

Global Trade, Local Jobs, and the Rise of Trump 1.0

Jiatao Liu, Jun Pan and Yang Ye*

First draft: July 31, 2026. Current draft: October 24, 2026

Abstract

This paper examines how the uneven distribution of globalization’s benefits and costs across local economies contributed to the rise of Trump 1.0. Central to our analysis are two opposing local economic experiences of globalization: efficiency gains from global sourcing and job losses from manufacturing dislocations. Focusing on the two-party pro-Republican vote share (R-Vote), we document a substantial shift toward Trump in 2016 among counties with less participation in global sourcing (IM = imports/GDP), and counties more dependent on manufacturing employment (L-Share = manufacturing share of local employment). Interestingly, L-Share measured in the 1970s-80s – well before the China Shock – predicts this pro-Trump shift, reflecting globalization’s long shadow. The effects are economically large: a one-standard-deviation cross-county difference in IM and L-Share is associated with a 0.74% and 1.29% shift in R-Vote, respectively. Aligning the IM and L-Share effects by industry, we further document a striking alignment of the benefits (e.g., electronics) and costs (e.g., steel) of globalization. Overall, the 2016 election is unique in that the globalization-related divide – global trade and local jobs – drives the most significant pro-Republican shift than any other elections from 2008 to 2024. The ensuing political realignment persisted through 2024, marking 2016 as a distinct political turning point.

*Liu (Jiatao.Liu@xjtlu.edu.cn) is from International Business School Suzhou at Xi’an Jiaotong-Liverpool University and Pan (junpan@saif.sjtu.edu.cn) and Ye (yye.23@saif.sjtu.edu.cn) are from Shanghai Advanced Institute of Finance at Shanghai Jiao Tong University. We benefit from comments and discussions with Ran Guo, Yongxiang Wang, Shang-Jin Wei, Dong Yan, Eyüb Yegen, Xiao Zhao, and seminar participants from the 2026 Taiyuan Conference.

1 Introduction

Opposition to globalization was a central theme of Trump’s 2016 presidential campaign. In his signature economic policy speech, “*Declaring America’s Economic Independence*,” delivered in Monessen, Pennsylvania, Trump lamented the discontent with globalization. “*Globalization has made the financial elite who donate to politicians very wealthy. But it has left millions of our workers with nothing but poverty and heartache.*” Blaming globalization for lost jobs, Trump promised to restore manufacturing through trade protection.¹

On the ground, at the local county level, the U.S. voters entered the 2016 election with two opposing experiences of globalization, shaped by decades of industrial adjustment and uneven participation in global sourcing. Amid deepening integration into global supply chains beginning in the early 1990s, the U.S. economy underwent a sustained transition away from labor-intensive industries. Counties that remained heavily dependent on manufacturing employment bore the costs of manufacturing job losses, while counties that emerged as leaders in globalization benefited from their integration into global supply chains. From this perspective, Trump’s choice of Monessen was emblematic – once a thriving steel town, it had experienced decades of industrial decline and population loss.² His protectionist agenda tapped right into this group of voters and their discontent with globalization, seeded as far back as in the 1970s and 1980s. In essence, while the U.S. economy as a whole benefited substantially from globalization, its uneven domestic distributions of gains and losses powered Trump 1.0.

In this paper, we focus on the two-party pro-Republican vote share (R-Vote) at the county level to document the extent to which the globalization-related divide drove the pro-Republican shift in 2016. Tracking the post-2016 presidential elections, we further examine the persistence of this political realignment engendered by Trump 1.0. Central to our analysis are two opposing local economic experiences of globalization: efficiency gains from global trade and job losses from manufacturing dislocations. To capture the two opposing county-level experiences, we measure a county’s participation in global trade by its total import-to-GDP ratio (IM), and its dependence in manufacturing employment by the manufacturing share of its local employment (L-Share). Our main empirical results can be summarized along the following three segments: (1) the benefits of global participation; (2) the costs of local jobs; and (3) the interaction of benefits and costs.

Global Trade (IM) – We begin with the benefit side of globalization: local participation in global sourcing. Access to foreign suppliers can lower input costs and broaden the range

¹See Donald J. Trump’s June 28, 2016, [Remarks in Monessen, Pennsylvania](#).

²The irony is that Monessen lost its steel mills in the 1970s and 1980s to more efficient factories in other parts of the country – not killed by China or imports.

of inputs available to domestic firms, creating new opportunities for production (Aghion et al., 2024; Amiti and Konings, 2007; Goldberg et al., 2010). To capture this dimension of globalization across U.S. counties, we draw on shipment-level bills of lading from S&P Global Panjiva and construct the import-to-GDP ratio, IM, as the value of imports recorded for firms in each county scaled by county GDP. IM thus measures realized participation in global sourcing and distribution, identifying local economies more closely connected to foreign supply. Trump’s 2016 campaign, centered in part on restricting imports and protecting domestic manufacturing, brought these economic interests into sharper political focus. Our central question is whether participation in global sourcing emerged as a distinct political divide in the 2016 pro-Republican shift.

Grouping counties by their pre-election IM reveals a pronounced divide in the 2016 pro-Republican shift – one that stands out across elections from 2008 to 2024. Pro-Republican vote share rose by 7.4% in the lowest-IM counties, compared with 4.2% in the highest-IM counties, a gap of about 3.1% in $\Delta R\text{-Vote}$, the change in pro-Republican vote share from the previous presidential election. Election-specific regressions reinforce this distinction: a one-standard-deviation higher IM is associated with a 0.74% smaller Republican shift in 2016, the most negative IM relationship across the 2008–2024 elections. In Trump’s first election, counties more deeply engaged in global sourcing thus exhibited their strongest relative anti-Trump tilt, moving less toward the Republican candidate.

Consistent with the 2016 cross-sectional divide between high- and low-IM counties, the county panel reveals a lasting change when we separate elections into two political regimes – 2008–2012 and 2016–2024. The relationship between IM and pro-Republican vote share ($R\text{-Vote}$) becomes 0.51% more negative per standard deviation of IM in the post-2016 regime. The economic tension is clear: as the Republican Party under Trump turned toward protectionism, its trade agenda came into conflict with the sourcing interests of local economies more deeply connected to foreign suppliers. This partisan divide persisted through 2024, marking 2016 as a political turning point in the politics of globalization, when participation in global sourcing acquired lasting partisan significance.

Local Jobs (L-Share) – The gains from global sourcing have come alongside substantial costs for American manufacturing communities. Import competition has generated persistent employment losses in exposed U.S. labor markets (Autor et al., 2013; Pierce and Schott, 2016), while technological change and broader industrial restructuring have further reshaped manufacturing employment (Fort et al., 2018). Yet job losses tell only part of the story. In many counties, manufacturing jobs that remain still anchor local livelihoods. We capture this continuing dependence through the L-Share – manufacturing employment divided by total county employment – which measures how much of the local workforce still relies on manufacturing. Trump’s 2016 promise to protect domestic manufacturing and bring

back jobs thus spoke to economic concerns whose importance varied considerably across communities. We ask whether counties where manufacturing remained more central to local employment shifted more strongly toward the Republican candidate in 2016.

For all its importance to local livelihoods, manufacturing dependence had left only a modest imprint on presidential vote swings before 2016. The difference in ΔR -Vote between counties in the highest and lowest L-Share groups was small in 2008 and virtually absent in 2012. This changed sharply in 2016, when Trump placed the protection and restoration of American manufacturing jobs at the center of his campaign. Counties in the highest L-Share group shifted 8.3% toward the Republican candidate, compared with 4.5% in the lowest group – a gap of 3.8%, the largest across the 2008–2024 elections. The longer electoral record makes 2016 stand apart: across eight presidential elections from 1996 to 2024, the positive relationship between manufacturing dependence and the Republican vote swing peaks in 2016, when a one-standard-deviation higher L-Share is associated with an additional 1.29% shift toward the Republican candidate. Manufacturing employment concerns that had shaped local economic life for generations thus acquired new electoral force in Trump’s first election.

The pronounced manufacturing-related Republican shift in 2016 raises a broader question: did the rise of protectionism in national politics give manufacturing dependence lasting additional weight in partisan competition? To examine this, we compare the relationship between L-Share and pro-Republican vote share (R-Vote) in 2008–2012 with that in 2016–2024. We find that the L-Share – R-Vote relationship becomes 1.01% more positive per standard deviation of L-Share from 2016 onward. Manufacturing dependence already carried a pro-Republican association before Trump, but its political weight increased sharply with his first election and remained elevated through 2024. This lasting realignment is consistent with a broader change in the politics of globalization, as protectionism moved to the center of electoral competition and manufacturing dependence became a more consequential source of partisan division.

Trump’s 2016 campaign placed foreign trade at the center of the debate over America’s declining manufacturing employment. Yet the erosion of manufacturing’s role in the U.S. economy was decades in the making. As documented by the U.S. Bureau of Labor Statistics, manufacturing’s share of U.S. nonfarm employment fell from 22% in 1979 to just 9% in 2019 (Harris, 2020). While manufacturing receded nationally, it continued to anchor employment in many local economies. We therefore ask whether manufacturing dependence established decades before Trump’s first election also predicts the political realignment beginning in 2016. Tracing the L-Share back to 1975, we find that a one-standard-deviation higher manufacturing employment share predicts a 0.41% more positive relationship with pro-Republican vote share in 2016–2024 relative to 2008–2012. The same positive change emerges for L-Shares

measured throughout 1975–2015. The political turning point came in 2016, but the economic concerns it brought to the forefront had roots stretching back four decades, revealing the long shadow of manufacturing dependence in the politics of globalization.

Interaction of Global Trade and Local Jobs – Trump’s protectionist agenda exposed a tension at the heart of globalization. Shielding domestic manufacturing from foreign competition could also threaten access to the foreign supplies on which U.S. production increasingly relied. With IM and L-Share pointing in opposite partisan directions, a further question emerges: where did manufacturing dependence acquire greater pro-Republican weight after 2016 – in counties with limited participation in global sourcing or those deeply connected to global trade?

The county-level interaction reveals an intriguing dimension of Trump’s manufacturing-related political realignment. In low-IM counties, manufacturing dependence already carried a pro-Republican tilt before Trump, with little additional strengthening after 2016. High-IM counties tell a very different story. Before Trump, manufacturing dependence had little association with Republican support in these counties, but its political weight increased sharply from 2016 onward. A one-standard-deviation higher L-Share is associated with a 2.55% more positive R-Vote relationship in 2016–2024 relative to 2008–2012, compared with virtually no additional change in low-IM counties. This contrast reveals an important political margin for Trump’s protectionist agenda. Even in counties deeply engaged in global sourcing, where IM itself carried a relative anti-Trump tilt, manufacturing dependence acquired substantial new Republican weight. The politics of protectionism thus reached beyond its established manufacturing-related partisan base, finding new political traction in local economies whose participation in foreign supply pointed in the opposite direction.

Benefits and Costs by Industry – The economic stakes of globalization also depend on how foreign supply enters domestic activity across industries. Imports can compete with domestic producers or provide inputs and specialized capabilities that support production and employment. This contrast is evident between mature industries such as steel, where foreign competition and global excess capacity have put pressure on domestic producers (OECD, 2015), and dynamic, technology-intensive industries such as electronics, where access to foreign components and specialized suppliers supports domestic manufacturing (Torsekar, 2018). To examine these differences, we classify consignee firms into manufacturing industries using their business descriptions, rather than the types of goods they import. For each industry k , we aggregate the imports recorded for these firms within each county and scale by county GDP to construct industry-specific IM. The corresponding industry-specific L-Share measures that industry’s share of total county employment.

The electoral evidence reveals a sharp divide. In steel and other traditional manufacturing industries, counties with higher industry-specific L-Shares exhibit a stronger pro-Republican

alignment from 2016 onward, while the corresponding IM relationship remains comparatively muted. Electronics tells a different story: both industry-specific IM and L-Share acquire stronger anti-Republican associations after 2016. These opposing patterns expose a central tension in the politics of protectionism. Trade restrictions intended to shield domestic manufacturing jobs from foreign competition may also threaten the global production networks supporting jobs in other industries. The partisan weight of globalization’s benefits and costs thus reflects both a local economy’s industrial structure and how its industries are connected to global production.

Relations to the China-Shock Literature – Our focus on the costs of globalization via the L-Share measure is very much motivated by the “China Shock” literature pioneered by Autor et al. (2020). To capture the loss of local manufacturing jobs caused by imports from China, the import-penetration measure of Autor et al. (2020) combines two pieces of information – aggregate increases in imports from China since 1991 and the pre-shock local manufacturing labor structure in 1990. Central to their identification is the industry variation – some industries are more affected by the rise of China than others. Mapping this industry-level variation into local economies, the import-penetration measure is higher for local economies whose labor shares are concentrated in industries affected by the rise of China.

Instead of focusing on China, our measure of L-Share zeroes in on the local manufacturing labor share, since the passage of globalization began much earlier than the rise of China and globalization’s negative impact on manufacturing jobs is much broader than China alone. Indeed, our empirical findings show that L-Share measured in the 1970s-80s – well before the China Shock – predicts the rise of Trump 1.0. To make a more direct link to the “China Shock” literature, we further decompose the import-penetration measure into two components: 1) 1990 L-Share; and 2) within-manufacturing import penetration. We find that while 1990 L-Share can predict the rise of Trump 1.0, the import-penetration component cannot. In other words, Trump 1.0’s marginal votes build on globalization’s discontent – the manufacturing job that was disrupted or is currently at risk. By contrast, the source of that disruption, China or any other countries, is not a high priority on voters’ minds.

Our focus on the impact of globalization by industry is also motivated by the “China Shock” literature. Indeed, we find stronger pro-Republican shift in 2016 among industries that had witnessed severe job disruptions due to globalization (e.g., steel, textile, furniture, and wood). Interestingly, these industries also benefit the least from global sourcing, as captured by our IM measure. Different from the “China Shock” literature, however, our paper also documents the benefits of globalization. One prominent example is the U.S. electronics industry, which is the undisputed leader of the global supply chain. In sharp contrast to the L-Share result in steel, counties with higher L-Share in electronics shifted away from Republican in 2016 relative to their low L-Share counterparts. The contrast and

the economic significance are large: a one-standard-deviation cross-county difference in steel L-Share is associated with a positive shift of 0.6% in R-vote, while that in electronics L-Share yields a negative shift of 0.5% in R-Vote. Consistent with its L-Share result, the electronics industry also benefits the most from global sourcing, as captured by our IM measure.

Related Literature — The political consequences of global trade have largely been studied through exposure to foreign competition and changes in trade policy. [Autor et al. \(2020\)](#) link Chinese import competition to political polarization and relative Republican gains in presidential elections, while [Che et al. \(2022\)](#) document an earlier pro-Democratic shift in congressional elections following trade liberalization with China. [Blanchard et al. \(2024\)](#) find electoral losses for Republican House candidates in counties more exposed to retaliatory tariffs during the U.S.–China trade war. Looking across tradable activities, [Jensen et al. \(2017\)](#) relate presidential voting to local employment in high-skilled tradable sectors and low-skilled manufacturing.

Our study introduces a different perspective on the politics of globalization: direct participation in global sourcing. As U.S. firms increasingly organize production and distribution across borders, foreign imports represent not only competition for domestic producers but also access to suppliers on which their own economic activities depend. This creates a distinct political stake in trade protection that conventional measures of import competition do not directly capture. Using shipment-level consignee records, we trace imports to firms and their county locations, identifying where local economic activity participates in foreign sourcing rather than where domestic industries face foreign competition. This allows us to examine how these sourcing interests acquire partisan significance when protectionism becomes central to electoral competition.

A second strand examines the employment costs of globalization. [Autor et al. \(2013\)](#) and [Pierce and Schott \(2016\)](#) document substantial manufacturing job losses associated with Chinese import competition, while [Margalit \(2011\)](#) and [Baccini and Weymouth \(2021\)](#) examine the electoral consequences of trade-related layoffs and deindustrialization. Yet jobs already lost and jobs on which local economies continue to depend represent different economic stakes. Even after decades of industrial decline, manufacturing can remain central to local employment. Our L-Share captures this continuing dependence, including industrial structures established long before the China Shock.

Importantly, the political significance of manufacturing dependence may also depend on how local economies participate in global trade. [Caliendo et al. \(2019\)](#) document uneven local consequences of trade, while [Wang et al. \(2018\)](#) and [Aghion et al. \(2024\)](#) show how imported inputs can support domestic production even as foreign competition puts other producers under pressure. This distinction motivates our joint analysis of IM and L-Share: we

examine where manufacturing dependence acquires greater partisan weight across counties with different levels of global sourcing, and how the political relationships of sourcing and manufacturing employment vary across industries. The resulting perspective moves beyond the employment costs of past trade shocks to ask whether protecting manufacturing jobs and preserving access to foreign supply represent competing or reinforcing local economic interests.

A third strand examines how political campaigns and policy promises shape electoral choices. [Kendall et al. \(2015\)](#) show experimentally that campaign information can change voters’ beliefs and votes, while [Cruz et al. \(2024\)](#) examine electoral responses to information about policy promises. [Le Pennec and Pons \(2023\)](#) further document changes in vote choice alongside shifts in issue salience and beliefs about candidates. These studies illuminate how political appeals influence voting within an election. We ask whether a political promise can also mark a turning point – giving longstanding economic interests new partisan significance that endures beyond the election itself. Trump’s 2016 protectionist agenda brought manufacturing employment and participation in global sourcing – two economic interests shaped by decades of industrial restructuring – into sharper political contention. Tracing county voting through 2024, we document a lasting change in their partisan relationships beginning with Trump’s first election. The political significance of a campaign promise may thus extend beyond an immediate electoral response, becoming associated with a new and enduring partisan divide in the politics of globalization.

The paper proceeds as follows. Section 2 provides the historical context. Section 3 describes the data and key measures. Section 4 presents the main empirical results. Section 5 reports robustness tests, and Section 6 concludes.

2 Globalization and the U.S. Industrial Landscape

The economic interests at stake in Trump’s 2016 protectionist campaign had been shaped by decades of changes in U.S. production and international trade. Figure 1 traces the evolution of U.S. imports from 1962 to 2024. During Globalization 1.0 (1962–1991), Canada, Japan, and West Germany were among the leading foreign suppliers to the United States. Globalization 2.0 (1992–2018) brought rapid growth in international trade, with China and Mexico gaining prominence among U.S. trading partners. The composition of imports also changed: traditional industries such as food, paper, and primary metals gradually gave way among the leading import categories to machinery, transportation equipment, electronics, and chemicals. These developments accompanied a broader transformation in how American firms organized production across borders. Since 2018, Globalization 3.0 has been marked

by renewed trade protection and growing concerns over supply-chain security.

Long before the expansion of modern global production networks, the U.S. manufacturing landscape had already undergone substantial restructuring. Traditional industrial centers in the Northeast and Midwest gradually lost ground as manufacturing activity shifted toward other regions, driven by technological change, domestic industrial relocation, differences in production costs, and foreign competition (Fort et al., 2018; Kim, 1995). Figure 2 places this transformation in a longer historical perspective. Panel A shows that the combined share of the U.S. population in five Rust Belt states—Illinois, Indiana, Michigan, Ohio, and Wisconsin—began declining steadily in the 1970s. Panel B shows that population growth in these states increasingly lagged behind the national average. Despite this relative demographic decline, the region remained heavily concentrated in traditional manufacturing industries, particularly industrial machinery and automobiles (Klier et al., 2005). By the time Trump entered the 2016 presidential race, the economic concerns surrounding traditional manufacturing communities had roots extending well before the China Shock.

Globalization 2.0 transformed the role of imports in the U.S. economy. As production became increasingly fragmented across borders, American firms could retain design, research, and supply-chain coordination domestically while sourcing components and assembly from foreign suppliers (Hummels et al., 2001; Johnson and Noguera, 2012; Yi, 2003). This transformation was particularly important for the electronics industry. As shown in Panel B of Figure 1, computers and electronics emerged as a leading U.S. import category, with China becoming a major source of supply from the mid-2000s. The economic importance of this industry extended well beyond its share of imports. BEA–BLS growth accounting shows that computer and electronic products accounted for most of manufacturing’s contribution to U.S. real value-added growth during 1987–2018 (Garner et al., 2020). Apple provides a prominent example of how this industry became deeply integrated into global production networks, retaining product design and development in the United States while relying on China’s extensive manufacturing capabilities for components and large-scale assembly (McGee, 2025). Access to foreign suppliers thus offered opportunities to lower costs and draw on specialized production capabilities in an industry central to U.S. technological innovation and economic growth. Such opportunities were nevertheless unevenly distributed, as establishing and managing international supplier relationships required substantial fixed costs (Antràs et al., 2017).

These gains from international sourcing came alongside substantial adjustment costs for American manufacturing. Foreign competition placed pressure on domestic producers, while technological change and the international reorganization of production further reshaped manufacturing employment. China’s integration into world markets intensified these pressures, generating persistent employment losses in labor markets exposed to Chinese import

competition (Autor et al., 2013, 2021; Pierce and Schott, 2016). Yet manufacturing remained economically important even after decades of industrial decline. The U.S. Department of Agriculture’s Economic Research Service identified 506 manufacturing-dependent counties in 2010–2012, down from 882 in 2001 (Parker, 2015). Manufacturing employment also supported jobs in local services through demand spillovers (Moretti, 2010). For these communities, protecting domestic manufacturing concerned not only the legacy of past industrial losses, but also the jobs and livelihoods that remained at stake.

These developments gave trade protection different economic implications across local economies. Restrictions on imports could shield domestic producers facing import competition, but they could also raise costs and disrupt the sourcing relationships on which other American firms depended. Trump’s 2016 campaign brought these competing economic interests into sharper political focus by placing the protection and restoration of domestic manufacturing at the center of his trade agenda. The political appeal of this agenda could therefore differ according to a county’s participation in global sourcing and its dependence on manufacturing employment. Moreover, the political weight of manufacturing dependence may itself vary with the extent of local sourcing participation, while the economic implications of foreign supply differ across industries. These differences motivate our examination of how longstanding economic interests associated with globalization acquired partisan weight with the rise of Trump 1.0.

3 Data and Measurement

3.1 Presidential Election Outcomes

County-level presidential election returns are from Dave Leip’s Atlas of U.S. Presidential Elections.³ Our main analysis covers the presidential elections of 2008, 2012, 2016, 2020, and 2024, with county-election pairs as the unit of observation.⁴ For county i in election year t , we define the Republican share of the two-party vote as

$$\text{R-Vote}_{it} = \frac{\text{Republican Votes}_{it}}{\text{Republican Votes}_{it} + \text{Democratic Votes}_{it}}. \quad (1)$$

Its change from the preceding presidential election is

$$\Delta \text{R-Vote}_{it} = \text{R-Vote}_{it} - \text{R-Vote}_{i,t-4}. \quad (2)$$

³David Leip, *Dave Leip’s Atlas of U.S. Presidential Elections*, <http://uselectionatlas.org>, accessed May 2, 2026.

⁴The 2004 vote shares provide the preceding-election benchmark for 2008.

R-Vote measures the two-party pro-Republican vote share, while Δ R-Vote captures the electoral movement toward or away from the Republican candidate. The former describes partisan alignment in a given election, whereas the latter identifies changes in that alignment from the preceding election. Both measures are multiplied by 100 for reporting.⁵

Panel A of Table I documents the changing distribution of Republican support across U.S. counties. The average county R-Vote increased from 57.1% in 2008 to 60.1% in 2012 and 66.0% in 2016. Cross-county dispersion also widened, with the standard deviation rising from 13.6% in 2008 to 14.5% in 2012 and 15.7% in 2016. Republican support thus increased substantially across counties, accompanied by growing differences in partisan alignment across local economies.

Figure 3 maps the geographic distribution of Δ R-Vote across five presidential elections from 2008 to 2024, revealing striking differences in the direction and magnitude of electoral movements. In 2008, much of the country shifted toward the Democratic candidate, particularly across the West, Midwest, and Northeast, although parts of Appalachia and the South moved in the Republican direction. The 2012 election saw a reversal across many counties in the interior United States, with Republican gains becoming more widespread across the Plains and Midwest. Panel B of Table I shows that the average county experienced a 3.1% decline in Republican vote share in 2008, followed by a 3.0% increase in 2012. The movement toward the Republican Party therefore preceded Trump’s first presidential election, but its magnitude and geographic distribution changed sharply in 2016.

The 2016 election stands out for the breadth and intensity of the pro-Republican shift. Figure 3 shows particularly large Republican gains across the northern Plains, industrial Midwest, Appalachia, and parts of the Northeast, while other counties experienced much smaller gains or moved toward the Democratic candidate. The average county shifted 5.9% toward Trump in 2016, nearly twice the Republican gain recorded in 2012. The movement was also highly uneven, with a cross-county standard deviation of 5.2% and an interquartile range of 2.6% to 9.6%. The pronounced Republican gains across traditional manufacturing regions are particularly notable given their long history of industrial restructuring, although the geographic reach of the shift extends well beyond these regions. This exceptional electoral movement raises the question of which longstanding local economic interests acquired greater political weight in Trump’s first election.

The subsequent elections reveal much smaller electoral movements. In 2020, many counties shifted modestly toward the Democratic candidate, while 2024 brought renewed but generally smaller Republican gains. Panel B reports average changes in R-Vote of -0.6% in

⁵The two-party measure excludes votes for third-party and independent candidates. Reported changes in vote shares, including those denoted by %, are absolute differences rather than relative growth rates.

2020 and 1.7% in 2024, substantially below the 2016 movement. Yet these smaller changes did not reverse the earlier shift in the overall distribution of Republican support. Returning to Panel A, the average county R-Vote remained at 65.5% in 2020 and reached 67.2% in 2024, compared with 60.1% before Trump’s first election in 2012. Cross-county dispersion also remained above its pre-2016 level. The electoral geography thus points to a distinctive movement in 2016, followed by a sustained difference in the distribution of Republican support. Whether this turning point also marked a lasting change in the partisan relationships associated with global sourcing and manufacturing employment is the central question of our empirical analysis.⁶

3.2 County Participation in Global Trade

We measure county participation in global sourcing using shipment-level records from S&P Global Panjiva. Compiled from U.S. customs records, shipping-company information, and digitized bills of lading, the data identify the recorded U.S. consignee, foreign shipper, country of origin, product classification, and reported shipment value. Our baseline import sample covers 2008–2023.

We assign imports to counties based on the recorded U.S. consignee rather than the port of entry. While ports identify where goods enter the United States, consignee locations provide information on the U.S. entities participating in international sourcing. Using the annual HUD–USPS ZIP Code Crosswalk files, we map consignee ZIP codes to counties and aggregate shipment values by county and calendar year. For ZIP codes spanning multiple counties, shipment values are allocated using the crosswalk’s residential allocation weights. Shipments without a valid consignee ZIP code that can be reliably mapped to a county are excluded.⁷

For county i in calendar year t , we define the import-to-GDP ratio as

$$\text{IM}_{it} = \frac{\text{Imports}_{it}}{\text{GDP}_{it}}, \quad (3)$$

where Imports_{it} is the total value of imports assigned to county i , and GDP_{it} is county GDP from the U.S. Bureau of Economic Analysis. IM is expressed as a percentage of county

⁶The county statistics give each county equal weight and therefore describe the geographic distribution of presidential voting rather than the national popular vote. The maps display changes in Republican vote shares, not which party received a majority of votes within each county.

⁷We retain shipments with either a single HS6 code or a dominant HS6 code accounting for at least 80% of all HS6-coded product entries in the record. Each retained shipment is assigned that unique or dominant code.

GDP.⁸ For each presidential election, we use IM from the preceding calendar year; the 2016 election is therefore matched to importing activity in 2015. The 2008 election is an exception, for which we use 2008 IM because the validated sample does not cover 2007.

IM captures a county’s direct participation in global sourcing through the import transactions of U.S. consignees located in the county. These transactions connect firms engaged in manufacturing, wholesale, retail, and distribution to foreign suppliers and international production networks. Unlike conventional measures of import competition that infer local exposure from industrial employment structures, IM traces actual import shipments to the U.S. entities engaged in foreign sourcing. This firm-level perspective reveals a distinct geography of globalization, identifying local economies more closely connected to international supply chains. Panel C of Table I shows that import participation varies substantially across counties. The mean IM is 2.1% of county GDP, compared with a median of 0.5% and a 75th percentile of 1.8%; at the 99th percentile, IM reaches 35.8%. This pronounced dispersion reveals how unevenly participation in global sourcing is distributed across U.S. local economies.

3.3 Manufacturing Dependence and Local Employment

Our second measure captures the importance of manufacturing jobs to local economies through manufacturing’s share of total county employment. Employment shares allow comparisons of manufacturing dependence across counties of different sizes, measuring the proportion of local employment accounted for by the sector (Klier et al., 2005).⁹ Building on the local-labor-market perspective of Autor et al. (2013), a given proportional decline in manufacturing employment represents a larger loss relative to the local employment base where manufacturing accounts for a greater share of jobs. The consequences of such adjustments can also persist as workers and economic activity adjust gradually across regions (Autor et al., 2021; Dix-Carneiro and Kovak, 2017).

For county i and employment base year τ , we define the manufacturing employment share, or L-Share, as

$$\text{L-Share}_{i,\tau} = \frac{L_{i,\tau}^{\text{mfg}}}{L_{i,\tau}}, \quad (4)$$

⁸The export-to-GDP ratio, EX_{it} , is constructed analogously using shipments assigned to the recorded location of the U.S. shipper.

⁹The Federal Reserve Bank of Chicago provides a telling example: during the early-2000s downturn, manufacturing employment declined at broadly similar rates in the Midwest and nationally, yet total employment fell by 3.6% in the Midwest compared with 0.9% nationally, reflecting the region’s greater concentration in manufacturing.

where $L_{i,\tau}^{\text{mfg}}$ is manufacturing employment and $L_{i,\tau}$ is total county employment, both from the U.S. Census Bureau’s County Business Patterns (CBP).¹⁰ L-Share is expressed as a percentage of county employment. Our main analysis uses the 2015 L-Share, held fixed across the 2008–2024 presidential elections, to examine changes in the political relationship with manufacturing dependence following Trump’s first election. We also trace L-Share back to 1975 to examine whether manufacturing employment structures established decades earlier remain informative about the political realignment beginning in 2016.

Manufacturing dependence varies substantially across U.S. counties. Panel C of Table I reports a mean L-Share of 15.9% and a median of 13.2%. The interquartile range extends from 6.5% to 22.8%, while the 99th percentile reaches 53.8%. Manufacturing therefore accounts for a relatively small fraction of employment in many counties but remains central to the local economy in others. These differences reveal how the employment stakes associated with manufacturing protection vary considerably across U.S. counties.

3.4 County Characteristics and Sample Construction

County GDP and GDP growth are obtained from the U.S. Bureau of Economic Analysis’s Regional Economic Accounts, unemployment rates from the U.S. Bureau of Labor Statistics’ Local Area Unemployment Statistics, and demographic and household characteristics from the U.S. Census Bureau’s American Community Survey (U.S. Bureau of Economic Analysis, 2026; U.S. Bureau of Labor Statistics, 2026; U.S. Census Bureau, 2026). Industry employment shares are constructed from County Business Patterns. Our county economic controls include GDP per employee, annual GDP growth, unemployment, the share of households with income below \$35,000, and the Gini coefficient. Demographic controls include the male, Black, Hispanic, and age-65-or-older population shares. We also control for agricultural and mining employment shares, and include the manufacturing employment share when L-Share is not the principal explanatory variable. Unless otherwise specified, time-varying characteristics are measured in the calendar year preceding each presidential election. For variables observed less frequently, we use the most recent available observation before the election.

We merge the election, trade, employment, and county characteristics using five-digit county Federal Information Processing Standards (FIPS) codes and harmonize county boundaries over time. The sample covers 49 U.S. states and the District of Columbia, excluding Alaska and Puerto Rico. We retain counties with available voting outcomes, IM, GDP, and the required county characteristics, and require at least ten years of valid trade observa-

¹⁰We use the imputed county-industry employment data constructed by Eckert et al. (2020), available at <https://www.fpeckert.me/cbp/>, covering 1975–2018. Manufacturing employment is aggregated using two-digit SIC codes 20–39 before 1998 and two-digit NAICS codes 31–33 from 1998 onward.

tions during the sample period. The resulting baseline panel contains 2,853 counties and 14,225 county-election observations. Panel C of Table I reports the distributions of the trade measures and county characteristics.

4 Empirical Results

Counties entered the 2016 election with different stakes in the gains from global sourcing and the protection of manufacturing jobs. We first examine how sourcing participation and manufacturing dependence relate to the pro-Republican shift in 2016 and the partisan alignment that persisted through 2024. We then ask whether manufacturing dependence acquired greater Republican weight after 2016 in high-IM counties than in low-IM counties.

4.1 Local Participation in Global Trade

Global sourcing provides firms in local economies with access to inputs for production, goods for distribution, and specialized capabilities abroad. These sourcing opportunities can lower costs, raise productivity, and support business expansion at home. We first examine the political significance of this benefit side of global trade, asking whether counties more engaged in global sourcing shifted less toward Trump in 2016 and whether the sourcing-related partisan divide persisted through 2024.

Panel A of Table II sorts counties into quintiles using IM measured in the year preceding each election.¹¹ In 2016, the Republican vote-share gain declines monotonically from 7.4% in the lowest-IM quintile to 4.2% in the highest. The reported high-minus-low difference in $\Delta R\text{-Vote}$ is -3.1% , the most negative difference across the 2008–2024 elections. Republican vote share increased in all five groups, but counties more engaged in global sourcing moved substantially less toward Trump.

The economic interest behind this relative anti-Trump pattern lies in the domestic opportunities supported by foreign supply. Imported inputs can improve firm productivity (Amiti and Konings, 2007), while access to new input varieties can enable domestic firms to introduce new products (Goldberg et al., 2010). For firms benefiting from these channels, import restrictions could raise production costs or constrain product offerings. Preserving these productive advantages provides an economic rationale for the smaller Republican gain in high-IM counties.

¹¹Entries are unweighted county means. IM quintiles are formed separately for each election, so comparisons across elections describe positions in the sourcing distribution rather than fixed groups of counties. For 2008 election, we use contemporaneous IM based on the bill of lading data availability.

The R-Vote comparisons reveal a partisan divide that predates Trump’s election. The high-minus-low gap was -10.0% in 2012 and -11.3% in 2016. It remained substantial in 2020 and 2024, at -10.8% and -10.1% , even as the corresponding differences in Δ R-Vote diminished to -0.9% and 0.2% . The unusually large sourcing-related movement in 2016 thus occurred against a backdrop of preexisting partisan differences.

We next estimate separate cross-sectional regressions for each presidential election from 2008 through 2024 to examine the timing and magnitude of the sourcing relationship:

$$Y_{it} = \alpha_t + \beta_t Z_{i,t-1} + \mathbf{X}'_{i,t-1} \boldsymbol{\gamma}_t + \varepsilon_{it}, \quad (5)$$

where Y_{it} is either Δ R-Vote $_{it}$ or R-Vote $_{it}$. Here, $Z_{i,t-1} = \text{IM}_{i,t-1}$, and $\mathbf{X}_{i,t-1}$ contains GDP per employee. Both explanatory variables are measured one year before the election. The IM coefficient reports the voting difference associated with a one-standard-deviation difference in sourcing participation.

Figure 4 brings the 2016 turning point into focus. The IM coefficient for Δ R-Vote, close to zero in 2008 and negative in 2012, reaches its most negative value in 2016: a one-standard-deviation higher IM is associated with a 0.74% smaller Republican vote-share gain. IM’s incremental explanatory power, measured by the increase in R^2 relative to the specification without IM, also peaks in that election. This unusually strong electoral differentiation coincides with Trump’s promise to protect American jobs by restricting imports. For counties whose firms relied on foreign sourcing, that promise also raised concerns about the costs of sustaining and expanding business at home. The gains from foreign supply thus acquired sharper partisan relevance in the contest over domestic jobs.

The subsequent elections show that this sourcing-related divide endured. The Δ R-Vote coefficient becomes substantially less negative in 2020 and small and positive in 2024, while the R-Vote coefficient remains significantly negative in all three elections from 2016 onward, with the later estimates similar in magnitude to the 2016 estimate. Counties more engaged in global sourcing therefore retain their relative anti-Republican tilt after the pronounced electoral movement in Trump’s first election. This combination of a concentrated vote swing in 2016 and persistent differences in Republican support suggests that the campaign gave greater political weight to an ongoing economic interest in foreign supply.¹²

To quantify the additional post-2016 relationship, we compare the conditional association between sourcing participation and Republican voting in 2008–2012 with that in 2016–2024:

$$\text{R-Vote}_{it} = \alpha + \beta \text{IM}_{i,t-1} + \theta \text{IM}_{i,t-1} \mathbb{1}_{t \geq 2016} + \pi \mathbb{1}_{t \geq 2016} + \mathbf{X}'_{i,t-1} \boldsymbol{\gamma} + \delta_{it} + \varepsilon_{it}. \quad (6)$$

¹²Figure A2 shows the distributions of vote-share changes in the lowest and highest IM quintiles. Their separation is particularly pronounced in 2016, smaller in 2020, and largely absent in 2024.

The indicator $\mathbb{1}_{t \geq 2016}$ equals one in 2016, 2020, and 2024 and zero in 2008 and 2012. The coefficient β measures the pre-2016 IM slope, θ measures its change in the later period, and $\beta + \theta$ is the post-2016 slope.

Columns (1)–(3) of Table III report the estimates. All specifications include GDP per employee. Column (2) adds the remaining county characteristics described in Section 3.4 and state fixed effects; column (3) replaces the state fixed effects with state-by-election fixed effects. Accordingly, δ_{it} equals zero, $\delta_{s(i)}$, and $\delta_{s(i),t}$ in columns (1)–(3), respectively, where $s(i)$ denotes county i ’s state. The state-by-election fixed effects absorb the common post-2016 indicator and account for each state’s electoral movements. The regressions are estimated by ordinary least squares, with standard errors clustered by county.¹³

The IM interaction is negative and statistically significant in all three specifications. In column (3), $\hat{\theta} = -0.506$, with a t -statistic of -3.70 . A one-standard-deviation difference in IM is therefore associated with a Republican vote-share gap that is approximately 0.51% more negative in 2016–2024 than in 2008–2012. The pre-2016 coefficient is -0.119 and statistically indistinguishable from zero, while the implied post-2016 coefficient is -0.625 . The additional negative relationship remains after accounting for county characteristics and state-specific electoral movements, reinforcing the turning point visible in the election-specific estimates.

The 2016 election marked a turning point in the politics of global sourcing. For firms in high-IM counties, foreign suppliers supported production, distribution, and expansion at home. Trump’s promise to defend American jobs by restricting imports could therefore put these business opportunities at risk. Counties more engaged in sourcing showed their strongest relative anti-Trump movement in 2016, and their anti-Republican tilt persisted through 2024. The political significance of foreign sourcing across local economies had changed: the interest in preserving its gains now carried greater and lasting partisan weight in the contest over American jobs.

4.2 Local Jobs and Manufacturing Dependence

Trump’s 2016 campaign blamed global trade for the loss of American manufacturing jobs and promised to bring them back.¹⁴ His message presented local job protection as an answer to globalization’s employment costs, offering manufacturing-dependent communities an economic reason to support his campaign. We examine whether counties more dependent

¹³Continuous regressors are winsorized at the 1st and 99th percentiles and standardized over the full panel before selecting election-year observations. Coefficients therefore describe one-standard-deviation differences.

¹⁴In his June 28, 2016, address in Monessen, Pennsylvania, Trump attributed manufacturing job losses to globalization and existing trade arrangements and proposed withdrawing from the Trans-Pacific Partnership and renegotiating NAFTA.

on manufacturing employment, as measured by L-Share, shifted more toward him in 2016 and whether that alignment persisted through 2024.

Panel B of Table II sorts counties into quintiles using their 2015 L-Share and holds membership fixed across elections. In 2016, Republican vote share rose by 8.3% in the highest-L-Share quintile, compared with 4.5% in the lowest, a 3.8% difference. The corresponding high-minus-low differences in $\Delta R\text{-Vote}$ were only 0.7% in 2008 and 0.0% in 2012.

Manufacturing-dependent counties already displayed a relative Republican tilt before Trump. The high-minus-low R-Vote gap was 2.9% in 2012. It widened to 6.7% in 2016 and remained elevated at 7.3% in 2020 and 7.1% in 2024, even as the differences in vote-share changes receded. Trump’s first election thus brought a pronounced additional movement toward the Republican candidate in communities where manufacturing remained an important source of employment.

Figure 5 extends the comparison to eight presidential elections from 1996 through 2024. For each election, we estimate equation (5), replacing $Z_{i,t-1}$ with $L\text{-Share}_{i,2015}$. The regressions control for pre-election personal income per employee because county GDP is unavailable for the earlier elections. Holding the employment measure fixed makes the earlier comparisons retrospective: they trace the voting history of counties with higher manufacturing dependence in 2015.

The longer record locates the turning point in 2016. A one-standard-deviation higher 2015 L-Share is associated with a 1.29% larger Republican vote-share gain in that election, the largest positive estimate in the series. L-Share’s incremental explanatory power also peaks in 2016. Manufacturing dependence already carried a positive R-Vote relationship in earlier elections: a one-standard-deviation difference corresponds to approximately 1.27% more Republican support in 2012. That relationship strengthens to about 2.67% in 2016 and remains elevated in 2020 and 2024, while the vote-swing coefficient attenuates sharply after 2016. An established manufacturing constituency acquired a stronger Republican expression in Trump’s first election, and that alignment outlasted the initial vote swing.

China-shock studies document how Chinese import competition can leave lasting employment losses in exposed communities (Autor et al., 2013, 2021). Our L-Share perspective focuses on the political significance of the manufacturing jobs on which communities continue to depend. That dependence can carry the imprint of an older manufacturing economy, reshaped over decades of industrial adjustment. For communities scarred by past job losses and facing uncertainty about the jobs that remain, restoring lost opportunities and safeguarding existing livelihoods are closely connected concerns. Trump’s 2016 message of restoration and protection spoke to both, giving voters concerned about globalization’s employment costs an economic reason to rally behind his campaign.

To trace the historical reach of this employment geography, we compare the elections of

2008–2012 with those of 2016–2024 using manufacturing employment shares from different base years. For an employment base year τ , we estimate

$$\text{R-Vote}_{it} = \alpha + \beta_{\tau} \text{L-Share}_{i,\tau} + \theta_{\tau} \text{L-Share}_{i,\tau} \mathbb{1}_{t \geq 2016} + \pi \mathbb{1}_{t \geq 2016} + \mathbf{X}'_{i,t-1} \boldsymbol{\gamma} + \delta_{it} + \varepsilon_{it}. \quad (7)$$

The coefficient β_{τ} measures the pre-2016 relationship between manufacturing dependence and Republican voting, while θ_{τ} measures its change in the later electoral period. The post-2016 slope is $\beta_{\tau} + \theta_{\tau}$. Varying τ allows us to examine how far back the employment geography associated with the additional Republican alignment reaches.

Table IV uses $\tau = 2015$ in columns (1)–(3) and $\tau = 1975$ in columns (4)–(5). All specifications include GDP per employee, and columns (2)–(5) add the remaining county characteristics. Columns (2) and (4) include state fixed effects; columns (3) and (5) include state-by-election fixed effects. Standard errors are clustered by county.

For the 2015 employment shares, the post-2016 interaction is positive and statistically significant in all three specifications. In column (3), which includes the full set of county controls and state-by-election fixed effects, $\hat{\theta}_{2015} = 1.011$, with a t -statistic of 8.24. The Republican vote-share gap associated with a one-standard-deviation difference in L-Share is therefore approximately 1.01% larger in 2016–2024 than in 2008–2012. The pre-2016 coefficient is also positive, at 0.706, with a t -statistic of 3.97. The additional alignment after 2016 builds on an existing Republican relationship with manufacturing dependence.

The employment geography behind this strengthening reaches back well before the China Shock. Columns (4)–(5) replace the 2015 L-Share with its 1975 counterpart. In column (5), the post-2016 interaction is 0.407, with a t -statistic of 2.73: a one-standard-deviation difference in the 1975 L-Share is associated with a Republican vote-share gap that is approximately 0.41% larger in 2016–2024 than in 2008–2012. The pre-2016 coefficient is 0.464, with a t -statistic of 2.17. An employment structure measured roughly four decades before Trump’s first election thus predicts both the earlier Republican tilt and its subsequent strengthening.

Figure 6 shows how broadly this historical relationship extends. For each base year from 1975 through 2015, we estimate equation (7), holding the election sample, county controls, and state-by-election fixed effects unchanged. Each historical L-Share measure is standardized separately. The estimated θ_{τ} is positive for every base year, at around 0.4–0.5% for employment structures measured in the mid-1970s and roughly 0.9–1.0% for many of the more recent base years. The point estimates rise particularly sharply for base years between approximately 1980 and 1992. Employment geographies from the 1970s and 1980s still help locate the Republican realignment that emerged decades later, alongside the stronger relationships associated with more recent manufacturing dependence.

Trump’s promise to bring manufacturing jobs back spoke to communities whose liveli-

hoods remained tied to the sector. It looked backward toward opportunities lost and forward toward the security of jobs that remained. His 2016 campaign tapped into employment concerns shaped by decades of industrial adjustment, presenting trade protection as the response. The election marked a new phase in the politics of globalization: these longstanding local employment interests acquired greater Republican weight, and that alignment endured through 2024.

4.3 Interaction between Global Trade and Local Jobs

The contrasting IM and L-Share results suggest that Trump’s 2016 trade agenda exposed a tension at the heart of globalization: communities entered the election with different experiences of its gains and costs. We therefore examine the geography of Trump’s marginal voters, asking whether manufacturing dependence gained greater Republican weight from 2016 onward in counties with limited sourcing participation or in those deeply engaged in global trade.¹⁵

Table II illustrates how closely sourcing participation and manufacturing dependence can overlap. In 2016, average L-Share rises from 11.1% in the lowest-IM quintile to 18.7% in the highest. In these globally connected communities, the trade debate concerns both the business opportunities foreign supply can support and the livelihoods tied to domestic manufacturing. Trump’s promise to defend local jobs therefore addressed an employment interest within economies actively participating in global trade.

We divide counties into low-, middle-, and high-IM groups using the 30th and 70th percentiles of the 2015 IM distribution. Group assignments remain fixed across the elections from 2008 through 2024. Within each group g , we estimate

$$\begin{aligned} \text{R-Vote}_{it} = & \alpha^g + \beta_L^g \text{L-Share}_{i,2015} + \theta_L^g \text{L-Share}_{i,2015} \mathbb{1}_{t \geq 2016} \\ & + \beta_P^g \text{GDP/Employee}_{i,t-1} + \theta_P^g \text{GDP/Employee}_{i,t-1} \mathbb{1}_{t \geq 2016} \\ & + \mathbf{X}'_{i,t-1} \boldsymbol{\gamma}^g + \delta_{s(i),t}^g + \varepsilon_{it}. \end{aligned} \quad (8)$$

L-Share enters continuously within each group, allowing us to compare counties with different degrees of manufacturing dependence within the same broad sourcing category. The coefficient β_L^g measures the pre-2016 relationship with Republican voting, while θ_L^g measures its change in 2016–2024. The post-2016 slope is $\beta_L^g + \theta_L^g$.

GDP per employee measures county labor productivity and is observed one year before

¹⁵We use “marginal voters” to describe the additional Republican support associated with manufacturing dependence from 2016 onward. Its empirical counterpart is the change in the conditional county-level L-Share – R-Vote relationship between 2008–2012 and 2016–2024, measured by θ_L^g within IM group g .

each election. Its interaction with the post-2016 indicator allows the productivity relationship to change alongside the manufacturing relationship. The vector $\mathbf{X}_{i,t-1}$ contains the remaining county characteristics, and $\delta_{s(i),t}^g$ denotes state-by-election fixed effects. All coefficients are estimated separately by IM group. Continuous regressors are winsorized at the 1st and 99th percentiles and standardized, and standard errors are clustered by county. Table V reports two specifications for each group: the first sets $\theta_P^g = 0$, while the second allows the productivity slope to change.

Low-IM counties enter the Trump period with an established manufacturing-related Republican tilt. In the first specification, the pre-2016 L-Share coefficient is 0.862, with a t -statistic of 2.70. The post-2016 interaction is only 0.093 and statistically indistinguishable from zero. Manufacturing dependence already carries a Republican association in these counties, with little estimated additional strengthening after 2016.

The larger change appears among high-IM counties. Their pre-2016 manufacturing coefficient is 0.162 and statistically indistinguishable from zero, while the post-2016 interaction is 2.552, with a t -statistic of 10.71. A one-standard-deviation difference in L-Share is therefore associated with a Republican vote-share gap that becomes 2.55% more positive in 2016–2024 relative to 2008–2012. The middle-IM group also exhibits additional Republican alignment, with an interaction of 1.265 and a t -statistic of 6.51. The point estimates place the strongest additional manufacturing-related Republican relationship among counties most engaged in global sourcing.

This pattern gives Trump’s employment appeal a globally connected setting. Foreign sourcing was part of doing business in these communities, while manufacturing remained an important source of local livelihoods. His promise to protect those jobs could therefore speak to an employment interest that coexisted with the opportunities offered by foreign supply.

Allowing the productivity relationship to change leaves the manufacturing pattern largely intact. The L-Share interactions are 0.085 in the low-IM group, 1.262 in the middle-IM group, and 2.383 in the high-IM group. In high-IM counties, the GDP-per-employee interaction is negative and statistically significant, at -2.011 ; its counterpart in low-IM counties is statistically insignificant. Within the globally engaged group, manufacturing dependence thus acquires additional Republican weight while productivity acquires a more negative relationship with Republican voting.

These opposing relationships bring the local economic tension into view. Foreign supply can help firms compete and expand at home, while manufacturing jobs sustain local livelihoods. When protection is promised through restrictions on imports, the appeal of defending those livelihoods can sit uneasily alongside the sourcing connections supporting local business activity. Both interests belong to the same globally connected economic geography.

Trump’s marginal manufacturing constituency thus extends into communities deeply en-

gaged in global trade. Local sourcing opportunities coexisted with dependence on manufacturing jobs, and that dependence acquired additional Republican weight from 2016 onward. The jobs-based appeal of protectionism found a constituency among globalization’s participants.

4.4 Benefits and Costs by Industry

Global trade creates different economic interests across the industries sustaining local economies. Foreign sourcing can support domestic production and growth, while import competition can threaten jobs in traditional manufacturing industries on which communities still depend. We examine which industries underlie the contrasting IM and L-Share relationships from 2016 onward, asking where manufacturing dependence gives communities an interest in trade protection and where access to foreign supply supports local production and business growth.

The manufacturing economy Trump promised to revive had been remaking itself for decades. Figure 7 traces this history. In the late 1970s and 1980s, autos occupied a leading position in U.S. imports, with steel and machinery also prominent. Electronics steadily gained ground. By the early 1990s, it had become the largest import category; by the later years of that decade, it accounted for roughly one-fifth of total imports. It retained the lead through 2023, while autos remained important and chemicals gained prominence. Behind these changing industry ranks lay a broader transformation: between 1975 and 2023, aggregate U.S. IM rose from approximately 5% to 11%, while manufacturing’s share of employment fell from about 30% to 9%.¹⁶ Trade and technological change had reshaped the industries on which manufacturing communities were built (Sposi et al., 2026).

The employment base changed in composition as well. Food and chemicals accounted for larger shares of manufacturing employment, while electronics and machinery carried less weight. Steel retained a substantial presence within a sector whose share of total U.S. employment had contracted sharply. Electronics remained prominent in imports even as its employment weight declined. The industries sustaining manufacturing jobs thus entered the trade debate with different histories of adjustment and participation in global production.

To examine how these industry interests figured in Trump’s rise to the presidency in 2016 and the Republican alignment that followed, we classify Panjiva consignee firms by their business activities and assign imports to the receiving firms’ industries rather than to product

¹⁶The bars report the shares of the five largest industries, selected separately for each year and panel. Their membership can therefore change over time and differ between panels. Industry shares use total U.S. imports in Panel A and total manufacturing employment in Panel B as denominators.

categories. We apply the same 14 manufacturing groups to imports and employment.¹⁷ This directly links foreign sourcing to local business activity, allowing us to examine firms’ sourcing opportunities alongside communities’ dependence on jobs in the same industries.¹⁸

For industry k in county i , industry L-Share is employment in that industry divided by total county employment in 2015. Industry IM is the average annual value of imports during 2008–2015 received by consignee firms in industry k located in county i , divided by county GDP in 2015. Both measures are constructed from pre-2016 data and held fixed across elections. For each industry, we estimate

$$\text{R-Vote}_{it} = \alpha_k + \beta_k Z_{ik} + \theta_k Z_{ik} \mathbb{1}_{t \geq 2016} + \mathbf{X}'_{i,t-1} \boldsymbol{\gamma}_k + \delta_{s(i),t}^k + \varepsilon_{it}, \quad (9)$$

where Z_{ik} is either industry IM or industry L-Share, with each measure entering a separate regression. The election sample covers 2008–2024. We include county economic and demographic controls and state-by-election fixed effects, and cluster standard errors by county. The coefficient θ_k measures the change in the corresponding Republican vote-share relationship between 2008–2012 and 2016–2024.

The sourcing-related anti-Republican pattern extends across most manufacturing industries. Figure 8 reports the interaction coefficients and their 95% confidence intervals, with IM in Panel A and L-Share in Panel B. Electronics, machinery, and oil refining exhibit pronounced negative IM interactions. The sourcing interests identified in the aggregate analysis therefore reach into domestic manufacturing itself. For firms using imported intermediates, access to foreign supply can support production and competitiveness at home (Aghion et al., 2024; Torsekar, 2018). Restrictions intended to defend American industry can consequently raise the costs of operating within it.

Manufacturing dependence draws a more divided political map. Steel, textiles, furniture, and wood products display pronounced positive L-Share interactions: counties relying more heavily on these industries for employment show additional Republican alignment after 2016. Their IM relationships are comparatively muted. These industries give concrete employment content to the overall pro-Republican L-Share relationship, placing the security of established manufacturing livelihoods at the center of the comparison.

¹⁷The groups aggregate three-digit NAICS manufacturing subsectors: Food (311–312), Textile (313–315), Footwear (316), Wood (321), Paper (322–323), Oil (324), Chemical (325–326), Mineral (327), Steel (331–332), Machinery (333), Electronics (334–335), Auto (336), Furniture (337), and Misc (339). The names abbreviate the corresponding NAICS groups. Steel includes primary and fabricated metal products; Electronics includes computer and electronic products and electrical equipment, appliances, and components; Auto includes transportation equipment; and Footwear includes leather and allied products.

¹⁸Appendix A.1 describes the classification procedure, which uses large language models and information on consignee names, locations, and business activities.

The pressures facing these activities help explain the appeal of protection. In steelmaking, technological improvements have raised productivity and reorganized production (Collard-Wexler and De Loecker, 2015). Global excess capacity adds competitive pressure that can depress prices, weaken profitability, and displace domestic production (OECD, 2015). The BEA–BLS accounts also document long-run declines in real output and labor input in textiles and furniture (Garner et al., 2025). In local economies still reliant on these industries, Trump’s promise to restore manufacturing addressed two connected concerns: recovering opportunities lost through decades of adjustment and safeguarding the jobs that continued to sustain local livelihoods.

Strikingly, electronics reverses this employment pattern. It combines a pronounced negative IM interaction with a statistically significant negative L-Share interaction. Both sourcing participation and dependence on electronics jobs are therefore associated with additional anti-Republican alignment. The industry’s production history helps explain why a decline in its employment share need not create a constituency for trade protection. Within our broader electronics group, computer and electronic products recorded the fastest real gross-output growth among the manufacturing industries reported in the BEA–BLS accounts over 1997–2023, together with rapid productivity growth and declining labor input (Garner et al., 2025).¹⁹

International sourcing forms part of the production structure in these activities. Imported components connect domestic manufacturers to foreign suppliers, while semiconductor production draws on specialized fabrication, assembly, and testing capabilities abroad (Torsekar, 2018; VerWey, 2018). For communities dependent on electronics employment, maintaining these connections can help sustain the competitiveness of the firms supporting local jobs. Import restrictions can threaten the production networks supporting the very jobs they are intended to protect. The negative electronics L-Share relationship thus reveals an employment interest in continued global integration within manufacturing itself.

The distinction also appears within individual industries. Chemicals and mineral products combine negative IM interactions with positive L-Share interactions. Machinery and oil refining exhibit pronounced negative IM interactions alongside relatively modest employment interactions. These patterns show how sourcing opportunities and employment concerns can acquire different partisan expressions within the same broad activity. Firms’ participation in foreign supply and communities’ dependence on manufacturing jobs capture distinct local economic interests.

These industry contrasts give economic content to the geography of Trump’s marginal

¹⁹These production statistics concern NAICS 334, one component of our broader electronics group. Average annual real gross-output growth was 3.85%, and total-factor-productivity growth was 5.12% over 1997–2023.

voters. The employment-related Republican alignment has clear counterparts in traditional manufacturing, while electronics shows that dependence on manufacturing jobs can also accompany additional anti-Republican alignment. The political meaning of local job protection therefore varies with the industries sustaining those jobs: communities may seek shelter from foreign competition or continued access to the foreign suppliers supporting domestic production.

4.5 Relations to the China-Shock Literature

The China-Shock literature highlights the importance of import competition from China in displacing U.S. manufacturing jobs and its ensuing impact on local communities. We connect our findings to this literature from two angles – the information content of local manufacturing labor share and the cross-industry impact of global trade.

4.5.1 Local Manufacturing Labor Share

Our examination of globalization’s employment costs through the lens of L-Share is motivated by the China-shock literature, particularly [Autor et al. \(2020\)](#). Their import-penetration measure combines industry-level increases in Chinese import penetration since 1991 with the local employment structure in 1990. Industry variation is central to this approach: China’s rise exposed some manufacturing activities to greater competitive pressure than others, while local employment weights identify the places whose jobs were concentrated in the sectors most affected. This employment weighting provides a direct link to our L-Share perspective.

With L-Share, we shift the focus from the source of competitive pressure to the manufacturing jobs on which local economies depend. The historical analysis in Section 4.2 shows that L-Share measures from the 1970s and 1980s predict additional Republican alignment from 2016 onward, with Table IV tracing this relationship back to 1975. Figure 9 shows the scale of the transformation preceding China’s WTO accession: L-Share fell from about 30% in 1975 to 20% in the early 1990s and 14% by 2001, before declining further to around 10% by 2010. Most of this cumulative percentage-point decline in manufacturing’s employment share preceded WTO accession, whereas the sharp job losses associated with Chinese competition came in the 2000s ([Fort et al., 2018](#); [Pierce and Schott, 2016](#)). The 1990 employment structure used to construct the China-shock exposure measure thus reflected a manufacturing geography already shaped by substantial industrial adjustment.

Conventional import penetration already contains this manufacturing dependence. Following [Autor et al. \(2020\)](#), we construct the measure and its two components at the commuting zone (CZ) level, retaining each CZ’s 1990 employment structure. We measure industry-

level penetration changes over 1991–2015 to capture the accumulated Chinese import competition preceding Trump’s rise in 2016, yielding

$$\Delta \text{IP}_z^{cu} = \sum_{k \in \text{mfg}} \frac{L_{zk,1990}}{L_{z,1990}} \Delta \text{IP}_k^{cu}, \quad (10)$$

$$= \text{L-Share}_{z,1990} \times \Delta \text{IP}_z^{cu-\text{mfg}}. \quad (11)$$

Here, $L_{zk,1990}$ denotes employment in manufacturing industry k within CZ z , and $L_{z,1990}$ denotes total CZ employment. The first factor, $\text{L-Share}_{z,1990}$, is manufacturing’s fraction of local employment. The second, $\Delta \text{IP}_z^{cu-\text{mfg}}$, averages industry penetration changes using each industry’s share of CZ manufacturing employment.²⁰ Two CZs with the same industry mix within manufacturing therefore have identical within-manufacturing penetration, but conventional exposure is greater where manufacturing accounts for a larger share of local jobs.

We first examine whether conventional China-shock exposure predicts additional Republican alignment from 2016 onward, then compare this relationship with those of its two components. Table VI reports separate regressions for conventional exposure, initial manufacturing dependence, and within-manufacturing penetration. Each specification also includes county-level IM and its post-2016 interaction to account for local participation in global sourcing. Conventional import penetration carries an additional pro-Republican association in columns (1) and (2). The within-manufacturing component shows no statistically significant strengthening in columns (3) and (4). Initial manufacturing dependence, however, displays a strong additional Republican relationship in columns (5) and (6). In column (6), the Republican vote-share gap associated with a one-standard-deviation higher 1990 L-Share widens by 1.20% in 2016–2024 relative to 2008–2012. The results remain similar when we construct exposure and its components using county employment weights or retain the CZ construction but end the penetration window in 2010.

The decomposition distinguishes two dimensions of the local politics of trade: how much Chinese competition manufacturing industries face and how heavily local communities depend on those industries for jobs. The contrasting electoral relationships give particular prominence to this employment dependence. The 1990 manufacturing share predicts additional Republican alignment after 2016, while within-manufacturing penetration shows no corresponding strengthening. This adds a distinct perspective to the China-shock literature

²⁰Industry penetration is $\Delta \text{IP}_k^{cu} = \Delta M_{k,1991-2015}^{cu} / (Y_{k,1991} + M_{k,1991} - X_{k,1991})$, where the numerator is the change in U.S. imports from China and the denominator is 1991 domestic absorption: shipments plus total imports minus exports. Industries follow the harmonized SIC87dd classification. CZ measures are assigned to their constituent counties. The identity applies to CZs with positive manufacturing employment and uses L-Share as a fraction before winsorization and standardization.

by highlighting the political significance of local manufacturing dependence already embedded in conventional China-shock exposure.

We further examine whether the additional Republican relationship with manufacturing dependence also appears among counties sourcing heavily from countries other than China. Returning to the 2015 county L-Share used in Section 4.3, we separately sort counties into low-, middle-, and high-IM groups using their 2015 China and non-China IM. Table VII shows parallel patterns under the two groupings. Among high-China-IM counties, a one-standard-deviation higher L-Share is associated with a widening of the Republican vote-share gap by 2.49% in 2016–2024 relative to 2008–2012. The corresponding estimate among high-non-China-IM counties is 2.65%. In both high-IM groups, the pre-2016 L-Share relationship was muted and statistically insignificant. The post-2016 interaction estimates are about 1.29% in both middle-IM groups, while neither low-IM group shows statistically significant additional Republican alignment.

In sum, our L-Share perspective brings into focus the local employment interests embedded in conventional China-shock exposure. The initial manufacturing weight in that measure predicts additional Republican alignment, as does contemporary manufacturing dependence among counties sourcing heavily from countries other than China. In communities where manufacturing had anchored economic life, concerns about global trade weighed on voters’ minds: opportunities already lost and livelihoods still at risk. Trump’s 2016 promise to restore manufacturing and defend local jobs spoke to both.

4.5.2 Cross-Industry Impact of Global Trade

Industry differences in the effects of global trade provide a second link between our study and the China-shock literature. Uneven competitive pressure across manufacturing activities is central to the exposure measure of Autor et al. (2020) and motivates our analysis in Section 4.4. We extend this industry perspective by examining manufacturing employment concerns alongside the opportunities arising from direct foreign sourcing. By identifying the domestic firms receiving foreign goods, our shipment records bring China’s role as a supplier into the political comparison.

The traditional-industry results provide a counterpart to the employment concerns emphasized in China-shock studies. Figure 8 shows pronounced additional Republican alignment after 2016 in counties with higher employment shares in steel, textiles, furniture, and wood products. Their IM relationships are comparatively muted. These activities give concrete industry content to our overall positive L-Share finding: after prolonged adjustment, local livelihoods remain tied to production facing further competitive pressure. Communities still dependent on those jobs therefore have a direct employment interest in protecting that

production.

Electronics provides a contrasting case. A one-standard-deviation higher industry L-Share is associated with an additional Republican vote-share difference of approximately 0.6% in steel, compared with -0.5% in electronics, in 2016–2024 relative to 2008–2012. Electronics also displays the most negative estimated post-2016 IM interaction among the industries examined. Manufacturing dependence and sourcing participation thus point in the same anti-Republican direction. This contrast concerns an industry central to U.S. manufacturing growth: within our broader electronics group, computer and electronic products recorded the fastest real gross-output growth among manufacturing industries over 1997–2023 (Garner et al., 2025). These activities operate within international production networks drawing on imported components and specialized fabrication, assembly, and testing capabilities abroad (Torsekar, 2018; VerWey, 2018). Continued access to foreign suppliers can therefore support both domestic competitiveness and the local employment sustained by these businesses.

Panel B of Figure 9 brings China’s supply role into this comparison. Imports from China expanded sharply following WTO accession, exceeding 2.5% of U.S. GDP through much of the 2010s, with electronics accounting for the largest industry contribution. China was also the largest U.S. supplier of electronic products in 2015.²¹ China’s prominence in these product flows places its supplier role alongside the competitive pressures emphasized in China-shock studies. It also makes China directly relevant to the sourcing interests illustrated by the electronics results.

The county-level IM results show that the sourcing-related electoral divide extends to China itself. When China and non-China IM enter jointly in column (5) of Table III, both exhibit significantly more negative Republican vote-share relationships after 2016. A one-standard-deviation higher China IM is associated with a vote-share gap that becomes approximately 0.32% more negative in 2016–2024 relative to 2008–2012; the corresponding estimate for non-China IM is 0.44%. The additional negative China-sourcing relationship therefore remains after accounting for sourcing from other countries. These patterns show that U.S. businesses’ sourcing from China forms part of the local partisan divide over globalization. For businesses relying on these suppliers, restrictions on Chinese goods can raise costs or disrupt operations at home.

Our contribution is to document the electoral significance of U.S. firms’ direct sourcing from China alongside the employment concerns motivating China-shock studies. Electronics illustrates how the interests of sourcing businesses and communities dependent on manufac-

²¹U.S. International Trade Commission, “Electronic Products,” *Shifts in U.S. Merchandise Trade 2015*, Table EL.1.

turing jobs can align around continued access to foreign supply. The economic relationship with China thus includes a domestic interest in preserving supply connections alongside the employment concerns associated with foreign competition.

5 Robustness

5.1 Geographic Heterogeneity

One concern is that the negative post-2016 association between direct import participation and Republican voting may be driven by a particular part of the country. Import-intensive counties are not distributed uniformly across space, and the economic role of importing may differ between coastal trade centers, the industrial Midwest, and manufacturing regions in the South. The Panjiva bill-of-lading data allow us to examine this possibility using directly measured county importing rather than assigning national trade shocks to locations according to their industry composition.

We divide the county sample into the nine U.S. Census divisions and re-estimate the baseline panel specification separately within each division. Each regression retains the county-level unit of observation and includes time-varying economic and demographic controls, state-by-election-year fixed effects, and county-clustered standard errors. Figure A4 plots the estimated coefficient on $IM_{i,t-1} \times \mathbb{1}_{t \geq 2016}$, together with its 95 percent confidence interval.

The estimated coefficient is negative in seven of the nine Census divisions. The largest negative point estimates appear in the East North Central, West North Central, and West South Central divisions, where the confidence intervals are also comparatively narrow. The post-2016 IM relationship is likewise negative in the Middle Atlantic, all three Southern divisions, and the Pacific division. In the Mountain division, the point estimate is slightly positive, but the confidence interval is sufficiently wide to include both substantial negative and positive values.

The geographic pattern indicates that the baseline result is not attributable solely to import-intensive coastal counties. Nor is it confined to a single legacy manufacturing region. Negative coefficients appear across the Northeast, Midwest, South, and Pacific, although their precision varies with the number of counties and the amount of within-division variation in importing. The particularly clear estimates in the industrial Midwest show that the negative IM relationship is also present in counties where manufacturing has historically played a central economic role.

The separate regressions use samples that differ in size and economic composition, and the confidence intervals overlap across most divisions. The evidence therefore does not establish

that the effect is larger in one region than another. It shows that the negative post-2016 association between direct import participation and Republican voting is geographically broad and is not driven by any single Census division.

5.2 Alternative Specifications and Import Measures

Table A1 examines whether the post-2016 change in the IM relationship is sensitive to the weighting of counties, metropolitan status, the inclusion of trade intermediaries, the timing of measured import activity, or the composition of imported goods. Columns (1) and (2) reestimate the baseline panel regression using total presidential votes and county population as weights, respectively. The coefficient on $IM_{i,t-1} \times \mathbb{1}_{t \geq 2016}$ remains negative and statistically significant in both specifications, at -0.444 when weighting by vote count and -0.455 when weighting by population. Although these estimates are somewhat smaller in magnitude than the unweighted benchmark, they show that the post-2016 shift is not driven by the equal weighting of a large number of sparsely populated counties. The weighted specifications remain county-level regressions: they place greater weight on county environments containing more voters or residents, rather than identifying individual-level voting responses.

Column (3) absorbs state-by-metropolitan-status-by-election-year fixed effects, using the most recent metropolitan classification available for each election year. The interaction coefficient remains negative at -0.235, with a t -statistic of -1.75. This specification allows a separate intercept for each state, metropolitan-status group, and election year.

Column (4) addresses a measurement concern in consignee-based imports. Freight forwarders, distributors, and retailers may appear as consignees even when intermediate goods are transported to other counties or final goods are sold directly, so their recorded imports need not represent inputs used in the consignee’s county. We link Panjiva consignees to S&P Global business descriptions and Foundation firm records, retain firms with at least \$1 million in cumulative imports, and require at least \$0.5 million in imports not identified as final goods under the BEC classification for firms without linked S&P evidence.²² The resulting API sample contains 220,045 firms. We use GPT-5.6 Luna for the first-stage classification of firm industry and trade-intermediary status and GPT-5.6 Terra to review uncertain cases. Firms without a sufficiently reliable industry classification after both stages are excluded from the final firm-record sample; uncertain trade-intermediary classifications are conservatively retained. Among the 203,299 firms in the final sample, those classified as non-trade intermediaries account for 66.1 percent of its import value. We aggregate im-

²²Small importers are harder to identify reliably and contribute more classification noise. These screening rules exclude less than 2 percent of total Panjiva import value while reducing the cost of API-based firm classification.

ports of these firms by county and year and scale them by county GDP to construct the Ex. Trade-Intermediary IM. Its interaction with $\mathbb{1}_{t \geq 2016}$ is -0.465, with a t -statistic of -3.55, close to the baseline estimate.

Column (5) replaces annual IM with each county’s average IM over 2008–2015. Annual county observations with no recorded imports are assigned a value of zero; the county-level average is then constructed and standardized across counties. The interaction between this fixed pre-2016 measure and $\mathbb{1}_{t \geq 2016}$ is -0.694, larger in absolute value than the baseline estimate. This result is particularly informative about timing. Because the measure is determined entirely from import activity observed before the 2016 election, the post-2016 relationship cannot be mechanically generated by subsequent changes in firms’ sourcing decisions or by the tariffs introduced during the 2018–2019 trade war. Instead, the political realignment was already associated with a persistent preexisting geography of direct import participation.

Column (6) assesses whether the result is driven solely by imports of retail-oriented final goods. We use the BEC goods classification to map the HS6 product codes supplied by Panjiva into final and non-final goods, with the latter comprising intermediate and capital goods. Final-goods IM and non-final-goods IM, together with their respective interactions with $\mathbb{1}_{t \geq 2016}$, enter the regression jointly. Both interactions are negative and statistically significant: -0.355 for final-goods IM ($t = -2.38$) and -0.420 for non-final-goods IM ($t = -3.09$). Thus, the post-2016 relationship is also present in imports beyond final goods.

Across all six columns, the relevant post-2016 IM interactions remain negative and statistically significant at the 10 percent level or better. The post-2016 downward shift in the IM relationship is therefore robust to alternative weighting schemes, controls for metropolitan status, the exclusion of trade intermediaries, a fixed measure of pre-2016 import participation, and the division of imports by goods type.

5.3 Panel Regression with Additional Controls

The main panel estimates show that the electoral relationships with direct importing and manufacturing dependence persist after accounting for county economic and demographic characteristics. Table III documents a negative post-2016 change in the IM relationship. The significant estimates in these specifications motivate a more detailed check of whether the joint IM and manufacturing relationships reflect other measured county characteristics.

Table A2 adds three cumulative groups of controls to a joint panel regression with the county IM and the county L-Share measured in 2015. The county economic group includes GDP per employee, GDP growth, unemployment, and agriculture and mining employment shares. The demographic group adds age, sex, race and ethnicity, low-income household

share, income inequality, college share, population density, white non-college share, and domestic, international, and net migration rates. The occupation group further adds employment shares in management and professional; service; sales and office; natural resources, construction, and maintenance; and production and transportation occupations. Each control set appears once with state fixed effects and once with state-by-election-year fixed effects. All specifications are unweighted and cluster standard errors by county.

Both post-2016 interactions retain their respective negative and positive signs and are statistically significant in every control group. In column (6), which includes all three groups and state-by-election-year fixed effects, the interaction is -0.394 for IM ($t = -3.23$) and 0.641 for the L-Share ($t = 6.41$). For a one-standard-deviation difference in each measure, these coefficients correspond to post-2016 changes in the conditional Republican vote-share relationship of -0.394 and 0.641 percentage points, respectively, relative to the pre-2016 elections. This pattern suggests that the observed divergence is not explained by the economic, demographic, and occupational characteristics included here.

6 Conclusions

Global trade and local jobs were central to Trump’s 2016 campaign, reflecting the uneven benefits and costs of globalization across U.S. local economies. Restricting imports promised relief to manufacturing communities under pressure from foreign competition, but could also threaten the sourcing connections supporting American businesses. Our evidence shows a pronounced electoral divide. Counties more engaged in global sourcing, measured by the import-to-GDP ratio (IM), shifted less toward Trump; those more dependent on manufacturing employment, measured by L-Share, shifted more strongly toward him. The largest relative vote swings came in 2016. The strengthened partisan relationships persisted through 2024, even as subsequent vote swings diminished. Trump’s first election thus marked a turning point in the politics of globalization.

The manufacturing concerns behind this turning point had a much longer history. L-Share measured as early as 1975—well before the China Shock—predicts additional Republican alignment from 2016 onward. For communities whose livelihoods remained tied to manufacturing, Trump’s promise to bring jobs back looked both backward and forward—to opportunities already lost and jobs still at risk. Interestingly, manufacturing dependence gained the most additional pro-Republican weight in counties deeply engaged in global sourcing. Low-IM counties already exhibited a manufacturing-related Republican tilt before 2016, with little further strengthening. His employment appeal thus reached into local economies actively participating in global trade, where sourcing opportunities coexisted with depen-

dence on domestic manufacturing jobs.

The industry evidence brings out a broader distinction between the employment pressures facing mature manufacturing activities and the opportunities global sourcing offers for industrial growth. Counties more dependent on steel, textiles, wood products, and furniture exhibit additional pro-Republican alignment from 2016 onward, while their corresponding IM relationships are comparatively muted. Sourcing participation, meanwhile, carries additional anti-Republican associations across most manufacturing industries. Steel and electronics illustrate how these interests can align differently. Steel represents the concern for protecting an established employment base under continued competitive pressure. In growth industries such as electronics, foreign components and specialized production capabilities help sustain domestic competitiveness and jobs. Both electronics employment and sourcing participation are associated with additional anti-Republican alignment. The employment interest in continued global integration thus reaches into manufacturing itself.

These findings connect to the China-shock literature through both manufacturing dependence and industry variation. Decomposing conventional China-shock exposure, we find that its 1990 L-Share component predicts additional Republican alignment from 2016 onward, while within-manufacturing import penetration shows no statistically significant strengthening. This comparison brings into focus the longstanding manufacturing dependence embedded in the exposure measure—a manufacturing geography shaped by decades of industrial adjustment, whose political significance extends well beyond the China Shock. Industry variation provides another link. IM brings the productive opportunities from foreign supply into the comparison alongside competitive pressure. China is an important supplier to American businesses, including those in electronics, and direct sourcing from China is associated with additional anti-Republican alignment after 2016. The same pattern appears for sourcing from other countries. The question therefore extends beyond China to how the benefits and costs of global trade are distributed across local economies.

The political meaning of protecting American jobs depends on the industries sustaining those jobs and their connections to global production. Manufacturing dependence can sustain an interest in protection, while manufacturing employment can also rely on the foreign supply that protection would restrict. Trump’s 2016 campaign brought these different local stakes to the forefront of partisan competition, giving longstanding economic concerns new political force.

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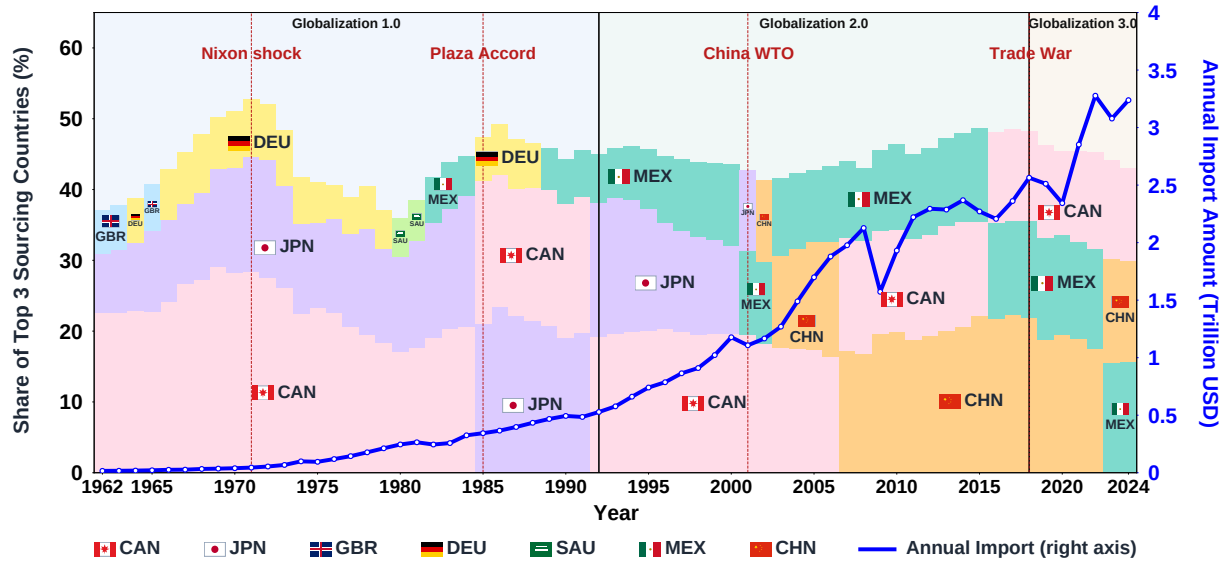
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Figure 1: The Evolution of U.S. Total Imports: From Globalization 1.0 to 3.0

This figure plots the time-series of U.S. imports by sourcing countries and industries from 1962 to 2024, spanning Globalization 1.0 to 3.0. In both panels, the blue line on the right axis reports the annual U.S. total import value in trillion USD. Panel A reports the shares of annual imports from top 3 sourcing countries, while Panel B reports the shares from top 3 industries and their respective top sourcing countries.

(a) Yearly U.S. Imports and Top 3 Sourcing Countries



(b) Yearly U.S. Imports and Top 3 Industries

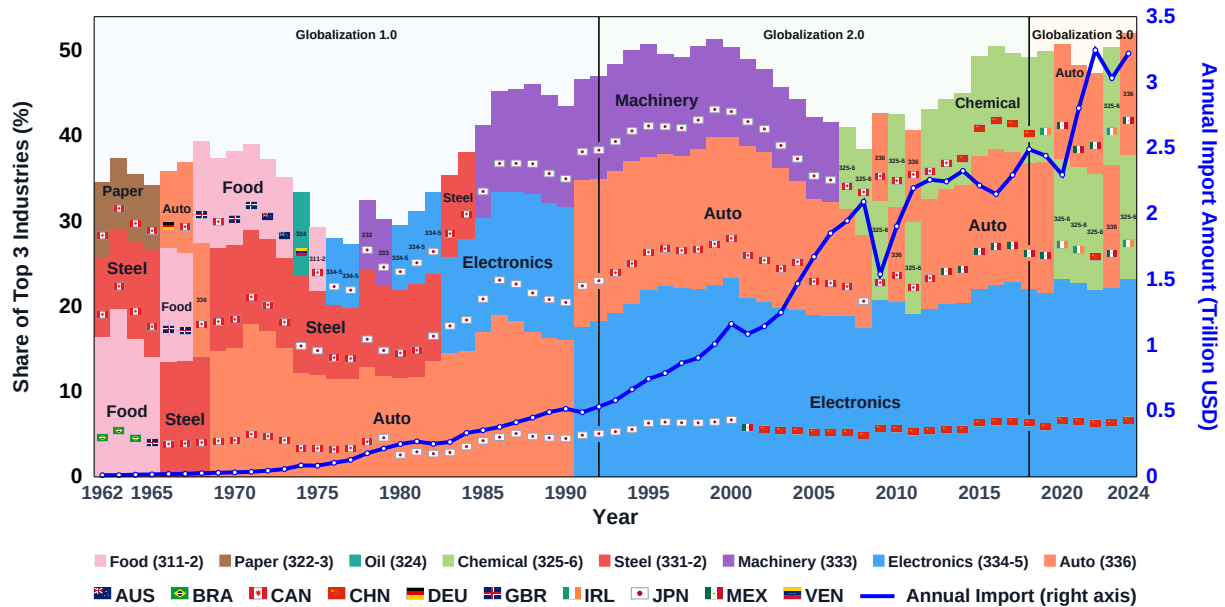


Figure 2: Globalization 1.0: The “Hollowing-Out” of the Rust Belt

This figure plots population trends for U.S. Rust Belt region, including Illinois, Indiana, Michigan, Ohio, and Wisconsin states using U.S. Census Bureau *Intercensal Estimates of the Total Resident Population of States* at ten-year intervals. Panel A shows these states’ combined share of the U.S. population. Panel B compares their combined population with the national total, with both series normalized to 100 relative to 1900.

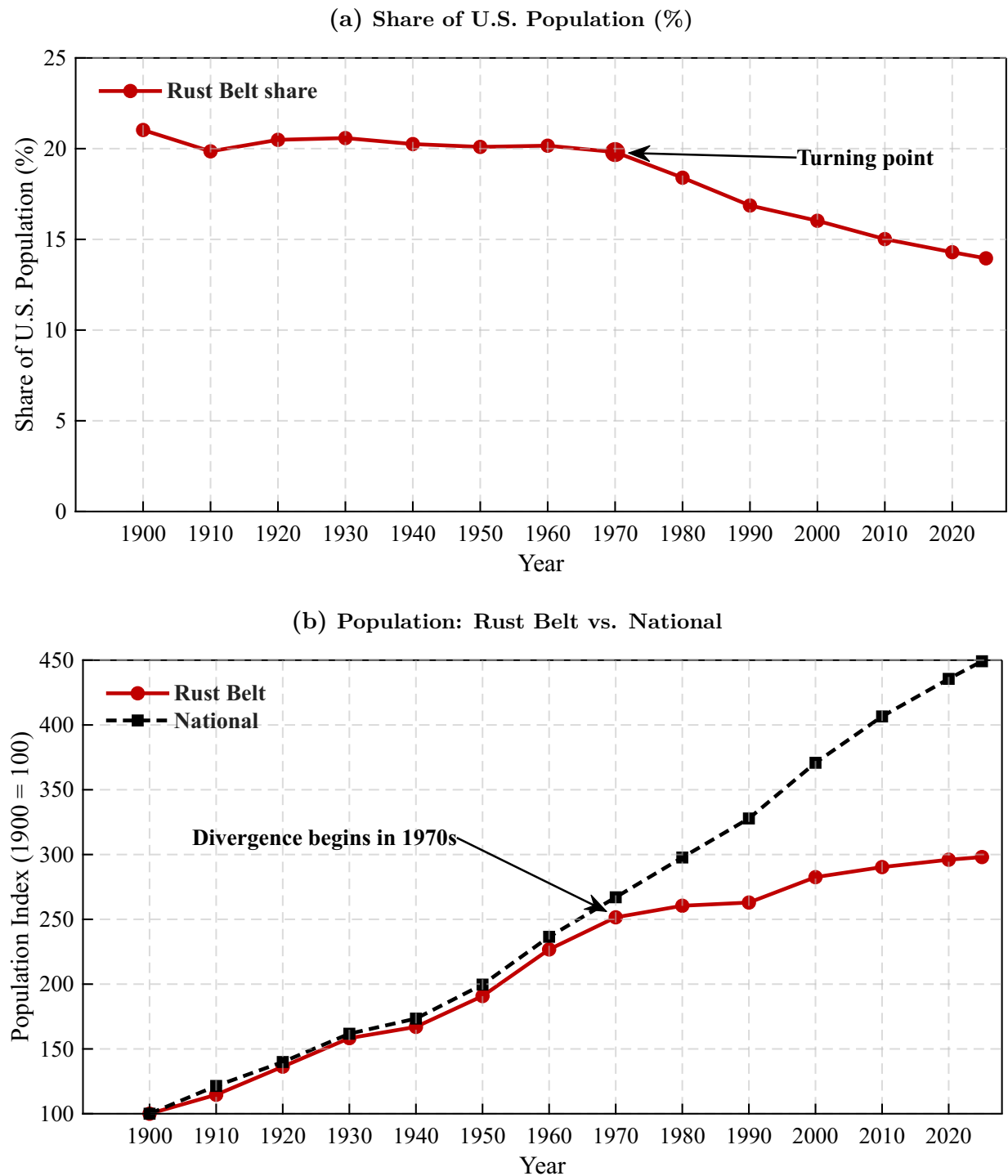


Figure 3: U.S. County-Level ΔR -Vote – Changes in Pro-Republican Vote Shares

This figure plots ΔR -Vote – changes in county-level pro-Republican vote shares – across the 2008–2024 presidential elections in U.S. maps. For each presidential election year t , $\Delta R\text{-Vote}_t = R\text{-Vote}_t - R\text{-Vote}_{t-1}$, where $t - 1$ is the preceding presidential election. Panels A–E report ΔR -Vote for 2008, 2012, 2016, 2020, and 2024, respectively. Red indicates an increase in Republican vote share, and blue indicates a decrease.

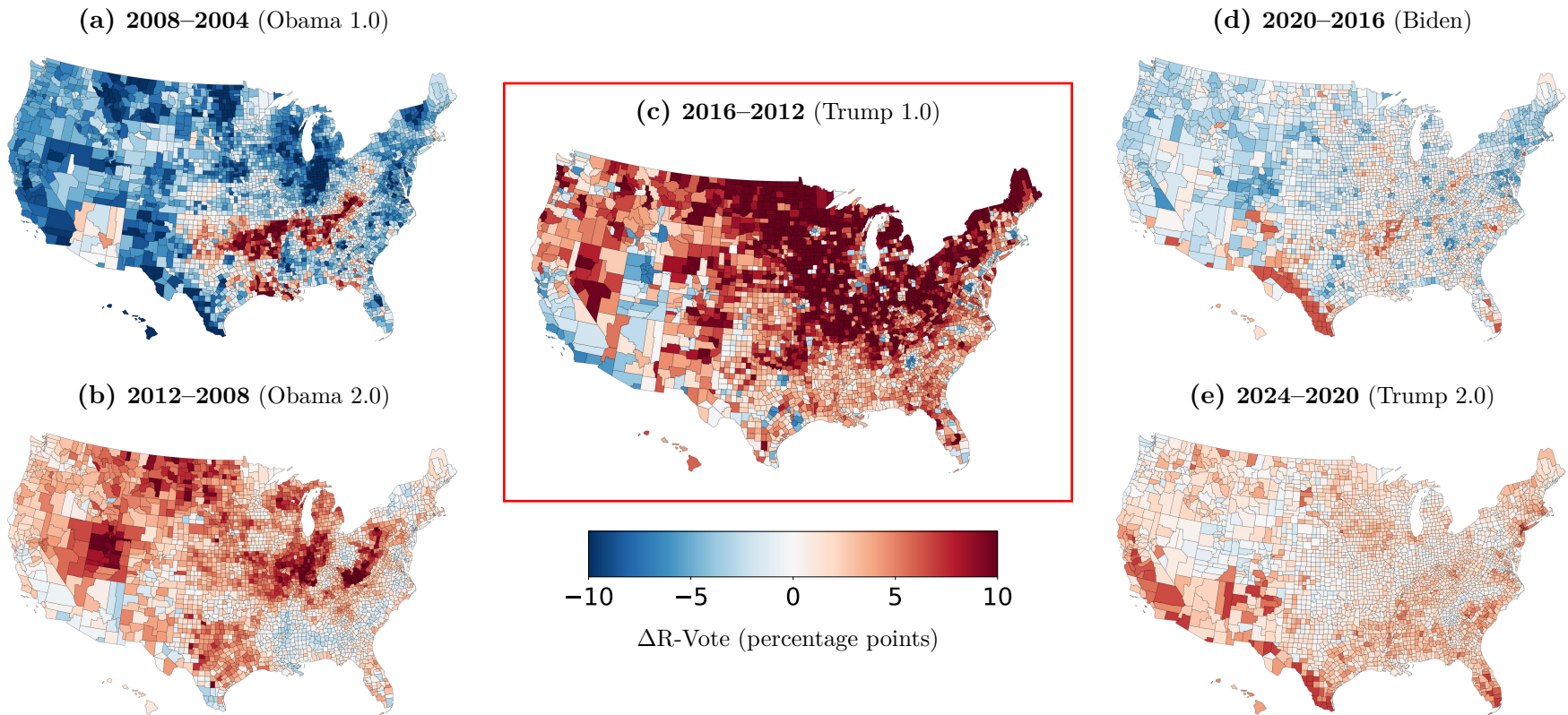


Figure 4: Vote Sensitivity to IM (2008-2024)

This figure reports the sensitivity of Republican voting outcomes to county IM across presidential elections, estimated via

$$\text{R-Vote}_{it} = a_t + b_t \text{IM}_{i,t-1} + \gamma_t \text{GDP/Employee}_{i,t-1} + \epsilon_{it}.$$

For each presidential election $t \in \{2008, 2012, 2016, 2020, 2024\}$, we estimate a separate cross-sectional regression. The dependent variable in the bottom panel is R-Vote_{it} , county i 's two-party Republican vote share, while the top panel replaces it with $\Delta \text{R-Vote}_{it}$, its change from the preceding presidential election. $\text{IM}_{i,t-1}$ is county i 's import-to-GDP ratio, and $\text{GDP/Employee}_{i,t-1}$ is GDP per employee, both measured one year before election t . All regressors are winsorized at the 1st and 99th percentiles and standardized. Red circles report the coefficients b_t , with vertical bars showing 95% confidence intervals. Blue dashed lines report IM's unique R^2 on the right axis, measured as the increase in R^2 from adding IM to the regression.

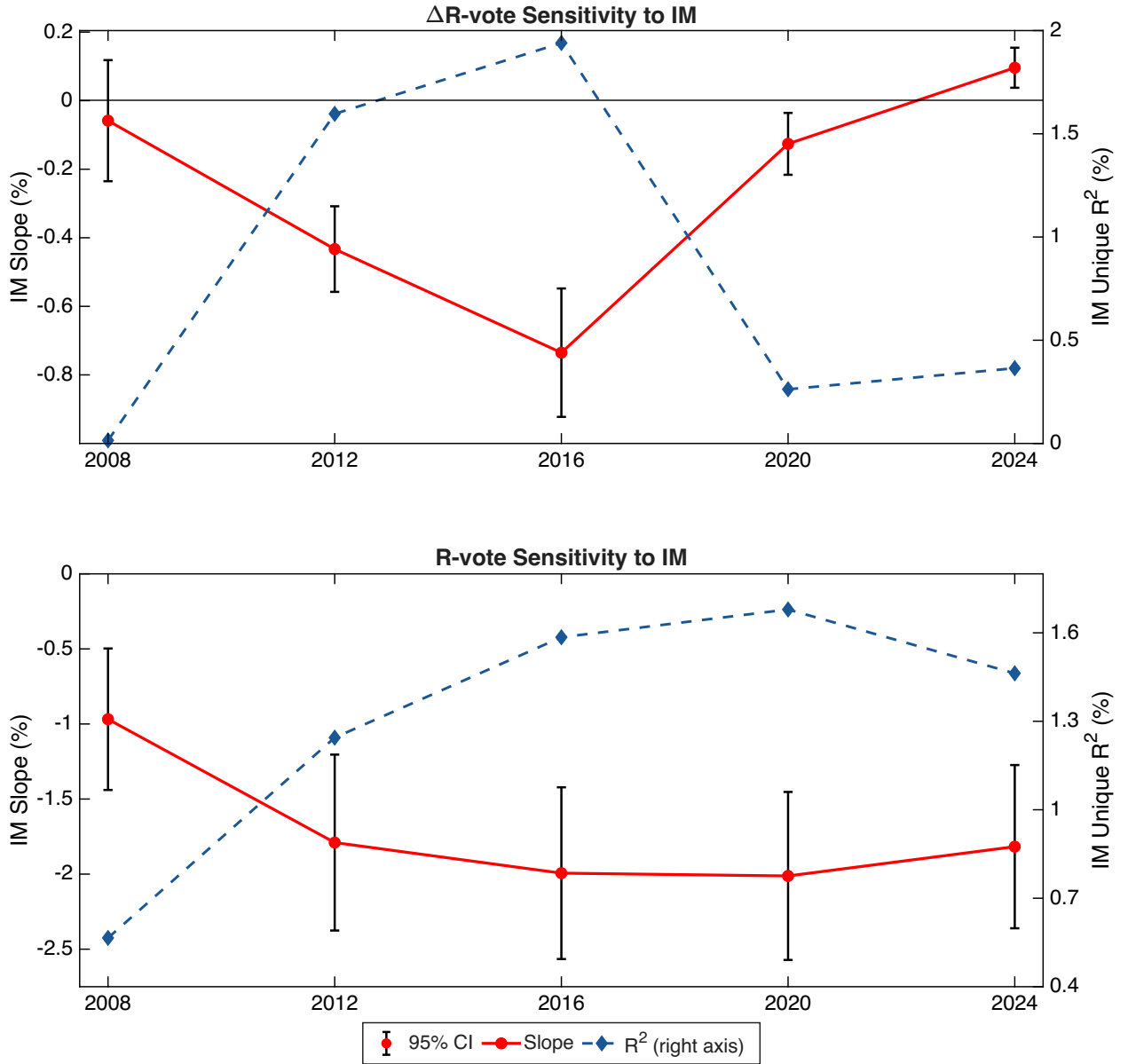


Figure 5: Vote Sensitivity to L-Share (1996-2024)

This figure reports the sensitivity of Republican voting outcomes to county L-Share across presidential elections, estimated via

$$\text{R-Vote}_{it} = a_t + b_t \text{L-Share}_{i,2015} + \gamma_t \text{PI/Employee}_{i,t-1} + \epsilon_{it}.$$

For each presidential election $t \in \{1996, 2000, 2004, 2008, 2012, 2016, 2020, 2024\}$, we estimate a separate cross-sectional regression. The dependent variable in the bottom panel is R-Vote_{it} , county i 's two-party Republican vote share, while the top panel replaces it with $\Delta \text{R-Vote}_{it}$, its change from the preceding presidential election. $\text{L-Share}_{i,2015}$ is county i 's manufacturing employment share in 2015, and $\text{PI/Employee}_{i,t-1}$ is personal income per employee measured one year before election t . County personal income is obtained from the BEA and used in place of GDP because county GDP is available only from 2001. All regressors are winsorized at the 1st and 99th percentiles and standardized. Red circles report the coefficients b_t , with vertical bars showing 95% confidence intervals. Blue dashed lines report L-Share's unique R^2 on the right axis, defined as the increase in R^2 from adding L-Share to a regression containing PI per employee and an intercept, using the same sample.

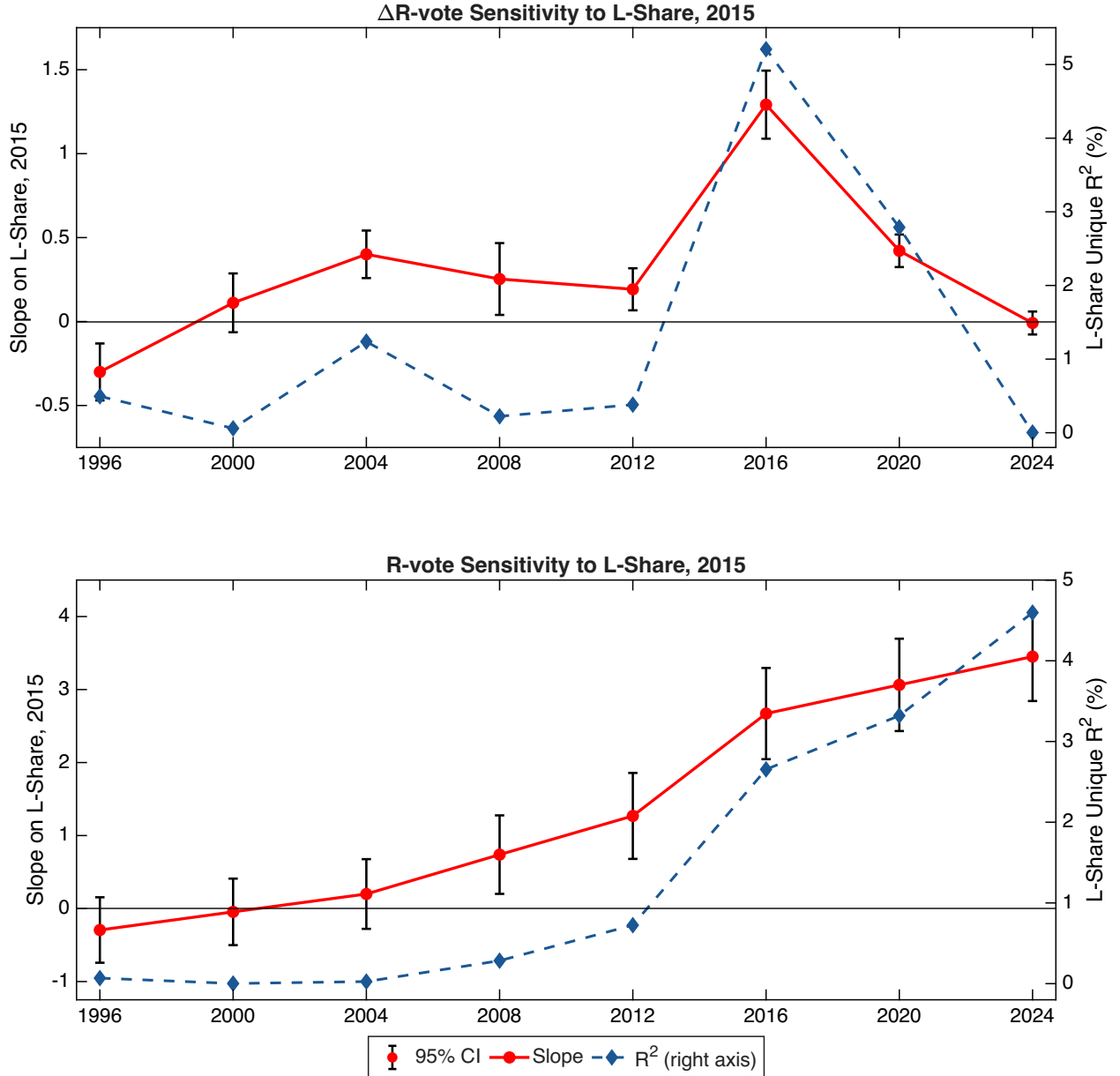


Figure 6: Sensitivity of Trump 1.0's Incremental Vote to Historical L-Share

This figure reports the sensitivity of Trump 1.0's incremental vote to historical L-Share, estimated via

$$\text{R-Vote}_{it} = \alpha_{\tau} + \beta_{\tau} \text{L-Share}_{i,\tau} + \theta_{\tau} \text{L-Share}_{i,\tau} \mathbb{1}_{t \geq 2016} + \mathbf{X}'_{i,t-1} \boldsymbol{\gamma} + \delta_{s(i),t} + \varepsilon_{it}.$$

For elections $t \in \{2008, 2012, 2016, 2020, 2024\}$, the dependent variable R-Vote_{it} is county i 's two-party Republican vote share. $\text{L-Share}_{i,\tau}$ is county i 's manufacturing employment share in historical year $\tau \in \{1975, \dots, 2015\}$; a separate panel regression is estimated for each τ . $\mathbb{1}_{t \geq 2016}$ equals one for $t \geq 2016$ and zero otherwise. The coefficient θ_{τ} captures the sensitivity of Trump 1.0's incremental vote to historical L-Share. $\mathbf{X}_{i,t-1}$ contains the same county economic and demographic controls, and $\delta_{s(i),t}$ denotes State $\times$ Year fixed effects. Regressors are winsorized at the 1st and 99th percentiles and standardized. Reported are the coefficients θ_{τ} for each historical year, with 95% confidence intervals using county-clustered standard errors.

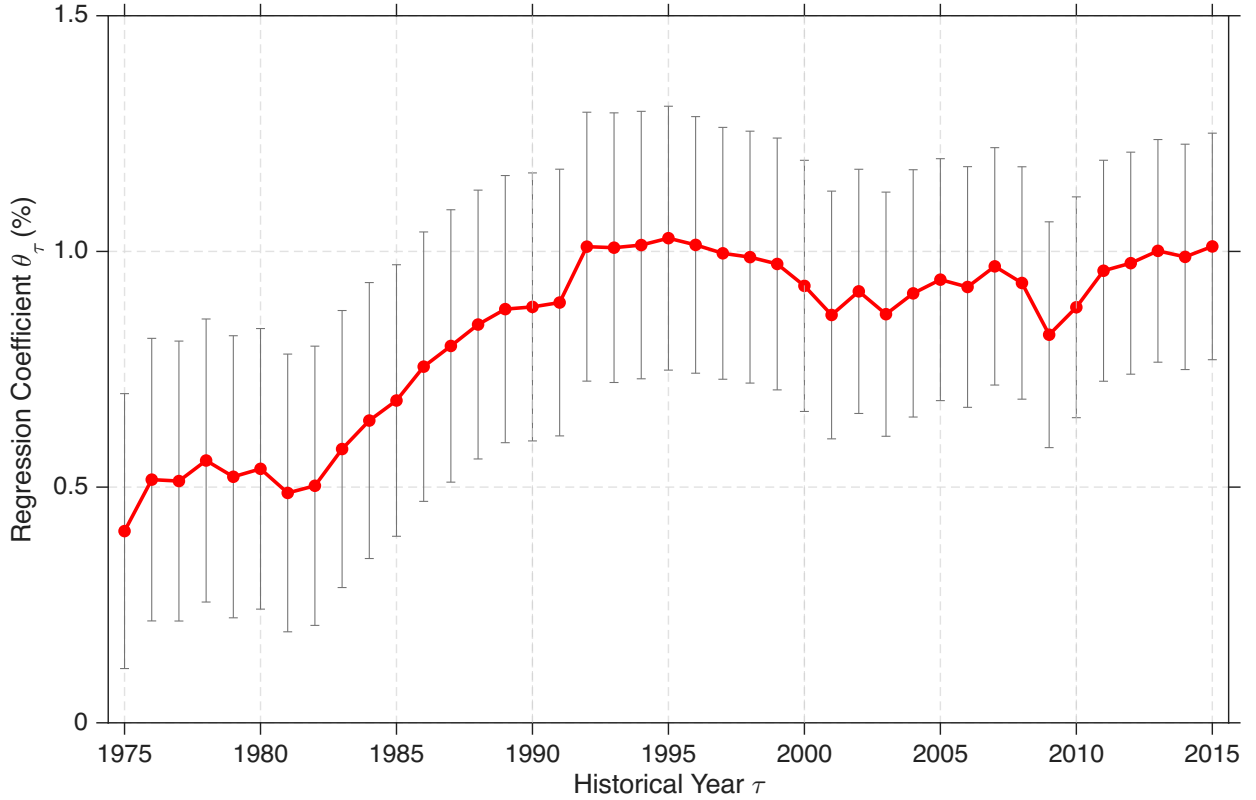


Figure 7: U.S. Import-to-GDP and Manufacturing Employment by Industry

This figure reports annual U.S. IM (import-to-GDP ratio) and L-Share (manufacturing employment share) from 1975 to 2023. Panel A reports the annual aggregate IM (right axis) and the relative contributions from the five leading import industries. Panel B reports the annual aggregate L-Share (right axis) and the relative contributions from the five leading manufacturing industries by employment.

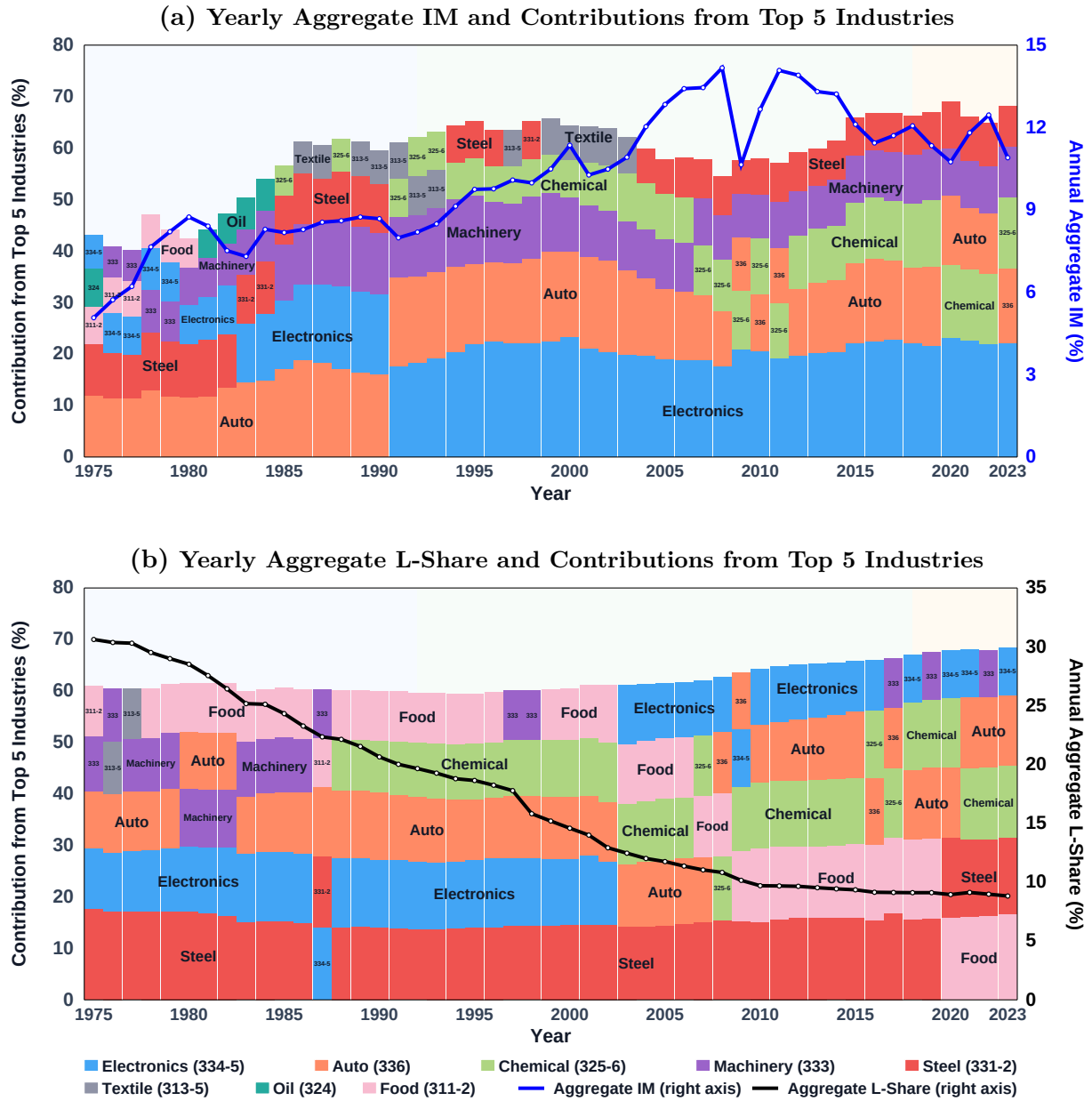


Figure 8: Benefits and Costs by Industry: θ^{IM} and θ^{L}

This figure reports the drive of Trump 1.0's marginal vote by industry-level IM and L-Share, estimated via

$$\text{R-Vote}_{it} = \alpha_k + \beta_k Z_{ik} + \theta_k Z_{ik} \mathbb{1}_{t \geq 2016} + \mathbf{X}'_{i,t-1} \gamma + \delta_{s(i),t} + \varepsilon_{it}.$$

For each election $t \in \{2008, 2012, 2016, 2020, 2024\}$, the dependent variable of this panel regression R-Vote_{it} is county- i 's Republican vote share. For county i and industry k , the key explanatory variable Z_{ik} is IM_{ik} in Panel A and L-Share_{ik} in Panel B. To estimate IM_{ik}, we identify Panjiva consignee firms in industry k and county i – averaging their total annual imports from 2008 to 2015 and dividing it by county i 's 2015 GDP. For L-Share_{ik}, we use county i 's industry- k manufacturing employment share in 2015. Capturing the Trump 1.0 effect, $\mathbb{1}_{t \geq 2016}$ is one for $t \geq 2016$ and zero otherwise. $\mathbf{X}'_{i,t-1}$ is a set of county-level economic and demographic control variables and $\delta_{s(i),t}$ is State $\times$ Year fixed effects. Reported are the regression coefficients θ_k^{IM} in Panel A and θ_k^{L} in Panel B for industry k , with the respective 95% confidence intervals using county-clustered standard errors.

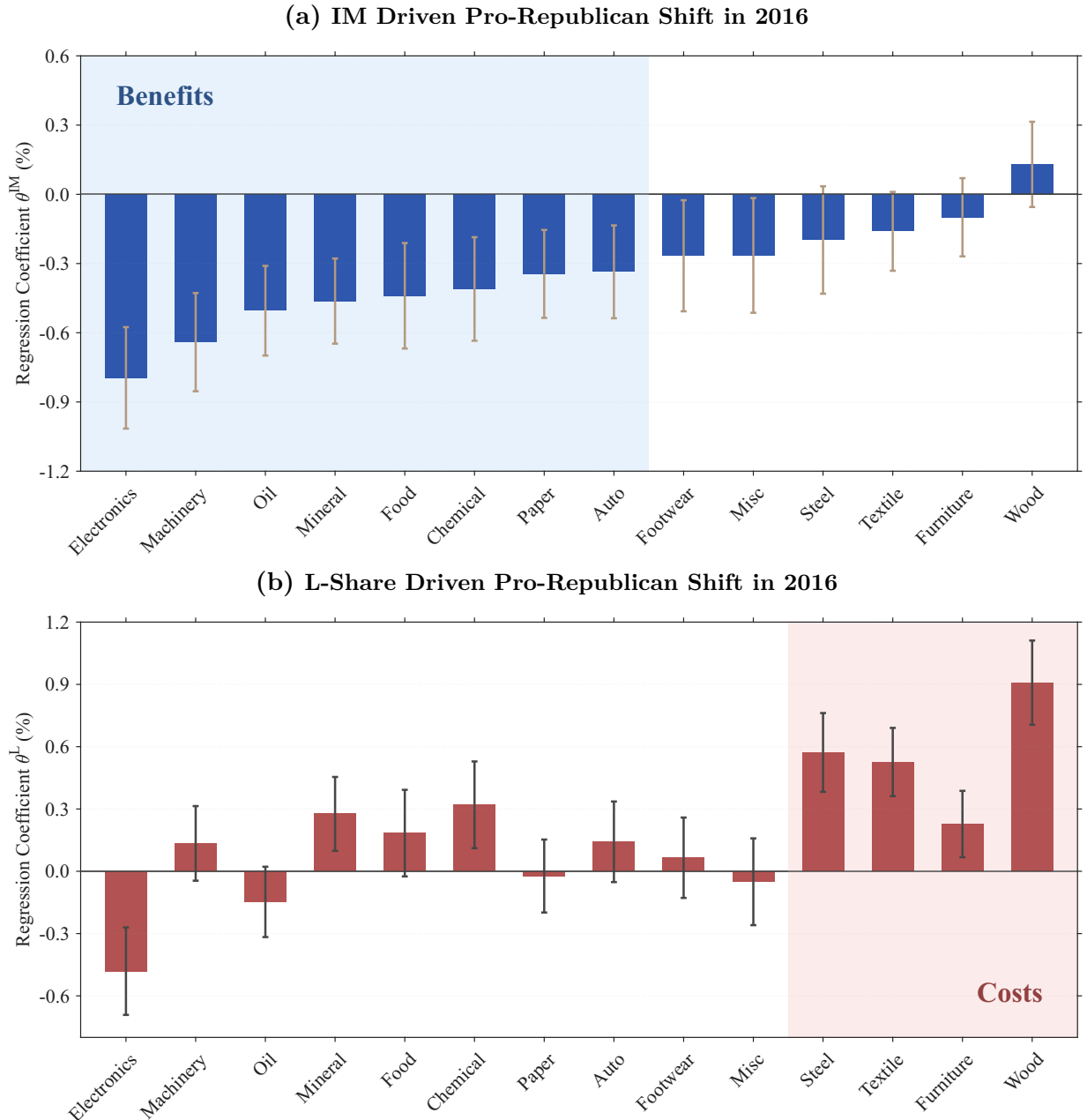


Figure 9: U.S. Imports From China and U.S. Manufacturing Employment

This figure reports the industry composition of U.S. imports from China and U.S. manufacturing employment trends. Panel A reports the annual manufacturing employment share (L-Share) in solid line using data from County Business Patterns (CBP), and the U.S. manufacturing employment in millions in dashed line (right axis) using data from the Bureau of Labor Statistics (BLS). Panel B reports the U.S. import-to-GDP (IM) using imports from China, both in aggregate (the blue line) and industry compositions (stacked bars), from 1975 to 2024. Industries accounting for more than 2% of annual imports from China are displayed; mining is excluded.

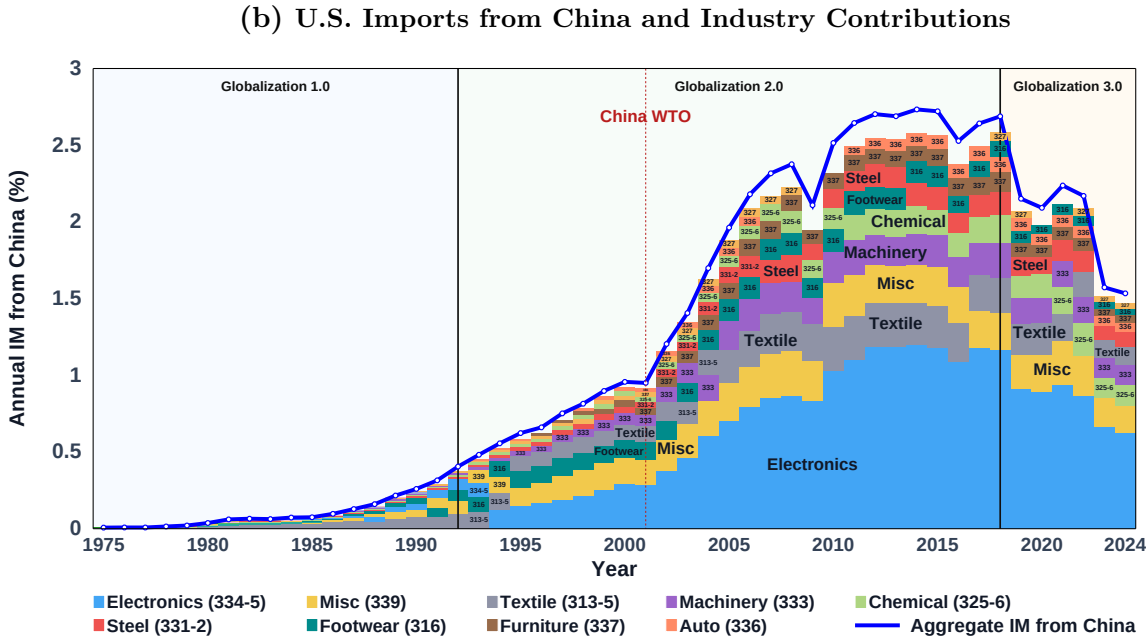
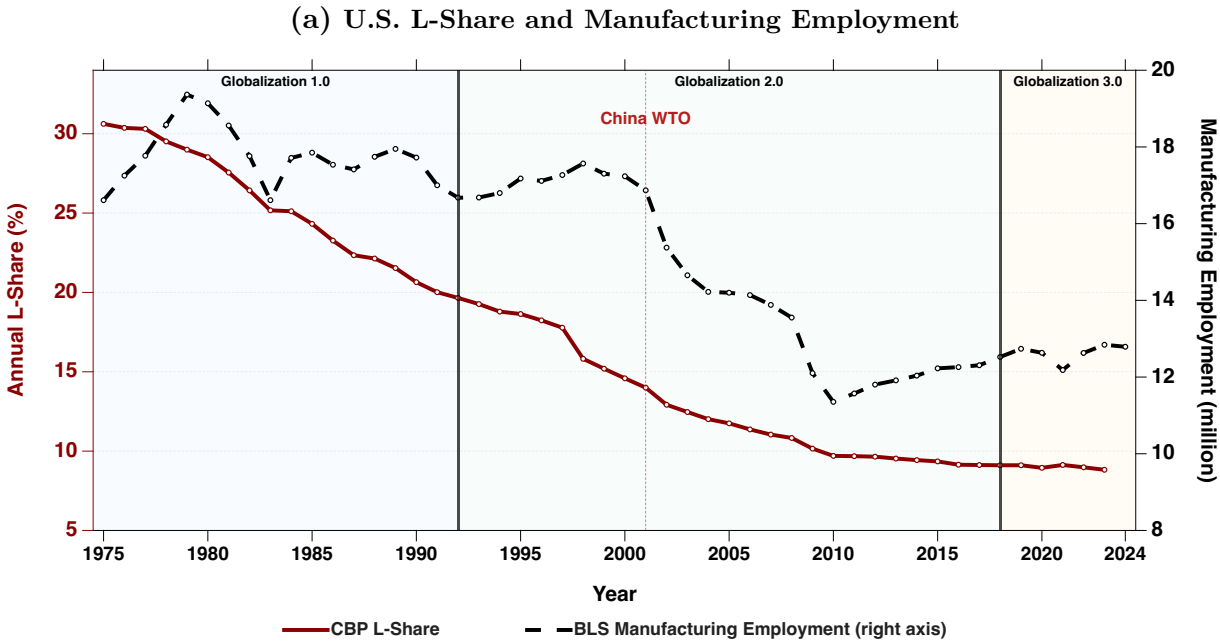


Table I: Summary Statistics: Full Sample

This table reports summary statistics for the county-level observations used in the empirical analysis. Panel A presents the county-level Republican two-party vote share (R-Vote) in each presidential election year, and Panel B reports the corresponding change in Republican vote share (Δ R-Vote) between consecutive presidential elections. Each election-year cross section contains 2,853 counties. Panel C summarizes the main trade, economic, demographic variables over the county-election year panel from 2008 to 2024. IM and EX denote county imports and exports divided by county GDP, respectively, and are reported as percentages of GDP. GDP per Employee is measured in thousand U.S. dollars. All trade and county-level characteristics reported in Panel C are winsorized at the 1st and 99th percentiles. For each variable, the table reports the number of non-missing observations, mean, standard deviation, and the 1st, 25th, 50th (median), 75th, and 99th percentiles.

Variables	Count	Mean	Std.	1%	25%	50%	75%	99%
Panel A: Republican Vote Share								
R-Vote, 2008 (%)	2,853	57.1	13.6	22.0	48.3	57.5	67.1	83.8
R-Vote, 2012 (%)	2,853	60.1	14.5	21.2	51.2	61.3	70.6	87.7
R-Vote, 2016 (%)	2,853	66.0	15.7	20.5	57.3	69.5	77.8	90.3
R-Vote, 2020 (%)	2,853	65.5	15.9	21.0	56.3	68.8	77.7	89.8
R-Vote, 2024 (%)	2,853	67.2	15.5	23.2	58.4	70.5	79.3	90.4
Panel B: Change in Republican Vote Share								
Δ R-Vote, 2008–2004 (%)	2,853	-3.1	5.1	-13.3	-6.3	-3.7	-0.4	11.9
Δ R-Vote, 2012–2008 (%)	2,853	3.0	3.1	-3.0	0.9	2.7	4.8	12.0
ΔR-Vote, 2016–2012 (%)	2,853	5.9	5.2	-6.5	2.6	5.5	9.6	17.4
Δ R-Vote, 2020–2016 (%)	2,853	-0.6	2.5	-6.1	-2.1	-0.6	0.8	6.1
Δ R-Vote, 2024–2020 (%)	2,853	1.7	1.6	-1.7	0.7	1.6	2.6	7.0
Panel C: Trade and County Characteristics								
IM (% of GDP)	14,225	2.1	4.9	0.0	0.1	0.5	1.8	35.8
L-Share(%)	14,225	15.9	12.1	0.0	6.5	13.2	22.8	53.8
EX (% of GDP)	14,225	0.3	1.4	0.0	0.0	0.0	0.1	11.1
GDP per Employee (K-USD)	14,225	98.3	53.6	33.2	65.0	85.9	115.0	380.2
GDP Growth (%)	14,225	4.0	8.1	-23.5	0.6	4.0	7.5	35.1
Unemployment Rate (%)	14,225	5.4	2.6	2.0	3.5	4.6	6.5	13.8
Gini Index (%)	14,225	44.0	3.4	36.5	41.6	43.8	46.2	53.5
Share Income Under \$35K (%)	14,225	36.5	10.6	13.7	28.8	36.4	43.9	61.8
Male Share (%)	14,225	49.9	1.9	46.5	48.9	49.6	50.5	58.8
Black Share (%)	14,225	9.2	14.3	0.0	0.7	2.4	10.9	64.3
Hispanic Share (%)	14,225	7.0	11.0	0.2	1.4	2.8	6.7	60.6
Share Age Over 65 (%)	14,225	17.2	4.5	8.2	14.1	16.8	19.9	30.8
Agricultural Employment Share (%)	14,225	12.1	14.0	0.0	2.3	6.8	16.7	69.0
Mining Employment Share (%)	14,225	1.6	4.3	0.0	0.0	0.1	0.6	26.4

Table II: Summary Statistics for Counties Sorted by IM and L-Share

This table reports average county characteristics across quintiles sorted by Import-per-GDP ratio (IM) in Panel A and manufacturing employment share (L-Share) in Panel B. In Panel A, counties are sorted in each election year by their IM. In Panel B, counties are sorted by their 2015 L-Share. Quintiles 1 and 5 have the lowest and highest sorting values, respectively. R-vote is the county-level two-party Republican vote share, and ΔR -vote is its change between consecutive presidential elections. IM is imports as a percentage of county GDP, and L-Share is manufacturing employment as a percentage of total county employment; both are measured one year prior to each election. HML is the difference between quintiles 5 and 1.

Year	1	2	3	4	5	HML	Year	1	2	3	4	5	HML
Panel A: Counties Sorted by IM													
ΔR -vote (%)							R-vote (%)						
2008	-2.4	-2.9	-3.2	-3.4	-3.5	-1.2	2008	61.2	58.7	56.5	55.2	54.0	-7.3
2012	3.7	3.2	3.1	2.9	2.0	-1.7	2012	65.4	61.1	60.2	58.6	55.3	-10.0
2016	7.4	6.6	6.4	5.0	4.2	-3.1	2016	71.6	68.6	66.5	63.2	60.3	-11.3
2020	0.1	-0.4	-0.8	-1.0	-0.8	-0.9	2020	70.6	68.5	65.8	62.5	59.9	-10.8
2024	1.7	1.7	1.7	1.7	1.9	0.2	2024	72.7	70.1	66.9	63.6	62.6	-10.1
IM (%)							L-Share (%)						
2008	0.0	0.1	0.5	1.4	12.2	12.2	2008	12.8	15.8	17.3	19.4	20.7	7.9
2012	0.0	0.1	0.4	1.1	10.9	10.9	2012	10.2	15.0	15.4	18.0	18.0	7.8
2016	0.0	0.1	0.5	1.5	12.7	12.7	2016	11.1	14.7	16.5	17.6	18.7	7.6
2020	0.0	0.1	0.5	1.6	11.5	11.5	2020	10.9	14.7	16.7	17.9	18.6	7.7
2024	0.0	0.2	0.6	1.7	11.1	11.1	2024	11.1	15.4	16.8	16.8	18.4	7.2
Panel B: Counties Sorted by L-Share													
ΔR -vote (%)							R-vote (%)						
2008	-3.3	-3.5	-3.2	-2.8	-2.6	0.7	2008	56.1	56.7	56.1	57.8	58.9	2.8
2012	3.1	2.8	3.0	3.0	3.1	0.0	2012	59.2	59.5	59.1	60.8	62.0	2.9
2016	4.5	3.9	5.9	7.2	8.3	3.8	2016	63.6	63.3	65.0	68.0	70.3	6.7
2020	-0.4	-1.4	-0.9	-0.4	0.2	0.6	2020	63.2	61.9	64.1	67.5	70.5	7.3
2024	2.0	1.6	1.7	1.6	1.8	-0.2	2024	65.2	63.5	65.7	69.2	72.3	7.1
IM (%)							L-Share (%)						
2008	1.4	2.5	2.5	3.2	4.6	3.1	2008	4.4	9.4	14.7	21.8	35.6	31.1
2012	1.2	2.5	2.6	2.1	4.2	3.0	2012	3.2	7.7	12.9	19.6	33.2	29.9
2016	1.3	3.0	3.3	2.4	4.7	3.4	2016	2.6	7.5	13.0	20.1	35.3	32.7
2020	1.8	2.1	3.1	2.8	4.1	2.2	2020	2.7	7.6	13.2	20.5	34.8	32.0
2024	1.8	1.8	2.9	3.0	4.2	2.5	2024	3.0	7.7	13.5	20.3	33.9	30.9

Table III: The 2016 Marginal Shift: Panel Regression of R-Vote on IM

This table reports the sensitivity of Trump 1.0's marginal vote to county IM, estimated via

$$\text{R-Vote}_{it} = \alpha + \beta \text{IM}_{i,t-1} + \theta \text{IM}_{i,t-1} \mathbb{1}_{t \geq 2016} + \pi \mathbb{1}_{t \geq 2016} + \mathbf{X}'_{i,t-1} \boldsymbol{\gamma} + \delta_{it} + \varepsilon_{it}.$$

For elections $t \in \{2008, 2012, 2016, 2020, 2024\}$, the dependent variable R-Vote_{it} is county i 's two-party Republican vote share. In columns (1)–(3), $\text{IM}_{i,t-1}$ is county i 's total imports as a percentage of county GDP, measured one year before each election; columns (4)–(5) jointly use China IM, based on imports with China as the recorded country of origin, and Non-China IM, defined as total IM minus China IM. $\mathbb{1}_{t \geq 2016}$ equals one for $t \geq 2016$ and zero otherwise. The coefficient θ captures the sensitivity of Trump 1.0's marginal vote to IM, while β is the pre-2016 R-vote slope. $\mathbf{X}_{i,t-1}$ includes GDP per employee in all columns; columns (2)–(5) add GDP growth, unemployment, manufacturing, agriculture, and mining employment shares, age-over-65, Male, Black, Hispanic, and low-income household shares, and the Gini coefficient. δ_{it} is zero in (1), State fixed effects in (2) and (4), and State $\times$ Year fixed effects in (3) and (5). Reported are regression coefficients, with county-clustered t -statistics in brackets. ***, **, and * denote $p < 0.01$, $p < 0.05$, and $p < 0.10$.

Variables	R-Vote				
	IM			China/Non-China IM	
	(1)	(2)	(3)	(4)	(5)
IM $\times \mathbb{1}_{t \geq 2016}$	-0.607*** [-2.71]	-0.614*** [-4.39]	-0.506*** [-3.70]		
IM	-1.349*** [-5.31]	-0.181 [-1.25]	-0.119 [-0.81]		
CN IM $\times \mathbb{1}_{t \geq 2016}$				-0.238 [-1.43]	-0.317** [-1.99]
CN IM				-0.292 [-1.62]	-0.132 [-0.74]
Non-CN IM $\times \mathbb{1}_{t \geq 2016}$				-0.556*** [-3.75]	-0.435*** [-2.99]
Non-CN IM				-0.050 [-0.34]	-0.038 [-0.25]
GDP/Employee	-1.290*** [-3.47]	-0.232 [-1.18]	-0.337* [-1.69]	-0.249 [-1.27]	-0.351* [-1.76]
GDP Growth		-0.288*** [-3.31]	-0.237*** [-2.70]	-0.275*** [-3.16]	-0.227*** [-2.58]
Unemployment Rate		0.050 [0.32]	-3.037*** [-7.11]	0.053 [0.34]	-3.039*** [-7.11]
Manufacturing Employment Share		1.406*** [9.38]	1.377*** [9.20]	1.428*** [9.49]	1.394*** [9.28]
Agriculture Employment Share		1.120*** [8.06]	1.131*** [8.22]	1.106*** [7.99]	1.122*** [8.17]
Mining Employment Share		1.367*** [6.56]	1.404*** [6.88]	1.358*** [6.53]	1.397*** [6.86]
Age Over 65 Share		2.322*** [11.89]	2.119*** [9.32]	2.282*** [11.67]	2.091*** [9.21]
Male Share		1.665*** [9.83]	1.551*** [9.23]	1.643*** [9.73]	1.536*** [9.16]
Black Share		-10.166*** [-41.42]	-9.990*** [-39.42]	-10.177*** [-41.40]	-9.996*** [-39.41]
Hispanic Share		-2.650*** [-10.51]	-3.366*** [-10.28]	-2.635*** [-10.53]	-3.352*** [-10.29]
Low-Income Household Share		0.912*** [4.28]	2.466*** [8.22]	0.885*** [4.14]	2.439*** [8.10]
Gini Coefficient		-2.441*** [-12.28]	-2.758*** [-13.38]	-2.428*** [-12.21]	-2.745*** [-13.30]
$\mathbb{1}_{t \geq 2016}$	8.448*** [37.13]	7.428*** [25.83]		7.477*** [26.08]	
Constant	58.204*** [186.33]	58.589*** [291.86]	62.370*** [335.49]	58.560*** [290.98]	62.372*** [335.30]
State FE	N	Y	N	Y	N
State $\times$ Year FE	N	N	Y	N	Y
Observations	14,225	14,225	14,220	14,225	14,220
R^2 (%)	7.8	68.3	71.7	68.3	71.8

Table IV: The 2016 Marginal Shift: Panel Regression of R-Vote on L-Share

This table reports the sensitivity of Trump 1.0's marginal vote to county L-Share, estimated via

$$\text{R-Vote}_{it} = \alpha + \beta \text{L-Share}_{i,\tau} + \theta \text{L-Share}_{i,\tau} \mathbb{1}_{t \geq 2016} + \pi \mathbb{1}_{t \geq 2016} + \mathbf{X}'_{i,t-1} \boldsymbol{\gamma} + \delta_{it} + \varepsilon_{it}.$$

For elections $t \in \{2008, 2012, 2016, 2020, 2024\}$, R-Vote_{it} is county i 's two-party Republican vote share. $\text{L-Share}_{i,\tau}$ is county i 's manufacturing employment as a share of total employment in base year τ : 2015 in columns (1)–(3) and 1975 in columns (4)–(5). $\mathbb{1}_{t \geq 2016}$ equals one for $t \geq 2016$ and zero otherwise. The coefficient θ captures the sensitivity of Trump 1.0's marginal vote to L-Share, while β is the pre-2016 R-vote slope. $\mathbf{X}_{i,t-1}$ includes GDP per employee in all columns; columns (2)–(5) add GDP growth, unemployment, agriculture and mining employment shares, age-over-65, male, Black, Hispanic, and low-income household shares, and the Gini coefficient. δ_{it} is zero in (1), State fixed effects in (2) and (4), and State $\times$ Year fixed effects in (3) and (5). Reported are regression coefficients, with county-clustered t -statistics in brackets. ***, **, and * denote $p < 0.01$, $p < 0.05$, and $p < 0.10$.

Variables	R-Vote				
	L-Share, 2015			L-Share, 1975	
	(1)	(2)	(3)	(4)	(5)
L-Share₂₀₁₅ $\times \mathbb{1}_{t \geq 2016}$	1.780*** [15.88]	1.944*** [14.90]	1.011*** [8.24]		
L-Share ₂₀₁₅	0.937*** [3.79]	0.201 [1.13]	0.706*** [3.97]		
L-Share₁₉₇₅ $\times \mathbb{1}_{t \geq 2016}$				0.512*** [3.75]	0.407*** [2.73]
L-Share ₁₉₇₅				0.373* [1.75]	0.464** [2.17]
GDP/Employee	-1.101*** [-2.95]	-0.243 [-1.24]	-0.356* [-1.79]	-0.134 [-0.69]	-0.260 [-1.31]
GDP Growth		-0.402*** [-4.62]	-0.286*** [-3.26]	-0.408*** [-4.61]	-0.314*** [-3.58]
Unemployment Rate		0.105 [0.67]	-2.993*** [-6.96]	-0.014 [-0.08]	-3.166*** [-7.11]
Agriculture Employment Share		1.142*** [8.21]	1.151*** [8.36]	1.124*** [8.04]	1.121*** [8.10]
Mining Employment Share		1.359*** [6.53]	1.406*** [6.90]	1.263*** [5.99]	1.316*** [6.34]
Age Over 65 Share		2.359*** [12.12]	2.142*** [9.43]	2.337*** [11.78]	2.100*** [9.08]
Male Share		1.720*** [10.20]	1.590*** [9.46]	1.703*** [10.07]	1.560*** [9.29]
Black Share		-10.188*** [-41.54]	-10.004*** [-39.48]	-10.215*** [-41.42]	-10.034*** [-39.12]
Hispanic Share		-2.716*** [-10.59]	-3.389*** [-10.25]	-2.649*** [-10.11]	-3.339*** [-9.81]
Low-Income Household Share		0.998*** [4.75]	2.541*** [8.59]	1.189*** [5.72]	2.821*** [9.67]
Gini Coefficient		-2.454*** [-12.35]	-2.777*** [-13.51]	-2.685*** [-13.26]	-3.027*** [-14.55]
$\mathbb{1}_{t \geq 2016}$	8.246*** [36.27]	7.394*** [25.67]		7.466*** [25.57]	
Constant	58.310*** [187.25]	58.638*** [292.70]	62.400*** [335.42]	58.594*** [291.61]	62.388*** [326.35]
State FE	N	Y	N	Y	N
State $\times$ Year FE	N	N	Y	N	Y
Observations	14,225	14,225	14,220	14,190	14,185
R^2 (%)	8.5	68.5	71.7	67.6	71.2

Table V: Trump’s Marginal L-Share Votes: High vs. Low IM

This table reports the sensitivity of Trump 1.0’s marginal vote to L-Share across different IM groups. Counties are sorted into Low (bottom 30%), Med (middle 40%), and High (top 30%) grouped by their IM_{2015} . For each group $g \in \{\text{Low, Med, High}\}$, we estimate

$$\begin{aligned} R\text{-Vote}_{it} = & \alpha^g + \beta_L^g \text{L-Share}_{i,2015} + \theta_L^g \text{L-Share}_{i,2015} \mathbb{1}_{t \geq 2016} + \beta_P^g \text{GDP/Employee}_{it} \\ & + \theta_P^g \text{GDP/Employee}_{it} \mathbb{1}_{t \geq 2016} + \mathbf{X}'_{i,t-1} \boldsymbol{\gamma}^g + \delta_{s(i),t}^g + \varepsilon_{it}. \end{aligned}$$

For elections $t \in \{2008, 2012, 2016, 2020, 2024\}$, $R\text{-Vote}_{it}$ is county i ’s two-party Republican vote share. $\text{L-Share}_{i,2015}$ is county i ’s manufacturing employment share in 2015, while GDP/Employee_{it} is GDP per employee measured one year before election t . $\mathbb{1}_{t \geq 2016}$ equals one for $t \geq 2016$ and zero otherwise. The coefficients θ_L^g and θ_P^g capture the sensitivity of Trump 1.0’s marginal vote to L-Share and GDP per employee within group g , respectively. $\mathbf{X}_{i,t-1}$ contains county economic and demographic control variables. $\delta_{s(i),t}^g$ denotes State $\times$ Year fixed effects. Columns (1)–(2), (3)–(4), and (5)–(6) correspond to the Low, Med, and High import groups. Reported are regression coefficients, with county-clustered t -statistics in brackets. ***, **, and * denote $p < 0.01$, $p < 0.05$, and $p < 0.10$.

Variables	Counties Sorted by IM					
	Low IM		Med IM		High IM	
L-Share $\times \mathbb{1}_{t \geq 2016}$	0.093	0.085	1.265***	1.262***	2.552***	2.383***
	[0.46]	[0.43]	[6.51]	[6.51]	[10.71]	[9.93]
L-Share	0.862***	0.870***	0.795***	0.798***	0.162	0.239
	[2.70]	[2.73]	[2.77]	[2.78]	[0.48]	[0.71]
GDP/Employee $\times \mathbb{1}_{t \geq 2016}$		-0.305		-0.319		-2.011***
		[-0.85]		[-1.15]		[-5.88]
GDP/Employee	0.773**	0.979**	-0.717**	-0.493	-1.791***	-0.285
	[2.42]	[2.48]	[-2.51]	[-1.54]	[-5.05]	[-0.65]
GDP Growth	-0.210	-0.237*	-0.171	-0.192	-0.211	-0.272
	[-1.64]	[-1.66]	[-1.25]	[-1.37]	[-0.93]	[-1.21]
Unemployment Rate	-4.373***	-4.363***	-2.469***	-2.458***	0.115	0.174
	[-5.97]	[-5.94]	[-3.61]	[-3.59]	[0.14]	[0.22]
Agriculture Employment Share	1.101***	1.099***	0.767***	0.767***	1.403***	1.436***
	[5.58]	[5.57]	[3.16]	[3.16]	[3.88]	[3.99]
Mining Employment Share	0.662**	0.652**	1.366***	1.360***	2.124***	2.086***
	[2.37]	[2.33]	[4.35]	[4.33]	[2.86]	[2.85]
Share Age Over 65	1.875***	1.868***	1.661***	1.658***	1.874***	1.814***
	[4.62]	[4.60]	[4.74]	[4.72]	[4.46]	[4.33]
Male Share	1.022***	1.027***	1.360***	1.356***	2.182***	2.170***
	[3.92]	[3.94]	[5.09]	[5.07]	[5.54]	[5.53]
Black Share	-9.244***	-9.249***	-9.948***	-9.955***	-10.007***	-10.086***
	[-17.33]	[-17.32]	[-24.22]	[-24.24]	[-23.71]	[-23.99]
Hispanic Share	-3.771***	-3.778***	-2.462***	-2.470***	-3.755***	-3.850***
	[-7.18]	[-7.21]	[-4.83]	[-4.83]	[-5.79]	[-5.94]
Low-Income Household Share	1.247*	1.260*	3.101***	3.100***	0.966*	1.049**
	[1.94]	[1.95]	[6.51]	[6.50]	[1.88]	[2.04]
Gini Coefficient	-2.034***	-2.042***	-2.546***	-2.547***	-2.316***	-2.376***
	[-5.43]	[-5.44]	[-7.71]	[-7.70]	[-5.87]	[-6.00]
Constant	64.198***	64.241***	61.703***	61.747***	62.865***	63.153***
	[145.10]	[143.24]	[200.26]	[201.40]	[152.08]	[155.28]
State $\times$ Year FE	Y	Y	Y	Y	Y	Y
Observations	4,265	4,265	5,665	5,665	4,245	4,245
R^2 (%)	66.6	66.6	73.8	73.8	78.9	79.1

Table VI: Decomposition of China Import Penetration ΔIP^{cu}

This table reports the sensitivity of Trump 1.0's marginal vote to Chinese import penetration and its components. Following Autor et al. (2020), ΔIP^{cu} weights industry import increases over 1991–2015 relative to 1991 domestic absorption by 1990 employment shares. We decompose it as $\Delta IP^{cu} = L\text{-Share}_{1990} \times \Delta IP^{cu\text{-mfg}}$; the initial manufacturing employment share times import penetration weighted within manufacturing. We estimate

$$R\text{-Vote}_{it} = \alpha + \beta_I IM_{i,t-1} + \theta_I IM_{i,t-1} \mathbb{1}_{t \geq 2016} + \beta_Z Z_{z(i)} + \theta_Z Z_{z(i)} \mathbb{1}_{t \geq 2016} + \mathbf{X}'_{i,t-1} \gamma + \delta_{s(i),t} + \varepsilon_{it}.$$

For elections $t \in \{2008, 2012, 2016, 2020, 2024\}$, $R\text{-Vote}_{it}$ is county i 's two-party Republican vote share, and $IM_{i,t-1}$ is its prior-year import-to-GDP ratio. $\mathbb{1}_{t \geq 2016}$ equals one for $t \geq 2016$ and zero otherwise. θ_I and θ_Z capture changes in the IM and Z slopes from 2016 onward. $\mathbf{X}_{i,t-1}$ contains the listed county controls. $\delta_{s(i),t}$ includes State fixed effects and a post-2016 indicator in odd columns, and State $\times$ Year fixed effects in even columns. Regressions are unweighted; continuous regressors are winsorized at 1%–99% and standardized before restricting the loaded panel to election years. Reported are coefficients, with CZ-clustered t -statistics in brackets. ***, **, and * denote $p < 0.01$, $p < 0.05$, and $p < 0.10$.

Variables	R-Vote					
	ΔIP		Within-mfg ΔIP		L-Share	
	(1)	(2)	(3)	(4)	(5)	(6)
$IM \times \mathbb{1}_{t \geq 2016}$	-0.798*** [-5.27]	-0.591*** [-4.05]	-0.756*** [-4.99]	-0.606*** [-4.20]	-0.775*** [-5.18]	-0.539*** [-3.76]
IM	0.078 [0.54]	0.065 [0.44]	0.086 [0.61]	0.107 [0.72]	0.061 [0.43]	0.029 [0.20]
$\Delta IP^{cu} \times \mathbb{1}_{t \geq 2016}$	1.141*** [5.60]	0.670*** [3.84]				
ΔIP^{cu}	-0.414 [-1.49]	-0.224 [-0.82]				
$\Delta IP^{cu\text{-mfg}} \times \mathbb{1}_{t \geq 2016}$			0.146 [0.57]	-0.167 [-0.93]		
$\Delta IP^{cu\text{-mfg}}$			-1.002*** [-3.43]	-0.830*** [-3.02]		
$L\text{-Share} \times \mathbb{1}_{t \geq 2016}$					1.446*** [6.39]	1.202*** [5.67]
L-Share					0.628** [2.13]	0.660** [2.29]
GDP/Employee	-0.140 [-0.67]	-0.277 [-1.27]	-0.241 [-1.15]	-0.372* [-1.72]	-0.191 [-0.92]	-0.312 [-1.45]
GDP Growth	-0.480*** [-4.58]	-0.381*** [-3.86]	-0.426*** [-4.14]	-0.375*** [-3.91]	-0.475*** [-4.51]	-0.357*** [-3.66]
Unemployment Rate	0.133 [0.60]	-2.726*** [-4.56]	0.048 [0.22]	-2.795*** [-4.77]	0.180 [0.81]	-2.679*** [-4.50]
Agriculture Employment Share	1.558*** [6.43]	1.375*** [5.86]	1.567*** [6.47]	1.386*** [5.91]	1.626*** [6.72]	1.437*** [6.14]
Mining Employment Share	1.249*** [5.33]	1.294*** [5.58]	1.215*** [5.19]	1.264*** [5.45]	1.425*** [6.00]	1.458*** [6.22]
Share Age Over 65	1.990*** [7.81]	1.801*** [6.15]	1.932*** [7.64]	1.727*** [5.93]	1.893*** [7.61]	1.766*** [6.15]
Male Share	1.609*** [8.54]	1.496*** [8.10]	1.552*** [8.33]	1.440*** [7.87]	1.615*** [8.75]	1.523*** [8.36]
Black Share	-9.995*** [-28.54]	-9.871*** [-27.37]	-10.097*** [-29.41]	-9.967*** [-28.48]	-9.914*** [-28.61]	-9.762*** [-27.30]
Hispanic Share	-2.606*** [-6.97]	-3.290*** [-6.81]	-2.617*** [-7.03]	-3.325*** [-6.88]	-2.557*** [-7.00]	-3.221*** [-6.84]
Low-income Household Share	0.936*** [3.25]	2.571*** [6.38]	0.922*** [3.32]	2.549*** [6.56]	0.629** [2.29]	2.185*** [5.61]
Gini Coefficient	-2.602*** [-10.87]	-2.972*** [-12.17]	-2.547*** [-10.70]	-2.914*** [-12.04]	-2.468*** [-10.61]	-2.819*** [-11.84]
$\mathbb{1}_{t \geq 2016}$	7.894*** [18.96]		7.909*** [19.12]		7.780*** [18.75]	
Constant	58.441*** [195.57]	62.554*** [218.10]	58.414*** [195.04]	62.539*** [220.48]	58.497*** [196.87]	62.550*** [221.24]
State FE	Y	Y	Y	Y	Y	Y
State $\times$ Year FE	N	Y	N	Y	N	Y
Observations	14,200	14,195	14,200	14,195	14,205	14,195
R-squared	67.8	71.1	67.9	71.4	68.4	71.6

Table VII: Trump’s Marginal L-Share Vote: China and Non-China IM

This table reports the sensitivity of Trump 1.0’s marginal vote to L-Share. China IM is imports with China as the recorded country of origin as a percentage of county GDP; Non-China IM is total IM minus China IM. Counties are separately sorted by 2015 China or Non-China IM into groups $g \in \{\text{Low, Med, High}\}$ (bottom 30%, middle 40%, top 30%), with membership fixed across elections. Each Low, Med, and High pair reports China and non-China groups, respectively. We estimate

$$\text{R-Vote}_{it} = \alpha^g + \beta_L^g \text{L-Share}_{i,2015} + \theta_L^g \text{L-Share}_{i,2015} \mathbb{1}_{t \geq 2016} + \mathbf{X}'_{i,t-1} \boldsymbol{\gamma}^g + \delta_{s(i),t}^g + \varepsilon_{it}.$$

For elections $t \in \{2008, 2012, 2016, 2020, 2024\}$, R-Vote_{it} is county i ’s two-party Republican vote share. $\text{L-Share}_{i,2015}$ is county i ’s manufacturing employment share in 2015. $\mathbb{1}_{t \geq 2016}$ equals one for $t \geq 2016$ and zero otherwise. θ_L^g captures the sensitivity of Trump 1.0’s marginal vote to L-Share within group g , while β_L^g is the pre-2016 R-vote slope. $\mathbf{X}_{i,t-1}$ contains GDP per employee and other county economic and demographic controls measured one year before each election. $\delta_{s(i),t}^g$ denotes State $\times$ Year fixed effects. Reported are regression coefficients, with county-clustered t -statistics in brackets. ***, **, and * denote $p < 0.01$, $p < 0.05$, and $p < 0.10$.

Variables	Low IM		Med IM		High IM	
	China	Non-China	China	Non-China	China	Non-China
L-Share $\times \mathbb{1}_{t \geq 2016}$	0.028 [0.14]	0.129 [0.66]	1.285*** [7.19]	1.286*** [7.00]	2.488*** [10.38]	2.648*** [10.75]
L-Share	0.600* [1.88]	0.564* [1.77]	0.838*** [3.07]	0.818*** [2.85]	0.213 [0.62]	0.112 [0.33]
GDP/Employee	0.732** [2.55]	0.863*** [2.75]	-0.680** [-2.29]	-0.866*** [-2.99]	-2.181*** [-5.51]	-1.673*** [-4.67]
GDP Growth	-0.113 [-0.96]	-0.257** [-2.10]	-0.350** [-2.49]	-0.221 [-1.47]	0.079 [0.33]	-0.121 [-0.58]
Unemployment Rate	-4.805*** [-6.85]	-5.191*** [-7.39]	-1.589** [-2.45]	-1.900*** [-2.85]	-0.449 [-0.53]	0.123 [0.15]
Agriculture Employment Share	1.122*** [5.87]	0.961*** [5.26]	0.876*** [3.55]	0.901*** [3.18]	1.173*** [2.65]	1.386*** [3.72]
Mining Employment Share	0.366 [1.44]	0.539** [2.00]	2.039*** [5.93]	1.514*** [4.94]	2.677*** [3.80]	2.123*** [2.80]
Share Age Over 65	1.357*** [3.36]	1.919*** [4.81]	1.399*** [4.12]	1.660*** [4.59]	2.874*** [6.40]	1.617*** [3.95]
Male Share	1.275*** [5.18]	1.111*** [4.34]	1.225*** [4.68]	1.127*** [4.22]	1.333*** [3.47]	2.237*** [5.69]
Black Share	-9.506*** [-20.41]	-9.186*** [-16.97]	-9.624*** [-25.56]	-9.920*** [-23.72]	-10.163*** [-20.71]	-10.067*** [-24.53]
Hispanic Share	-4.136*** [-7.99]	-3.817*** [-7.41]	-2.840*** [-5.52]	-2.554*** [-4.87]	-3.257*** [-4.66]	-3.763*** [-6.03]
Low-Income Household Share	1.428** [2.51]	0.931 [1.58]	2.522*** [5.12]	2.794*** [5.71]	0.931* [1.79]	1.271** [2.51]
Gini Coefficient	-1.469*** [-4.78]	-1.405*** [-4.92]	-2.773*** [-8.11]	-3.048*** [-8.22]	-2.276*** [-5.65]	-2.348*** [-6.08]
Constant	64.231*** [143.65]	64.194*** [151.47]	62.235*** [210.04]	61.644*** [198.77]	62.192*** [154.65]	62.924*** [158.05]
State $\times$ Year FE	Y	Y	Y	Y	Y	Y
Observations	4,265	4,265	5,680	5,670	4,250	4,245
R^2 (%)	69.2	68.8	73.6	72.5	79.1	78.6

A Appendix

A.1 Industry Identification of S&P Panjiva Consignee Firms

In section 4.4 of the main text, we discuss the benefits and costs of globalization based on the industries of local consignee firms and employment. Panjiva shipment records identify imported goods and their U.S. consignees, but do not establish the consignee’s industry or whether the firm uses the goods in its own operations. To figure out the major industry of Panjiva firms, we deploy LLM API-based identification methods. This appendix provides additional details on the procedure and its results.

We identify each consignee’s core activity and distinguish operational users from trade intermediaries to link goods to the firms receiving them in the supply chain. This classification provides a basis for examining how county imports relate to local voting outcomes; it does not establish where each shipment is ultimately used.

Our unit of classification is a unique Panjiva consignee ID. We aggregate its imports across counties, HS6 products, and all years observed in the cleaned, county-linked firm file. Retaining firms with at least \$1 million in import value over the full sample period yields 255,646 firms, accounting for 99.3% of the organized total import values. Panjiva provides consignee names and locations. To supplement this information, we link each firm’s `conPanjivaId` to S&P Global’s `companyId` through the Panjiva cross-reference. We then obtain business descriptions from the Additional Company database of [S&P Global Company Intelligence](#), and industry descriptions and reporting-template labels from [S&P Capital IQ Base Files \(Foundation Company v2\)](#).

Not all consignees can be linked to these sources, and many small private firms have limited descriptive information. We therefore adapt the identification procedure to the available evidence and distinguish three types. Type A1 comprises 33,186 firms for which Foundation information supports a preliminary mapping to a three-digit NAICS industry. Type A2 comprises 79,091 firms with an S&P company link or supplementary company business description. Type B comprises 143,369 firms without this linked evidence, for which identification relies on Panjiva names and locations. Given the more limited information for Type B, we additionally require at least \$0.5 million in cumulative imports not explicitly classified as final goods under the BEC classification, retaining 107,768 firms in this group. This screening threshold does not imply that all retained goods are verified production inputs. Together, the three groups yield an API sample of 220,045 firms, accounting for 99.3% of the full sample used for our main results.

We classify firms in two stages using an OpenAI-compatible API with structured responses. In the first stage, we use `gpt-5.6-luna` to identify each consignee’s primary indus-

try and determine whether it uses imports in its own operations or acts as a trade intermediary. Each request includes the firm’s name, available business descriptions and Foundation information, and selected addresses and locations. The structured response contains (i) a three-digit NAICS code, accompanied by a confidence score and a brief explanation, and (ii) an indicator of Non-Trade status, which excludes wholesalers, distributors, freight forwarders, and other firms primarily engaged in moving or reselling goods. At this stage, we retain only nonmissing responses with confidence scores above 0.8, yielding valid three-digit NAICS codes for 154,866 firms. In the second stage, we use the more capable `gpt-5.6-terra` model to reassess 65,179 firms flagged primarily for uncertainty in their industry or trade-role classifications. We select the final classification separately for each field. A nonmissing second-stage response with confidence above 0.5 takes precedence, followed by a first-stage response with confidence above 0.5. Otherwise, we accept a lower-confidence classification if both stages agree and both confidence scores exceed 0.2.

Of the 220,045 firms in the API sample, 203,299 receive a three-digit NAICS classification under the final acceptance criteria and account for 96.5% of total import value in the full sample used for our main results. We retain 148,619 firms as Non-Trade, representing 65.0% of import value in the All sample. The 90,146 firms classified as manufacturers account for 51.5% of total import value in the same full sample. Of these manufacturers, 88,493 are also classified as Non-Trade and account for 78.6% of import value among Non-Trade firms.

Figure A1: County-Level Quintile Maps of IM and L-Share

This figure maps U.S. counties grouped into quintiles of IM (import-to-GDP ratio) and L-Share (manufacturing employment share). Panels A and B show average IM over 2008–2015 and IM in 2015, respectively. Panels C and D show L-Share in 1975 and 2015, respectively. Counties are grouped into quintiles separately for each measure and period, with darker shades indicating higher quintiles.

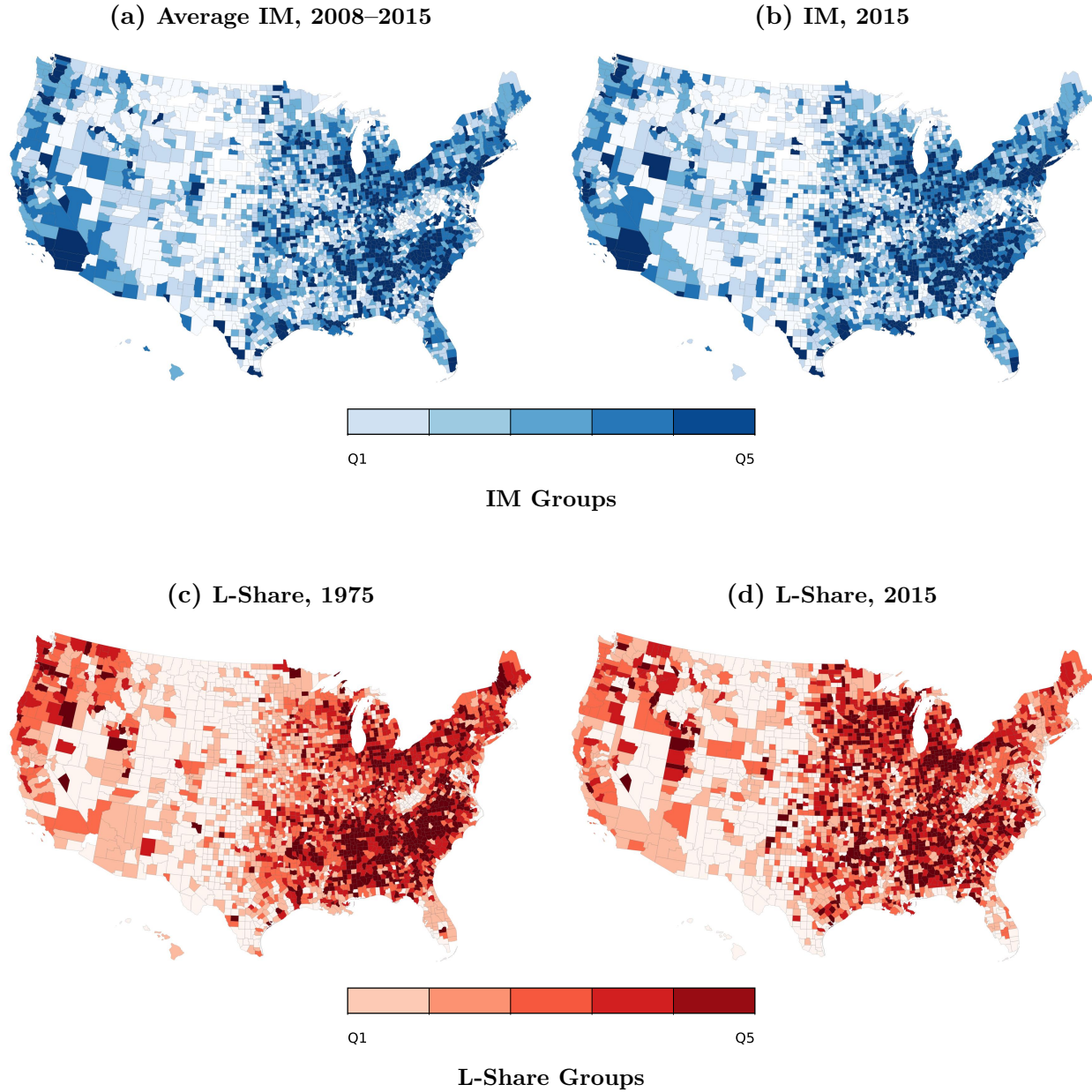


Figure A2: Histograms of ΔR -vote (Low- vs. High-IM Counties)

This figure compares the distributions of ΔR -vote between low- and high-IM counties. For each election $t \in \{2008, 2012, 2016, 2020, 2024\}$, counties are sorted by IM, their imports as a percentage of county GDP measured one year before the election. ΔR -vote is the change in a county's two-party Republican vote share from the preceding presidential election. Red and blue histograms show counties in the bottom and top IM quintiles, respectively. Low-High reports the difference in mean ΔR -vote between these groups (bottom minus top quintile). p reports the p -value from a one-sided Welch two-sample t -test of whether mean ΔR -vote is higher in the bottom IM quintile than in the top quintile, allowing for unequal variances.

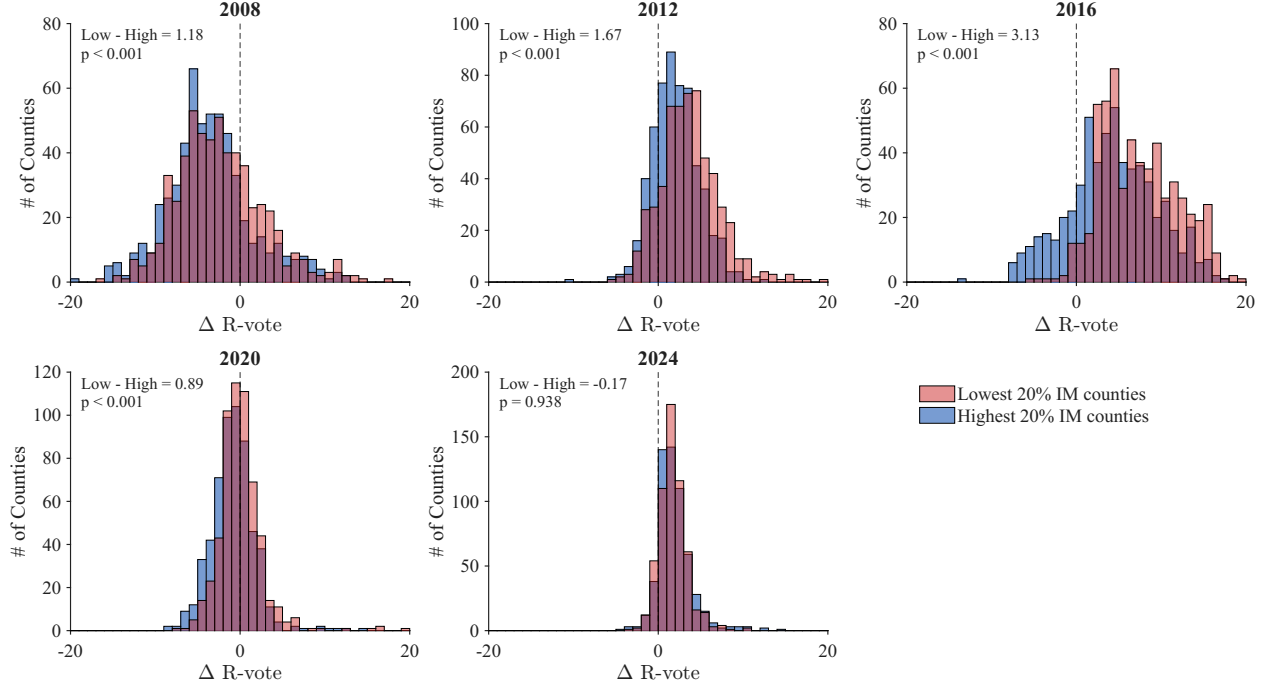


Figure A3: High-Minus-Low Voting Difference

This figure reports high-minus-low (HML) Republican voting differences by IM, L-Share, and ΔIP^{cu-mfg} . For each presidential election $t \in \{1996, 2000, 2004, 2008, 2012, 2016, 2020, 2024\}$, counties are sorted into five groups by each measure. IM is average import-to-GDP ratio from 2008 to 2015; L-Share is the 2015 county manufacturing employment share; and ΔIP^{cu-mfg} is 1991–2015 Chinese import penetration within-manufacturing measured at the commuting-zone level and assigned to counties. The top panel reports $\Delta R\text{-Vote}_{it}$, the change in county i 's Republican two-party vote share since the preceding presidential election; the bottom panel reports the vote share, $R\text{-Vote}_{it}$. HML is the difference in group R-Vote or $\Delta R\text{-Vote}$ means between the highest and lowest quintiles, using voting outcomes adjusted separately in each election year for the county GDP per employee measure, GDP growth, and unemployment. Error bars denote 95% confidence intervals.

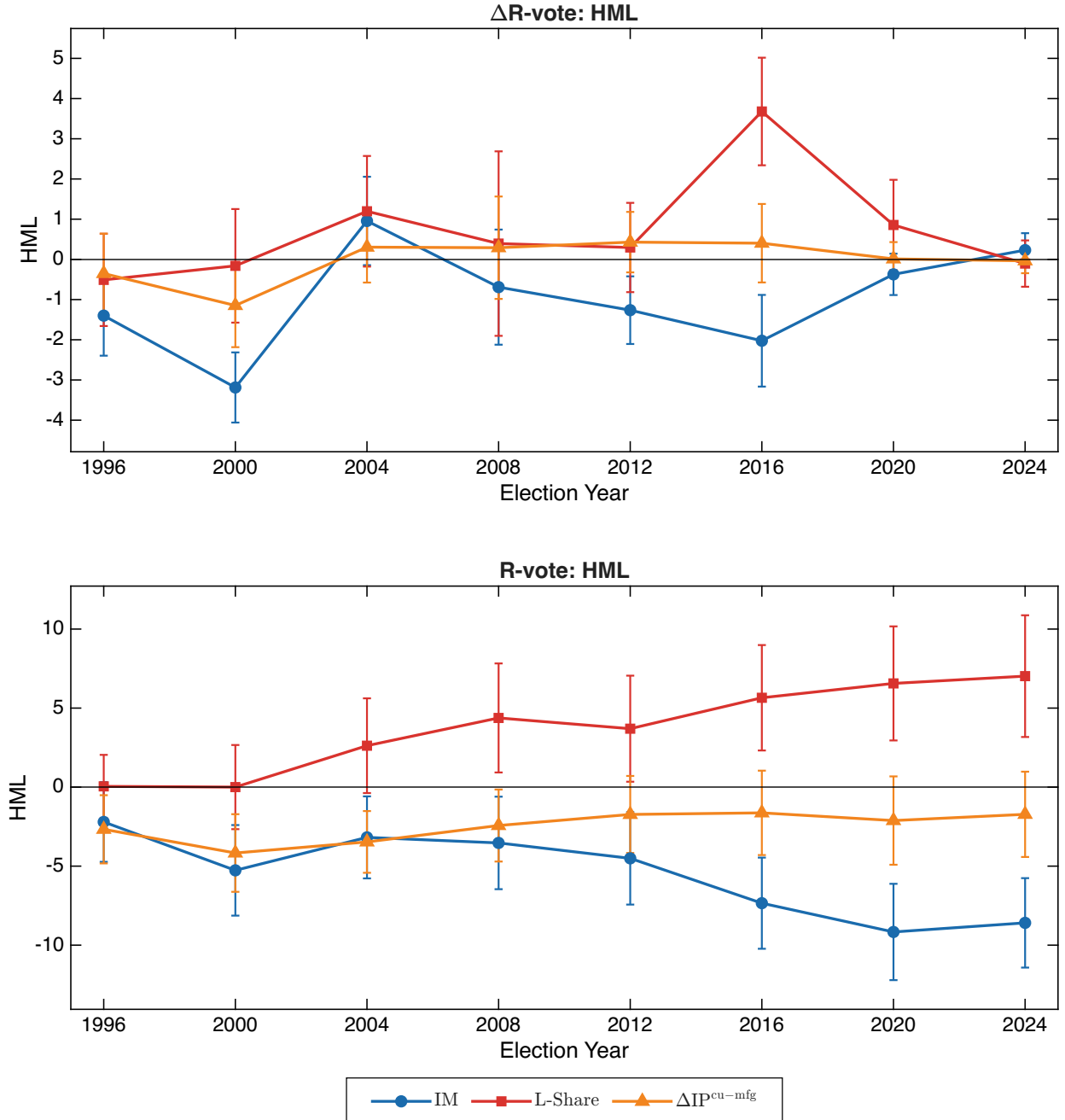


Figure A4: Panel Regression within Census Divisions

This figure reports the panel regression coefficients θ on the interaction term $IM_{i,t-1} \mathbb{1}_{t \geq 2016}$ from subsample county-level panel regressions estimated within each of the nine U.S. Census divisions. All regressions use the baseline specification with the full set of county-level economic and demographic controls, State $\times$ Year fixed effects, and county-clustered standard errors. Bars denote the estimated coefficients, and whiskers indicate 95% confidence intervals. Colors correspond to the four U.S. Census regions: Northeast, Midwest, South, and West.

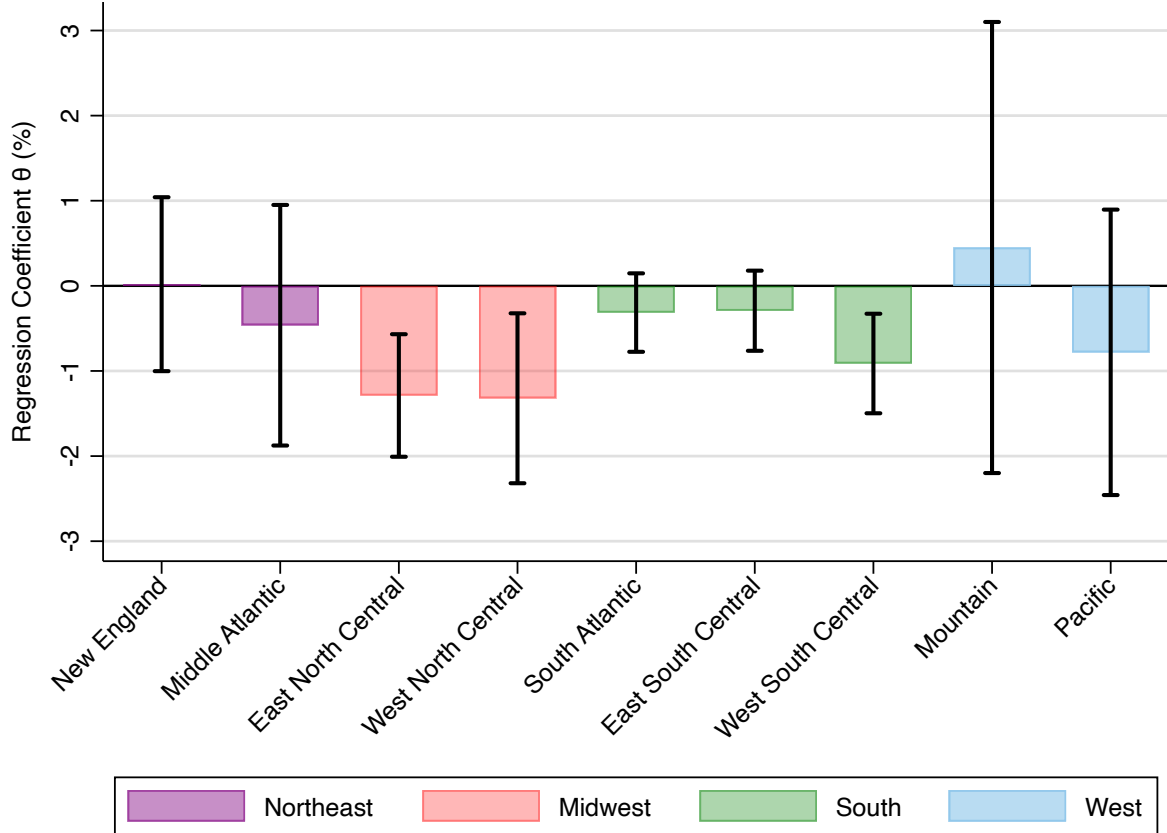


Table A1: Robustness Tests: Panel Regression of R-Vote on IM

This table reports robustness tests for the county-level panel regression of the Republican two-party vote share on import exposure. Column (1) uses the total number of votes cast in each presidential election as analytic weights, and column (2) uses county population as analytic weights. Column (3) absorbs state-by-metropolitan-status-by-election-year fixed effects. Column (4) uses the Ex. Trade-Intermediary IM, which excludes trade-intermediary firms in the S&P Panjiva shipment records before scaling imports by county GDP to construct IM. Column (5) replaces the annual IM with the county's average IM over 2008–2015. Column (6) replaces total IM and its interaction with $\mathbb{1}_{t \geq 2016}$ with the final- and non-final-goods IM and their respective interactions, included jointly. Goods types follow the BEC HS6 classification; non-final goods comprise intermediate and capital goods. Columns (1), (2), (4), (5), and (6) absorb State $\times$ Year fixed effects. $\mathbb{1}_{t \geq 2016}$ equals one for $t \geq 2016$ and zero otherwise. Continuous regressors are winsorized at the 1st and 99th percentiles and standardized over the full loaded panel before the election-year sample restriction. All specifications include the full set of economic and demographic controls reported in Table III, including manufacturing, agriculture, and mining employment shares. Reported are regression coefficients, with county-clustered t -statistics in brackets; R^2 is reported in percentage points. ***, **, and * denote $p < 0.01$, $p < 0.05$, and $p < 0.10$.

Variables	R-Vote					
	WLS: Vote Count	WLS: Population	State $\times$ Metro $\times$ Year FE	Ex. Trade-Intermediary	Avg. IM, 2008–2015	Final vs. Non-Final
	(1)	(2)	(3)	(4)	(5)	(6)
IM $\times \mathbb{1}_{t \geq 2016}$	-0.444**	-0.455**	-0.235*			
	[-2.07]	[-2.06]	[-1.75]			
IM	0.440*	0.404	-0.233			
	[1.88]	[1.56]	[-1.62]			
Ex. Trade-Intermediary IM $\times \mathbb{1}_{t \geq 2016}$				-0.465***		
				[-3.55]		
Ex. Trade-Intermediary IM				-0.042		
				[-0.30]		
Average IM, 2008–2015 $\times \mathbb{1}_{t \geq 2016}$					-0.694***	
					[-5.27]	
Average IM, 2008–2015					0.008	
					[0.05]	
Final IM $\times \mathbb{1}_{t \geq 2016}$						-0.355**
						[-2.38]
Final IM						-0.073
						[-0.51]
Non-Final IM $\times \mathbb{1}_{t \geq 2016}$						-0.420***
						[-3.09]
Non-Final IM						-0.073
						[-0.50]
GDP per Employee	-2.879***	-2.774***	-0.467**	-0.345*	-0.332*	-0.341*
	[-8.00]	[-7.48]	[-2.34]	[-1.73]	[-1.66]	[-1.71]
GDP Growth	-0.715***	-0.699***	-0.162*	-0.240***	-0.244***	-0.232***
	[-2.96]	[-2.72]	[-1.88]	[-2.74]	[-2.77]	[-2.64]
Unemployment Rate	0.593	0.333	-2.571***	-3.046***	-3.032***	-3.045***
	[0.65]	[0.34]	[-5.72]	[-7.13]	[-7.08]	[-7.13]
Manufacturing Employment Share	2.643***	2.858***	1.235***	1.376***	1.380***	1.378***
	[7.27]	[7.29]	[8.19]	[9.19]	[9.20]	[9.20]
Agriculture Employment Share	1.832***	2.151***	1.107***	1.137***	1.136***	1.126***
	[4.90]	[5.13]	[8.14]	[8.26]	[8.24]	[8.19]
Mining Employment Share	3.723***	3.940***	1.324***	1.413***	1.413***	1.397***
	[8.88]	[8.76]	[6.47]	[6.92]	[6.92]	[6.85]
Age Over 65 Share	2.137***	2.161***	1.764***	2.127***	2.135***	2.100***
	[5.45]	[5.16]	[7.32]	[9.36]	[9.40]	[9.22]
Male Share	2.171***	2.369***	1.304***	1.561***	1.549***	1.545***
	[5.52]	[5.90]	[7.68]	[9.28]	[9.19]	[9.18]
Black Share	-8.685***	-8.396***	-9.849***	-9.995***	-9.983***	-9.984***
	[-16.06]	[-13.87]	[-38.69]	[-39.46]	[-39.50]	[-39.36]
Hispanic Share	-2.470***	-2.682***	-3.460***	-3.378***	-3.366***	-3.358***
	[-4.54]	[-4.78]	[-10.39]	[-10.31]	[-10.27]	[-10.26]
Low-Income Household Share	1.241**	1.001	1.705***	2.497***	2.481***	2.449***
	[2.15]	[1.60]	[5.17]	[8.38]	[8.25]	[8.15]
Gini Coefficient	-3.100***	-3.051***	-2.699***	-2.766***	-2.757***	-2.742***
	[-6.89]	[-6.31]	[-12.93]	[-13.45]	[-13.38]	[-13.29]
Constant	59.532***	59.903***	62.457***	62.369***	62.340***	62.368***
	[171.08]	[159.94]	[331.67]	[335.96]	[334.36]	[335.59]
Controls	Y	Y	Y	Y	Y	Y
Absorbed FE	State $\times$ Year	State $\times$ Year	State $\times$ Metro $\times$ Year	State $\times$ Year	State $\times$ Year	State $\times$ Year
Observations	14,220	14,220	14,213	14,220	14,220	14,220
R^2	79.1	79.2	73.3	71.7	71.7	71.8

Table A2: Robustness Tests: Panel Regression with Additional Controls

This table reports panel regressions of R-Vote for elections $t \in \{2008, 2012, 2016, 2020, 2024\}$. $\mathbb{1}_{t \geq 2016}$ equals one for $t \geq 2016$ and zero otherwise. Continuous regressors are winsorized at the 1st and 99th percentiles and standardized over the full loaded panel before the election-year sample restriction. County economic controls comprise GDP per employee, GDP growth, unemployment, and agriculture and mining employment shares. Demographic controls add age, sex, race and ethnicity, low-income share, the Gini coefficient, college share, population density, white non-college share, and domestic, international, and net migration rates. Occupation controls add management/professional, service, sales/office, natural-resources/construction/maintenance, and production/transportation shares. Control coefficients are suppressed. Each control block is estimated with State fixed effects and State $\times$ Year fixed effects in adjacent columns. Reported are regression coefficients, with county-clustered t -statistics in brackets. ***, **, and * denote $p < 0.01$, $p < 0.05$, and $p < 0.10$.

Variables	County Economic		+ Demography		+ Occupation	
IM $\times \mathbb{1}_{t \geq 2016}$	-0.716***	-0.475**	-0.608***	-0.424***	-0.577***	-0.394***
	[-3.76]	[-2.49]	[-4.95]	[-3.43]	[-4.76]	[-3.23]
IM	-0.756***	-0.877***	0.133	0.111	0.086	0.071
	[-3.35]	[-3.95]	[0.95]	[0.77]	[0.63]	[0.50]
L-Share $\times \mathbb{1}_{t \geq 2016}$	1.640***	0.905***	1.454***	0.675***	1.418***	0.641***
	[13.08]	[7.41]	[13.34]	[6.74]	[13.06]	[6.41]
L-Share, 2015	1.392***	1.859***	-0.808***	-0.434***	-0.567***	-0.189
	[5.74]	[8.12]	[-4.78]	[-2.63]	[-3.13]	[-1.08]
County economic controls	Y	Y	Y	Y	Y	Y
Demographic controls	N	N	Y	Y	Y	Y
Occupation controls	N	N	N	N	Y	Y
State FE	Y	N	Y	N	Y	N
State $\times$ Year FE	N	Y	N	Y	N	Y
Observations	14,225	14,220	14,225	14,220	14,225	14,220
R^2 (%)	41.0	45.4	78.1	80.7	78.7	81.4