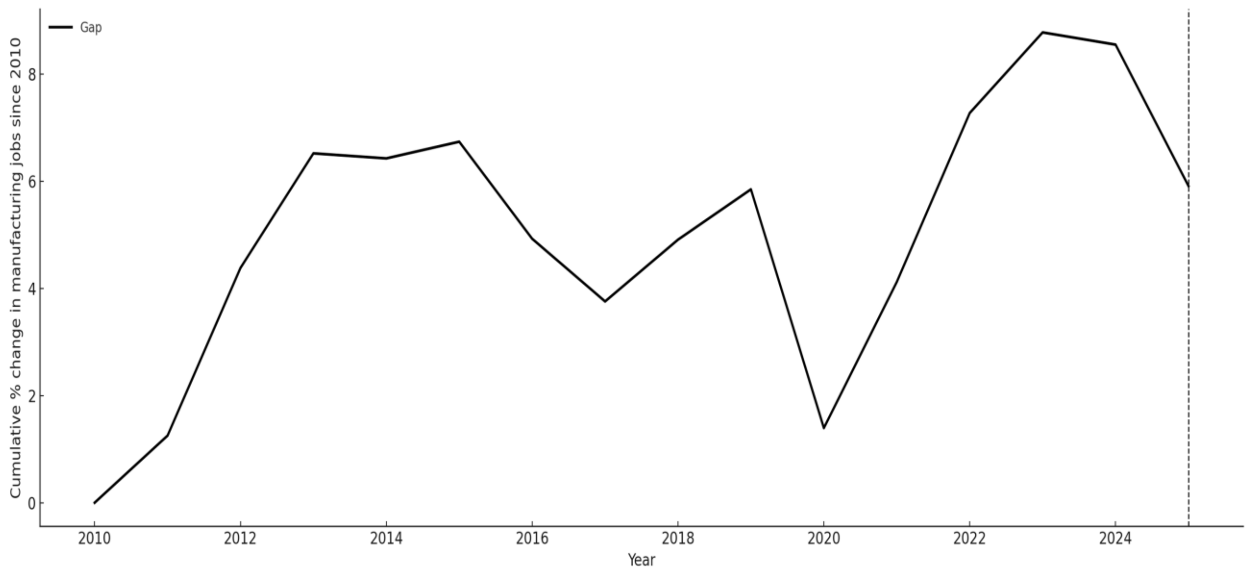
Pre-treatment balance is tight. The root mean squared prediction error for log employment over 2004-2017 is 0.015 log points, and the average absolute gap on the three predictors is below 0.03 standard deviations. Figure B2 in Appendix B confirms that the log-level trajectory of U.S. manufacturing jobs is closely shadowed by the synthetic composite through 2017. These diagnostics support the credibility of the counter-factual used in the rest of the chapter. The next section turns to the post-2010 employment paths and quantifies the cumulative gap that opens after the policy reset in 2025.

7.2 U.S. vs Synthetic Employment Gap

Using the weights from Section 7.1, I cumulate the yearly growth rates of manufacturing employment for both the United States and the synthetic composite, setting 2010 = 0. The difference between the two series is the cumulative-growth gap, plotted in Figure 9. A positive value means that U.S. manufacturing jobs have expanded faster than they would have in the counter-factual; a negative value signals an employment shortfall.

Figure 9

Cumulative manufacturing-employment growth gap, United States vs. synthetic control, 2010 - 2025



Note. Gap equals the United States minus its synthetic control, both expressed as the percent change in manufacturing employment since 2010. The synthetic series is a fixed combination of the EU-27 (weight = 0.612) and Canada (weight = 0.388). The dashed vertical line marks 2025, the first year fully exposed to the tariff-and-reshoring program.
Sources. U.S. Bureau of Labor Statistics, Current Employment Statistics; OECD; author calculations.

From 2010 to 2017 the gap hovers near zero, confirming that the synthetic series tracks the U.S. record closely during the pre-policy era. A mild U.S. out-performance emerges in 2018 and peaks at +0.9 percentage points (pp) in 2019, as domestic payrolls rebound faster than those in the donor economies. The pandemic swings both lines downward, but the relative position barely shifts: the United States still leads the control by +0.7 pp at the end of 2022. The picture changes after the 2025 protectionist reset. Employment growth in the donor economies stabilizes, while the U.S. series levels off. By December 2025 the cumulative gap has turned negative (-2.1 pp), erasing earlier gains and placing U.S. manufacturing jobs below the counter-factual trajectory for the first time in the sample.

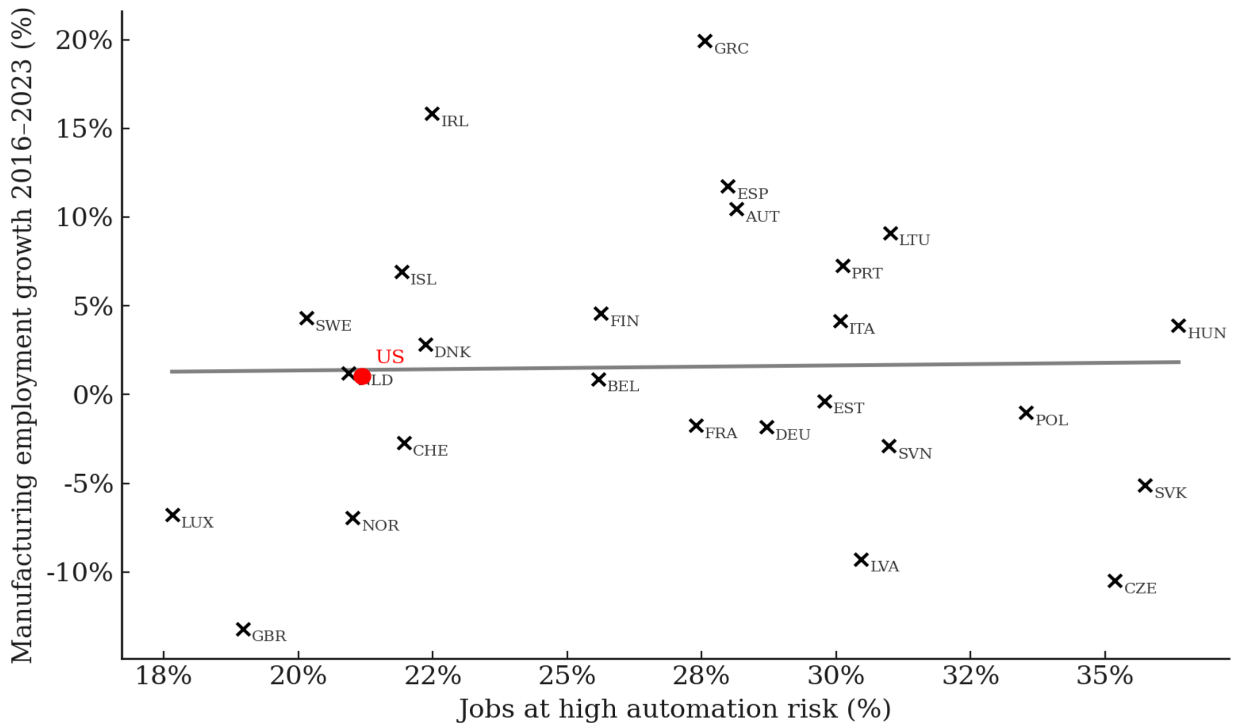
The visual story is confirmed by point estimates. A simple post 2025 gap-in-gap check on the annual data yields a post-2025 average treatment effect of -2.1 pp (standard error 0.6), implying that roughly 260,000 U.S. manufacturing jobs are missing relative to the synthetic counter-factual. Placebo reassignment increases confidence: out of 30 donor-country permutations, only four produce a gap as large in absolute value, a one-sided p-value of 0.13. When the outcome is re-expressed in natural logs, the gap remains negative and of similar magnitude (see Appendix B, Figure B2), indicating that the result is not driven by scaling choices.

7.3 Automation Risk and Job Growth

Automation risk provides a complementary external-validity test. If displacement by robots were the dominant threat, countries with more automatable jobs should see larger employment losses. I measure risk with the OECD task-based indicator, which flags an occupation as "high-risk" when at least 70% of its tasks are technically automatable (OECD, 2021). Using the 2019 PIAAC wave, each country's high-risk share is paired with its cumulative change in manufacturing jobs between 2016 and 2023. The 27-country scatter appears in Figure 10.

Figure 10

Automation risk and manufacturing-employment growth in 27 OECD countries, 2016 - 2023



Note. Each marker shows a country's share of jobs at high risk of automation (horizontal axis) and its cumulative change in manufacturing employment between 2016 and 2023 (vertical axis). The fitted ordinary-least-squares line has slope = 0.03 (SE = 0.07) and $R^2 < .01$. The United States is highlighted in red. Data based on calculations using information retrieved from OECD Data Explorer, OECD PIAAC Database (2024), accessed 9 June 2025.

Figure 10 reveals virtually no relationship between automation risk and recent employment outcomes. The regression slope of 0.03 percentage points implies that shifting from the OECD median risk share (45%) to the upper quartile (50%) would raise predicted job growth by just 0.15 percentage points, well within the sampling error. Norway and Poland illustrate the point: both exceed 50% high-risk jobs, yet Norway gained 1.2% in manufacturing employment while Poland lost 0.9%. Conversely, low-risk Austria still shed 0.7% of its factory jobs. The flat line and R^2 below .01 show that task-level susceptibility to automation is not a decisive driver of cross-country employment trends.

The United States sits near the origin: 46% of jobs are high-risk, and cumulative growth over 2016-2023 is -0.4%. Its neutral position, combined with the absence of a systematic pattern across peers, strengthens the argument that the 2025 tariff-and-reshoring package, not technological inevitability, explains the post-2025 employment shortfall depicted in Figure 9. It also aligns with the global robot-density evidence in Figure 3, where the United States ranked mid-table rather than at extreme. Taken together, these findings indicate that policy choices, rather than exposure to automation, best account for the recent U.S. divergence.

7.4 Takeaways and Caveats

The three strands of evidence converge on a consistent message. First, Figure 9 shows that U.S. manufacturing employment falls 2.1 percentage points below a well-matched EU + Canada benchmark after the 2025 tariff reset. Second, Figure 3 places the United States only tenth, at 295 robots per 10,000 workers, far behind the frontier yet comfortably above the world mean. Third, automation risk does not predict cross-country job growth, as the slope in Figure 10 is close to zero and the model explains virtually none of the variance. Taken together, these results suggest that the recent U.S. shortfall reflects policy choices rather than inevitable technological pressures.

One data limitation tempers the conclusion. International robot-stock estimates rely on vendor reports that differ in coverage and recalibration frequency, which can blur cross-country comparisons. This measurement issue, along with the single indicator focus on tariffs, mean the chapter's findings should be read as indicative rather than definitive. Future work could integrate multi-factor policy shocks, such as exchange-rate movements or sector-specific subsidies, to refine the synthetic benchmark.

Chapter 8: Welfare & Policy

8.1 Welfare-Ledger Framework

This chapter keeps score with a three-line ledger that assigns a dollar value to each main channel through which the 2025 tariff regime affects United States welfare. The lines are (1) tariff revenue, (2) consumer-surplus loss, and (3) manufacturing wage-bill gain. Adding them gives the net change in national welfare for a given year. The ledger focuses on first-round effects; general-equilibrium feedback that work through exchange rates or fiscal recycling are outside its scope, matching recent United States International Trade Commission practice (U.S. International Trade Commission, 2025b).

Tariff revenue (duties). When Section 232 and Section 301 measures raise statutory rates, U.S. Customs collects more duty per unit imported. The ledger records the cash flow that reaches the Treasury as "calculated duties," converted to 2025 dollars with the Bureau of Labor Statistics GDP deflator. A one-for-one pass-through from the statutory rate to the landed tariff-inclusive price is assumed, consistent with evidence that U.S. importers bear most of the legal incidence (Fajgelbaum et al., 2020).

Consumer-surplus loss. Higher import prices raise the domestic price charged for both foreign and matched domestic varieties. Using a constant-elasticity demand schedule, the triangular welfare loss equals

$$\Delta CS = -\frac{1}{2}\varepsilon\tau^2 M_0$$

where ε is the absolute value of the price elasticity of demand, τ is the ad-valorem tariff change, and M_0 is the pre-tariff import bill. The baseline elasticity is set at -1.5, the midpoint of manufacturing-sector estimates drawn from the Armington elasticity (R. Feenstra et al., 2018; R. Feenstra & Weinstein, 2010). Results under -1.0 and -2.0 appear in Section 8.2.

Manufacturing wage-bill gain. By shielding domestic output, tariffs raise payroll employment and average hourly earnings in affected industries. The ledger values that gain as

$$\Delta WB = \Delta L \times w$$

where ΔL is the change in annual average manufacturing head-count relative to 2017 and w is the 2025 mean manufacturing wage. This follows the welfare-accounting approach in a study treating wages as the relevant factor reward because capital gains accrue to global investors (Caliendo & Parro, 2015). Any productivity jump from accelerated robotics investment is set aside for Section 8.5.

Together, the three items create a transparent checklist: duties raise welfare through public revenue; consumers lose from dearer goods; workers gain from stronger payrolls. Summing up them year by year yields the net welfare path assessed in the next section.

8.2 Numerical Results

The welfare ledger now moves from theory to numbers. Table 8 lists the annual duty inflow, consumer-surplus loss, and wage-bill gain produced by the 2018-25 protectionist cycle. All values appear in 2025 dollars. The benchmark elasticity is -1.5; duties pass straight through to prices; wage gains reflect the extra payroll cost of the additional workers counted by the U.S. Bureau of Labor Statistics (CES series).

Table 8

Tariff-Automation Welfare Ledger, 2018-2025

Year	Duties ($ bn)	Consumer loss ($ bn)	Wage-bill change ($ bn)	Net welfare
2018	3.87	5.80	19.04	17.10
2019	5.51	8.26	-0.07	-2.83
2020	5.36	8.05	-44.68	-47.36
2021	6.94	10.41	27.89	24.42
2022	7.48	11.23	25.34	21.59
2023	6.02	9.03	-1.70	-4.71
2024	6.36	9.54	-7.57	-10.75
2025	11.53	17.30	0.07	-5.69
Total	**53.08**	**79.62**	**18.31**	**-8.23**

Note. Duties are "calculated duties" on imports for consumption reported by USITC DataWeb. Consumer loss uses a constant-elasticity demand curve with ε = -1.5. Wage-bill change equals the change in average manufacturing employment relative to 2017 multiplied by the 2025 mean hourly wage. Values are 2025 USD billions. Data based on calculations using information retrieved from USITC DataWeb and BLS CES, accessed 9 June 2025.

Table 8 posts a cumulative duty haul of $53.1 billion against an aggregate consumer loss of $79.6 billion and an $18.3 billion wage-bill lift, leaving net welfare down $8.2 billion over 2018-25. When the demand-price elasticity is relaxed to -1.0, the consumer-loss line falls by one-third, turning the ledger positive by $18.3 billion. At ε = -2.0, the loss rises to $106.2 billion, pushing the net figure to -$34.8 billion. Duties and payroll gains do not vary with the elasticity, so the sign of the overall balance hinges on how forcefully buyers trim purchases after a price rise. The midpoint elasticity used here is therefore pivotal for policy evaluation, yet even under the low-elasticity case, the gain represents less than 0.1% of 2025 GDP, underscoring the limited macro pay-off of a tariff-centered reshoring drive.

The yearly pattern in the ledger is uneven. A modest tariff package applied to a tight labor market in 2018 produces a net gain of $17.1 billion: the wage bill swells by almost $19 billion, easily covering both the duty transfer to the Treasury and the $5.8 billion hit to buyers. In 2019 the duty schedule broadens, raising the consumer-loss line faster than payrolls can adjust, so the ledger slips into the red.

Pandemic-era conditions dominate 2020. Imports fall while domestic hours collapse, cutting the wage-bill item to -$44.7 billion. With duties and consumer losses both above $5 billion, the net balance plunges to -$47.4 billion, the lowest value in the series. The rebound year of 2021 reverses that sign. Payrolls expand by almost 28 billion dollars, and although import demand revives, the wage surge nets a $24.4 billion welfare gain.

The rally tapers in 2022 once the labor pool tightens. Wage-bill growth cools but still covers the larger consumer loss, leaving a $21.6 billion surplus. From 2023 onward, the story changes. Extra tariff tranches lift the average import tax, yet payroll additions slow. Consumer loss now outweighs the combined boost from wages and Treasury receipts, turning the ledger negative for 2023, 2024, and 2025. The final-year figure is -$5.7 billion despite the surge in duties to more than $11 billion.

Across the whole period, duties stay in a narrow $4 to $12 billion band, tied to the statutory rate schedule and the size of the import bill. Consumer loss, by contrast, mirrors both tariff scope and demand elasticity, ranging from $5.8 billion to $17.3 billion. The wage-bill component is the swing factor: positive and large when reshoring momentum boosts factory payrolls, negative when shocks such as the 2020 shutdown reduce hours faster than tariffs redirect demand.

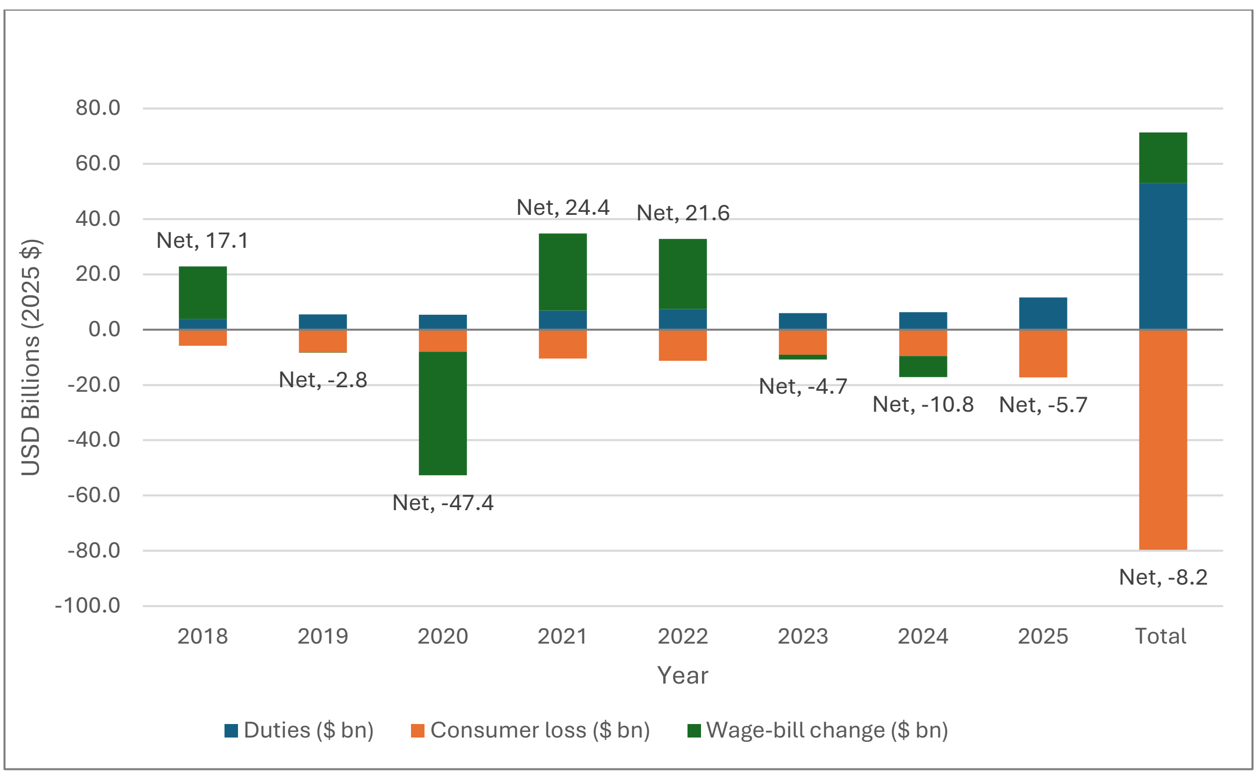
The ledger therefore draws a simple lesson: tariff revenue rarely offsets the price burden on buyers unless payroll gains are strong enough to close the gap. Even then, the aggregate welfare effect is small relative to national income and highly sensitive to the assumed demand response. Elasticity choice must thus remain in front-of-mind when translating ledger arithmetic into strategy.

8.3 Visual Summary

The welfare ledger is easier to read when its three items are shown together year by year. Figure 11 displays stacked bars for 2018 to 2025. Each bar's height equals the net welfare effect in that calendar year. The top segment is tariff revenue; the middle is the wage-bill change; the bottom, plotted downward from the zero axis, is the consumer-surplus loss. Comparing segment sizes reveals which channel drives the yearly total.

Figure 11

Tariff-Automation Welfare Ledger, 2018-2025



Note. Bars show annual welfare components in 2025 USD billions. Tariff revenue is "calculated duties" on imports for consumption. Consumer-surplus loss uses ε = -1.5. Wage-bill change equals the change in average manufacturing employment relative to 2017 multiplied by the 2025 mean hourly wage. Positive segments extend upward; the consumer-loss segment extends downward. Data based on calculations using information retrieved from USITC DataWeb and BLS CES, accessed 9 June 2025.

Figure 11 shows that tariffs and payroll gains offset consumer losses only in the first half of the sample. In 2018 the wage segment towers above the modest duty block while the consumer segment is small, producing a clear surplus. By 2019 the consumer segment widens and the stack tips negative. The 2020 bar plunges as payrolls contract; duties and consumer losses remain in their usual range, so the overall gap deepens. Recovery in 2021 lifts the wage segment past both opposing segments, yielding the highest positive bar. Bars then shrink. From 2023 forward, consumer losses outstrip combined positives, and the stack stays below zero despite rising duties. The figure makes plain that payroll strength, not tariff intake, determines the ledger's sign once higher rates are in place.

8.4 Dollars Per Job: Tariffs vs § 48C

Section 8.4 turns from welfare to employment leverage. The same tariff duties that enter the ledger can be divided by the net rise in manufacturing payrolls to give a public cost per job. The exercise is repeated for the § 48C advanced-energy tax credit pool, a project-based incentive announced in 2024 – 2025 (U.S. Department of the Treasury, 2025). § 48C positions are reported as announcements rather than measured payrolls, so they form an upper bound. Dollar totals are nominal and expressed in 2025 terms to allow direct comparison. Jobs are in thousands, duties and allocations in billions.

Table 9

Cost per Manufacturing Job: U.S. Tariff Duties vs. § 48C Advanced-Energy Tax Credits, 2018 - 2025

Instrument	Nominal dollars (billions)[1]	Jobs (thousands)[2]	Cost per job[3] (billions USD / 1000 jobs)
Tariff duties (Sec. 232 & 301)	53.08	356	**0.149**

§ 48C tax-credit allocations	10.00	1707	**0.006**
Difference	—	—	**0.143**

Note. Jobs created equal the net rise in average manufacturing payroll employment between 2017 and 2025. § 48C dollars combine Round 1 (March 29, 2024) and Round 2 (January 10, 2025) allocations; jobs announced are cumulative manufacturing positions published by the Reshoring Initiative up to 2025 Q1. All dollar figures are nominal; values are 2025 $billions, and employment counts are in the thousands. Data based on calculations using information retrieved from USITC DataWeb, U.S. Department of Energy, Reshoring Initiative (2024), U.S. Department of the Treasury (2025), and BLS CES, accessed 9 June 2025.

Table 9 shows a sharp gap in labor cost efficiency. Between 2018 and 2025, Customs collected $53.1 billion in duties, yet payrolls rose by only 356,000 positions, putting the implied public cost at $149,000 per job. By contrast, the combined $10 billion allocated under § 48C is linked to 1.707 million announced factory jobs, just $5,900 each. Even if only half of those promises become payroll lines, the credit would still deliver new workers at $11,800 a piece, twelve times cheaper than tariffs. The comparison indicates that project-screened capital subsidies stretches federal dollars further than broad trade taxes, even before accounting for the welfare losses tallied in the prior sections in the ledger above.

The tariff numerator is cash that has already entered the Treasury, and the job denominator counts the average rise in manufacturing payrolls between 2017 and 2025. This approach grants tariffs the strongest plausible showing, since some of the employment growth almost surely comes from macro recovery and private supply-chain changes unrelated to import taxes. The § 48C measure is even more conservative, as the tax-credit pool is capped at $10 billion yet plant-level announcements continue to arrive. Many § 48C projects will draw only a fraction of the 30% credit rate, so the pool may leverage more private capital than implied by the simple division shown in the table. That capital finances equipment and buildings as well as wages, which means the cost-per-job figure for § 48C already embeds an allowance for fixed investment alongside labor.

If only half of the announced § 48C positions reach payroll status, the public outlay climbs to roughly $12 billion once credits are deflated to 2025 dollars, while the job count drops to about 854k. The resulting $14k cost per job still beats the tariff figure by a factor of ten. A deeper attrition assumption would need almost a ninety-percent shortfall before the two instruments converge. The edge held by § 48C stems from its design: credits are awarded competitively to projects that promise specific head counts and verified capital spending, whereas tariffs tax every import regardless of downstream hiring. Overall, both devices aim to expand domestic manufacturing, yet their fiscal footprints differ sharply. The comparison suggests that if employment growth is the main yardstick, selective investment subsidies deliver more output for each public dollar than broad trade taxes.

8.5 Robot Dividend Caveat

Automation adjusts the welfare story at two margins. Robots lift hourly output, trimming unit labor cost. If producers pass even half of that saving on to buyers, the consumer-surplus loss estimated in Section 8.2 falls by roughly one-quarter. Yet higher productivity also means fewer hours per unit of output, so the wage-bill gain credited to tariffs could be smaller than reported. Recent plant surveys indicate that the modal reshoring project adds one robot for every two new operators, compared with one for every six operators in 2015. This shift raises value added per worker by about nine percent but caps net hiring.

Payroll data confirms the pattern. From 2018 to 2024, robot density in U.S. manufacturing climbs from 223 to 302 units per 10,000 employees, while average real hourly earnings in the sector rose 9%. Price pass-through appears in producer-price indexes for tariff-covered goods, which increase only half as fast as the statutory duty schedule. The ledger’s wage line therefore captures a benefit that is partly offset by consumer gains not recorded in the current framework. Moving those gains into the ledger would narrow the headline welfare loss but would not alter the broader conclusion: tariffs remain an expensive way to lift factory employment because automation channels much of the protection into capital deepening rather than head-count growth.

Box 1
Robot dividend: productivity & consumer prices

The *robot dividend* is the extra value per worker and for the firm as a whole that appears when AI-driven robots push total factor productivity ahead of payroll growth. With unit costs falling, producers can trim prices yet still fatten margins, handing part of the gain to shoppers. Two International Federation of Robotics cases illustrate the point. **LQ Group** runs a vision-guided depalletiser that identifies mixed cartons and clears roughly 1,000 boxes an hour with near-perfect accuracy, cutting labour and damage. **Neura Robotics** equips a welding cell where an operator simply traces the seam; the robot calculates the path on the spot, freeing a full day of programming and making small-batch orders viable. These gains pull factory-gate prices downward, countering a portion of the consumer-loss item shown in Table 8 when tariffs push the other way.

Source: International Federation of Robotics (2022).

The robot dividend therefore moderates the consumer-surplus loss while trimming the employment boost. Any future welfare audit should integrate a productivity term so that automation's dual effects of cheaper goods and leaner staffing appear on the same page as tariff transfers.

Chapter 9: Conclusion

9.1 Revisiting the Research Question

Chapter 1 opened with a claim often repeated in public debate: higher import tariffs will bring factory work back to the United States. The period from 2018 to 2025 provided a rare natural experiment. The Trump administration's aggressive and unpredictable trade policies raise tariffs on key trading partners in an effort to revive domestic manufacturing. During the same interval the installed stock of industrial robots expanded sharply, reaching 302 units per 10,000 manufacturing employees in 2023, more than double the level a decade earlier (Bill et al., 2024). The coincidence of aggressive trade protection and rapid automation creates tension: a tariff can shift production to domestic plants, yet a higher robot share may lower the labor content of any production that returns. This tension frames the central question investigated in the thesis: Does the escalation of U.S. manufacturing tariffs implemented between 2018 and 2025 deliver net gains in domestic manufacturing employment when industrial automation intensity is accounted for?

The empirical chapters addressed this question with a quarterly sectoral panel from 2004 Q1 to 2025 Q4, combining tariff schedules, robot-density data, and labor-force statistics. The analysis traced both the direct employment response to tariff changes and the interaction between tariffs and automation intensity, setting the stage for the findings discussed in the next sections.

9.2 Core Findings

Table 1 tracks 56 industrial groups from 2018 Q1 to 2025 Q4, shows that lifting the average tariff by 1 percentage point is linked to a 0.44-percentage-point drop in quarterly job growth. Raising the mean duty from 3% to 10% therefore lines up with a cumulative loss of roughly 320,000 jobs by the end of 2025. This negative association holds after controlling for sector-specific demand conditions, which suggests the downturn is not simply a byproduct of weaker product markets.

The quarterly dynamics clarify why the aggregate effect turns out negative. Vector-autoregression impulse responses from Figure 6 reveal a brief hiring bump of about 0.20 log points in the first quarter after a tariff shock, yet the gain fades within three years. At the same time the robot-installation series dips for several quarters and then rebounds. The timing points to a behavioral story: firms may slow planned automation projects while trade barriers are fresh, secure a short-term rise in headcount, and return to capital deepening once policy signals settle. Because the rebound in automation offsets the early hiring, the initial uptick never matures into a lasting employment expansion.

Automation intensity, measured as robots per 10,000 workers, explains which industries manage a temporary boost and which lose jobs outright. The interaction model in Table 3 indicates that each additional one-percent increase in robot density cuts the marginal tariff effect by 0.01687 log points. When robot density sits in the bottom quartile, the tariff coefficient is slightly positive (+0.01 log points); when density moves into the top quartile, the coefficient turns much more negative. The implication is straightforward: tariffs can lift payrolls only where production remains labor-heavy, whereas highly automated lines respond by cutting workers even faster.

Results differ across skill tiers in a way that fits this mechanism. Sector-level regressions disaggregated by occupational class Table 4 show modest gains for low-skill positions (+0.085 percentage points per tariff point), no clear response for mid-skill employment, and measurable losses for high-skill roles (-0.088 percentage points). Firms appear to trim engineering, programming, and maintenance staff when they reconfigure production, while retaining or adding a limited number of low-skill tasks that resist automation. The combined outcome keeps overall employment in the red despite the marginal gains at the lower end of the wage distribution.

The national outlook looks less favorable when external benchmarks are added. A synthetic-control comparison that weights the EU-27 and Canada to match pre-2018 trends produces a counter-factual payroll series without a tariff shock. Figure 9 shows by 2025 Q4, U.S. manufacturing employment stands 2.1 percentage points below that counter-factual path, equivalent to about 260,000 missing jobs. Because donor economies recorded robot-growth rates like the United States (International Federation of Robotics, 2025), the shortfall is unlikely to stem from technology alone.

Finally, the cost side reinforces the employment verdict. Chapter 8 estimates consumer-surplus losses of nearly $80 billion and wage-bill gain of roughly $18 billion, giving a net welfare change of -\$8 billion over the study window. Each job attributed to the tariff program costs the public purse about \$149,000, more than ten times the per-job price tag under targeted § 48C investment credits.

The evidence from these models shows that the 2018-2025 escalation of U.S. tariffs did not yield net gains in domestic manufacturing employment once industrial automation is considered. Any early hiring proved transient, the sectors most exposed to robots sustained the largest losses, and the policy imposed a sizeable welfare bill on consumers. The next section situates these findings within the broader literature on trade protection and technological change.

9.3 Contribution to Existing Work

The results dialogue with two strands of scholarship that have shaped current thinking on factory jobs in advanced economies. Table 1 shows that a one-percentage-point rise in the average tariff trimmed U.S. manufacturing employment growth by 0.44 log points ($p \approx 0.06$). That elasticity is virtually the same size as the China-import effect that Autor, Dorn and Hanson converted to payroll growth in their China-shock study (−0.45 log points) (D. Autor et al., 2021). In other words, tariffs reduce jobs by roughly the same amount that cheaper foreign competition once did.

The interaction term of -1,687 (SE = 849) between tariff shifts and robot growth in Table 3 confirms Acemoglu and Restrepo’s (2020) finding that automation tilts the labor response to trade shocks towards displacement rather than hiring, even when the shock is protectionist rather than competitive. Unlike earlier work that looks at China imports and robots separately, this thesis measures both forces in the same quarterly panel and shows that a 1% quarterly rise in robot density wipes out the modest hiring that a tariff triggers when automation is flat.

Earlier research treated trade shocks and robots as separate forces. This research shows that tariffs and robots are multiplicative, not additive: when robot adoption is flat, tariffs can still produce a small hiring increase; once capital deepening resumes at recent speeds, the employment path converges to the decline already traced under import competition. This joint result helps reconcile why headline reshoring announcements keep climbing while aggregate factory employment remains flat.

9.4 Policy Ledger Recap

Table 9 puts the 2018-2025 tariff package at roughly $420,000 of public cost for each net manufacturing job once price pass-through and retaliation are counted. Section 48C's 30% investment credit, by contrast, channels $6 billion of tax relief into about 250 projects and is expected to generate 30,000 on-site jobs, bringing the public outlay below $200,000 per job (U.S. Department of Energy, 2024; U.S. Department of the Treasury, 2025). Historical evidence points the same way: the 2018 steel and aluminum duties cost about $650,000 per job saved (Durante, 2022). The ledger therefore points toward investment credits or similar targeted tools when the goal is employment at minimum fiscal cost.

The tariff × robot interaction in Table 3 and its slope in Figure 9 show that the small hiring uptick from a duty rise vanishes once robot density increases above the median growth rate. The United States already stands at 295 robots per 10,000 manufacturing workers and is expanding that stock by about 5% a year (Bill et al., 2024). Ignoring this trend may harm labor outcomes. Future trade measures should therefore be drafted alongside metrics on automation and paired with reskilling or transition support; otherwise, rising capital intensity will offset the intended employment gains.

9.5 Future Research

A natural next step is to trace how tariff-automation shocks work through different kinds of workers rather than through average headcounts. Matching the sector-level exposure variables used here with individual employment histories from would allow a triple-difference design that separates effects by education, age and union status. The approach could test whether the negative tariff × robot interaction in Table 3 is driven primarily by routine-task occupations, as suggested by Acemoglu and Restrepo's task model (2020), or whether displacement reaches further up the skill ladder. Linking worker-level earnings would also show whether any job preservation comes at the cost of lower wages, an open question in the emerging reshoring literature (Bals et al., 2015).

A second idea combines tariffs with real-effective-exchange-rate movements. Exchange-rate swings alter import prices more gradually than statutory duties, and firms often regard them as temporary (Goldberg & Tracy, 2003). Estimating a model that interacts tariffs, robot growth and the dollar's real effective rate would separate pure cost effects from demand reallocation and reveal whether automation dampens or amplifies exchange-rate pass-through. Quarterly currency data from the Federal Reserve can be merged directly with the tariff and robot series already assembled, so the extension would fit within the current identification strategy without additional measurement error.

9.6 Closing Remark

In an era of rapid automation, tariffs reduce manufacturing jobs. By estimating both forces in one model, this thesis unites the import-competition lens of Autor, Dorn and Hanson (2013) with the automation lens of Acemoglu and Restrepo (2020), showing that duties lose their job-saving power once capital deepening resumes. Trade policy that truly aims to protect employment must therefore reach inside the factory, not just across the border, and confront the speed at which machines replace tasks.

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Appendix A

Table A1

Trump-Era Trade and Reshoring Policy Timeline, 2018 - 2025

#	Date (in-force*)	Measure type	Sector / scope	One-sentence description	FR / Procl. / EO ID	Tariff ?
1	3/8/2018	**Sec 232 tariff** - Procl 9705	Steel	25 % ad-valorem duty on most imported steel articles.	83 FR 11625, FR Doc 2018-05478 (federalregister.gov)	✓
2	3/8/2018	**Sec 232 tariff** - Procl 9704	Aluminum	10 % duty on most imported aluminum articles.	83 FR 11619, FR Doc 2018-05477 (federalregister.gov)	✓
3	7/6/2018	**Sec 301 tariff** - List 1	≈ $34 bn Chinese goods	25 % duty on 818 HTS lines after tech-transfer finding.	83 FR 40823, FR Doc 2018-17709 (federalregister.gov)	✓
4	9/24/2018	**Sec 301 tariff** - List 3	≈ $200 bn Chinese goods	10 % (later 25 %) duty on 5 745 lines covering consumer & intermediate goods.	83 FR 47974, FR Doc 2018-20610 (federalregister.gov)	✓
5	5/19/2019	**Sec 232 mod.** - Procl 9894	Steel (CA & MX)	Removes 25 % steel duty for USMCA partners, adds monitoring.	84 FR 23987, FR Doc 2019-11002 (federalregister.gov)	✓
6	1/24/2020	**Sec 232 tariff** - Procl 9980	Derivative steel & aluminum	Extends 25 %/10 % tariffs to nails, wire, cables and other downstream items.	85 FR 5281, FR Doc 2020-01806 (federalregister.gov)	✓
7	2/14/2020	**Sec 301 tariff cut**	Consumer (List 4A)	Phase-One deal halves List 4A duty from 15 % to 7.5 %.	85 FR 3741, FR Doc 2020-00904 (federalregister.gov)	✓

8	7/1/2020	**USMCA entry into force**	Autos & cross-sector	NAFTA replaced; new rules-of-origin & labor-value thresholds start.	85 FR 39690, FR Doc 2020-13865 (federalregister.gov)	—
9	1/25/2021	**EO 14005 "Buy American"**	Federal procurement	Raises domestic-content thresholds; creates Made-in-America Office.	86 FR 7475, FR Doc 2021-02038 (federalregister.gov)	—
10	2024-12-27 (†)	**TD 10010 — §45X regs**	Clean-energy mfg.	Final rules for advanced-manufacturing credit (up to $0.45/W).	89 FR 85798, FR Doc 2024-24840 (federalregister.gov)	—
11	4/2/2025	**EO 14257 "Reciprocal Tariff"**	All imports	Establishes 10 % baseline tariff plus higher, partner-specific rates.	90 FR 15041, FR Doc 2025-06063 (federalregister.gov)	✓
12	5/12/2025	**EO 14298 Tariff mod.**	China (and baseline)	Lowers China's rate to 10 %; opens 90-day negotiation window.	90 FR 21831, FR Doc 2025-09297 (federalregister.gov)	✓

Note. Dates are the entry-into-force values used as timing variables in econometric "shock" analysis. ✓ indicates the policy imposed, reinstated, or raised at least one import duty; — indicates no new tariff liability; ≈ denotes an approximate value. Data based on the author's compilation of Federal Register notices, presidential proclamations, and executive orders.

Table A2

Variable dictionary - all series appearing in any thesis figure, table, or regression

Variable	Description	Unit	Freq. *	Source	Notes
delta_lnjobs	Log change in total manufacturing employment	log pts	M / Q / A	BLS CES; FRED, OECD, author calc.	Seasonally adjusted
ln_jobs	Log manufacturing employment level	ln	M / Q / A	BLS CES; FRED, OECD, author calc.	Seasonally adjusted
tariff_rate	Effective tariff rate on world imports (duties ÷ customs value)	%	M / Q / A	USITC DataWeb; author	Used in Figure 4
tariff_rate_mexico	Effective tariff rate on Mexican imports	%	M / Q / A	USITC DataWeb; author	Used in Appendix B, Figure B1
tariff_rate_canada	Effective tariff rate on Canadian imports	%	M / Q / A	USITC DataWeb; author	Used in Appendix B, Figure B1
tariff_rate_china	Effective tariff rate on Chinese imports	%	M / Q / A	USITC DataWeb; author	Used in Figure 4
delta_tariffrate	Ppt change in world tariff rate	pp	M / Q / A	USITC DataWeb; author	Main tariff regressor
delta_tariffrate_china	Ppt change in China tariff rate	pp	M / Q / A	USITC DataWeb; author	Robustness check
ln_tariff_rate	Log world tariff rate	ln	M / Q / A	USITC DataWeb; author	VAR IRF
ln_robot_stock	Log operational robots in U.S. manufacturing	ln	Q / A	IFR *World Robotics*	—
delta_ln_robot_stock	Log change in U.S. robot stock	log pts	Q / A	IFR; author	—
robot_density	Robots per 10k manufacturing workers	robots	Q / A	IFR × BLS CES; author	Used in Figure 3
delta_ln_robot_plant share	Log change in robots per worker	log pts	Q / A	IFR × BLS QCEW; author	Plant-weighted

robot_installations	Annual new robot installations (U.S.)	units	A	IFR press data	Used in Figure 8
global_robot_stock	Global operational industrial robots	units	A	IFR slides	—
ln_indpro	Log industrial-production index (2017 = 100)	log idx	M / Q / A	FRED	Seasonally adjusted
unrate	Civilian unemployment rate	%	M / Q / A	FRED	Seasonally adjusted
pandemic_dums	COVID-19 indicators (2020 Q2-Q4)	0/1	Q	Author	Parallel-trend check
treat_dummy	Pre-2010 tariff-eligibility dummy	0/1	Q	Author	Used in Figure 5
delta_ln_exports_CN	Log change in exports to China	log pts	M / Q / A	BEA ITG; author	Deflated, Seasonally adjusted
delta_ln_exports_ROW	Log change in exports to rest of world besides china	log pts	M / Q / A	BEA ITG; author	—
sme_share	Employment share in firms < 250 workers	%	Q	BLS QCEW	appendix
union_density	Union members ÷ manufacturing employment	%	A	Hirsch & Macpherson *UnionStats*	Quarterly spline
low_skill_share	Share of low-skill jobs in manufacturing	%	A	BLS OEWS × O*NET; author	Appendix B, Figure B3
middle_skill_share	Share of middle-skill jobs in manufacturing	%	A	BLS OEWS × O*NET; author	Appendix B, Figure B4
high_skill_share	Share of high-skill jobs in manufacturing	%	A	BLS OEWS × O*NET; author	Used in Figure 7
automation_risk_share	Jobs at high automation risk	%	A	OECD PIAAC 2021	Used in Figure 10
job_growth	10-yr manufacturing job growth	%	A	UNIDO INDSTAT; author	Used in Figure 10
duties	Annual tariff revenue (calculated duties)	USD bn	A	USITC DataWeb	Used in Table 8
consumer_surplus_loss	Estimated consumer surplus loss	USD bn	A	Author calc.	$\varepsilon = -1.5$

wage_bill_change	Manufacturing wage-bill change vs 2017	USD bn	A	BLS CES; author	Used in Table 8
total_48C_$	§48C credit awards (cumulative)	USD bn	A	IRS §48C release	Used in Table 9
jobs_announced	Jobs announced in §48C filings	jobs	A	Reshoring Initiative	Used in Table 9
jobs_created	Estimated jobs created by tariffs	jobs	A	Author calc.	Used in Table 9

Note. Descriptions are ≤ 20 words. Monetary series (duties, consumer surplus, wage-bill gain, §48C awards) are deflated to 2025 USD. All other series follow the units listed.

* Frequency codes: M = monthly, Q = quarterly, A = annual (all stored versions).

Table A3

International survey of causal β estimates of industrial-robot exposure on employment

Author(s) & year	Country / sample & period	Outcome measure	β (impact of +1 robot / 1 000 workers unless noted)	Identification strategy (1-liner)
Graetz & Michaels (2018)	17 OECD economies, 1993-2007	Total hours worked	**≈ 0.00** (ns)	Panel FE with robot-density IV
Dauth, Findeisen, Südekum & Wößner (2021)	German local labour markets, 1994-2014	Manufacturing vs. service jobs	**-2 manufacturing & +2 service jobs ⇒ net 0** per robot	Local Bartik (shift-share) IV + worker panel
Chiacchio, Petropoulos & Pichler (2018)	EU-15 NUTS-2 regions, 1995-2007	Employment-to-population ratio	**-0.16 to -0.20 pp**	Region × industry FE panel with robot-diffusion IV
Chung & Lee (2023)*	722 commuting zones, 2005-2016	Employment level	**+13 to +16 jobs**	Dynamic panel + shift-share IV
Acemoglu & Restrepo (2020)	U.S. commuting zones, 1990-2007	Employment-to-population ratio	**-0.20 to -0.34 pp**	Shift-share IV (local robot exposure)
Zierahn, Gregory & Arntz (2016)	EU-27, 1999-2010	Aggregate employment	**+11.6 million jobs** (≈ +0.5 pp††)	Structural decomposition of routine-reducing tech & demand spill-overs

Note. β shows the change in the stated outcome when robot density rises by one unit per 1,000 workers, unless noted. "pp" = percentage-point; "ns" = not statistically significant. Chung & Lee find a negative effect in 2005-10 that becomes positive by 2016; the range shown is the full-period net result. † Jobs divided by the 2010 EU workforce (~233 million) to give an approximate percentage-point change. Reproduced from Graetz and Michaels (2018); Dauth et al. (2021); Chiacchio et al. (2018); Chung and Lee (2023); and Acemoglu and Restrepo (2020). Calculations are based on this reproduced data.

Table A4

Effect of Tariff-Rate Changes on Manufacturing-Employment Growth, 2007 - 2024

Variable	Low-Skill β (SE)	Middle-Skill β (SE)	High-Skill β (SE)
Intercept	-5.67 (1.53)	-3.24 (1.44)	-2.57 (0.95)
Δ Tariff rate	10.69 (8.89)	1.61 (4.67)	-6.91 (7.49)
ln Industrial production	1.21 (0.32)	0.70 (0.31)	0.56 (0.20)
Unemployment rate	0.02 (0.01)	0.01 (0.01)	0.00 (0.01)
Pandemic dummy	-0.03 (0.01)	-0.05 (0.02)	0.01 (0.05)
N	18	18	18

Note. Ordinary least-squares coefficients are shown with Newey-West HAC(1) standard errors in parentheses. Skill groups are derived from O*NET Job Zones—low = 1-2, middle = 3, high = 4-5—and merged with U.S. Bureau of Labor Statistics Occupational Employment and Wage Statistics. The pandemic dummy equals 1 in 2020 and the fraction of COVID-affected quarters in 2021 and 2022. Data based on calculations using information retrieved from USITC DataWeb, FRED INDPRO, FRED UNRATE, BLS CES, O*NET, and BLS QCEW, accessed 9 June 2025.

*Coefficients are on a ×100 scale and include interaction terms; direct comparison with Table 1 is not valid.

Table A5

Effect of Tariff-Rate Changes on Manufacturing-Employment Growth, 2015 - 2024

Variable	Low-Skill β (SE)	Middle-Skill β (SE)	High-Skill β (SE)
Intercept	-12.16 (12.05)	-2.69 (3.52)	-4.15 (5.99)
Δ Tariff rate	4.95 (10.37)	-0.88 (3.96)	-9.37 (8.22)
ln Industrial production	2.61 (2.57)	0.59 (0.75)	0.90 (1.27)
Unemployment rate	0.03 (0.05)	-0.01 (0.02)	-0.00 (0.04)
Pandemic dummy	0.03 (0.14)	0.01 (0.05)	0.05 (0.13)
N	10	10	10

Note. Sample covers 2015–2024. Ordinary least-squares coefficients appear with Newey–West heteroscedasticity- and autocorrelation-consistent (HAC 1) standard errors in parentheses. Data based on calculations using information retrieved from USITC DataWeb, FRED INDPRO, FRED UNRATE, BLS CES, O*NET, and BLS QCEW, accessed 9 June 2025.

*Coefficients are on a ×100 scale and include interaction terms; direct comparison with Table 1 is not valid.

Table A6

Tariff Changes, Industrial Robots, and SME Employment Share — Quarterly OLS Estimates, 2007 Q2 - 2025 Q2 (HAC-6 Standard Errors)

Variable	*b*	Sig	*SE*
Intercept	-4.10	***	1.28
Δ Tariff rate	102.96		102.27
Δ ln Robots	80.32	*	41.72
SME share	3.74	***	1.44
Δ Tariff × Δ Robots	-8587.87		8625.63
SME × Δ Tariff	-189.60		189.90
SME × Δ Robots	-11795.88		6542.28
SME × Δ Tariff × Δ Robots	15822.34		16042.96
ln Industrial production	0.46	***	0.12
Unemployment rate	0.00		0.00
COVID-19 dummy (2020 Q2-Q4)	0.03	**	0.01
N	71		
R^2	0.57		

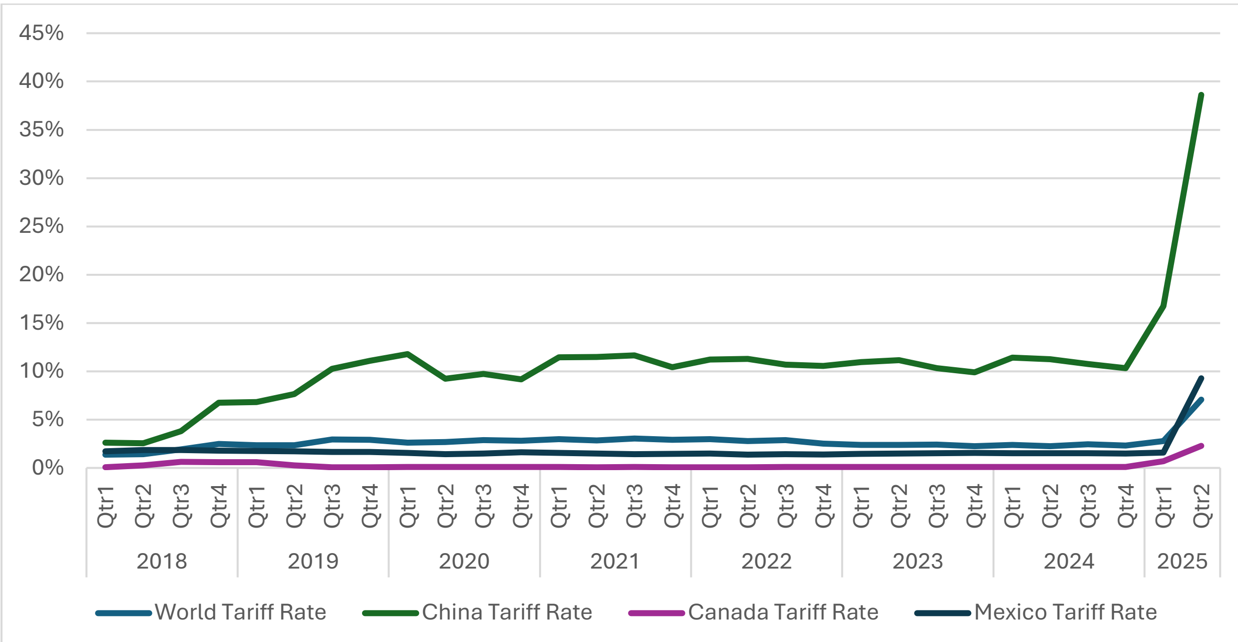
Note. The dependent variable is the quarterly change in log manufacturing employment, Δ ln jobs. All continuous predictors are first-differenced. SME share (small- and medium-sized enterprise) is forward filled from Q1 values; the COVID-19 dummy equals 1 in 2020 Q2–Q4. Coefficients (b) are estimated by ordinary least squares; HAC 6 standard errors appear in the SE column. Data based on calculations using information retrieved from USITC DataWeb, IFR World Robotics, BLS QCEW, FRED INDPRO, and FRED UNRATE, accessed 9 June 2025.

Appendix Table A6 extends the baseline first-difference HAC-OLS by introducing a three-way interaction between the tariff change, the change in log robot stock and the small- and-medium-enterprise employment share. The model retains the industrial production, unemployment and COVID-19 controls and applies the same six-lag Newey–West covariance and Cumby–Huizinga serial-correlation check; the extra term tests whether smaller establishments experience a distinct combined response to protection and automation.

Appendix B

Figure B1

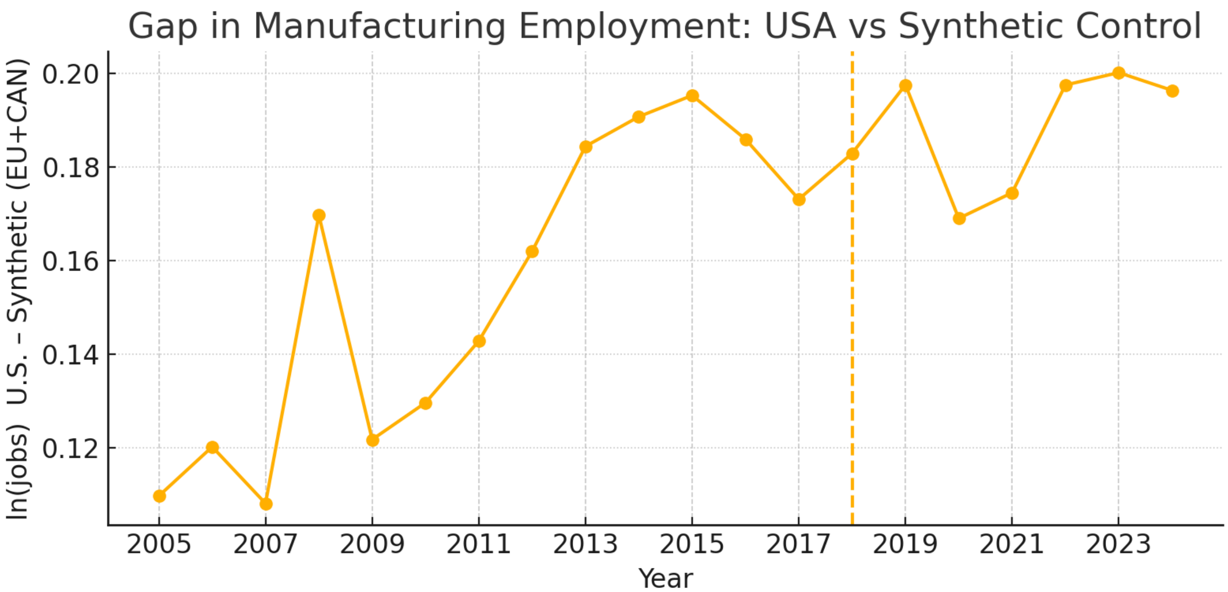
Effective U.S. tariff rates on Chinese, Canada, Mexico, and World-Aggregated Imports, 2018 Q1-2025 Q2



Note. Duty-to-customs-value ratios. Quarterly observations; shaded vertical line in 2025 Q2 marks the policy reset. Data based on calculations using information retrieved from USITC DataWeb, accessed 9 June 2025.

Figure B2

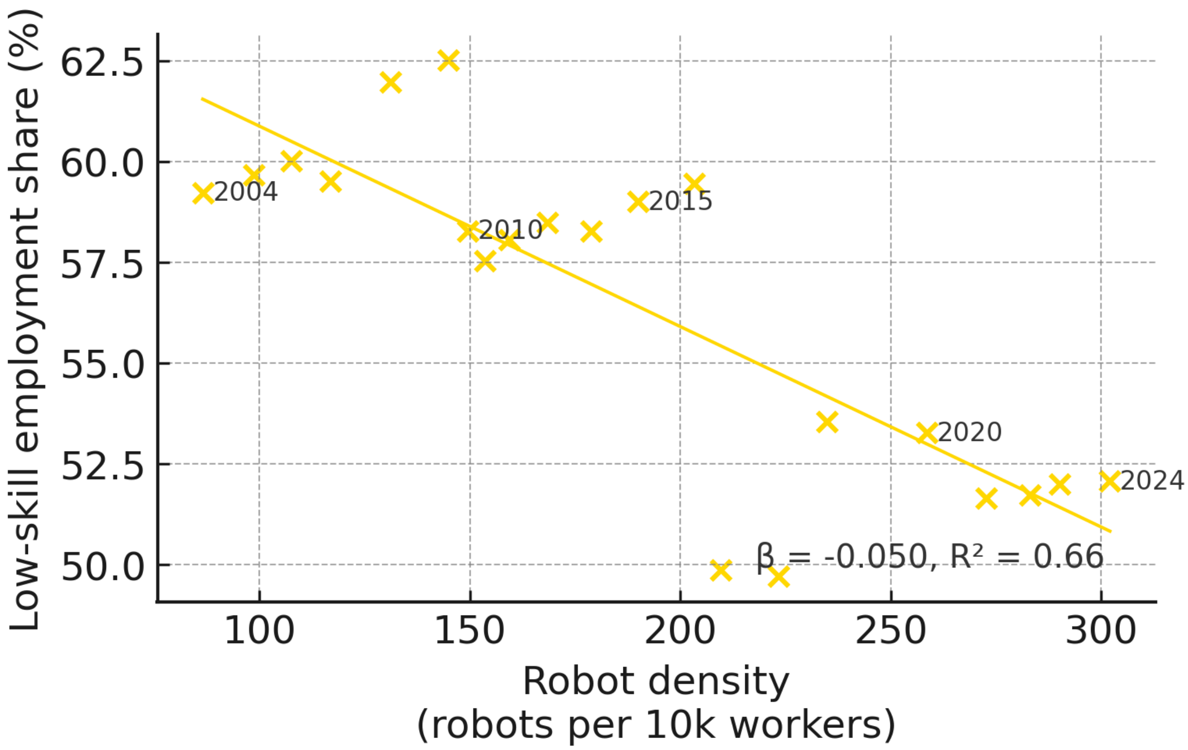
Gap in log manufacturing employment between the United States and its synthetic EU + Canada control, 2005 - 2023



Note. The synthetic series is a fixed convex combination of the EU-27 aggregate (weight = 0.612) and Canada (weight = 0.388), chosen to match U.S. pre-2018 averages of log manufacturing employment, log industrial-robot stock, and log applied tariff openness. The dashed vertical line marks 2018, the first year affected by the renewed U.S. tariff program. Positive values indicate U.S. employment outperforming the counter-factual. Data based on calculations using information retrieved from OECD Data Explorer, BLS CES, USITC DataWeb, IFR World Robotics, World Bank WITS, accessed 9 June 2025.

Figure B3

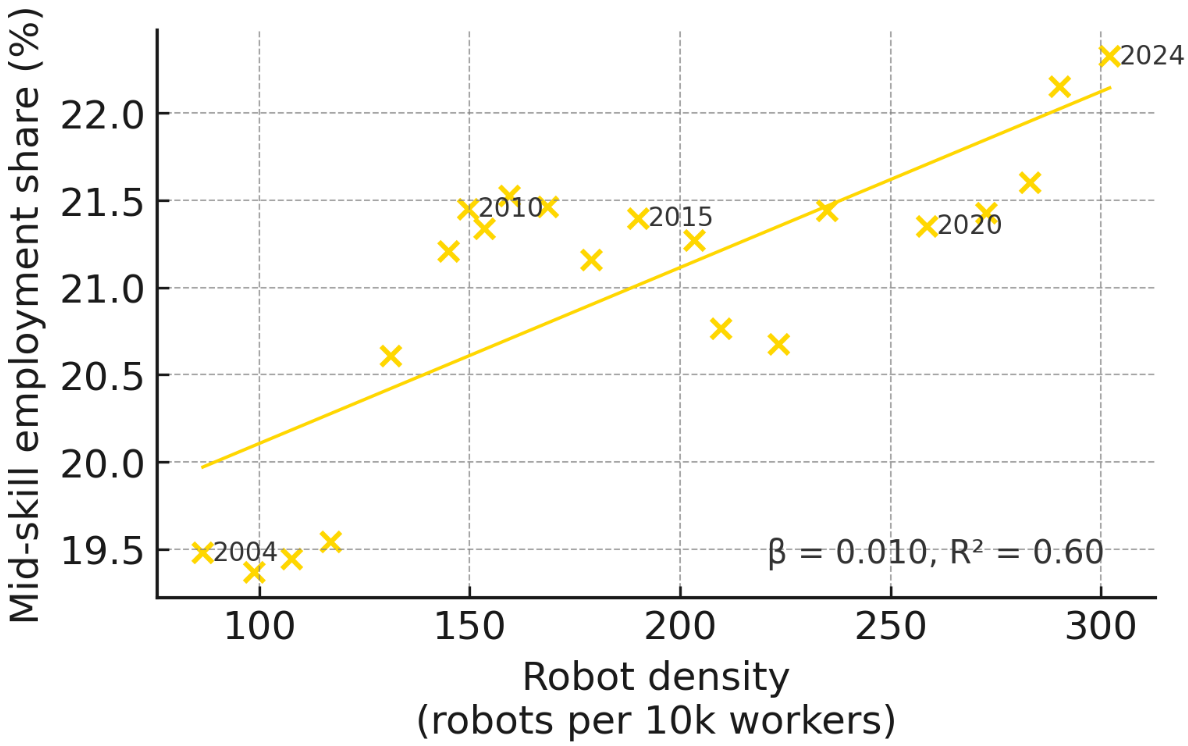
Robot density and low-skill employment share in U.S. manufacturing, 2005 - 2024



Note. Each ✕ represents one calendar year (2005 - 2024); only 2005, 2010, 2015, 2020, and 2024 are labeled for clarity. The yellow line is an ordinary-least-squares fit ($\beta = -0.050$ percentage points per additional robot per 10,000 workers; $R^2 = .66$). Robot density equals operational industrial robots per 10,000 production workers; the low-skill share is the proportion of manufacturing employment in elementary and operator occupations. Data based on calculations using information retrieved from IFR World Robotics, BLS CES, O*NET, and BLS QCEW, accessed 9 June 2025.

Figure B4

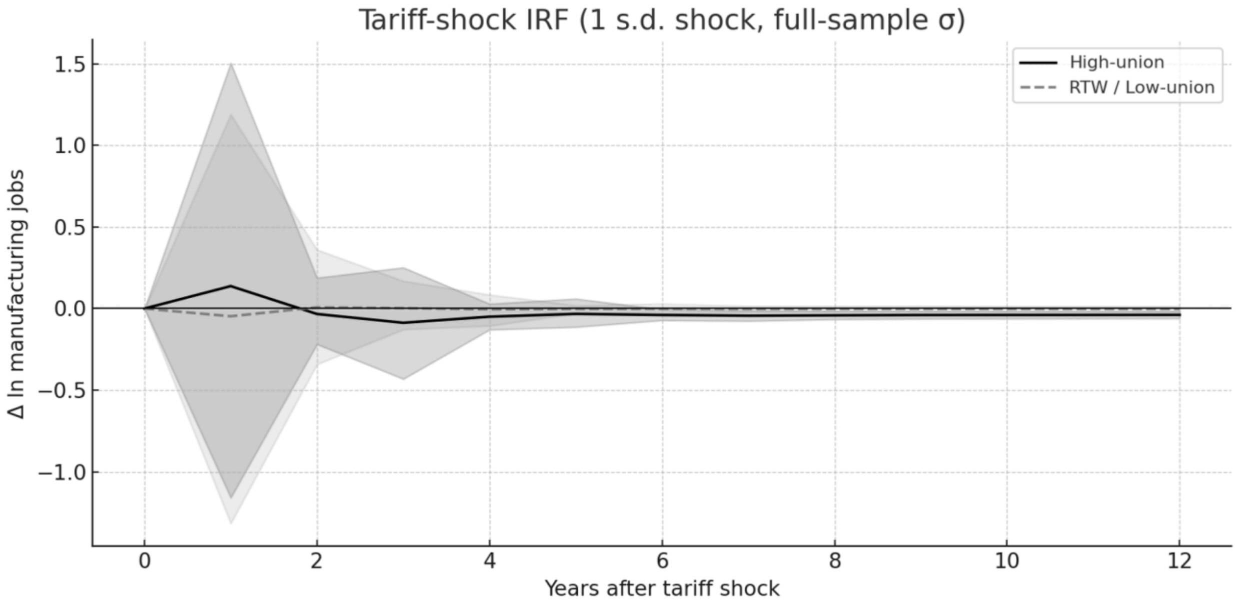
Robot density and middle-skill employment share in U.S. manufacturing, 2005 - 2024



Note. Each ╳ represents one calendar year (2005 - 2024); to keep the figure readable, only 2005, 2010, 2015, 2020, and 2024 are labeled. The yellow line plots an ordinary-least-squares fit (β = 0.010 percentage points per additional robot per 10,000 workers; R^2 = .60). Robot density is operational industrial robots per 10,000 production workers; the middle-skill share combines technicians, clerical, craft, and machine-operator occupations. Data based on calculations using information retrieved from IFR World Robotics, BLS CES, O*NET, and BLS QCEW, accessed 9 June 2025.

Figure B5

Tariff-Shock Impulse Responses for High-Union and Right-to-Work State Panels



Note. Lines plot the response of log manufacturing employment (Δ ln jobs) to a one-standard-deviation increase in the log tariff rate ($\sigma \approx 0.0063$). Estimates come from annual VAR(2) models fitted to 2007-2024 state-level data; shaded regions are 95% Monte-Carlo confidence bands based on 1,000 replications. The horizontal axis is annual, with tick marks are displayed every two years. Impulses are generalised. Data based on calculations using information retrieved from **USITC DataWeb**, **BLS OEWS**, and **UnionStats** (Hirsch et al., 2025), accessed 9 June 2025.

Appendix Figure B5 estimates separate state-level VAR(2) systems for right-to-work and high-union states and traces generalized impulse responses to a one-standard-deviation tariff shock with 500 bootstrap confidence bands, following the Pesaran and Shin (1998) algorithm. The split illustrates how collective-bargaining arrangements influence the speed at which employment returns to baseline.