

Dependence, Chokepoints, and Robots*

Preliminary draft prepared for GRIPE

Stephen Chaudoin
Harvard University

Michael-David Mangini
University of Southern California

October 12, 2026

Abstract

Policymakers are obsessed with how trade flows create dependencies and vulnerabilities. They've spent billions of dollars on subsidies and deployed industrial policy to decrease their foreign dependence and remove chokepoint vulnerabilities that their adversaries could exploit. Where are these vulnerabilities? Have they become more concentrated in chokepoints over time? Will industrial policy to reshore production via automation actually decrease dependence? We answer all three questions for the United States using an original measure of dependence constructed at the most fine-grained detail possible, building on the work of Mangini and Chaudoin (2026). The measure is microfounded in structural models of the welfare gains from trade, and it incorporates downstream input-output consequences as well as alternative products and suppliers. We first show how U.S. dependence originates from some products associated with so-called chokepoints and many others that are not. The degree to which U.S. dependence is concentrated in chokepoints has not increased over time. We then use data from the wave of industrial automation in the 1990s and 2000s to assess whether automation decreased dependence. We show that, if anything, automation increased dependence. Industries that automated more quickly were a source of greater dependence in later years. These findings have major implications for where we identify chokepoints and what can be done about them.

*We appreciate the helpful feedback from Jiayu Lai and audiences at the Northeastern University conference on AI and Politics and UC Berkeley. Sandy Shao and Christina Wang provided valuable research assistance.

1. Introduction

Trade can generate welfare gains, but it also creates new points of pressure that one country can exploit against an adversary. Where *are* a country’s most important dependencies? Have they gotten more or less concentrated into “chokepoints” over time? What can a country do to address its dependencies on foreign countries? These questions rose to the top of policymakers’ minds after the COVID pandemic exposed key vulnerabilities, the United States led a retreat from global integration, and national leaders “rediscovered” the potential and peril of economic coercion. These questions now dominate the focus of political elites around the world. In 2020, President Xi Jinping described how cultivating foreign dependence on China while increasing its own self-reliance was a “major issue” for long-term national security.¹ In 2021, Japan created a cabinet-level Minister for Economic Security to coordinate economic security measures across military and economic offices.² In 2023, the European Union instituted the European Economic Security Strategy and created the Anti-Coercion Instrument to counter attempts to exploit dependencies.³ In 2026, fear of economic coercion led Canadian Prime Minister Mark Carney to argue that “[m]iddle powers must act together because if we’re not at the table, we’re on the menu.”⁴

To answer these questions, we generate new measures of dependence via trade at the most detailed, granular level to date. Our approach builds on the work of Arkolakis, Costinot, and Rodríguez-Clare (2012) and Mangini and Chaudoin (2026) (MC) to describe the harm one country could do to another by cutting off trade flows. This approach grounds the measure in a structural model of the welfare gains from trade which accounts for the size of the trade flow, the availability of substitute products or producers, and the downstream consequences of lost inputs and intermediate goods. We construct these detailed measures for the United States. We nest trade data at the HS-10-digit product level within over 235 detailed BEA commodities, covering 1997-2017. The resulting measure describes the consequences for aggregate U.S. welfare if a partner cut off all or some of its exports of particular product(s) to the United States.

Our first contribution is descriptive. We show that the “chokepoints” narrative is incorrect. Chokepoints are instances where one partner controls an overwhelming proportion of the dependence originating from an important commodity. Policymakers and academics are so focused on chokepoints that author Edward Fishman recently described the global economy as “one choke point after another.”⁵ The economist Soumaya Keynes created chokepoint trading cards to show the potency of various economic weapons.⁶ While certain things like the SWIFT banking system or the Strait of Hormuz are undoubtedly chokepoints, dependence from trade has become *less* characterized by chokepoints over time. Within a particular commodity or product, the degree to which dependence is concentrated has mostly remained stable, with a small increase in the tails of the distribution.

The share of U.S. dependence originating from past powers and allies, like Germany, Canada, and Mexico, has stayed relatively stable. The Chinese share increased substantially, at the expense of a more diffuse set of previous partners. This concentrated U.S. dependence into fewer partners. Looking at U.S. dependence on China more specifically, U.S. dependence has become more spread

¹Xi (2020).

²Glosserman (2021).

³European Commission and High Representative of the Union for Foreign Affairs and Security Policy (2023).

⁴Stavis-Gridneff and Austen (2026).

⁵Emily Peck, “It’s One Choke Point After Another in the Global Economy,” Axios, July 24, 2026, <https://www.axios.com/2026/07/24/choke-point-oil-strait-economy>.

⁶Soumaya Keynes, “Which Chokepoint Wins in a Game of Geoeconomic Top Trumps?,” Financial Times, March 12, 2026, <https://www.ft.com/content/b9f1b5ed-3bd4-4e03-9f11-a9681127befc>.

out over more commodities over time. China has more commodity-level dependence levers that affect more welfare, but it is not the case that U.S. dependence on China (or other partners) has become heavily concentrated in fewer chokepoints or pressure points.

In total, the chokepoints narrative is misplaced in the domain of trade. Chokepoints certainly exist, as with rare earths. But they have generally not become more prominent over time. Policymaker and elite discourse emphasizing a fear of chokepoints is actually better described as a fear of deepening dependence on China. Concentrated dependence on China is also more prominent in relatively mundane products, like apparel or toys, than in highly specialized, high-tech products.

Our second contribution is to provide direct evidence about one of the primary hopes for decreasing dependence: automation. Policymakers in richer, more capital-abundant countries in the Global North attribute much of their dependence on China and other countries in the Global South to their relative abundance of cheap labor. In their telling, dependence arose because Northern firms outsourced production to cheap, foreign labor. Policymakers have placed great hope in (and spent billions of dollars of subsidies on) industrial automation as a way to reshore production and ameliorate their vulnerabilities.

Yet, these solutions are partial at best and counterproductive at worst. Building an automation-heavy production facility at home may put a band-aid over a particular dependency, but it also creates new dependencies. Some pathways to increased dependence are direct: buying more automation capacity creates a new dependence on automation itself. Other pathways are indirect: increased production from replacing labor in one stage can increase dependence on upstream inputs or downstream complements. For example, returning production of a car plant via automation could increase demand for steel, an upstream input, or tires, a downstream complement.

We show that the industries in the United States that automated more quickly did *not* decrease as points of dependence. We regress the change in dependence on the change in robot adoption, at the commodity level. We use U.S. robot adoption as the direct explanatory variable and then instrument for U.S. robot adoption with E.U. robot adoption. Robot adoption is *positively* associated with dependence. We find suggestive, though statistically weaker, evidence that automation in one industry increases dependence in the upstream sources that supply its inputs.

These findings together shape how we understand the topology of dependence and the ability of states to manipulate their dependencies. Policymakers and academics are, understandably and rightfully, focused on chokepoints. These headline-grabbing vulnerabilities, like rare earths, are undoubtedly important. Once identified, remedying the vulnerability from a particular chokepoint has a natural “fix”: develop that particular capacity domestically. This was the clear impetus behind major policy initiatives like the CHIPS Act, which sought to bring more semiconductor fabrication back to the United States.⁷

However, if dependencies are actually very diffuse, then a focus on chokepoints is destined to fail or be incomplete, at best. Most chokepoints are just the tip of the iceberg. A particular product or input pierces the surface and is a prominent focal point. But underneath the surface is an entire production ecology of inputs, outputs, and production knowledge.⁸ Reshoring a chokepoint doesn’t remove dependence on all of its upstream inputs. Reshoring one link in the production chain can even exacerbate dependence, by making all the other links even more important. U.S.

⁷The very first paragraph of the Executive Order introducing the CHIPS Act says that one goal is to “reduce our dependence on critical technologies from China and other vulnerable or overly concentrated foreign supply chains.” Executive Order 14080, “Implementation of the CHIPS Act of 2022,” August 25, 2022, Sec. 1 (87 FR 52847).

⁸Wang (2025).

policymakers are now having to deal with the fact that chip manufacturing relies heavily on highly refined specialized gases, many of which are produced in China.⁹ The contrast between China’s Integrated Circuit Industry Investment Fund and the CHIPS Act is demonstrative of this. The latter may partially remedy dependencies. The former heavily subsidized domestic production along the entire production chain for semiconductors. Identifying and fixing individual chokepoints becomes a never-ending game of whack-a-mole. Diffuse dependencies require different solutions that address differences in the broader ecology of innovation and production.

2. Conceptual Framework

What is Dependence?

Before describing chokepoints of dependence or whether automation affects dependence, we have to first pin down our concept of dependence itself. Dependence describes how much damage country i could do to country j if it disrupted trade flows, e.g. by cutting off its exports to j . This is an inherently counterfactual concept. We only observe the consequences of disruptions that occur, but possible disruptions shape countries’ actions and policies even without threats being carried out. This puts a premium on approaches that use an underlying theoretical model to describe possible harm. Arkolakis, Costinot, and Rodríguez-Clare (2012) (ACR) was a landmark paper that unified the welfare predictions of broad classes of trade models into a single quantity that consists mostly of observable ingredients. This quantity was a ratio: the country’s welfare in a world with uninterrupted trade relative to a world of interrupted trade. Costinot and Rodríguez-Clare (2014) extended this approach to incorporate multiple sectors, with input-output linkages. The observable ingredients for each sector included a measure of the domestic production share, meaning the proportion of the consumption of that sector that came from domestic sources versus imports. This is equivalent to one minus the import penetration ratio. This needs to be measured before *and after* an interruption. The quantity also requires, for each sector, its share of the country’s total consumption, a trade elasticity, and a measure of the downstream consequences of interrupted inputs. An estimate of import penetration *after* an interruption is *unobservable*. ACR conduct conservative counterfactual estimates of the aggregate gains from trade where they consider an interruption to *all* trade, since the import penetration ratio is known in that scenario. Under autarky, import penetration is zero; the domestic share of production is 1.

Mangini and Chaudoin (2026) (MC) pushed this approach forward by constructing two measures based on plausible values for the unobservable quantities. They first constructed an “Upper Bound” measure that describes the maximum welfare harm that i can do to j by cutting off all of its exports. For the unobservable import penetration ratio, they calculated welfare lost when the trade flow is deleted and no adjustments are made to domestic production or foreign sourcing. This measure is plausible and intuitive. It assumes that the harmed country cannot easily or quickly adjust to interruptions. By being willing to consider welfare harm before adjustments, this measure can accommodate a much richer set of counterfactual quantities, beyond comparing autarky with a status quo *ex ante*.

They constructed an additional measure to intuitively account for the possibility that the harmed country can absorb the pain of an interruption by increasing its imports from existing partners. This “Compensation” measure describes how much country j would need to scale up its trade from

⁹Schneider et al. (2026).

the rest of the world in order to make itself whole again after an interruption of trade from i . If the country would need to scale up its imports by a large degree, then this indicates greater dependence. If a country need only scale up trade from its other partners by a small factor to compensate, this indicates lesser dependence. This measure also allows for a richer set of counterfactual comparisons, beyond free trade versus autarky.

We improve on the MC measures here by adding a much more detailed level of granularity. The MC measures were at a relatively high level of aggregation. MC are able to calculate their measures using TiVA data, which is at the industry level. There are 50 industries in the 2025 TiVA release (classified under ISIC Revision 4). Examples include “motor vehicles, trailers and semi-trailers,” “textiles, wearing apparel and leather,” and “agriculture, forestry and fishing.” The ingredient of their measure that described downstream, input-output consequences of interruptions was based on the domestic value-added share of production at the industry level. This was based on underlying TiVA input-output tables.

The MC measures were appropriate for their research questions. They show that the distribution of dyadic dependencies is very asymmetric, and over time, it has become more asymmetric for many of the most important dyads. Dependence on China skyrocketed, with Chinese foreign assistance making recipients more dependent on China, without a reciprocal increase in Chinese dependence on the recipient.

For our research objectives, such as identifying chokepoints, we need a more precise measurement of the downstream consequences of an interruption to trade. The MC measures did not directly describe second- (or third- or fourth-) order downstream consequences of an interruption. In the measure construction below, we use a much more detailed level of aggregation that propagates the downstream consequences of an interruption using a full, detailed I-O description. An interruption to commodity c_1 affects consumption of c_1 , and it disrupts consumption of commodity c_2 that uses c_1 as an input, and c_3 that uses c_2 as an input, and so on.

Chokepoints and the topology of dependence

“Chokepoint” has become an umbrella term for a wide array of phenomena. The common feature of all definitions and examples of chokepoints is that an actor, usually a state, can interrupt some point of economic activity to do an acute amount of damage to a target, also usually another state. In the domain of trade, “chokepoint” usually refers to a particular trade flow where an interruption of that flow is particularly consequential and for which there are few available substitute suppliers or products. This definition has two parts: consequence and concentration. Interrupting the flow must be consequential: it must be painful for the target. The direct consequential-ness of an interruption depends on the utility gained from consuming the flow in question, either as an enjoyed final good or as an input into something else which is enjoyed. The ability to interrupt the flow also must be concentrated in the sender: if other products or partners, or a shift to domestic production, can easily replace the interruption, then the interruption is temporarily painful, at worst.¹⁰ Recent work on geoeconomics conceives of leverage in a similar way. For example, Clayton, Maggiori, and Schreger (2026) define strategic sectors as “those that supply inputs that are widely used, with high value added for targets, and with poor available substitutes” (107).

Consequential-ness motivated many of the commonly used measures of economic dependence. O Neal and Russett (1997) measured dependence as bilateral trade divided by a country’s GDP. Interrup-

¹⁰See Keohane and Nye (1973) for an early discussion of vulnerability and sensitivity from trade dependence.

tions are more consequential when they affect more trade (the numerator) and less consequential when they are a smaller share of the target’s economy (the denominator). Barbieri (1996) gives another often-used measure, which is bilateral trade divided by total trade. It has similar intuition. Interruptions are less consequential if they are a smaller share of the target’s overall trade. There are many other permutations of these concepts.¹¹ Other studies of dependence have directly incorporated substitutability into their analyses.¹² Clayton, Maggiori, and Schreger (2024) describe choke points similarly, as places where a small amount of diversification would go a long way towards decreasing a hegemon’s power.

Farrell and Newman (2019) super-charged political scientists’ interest in a related notion of chokepoints as sources of coercive power. They describe a “chokepoint effect,” which emphasizes a network aspect of power. If a state controls a hub through which a lot of economic activity passes and there are few suitable substitutes, then that state has power through a chokepoint effect. In their canonical example, the United States controls the SWIFT banking system so it can limit other actors’ ability to move money through certain points, even without controlling the money directly. The analogue for the domain of trade is a critical port. Controlling, say, the Suez Canal gives a state power since that state can control movement of trade, even without confiscating and possessing the goods on the ship.

Other work blends the two concepts - control of an object versus position in a network over which the object flows. Beaumier and Cartwright (2024) associate chokepoints with a high degree of centrality in a semiconductor supply chain network, measured by the sum of one’s weighted connections. Winecoff (2020) does not use the language of chokepoints, but describes centrality as a combination of betweenness centrality and eigenvector centrality in the network of global portfolio investment. Betweenness centrality describes whether a node connects disparate parts of a network and eigenvector centrality describes whether a node has more connections to more or less important partners.

Two remarks are in order. First, the difference between the first set of papers and work emphasizing network effects is about the *origin* of power, not its nature. All of them share the common trait that an actor can do *something* that harms the target and the target cannot easily respond with adjustments. Our point here is not to resolve or debate these differences. They aren’t mutually exclusive.

Second, in the context of trade flows, we focus on first order dependency. By first order, we mean direct connections between countries i and j , not connections between i and j that run “through” another node, k . Our measure of dependence does not capture the ability of i to cut off its exports to j so that j cannot produce something that k consumes. These indirect coercive attempts are important, though less common. Stehrer (2026) distinguishes between “size dependence” which refers to dependence arising from sourcing a large amount of output originating from one partner, and “choke dependency” which refers to partners through which third party inputs must first travel. Most policymaker attention and resources are focused on first order connections, though indirect connections are worth future study.

We do not have strong theoretical reasons to expect that chokepoints have become more or less prevalent. On the one hand, trade has exploded at the extensive margin over the last 20 years. More countries trade more products with a larger number of partners. This would suggest that chokepoints should be less prevalent or intense. On the other hand, fear of chokepoints has cap-

¹¹For a summary of these measures, see Gartzke and Li (2003).

¹²Gowa (1995), Polachek (1997), Crescenzi (2003), Liu and Yang (2025).

tivated policymakers, especially after the COVID pandemic exposed supply chain vulnerabilities. Since 2020 the United States, the European Union, Japan, the United Kingdom, Australia, South Korea, India and Canada have each run a formal exercise to find the imports for which they depend on one supplier. In 2021, the European Commission screened 5,200 products and flagged 137 as strategic dependencies.¹³ Australia’s Productivity Commission screened 5,862 and flagged 292, two thirds of them from China.¹⁴ In 2022, the Japanese Diet passed the Economic Security Promotion Act, which created a statutory designation for “specified critical products” based in part on dependence on foreign supply.¹⁵

Robots, trade, and dependence

The predominant view among policymakers is that automation will reshore production, decrease imports, and by extension, decrease dependence. The theory for this is plausible and intuitive. Robots can perform production tasks that were previously done by labor in another country. Robots are also a positive labor productivity shock.¹⁶ Firms in the home country can use robots to either “replace” that foreign labor or augment the productivity of domestic labor enough to justify reshoring those tasks.

Some empirical work supports the reshoring effect. Krenz, Prettnner, and Strulik (2021) measure reshoring as a positive change in the ratio of domestically sourced to foreign-sourced intermediate inputs at the sectoral level. Using an unbalanced panel of 27 countries and 9 manufacturing industries over 2000–2014, they find that greater robot density is associated with greater reshoring. A related strand of research looks at whether robot adoption decreases imports from less developed countries into richer countries. Artuc, Christiaensen, and Winkler (2019) and Faber (2020) argue that U.S. robot adoption decreased demand for imports from Mexico.¹⁷

However, there are several indirect effects of automation that can *increase* imports and dependencies. First, the automation technology itself is an import, which can be a source of dependence. Ding (2026) incorporates capital services into a model of trade, showing that accounting for the persistent production from capital, like automation, increases the welfare gains associated with trade.¹⁸ An increase in productivity from automation can increase demand for all upstream imports in that product, even aside from the automation machinery itself. For example, an automated semiconductor facility will demand highly specialized polysilicon and gases to make chips. If those inputs are foreign-sourced, as opposed to domestically produced, then this can increase dependence.

Second, automation has implications for how firms perform production tasks. Stapleton and Webb (2026) model automation as a positive productivity shock for certain tasks, and a firm can perform tasks with labor at home, offshore labor, or automation. An increase in the availability of automation can cause the firm to replace domestic and/or foreign labor with automation, which matches

¹³https://ec.europa.eu/commission/presscorner/detail/en/ip_21_1884.

¹⁴<https://www.pc.gov.au/inquiries/completed/supply-chains/report>; <https://theconversation.com/mid-covid-we-find-few-vulnerabilities-in-australias-supply-chains-165962>.

¹⁵<https://www.meti.go.jp/english/report/data/wp2023/pdf/2-1-2.pdf>; <https://www.japaneselawtranslation.go.jp/en/laws/view/5008>.

¹⁶Graetz and Michaels (2018).

¹⁷Political scientists have also linked the relationship between robots and trade with their political consequences. For example, Boix, Gonzalez-Rostani, and Owen (2026) argue that U.S. industrial automation decreased imports from Mexico, which led to increased violence and support for left-wing populists.

¹⁸Linking this to politics, Chaudoin and Mangini (2025) show how a fear of foreign dependencies is a powerful source of popular support for regulating automation.

the “usual” reshoring intuition. However, it also increases the firm’s overall productivity which can increase demand for tasks that are not automatable, and which are performed by labor at home or abroad. It can also increase productivity enough to allow a firm to overcome the fixed costs of importing in the first place.¹⁹

Third, an increase in one sector’s productivity can attract resources that would have gone to other sectors. Consider a simple example where a financier can provide capital to build a car factory or a truck factory. If they are equally productive facilities, then she may be indifferent between the two investments. If automation provides a positive shock to the productivity of a car factory, she may be more willing to provide capital to that project, and less likely to invest in the truck factory. The eventual result is lower domestic production of trucks, demand for which must be sourced from somewhere, potentially via imports.

Fourth, as we make clear in the next section, not all trade flows have equal effects on *dependence*. If automation increases the degree to which a particular industry or product is consumed, then this can magnify the consequences of interruptions to trade from upstream inputs. Put differently, if automation raises the value of industry j , then it also magnifies the welfare consequences of interruptions to trade in upstream industries, even if the nominal value of those upstream flows stays the same.

We do not have strong theoretical priors about which effect will dominate. Our main purpose is to assess the mainstream hypothesis that automation *decreases* dependence. We focus there because it is the hypothesis underlying billions of dollars of industrial policy expenditures.

3. USA detailed analysis

To construct a more detailed measure of dependence, we need more granular versions of each component of the original MC measures.

3.1 Domestic production and trade

The domestic production share (one minus the import penetration ratio) before a shock is defined as: $\lambda = 1 - \frac{\text{Imports}}{\text{Production} - \text{Exports} + \text{Imports}}$. We can observe this quantity. The most granular available data source for production, i.e. domestic output, is at the BEA detailed commodity level. BEA publishes these detailed benchmark commodity accounts for the years 1997, 2002, 2007, 2012, and 2017.²⁰ The exact number of commodities depends on the year of the data. In the years we use, the numbers are: 325 for 1997, 283 for 2002, 241 for 2007, 235 for 2012, and 243 for 2017. To give an idea of the level of aggregation of these commodities, some examples are: automobile manufacturing, apparel manufacturing, and audio and video equipment manufacturing. BEA also has data about aggregate imports and exports for each of these commodities. We leave the production, aggregate imports and exports data all in their native BEA commodity schema.

For trade flows, we use the Census Bureau’s detailed trade data at the HS-10 level. Across our benchmark years, the measure covers 24,775 distinct HS-10 import codes—for example, passenger motor vehicles (HS 8703.24.0058), petroleum oils and oils obtained from (HS 2709.00.2090), and

¹⁹For other work theorizing and finding a positive relationship between automation and imports, see Artuç, Bastos, and Rijkers (2023).

²⁰2022 is not yet released. If the BEA follows its past cadence, it will be released in 2027.

portable digitl automatic data processing machines (HS 8471.30.0100).²¹ We use this to construct a dyad-year measure of the share of a particular BEA commodity’s imports that come from a particular partner ($\alpha_{c,j,t}$). To construct the counterfactual domestic production share, λ' , we remove that country’s share of a particular commodity’s imports by multiplying imports of that commodity by one minus the share of affected trade. Writing the two shares side by side (and dropping subscripts for readability), $\lambda = \frac{\text{Production}-\text{Exports}}{\text{Production}-\text{Exports}+\text{Imports}}$ and $\lambda' = \frac{\text{Production}-\text{Exports}}{\text{Production}-\text{Exports}+(1-\alpha)\text{Imports}}$, so that $\lambda' \geq \lambda$ follows from the denominators alone. For example, if i imported 30% of commodity c from partner j in year t , then we would multiply aggregate imports of that commodity by 0.7 to construct λ' .

Our measures here cover merchandise trade, but not services. In 2017, there are 402 total commodities. We measure dependence for the 243 of them that consist of merchandise. Services are obviously important to the economy and they are traded. However, the merchandise commodities that we measure account for 80.2 percent of total χ in 2017, and the share is 73.6, 77.3, 75.7 and 76.5 percent in the four earlier benchmarks.

3.2 Elasticities

To estimate trade elasticities, we use a modification of the MC approach, which was an extension of the Caliendo and Parro (2015) triplets approach. We are able to get global elasticity estimates at the HS-4 level.²² We estimate θ for 1,257 HS-4 headings—for example, passenger motor vehicles (HS 8703), electronic integrated circuits (HS 8542), and petroleum oils and oils obtained from (HS 2709). The MC approach used a truncated Bayesian regression, with the prior set to a global mean elasticity from existing work. Here, we set the prior to the product-level trade elasticities of Fontagné, Guimbard, and Orefice (2022), hereafter FGO, attached to each HS-4 heading.²³

3.3 Consumption and Intermediates

Cutting off imports of a commodity has a direct effect on consumption, since it directly removes a source of a particular commodity. It also has an indirect effect, by affecting consumption of things that use that import as an input (or as an input of an input, and so forth). We capture both of these channels with an exposure weight $\chi = L\beta$. Here, β is the vector of consumption shares. An entry in this vector describes the share of final demand for that commodity, with the shares summing to one. $L = (I - A)^{-1}$ is the Leontief inverse. A row of this matrix, row c , describes how much each commodity c contributes to production of the commodities in the columns. Element c in the vector $\chi = L\beta$ describes the direct and indirect effects of disruptions to commodity c ,

²¹To concord the HS-10 trade lines to BEA commodities we use, for 1997, BEA’s published weighted HS10-to-commodity concordance, and for 2002, 2007, 2012, 2017 (which that concordance does not cover) a documented two-step crosswalk. The two-step crosswalk first assigns each HS-10 import line to the industry that primarily makes that product, using the standard Census product-to-industry keys, and then maps that industry to its BEA commodity using BEA’s own year-specific industry-to-commodity bridge. When one HS-10 line legitimately corresponds to more than one commodity, we split its trade value across those commodities in proportion to how the underlying classifications overlap, rather than forcing the whole line onto a single code. Because each split is weighted by the line’s actual import value and the weights for every line sum to one, the crosswalk reallocates the full value of trade in the measure, with none of it dropped or double-counted.

²²Attempting to estimate elasticities from finer-grained HS-6 digit data gives highly unstable, often implausibly large or small estimates of θ . HS-4 is the best Goldilocks approach, the finest-grained quantity that is still plausible.

²³Appendix A gives the full estimation detail, including how the FGO prior is matched to each heading. When a BEA commodity is composed of multiple HS4 constituent flows, we average their FGO priors to get a BEA-level prior.

weighted by the consumption shares of the affected commodities. We take β and L from the BEA benchmark detailed input-output (Make/Use) accounts at the same commodity-level resolution as the production and aggregated trade data, so the intermediates channel is measured on exactly the commodity schema used elsewhere in the measure.

3.4 A Note about aggregation

We want to be clear about how the measure is constructed at different levels of aggregation. Some components are at more granular levels than other components. Our general approach was to construct the measures to allow for counterfactuals at the most granular level possible. This is the best-feasible approach. Where necessary, we apply a higher level of aggregation to individual inputs. For example, to consider a counterfactual where a specific HS-10 trade flow is interrupted, it is necessary to “assign” a commodity-level measure of input-output linkages and an HS-4 level elasticity estimate.²⁴

3.5 The detailed dependence measure

With those ingredients, we can construct a detailed Upper Bound measure in the same way as MC.

The Upper Bound measure is: $UB_{j,t} = 1 - \prod_c (\hat{\lambda}_{jt}^c)^{-\chi_t^c/\theta_t^c}$, where $\hat{\lambda}_{j,t}^c \equiv \lambda'_{j,t}/\lambda_{j,t}^c \geq 1$ is the ratio of post-shock domestic absorption to its pre-shock amount. Note that the j indexing refers to the trade flow(s) implicated in a particular interruption. For example, it could refer to the interruption of a particular flow from a particular partner, or any aggregation of those interruptions to the partner or commodity level. We will generally consider two types of interruptions: the removal of a particular flow from a particular partner or the removal of *all* flows from a particular partner.

An equivalent expression writes the same measure as an additive welfare loss. Taking logs of the product turns it into a sum across commodities, $-\ln(1 - UB_{j,t}) = \sum_c \frac{\chi_t^c}{\theta_t^c} \Delta \ln(\lambda_{j,t}^c)$, where $\Delta \ln(\lambda_{j,t}^c) = \ln \lambda'_{j,t} - \ln \lambda_{j,t}^c \geq 0$ is the log rise in the home-absorption share of commodity c when partner j ’s share of its imports is removed; equivalently, $UB_{j,t} = 1 - \exp\left(-\sum_c \frac{\chi_t^c}{\theta_t^c} \Delta \ln(\lambda_{j,t}^c)\right)$.²⁵ This expression of the measure makes it clear that we can think of a shock as having two parts: (1) the change to the location of production ($\Delta \ln(\lambda_{j,t}^c)$) and (2) the “weights” assigned to that change, which are a function of consumption shares, elasticities, and input-output consequences.

3.6 Comparison with the Original MC Measure

Before turning to analysis of the prevalence of chokepoints, we first validate our detailed measure of dependence against the original MC measures. Figure 1 shows the United States’ dependence on several partners using the Upper Bound measure, estimated both with our detailed data and with

²⁴As mentioned above, when an HS-10 product flow concurs to more than one BEA commodity, we split its value across those commodities, and those values are *each* deleted separately, just as deleting all of a partner’s trade flows deletes things from several commodities. In practice, this is uncommon. Only about 1% of lines (9{,}439 of 1{,}371{,}235 partner-line-years) span more than one commodity

²⁵These expressions are shown to be equivalent in Appendix B.

the updated TiVA 2025 data following the MC approach.²⁶ The original MC measure is calculated for every year, while our measure is calculated only at the BEA benchmark years.²⁷

The dependence measures calculated with our detailed data track the original MC measures in their broad pattern. Across the five BEA benchmark years the detailed upper-bound measure and the updated TiVA measure are strongly correlated across partners. Pooling all overlapping partner-year cells gives a Pearson correlation of about 0.91. For the countries listed in Figure 1, the pooled correlation coefficient is approximately 0.83. The pooled Spearman rank correlation coefficient is approximately 0.94, and the agreement tightens over time, rising from about 0.75 in 1997 to about 0.97 in 2017.

The two series differ in levels. The TiVA dependence measure is roughly 1.7 times the detailed measure on average, though the gap is not uniform across countries or years. For China, for instance, the detailed measure is the larger of the two through 2007 and the smaller by 2012.

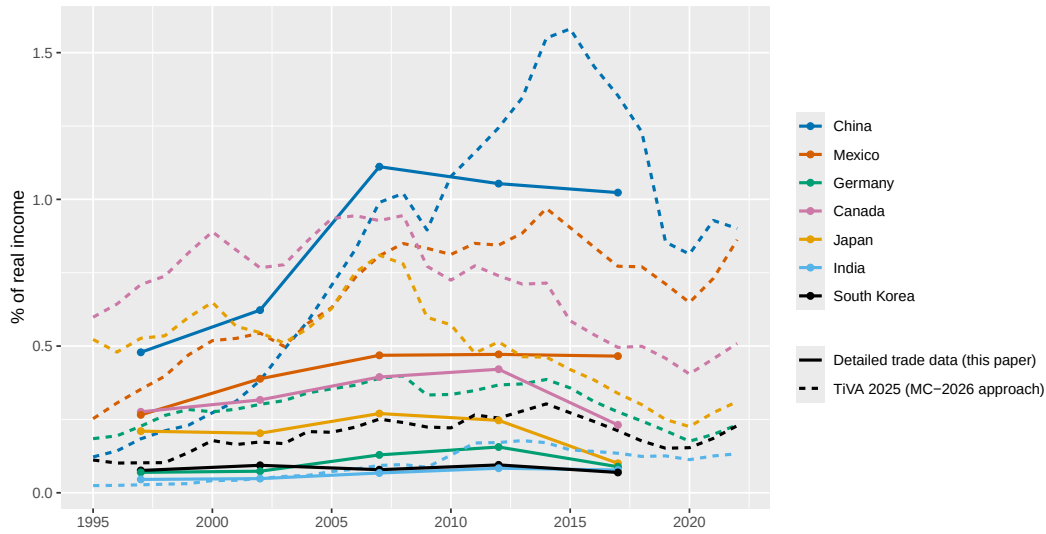


Figure 1: Upper-bound measure of U.S. dependence on selected partners. Solid lines show this paper’s detailed measure. Dashed lines show an updated version of the MC measure, based on updated TiVA 2025 data.

4. Chokepoints Over Time

Have chokepoints increased in their prevalence or intensity over time? Here, we show that the answer is predominantly “no.”

²⁶Mangini and Chaudoin (2026) used the 2023 release of the TiVA data. We update that measure to use the TiVA 2025 release, which revised some amounts and added some industries. The TiVA upper-bound welfare loss is one minus the intermediates-inclusive retained-welfare share ($1 - \text{dependence_inters}$), so both series are expressed in the same welfare-loss units and plotted on the same axes.

²⁷We are working on making these measures yearly as well. It would require deciding how to impute the various inputs to the measure that are only observed at benchmark years.

4.1 Concentration of dependence over time: By Commodity, Across Suppliers

Is U.S. dependence becoming concentrated in fewer suppliers *within* a commodity or product? In other words, when the U.S. considers its dependence on imports of a particular commodity or product, has that dependence become more concentrated in fewer partner countries? In Figure 2, for each year and each BEA commodity, we compute the HHI of U.S. dependence across partner countries. Higher HHI numbers indicate greater concentration of dependence in fewer partners. We then plot the distribution of that HHI across commodities as a violin plot. The inset box shows the median and interquartile range.

For most commodities, the HHI score is not especially high. The degree to which dependence is spread across partners varies greatly by commodity. However, the United States' dependence within most commodities is spread over multiple suppliers most of the time. An HHI score of 0.20, which is approximately the median, is roughly equivalent to 5 suppliers each being responsible for 20% of U.S. dependence in that commodity.

Concentration does not show signs of increasing sharply over time. The median and inter-quartile ranges stay relatively flat over time. There are fewer commodities in the extreme upper portions of the distributions over time. For example, by 2017, there are very few commodities with an HHI above 0.75, which would roughly correspond to one supplier being responsible for 85% of U.S. dependence.

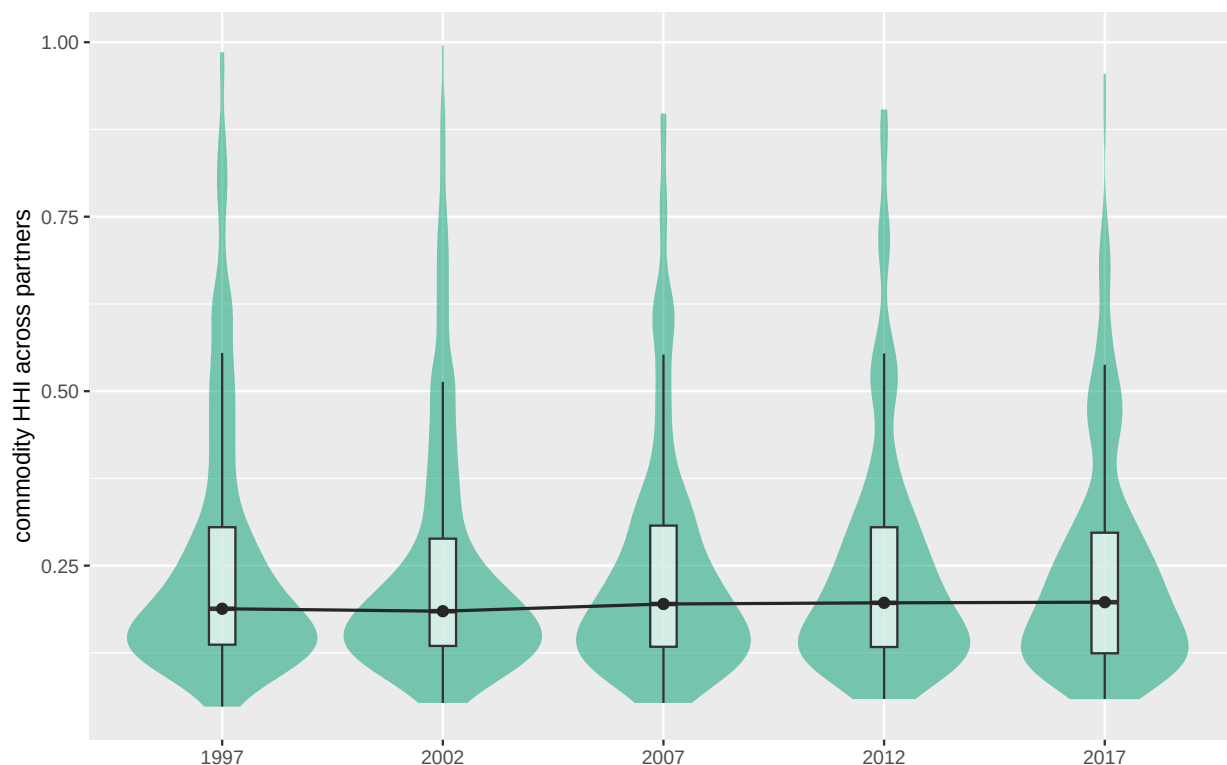


Figure 2: Distribution across BEA commodities of the commodity-level HHI of U.S. dependence across partner countries, by year. The inset box shows the medians and IQRs.

Figure 3 counts the commodities in which one supplier alone is responsible for most of U.S. dependence. It shows the number of commodities where a single supplier was responsible for greater

than 50% of U.S. dependence (blue line) and 80% of U.S. dependence (orange line). In 1997, only 86 of the 323 commodities had a single partner make up 50% of that commodity's dependence, and 17 had a single partner above 80%. By 2017 those counts were 58 and 9, out of 240 commodities.²⁸

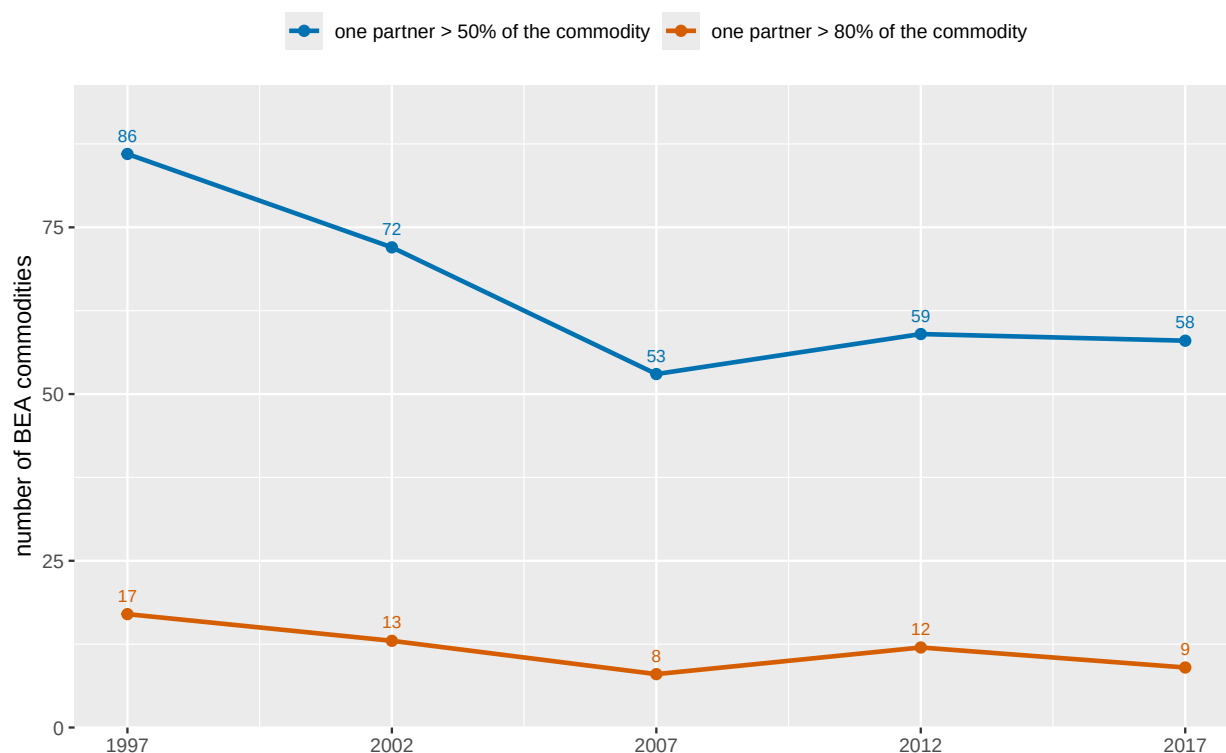


Figure 3: Number of BEA commodities dominated by a single supplier, by year.

4.2 Concentration of dependence over time: By Product, Across Suppliers

What if we look instead at concentration in finer-grained product-level flows? Here, we construct similar plots at the HS-10-digit level, as opposed to the commodity level. This is much finer grained, so by definition the degree of concentration will be higher. For example, there are only so many places in the world that produce tequila (HS 2208905500), so trends are more informative.

Figure 4 shows the share of product lines for each year where the HHI reaches certain levels. The trends for all four levels are relatively flat, with a slight increase in later years.

Figure 5 shows how the distribution of dependence has become slightly more concentrated in the upper extremes of the distribution. There has been an increase in the number of products where one partner country is responsible for greater than 50% or 80% of U.S. dependence. Even still, there are thousands of HS-10 digit products. So these are increases of only about 2% in the share of products reaching each threshold.

²⁸Recall that the total number of commodities changes over time. Measured as a share of commodities, the 50% threshold is close to flat (26.6% to 24.2%), while the 80% threshold falls by about a third (5.3% to 3.8%).

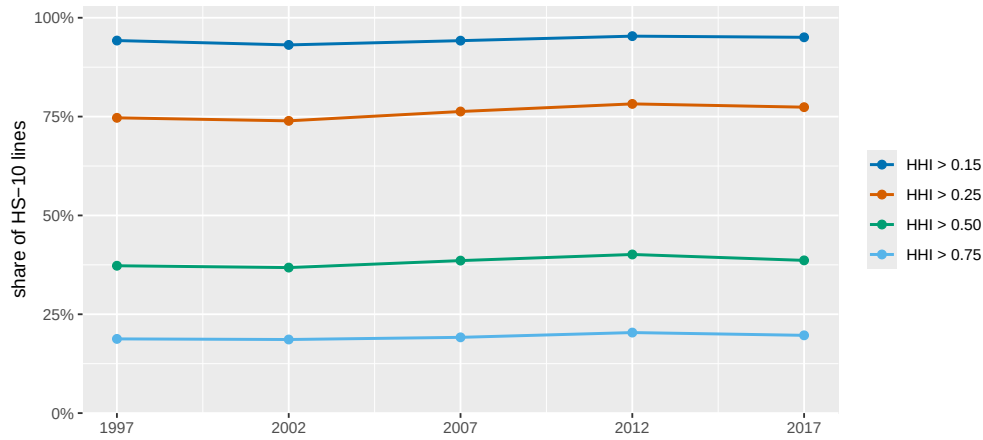


Figure 4: Percentage of HS-10 import lines whose cross-partner HHI of US dependence is above each threshold, by year.

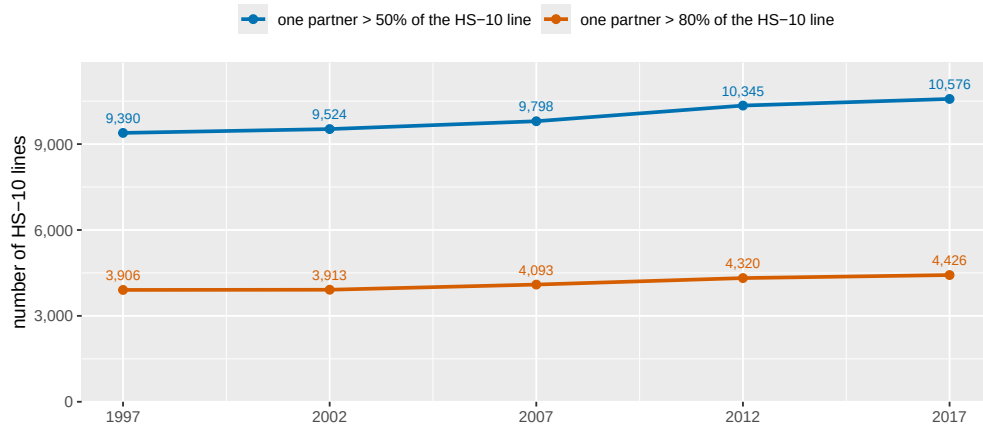


Figure 5: Number of HS-10 import lines dominated by a single supplier, by year.

4.3 What has happened

If chokepoints have not really become more prevalent over time, then what *has* happened to capture so much elite and policymaker attention? Here, we show that (1) the worry about chokepoints is better understood as a worry about dependence on China and (2) many chokepoints are actually fairly mundane, unglamorous products.

4.3.1 Greater dependence on China

Another way to think about chokepoints is to ask whether U.S. dependence has become more concentrated over time in certain partners, aggregating across all of the things that partner supplies.

Figure 6 shows the percentage of U.S. import dependence attributable to China, Mexico, Germany, Canada, Japan, India, and South Korea, plus an “all other combined” category, over time. Most countries’ shares of U.S. dependence have stayed relatively flat. China is, of course, the exception. Its share of U.S. dependence increases substantially, largely at the expense of smaller countries. To the extent that U.S. dependence has gotten more concentrated across partners, this is largely a China phenomenon. A large portion of U.S. dependence that was previously associated with countries other than its largest allies has instead become concentrated in dependence on China.

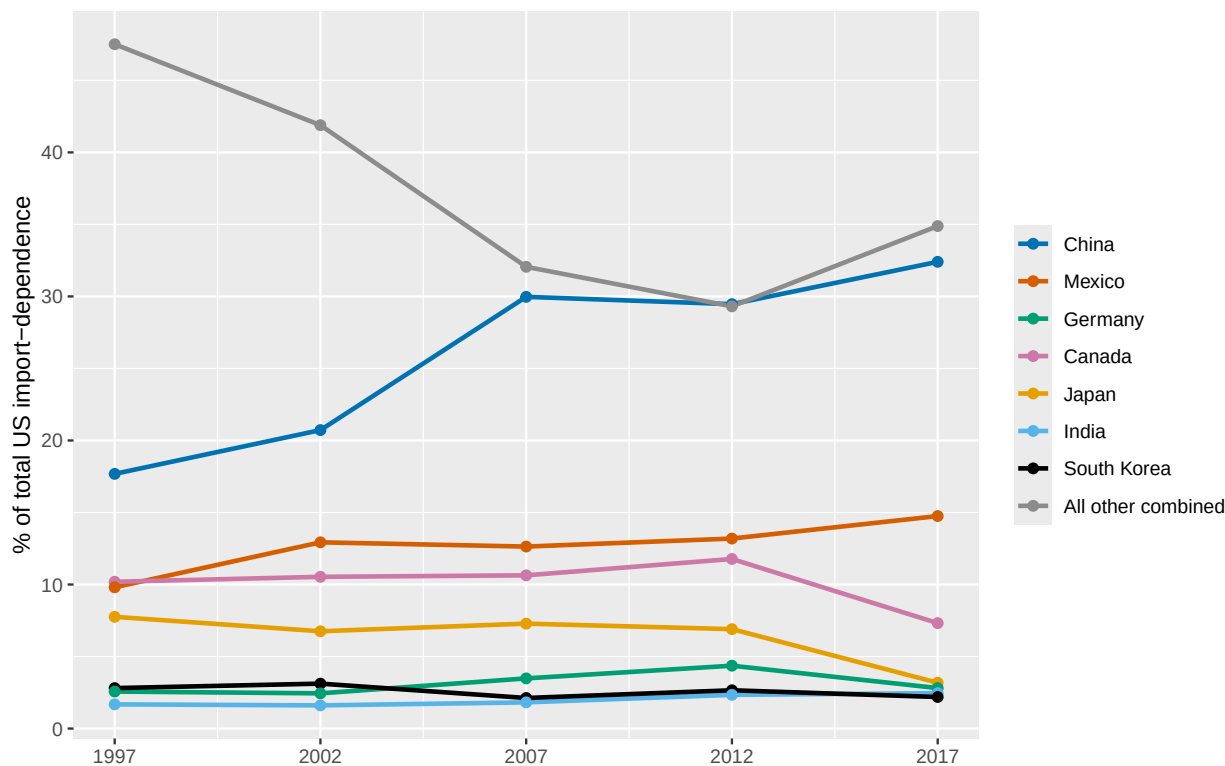


Figure 6: Share of total US upper-bound import-dependence attributable to each named partner, plus all other suppliers combined, by year.

Figure 7 shows another way of visualizing how trade has become concentrated in China and how this is the correct read of the changing contours of dependence. We start by looking at which country is the greatest source of U.S. dependence for a particular HS-10 product in period t . Then,

we see whether that same supplier or a new supplier is the greatest source of dependence in period $t + 1$. Observations on the diagonal have the most weight. Most primary suppliers are the same across years. Off-diagonal elements show who was the original top supplier and who is the new top supplier. Within each column, there is a lot of weight placed on the bottom row. Weight in the bottom row indicates an HS-10 product whose top supplier was a country other than China and whose top supplier then became China.

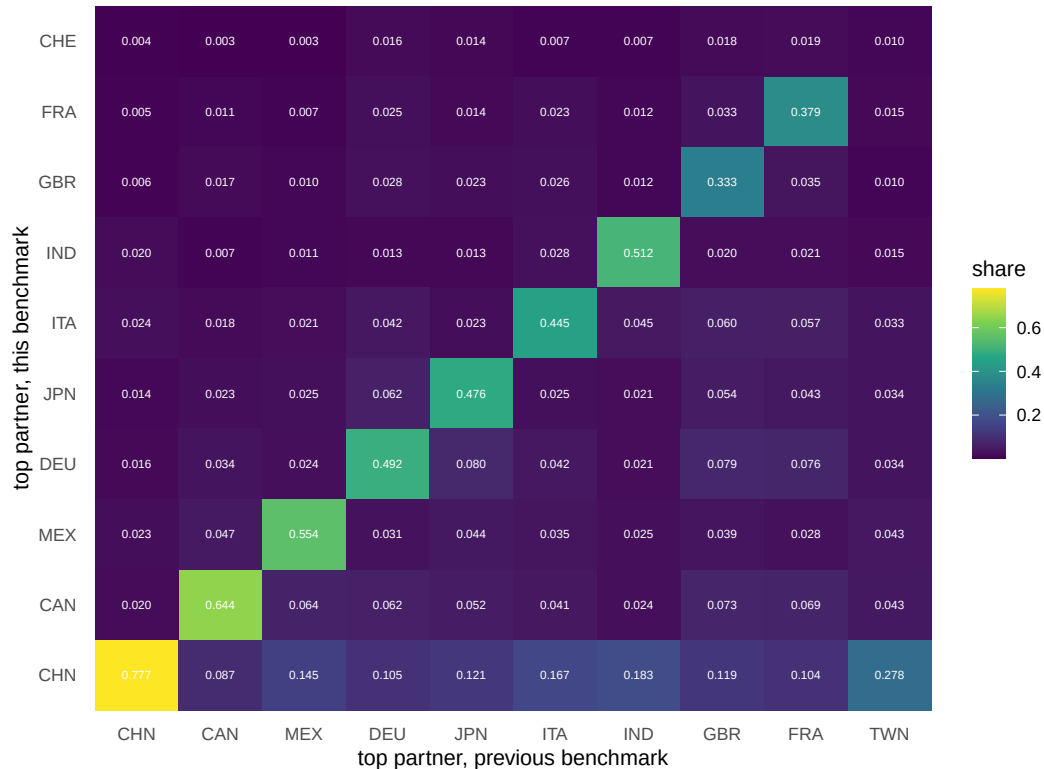


Figure 7: Transition matrix of the top supplier of an HS-10 line between consecutive benchmark years. This shows only the ten largest partners in 2017. A column is the top supplier in the earlier year. Rows show the top supplier five years later. Each column sums to one.

Up until this point, we have looked at concentration and damage separately to identify chokepoints. One conception of a chokepoint requires *both* elements to be present. In Figures 8 and 9 we show chokepoints in this two-dimensional way. The horizontal axis in each figure shows the damage per dollar of imports for an HS-10 product. This is the dependence measure divided by the nominal amount of the trade flow. The vertical axis shows the HHI for supplier concentration in that product. We limit each figure to the 1500 largest product flows in each year. Products in the upper right are chokepoints in this two-dimensional sense. They are potent in terms of damage and concentrated in one or few suppliers. For each product, we color the dots red if China is the primary supplier.

China is again the primary driver of the story. If anything, products tend to shift left from 1997 to 2017, suggesting less damage per dollar of imports. But across the entire picture, China-dominated products become much more prevalent.

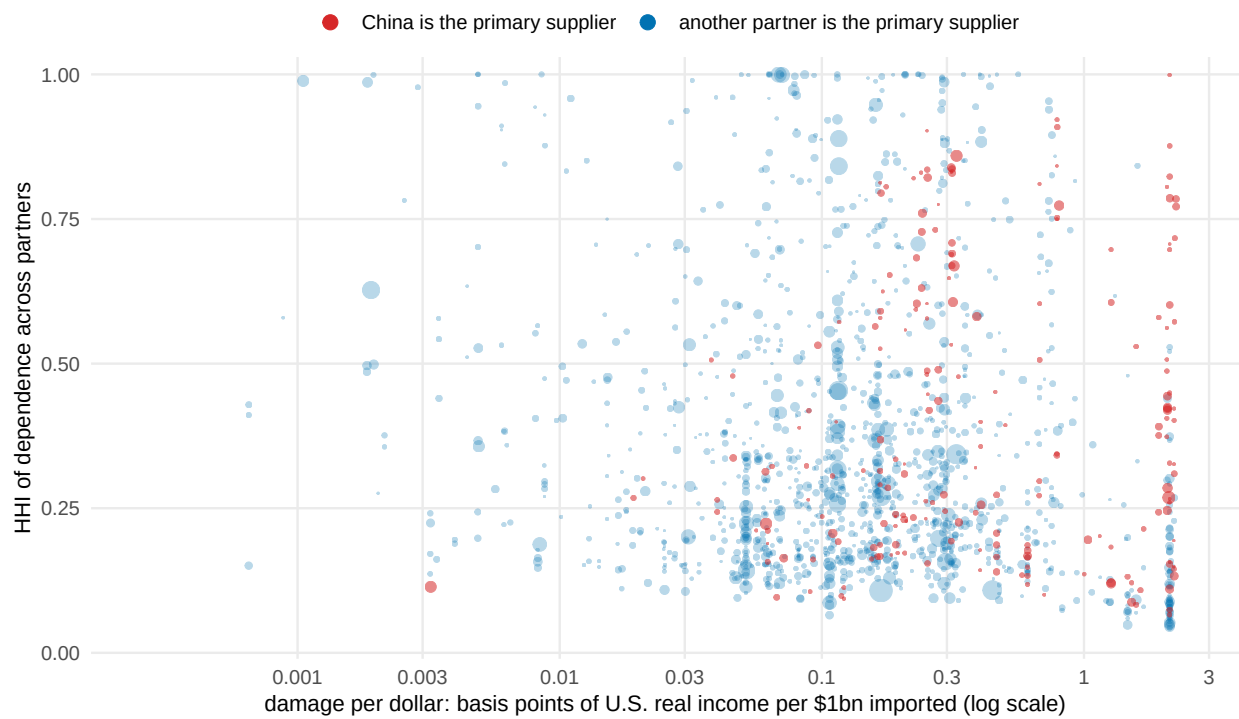


Figure 8: Damage per dollar against supplier concentration, HS-10 lines, 1997. Each dot is one of the 1,500 largest HS-10 lines by import value. Dot area is the line's share of that year's imports. Red marks a line whose largest supplier is China.

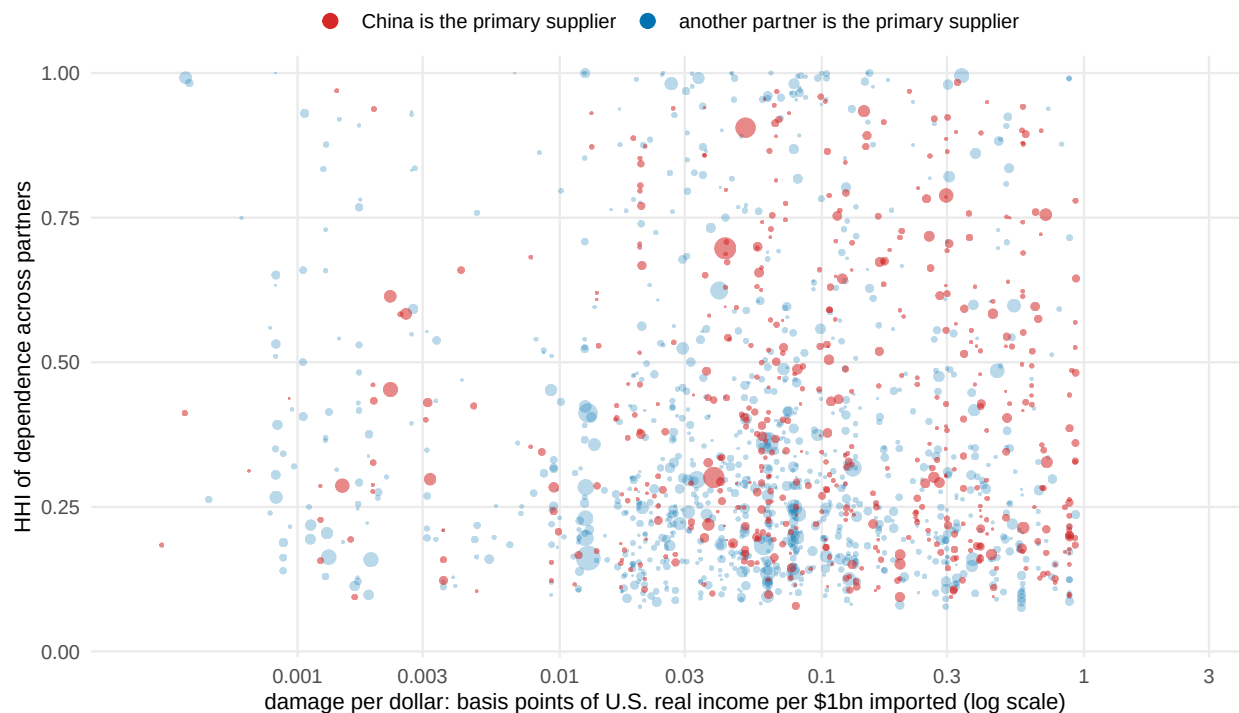


Figure 9: Damage per dollar against supplier concentration, HS-10 lines, 2017. Axes and dot areas are the same as in Figure 8, so the two panels compare directly.

4.3.2 Mundane chokepoints

When we look at the commodities that make up the greatest share of U.S. dependence on China, they are a mix of things associated with chokepoints and things associated with end-use consumption. Figure 10 shows the picture at two levels of granularity: the 15 BEA commodities that drive the most China dependence (left), and the twenty-five individual HS-10 lines that do (right), both for 2017. The color of each bar shows China’s share of nominal imports into the United States for that commodity or product.

Some of the largest sources of dependence are decidedly *not* the products usually associated with chokepoints in the media or elite discourse about high-tech industries. For example, apparel manufacturing makes up the largest portion of the United States’ dependence on China, even though China is a comparatively modest share of overall U.S. apparel imports. Leather goods are associated with the second-largest degree of U.S. dependence on China. Fourth on the list is “Dolls, toys, and games,” imports of which Trump famously maligned as indicative of excessive consumption:

“I don’t think that a beautiful baby girl needs — that’s 11 years old — needs to have 30 dolls,” Trump said. “I think they can have three dolls or four dolls, because what we were doing with China was just unbelievable. We had a trade deficit of hundreds of billions of dollars with China.”

— Donald Trump, quoted in *The Hill*, May 5, 2025.²⁹

²⁹Alex Gangitano, “Donald Trump’s dolls remarks ‘really damaging messaging’: Marc Short,” *The Hill*, May 5, 2025, <https://thehill.com/homenews/5283281-trump-dolls-economic-policy/>.

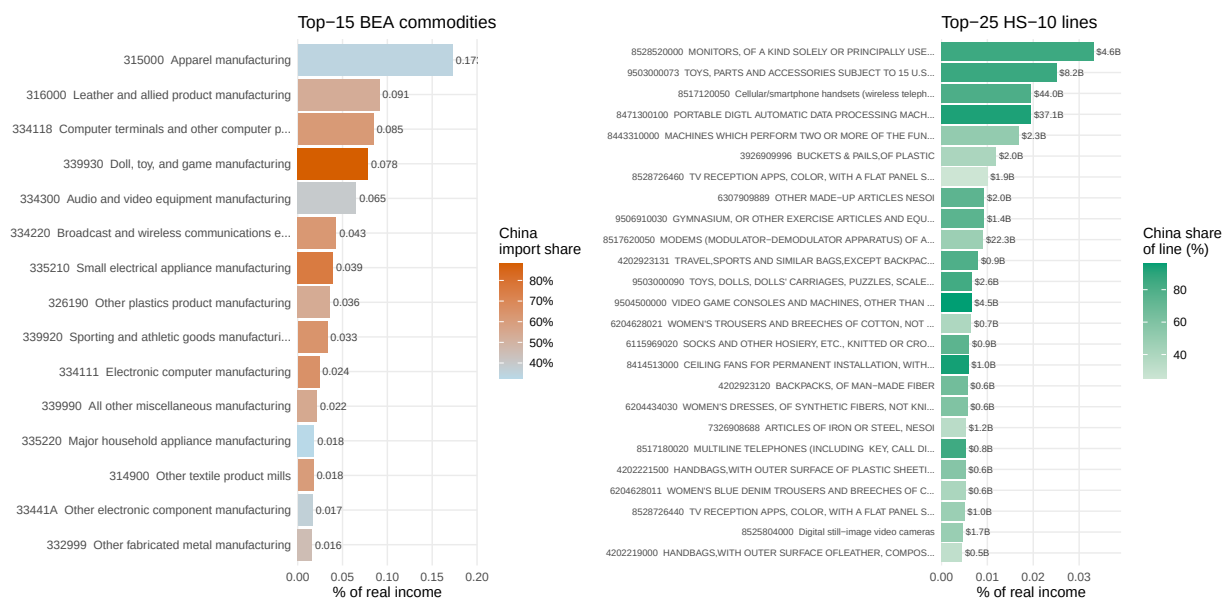


Figure 10: What drives US dependence on China, 2017: top-15 BEA commodities (left) and top-25 HS-10 lines (right). Color = China's share of that commodity/line's US imports.

Other prominent sources of dependence *are* associated with chokepoint products or electronics with downstream consequences, like computer equipment. But the overall picture is one in which chokepoints are far from dominating U.S. dependence on China. If anything, “mundane” products make up a much larger share of U.S. dependence.

What about “hidden” chokepoints? Hidden chokepoints are products whose nominal trade value is not especially high, but whose dependence implications are large. These are potential chokepoints that a country could use as leverage that would not necessarily attract immediate attention. Even these chokepoints are relatively mundane.

We start by collecting all of the HS-10×partner trade flows whose damage is high.³⁰ We then look for high-damage, low-trade-value products on that list. Table 1 shows the high-damage products with the 15 lowest nominal trade flow values for the year 2017. The bottom part of the table shows the values associated with smartphones, for reference.

“Hidden” chokepoints are also relatively mundane products that would not grab many headlines. Canadian almonds are responsible for a lot of dependence, approximately half as much as smartphone imports from Korea, even though their trade value is much lower. Peanut butter and textiles are other flows that account for a much larger degree of dependence than their nominal trade flows would suggest.

³⁰What constitutes a high degree of damage is a relatively arbitrary quantity. We choose the threshold based on looking for natural breaks in the data. We call any flow “high-damage” if it is greater than $1e^{-5}$.

Table 1: Hidden chokepoints in 2017: the fifteen smallest import values among the flows above the damage cutoff, with the three largest smartphone suppliers of the same year for reference.

Partner	HS10	Description	Imports (USD m)	Value pct.	damage_hs10 (fraction)
Lowest import value above the cutoff					
CAN	2008194000	ALMONDS, PREPARED OR PRESERVED NESOI	36.7	3	1.04e-05
THA	2008191040	CASHEWS, PREPARED OR PRESERVED NESOI	41.3	3	1.17e-05
CAN	2008110500	PEANUT BUTTER AND PASTE, DESCRIBED IN ADDIT...	53.1	2	1.50e-05
VNM	2008191040	CASHEWS, PREPARED OR PRESERVED NESOI	65.3	2	1.85e-05
NIC	6109901007	MEN'S T-SHIRTS, KNITTED OR CROCHETED, OF OT...	115.2	1	1.01e-05
CHN	4202228100	HANDBAGS, OUTER SURFACE TEXTILE MATERIAL, EXC...	116.9	1	1.08e-05
IDN	6204628021	WOMEN'S TROUSERS AND BREECHES OF COTTON, NO...	118.0	1	1.04e-05
CHN	6104622011	WOMEN'S TROUSERS AND BREECHES, KNITTED OR C...	118.7	1	1.04e-05
MEX	6109901007	MEN'S T-SHIRTS, KNITTED OR CROCHETED, OF OT...	118.7	1	1.04e-05
VNM	4202919030	TRAVEL, SPORTS AND SIMILAR BAGS, OUTER SURFAC...	123.0	1	1.14e-05
MEX	6114301020	WOMEN'S OR GIRLS' OTHER GARMENTS, KNITTED O...	123.1	1	1.04e-05
VNM	6204434030	WOMEN'S DRESSES, OF SYNTHETIC FIBERS, NOT K...	123.2	1	1.08e-05
HND	6109901007	MEN'S T-SHIRTS, KNITTED OR CROCHETED, OF OT...	128.0	1	1.13e-05
IND	6204444010	WOMEN'S DRESSES, OF ARTIFICIAL FIBERS, NOT ...	128.3	1	1.13e-05
HTI	6109100012	MEN'S COTTON OTHER T-SHIRTS, KNITTED OR CRO...	131.9	1	1.16e-05
Smartphones (HS 8517.12), for reference					
CHN	8517120050	Cellular/smartphone handsets (wireless tele...	44038.5	1	1.94e-04
KOR	8517120050	Cellular/smartphone handsets (wireless tele...	5405.4	1	2.03e-05
VNM	8517120050	Cellular/smartphone handsets (wireless tele...	4193.7	1	1.57e-05

5. Can Robots Decrease Dependence?

Has robot adoption blunted foreign dependence? We assess this question by looking at whether the change in the density of robots for a particular commodity in the United States decreased dependence in that commodity. We instrument for the change in U.S. robot density with changes in E.U. robot density. We generally find *positive* effects. Commodities whose robot density rose the fastest saw greater increases in dependence.

5.1 Robot Data

We start with data measuring robot density, robots per 1,000 workers, by International Federation of Robotics (IFR) industry. The IFR defines an industrial robot as a machine that is automatically controlled, reprogrammable and multipurpose. We then map each IFR industry to the BEA commodity schema used in the dependence measures.³¹ The IFR industry is a coarser level of aggregation than the BEA detailed commodity: there are 19 IFR industries in all, of which 13 are manufacturing industries (our estimation sample), spanning categories such as Automotive, Electronics, Basic metals, and Textiles.

The denominator of robot density is industry employment, and we hold it fixed at a base year rather than letting it move with the robot stock. For the United States the base year is 1990 and the employment counts are the annual averages of the Bureau of Labor Statistics Current Employment Statistics survey, aggregated from NAICS industries to the IFR classes.³²

³¹Each BEA commodity is first linked to its 2017 NAICS industries through the official BEA–NAICS correspondence, as with the dependence measures. This is done at the four-digit level so that NAICS 336 splits into automotive (3361–63) and other transportation equipment (3364–69). Each four-digit NAICS is then assigned to one of the 19 IFR industries by a documented rule map based on the code digits and the most likely matches. Appendix D gives the full rule map and the estimation sample.

³²Using employment measured in the same years as the changes in robot stock would create a threat to inference when looking at trade and dependence. Import competition could cause a decrease in industry-level employment,

For the instrument, European employment comes from the Eurostat national accounts series,³³ and the base year is 1995 rather than 1990, because Eurostat does not reach 1990 for Germany, Italy, Spain or Sweden, which are among the largest European adopters.³⁴

We also measure E.U. robot density from the same source as an instrument for U.S. adoption. A potential endogeneity concern arises if U.S. industries adopt robots faster when they anticipate greater foreign import penetration or import competition. Instrumenting U.S. adoption with E.U. adoption partially alleviates this concern, since E.U. adoption and global adoption are partially driven by technological advances that make robot adoption more attractive to firms. An E.U. industry's robot adoption is unlikely to be driven by a U.S. industry's fear of import competition.

There are potential challenges to this identification strategy that we are aware of. First, a common shock could drive both U.S. and E.U. robot adoption, and this common shock could also affect U.S. dependence. If Chinese exports spurred both U.S. and E.U. firms to increase their automation, then this violates an ignorability assumption for the instrumental variables approach. Second, E.U. automation could have a direct effect on U.S. dependence via E.U. exports. If E.U. automation lowered the marginal cost of production in industry j for E.U. firms, then the U.S. might import more of the products in that industry from the E.U. which increases dependence.

5.2 The panel and the two time periods

The BEA benchmark data allow us to directly measure dependence in certain years (1997, 2002, 2007, 2012, 2017). Robot density is annual, so we use lagged first differences: we align each five-year dependence change to the robot change that immediately precedes it, annualized. The outcome variable, Δdep , is in percentage points. The two time periods in the regressions are:

- **Pair A:** $\Delta\text{dep } 2007 \rightarrow 2012 \sim \Delta\text{robots } 2004 \rightarrow 2007$
- **Pair B:** $\Delta\text{dep } 2012 \rightarrow 2017 \sim \Delta\text{robots } 2007 \rightarrow 2012$

Figure 11 shows US robotization over time for the IFR industries. Note the log scale. The automotive industry is responsible for a large proportion of U.S. robot adoption. Nearly all industries have consistently rising robot density.

Figure 12, however, shows that robot adoption and dependence are positively correlated over time. Dependence did not fall in the industries that automated most. If anything, it is highest, and rose fastest, in exactly the high-robot industries. Robots and import-dependence climbed together, not in opposition.

which would mechanically raise the robots per worker density measure. Holding employment in the denominator fixed at a pre-period level removes that effect.

³³`nama_10_a64_e`.

³⁴The European mean is taken over eight countries, Denmark, Finland, France, Germany, Italy, Norway, Spain and Sweden. It excludes the United Kingdom, which Eurostat dropped from this series.

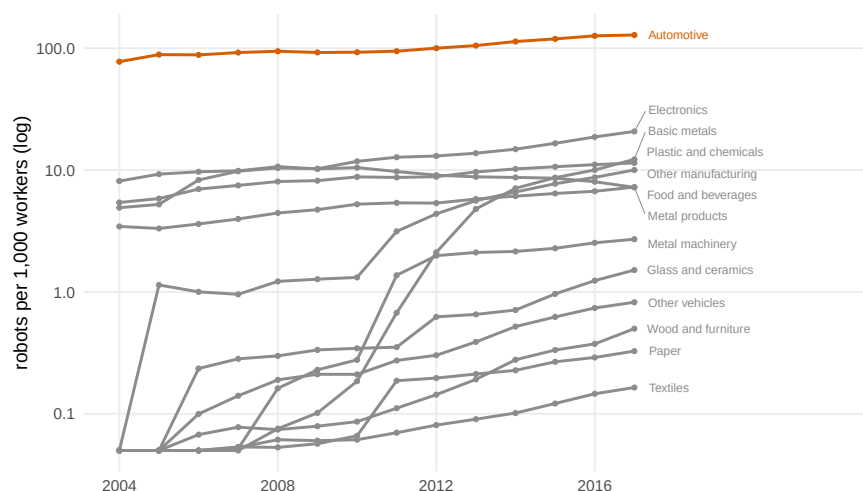


Figure 11: U.S. manufacturing robot adoption, 2004 to 2017, robots per 1,000 workers on a log scale. Source: IFR *World Robotics 2025*, U.S. density, employment denominator fixed at 1990.

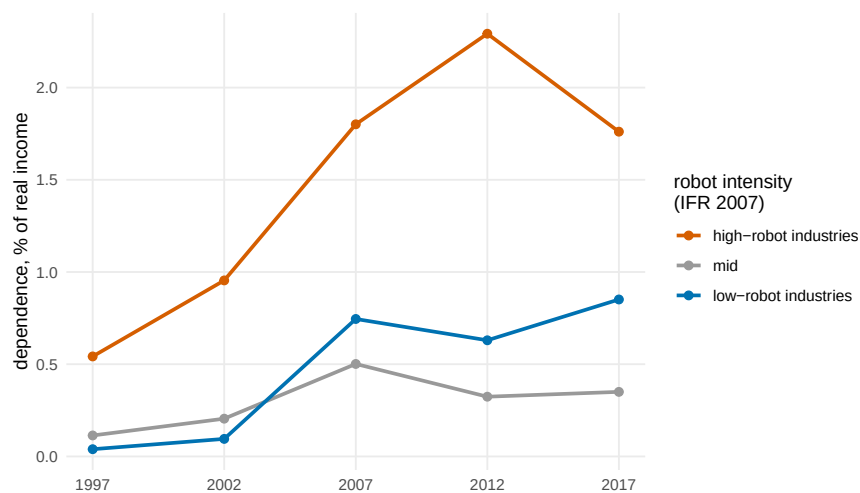


Figure 12: U.S. import-dependence over time by industry robot intensity. BEA commodities are grouped into high/mid/low terciles by their IFR industry's 2007 US robot density. Each group's dependence is summed over its commodities.

5.3 Results: Change in robot density

We regress the change in dependence on the change in robot adoption across three specifications. The first specification is ordinary least squares: the change in U.S. dependence on the change in U.S. robot adoption. The second is the reduced form: the change in U.S. dependence regressed on the change in E.U. robot adoption. The third is two-stage least squares, instrumenting the change in U.S. adoption with the change in E.U. adoption. For each specification we report three fixed-effects specifications: no fixed effects, commodity fixed effects, and commodity + year (time period pairing) fixed effects. This gives the nine columns. Table 2 covers all manufacturing commodities. Table 3 repeats the sequence excluding automotive commodities. Table 4 reports the first stage of the 2SLS specifications: the coefficient from regressing U.S. adoption on E.U. adoption and its first-stage F for each specification. We cluster standard errors at the BEA commodity level.

If anything, faster robot adoption is associated with *faster*-growing dependence. The 2SLS point estimate is positive without fixed effects and stays positive, though imprecise, once commodity and year effects are added.³⁵

Table 2: Effect of robot adoption on dependence, full manufacturing sample.

	OLS			Reduced form			2SLS		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ robot density	0.0008 (0.0006)	0.0102 (0.0081)	0.0112 (0.0085)	0.0023* (0.0013)	0.0072 (0.0058)	0.0077 (0.0060)	0.0026* (0.0014)	0.0101 (0.0080)	0.0111 (0.0086)
First-stage F							311	257	232
Commodity FE	×	✓	✓	×	✓	✓	×	✓	✓
Year (pair) FE	×	×	✓	×	×	✓	×	×	✓
Observations	416	402	402	416	402	402	416	402	402

Note:

Outcome: change in dependence. Columns 4-6 report the reduced-form coefficient on E.U. robot density. All other columns the coefficient on U.S. robot density. Cluster-robust (commodity) standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

³⁵Since the BEA commodity list changes over time, some commodities only appear in one pair of years. Those observations are dropped with commodity fixed effects, because there is no within-commodity variation on which to identify coefficients. 201 commodities appear in both pairs and 14 appear in one pair only, so commodity fixed effects reduce the count by 14. All 14 belong to the pair $\Delta\text{dep } 2012\text{--}2017 \sim \Delta\text{rob } 2007\text{--}2012$.

Table 3: Effect of robot adoption on dependence, automotive commodities excluded.

	OLS			Reduced form			2SLS		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ robot density	-0.0003 (0.0016)	0.0074** (0.0033)	0.0088** (0.0040)	0.0028* (0.0014)	0.0028* (0.0017)	0.0032* (0.0019)	0.0100* (0.0052)	0.0067* (0.0040)	0.0085* (0.0049)
First-stage F							353	286	396
Commodity FE	×	✓	✓	×	✓	✓	×	✓	✓
Year (pair) FE	×	×	✓	×	×	✓	×	×	✓
Observations	390	376	376	390	376	376	390	376	376

Note:

Outcome: change in dependence. Columns 4-6 report the reduced-form coefficient on E.U. robot density. All other columns the coefficient on U.S. robot density. Cluster-robust (commodity) standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 4: First stage of the 2SLS specifications (change in U.S. regressed on E.U. robot density).

	no FE	commodity	commodity+year
Δ robots (EU)	0.8934*** (0.0507)	0.7181*** (0.0448)	0.6944*** (0.0456)
First-stage F	311	257	232
Observations	416	402	402

Note:

First stage of the 2SLS specifications: change in U.S. robot density on change in E.U. robot density, full manufacturing sample. Cluster-robust (commodity) SEs in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

5.4 Automation and upstream dependence

If automation is a positive productivity shock to industry i , then this should also increase demand for inputs of production from an upstream industry, j . In the previous sections, we looked at whether automation affected dependence in the same industry. Here, we examine possible upstream effects.

What are the upstream industries? In the Leontief inverse matrix, $L = (I - A)^{-1}$, cell L_{ij} gives the total output of commodity i that one dollar of final demand for commodity j requires. Column j is therefore the upstream supplier profile of j , and row j is the customer profile of j .

Figure 13 draws column j for automobile manufacturing (BEA 336111) using the 2007 BEA data. Each bar takes one cell of the column and shows it as a share of the raw column total. The figure also shows what we include and exclude from the measure of upstream dependence. Commodities are inputs to themselves. $L_{jj} = 1.0012$, which is 35.3 percent of the raw column. We exclude own-industry dependence when we construct the outcome measure in this section, since it is not possible to disentangle the upstream effects from own-industry effects when looking at the same industry. As mentioned above, the IFR data are also at a higher level of aggregation. So we also exclude upstream industries that are in the same IFR industry as the commodity in question. Including them in the upstreamness measure would bias the coefficients upward, since both the industry in

question and its upstream supplying industries are receiving the same “shock” according to the IFR data.

We use the remaining upstream commodities to construct an upstreamness weight for each industry. The weight (ω_{ij}) describes the degree to which j depends on upstream inputs from $i \neq j$. We then calculate the upstream-weighted change in dependence and use this as the outcome measure:

$$Up_j = \sum_i \omega_{ij} \Delta y_i.$$

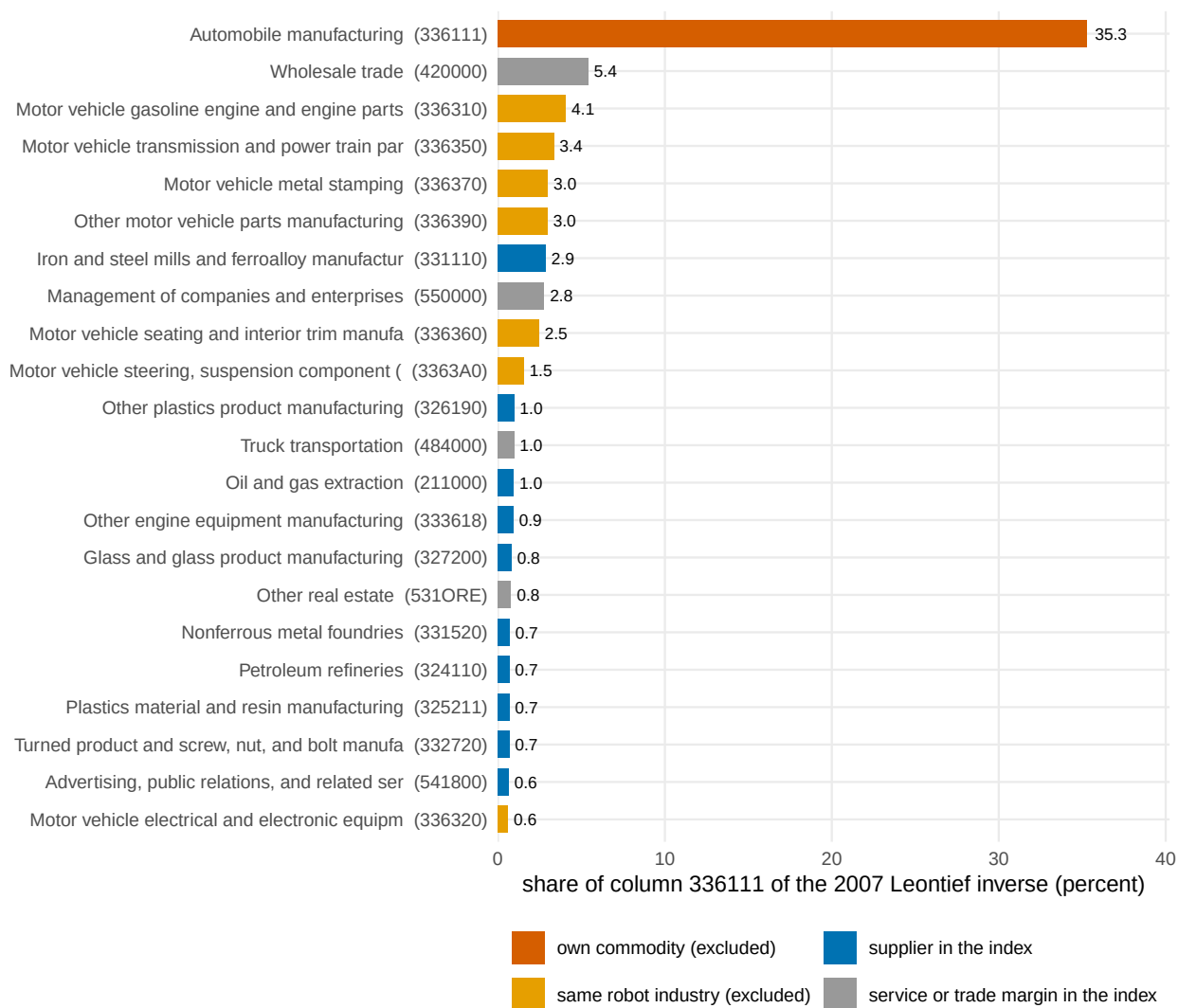


Figure 13: The upstream supplier profile of automobile manufacturing (BEA 336111), 2007 benchmark vintage. Each bar is one cell of column 336111 of the Leontief inverse, as a share of the column total. Blue and gray bars are the suppliers the upstream index includes. The orange bar is the own commodity and the yellow bars are other commodities of the same IFR-19 industry; both are excluded. The panel shows the top 14 suppliers that the index includes and every excluded cell above 0.5 percent of the column.

Table 5 reports three rows. Each row is one regression of a supplier-weighted change on the annualized change in the robot density of the commodity, with a period-pair fixed effect. The first row is the upstream-weighted change in dependence: for each supplier i we take the change in

dependence across the two benchmark years, put it in percentage points, and average it over the suppliers of j with the weights ω_{ij} . The second row applies the same weights to the change in the import penetration of the supplier, also in percentage points. This helps isolate changes in trade and import penetration as possible sources for changes in dependence. The third row applies them to the change in the import value of the supplier.

The upstream coefficient is positive for all three outcomes, though insignificant. The upstream point estimate on dependence is 0.00120 with a 13-cluster p of 0.126.

Table 5: Automation in a commodity and outcomes in its suppliers. Each row is one regression of a supplier-weighted change on the annualized change in the commodity’s robot density, with a period-pair fixed effect. Standard errors cluster on the IFR-19 industry, which is the level at which the robot measure varies.

Outcome	Coef.	S.E.	p	N	Clusters
Upstream: dependence (pp)	0.00120	(0.00073)	0.126	405	13
Upstream: import penetration (pp)	0.09731	(0.12660)	0.457	405	13
Upstream: import value (asinh)	0.03817	(0.02337)	0.128	405	13

Note:

Outcome measure is the upstream-weighted dependence for a commodity.

The manufacturing sample has 405 commodity-period observations, but the robot stock measure has only thirteen different values, one per IFR-19 industry. As noted above, the automotive industry, which is one of the IFR-19 industries, is an outlier in the robots measure. It had 99.9 robots per thousand workers in 2012, while the next-highest industry had only 13.0. Figure 14 therefore re-estimates the regression for the effect of automation on upstream dependence thirteen times, dropping one industry each time. Dropping the automotive industry changes the coefficient from 0.00120 to 0.00050, with $p = 0.78$. Dropping any of the other twelve produces coefficients between 0.00066 and 0.00158.

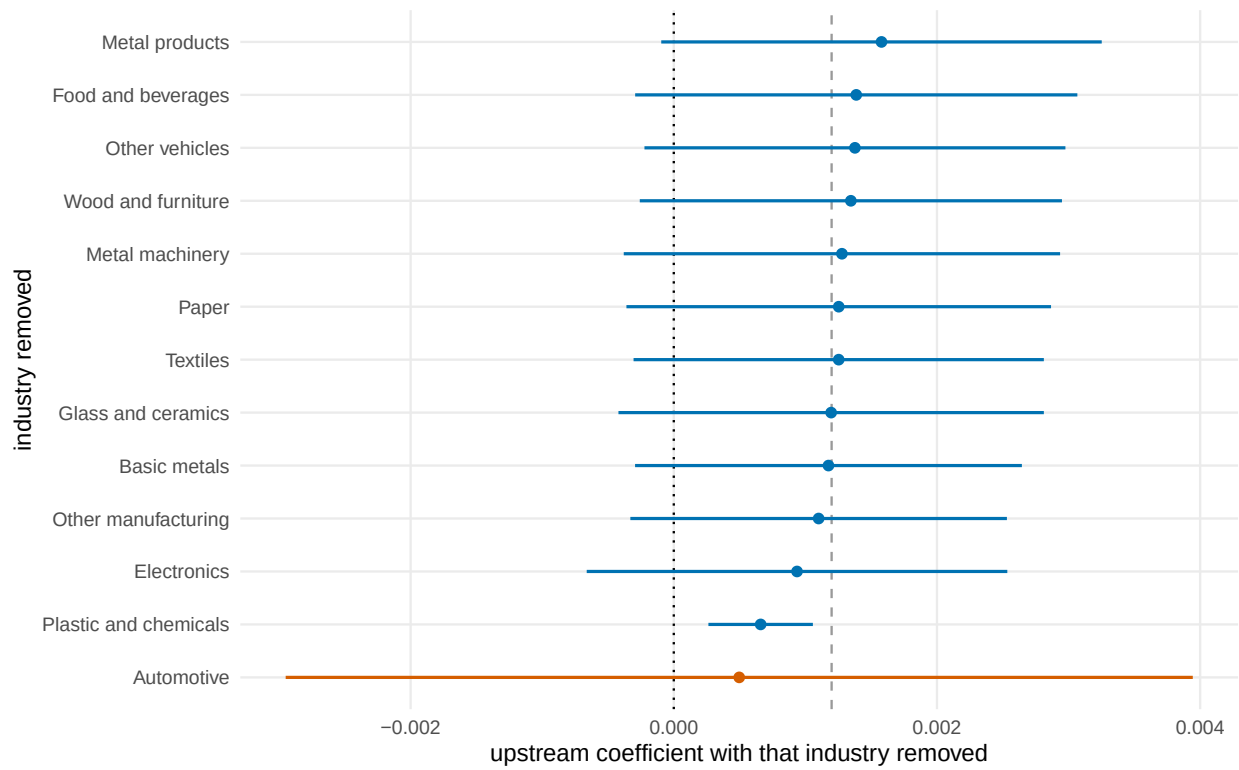


Figure 14: Leave-one-industry-out estimates of the effect of robots on upstream dependence. Each point re-estimates the effect with one IFR-19 industry removed, with 95 percent intervals from industry-clustered standard errors. The dashed line is the full-sample estimate and the dotted line is zero.

5.5 Dependence on industrial-automation products

Is the United States dependent on other countries for automation technology itself? If so, how has this changed over time? In this section, we describe this dependence but do not make any causal claims. We first classify products according to different tiers of relationships to automation. There are some complications with product classifications that make comparisons over time more challenging. We divide products into “tiers” to classify them based on which codes were available when.

There is one HS code that is directly described as *industrial robots, n.e.s.* (HS 8479.50).³⁶ This code was created in the HS1996 revision of codes, so we can observe it in all five of our benchmark years. The literature uses this as the primary code for industrial automation.³⁷ Tier 1 consists of just this HS 6-digit code. It is consistent and clearly related to industrial automation.

Tier 2 contains HS codes that are composed of automation capital equipment. For example, we include in this tier machining centers and transfer machines. Some categories of machines differentiate between those that are manually controlled versus numerically controlled. We include the subheadings that are labeled as numerically controlled for lathes, drilling, milling and grinding headings, and parts for those machines. We also include the “fully or partly automatic” welding subheadings 8515.21 and 8515.31.³⁸

Tier 3 contains the control and drive inputs that automated production consumes: control panels, automatic regulating and measuring instruments, servo-range motors, ball screws and gearboxes, and the residual machinery lines 8479.89 and 8479.90.³⁹ Table 6 lists every code with its tier and its 2017 import value.

The fact that HS codes change across revisions creates an issue worth noting. There are two HS6-digit codes for semiconductors: 8542.31 (processors and controllers) and 8542.39 (other integrated circuits). However, these codes were created in HS2007. In earlier HS code revisions, those products were included under broader headings. And in those earlier HS revisions, the four-digit heading 8542 split integrated circuits by technology (MOS versus bipolar) rather than by function. Controllers for automation cannot be separated from memory chips at the six-digit level in 1997 or 2002. We therefore list them separately and hold out their antecedent HS codes from earlier revisions from the tiers.

³⁶*n.e.s.* means “not elsewhere specified”.

³⁷Eg Acemoglu, Lelarge, and Restrepo (2020).

³⁸This excludes the manual versions of these products, like 8515.29 and 8515.39. We exclude the non-numerically-controlled versions of each machine-tool HS code, as well.

³⁹The literature includes 8479.89 as “dedicated machinery (including robots),” so we include it here, too (Acemoglu and Restrepo 2022). Industrial servo motors fall in HS 8501.32, DC motors with output above 750 W up to 75 kW. The neighboring codes are defined by power class and fall outside the industrial servo range: 8501.31 covers motors up to 750 W, the hobby and appliance scale, and 8501.33 covers motors above 75 kW, the traction and large-drive scale. We include 8501.32 only.

Table 6: Imports of industrial automation, by tiers.

HS6	Group	Imports, 2017 (USD m)
Tier 1: Core robots, 1 code		
8479.50	Industrial robots	430
Tier 2: Automation capital equipment, 20 codes		
8457.10	Machining centres	1,195
8466.93	Machine-tool parts	766
8458.11	NC lathes	683
8515.21	Automatic welding	660
8466.94	Machine-tool parts	469
8515.31	Automatic welding	204
8458.91	NC lathes	155
8459.61	NC drilling/boring/milling	102
8459.31	NC drilling/boring/milling	97
8460.23	NC grinding	67
8460.31	NC grinding	59
8460.12	NC grinding	57
8457.30	Machining centres	56
8460.24	NC grinding	52
8460.22	NC grinding	49
8459.21	NC drilling/boring/milling	29
8457.20	Machining centres	21
8459.51	NC drilling/boring/milling	5
8460.11	NC grinding	35 (2012)
8460.21	NC grinding	219 (2012)
Tier 3: Control and drive inputs, 7 codes		
8537.10	Control panels	10,108
8479.89	Machines nec	4,349
9032.89	Automatic regulating instruments	3,172
9031.80	Measuring/checking instruments	2,712
8483.40	Gears and ball screws	2,531
8479.90	Machines nec	2,192
8501.32	Servo-range motors	348
Tier 4: Semiconductor controllers, 2 codes		
8542.31	Processors and controllers	21,055
8542.39	Processors and controllers	8,261

Note:

Import values are in-measure imports, concordance-weighted to the HS6 line, in nominal USD millions. A code retired before 2017 shows its last observed value, with that year in parentheses.

Figure 15 shows how dependence from each of the first three tiers plus semiconductors has changed over time. Industrial robots themselves and capital equipment are only a small part of U.S. dependence. The much larger proportion of dependence comes from the components that go into industrial automation. In 2012, dependence from these components was as substantial as dependence from semiconductors. The trend in overall automation dependence is positive, peaking in 2012. Dependence on the automation bundle rises from 0.0072 percent of real income in 1997 to 0.0187 percent in 2017.

Figure 16 shows how much each of the top 12 HS lines contributes to dependence. We color each line by its tier. Tier 3 lines, the (literal) nuts and bolts of automation imports, are much more important sources of dependence. Note that the vertical axis is on the logarithmic scale.

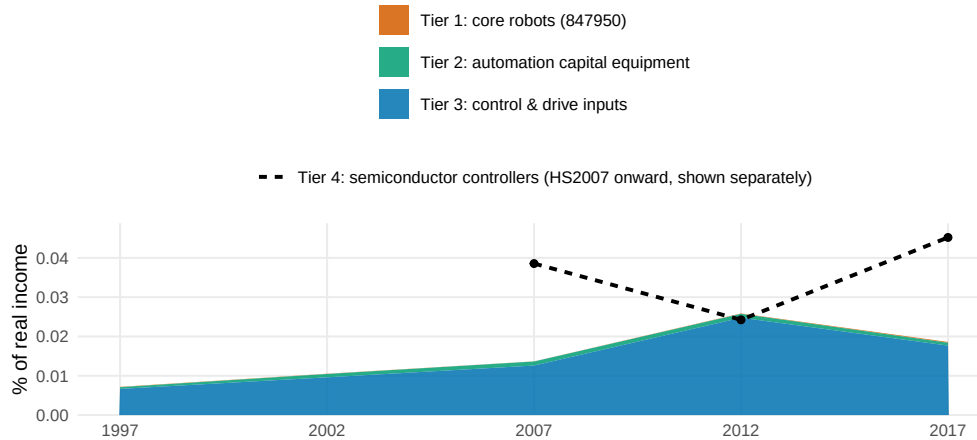


Figure 15: U.S. upper-bound import dependence on industrial-automation products, by tier.

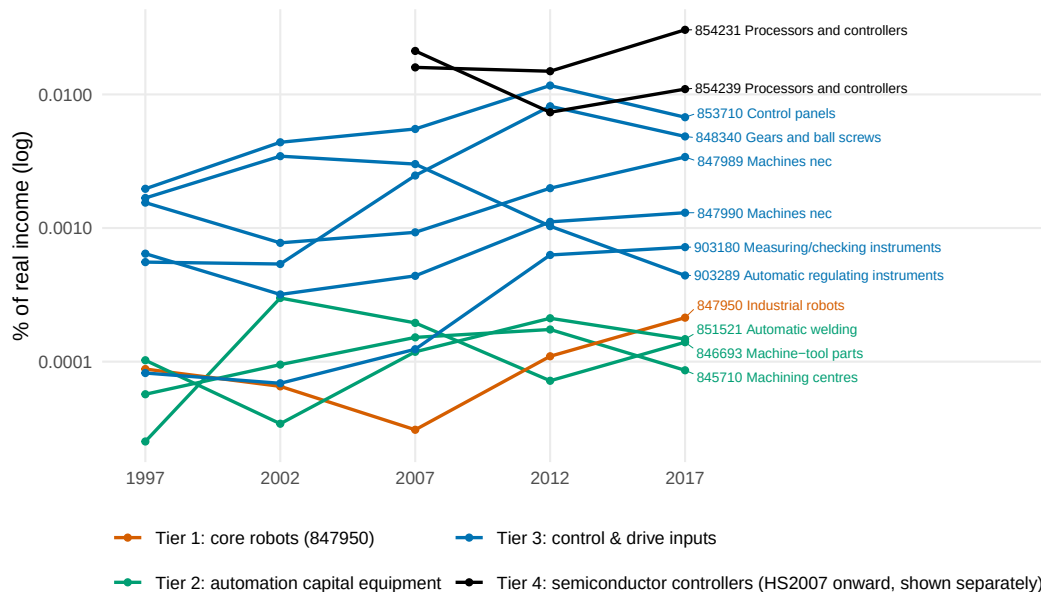


Figure 16: Individual HS6 lines of the automation bundle, ranked by 2017 dependence. Colors indicate the tier of the bundle that a line belongs to.

As in the chokepoints section, *who* the United States depends on is a larger part of the story. Figure 17 shows changes over time in which suppliers contribute the most to U.S. dependence on automation technologies. Figure 18 shows this in terms of the share of U.S. dependence by supplier, by year. The height of each bar shows what percentage of U.S. automation dependence comes from each supplier in each year.

In 1997, Japan accounted for 28 percent of U.S. automation dependence, with Mexico and Canada together another 32 percent. China ranked 7th with 2.8 percent. By 2017, China became one of the largest sources of U.S. automation dependence, at 15 percent, with Japan's share halved to 13 percent.

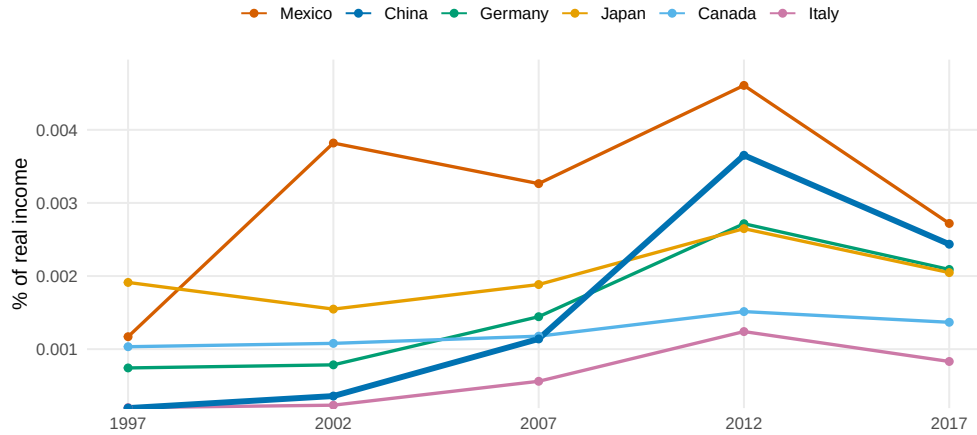


Figure 17: U.S. upper-bound dependence on individual suppliers for automation. The supplier set is fixed at the six largest sources in 2017.

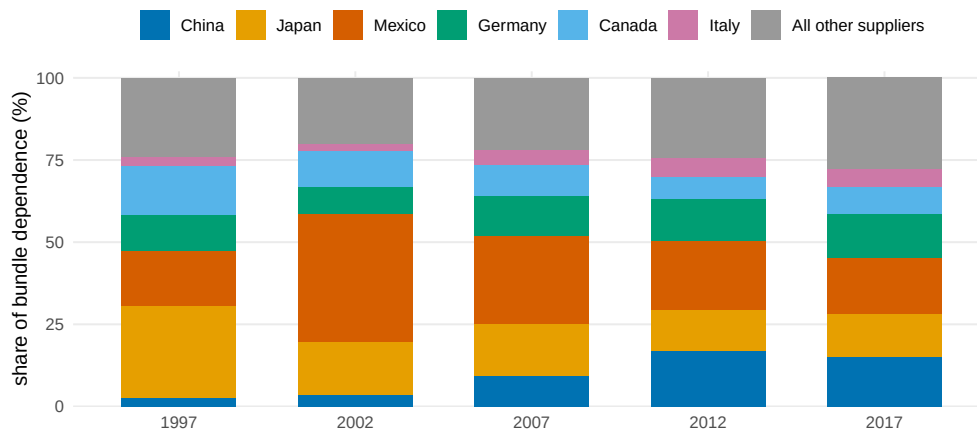


Figure 18: Composition of U.S. automation-bundle dependence by supplier. Shares are of the geographic-partner total in each year; suppliers outside the fixed 2017 top six are pooled into the residual category. China and Japan are stacked at the base so that the two suppliers of interest are comparable across years. Colors match Figure 17.

6. Conclusions

As policymakers and scholars worldwide think about how to navigate a complex web of dependencies from trade, they need to understand its precise nature and how it has evolved over time. This shows them where their true dependencies lie and whether their attempts to manipulate dependencies will be successful. This paper offered the most detailed accounting of U.S. dependencies from trade that is possible with currently available data. The data show two things that run counter to the status quo's dominant understanding of dependence. First, the data show that chokepoints are not a phenomenon that has become more prevalent or severe over time. And most things that look like chokepoints are fairly mundane. They are consumer facing products like toys or apparel.

While concern over chokepoints is warranted, most chokepoints are not things that would grab many headlines. Our claim is not that no chokepoints exist or that the international dependency network is devoid of bilateral pressure points. But we do claim that fear of chokepoints would more accurately be described as fear of dependence on China.

Second, our examination of automation and dependence should give pause to policymakers who think that industrial policy and heavy subsidies will alleviate overall dependence. The adoption of industrial robots in the United States did not decrease U.S. dependence. If anything, evidence suggests that it had the opposite effect. Since billions of dollars are being poured into similar efforts today, policymakers should have a better idea of their likely returns on investment.

This is a very preliminary draft and there are several next steps. First, we are working on additional ways to assess the effects of robots on dependence. One potential approach would mirror the commonly-used shift-share identification strategy. The share would be the degree of robot adoption in a particular industry in a pre-period year. The shift would be based on the fact that robots have generally decreased in price and increased in quality over time. The challenge here is that there are not fine-grained industry-level measures of the shift. IFR provides a time series of price and quality-adjusted price data for several countries, including the United States, that goes through 2005. However, the series is not industry-specific. The Japan Robot Association (JARA) provides data on Japanese robot prices that *is* industry-specific. We are working on the feasibility of using the JARA data to create an industry-specific adjustment to the IFR series, which would potentially give us a shift.

Second, we also need to fill in measures of dependence for non-BEA-benchmark years. This is feasible, but requires making choices over how to impute things like domestic production, consumption, and the input-output matrix. Trade elasticities are already estimated for each year. One approach would be to simply assume that the various inputs that are only measured in BEA benchmark years follow a linear trend, which we could use to have imputed estimates of any inputs to our measure that are not yearly.

Finally, we want to expand this research beyond the United States. We have “beta” versions of detailed dependence measures for the United Kingdom, Japan, Canada, and Australia, too. They are generally at higher levels of aggregation, i.e. not as detailed as the U.S. measures, and they cover fewer years. For the U.K., the necessary inputs for the dependence measures are available for 2017 and 2023, for 105 products. For Japan, data on 107 products are available for 2015. For Australia, data on 115 industries are available for 2023. And for Canada, data on 237 industries are available for 2017. Over the coming months, we will try and expand our measures beyond the United States.

References

- Acemoglu, Daron, Claire Lelarge, and Pascual Restrepo. 2020. "Competing with Robots: Firm-Level Evidence from France." *AEA Papers and Proceedings* 110: 383–88.
- Acemoglu, Daron, and Pascual Restrepo. 2020. "Robots and Jobs: Evidence from US Labor Markets." *Journal of Political Economy* 128 (6): 2188–2244.
- . 2022. "Demographics and Automation." *Review of Economic Studies* 89 (1): 1–44.
- Adão, Rodrigo, Michal Kolesár, and Eduardo Morales. 2019. "Shift-Share Designs: Theory and Inference." *The Quarterly Journal of Economics* 134 (4): 1949–2010.
- Arkolakis, Costas, Arnaud Costinot, and Andrés Rodríguez-Clare. 2012. "New Trade Models, Same Old Gains?" *American Economic Review* 102 (1): 94–130.
- Artuc, Erhan, Luc Christiaensen, and Hernan Winkler. 2019. "Does Automation in Rich Countries Hurt Developing Ones? Evidence from the U.S. and Mexico." Policy Research Working Paper 8741. Washington, DC: World Bank. <https://doi.org/10.1596/1813-9450-8741>.
- Artuç, Erhan, Paulo S. R. Bastos, and Bob Rijkers. 2023. "Robots, Tasks, and Trade." *Journal of International Economics* 145: 103828. <https://doi.org/10.1016/j.jinteco.2023.103828>.
- Barbieri, Katherine. 1996. "Economic Interdependence: A Path to Peace or a Source of Interstate Conflict?" *Journal of Peace Research* 33 (1): 29–49.
- Beaumier, Guillaume, and Madison Cartwright. 2024. "Cross-Network Weaponization in the Semiconductor Supply Chain." *International Studies Quarterly* 68 (1): sqae003.
- Boehm, Christoph E, Andrei A Levchenko, and Nitya Pandalai-Nayar. 2023. "The Long and Short (Run) of Trade Elasticities." *American Economic Review* 113 (4): 861–905.
- Boix, Carles, Valentina Gonzalez-Rostani, and Erica Owen. 2026. "The Political Economy of Automation and Fragmented Production: Evidence from Mexico." *Available at SSRN 5553058*.
- Borusyak, Kirill, Peter Hull, and Xavier Jaravel. 2022. "Quasi-Experimental Shift-Share Research Designs." *The Review of Economic Studies* 89 (1): 181–213.
- Caliendo, Lorenzo, and Fernando Parro. 2015. "Estimates of the Trade and Welfare Effects of NAFTA." *The Review of Economic Studies* 82 (1): 1–44.
- Chaudoin, Stephen, and Michael-David Mangini. 2025. "Robots, Foreigners, and Foreign Robots: Policy Responses to Automation and Trade." *The Journal of Politics*. <https://doi.org/10.1086/737849>.
- Clayton, Christopher, Matteo Maggiori, and Jesse Schreger. 2024. "A Theory of Economic Coercion and Fragmentation." NBER Working Paper 33309. Cambridge, MA: National Bureau of Economic Research. <https://doi.org/10.3386/w33309>.
- . 2026. "A Framework for Geoeconomics." *Econometrica* 94 (1): 105–36.
- Costinot, Arnaud, and Andrés Rodríguez-Clare. 2014. "Trade Theory with Numbers: Quantifying the Consequences of Globalization." In *Handbook of International Economics*, 4:197–261. Elsevier.
- Crescenzi, Mark JC. 2003. "Economic Exit, Interdependence, and Conflict." *The Journal of Politics* 65 (3): 809–32.
- Ding, Xiang. 2026. "Capital Services in Global Value Chains." *Quarterly Journal of Economics*, *Forthcoming*.
- European Commission, and High Representative of the Union for Foreign Affairs and Security Policy. 2023. "Joint Communication to the European Parliament, the European Council and the Council on a European Economic Security Strategy." Joint Communication JOIN(2023) 20 final. Brussels: European Commission. <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52023JC0020>.

- Faber, Marius. 2020. "Robots and Reshoring: Evidence from Mexican Labor Markets." *Journal of International Economics* 127: 103384.
- Farrell, Henry, and Abraham L Newman. 2019. "Weaponized Interdependence: How Global Economic Networks Shape State Coercion." *International Security* 44 (1): 42–79.
- Fontagné, Lionel, Houssein Guimbard, and Gianluca Orefice. 2022. "Tariff-Based Product-Level Trade Elasticities." *Journal of International Economics* 137: 103593. <https://doi.org/10.1016/j.jinteco.2022.103593>.
- Gartzke, Erik, and Quan Li. 2003. "Measure for Measure: Concept Operationalization and the Trade Interdependence-Conflict Debate." *Journal of Peace Research* 40 (5): 553–71.
- Glosserman, Brad. 2021. "Kishida Doubles down on Economic Security." *The Japan Times*, October. <https://www.japantimes.co.jp/opinion/2021/10/12/commentary/japan-commentary/kishida-economic-security/>.
- Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift. 2020. "Bartik Instruments: What, When, Why, and How." *American Economic Review* 110 (8): 2586–2624.
- Gowa, Joanne. 1995. *Allies, Adversaries, and International Trade*. Princeton University Press.
- Graetz, Georg, and Guy Michaels. 2018. "Robots at Work." *The Review of Economics and Statistics* 100 (5): 753–68.
- Keohane, Robert O, and Joseph S Nye. 1973. "Power and Interdependence." *Survival* 15 (4): 158–65.
- Krenz, Astrid, Klaus Prettnner, and Holger Strulik. 2021. "Robots, Reshoring, and the Lot of Low-Skilled Workers." *European Economic Review* 136: 103744.
- Liu, Ernest, and David Y. Yang. 2025. "International Power." NBER Working Paper 34006. Cambridge, MA: National Bureau of Economic Research. <https://doi.org/10.3386/w34006>.
- Mangini, Michael-David, and Stephen Chaudoin. 2026. "Trade Interdependence in the Modern Global Economy." *American Political Science Review*.
- Oneal, John R., and Bruce M. Russett. 1997. "The Classical Liberals Were Right: Democracy, Interdependence, and Conflict, 1950–1985." *International Studies Quarterly* 41 (2): 267–93. <https://doi.org/10.1111/1468-2478.00042>.
- Polachek, Solomon W. 1997. "Why Democracies Cooperate More and Fight Less: The Relationship Between International Trade and Cooperation." *Review of International Economics* 5 (3): 295–309.
- Schneider, Jordan, Chris Miller, Aqib Zakaria, and Phoebe Chow. 2026. "The Chemistry of Chips." *ChinaTalk*, July. <https://www.chinatalk.media/p/the-chemistry-of-chips>.
- Stapleton, Katherine, and Michael Webb. 2026. "Automation, Trade and Multinational Activity: Micro Evidence from Spain." *Research Policy* 55 (5): 105472. <https://doi.org/10.1016/j.respol.2026.105472>.
- Stehrer, Robert. 2026. "Structural Dependencies and Choke Points in GVCs: An Industry-Level Analysis." Research Report 480. Vienna: The Vienna Institute for International Economic Studies (wiiw). <https://wiiw.ac.at/structural-dependencies-and-choke-points-in-gvcs-an-industry-level-analysis-dlp-7524.pdf>.
- Stavis-Gridneff, Matina, and Ian Austen. 2026. "Canada Flexes on Global Stage with an Eye to Its Own Survival." *The New York Times*, January. <https://www.nytimes.com/2026/01/20/world/canada/carney-speech-davos-trump.html>.
- United Nations Conference on Trade and Development. 2024. "Trade Analysis and Information System (TRAINS)." United Nations.
- Vries, Gaaitzen J. de, Elisabetta Gentile, Sébastien Miroudot, and Konstantin M. Wacker. 2020. "The Rise of Robots and the Fall of Routine Jobs." *Labour Economics* 66: 101885.
- Wang, Dan. 2025. *Breakneck: China's Quest to Engineer the Future*. New York: W. W. Norton.

- Winecoff, William Kindred. 2020. “‘The Persistent Myth of Lost Hegemony,’ Revisited: Structural Power as a Complex Network Phenomenon.” *European Journal of International Relations* 26 (1_suppl): 209–52.
- Xi, Jinping. 2020. “Certain Major Issues for Our National Medium- to Long-Term Economic and Social Development Strategy.” Speech to the seventh meeting of the Central Financial and Economic Affairs Commission, April 2020; published in *Qiushi*, 1 November 2020. Translated by the Center for Security and Emerging Technology, 10 November 2020. <https://cset.georgetown.edu/publication/xi-jinping-certain-major-issues-for-our-national-medium-to-long-term-economic-and-social-development-strategy/>.

Robots and Import Dependence

Appendix

Appendix

A Trade-elasticity estimation	A-3
B Equivalence of the two Upper Bound expressions	A-3
C Working example of the dependence measure	A-5
D Robot data and the estimation sample	A-7

A Trade-elasticity estimation

We estimate a trade elasticity θ for each of the 1,257 HS-4 headings in our data. We do this separately for the BEA benchmark windows (1997, 2002, 2007, 2012, and 2017). The estimator follows the Caliendo and Parro (2015) triplets approach as extended by Mangini and Chaudoin (2026). Within each heading and window, we form the triple-ratio moments across country triangles from bilateral trade and tariffs. The estimate of θ is global. It is not specific to an importer, exporter, or particular dyad.

MC used a Bayesian approach and they set the priors for each TiVA industry based on a global mean. Here, we used priors from existing work that are already estimated at the HS-4 heading level from Fontagné, Guimbard, and Orefice (2022) (FGO). If FGO reported an elasticity for that heading, we use that as the prior here. If FGO did not report an elasticity for that heading, we aggregate up to the HS-2 chapter level and use the median elasticity of the headings under that chapter. This makes sure that every heading gets a prior that is based on comparable products. We compute the posterior for θ in closed form (a conjugate normal update). We followed MC in constraining θ to be less than -0.25.

B Equivalence of the two Upper Bound expressions

Here we show that the product form of the Upper Bound measure used in the text,

$$UB_{j,t} = 1 - \prod_c \left(\hat{\lambda}_{j,t}^c \right)^{-\chi_t^c / \theta_t^c},$$

and its additive “welfare-loss” form are the same object, and we record the sign conventions the pipeline uses.

Fix a partner (or a set of flows) j and a year t . For each commodity c , let $\lambda_{j,t}^c$ be the pre-shock home-absorption share and $\lambda'_{j,t}^c$ the counterfactual share after partner j ’s share of commodity c ’s imports is removed,

$$\lambda^c = \frac{Y^c - X^c}{Y^c - X^c + M^c}, \quad \lambda'^c = \frac{Y^c - X^c}{Y^c - X^c + (1 - \alpha_{j,t}^c) M^c},$$

where Y^c , X^c , and M^c are commodity c ’s domestic production, exports, and imports, and $\alpha_{j,t}^c$ is partner j ’s share of those imports (the j, t subscripts on Y, X, M are suppressed). Because removing imports raises the home share, $\lambda'_{j,t}^c \geq \lambda_{j,t}^c$. Define the change ratio in the usual ACR direction, $\hat{\lambda}_{j,t}^c \equiv \lambda'_{j,t}^c / \lambda_{j,t}^c \geq 1$, and the log shock

$$\Delta \ln \lambda_{j,t}^c \equiv \ln \lambda'_{j,t}^c - \ln \lambda_{j,t}^c = \ln \hat{\lambda}_{j,t}^c \geq 0.$$

Taking logs of the product form,

$$-\ln(1 - UB_{j,t}) = \sum_c \frac{\chi_t^c}{\theta_t^c} \ln \hat{\lambda}_{j,t}^c = \sum_c \frac{\chi_t^c}{\theta_t^c} \Delta \ln \lambda_{j,t}^c,$$

so, equivalently,

$$UB_{j,t} = 1 - \exp \left(- \sum_c \frac{\chi_t^c}{\theta_t^c} \Delta \ln \lambda_{j,t}^c \right).$$

The right-hand sum is the additive welfare loss: each commodity contributes its log shock $\Delta \ln \lambda_{j,t}^c$, weighted by the exposure-to-elasticity ratio χ_t^c/θ_t^c , and the level measure $UB_{j,t}$ is the monotone transform $1 - e^{-(\cdot)}$ of that sum. This is exactly how the measure is built: each commodity's log contribution $(\chi_t^c/\theta_t^c) \Delta \ln \lambda_{j,t}^c$ is accumulated across commodities, and the total is passed through $1 - e^{-(\cdot)}$ to return a welfare share in $[0, 1)$.

Two remarks. First, on signs: θ_t^c enters as its magnitude $|\theta_t^c|$, which is why the exponent has an explicit minus sign, and the pipeline stores the estimates with their negative sign and takes $|\theta_t^c|$ at the point of use. Keeping the negative sign instead makes the two minus signs cancel, so that $UB_{j,t} = 1 - \exp(\sum_c (\chi_t^c/|\theta_t^c|) \Delta \ln \lambda_{j,t}^c)$ with $\theta_t^c < 0$ is the same number; the sign convention must be stated once and then held. Since $\chi_t^c > 0$ and $\Delta \ln \lambda_{j,t}^c \geq 0$, every commodity contributes non-negatively and $UB_{j,t} \geq 0$. Second, for a single commodity and a small shock the two forms coincide to first order, $UB \approx (\chi/\theta) \Delta \ln \lambda$; the exponential wrapper is what keeps the aggregate over many commodities a valid welfare share rather than letting the linear sum run past one.

C Working example of the dependence measure

This section shows numerical values for a small economy so that the reader can easily see how our dependence measure is constructed. Recall the two forms of the Upper Bound measure. The product form is

$$UB_{j,t} = 1 - \prod_c \left(\frac{\lambda'_{j,t}}{\lambda_{j,t}^c} \right)^{-\chi_t^c / \theta_t^c},$$

and the additive welfare-loss form is

$$-\ln(1 - UB_{j,t}) = \sum_c \frac{\chi_t^c}{\theta_t^c} \Delta \ln \lambda_{j,t}^c, \quad \text{so} \quad UB_{j,t} = 1 - \exp \left(- \sum_c \frac{\chi_t^c}{\theta_t^c} \Delta \ln \lambda_{j,t}^c \right).$$

Appendix B shows that the two forms give the same number.

The additive form makes it easier to see how changes in the inputs to the measure change the measure. Each commodity adds one term, $(\chi_t^c / |\theta_t^c|) \Delta \ln \lambda_{j,t}^c$, to the sum, and $UB_{j,t}$ rises with the sum. A lower elasticity magnitude $|\theta_t^c|$ raises the measure, because the term divides by it. A higher exposure weight χ_t^c raises the measure, because the term multiplies by it. A larger log shock $\Delta \ln \lambda_{j,t}^c$ raises the measure for the same reason.

The example below, in Table A.1, makes $\chi = L\beta$ clearer. One component is the commodity's own consumption share β_c , which is the demand that households put on the commodity itself. The second channel is the commodity's downstream input-output position, which is row c of the Leontief inverse L . It describes the demand that other commodities put on the commodity when households buy those other commodities. The example separates the two channels. The economy has three commodities: semiconductors, electronics, and food. The consumer buys electronics and food, and buys no semiconductors at all, so the second channel supplies the whole weight of semiconductors.

Table A.1: The toy economy. Column k is the recipe of commodity k : a dollar of electronics needs 40 cents of semiconductors and 10 cents of electronics. The final column is the consumption basket β , which sums to one. Every column of A sums to less than one, so the Leontief inverse exists and is non-negative.

input from	used by commodity k			final demand
	semiconductors	electronics	food	β_c
semiconductors	0.100	0.400	0.000	0.00
electronics	0.000	0.100	0.000	0.50
food	0.000	0.000	0.200	0.50
value added $\eta_k = 1 - \sum_c A_{ck}$	0.900	0.500	0.800	—

Table A.2 inverts that input-output matrix. The Leontief inverse $L = (I - A)^{-1}$ reports total requirements, direct and indirect, and the exposure weight is $\chi = L\beta$. Food has a consumption share of $\beta = 0.50$ and a weight of $\chi = 0.6250$, so the first channel gives it 0.50 and the second channel adds 0.1250, because food uses food. Electronics has the same consumption share and a weight of $\chi = 0.5556$, so its second channel adds only 0.0556. Semiconductors have a consumption share of $\beta = 0.00$ and still have $\chi = 0.2469$, which is 17 percent of the total exposure weight. The second channel supplies all of it, through the electronics that the consumer does buy.

Table A.2: Total requirements and the exposure weight. The weight is $\chi = L\beta$, the row orientation: row c of L dotted with the basket answers how much of commodity c one dollar of final demand pulls, directly and indirectly. Two channels set the weight: the consumption share β_c , and the downstream input-output position, which is row c of L . Semiconductors enter no consumption basket and still carry a weight of 0.2469, which is 17 percent of the total.

commodity	$L = (I - A)^{-1}$			β_c	χ_c
	semiconductors	electronics	food		
semiconductors	1.111111	0.493827	0.000000	0.00	0.246914
electronics	0.000000	1.111111	0.000000	0.50	0.555556
food	0.000000	0.000000	1.250000	0.50	0.625000
sum				1.00	1.427469

Table A.3 completes the measure by adding hypothetical values for trade and home country production. The removed partner supplies the share α_c of commodity c 's imports, so the home-absorption share rises from λ_c to λ'_c . The quantity $\Delta \ln \lambda_c$ is the log rise. Each commodity then contributes $\text{dep}_c = (\chi_c/\varepsilon_c) \Delta \ln \lambda_c$, and the upper bound is $1 - \exp(-\sum_c \text{dep}_c) = 5.4089$ percent of real income.

The last column separates the two channels once more. Semiconductors have the highest elasticity magnitude of the three, $\varepsilon = 4$, so the elasticity lowers their contribution, and their exposure weight is the smallest of the three. They still are responsible for 31.9 percent of the loss, even though the consumer never consumes semiconductors directly. Semiconductors only contribute loss through the second channel of χ , via downstream effects. Food contributes to loss primarily through the first channel, direct consumption. Its consumption share and its own use of food give it the highest weight, $\chi = 0.6250$, and the floor holds its elasticity at 1, so its ratio χ_c/ε_c is 0.6250, the highest of the three. Food still contributes only 18.9 percent of the loss, because its shock $\Delta \ln \lambda$ is the smallest. Electronics contribute loss via both channels and are responsible for 49.2 percent of the loss. They have a large consumption share which increases their exposure weight, and they have downstream input-output consequences.

Table A.3: The measure of Section 3.5 on the toy economy. The upper bound is $1 - \exp(-\sum_c \text{dep}_c)$, which is 5.4089 percent of real income here.

commodity	trade block				home-absorption share			elasticity		contribution		
	Y_c	X_c	M_c	α_c	λ_c	λ'_c	$\Delta \ln \lambda_c$	θ_c	ε_c	χ_c	dep_c	share of loss (%)
semiconductors	25	5	20	0.50	0.5000	0.6667	0.2877	-4.0	4	0.2469	0.017758	31.9
electronics	55	5	30	0.25	0.6250	0.6897	0.0984	-2.0	2	0.5556	0.027344	49.2
food	60	10	10	0.10	0.8333	0.8475	0.0168	-0.8	1	0.6250	0.010504	18.9
total											0.055607	100.0

Note:

Y_c , X_c and M_c are domestic production, exports and imports, and α_c is the removed partner's share of commodity c 's imports. $\lambda_c = (Y_c - X_c)/(Y_c - X_c + M_c)$ and λ'_c replaces M_c by $(1 - \alpha_c)M_c$. $\varepsilon_c = \max(|\theta_c|, 1)$ is the floored elasticity magnitude of Appendix A; the floor binds on food, whose native estimate is -0.8 . The last column is dep_c as a percentage of the total, and it does not sum to the upper bound, which is the monotone transform $1 - e^{-(\cdot)}$ of that total. The trade block is a round overlay chosen for legibility and is not balanced against A and β .

D Robot data and the estimation sample

This section gives more information about the robot data of Section 5, the map from the IFR industry to the BEA commodity, and the estimation sample.

Table A.4: Section 5 estimation sample. One row per IFR industry: the four-digit NAICS codes the rule map collects into it, the U.S. robot density path in robots per 1,000 workers, the number of manufacturing BEA commodities it covers before and after the merchandise-measure restriction, and the observation count.

IFR industry	NAICS-4 collected	U.S. robot density			BEA (all)	BEA (used)	Obs.
		2004	2007	2012			
Automotive	3361, 3362, 3363	77.407	91.994	99.929	14	13	26
Electronics	3341, 3342, 3343, 3344, 3345, 3346, 3351,...	4.862	9.730	12.993	34	34	66
Metal products	3321, 3322, 3323, 3324, 3325, 3326, 3327,...	8.073	9.797	9.026	20	15	28
Plastic and chemicals	3241, 3251, 3252, 3253, 3254, 3255, 3256,...	5.369	7.430	8.762	33	28	56
Food and beverages	3111, 3112, 3113, 3114, 3115, 3116, 3117,...	3.395	3.917	5.305	29	29	57
Other manufacturing	3391, 3399	0.000	0.906	4.322	11	10	20
Basic metals	3311, 3312, 3313, 3314, 3315	0.000	0.000	2.062	9	8	14
Metal machinery	3331, 3332, 3333, 3334, 3335, 3336, 3339	0.000	0.002	1.933	28	27	48
Glass and ceramics	3271, 3272, 3273, 3274, 3279	0.000	0.233	0.574	12	12	24
Other vehicles	3364, 3365, 3366, 3369	0.000	0.091	0.252	11	10	20
Paper	3221, 3222, 3231	0.000	0.003	0.146	10	10	20
Wood and furniture	3211, 3212, 3219, 3371, 3372, 3379	0.000	0.028	0.094	12	11	21
Textiles	3131, 3132, 3133, 3141, 3149, 315, 316	0.000	0.003	0.031	8	8	16

Note:

The robot measure is constant inside an IFR industry, so the industry count, not the commodity count, sets the number of independent shocks. Density is from IFR emphWorld Robotics 2025, on the Acemoglu and Restrepo (2020) 19-industry roster. BEA (used) counts the commodities that carry a dependence measure in both benchmark years of a period pair; BEA (all) counts them before that restriction.