Supplying Influence: Domestic Production Networks in Trade Politics[1]

Timm Betz[†] Leonhard Hummel[§]

April 28, 2025

Forthcoming, *International Organization*

Abstract

Why are some firms more successful than others in obtaining privileged treatment from their government? Trade policy, as an unusually targeted redistributive tool, offers a rich context to understand such questions of special interest politics and corporate power. Studying decisions on anti-dumping petitions in the U.S., we introduce a novel source of privileged treatment. We argue that firms with more linkages throughout the domestic economy enjoy a privileged political position. Benefits to these firms extend indirectly to a broader set of constituents, which allows firms to assemble broader coalitions and to portray protectionist policy as more than purely particularistic politics. We provide evidence for this argument by developing original measures of linkages between firms, derived from over 600,000 customer-supplier relationships among industries, matching them with data on anti-dumping petitions filed by U.S. firms, written briefs filed by Members of Congress on behalf of these firms, and the geographic distribution of industries. Our account identifies a new explanation of differences in the political influence of firms, underscores the relevance of domestic production networks in politics, and offers a new perspective on cleavages and coalitions in trade politics. Our results also suggest that the expansion of global supply chains, long considered a hallmark of political power, may have weakened the political clout of some of the largest firms by limiting their domestic footprint.

Word Count: 13,949 words
(including tables and figures; excluding references and online appendix)

[1]For helpful comments, we are indebted to Stephen Chaudoin, Ben Graham, Ye June Jung, In Song Kim, Lukas Linsi, Amy Pond, Dennis Quinn, Randy Stone, Rachel Wellhausen, and participants at the Annual Meetings of the American Political Science Association, the European Political Science Association, the International Political Economy Society, the Midwest Political Science Association, and the Bureaucracies in International Relations Conference at the University of Southern California. The IO editors and two anonymous reviewers provided extraordinarily constructive feedback. Michael Stelzig and Jonas Geus provided excellent research assistance. This research was funded by the European Research Council (Grant Agreement No. 101041658, Project PINPOINT), funded by the European Union. Views and opinions expressed are those of the authors only and do not necessarily reflect those of the European Union or the European Research Council Executive Agency. Neither the European Union nor the granting authority can be held responsible for them.

[†]Washington University in St. Louis, Department of Political Science; and LMU Munich, Geschwister-Scholl-Institute of Political Science. Email: betzt@wustl.edu.

[§]Technical University of Munich; TUM School of Social Sciences and Technology, Department of Governance; and Munich School of Politics and Public Policy. Email: leonhard.hummel@tum.de.

In 2020, several Members of Congress wrote a joint letter to the U.S. International Trade Commission, supporting a petition for anti-dumping duties filed by mattress manufacturers. The mattress manufacturers had requested new trade barriers to shield them from foreign competition. The letter noted that these manufacturers had a long history in the U.S., securing jobs for over a century – a common enough argument. But the letter also noted that any benefit to the mattress industry had much broader reach: firms in other industries, producing textiles, foams, and innersprings, would also benefit from anti-dumping duties for mattress manufacturers, because mattress manufacturing draws on an extensive, predominantly domestic, supply chain.[1]

Similar examples can be found in other contexts. In 2017, German auto manufacturer BMW pushed for changes in trade policy, emphasizing how even suppliers that don't export themselves benefit indirectly from new export opportunities for BMW – asking for, and defending, policies in line with BMW's interests.[2] In 2013, U.S. Senator Sherrod Brown highlighted how investments in Ohio's auto industry created benefits for firms across Ohio indirectly throughout the supply chain, calling for favorable policies for auto manufacturers.[3]

Such claims don't sit easily with existing frameworks. Economic ties among firms across industries remain largely outside their purview. In the literature on trade politics, in particular, dominant frameworks emphasize cleavages across classes,[4] industries,[5] firms,[6] or occupations,[7] not ties among firms that cross industry boundaries. Indeed, much of the contemporary literature pays attention to individual firms, ignoring the economic and institutional context in which firms operate. Similarly, firm-specific attributes, not economic ties among firms, feature prominently in the literature on the political influence of firms.

Yet, firms don't operate in isolation. As the examples above illustrate, they are embedded in production networks, composed of customer-supplier relationships, within the domestic economy; and firms and policy-makers appear to invoke these networks to justify particularistic policies. To the extent that previous work has considered networks among firms, it does not account for these examples, either. A related body of literature observes that networks among firms – including custumer-supplier relationships – predict similarities in political behavior,[8] rather than how firms use these networks to justify and receive privileged treatment. Work on multinational investment comes closest, showing

[1] Congress of the United States 2020.

[2] Lütkehus 2017.

[3] Brown 2013.

[4] Rogowski 1987*a*.

[5] Schattschneider 1935.

[6] Kim and Osgood 2019.

[7] Owen and Johnston 2017.

[8] Useem 1986; Mizruchi 1992; Cory, Lerner and Osgood 2021.

that in weak institutional environments, foreign firms with ties to domestic firms are less concerned about expropriation by host governments.[9] For the most part, however, prior work has emphasized other types of networks: for example, networks created by global value chains,[10] interlocks among corporate boards,[11] shared membership in business associations,[12] social ties among firm owners,[13] and shareholder chains.[14]

Mirroring this emphasis on networks among firms as an important aspect of politics, we contend that the examples above are part of a broader pattern. We argue, and demonstrate empirically, that differences in their embeddedness in production networks translate into differences in the political influence of firms. Connections to other firms extend the economic and political footprint of a firm. This enables firms to assemble a broader coalition, and to portray privileged treatment as more than a purely particularistic policy. A firm's position within the domestic economy emerges as an important source of political influence: firms are more likely to gain privileged treatment by their government if other firms benefit indirectly.

We situate this argument in the context of trade politics to explain government responses to protectionist demands by firms. Which firms drive trade policy shapes a country's integration into global markets and the ability to sustain that integration, as well as the distribution of power and wealth within societies. Understanding which firms succeed in gaining protection has long been a central question in international political economy, and it has been a prominent application to understand the political influence of firms since at least Schattschneider.[15] The resurgence of protectionist trade policy, and industrial policy more broadly, in recent years underscores the renewed relevance of this question.[16]

Specifically, we examine decisions on the imposition of U.S. anti-dumping duties as a manifestation of firm influence in politics. Anti-dumping duties are imposed temporarily to protect domestic firms from foreign competition. They have attractive features for our purposes. They exceed pre-existing tariff rates substantially, underscoring their relevance to firms.[17] They can be imposed unilaterally, without negotiations with foreign governments. And they are imposed in response to specific requests by firms, requiring an unambiguous decision by the government and allowing us to identify firms that voiced protectionist demands. While imposed through an administrative process and ruled on by their

[9] Johns and Wellhausen 2016.
[10] Jensen, Quinn and Weymouth 2015.
[11] Dreiling and Darves 2011.
[12] Murray 2017.
[13] Cruz and Graham 2022.
[14] Petry, Fichtner and Heemskerk 2021.
[15] Schattschneider 1935.
[16] Juhász, Lane and Rodrik 2023.
[17] Typical anti-dumping duties imposed by the U.S. range from 20% to 40%, but frequently exceed 100% (Bown, 2011). In comparison, the average U.S. tariff rate has long remained well under 5%.

legal and economic merits, decisions on anti-dumping petitions remain subject to political contestation and influence.[18] Differences in the political influence of firms should therefore be reflected in the success rates of anti-dumping petitions.

Combining data on over 900 U.S. anti-dumping petitions for about 2,000 distinct products with original measures of supplier-customer relationships, we show that a firm's position within the domestic production network shapes the success rates of its anti-dumping petitions. Firms are more likely to obtain privileged treatment by their government and have their anti-dumping petitions approved for products tied into domestic production networks. This effect exists in addition to, and is distinct from, standard predictors in the literature, such as firm and industry size, geographic location in swing states, asset mobility, and industry-specific attributes.

The upside of our research design is that we can evaluate government responses to explicit requests by firms. This upside comes with an inherent trade-off: firms must have made such requests in the first place. While we cannot eliminate the resulting selection problem, we show that such selection would have to be implausibly strong to account for the relationship we report. Several additional pieces of evidence suggest a causal relationship. First, we exploit that trade flows have shifted throughout our sample period, in part due to exogenous changes in trade policy uncertainty, resulting in differential increases in imports across inputs. As the domestic footprint of an industry declines, so does its political clout.[19] Second, tracing sourcing decisions to exchange rate movements at the level of an industry's suppliers, we corroborate our results with instrumental variable estimates. Third, numerous firms submitted anti-dumping requests for different products. We present evidence that the success rate of anti-dumping petitions increases for products that draw on a larger domestic production network, even for the same firm – which, together with industry-level attributes, captures the majority of existing explanations in the literature.

To elaborate on the role of politics, we offer evidence from written briefs submitted by Members of Congress in the process of anti-dumping investigations. Despite being short – many briefs are barely a page long – Members of Congress repeatedly invoke the indirect benefits to suppliers throughout the economy. Analyzing hundreds of these briefs, we demonstrate that firms drawing on a larger domestic production network receive support from more Members of Congress, consistent with our argument that these are benefitting broader constituencies.

Additionally, we provide evidence for one specific mechanism. Building on recent work highlight-

[18] Hansen 1990; Chaudoin 2014; Aquilante 2018; Egerod and Justesen 2022; Bown et al. 2024.

[19] We thus complement Jensen, Quinn and Weymouth (2015), who show that multinationals are less likely to demand anti-dumping duties on inputs sourced from abroad. We suggest that firms sourcing more inputs from abroad are less likely to receive anti-dumping duties on their outputs produced in the U.S.

ing the role of swing states in anti-dumping petitions,[20] we show that firms drawing on a larger domestic production network are more likely to be of *indirect* relevance to swing states. This indirect exposure of swing states, which potentially leads to political pressure on decision-makers on anti-dumping petitions, explains a substantial portion of the associations we report. This finding establishes how, through a firm's production network, the effects of a policy can build a broader and politically relevant constituency.

Our account identifies a distinct source of corporate power: firms embedded in domestic production networks enjoy outsized political influence. While we focused on anti-dumping petitions as one manifestation of such influence, the argument readily extends to other issue areas as well. Additionally, we highlight two key contributions. First, we offer an initial step toward incorporating domestic production networks into explanations of trade politics. Our account speaks to several prominent themes in this literature: the role of individual firms, including multinationals, in driving trade and trade policy;[21] the expansion of global production networks and the resulting political backlash;[22] and the political consequences of the geographic concentration of industries.[23] The nuances of domestic production networks have received scant attention in these strands of literature. Yet, production networks tie firms across industries together and connect smaller firms to global markets through their customers and suppliers. They are the counterpart to global production networks, which upend domestic production networks. And they extend the geographic footprint of industries indirectly, such that the effects of policies are not limited to the directly targeted industries. We thus offer a starting point for developing a different perspective on trade politics: taking into account firm-to-firm linkages promises new implications for understanding political coalitions, the drivers of trade policy, and – as we outline in the conclusion – the role of geography and institutions in trade politics and politics more generally.

Second, drawing on contributions in sociology and organization theory,[24] a body of literature examines the sources of corporate unity in politics. This literature documents that network ties among firms are reflected in similarities in political behavior.[25] Similar to Dreiling and Darves, who highlight how board interlocks and membership in business associations predict joint support for trade liberalization among firms,[26] we note the fruitfulness of extending insights from this literature to trade politics. We contribute in several ways to this literature. We show that networks among firms confer

[20] Bown et al. 2024.
[21] Jensen, Quinn and Weymouth 2015; Bernard et al. 2018; Kim and Osgood 2019.
[22] Mansfield and Mutz 2013; Owen and Johnston 2017; Kim and Rosendorff 2021.
[23] Busch and Reinhardt 1999; Colantone and Stanig 2018; Rickard 2020.
[24] Useem 1986; Mizruchi 1992.
[25] Murray 2017; Cory, Lerner and Osgood 2021.
[26] Dreiling and Darves 2011.

a form of (structural) political power that is unevenly distributed across firms within these networks; we emphasize a dimension of networks – a firm's relevance to upstream suppliers – not present in this literature; we identify mechanisms that render these networks relevant in the context of democratic policy-making; and we provide novel empirical measures of embeddedness into production networks, relating them to the success of firms in securing protectionist trade policy.

1 Firms, Production Networks, and Anti-Dumping Petitions

Trade policy has long been used to understand questions of firm influence.[27] We focus on a specific type of trade policy: anti-dumping duties.[28] Anti-dumping duties are short-term, targeted instruments. For firms, they present an opportunity to obtain protection from foreign competition outside the standard policy-making process: Dumping occurs when foreign firms sell products below cost or below the price in their home market.

The process for the filing and investigation of petitions varies by countries. In the U.S., anti-dumping duties are imposed in response to petitions by firms (and other petitioners, such as labor unions). Petitioners need to define the imported product, identify a comparable product in U.S. classifications, document that the imported product affects a sufficiently large share of the U.S. industry, and establish that the imported product imposes or threatens to impose material injury to the U.S. industry. These petitions reflect protectionist demands. They require an unambiguous decision by the government: whether to impose anti-dumping duties. Unlike in many other cases of policy-making, it is therefore possible to observe both whether a firm made protectionist demands and how the government responded to that request.

Petitions involve a fair amount of documentation. Typically, they are prepared with the support of law firms. At the same time, as one of these law firms highlights, "the standard for initiation is low".[29] Petitions only have to include the above information "to the extent reasonably available to the petitioner."[30] As a consequence, some firms view anti-dumping petitions as part of a broader tool-kit of business strategy[31] – so much so that government agencies voice concerns about firms requesting anti-dumping duties without much merit.[32] Nonetheless, anti-dumping petitions are not a random sample of protectionist demands. Plausibly, they are based on substantiated concerns, and firms incorporate

[27] Pareto 1927; Schattschneider 1935.

[28] In the U.S., anti-dumping duty investigations are frequently conducted simultaneously with countervailing duty investigations. We limit the discussion and analysis to anti-dumping duties.

[29] White & Case, `https://www.whitecase.com/insight-alert/information-regarding-antidumping-and-countervailing-duty-petitions-vanillin-china`, last accessed January 31, 2025.

[30] 19 CFR 351.202.

[31] Prusa 1992.

[32] U.S. Government Accountability Office 2022.

the odds of a succesful outcome in the decision of whether to file a petition. In the empirical section, we address the resulting selection problem.

Petitions are filed simultaneously with the Department of Commerce and the International Trade Commission (ITC). We provide details on the investigation process in the appendix. Broadly speaking, the Department of Commerce determines whether a foreign firms likely sells its products below fair market values; the ITC determines whether the imported product causes or threatens to cause material injury to domestic firms. Both determinations need to be affirmative for the imposition of anti-dumping duties.

Investigations are split into a preliminary phase with a lower evidentiary burden and a final investigation. The ITC, headed by six Commissioners, reviews documents, hears witnesses, and requests written information from petitioners, other domestic firms, and the firms alleged to engage in dumping. The investigation by the ITC ends in a vote by its Commissioners; tied votes are considered affirmative. If the ITC Commissioners vote affirmatively and the Department of Commerce determines that products are likely sold below fair market value, the Department of Commerce issues an anti-dumping order, imposing duties on the products under investigation.

Despite this rule-based process, many of the decisions it entails allow for discretion. In the calculation of fair market values, the Department of Commerce may declare a Particular Market Situation in the exporting country, arguing that market distortions justify an adjustment to the prices of imported products or production costs.[33] U.S. courts have repeatedly overturned decisions invoking Particular Market Situations, suggesting that the Department of Commerce took advantage of this discretion to approve anti-dumping duties that otherwise would have been declined.[34] In response, in 2024, the Department of Commerce introduced rules *expanding* its ability to invoke Particular Market Situations.[35]

Investigations require determining a 'like product' – a product essentially the same as the imported product – in U.S. classifications. The Department of Commerce retains discretion over how this determination is made. It is not a mere technicality: how this product is defined shapes which data are collected to assess fair market values and which industries are considered to assess injury to domestic firms. The time period for benchmarking also offers discretion. While domestic production is usually assessed over a twelve-month period, investigations can decide which twelve-month period to consider, may consider different time periods, and may use either value or volume.[36]

In assessing whether imported products caused or threaten to cause injury to domestic firms, the

---

[33] Declaring a Particular Market Situation falls short of declaring the exporting country a non-market economy.

[34] Kim and Roh 2022.

[35] White & Case, `https://www.whitecase.com/insight-alert/united-states-expands-and-strengthens-enforcement-antidumping-and-countervailing-duty`, last accessed January 31, 2025.

[36] 19 CFR 351.203.

ITC can exclude some firms from consideration, molding to some extent the group of firms it considers in this assessment. The ITC can also limit its assessment to specific geographic regions where affected firms are concentrated. Engaging in, as a court ruling put it, such "[a]rbitrary or free handed sculpting of regional markets"[37] has allowed the ITC to find material injury where otherwise a case would have been declined.

The interpretation of the assembled evidence is, likewise, not necessarily clear-cut. This is reflected in the voting outcomes. The Commissioner vote at the ITC is unanimous in only about 44% of decisions. In about 25% of decisions, at least two Commissioners dissented from the majority vote.[38]

The investigation process allows for discretion and differences in interpretation. It also allows politics to enter. Both institutions involved in investigations have close ties to the President and the Senate. The Department of Commerce is headed by the Secretary of Commerce. The Secretary of Commerce (and the Assistant Secretary for Enforcement and Compliance as its delegate) ultimately is responsible for the decisions by the Department of Commerce. Political considerations should be expected to factor into these: the Secretary of Commerce serves at the pleasure of the President and requires Senate confirmation.

The role of politics is potentially more questionable in decisions by ITC Commissioners. The ITC is nominally an independent and bipartisan agency. Yet, it is headed by six Commissioners who are nominated by the President and confirmed by the Senate. Based on observable indicators, the ITC is about as independent as the Securities and Exchange Commission, or SEC.[39] The SEC is a considerably more prominent agency. It typically is considered to be subject to political influence,[40] and firms with ties to Senators are less likely to face enforcement actions by the SEC.[41]

The broader literature on agency independence suggests specific mechanisms through which politics matters.[42] First, Congress ultimately controls agency resources. The ITC is a small agency, with a budget of $122 million in 2022 and a staff of about 400. As other agencies, it faces resource constraints. In its 2025 Budget Justification, the ITC noted the need for increased funding and the pains of being short-staffed, in particular in its offices related to anti-dumping investigations.[43] The six Commissioners, one of whom serves as Chair of the ITC, rely on this budget for their daily work. Sustaining the support of the President and key Members of Congress therefore remains important. Decisions

[37] 85 Atlantic Sugar, Ltd. v. United States, 519 F. Supp. 916, 920, CIT 1981; quoted in U.S. International Trade Commission 2015, II-37.

[38] Own calculations, based on data from the Investigation Database System, available at `https://catalog.data.gov/dataset/investigations-database-system`, last accessed December 5, 2024.

[39] Arel-Bundock, Atkinson and Potter 2015.

[40] Pond 2021.

[41] Correia 2014.

[42] Weingast and Moran 1983.

[43] U.S. International Trade Commission 2025.

that stray away from their interests may undermine that support.

Second, the threat of (uncomfortable) Congressional hearings, which potentially harm future career prospects,[44] constrains ITC Commissioners. And as in the context of central banks, at least implicitly the independence of agencies always remains conditional – it might get revoked if an agency fails to deliver on key goals of Congressional majorities and the President.[45] This presents a signifificant concern for the ITC, which in official communications prides itself on its independence.

Third, Commissioners have their own views on what U.S. trade policy should look like. The nomination process ensures that the views of Commissioners reflect at least partially those of the President and the Senate. Moreover, the Chair role rotates every two years. Because the President designates the Chair, voting against the interests of the President can entail career repercussions. The Chair role comes not just with visibility. It comes with influence. For example, in 2022, Commissioner Jason Kearns, at the time Chair of the ITC, implemented a new directive. A proponent of more protectionist trade policy, Kearns increased the influence of Commissioners over methodologies and data sources. The rationale behind the directive was to move policy advice to Congress and the President in a more protectionist direction, with a focus on domestic manufacturing and supply chain resilience. In 2024, Chair David Johanson rescinded the directive.[46]

A number of previous studies offer evidence that politics shapes decisions on anti-dumping petitions. Members of Congress frequently intervene by providing testimony in ITC hearings. Their involvement appears to matter for investigation outcomes.[47] Consistent with the appointment and confirmation process, the interests of the President and the Senate in particular are reflected in the outcomes of these investigations.[48] Finally, attributes that render firms politically influential, such as asset specificity[49] and industry size[50], shape the success rates of petitions, indicating the presence of political considerations.

Production Networks and Political Influence

We highlight a different attribute that renders firms politically influential. We contend that firms with linkages throughout the *domestic* economy enjoy privileged treatment, because benefits to such firms create indirect benefits to other constituents. Specifically, in the context of anti-dumping petitions, we expect that firms are more likely to see their petitions approved if protectionist trade policy creates

[44] Weingast and Moran 1983.
[45] Franzese 1999; Clark and Arel-Bundock 2013.
[46] Bade 2024.
[47] Caddel 2014.
[48] Liebman 2004; Aquilante 2018; Bown et al. 2024.
[49] Egerod and Justesen 2022.
[50] Hansen 1990.

indirect benefits for domestic suppliers.

Figure 1 illustrates the core of our argument in two stylized scenarios. Square boxes represent suppliers, labeled firms 1, 2, and 3; round boxes represent the firm in question, labeled firm A. The amount of filling of the square boxes displays what share of each supplier's output is provided as input to firm A.

In the left panel, production by firm A absorbs a small share of the output of other firms. Higher tariffs on products of firm A allow it to remain in business. But these benefits are largely confined to firm A. Keeping it in business is not that relevant to the suppliers, which sell most of their output to other firms. Few other firms, and as a consequence few other constituencies, voters, and policy-makers, thus benefit from higher tariffs for firm A.

This differs in the right panel, where firm A draws on a large share of other firms' output. If firm A were to go out of business, these firms would lose an important customer. Protectionist policy that allows firm A to keep producing benefits these firms indirectly, because it allows firm A to keep sourcing from them and alleviates cost pressures that firm A might otherwise pass on.

We note several related aspects of this illustration, which emphasizes the shares of output absorbed from multiple suppliers upstream. First, we focus on *domestic* suppliers, not foreign suppliers. Our account thus presents a counterpoint to the literature on global production networks. Second, we expect that firm A is politically more powerful if it is connected to *multiple* suppliers upstream, because this creates indirect benefits for more constituents. Third, because we are interested in whether firm A is import to upstream suppliers, we emphasized the shares of upstream suppliers' output, rather than the related question of whether suppliers upstream are large themselves and A's total domestic sourcing. In the appendix, we briefly discuss evidence pertaining to this latter aspect. Finally, in our account, firm A is not influential because it is large itself.[51] Larger firms can absorb larger shares of upstream suppliers' output, but we provide a theoretically and empirically different explanation for why they are politically powerful.

In short, we argue that the filled-in area in this illustration shapes a firm's influence. As we detail in the following, we contend that firm A has more influence in politics if it draws on a *larger share of output across multiple suppliers*, because this (1) results in a broader and more diverse political coalition, (2) increases the geographic footprint of a firm, and (3) allows firms and allied policy-makers to counter a narrative of particularistic policy-making.[52]

Coalition Size and Breadth. The larger are the benefits that accrue indirectly to suppliers, the broader becomes the overall constituency. For example, the major auto-makers located in Tennessee

[51] Weymouth 2012.

[52] The dispersed benefits from providing benefits to these firms do not result in collective action problems: It is the directly affected firm that needs to submit an anti-dumping petition. Suppliers cannot do that on its behalf.

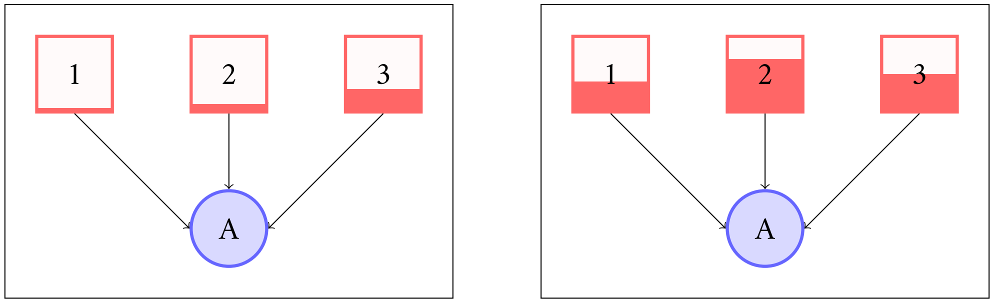

Figure 1 Illustration of a firm of low importance to suppliers (left panel) and of high importance to suppliers (right panel). Square boxes are suppliers, the amount of filling shows what share of each supplier's output is absorbed by Firm A. In both panels, firm A is downstream from the other firms, but its relevance to the other firms differs.

employ about 12,000 people directly; suppliers to these auto-makers employ another 82,000 people.[53] This suggests, most simply, strength by numbers. In hearings and written briefs, both affected employees and affected firms feature prominently. Following standard collective action arguments, employees tend to be referenced by others, whereas firms regularly provide their own submissions. We cannot ascertain how key policy-makers in the legislature and executive – and, as a result, decision-makers at the ITC and the Department of Commerce – weigh these different constituents, though prior work suggests that both factor into the calculus of policy-makers to some extent.[54]

Taking into account the indirect effects not only broadens the constituency. It also diversifies it across industries and occupations. Occupations, in turn, differ on multiple dimensions, including the education, income, gender, and race of employees. We illustrate this in Figure 2 for the mattress manufacturing industry mentioned in the introduction. Columns along the horizontal axis correspond to distinct occupations. In the top row, we depict the make-up of the mattress manufacturing industry across occupations, using the industry-occupation matrices from the Bureau of Labor Statistics. Darker colors indicate that the respective occupation accounts for a larger share of industry employment. We also depict the make-up of four major industries that are suppliers to the mattress manufacturing industry: urethane foams, springs and wires, fabric mills, and millwork.

As Figure 2 indicates, the occupational make-up differs markedly across these industries: these supplying industries employ many occupations that are either not at all or barely relevant to the mattress manufacturing industry. Protectionist trade policy supporting mattress manufacturing therefore affects a broad range of occupations *only* indirectly, and still others *predominantly* indirectly. These occupations differ on several observable dimesions, including wages, education, as well as gender and

[53]Muro et al. 2013.

[54]Grossman and Helpman 1994; Gawande, Krishna and Olarreaga 2009.

racial composition. The indirect constituency behind mattress manufacturing is, therefore, tapping into different socio-economic groups. Each of these, in turn, might heighten the political relevance to individual policy-makers beyond what the mattress manufacturing industry alone might do.

These attributes not only matter for which citizens are affected. The occupational make-up matters for how industries are perceived in politics, and consequently, for the effectiveness of special interest influence coming from these industries. Additionally, industries themselves differ in politically relevant attributes. We highlight two: unionization rates and firm size. Unions might become important political allies in anti-dumping petitions. Unionization rates in the U.S. are fairly low, but vary considerably across industries – unionization rates are twice as high in fabric milling than in mattress manufacturing,[55] even though fabric mills are, in terms of the occupational profile, the closest major supplier to mattress manufacturing. A firm with a larger domestic production network is more likely to tap into suppliers that are unionized, thus mobilizing support from unions and policy-makers supporting unions. Firm size, likewise, varies across industries and in particular across customers and suppliers: on average, supplying firms are significantly smaller and younger than their customers.[56] This allows large firms to highlight that policy benefits accrue to smaller firms as well, pre-empting pushback against particularistic policy that solely benefits large firms. Where firms source from large firms, it extends the indirect constituency to potentially political powerful interests.

Similarly, production networks extend the indirect effects across industries in different sectors of the economy. In the case of mattress manufacturing, for example, even the major suppliers are from very different parts of the industry spectrum, as reflected in their NAICS codes: they represent different sectors and sub-sectors (defined by two- and three-digit NAICS codes, respectively), which usually are used to indicate firms from similar industries. More minor suppliers extend well outside manufacturing, as well. The indirect constituency therefore adds enormous diversity – which, again, might be valuable in itself, but also might rope in constituents with heightened influence in politics.

Suppliers may get actively involved on behalf of a firm, consistent with Johns and Wellhausen, who note how suppliers to multinationals may pre-empt property rights violations.[57] This special interest channel is plausibly an important component of how domestic production networks become politically relevant. But such active involvement is not necessary. Policy-makers allied with a petitioning firm may be able to mobilize other policy-makers, whose constituents would benefit indirectly. Similarly, citizens and employees are frequently referenced in investigation hearings and political commentary, but they do not have to recognize this link explicitly: citizens reward and punish even those

[55] Hirsch, Macpherson and Even 2024.
[56] Patatoukas 2012.
[57] Johns and Wellhausen 2016.

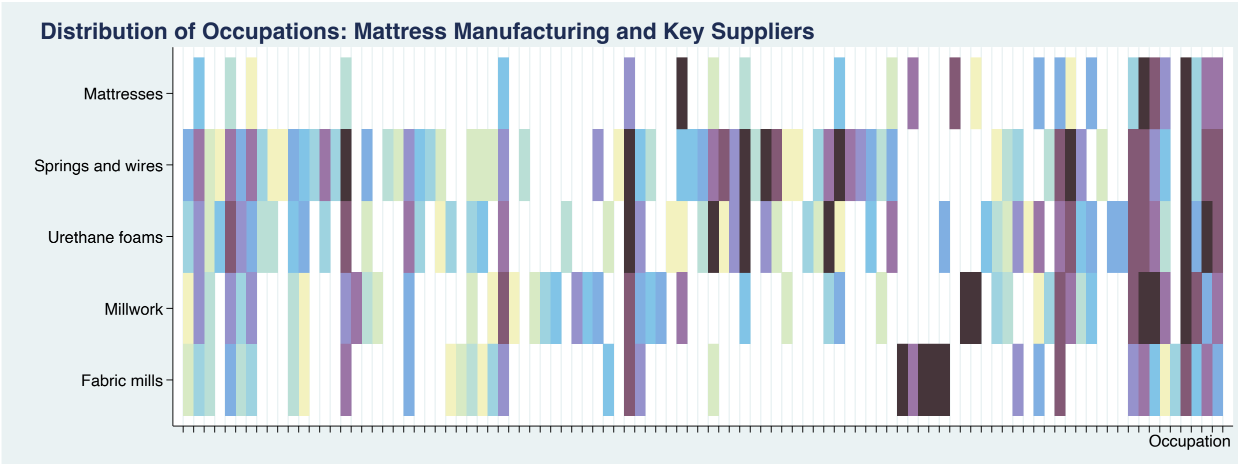

Figure 2 Occupational make-up of mattress manufacturing and four major supplying industries. Data from the input-output tables and the BLS Industry-Occupation matrices. The horizontal axis represents different occupations, sorted by occupation codes. Darker colors indicate occupations that account for a larger share of industry employment. The coloring corresponds to the percentile rank of the occupation within the industry. Occupations irrelevant to any of the five industries omitted.

outcomes without a clear link to policies.[58] As we discuss below, this broader constituency can be an important asset in political contests. The direct beneficiaries can invoke these indirect benefits to highlight the broader appeal, across a more diverse set of constituents, of policies that benefit them. Indeed, consistent with this argument, in U.S. politics more diverse coalitions can be politically more successful.[59]

Economic Geography. Taking the indirect effects into account extends the diversity of this coalition on another important dimension: geography. To return to the example of the auto-makers in Tennessee, the major auto-makers are located in just five counties. Suppliers to these auto-makers are located in 80 out of 95 counties.[60] Additionally, suppliers extend to multiple other states, with distinct representatives in the House of Representatives and the Senate.

We demonstrate in Figure 3 the extent of these indirect effects for anti-dumping petitions filed in 2015. We consider a county involved directly if at least 250 employees work in an industry associated with an anti-dumping petition. We consider a county involved indirectly if at least 250 employees work in industries that supply industries associated with an anti-dumping petition (we weight industry employment by the share of industry output supplied to a an industry). Counties that are only affected directly are depicted in light green; counties that are affected directly and indirectly are depicted in dark green; counties that are affected only indirectly are depicted in blue.

[58]Healy, Malhotra and Mo 2010.
[59]Lorenz 2020.
[60]Muro et al. 2013.

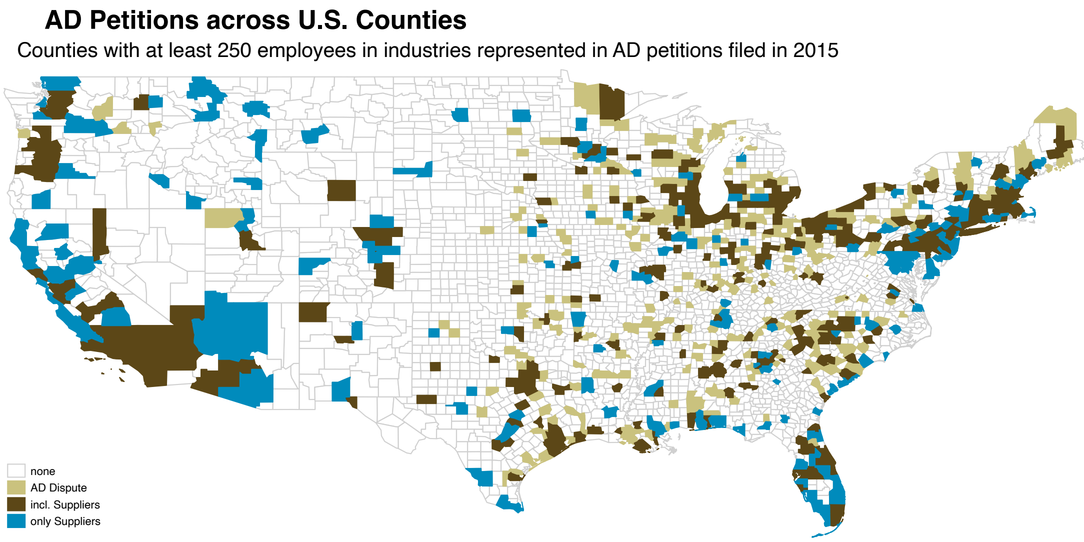

Figure 3 U.S. counties where at least 250 employees are affected directly (in light green), directly and indirectly (in dark green), or only indirectly (in blue) by anti-dumping petitions filed in 2015. Source: Author's calculations, combining data on anti-dumping disputes from Bown (2011), product-industry concordance from Schott (2008), data on employment by county from the County Business Patterns (Eckert et al., 2020), and data on input linkages from the 2012 Bureau of Economic Analysis Input-Output Accounts (see the next section for details).

Figure 3 reveals that a substantial number of counties is affected both directly and indirectly. This helps legislators build broader and more diverse coalitions within their districts, consistent with the points above. Additionally, however, a substantial number of counties are affected only indirectly, extending the geographic footprint of the constituency behind anti-dumping petitions.

Economic geography shapes political influence.[61] In the U.S.. politically influential industries tend to be geographically concentrated to facilitate collective action, but politically dispersed to enable coalition-building.[62] Production networks achieve this balance in a striking way: while industries themselves might be concentrated, the effects on other industries are politically dispersed.

In the context of anti-dumping petitions, this effect is particularly relevant. Representation by influential Members of Congress tends to increase the success rate of anti-dumping petitions.[63] Similarly, industries located in states relevant to Senators on the Finance Committee and industries relevant to swing states tend to have higher success rates in their anti-dumping petitions.[64] For firms tied into production networks, it is more likely that an anti-dumping petition gains such political relevance *indirectly*.

[61] Rickard 2020.

[62] Busch and Reinhardt (1999).

[63] Hansen 1990.

[64] Aquilante 2018; Bown et al. 2024.

Narrative. Firms can justify particularistic policy demands with language that emphasizes broader, indirect benefits. Trade protection that benefits other firms indirectly can be depicted as being more than just special interest politics: there is less special interest politics involved where tariffs benefit firms and workers across industries and across space. Of course, tariffs still have overall costs for societies, including on downstream consumers. Firms using products as inputs frequently oppose anti-dumping duties.[65] In the political calculus over whether to impose anti-dumping duties, then, the benefits of protectionism for other firms are an important counter-weight to such opposition to anti-dumping duties, both politically and economically.

Emphasizing the benefits to other *domestic* constituents allows firms and policy-makers to frame the debate more broadly in the context of fairness. This is consistent with the general perception of anti-dumping duties as an instrument for restoring fair trade. Spinning a narrative about providing fair treatment to domestic firms relative to foreign firms is already politically appealing.[66] The indirect benefits for suppliers complement this narrative with a narrative that highlights broadly shared, as opposed to concentrated, benefits for domestic firms – including, as we noted above, firms of different size and from different industries.

This discussion emphasizes *domestic* suppliers. Foreign suppliers add little to extending and diversifying the domestic constituency of a firm. Sourcing from foreign affiliates of U.S. firms upstream might take a middle ground in this distinction – upstream firms still benefit from tariffs protecting their customers, but the link to the domestic economy becomes more tenuous. Indeed, the above arguments suggest it would be difficult for an upstream supplier that offshored production of an input to become an effective ally in anti-dumping petitions, which are about unfair foreign competition threatening U.S.-produced goods. More broadly, however, our emphasis on domestic suppliers suggests systematic differences across firms, depending on how tied they are into global production networks: sourcing inputs from abroad upends domestic production networks. A related point emerges from the literature on the globalization backlash, which notes the increasing pushback against multinationals, in particular in response to offshoring.[67] We suggest a different mechanism. By offshoring suppliers, multinationals are eroding their domestic constituency, which reduces their political clout.

How do Commissioners learn about these benefits? The investigation process provides several opportunities. Through hearings and submissions, firms can relay information directly to the Department of Commerce and the ITC Commissioners. Additionally, firms can relay information to policy-makers, who in turn can include this information in briefs and in public statements, and possibly in closed-door meetings. Not every firm can claim such indirect benefits: During preliminary investiga-

[65] Caddel 2014.
[66] Brutger and Rathbun 2021.
[67] Butzbach, Fuller and Schnyder 2020.

tion hearings, speakers are reminded that false or misleading statements carry potential penalties. During final investigation hearings, all parties testify under oath, opening witnesses up to perjury charges for false and misleading statements.

Anecdotal evidence suggests that firms and policy-makers indeed convey such information. For example, in a 2021 letter to the ITC, Brian Higgins, a Member of Congress, highlighted that one of the petioning firms not only is located in his district, providing "highly skilled, good paying union jobs" – but that the company also "is an important customer of our nation's steel industry as it uses flat rolled American steel as an input product."[68]

Firms, likewise, are not shy to highlight that their suppliers depend on them. In 2001, in testimony before the ITC, a representative for LaBarge Pipe and Steel Company first emphasized that his company maintained a domestic supply chain, despite cost advantages of moving to overseas suppliers, and then noted how, "unless the United States imposes dumping duties to restore fairness to the marketplace for large diameter line pipe, in order for us to stay in business we will have to abandon our traditional relationship with domestic suppliers. In fact, if this dumping were allowed to continue we think one or two of our domestic suppliers would have gone out of business."[69]

Similarly, in a 2017 petition on paper products, involving NORPAC as one of the petitioners, both the CEO of the company and its Vice President of Manufacturing mentioned the indirect benefits to suppliers in their testimony. The CEO noted how his company "employs about 360 people directly and many more indirectly who provide a host of goods and services."[70] The Vice President of Manufacturing noted that "you're dealing with people and jobs. And not just the jobs of the people that are working in the mill, but the suppliers to the mill, anybody that's affiliated with an operation. There's just a lot of customers and employees and suppliers that are impacted on that."[71] In this petition, some of the customers – mostly from the newspaper industry – vehemently disagreed, but no similar concerns were raised by suppliers, who stood to gain from NORPAC gaining protection.

We highlight a notable aspect of these anecdotes: formally, the definition of material injury is limited to the industry producing the product in question. Downstream customers and upstream suppliers are explicitly not considered. The U.S. has long resisted the formal incorporation of these or other 'public interest' considerations.[72] The discussion of indirect effects therefore cannot be explained with legal or economic considerations.

Nonetheless, policy-makers, firms, and the legal representatives of firms repeatedly bring them up,

[68] Congress of the United States 2021.
[69] U.S. International Trade Commission 2001, p. 37.
[70] U.S. International Trade Commission 2017, p. 21.
[71] U.S. International Trade Commission 2017, p. 86.
[72] U.S. Government Accountability Office 2022.

despite a considerable opportunity cost. Hearings assign strict time limits to statements by interested parties. Using arguments about these indirect benefits crowds out other arguments. Similarly, in the example from the introduction, the letter on behalf of mattress manufacturers is barely a page long. The reference to U.S. suppliers who stand to benefit takes up valuable space, which comes at the expense of other arguments that could have been put forward – clearly, this reference appeared to be an important argument, and one that was perceived by Members of Congress to hold at least some sway in the decision of whether to impose anti-dumping duties.

We conclude with our main hypothesis:

Hypothesis 1. *Firms are more likely to see anti-dumping petitions approved for goods whose production absorbs a larger share of suppliers' output.*

2 Empirical evidence

We compile and combine two data sets. The first data set contains data on petitions for anti-dumping duties filed by U.S. firms.[73] We create product-, industry-, and firm-level identifiers to link this data set with other data sources. The second data set contains several variants of our main predictor. It delivers original measures of linkages between firms at the industry-level, which we derive from U.S. input-output tables and link to anti-dumping petititions. We describe these data sets in more detail below, together with the process to match the different data sets.

2.1 Anti-dumping petitions

We first compile data on U.S. anti-dumping petitions and their decisions between 1992 and 2019. We draw on the Global Anti-Dumping database (GAD).[74] This database provides information on which domestic firms acted as petitioners, identified by firm name; which products were concerned, identified by up to ten-digit HTS codes; and when a case was ruled on, including the outcome of that ruling. We maintain separate entries for each country listed in a petition, because rulings may vary across countries. For each petition, we have multiple observations if several firms acted as petitioner or several products were included in the petition. For example, case 731-TA-1271 relates to three petitioners, DAK Americas LLC, M&G Chemicals, and Nan Ya Plastics, and involves two products.

Our outcome variable is binary. If the investigation ends with an affirmative ruling, we consider it a successful petition, coded 1; we also consider a partially affirmative ruling as a success. Petitions with a negative ruling, either in the preliminary phase (where a negative ruling ends the petitioning process) or in the final phase, are coded as 0. We omit withdrawn and terminated cases, because we cannot ascertain the outcome of any private bargaining taking place. This affects about 5% of all petitions. As we report in Appendix Section G, the estimates remain statistically significant regardless of how we allocate successes and failures across unobserved outcomes.

Our data set comprises 918 anti-dumping petitions, which cover about 2,000 distinct products and 700 petitioners. 57.7% of the petitions are succesful. Figure 4 displays the percentage of successful petitions per year. Additionally, the line plot indicates the number of anti-dumping petitions that were filed per year. The figure documents an upwards trend in success rates over time. It also shows that anti-dumping petitions, though not more frequent, are more likely to be successful in Presidential election years, highlighted with darker color.

[73]While we use the term 'firms' to describe petitioners throughout, some petitioners, such as unions, are not firms. These represent a small number of petitioners. The results are robust to excluding them.

[74]Bown 2011, updated.

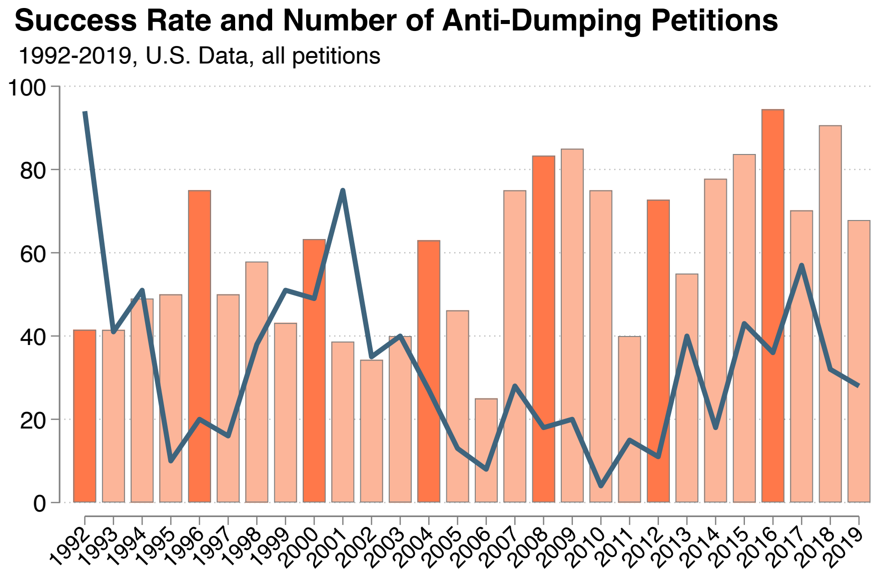

Figure 4 Success rate (bars, orange) and number of U.S. anti-dumping petitions (line, blue). Success rate is the share of successful petitions among all petitions. Presidential election years highlighted with darker color. Source: Authors' calculation, based on Bown (2011).

Product-Industry Concordance. We connect the data to other data sets in two ways. First, we match each HTS product code to the corresponding NAICS industry code, using the concordance from Schott.[75] We thereby associate each *product* listed in an anti-dumping petition with a six-digit *industry* code. If multipe product codes match onto the same industry, we drop these duplicates.

Petitions come from a wide variety of industries. For example, within the sector *Manufacturing*, we have the three-digit subsector *Electrical Equipment, Appliance, and Component Manufacturing*. Within this subsector, we can distinguish between six-digit industries representing *Household Cooking Appliance Manufacturing*, *Household Refrigerator and Home Freezer Manufacturing*, and *Household Laundry Equipment Manufacturing*. In some of our empirical specifications, we take advantage of differences within subsectors and control for differences across three-digit subsectors through fixed effects.

Firm-Level Concordance. Second, we match the petitioner data with a firm-level data set, Orbis from Bureau van Dijk. We start by standardizing firm names. For example, we remove 'corp', 'llc' and 'co' and special characters. We then match the data with Orbis, first with exact matches, then with fuzzy matches based on phonetic similarity and Jaro-Winkler similarity (a measure of string distance). We finally inspect the data manually to resolve inconsistencies and to obtain unique Orbis identifiers.

[75] Schott 2008. We manually adjust NAICS codes to ensure matches where discrepancies among NAICS vintages arise.

This allows matching the data with other variables, including the NAICS industry code derived from the firm (rather than the product). We rely on the firm identifier and the firm-derived industry code to merge in control variables for firm- and industry-level attributes.

2.2 Embeddedness in production networks

Our second data set collects three measures capturing to what extent an industry is important to suppliers upstream. The three measures are based on the U.S. Input-Output Accounts, published by the Bureau of Economic Analysis. We draw on the *Use Tables*, which indicate for each U.S. industry the purchases of different commodities. Detailed input-output tables are produced in benchmark years, those ending on "2" and "7". We use the input-output tables from 1997 through 2017. The 1997 tables are the first to be based on NAICS, which we can match with other data sources, while the 2017 tables are the last to be within the time span of our data set on anti-dumping petitions. Short of firm-level data, which are only available for a small number of countries and not publicly available,[76] these are the most detailed data available for capturing relationships between firms.[77] Overall, from the five vintages of the Use Tables, we obtain information on over 600,000 supplier-customer relationships between industries.

By using input-output tables from several years, our measure captures cross-industry differences as well as changes in input-output relationships over time. The latter are at least in part driven by exogenous changes in production technologies. For example, components needed by the automotive industry have changed with the rise of electric vehicles and electronic systems. The drawback of using measures from several years is that some of the differences we capture over time are not based on substantive changes in production technology, but on accounting changes in industry classifications – consolidations and disaggregations – over time. In the appendix, we show that our results are robust to using data from a single year imposed across the entire sample.

Following the discussion in the previous section, our first measure captures to what extent firms upstream rely on an industry downstream as a customer, such that benefits to firms in industry i also benefit other firms that supply industry i. Denoting with m_{ij} the value of inputs j of industry i, and with q_j total output of j, and ignoring time subscripts for simplicity in all of the following, we define

$$\sigma_{i,j} = \frac{m_{i,j}}{q_j}. \tag{1}$$

[76] Stocklisted companies have to disclose if key suppliers pose a risk (through 8-K filings) and if customers account for more than 10% of a company's revenue (through 10-K and 10-Q filings). These reports therefore do not provide a systematic account for customer-supplier relationships.

[77] Carvalho and Tahbaz-Salehi 2019.

$\sigma_{i,j}$ is the share of j's total production that is supplied to industry i. Alternatively, we can conceive of $\sigma_{i,j}$ as industry i's absorption of j's output. The larger is σ_j, the more indirect benefits j receives from policies that allow i to maintain or increase production.

Using this definition, we calculate the sum of industry i's input shares across j,

$$\eta_i = \sum_{j=1}^{N} \sigma_{i,j}. \tag{2}$$

We emphasize three attributes of this measure. First, the Use Tables capture purchases by domestic firms. Purchases by foreign firms are not included, which matches our theory. However, our measure does capture purchases by domestic firms from foreign firms, sourced through imports. This is justified to the extent that total demand for a product, regardless of whether this demand is satisfied from domestic or foreign suppliers, sustains a higher price for that product. At the same time, if an industry largely sources products from abroad, it can hardly claim to provide benefits to upstream suppliers. Below, we therefore provide a variant that strips out imports.

Second, the size of an industry enters our measure indirectly. Larger industries can absorb larger shares of other industries' total output, but industry size is not by construction related to the number of supplying industries or the distribution of inputs across supplying industries.

Third, the size of supplying industries enters indirectly as well. Industries that source a large share of smaller industries' output have, everything else equal, larger values of η than industries that source the same total amount of intermediates from a single industry with the same total output. This is consistent with our theory: everything else equal, our measure is larger for industries that are important to many smaller upstream suppliers than for industries that are important to a small number of large upstream suppliers – even if total purchases and the joint output of upstream suppliers are identical.

Total domestic inputs. The construction of η is based on immediate suppliers. We did not incorporate that these suppliers, in turn, source inputs, extending the reach of an industry throughout the economy. On the one hand, this is an attractive feature. Claiming that other firms benefit indirectly becomes increasingly less plausible as these other firms become more removed in the production process. On the other hand, at least to some extent these more indirect relationships remain important, because they capture the total reach of an industry.

To incorporate these higher-order relationships, we turn to the *Total Requirements Tables*. We draw again on tables from benchmark years to construct our measure. The Total Requirements Tables provide coefficients $c_{i,j}$, which capture how many dollar inputs industry i needs from industry j to produce one dollar of output. This coefficient captures all input relations for industry i, including inputs for inputs, and so on. To construct a measure analogously to our core measure η, we obtain total output of each industry, q_j, and match it with the Total Requirements Table, to calculate

$$\eta_i^T = \sum_{j=1}^{N} c_{i,j} \frac{q_i}{q_j}. \tag{3}$$

This measure effectively involves averaging across many indirect inputs, which has two immediate implications: η^T is generally larger than η, and it is a less precise measure of our core concept – it involves ties across industries that are unlikely to become politicized, because they are too far removed.

Imports. The Use Tables are based on purchases by domestic firms. A portion of these purchases stems from *foreign* suppliers. The Use Tables do not make this distinction between domestic and foreign sourcing, which leads us to over-estimate the importance of industries to *domestic* suppliers. [78]

This presents two potential problems for our analyses. First, because industries differ in their reliance on tradable inputs, η will vary in the resulting measurement bias across industries. Second, because the importance of imported inputs changes over time, η will vary in the resulting measurement bias across time. The entry into force of NAFTA in the second half of the 1990s, the extension of permanent normal trade relations to China, and China's subsequent entry into the World Trade Organization in the early 2000s were all associated with dramatic increases in imported inputs by U.S. firms.[79] Indeed, Quinn and Liu show that the sudden influx of imports from China, often captured under the label of the 'China Shock', was more akin to an 'MNC Shock', driven by increased sourcing by U.S. multinationals.[80]

At the same time, these changes in trade patterns offer opportunities for our research design, because they imply changes in the reliance on *domestic* suppliers that are driven by changes in trade policy – and some of these changes, such as the binding of tariff rates, are plausibly exogenous to domestic political factors at the level of individual products: the change in trade flows was not a consequence of differential cuts in tariff rates across specific products (which would plausibly be related to the political power of U.S. firms), but a reduction of uncertainty in U.S. trade policy as a consequence of reducing the gap between applied and bound tariffs.[81]

To account for imports of inputs, we combine data from the input-output tables with product-level data on U.S. imports. To hold constant changes in production technology and industry classifications, we use data from the 2012 version of the input-output tables. This ensures that the driver of differences over time in our measure are changes in trade flows. We then concord these data to BEA I-O codes and match them with the 2012 Use Table to adjust for imported inputs; we provide a detailed discussion

[78] In the appendix, we further distinguish between foreign suppliers that are U.S.-owned and those that are not.

[79] Pierce and Schott 2016.

[80] Quinn and Liu 2019.

[81] Handley and Limão 2017.

of this process, including the allocation of imports across industries, in the appendix.

With $m^*_{i,j}$ denoting industry i's purchases of imported inputs j, we calculate analogously to above

$$\sigma^*_{i,j} = \frac{m_{i,j} - m^*_{i,j}}{q_j} = \sigma_{i,j} - \frac{m^*_{i,j}}{q_j}, \tag{4}$$

resulting in our third measure as

$$\eta^M_i = \sum_{j=1}^{N} \sigma^*_{i,j}. \tag{5}$$

Descriptives. We use the concordances provided by the BEA to match these measures from the I-O format to NAICS 6-digit industry codes; where BEA codes match with multiple NAICS codes, we distribute these accordingly, using where available data on output shares by industry, provided by the BEA. We then match the data to different NAICS vintages using concordances from the U.S. Census Bureau. From there, we obtain for each product listed in an anti-dumping petition the three measures described above. We consolidate NAICS codes to the 2012 benchmark year throughout. The complete set of measures, across NAICS codes, is available from the authors.

Figure 5 displays the values of η, η^T, and η^M across NAICS industries for a single year, 2012, in the top, middle, and bottom panel, respectively. The figures include the same industry codes represented in our anti-dumping data set. The measures vary considerably across industries and from each other. Figure 6 displays how η^M varies over time for a subset of industries. The figure illustrates considerable variation across industries, including in the trajectories of different industries over time: some industries remained relatively stable over time; other industries replaced a large and increasing share of inputs over time with foreign suppliers; and other industries experience considerable swings throughout the sample period.

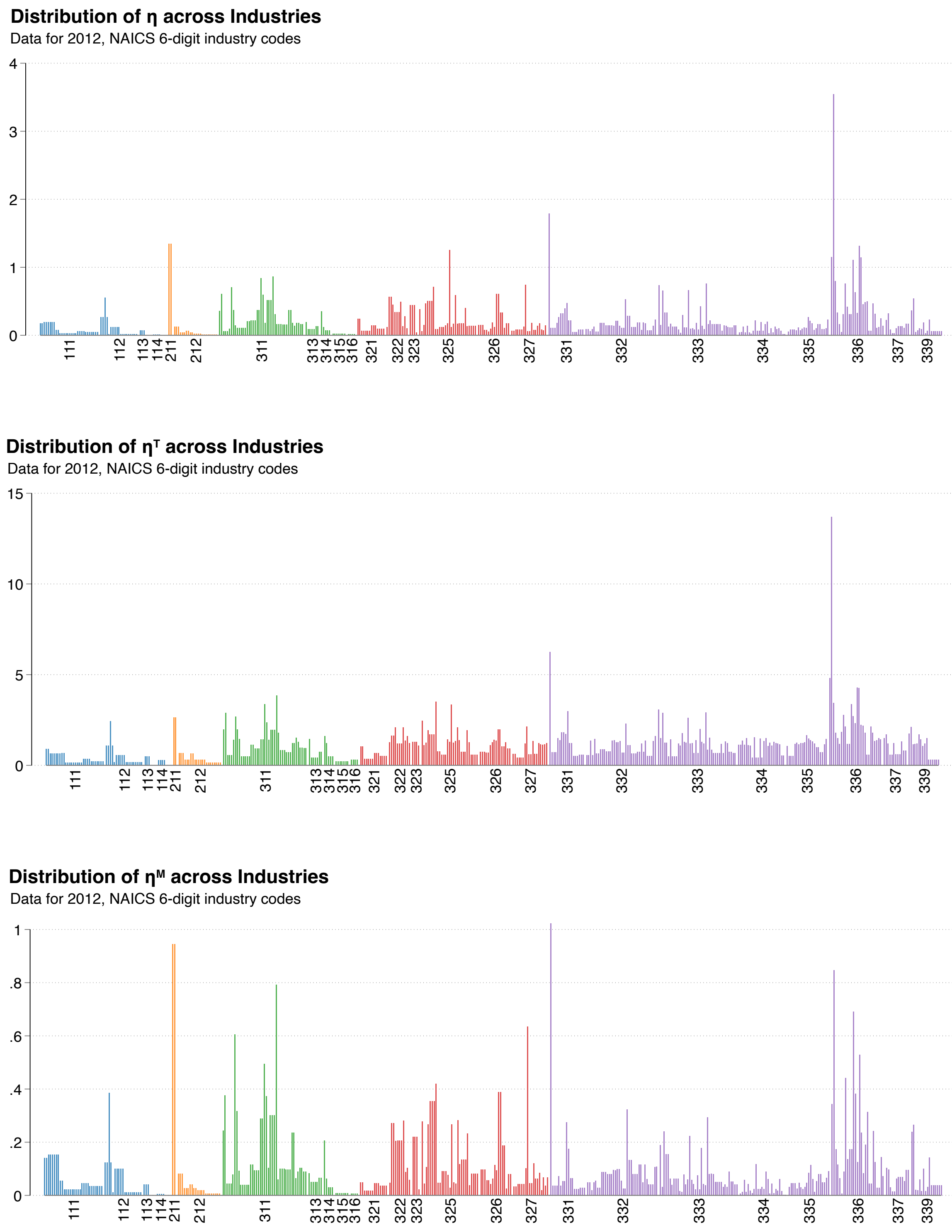

Figure 5 Distribution of η (top panel), η^T (middle panel), and η^M (bottom panel), for 2012, across NAICS six-digit industries associated with anti-dumping petitions. Calculated from US input-output tables.

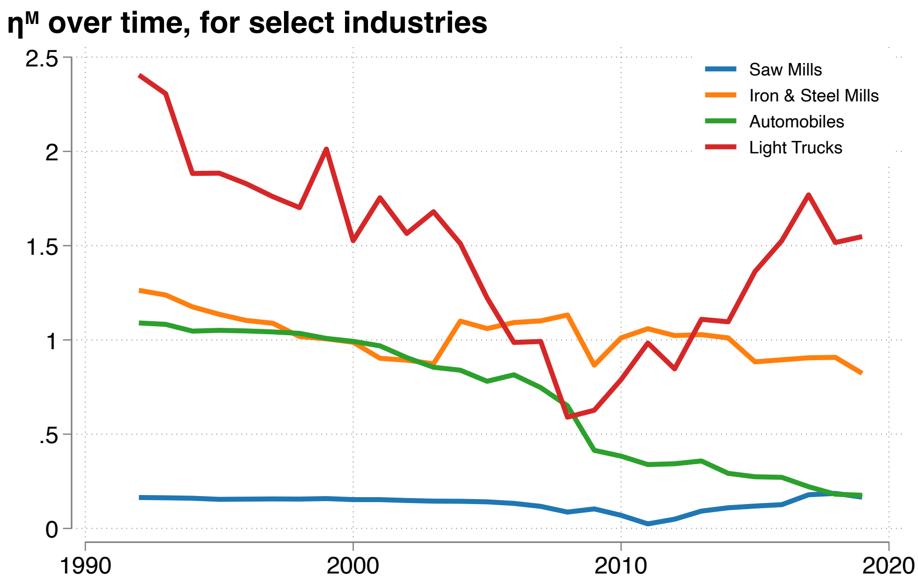

Figure 6 Values of η^M over time for select industries. Calculated from US input-output tables.

2.3 Results

An observation in our final data set corresponds to a petition-firm-product: For each petition, we have an observation for every firm and every product (identified by the corresponding NAICS industry code) that was listed in the petition. We maintain this structure for two main reasons. First, it allows incorporating a host of control variables at the firm- and industry-level that feature prominently in the literature. We can thus differentiate our argument from established arguments about firm and industry size, mobility, and location. Second, it allows for research designs where we employ firm fixed effects, exploiting product-level differences, and industry-level instrumental variables.

Because our outcome variable, a successful anti-dumping petition, is binary, we estimate logit models with robust standard errors. We cluster standard errors on the petition, because we otherwise might overcount the amount of information in our data set. We present results with alternative clustering structures, including clustering on the industry, in the appendix. We also report results from weighted regression models in the appendix, and from models that collapse the data by the petition.

We include several control variables in our base model. First, given the trends in the outcome, we include year, year squared, and year cubed, and a dummy variable for Presidential election years. Second, larger industries might be politically more powerful and absorb larger shares of output from upstream industries. We include logged industry output, obtained from the BEA. Third, to adjust for differences in the legal merit of cases, we control for the percentage change in imports of the products mentioned in the petition. This variable represents the most plausible observable measure of whether a product was, in fact, dumped. Fourth, we include a control variable for steel products, which feature prominently among anti-dumping petitions in the public discourse and in their political relevance. Fifth, we account for whether a firm made campaign contributions in the two years before or after filing a petition, a main alternative channel through which firms secure preferential policies;[82] we obtain data from DIME.[83] Finally, we include a control variable for non-market economies, where the rules for establishing and determining the occurrence of dumping differ markedly. We obtain the list of non-market economies, as determined by the U.S. Department of Commerce, from the Federal Register for every year in our data set.

In a variant of the base model, we include additional variables that capture firm- and industry-level attributes. First, multinational corporations play a prominent role in U.S. trade politics,[84] including in anti-dumping petitions.[85] We therefore include a dummy variable to indicate whether a firm is a multinational corporation or part of a multinational corporation. To identify multinational corpora-

[82] Quinn and Shapiro 1991.
[83] Bonica 2024.
[84] Osgood 2018.
[85] Jensen, Quinn and Weymouth 2015.

tions, we draw on the ownership data from Orbis and code a firm as multinational if it either owns a subsidiary in a foreign country or if its domestic ultimate owner owns a subsidiary in a foreign country. We describe results with different variants of measuring multinational corporations, including some accounting for vertical integration, below. Second, firms listed on a stock exchange gain political power through wide-spread public ownership of these firms.[86] We include whether a firm is listed on a stock exchange. We obtain this data again from Orbis, and consider a firm as stocklisted if either itself or its domestic ultimate owner at any point was listed on a stock exchange. Third, because more mobile firms are more likely to receive favorable treatment, we include the log-transformed current stock of fixed assets at the level of NAICS three-digit codes, obtained from the BEA. Fourth, following prior work on protectionist demands, we include the real exchange rate, weighted by import partners, at the level of NAICS three-digit codes.[87] Together with changes in imports, this variable captures the most prominent economic determinants of the filing of anti-dumping petititions. Finally, we include fixed effects by NAICS three-digit codes.

Column 1 presents results for the baseline model in odd columns and for the expanded model in even columns.[88] Results for η are reported in columns 1 and 2, for η^T in columns 3 and 4, for η^M in columns 5 and 6. The relationship between the sum of input shares and petition success is positive and statistically significant in all models. The effect sizes are considerable. In the baseline model from column 1, moving from the 25th to the 75th percentile on η results approximately in a 30% increase, from 61.8% to 82.1%, in the probability that an anti-dumping petition is approved – firms are considerably more likely to have petitions approved if benefits to their products extend to suppliers upstream. We obtain similar substantive results in the other models. The difference in coefficient size across the three measures is primarily driven by the different scales of the variables.

These results suggest a distinct source of corporate political power based on a firm's domestic production network. The results for η^M, in columns 5 and 6, lend themselves to a noteworthy interpretation: as firms increase their global sourcing, η^M declines, and this declines translates into a decline in political power. Firms thus face a trade-off between business and political goals. The globalization of supply chains undermines the domestic constituency of multinational corporations, resulting in a loss of political power.

Robustness: Control Variables and Model Specification

In the appendix, we present results from several robustness checks.

[86] Pond and Zafeiridou 2020.

[87] Broz and Werfel 2014.

[88] For a small number of subsectors, these fixed effects perfectly predict the outcome, which results in the respective observations dropping from the data set. The results are robust to estimating linear probability models.

Table 1 Success of AD Petitions: Base Models

	(1)	(2)	(3)	(4)	(5)	(6)
η	.43	.48				
	(.009)	(.007)				
η^T			.19	.23		
			(.002)	(.000)		
η^M					2.17	2.30
					(.000)	(.000)
Steel Products	-.93	-1.36	-1.08	-1.32	-1.30	-1.49
	(.024)	(.066)	(.010)	(.060)	(.001)	(.042)
Industry Output (log)	.027	.30	.012	.23	-.28	-.11
	(.856)	(.144)	(.937)	(.250)	(.107)	(.636)
Percentage Change Imports	1.91	2.95	1.96	3.12	1.69	2.68
	(.030)	(.000)	(.027)	(.000)	(.043)	(.000)
Non-Market Economy	.50	.79	.50	.81	.50	.85
	(.156)	(.024)	(.154)	(.021)	(.152)	(.017)
Campaign Contributions	-.48	-.49	-.47	-.48	-.38	-.38
	(.001)	(.000)	(.002)	(.000)	(.013)	(.002)
Presidential Election	2.23	2.61	2.23	2.61	2.23	2.62
	(.000)	(.001)	(.000)	(.000)	(.000)	(.001)
MNC		-.31		-.32		-.30
		(.051)		(.051)		(.061)
Stock-listed		-.11		-.11		-.040
		(.591)		(.608)		(.841)
Real Exchange Rate		2.10		2.19		2.07
		(.002)		(.001)		(.001)
Fixed Assets		-.036		-.036		-.0067
		(.762)		(.765)		(.955)
Constant	6.98	1.81	6.92	2.05	10.6	6.34
	(.012)	(.574)	(.011)	(.518)	(.001)	(.073)
Number Obs.	3,850	3,370	3,850	3,370	3,850	3,370
Time trend	✓	✓	✓	✓	✓	✓
NAICS 3-digit FE		✓		✓		✓

Logit models with robust standard errors, clustered by petition. p-values in parentheses.

Clustering. We clustered standard errors on the petition. Our variants of η are calculated at the level of NAICS industries. We therefore cluster standard errors instead on industries. We also consider two-way clustering on petitions and industries, and clustering on firms.

Weights. Within each petition, our data set includes varying numbers of observations as a function of (i) the products listed in the petition, (ii) the extent to which products map onto different NAICS codes, and (iii) the number of firms listed in the petition. This creates uneven numbers of observations across cases, such that our coefficient estimates give considerably more weight to cases with many observations, which might also deflate p-values. To offset this, we estimate weighted logistic regression models, with weights corresponding to the number of observations in each case.[89]

Related-party trade. Our third measure, η^M, accounts for imports of inputs, to isolate relevance to domestic suppliers. A substantial portion of U.S. imports constitutes related-party trade: imports sourced from U.S.-owned firms abroad. Sourcing products from abroad then still has benefits to U.S. firms. η^M stripped these out, as part of overall import volumes. To account for related-party trade, we obtain data on related-party imports by industry from the Census Bureau. We then re-construct our measure, adjusting only for imports sourced through arms-length transactions.

Case merits. If cases with higher values of η are cases with more observable evidence of dumping, success rates would be higher, but not for the reasons we identified. To adjust for observable evidence of dumping, we included changes in imports and exchange rate misalignments as control variables. Drawing on sensitivity analysis,[90] we report in the appendix that an omitted variable would have to be implausibly strong relative to these observed indicators of dumping to invalidate the reported association.

To further probe the legal merit of cases, we turn to disputes filed with the WTO's Dispute Settlement Body.[91] Almost 20% of U.S. decisions on anti-dumping petitions are challenged at the WTO.[92] Disputes at the WTO are relatively rare and typically not filed frivolously, at least not against wealthy countries such as the U.S. This indicates that other governments mostly challenge anti-dumping decisions they perceive as lacking legal merits. If differences in legal merit explain the association we reported, we would observe a negative correlation between our measures and a decision being challenged.

We draw on Schott and Jung,[93] as well as the one-page summaries of disputes provided by the WTO, to create two variables: whether the U.S. decision was challenged; and whether this challenge was successful.[94] In the appendix, we report that cases with higher values of our measures are not any

[89]We also report results when using averages for each petition. While we lose a considerable amount of information and observe a corresponding increase in p-values, the substantive size of the effects remains similar.

[90]Cinelli and Hazlett 2020.

[91]We thank a reviewer for these suggestions.

[92]Chaudoin 2014.

[93]Schott and Jung 2019.

[94]We consider a challenge successful when the panel ruled in favor of the complainant or, if the decision was appealed, when the appellate body ruled in favor of the complainant. We consider partial decisions, split cases, and settled cases in

less likely (and, in fact, more likely) to be challenged, suggesting that differences in the merits of cases are not explaining the pattern we reported.

Product characteristics. One justification for tariffs is the protection of industries further downstream. Some evidence suggests that governments are more sensitive to the protectionist interests of downstream industries producing final consumer goods.[95] To differentiate this explanation from ours, we include a measure of upstreamness.[96]

Firm-level and industry-level characteristics. We control for additional firm- and industry-level features. These include firm and industry size, measured by the log number of employees; the capital-labor ratio;[97] the number of counties in which an industry has more than 250 employees;[98] value added as a share of GDP and an industry's contribution to GDP growth, to distinguish our measure from industries that are of economic importance; and total imports of industry inputs, to isolate differences in the extent of domestic sourcing for any given amount of foreign sourcing.

Lobbying and campaign contributions. We focused on campaign contributions as a measure of political activities. Additionally, we match the company names with lobbying data from LobbyView[99] to control for whether a firm lobbied during the sample period.

Vertical Integration. The data from the input-output tables is based on establishments. Some of these might be within the boundaries of a firm, reflecting vertical integration, which promises efficiencies for firms when it comes to mobilizing political action among policy-makers. To account for differences in vertical integration, we combine data from Orbis on ownership structures with data from the input-output tables. From the input-output tables, we identify all supplier industries at the level of NAICS industries. We then match each firm in the anti-dumping data set with its subsidiaries, derived from the Orbis data on ownership structures. For each firm, we calculate the number of subsidiaries in industries that are considered upstream in the production process, based on the input-output tables.

A second dimension of vertical integration is whether a firm has a subsidiary in the target market. We identify from the Orbis data base whether a firm had a subsidiary in the target market or whether a parent in the petitioner's corporate family had a subsidiary in the target market.

Exporting markets. Anti-dumping petitions are filed against firms from a wide range of countries. This suggests confounding if country characteristics correlate with our key measures. In the appendix,

favor of the complainant, because they indicate that at least part of the U.S. decision lacked legal merit.

[95] Betz and Pond 2019.

[96] Antràs et al. 2012.

[97] Broz and Werfel 2014.

[98] Hansen 1990.

[99] Kim 2017.

we report that the results are robust to including exporting market fixed effects.

One salient distinction is that between market and non-market economies.[100] Anti-dumping petitions directed against firms from non-market economies follow a distinct process: there is more leeway in establishing the legal case for dumping, because firms and regulators have more flexibility in identifying counterfactuals and market prices. As a consequence, anti-dumping petitions directed against non-market economies have higher success rates. Together with the more flexible process for establishing legal merits, this might reduce the role of politics in these decisions.

In the appendix, we verify that the results are not contingent on including non-market economies in the sample, obtain data on the classification of countries as non-market economies from the Federal Register. Additionally, consistent with this argument, the effects are strongest in cases against market economies. In cases against non-market economies, the effects shrink in size and lose statistical significance. Moreover, several of the predictors change sign in the sample of non-market economies, suggesting distinct political dynamics.

Political representation. We consider several variables that account for differences in political representation. First, we control for the average partisan representation of an industry, calculated as the share of electoral districts with more than 250 employees in which an industry is represented in the U.S. House of Representatives by a member of the Democratic Party. Second, previous work has highlighted how industry location in swing states confers political advantages.[101] We define swing states as those states that were won by a vote margin of five percent or less in the past Presidential election. We then create industry- and firm-level measures. For industry-level measures, we create a swing state dummy variable whenever an industry involved in an anti-dumping petitition employs more than 250 people in a swing state;[102] and we calculate total employment in swing states by an industry involved in an anti-dumping petitition and include the resulting (log-transformed) variable. For the firm-level measure, we identify whether a petitioner is located in a swing state using information from the Global Anti-Dumping Database, company directories (including Orbis and Dun&Bradstreet), and information from anti-dumping petitions and press releases.

Identification: Fixed Effects and Instrumental Variables

Firm Fixed Effects. Several firms in our sample submitted multiple anti-dumping petitions. This allows us to include firm fixed effects: we can hold constant firm-specific attributes and evaluate petition success rates across different products. To the extent these are time-invariant within the time

[100]We thank a reviewer for highlighting this point.

[101]Aquilante 2018; Bown et al. 2024.

[102]Following a definition similar to Hansen (1990).

span of our panel, the firm fixed-effects account for several factors potentially associated with a firm's political influence, such as geographic location, company size and employment, integration into global markets, and political connections.

To allow including firms without changes on the outcome variable, we estimate linear probability models. The results, displayed in columns 1-6 of Table 2, show that even in this demanding specification, anti-dumping petitions are more likely to be approved for products important to firms upstream. The results are correctly signed in all models, and in the extended models retain their statistical significance at the 5% level for all variants of η.

Instrumental Variable Models. As a second route to address concerns over omitted variable bias, we pursue an instrumental variable strategy. We exploit that currency fluctuations shape sourcing decisions:[103] as the U.S. dollar appreciates, it becomes cheaper to source from abroad. We calculate our instrument in two steps. First, following Broz and Werfel, we calculate a trade-weighted real exchange rate at the industry-level.[104] To do so, we combine bilateral U.S. imports with bilateral real exchange rates to calculate the trade-weighted real exchange rate at the industry level. Second, we combine this measure with data from the input-output tables to calculate the average real exchange rate at the level of an industry's suppliers. The instrument is a weighted sum of the trade-weighted real exchange rate, with weights corresponding to each industry's share in industry i's total inputs.[105]

The instrument is plausibly exogenous: while an industry's exchange rate is correlated with anti-dumping petitions,[106] the trade-weighted real exchange rate in *upstream* industries is not evidently correlated with the success rate of anti-dumping petitions. Similarly, the input shares used in the construction of the instrument are not evidently correlated with the success rate of anti-dumping petitions in an industry. When we control for industry fixed effects and an industry's own exchange rate in our extended model, we can further rule out that correlation across industry-specific exchange rates creates a pathway from the instrument to the outcome.

The instrument is also plausibly relevant: as the U.S. dollar appreciates for an industry's supplying industries, sourcing inputs should become more attractive, and η^M should decline as a consequence. Empirically, this is borne out in the first stage, which indicates a negative and, with F-statistics well above 10, sufficiently strong correlation between the exchange rate of suppliers and η^M.

In the base model, we obtain relatively large standard errors, resulting in a correctly signed, but statistically insignificant coefficient estimate for η^M. The coefficient estimate on η^M regains statistical significance at the 5% level when including industry fixed effects and the extended set of control

[103]Jensen, Quinn and Weymouth 2015.

[104]Broz and Werfel 2014.

[105]The instrument resembles a shift-share instrument, with the exchange rate as the shift and input relations as shares.

[106]Broz and Werfel 2014.

variables (column 8).[107] As shown in the bottom row of the table, we also obtain statistically significant effects when using robust 95% confidence intervals.[108]

These estimates offer a causal interpretation: changes in the extent of the *domestic* production network that can be traced to exchange rate movements are reflected in a lower success rate of anti-dumping petitions. We obtain similar results in the reduced form regressions: as the U.S. dollar appreciates at the level of an industry's suppliers, the success rate of its anti-dumping petitions declines.

[107]The industry fixed effects imply isolating exchange rate movements over time. With industry fixed effects included and extended control variables excluded, the coefficient on η^M also returns to statistical significance at the 5% level.

[108]Lee et al. 2022.

Table 2 Success of AD Petitions: Firm-Fixed Effects and 2SLS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Firm FE		Firm FE		Firm FE		2SLS	
η	.052	.069						
	(.054)	(.020)						
η^T			.020	.026				
			(.019)	(.004)				
η^M					.12	.18	.14	.34
					(.087)	(.009)	(.360)	(.003)
Steel Products	-.14	-.28	-.14	-.27	-.13	-.26	-.13	-.29
	(.057)	(.004)	(.053)	(.005)	(.077)	(.005)	(.173)	(.011)
Industry Output (log)	-.0073	.0059	-.0060	.0069	-.010	-.0069	.0066	-.0051
	(.566)	(.735)	(.582)	(.644)	(.329)	(.646)	(.834)	(.855)
Percentage Change Imports	.23	.33	.23	.33	.20	.29	.31	.41
	(.001)	(.000)	(.001)	(.000)	(.002)	(.000)	(.004)	(.000)
Non-Market Economy	.082	.097	.081	.097	.080	.096	.089	.096
	(.021)	(.012)	(.021)	(.012)	(.022)	(.013)	(.087)	(.033)
Campaign Contributions	-.31	-.30	-.31	-.30	-.31	-.29	-.079	-.069
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.003)	(.000)
Presidential Election	.29	.37	.29	.37	.29	.37	.29	.28
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
MNC		0		0		0		-.039
		(.)		(.)		(.)		(.116)
Stock-listed		0		0		0		-.017
		(.)		(.)		(.)		(.583)
Real Exchange Rate		.13		.14		.14		.26
		(.010)		(.009)		(.009)		(.002)
Fixed Assets		-1.56		-1.57		-1.52		-.0077
		(.000)		(.000)		(.000)		(.666)
Constant	1.76	9.14	1.73	9.10	1.84	9.12	1.95	1.73
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.001)
Number Obs.	3,850	3,414	3,850	3,414	3,850	3,414	3,850	3,414
adj. 95% interval η^M							[-.17, .44]	[.12, .56]
Time trend	✓	✓	✓	✓	✓	✓	✓	✓
NAICS 3-digit FE		✓		✓		✓		✓
Firm FE	yes	yes	yes	yes	yes	yes		
2SLS							yes	yes

Columns (1)-(6): Linear probability models with robust standard errors, clustered by petition. Columns (7)-(8): 2SLS with robust standard errors, clustered by petition. p-values in parentheses. Adjusted 95% interval for 2SLS based on Lee et al. (2022).

Identification: Sample Selection Bias

Our research design exploits that anti-dumping petitions represent explicit demands by firms. The inherent trade-off is a selection problem: our sample only includes cases where firms have made such demands. While we cannot eliminate this selection problem, several pieces of evidence indicate this selection problem is unlikely to be accounting for the results.

First, selection bias is only a concern to the extent that the decision to file a petition is conditionally correlated with our measures. This is the case if firms file petitions based on the legal merits of a case (which, beyond control variables, remain unobserved) and their political clout (as captured by our measures). Then, petitions important to suppliers should on average have lower legal merits and lower success rates. This would introduce downward bias, reinforcing our interpretation. We discussed tentative evidence for such a pattern above: affirmative decisions on products important to suppliers are more likely to be overturned at the WTO.

Second, we adjust for the two arguably most important observable correlates: changes in imports and real exchange rate misalignments. In the appendix, we also include import volumes as an alternative measure of import penetration.

Our first argument above relies on a specific type of selection bias; likewise, adjusting for observables does not rule out unobserved sources of selection bias. For example, firms might get nudged by suppliers toward filing anti-dumping petitions, and suppliers might be able to provide crucial information in the process, increasing the success rate of petitions.

Selection problems are a form of omitted variable bias.[109] Consequently, we can assess to what extent selection problems are a concern for our results by assessing under what conditions an omitted variable would explain the observed correlation. Following Cinelli and Hazlett,[110] we employ a benchmarking approach. Changes in imports and real exchange rate misalignments are established predictors of the initiation and success rate of anti-dumping petitions. We assess how much stronger than these variables an omitted variable would have to be to invalidate our results. As we report in the appendix, such an omitted variable would have to be a more than ten times stronger predictor of the success rate of anti-dumping petitions. It appears therefore implausible that selection problems, and more generally omitted variable bias, account for the associations we report.

[109] Heckman 1979.
[110] Cinelli and Hazlett 2020.

Supplementary Evidence: Congressional Support

These patterns might capture a mostly economic rationale: governments protect firms that create positive spillovers. While part of our argument, our argument moves beyond that: We contend that these spillovers are politically relevant. In this and the subsequent section, we offer additional evidence for this political dimension.

If firms with larger domestic production networks enjoy broader political support, we should observe more Members of Congress willing to get involved on their behalf. To evaluate whether this is the case, we obtain all written briefs submitted by Members of Congress as part of anti-dumping investigations between 2009 and 2020. We access these from the Electronic Document Information System (EDIS) of the International Trade Commission. For each brief, we ascertain whether the brief supports or opposes a petition and retain only briefs in support. We then calculate the total number of signatories for each petition, separately for each stage of the investigation. For petitions that had submissions at several stages, we take the value from the earliest stage. We drop briefs signed by Congressional Caucuses that had an unusually high number of signatories. On average, a petition receives briefs with about five signatories in total.

We estimate negative binomial regression models, including the same control variables as previously. The results are reported in the appendix. Petitions on products more relevant to suppliers receive more support from Members of Congress. The results are statistically significant and substantively large: compared to a product at the 25th percentile of η, a product at the 75th percentile receives 20 additional signatures. We uncover two additional noteworthy results. First, Members of Congress are less likely to get involved for products that see large import surges. This provides further incidental evidence that their involvement is at least partially politically motivated. Second, Members of Congress shy away from supporting petitions on more upstream products. This is consistent with more lobbying competition among firms. Members of Congress appear unwilling to get caught in the middle of these clashes.

Supplementary Evidence: Indirect Exposure of Swing States

Ties to upstream suppliers extend the geographic footprint of firms. They might do so in politically relevant ways. Building on the argument in Bown et al. that firms from swing states are more successful in anti-dumping petitions,[111] our framework suggests that firms tied into larger production networks might have more success in part because they have ties to upstream suppliers in swing states.

To evaluate whether this is the case, we first identify the indirect exposure of swing states. As above,

[111] Bown et al. 2024.

we define swing states as those that were won with a vote margin of five percent or less in the previous Presidential election. We then calculate the weighted employment of an industry's suppliers in swing states, combining the share of upstream industry output absorbed by an industry as weights with data on employment by the upstream industry from the County Business Patterns.[112] The resulting measure captures to what extent an industry creates indirect exposure of employees in swing states.

The indirect exposure of swing states is on the causal path from our measures to the outcome. To assess what proportion of the effects is accounted for by this mechanism, we perform mediation analyses.[113] As we show in the appendix, all three variables measuring ties to upstream suppliers are strong predictors of the indirect exposure of swing states: firms that draw on a larger domestic production network are more likely to create spillovers into swing states. Depending on the model specification, between 25% and 35% of the effects we reported are accounted for by the indirect exposure of swing states. In contrast, we find no evidence that our mechanism is mediated by direct employment in swing states. These results provide evidence for a specific mechanism through which ties to suppliers upstream become politically relevant.

[112] Eckert et al. 2020.

[113] See Baron and Kenny (1986) and, for binary variables, MacKinnon et al. (2007). We obtain similar results following the approach outlined in Acharya, Blackwell and Sen (2016).

3 Conclusion

We introduced a novel explanation for differences in the political influence of firms, emphasizing connections between firms through production networks. Combining data from anti-dumping petitions in the U.S. with original measures of an industry's position in the domestic production network, we provided empirical evidence for our main argument: the larger are the indirect benefits for firms upstream, the more likely is a firm to see its anti-dumping petition approved.

We complement the vibrant literature on global production networks.[114] Multinational firms, which pair a credible exit threat with economic size, have long been considered as particularly powerful, driving the most recent wave of globalization politically and economically.[115] At the same time, offshoring resulted in a growing pushback against multinationals.[116] This literature identifies a key trade-off from the perspective of firms between remaining competitive in economic markets and facing opposition in political markets. Our work suggests a different mechanism underlying some of this trade-off. By offshoring, firms are not only creating opposition from those who lost their jobs. They are also eroding an important domestic political constituency, which previously conferred them unique political advantages. In the same vein, our paper suggests that recent trends of onshoring have the potential to fundamentally reconfigurate the distribution of political influence across firms, as a function of the ability for firms to find suppliers in the domestic market.

While not a focus of our analysis, we note a striking empirical pattern: the politics around anti-dumping petitions appear to work differently for cases against market and non-market economies. These results provide a backdrop for interpreting the contemporary protectionist turn in U.S. trade policy, which includes an array of policies directed against established trade partners that are market economies – such as Canada, Mexico, and the European Union. Whether this indicates an end to the differential politics around market and non-market economies remains an open question. At the same time, it is clear that domestic production networks play an important role in understanding the politics around this protectionist turn. For example, firms with large domestic production networks not only might find their government to be more responsive; they are also less exposed to the uncertainty and disruptions to global production networks resulting from the current policy environment, providing them with advantages relative to competitors.

How might the argument and findings travel outside the U.S.? We highlighted some mechanisms that are not unique, but also not ubiquitous, features of the political system of the U.S. To the extent that regulators are more politically insulated elsewhere, we would expect a smaller role of politics. At

[114] Kim and Rosendorff 2021.

[115] Bernard et al. 2018; Osgood 2018.

[116] Mansfield and Mutz 2013; Owen and Johnston 2017; Broz, Frieden and Weymouth 2021; Walter 2021.

the same time, the process to investigate anti-dumping petitions is not too dissimilar across countries. For example, Egerod and Justesen document that a prominent predictor of political relevance – asset mobility – shapes the imposition of anti-dumping petitions across countries with different political systems and development levels.[117] Whether similar patterns as the ones we reported extend to our countries remains, ultimately, an empirical question.

On a different level, our account suggests novel implications for understanding cross-country differences in (trade) policy-making. A long-standing literature examines the role of domestic institutions in shaping trade policy choices.[118] Whether support for a policy is broad or narrow, and the associated question of economic geography, plays a key role in these arguments:[119] some institutions, such as plurality rule, place a premium on interests that are concentrated; others, such as proportional representation, place a premium on interests that are dispersed.[120] This literature produced ambiguous results for trade policy outcomes, because not just the costs, but also the gains of trade liberalization tend to be concentrated.[121]

We provide a different perspective on the features of narrow versus broad interests. The *location* of a firm or an industry might be geographically concentrated. The *effects* of a policy targeted at this firm or industry, in contrast, might be geographically dispersed. The mechanism we highlight broadens interests considerably, because it creates more diverse coalitions across space, across industries, and across occupations. Domestic production networks therefore play a potentially important role in determining whether a policy affects narrow or broad interests.

This opens up new avenues for understanding differences in policy outcomes across and within countries. Within countries, Busch and Reinhardt highlight the distinction between the economic and political concentration of an industry.[122] The distinction between the concentration of an industry and the concentration of the effects of a policy targeted at that industry suggests the potential fruitfulness of analogous analyses. Across countries, we offer a distinct interpretation of what makes interests broad. Links to other firms should be most important under institutions placing a premium on broad interests. Extending our argument to different institutional contexts and different policy outcomes thus has the potential for both theoretical and empirical innovations in future research.

[117]Egerod and Justesen 2022.
[118]Rogowski 1987*b*; Gawande, Krishna and Olarreaga 2009.
[119]Rickard 2020.
[120]McGillivray 2004; Rickard 2012.
[121]Betz 2017.
[122]Busch and Reinhardt 1999.

References

Acharya, Avidit, Matthew Blackwell and Maya Sen. 2016. "Explaining Causal Findings Without Bias: Detecting and Assessing Direct Effects." *American Political Science Review* 110(3):512–529.

Antràs, Pol, Davin Chor, Thibault Fally and Russell Hillberry. 2012. "Measuring the Upstreamness of Production and Trade Flows." *American Economic Review* 102:412–416.

Aquilante, Tommaso. 2018. "Undeflected Pressure? The Protectionist Effect of Political Partisanship on US Antidumping Policy." *European Journal of Political Economy* 55:455–470.

Arel-Bundock, Vincent, James Atkinson and Rachel Augustine Potter. 2015. "The Limits of Foreign Aid Diplomacy: How Bureaucratic Design Shapes Aid Distribution." *International Studies Quarterly* 59:544–556.

Bade, Gavin. 2024. "A political appointee is accused of harassment." *Politico* .

Baron, Reuben M. and David A. Kenny. 1986. "The Moderator-Mediator Variable Distinction in Social Psychological Research: Conceptual, Strategic, and Statistical Considerations." *Journal of Personality and Social Psychology* 51:1173–1182.

Bernard, Andrew B., J. Bradford Jensen, Stephen J. Redding and Peter K. Schott. 2018. "Global Firms." *Journal of Economic Literature* 56:565–619.

Betz, Timm. 2017. "Trading Interests: Domestic Institutions, International Negotiations, and the Politics of Trade." *Journal of Politics* 79:1237–1252.

Betz, Timm and Amy Pond. 2019. "The Absence of Consumer Interests in Trade Policy." *Journal of Politics* 81:585–600.

Bonica, Adam. 2024. *Database on Ideology, Money in Politics, and Elections: Public version 4.0*. Stanford University Libraries.

Bown, Chad P. 2011. "Taking Stock of Antidumping, Safeguards and Countervailing Duties, 1990–2009." *World Economy* 34:1955–1998.

Bown, Chad P., Paola Conconi, Aksel Erbahar and Lorenzo Trimarchi. 2024. *Politically Motivated Trade Protection*. ADB Economics Working Paper Series, No. 729.

Brown, Sherrod. 2013. "Report to Ohioans." *Office of U.S. Senator Sherrod Brown* .

Broz, J. Lawrence, Jeffry A. Frieden and Stephen Weymouth. 2021. "Populism in Place: The Economic Geography of the Globalization Backlash." *International Organization* 75:464–494.

Broz, J. Lawrence and Seth H. Werfel. 2014. "Exchange Rates and Industry Demands for Trade Protection." *International Organization* 68:393–416.

Brutger, Ryan and Brian Rathbun. 2021. "Fair Share? Equality and Equity in American Attitudes Toward Trade." *International Organization* 75:880–900.

Busch, Marc L. and Eric Reinhardt. 1999. "Industrial Location and Protection: The Political and Economic Geography of U.S. Nontariff Barriers." *American Political Science Review* 43:1028–1050.

Butzbach, Olivier, Douglas B. Fuller and Gerhard Schnyder. 2020. "Manufacturing Discontent: National Institutions, Multinational Firm Strategies, and Anti-Globalization Backlash in Advanced Economies." *Global Strategy Journal* 10(1):67–93.

Caddel, Jeremy. 2014. "Domestic Competition over Trade Barriers in the US International Trade Commission." *International Studies Quarterly* 58:260–268.

Carvalho, Vasco M. and Alireza Tahbaz-Salehi. 2019. "Production Networks: A Primer." *Annual Review of Economics* 11:635–663.

Chaudoin, Stephen. 2014. "Audience Features and the Strategic Timing of Trade Disputes." *International Organization* 68:877–911.

Cinelli, Carlos and Chad Hazlett. 2020. "Making Sense of Sensitivity: Extending Omitted Variable Bias." *Journal of the Royal Statistical Society Series B: Statistical Methodology* 82(1):39–67.

Clark, William Roberts and Vincent Arel-Bundock. 2013. "Independent but not Indifferent: Partisan Bias in Monetary Policy at the Fed." *Economics& Politics* 25:1–26.

Colantone, Italo and Piero Stanig. 2018. "The Trade Origins of Economic Nationalism: Import Competition and Voting Behavior in Western Europe." *American Journal of Political Science* 62:936–953.

Congress of the United States. 2020. "Letter Regarding Investigations 701-TA-645 and 731-TA-1495-150." *EDIS* .

Congress of the United States. 2021. "Re: OCTG from Argentina, Mexico, Russia, and Korea. Inv. Nos. 701-TA-671-672 and 731-TA-1571-1573 (Preliminary).".
URL: *https://edis.usitc.gov/external/attachment/755992-1723116.pdf*

Correia, Maria M. 2014. "Political connections and SEC enforcement." *Journal of Accounting and Economics* 57(2):241–262.

Cory, Jared, Michael Lerner and Iain Osgood. 2021. "Supply Chain Linkages and the Extended Carbon Coalition." *American Journal of Political Science* 65:69–87.

Cruz, Cesi and Benjamin A. T. Graham. 2022. "Social Ties and the Political Participation of Firms." *Review of International Organizations* 17:117–142.

Dreiling, Michael and Derek Darves. 2011. "Corporate Unity in American Trade Policy: A Network Analysis of Corporate-Dyad Political Action." *American Journal of Sociology* 116:1514–1563.

Eckert, Fabian, Teresa C. Fort, Peter K. Schott and Natalie J. Yang. 2020. *Imputing Missing Values in the US Census Bureau's County Business Patterns*. NBER Working Paper Series, No. 26632.

Egerod, Benjamin C. K. and Mogens K. Justesen. 2022. "Asset Specificity, Corporate Protection and Trade Policy: Firm-Level Evidence from Antidumping Petitions in Nineteen Jurisdictions." *British Journal of Political Science* 52:1472–1481.

Feenstra, Robert C. and J. Bradford Jensen. 2012. *Evaluating Estimates of Materials Offshoring from U.S. Manufacturing*. NBER Working Paper Series, No. 17916.

Franzese, Robert J. Jr. 1999. "Partially Independent Central Banks, Politically Responsive Governments, and Inflation." *American Journal of Political Science* 43:681–706.

Gawande, Kishore, Pravin Krishna and Marcelo Olarreaga. 2009. "What Governments Maximize and Why: The View from Trade." *International Organization* 63:491–531.

Grossman, Gene M. and Elhanan Helpman. 1994. "Protection for Sale." *American Economic Review* 84:833–850.

Handley, Kyle and Nuno Limão. 2017. "Policy Uncertainty, Trade, and Welfare: Theory and Evidence for China and the United States." *American Economic Review* 107:2731–2783.

Hansen, Wendy L. 1990. "The International Trade Commission and the Politics of Protectionism." *American Political Science Review* 84:21–46.

Healy, Andrew J., Neil Malhotra and Cecilia Hyunjung Mo. 2010. "Irrelevant Events Affect Voters' Evaluations of Government Performance." *Proceedings of the National Academy of Sciences of the United States of America* 107:12804–12809.

Heckman, James J. 1979. "Sample Selection Bias as a Specification Error." *Econometrica* 47:153–161.

Hirsch, Barry T., David A. Macpherson and William E. Even. 2024. "Union Membership, Coverage, and Earnings from the CPS.".
URL: *https://unionstats.com*

Jensen, J. Bradford, Dennis P. Quinn and Stephen Weymouth. 2015. "The Influence of Firm Global Supply Chains and Foreign Currency Undervaluations on US Trade Disputes." *International Organization* 69:913–947.

Johns, Leslie and Rachel Wellhausen. 2016. "Under One Roof: Supply Chains and the Protection of Foreign Investment." *American Political Science Review* 110:31–51.

Juhász, Réka, Nathan Lane and Dani Rodrik. 2023. "The New Economics of Industrial Policy." *Annual Review of Economics* 16:213–242.

Kim, In Song. 2017. "Political Cleavages within Industry: Firm-level Lobbying for Trade Liberalization." *American Political Science Review* 111:1–20.

Kim, In Song and Iain Osgood. 2019. "Firms in Trade and Trade Politics." *Annual Review of Political Science* 22:399–414.

Kim, Kyounghwa and Jaeyoun Roh. 2022. "US Anti-Dumping Practices Evolving against Market Economies." *World Trade Review* 21(4):479–496.

Kim, Soo Yeon and B. Peter Rosendorff. 2021. "Firms, States, and Global Production." *Economics & Politics* 33:405–414.

Lee, David S., Justin McCrary, Marcelo J. Moreira and Jack Porter. 2022. "Valid t-ratio Inference for IV." *American Economic Review* 112:3260–3290.

Liebman, Benjamin H. 2004. "ITC voting behavior on sunset reviews." *Review of World Economics* 140(3):446–475.

Lorenz, Geoffrey M. 2020. "Prioritized Interests: Diverse Lobbying Coalitions and Congressional Committee Agenda Setting." *Journal of Politics* 82:225–240.

Lütkehus, Rainer. 2017. "Gemeinsam gegen die Angst vorm Freihandel." *Bayerische Staatszeitung* .

MacKinnon, David, Chondra M. Lockwood, C. Hendricks Brown, Wei Wang and Jeanne M. Hoffman. 2007. "The Intermediate Endpoint Effect in Logistic and Probit Regression." *Clinical Trials* 4:499–513.

Mansfield, Edward D. and Diana C. Mutz. 2013. "US versus Them: Mass Attitudes toward Offshore Outsourcing." *World Politics* 65:571–608.

McGillivray, Fiona. 2004. *Privileging Industry. The Comparative Politics of Trade and Industrial Policy*. Princeton University Press.

Mizruchi, Mark S. 1992. *The Structure of Corporate Political Action*. Harvard University Press.

Muro, Mark, Scott Andes, Kenan Fikri, Martha Ross, Jessica Lee, Neil Ruiz and Nick Marchio. 2013. "Drive! Moving Tennesee's Automotive Sector Up the Value Chain." *Brookings Advanced Industries Series* 53:1–79.

Murray, Joshua. 2017. *Interlock Globally, Act Domestically: Corporate Political Unity in the 21st Century*. Vol. 122.

Osgood, Iain. 2018. "Globalizing the Supply Chain: Firm and Industrial Support for US Trade Agreements." *International Organization* 72:455–484.

Owen, Erica and Noel P. Johnston. 2017. "Occupation and the Political Economy of Trade: Job Routineness, Offshorability, and Protectionist Sentiment." *International Organization* 71:665–699.

Pareto, Vilfredo. 1927. *Manual of Political Economy*. A. M. Kelley.

Patatoukas, Panos N. 2012. "Customer-Base Concentration: Implications for Firm Performance and Capital Markets." *The Accounting Review* 87(2):363–392.

Petry, Johannes, Jan Fichtner and Eelke Heemskerk. 2021. "Steering Capital: The Growing Private Authority of Index Providers in the Age of Passive Asset Management." *Review of International Political Economy* 28:152–176.

Pierce, Justin R. and Peter K. Schott. 2016. "The Surprisingly Swift Decline of US Manufacturing Employment." *American Economic Review* 106:1632–1662.

Pond, Amy. 2021. "Biased Politicians and Independent Agencies." *Journal of Theoretical Politics* 33(3):279–299.

Pond, Amy and Cristina Zafeiridou. 2020. "The Political Importance of Financial Performance." *American Journal of Political Science* 64:152–168.

Prusa, Thomas J. 1992. "Why Are So Many Antidumping Petitions Withdrawn?" *Journal of International Economics* 33:1–20.

Quinn, Dennis P. and Lizhi Liu. 2019. *A China Shock or a Multinational Shock?: The Role of MNC Value Chains in the Trade Shock*. Annual Meeting of the International Political Economy Society.

Quinn, Dennis P. and Robert Y. Shapiro. 1991. "Business Political Power: The Case of Taxation." *American Political Science Review* 85:851–874.

Rickard, Stephanie J. 2012. "Electoral Systems, Voters' Interests and Geographic Dispersion." *British Journal of Political Science* 42(4):855–877.

Rickard, Stephanie J. 2020. "Economic Geography, Politics, and Policy." *Annual Review of Political Science* 23:187–202.

Rogowski, Ronald. 1987*a*. "Political Cleavages and Changing Exposure to Trade." *American Political Science Review* 81:1121–1137.

Rogowski, Ronald. 1987*b*. "Trade and the Variety of Democratic Institutions." *International Organization* 41:203–223.

Schattschneider, Elmer E. 1935. *Politics, Pressures and the Tariff. A Study of Free Private Enterprise in Pressure Politics, as Shown in the 1929-1930 Revision of the Tariff*. Prentice Hall.

Schott, Jeffrey J. and Euijin Jung. 2019. *The WTO's Existential Crisis: How to Salvage Its Ability to Settle Trade Disputes*. Peterson Institute for International Economics, Policy Briefs 19-19.

Schott, Peter K. 2008. "The Relative Sophistication of Chinese Exports." *Economic Policy* 23:5–49.

U.S. Government Accountability Office. 2022. *Antidumping and Counterveiling Duties: Report to the Ranking Member Subcommittee on Competition Policy, Antitrust, and Consumer Rights Committee on the Judiciary U.S. Senate*. GAO-23-105794 Trade Remedies.

U.S. International Trade Commission. 2001. "Hearing Transcript in the Matter of Certain Welded Large Diameter Line Pipe from Japan and Mexico, Investigation No. 731-TA-919-920 (Final).".
URL: *https://edis.usitc.gov/external/attachment/41207-41207.pdf*

U.S. International Trade Commission. 2015. *Antidumping and Countervailing Duty Handbook*. USITC.

U.S. International Trade Commission. 2017. "Hearing Transcript in the Matter of Uncoated Groundwood Paper from Canada, Investigation Nos. 701-TA-584 and 731-TA-1382 (Preliminary).".
URL: *https://edis.usitc.gov/external/attachment/621804-1222155.pdf*

U.S. International Trade Commission. 2025. *Budget Justification: Executive Summary, FY 2025*. USITC.

Useem, Michael. 1986. *The Inner Circle*. Oxford University Press.

Walter, Stefanie. 2021. "The Backlash Against Globalization." *Annual Review of Political Science* 24:1–36.

Weingast, Barry R. and Mark J. Moran. 1983. "Bureaucratic Discretion or Congressional Control? Regulatory Policymaking by the Federal Trade Commission." *Journal of Political Economy* 91(5):765–800.

Weymouth, Stephen. 2012. "Firm Lobbying and Influence in Developing Countries: A Multilevel Approach." *Business and Politics* 14:1–26.

ONLINE APPENDIX

A Background on Anti-Dumping Investigations

Petitions are filed simultaneously with the Department of Commerce and the International Trade Commission (ITC). Once a petition is filed, the Department of Commerce decides whether to initiate an investigation. This decision is affirmative as long as the petition contains the requisite information. An affirmative decision results in a preliminary investigation by the ITC.

This preliminary investigation assesses whether there is any indication that U.S. firms are injured or threatened to be injured by the imported goods under investigation. In this preliminary phase, the ITC reviews documents, involves witness hearings, and requests written information from petitioning firms, other domestic firms, and the firms alleged to engage in dumping. It concludes with a vote by the Commissioners. As long as there is any reasonably indication of potential injury or a potential threat of injury to U.S. firms, this preliminary determination is affirmative; tied votes among the six Commissioners are considered affirmative.

Once the Department of Commerce likewise reaches an affirmative decision about whether products are likely sold below fair market value, importing firms have to start posting cash deposits or bonds in the amount of estimated anti-dumping duties. The decision by the Department of Commerce requires a fairly low evidentiary burden. It is sufficient if the Secretary of Commerce (or the Assistant Secretary for Enforcement and Compliance as delegate) determines to have "a reasonable basis to believe or suspect that the subject imported merchandise is being sold or is likely to be sold" below fair market values (U.S. International Trade Commission, 2015, II-13).

The investigation process then turns to the final investigation phase. As in the preliminary phase, the Department of Commerce seeks to establish whether products are likely to be sold below fair market value, while the ITC seeks to establish whether U.S. firms are materially injured or threatened with material injury. The process is similar to the preliminary investigation, but allows for more time and is more rigorous. In particular, it includes formal hearings and also allows for the submission of written briefs by other parties. Notably, all parties testifying at these hearings are sworn in by the Secretary to the ITC, implying penalties for false and misleading statements in these hearings. The final investigation ends again in a vote by the Commissioners of the ITC. If this vote is affirmative and the Department of Commerce determines that products are likely sold below market value, the Department of Commerce issues an anti-dumping order, imposing duties on the imported products are investigation.

B Case Merits

The empirical specifications included several predictors of whether dumping did, in fact, occur: most notably, import shocks and the real exchange rate. In particular, we sought to rule out that cases with higher values of our key measures are also cases with stronger merits, which would explain the reported association due to omitted variable bias.

Here, we present additional evidence based on disputes at the World Trade Organization. The concern above suggests that our key measures should be negatively correlated with being challenged: If case merit as an omitted variable explain the results, then cases on products important to upstream suppliers must have higher merits on average, and therefore should be less likely to be challenged at the WTO.

To evaluate whether this concern might explain our results, we first identify all anti-dumping petitions in our data set that were challenged at the WTO's Dispute Settlement Body. We draw on Schott and Jung (2019), as well as the one-page summaries of disputes provided by the WTO, to create two variables: whether the U.S. decision was challenged at the World Trade Organization Dispute Settlement Body; and whether this challenge was successful.[123]

We can only observe challenges at the WTO where the U.S. imposed anti-dumping duties. This, then, suggests an additional sample selection step, and we interpret the following results tentatively. Of cases for which the U.S. imposed anti-dumping duties in our data set, just under 20% were challenged at the WTO; the complaining party won at least a partial ruling in favor in 95% of those cases. In the top half of Table B1, we report the mean of η, η^T, and η^M for cases that were challenged at the WTO and for all other cases in which the U.S. imposed anti-dumping duties, together with the difference in means; in the bottom half we report the same for cases that were challenged at the WTO successfully. All numbers are conditional on export market fixed effects and industry size. As the table shows, both cases that were challenged at the WTO and cases that were challenged at the WTO successfully have considerably *higher* values of our key measures, between 14% and 25%; the difference is statistically signifciant at the 10% level in all cases. Petitions with higher values of our key measures thus appear to have higher approval rates not based on rules and legal merits, but for other – arguably, political – reasons.

C Mediation Analyses

Production networks extend the effects of protectionism to suppliers upstream. We suggested one specific mechanism through which this becomes politically relevant: the indirect effects extend to swing states, which are politically relevant to the President. The President's interests, in turn, tend to be reflected in anti-dumping investigations (Bown et al., 2024).

This offers us an opportunity to evaluate this specific mechanism: whether the effects of anti-dumping duties extend into swing states is on the causal pathway from our measures to the outcome. Accordingly, we turn to mediation analysis (Baron and Kenny, 1986; MacKinnon et al., 2007). First,

[123]We consider a challenge successful when the panel ruled in favor of the complainant or, if the decision was appealed, when the appellate body ruled in favor of the complainant. We consider partial decisions, split cases, and settled cases in favor of the complainant, because they indicate that at least part of the U.S. decision lacked legal merit.

Table B1 Legal Merits: WTO Disputes

Challenged at the WTO				
	challenged	unchallenged	difference	% difference
η	1.50	1.20	.298	25%
	(1.22)	(.062)	(.140)	
η^T	4.56	3.90	.659	17%
	(.304)	(.154)	(.351)	
η^M	.531	.463	.068	15%
	(.029)	(.015)	(.034)	

Challenged successfully at the WTO				
	challenged	unchallenged	difference	% difference
η	1.50	1.21	.288	24%
	(.127)	(.062)	(.145)	
η^T	4.55	3.91	.642	16%
	(.317)	(.153)	(.364)	
η^M	.529	.464	.065	14%
	(.030)	(.014)	(.035)	

Mean of η, η^T, and η^M for cases challenged at the WTO and those not challenged; and for cases challenged at the WTO successfully and those unsuccessfully challenged or not challenged. Only cases on which the U.S. imposed anti-dumping duties considered. Robust standard errors in parentheses. All values conditional on industry size and export market fixed effects.

we show that our measures do indeed correlate with the indirect exposure of swing states. To evaluate this, as before, we define swing states as those that were won with a vote margin of five percent or less in the previous Presidential election. We then calculate the weighted employment of an industry's suppliers in swing states, combining the shares of industry output absorbed by an industry as weights with data on employment by industry from the County Business Patterns provided by Eckert et al. (2020). With $\sigma_{i,j}$ as the share of output of industry j absorbed by industry i, $r_{j,s}$ as employment of industry j in state s, and $I(s)$ as an indicator equal to 1 if state s is a swing state, we thus calculate for each industry i total indirect employment in swing states as $\rho_i = \sum_s I(s) \sum_j \sigma_{i,j} r_{j,s}$.

In Table C2 we present results from linear regression models with (log) indirect employment in swing states as the outcome variable, retaining the same models as before for simplicity. Note that it is *plausible* that industries with larger upstream spillovers are correlated with higher indirect employment in swing states, but this is not true by construction. In particular, our measure is not directly related to the size of upstream industries, and it is not a given that the indirectly exposed employment is located in meaningful numbers in swing states. Nonetheless, as the results indicate, in our data set our measures of upstream spillovers are correlated with increased indirect employment in swing states. We find much smaller (and not always statistically significant) effect sizes for direct employment (not reported).

To evaluate whether this indirect employment in swing states is part of the causal mechanism, we follow MacKinnon et al. (2007), who outline mediation analyses for binary outcome variables, as in our case. Our model specifications remain the same as usual, with the full set of control variables. In the top panel of Table C1, we first report the total effect of our respective measures; we then report the direct effects – which are not explained by the pathway through indirect employment in swing states – as well as the proportion of the effect that is mediated by indirect employment in swing states. Depending on the model specification, between 25% and 35% of the effects we reported are accounted for by the indirect exposure of swing states. In contrast, we find no evidence that our mechanism is mediated by direct employment in swing states, as shown in the last column of the table.

Table C1 Mediation Analysis

			proportion mediated by:	
	total effect	direct effect	indirect employment	direct employment
η	.485	.315	35%	1.3%
η^T	.232	.164	29%	1.4%
η^M	2.30	1.57	32%	1.4%

D Sensitivity Analyses

We cannot enumerate all possible sources of selection bias, just like we cannot enumerate all possible sources of confounding more generally. As suggested by Cinelli and Hazlett (2020), we turn to a benchmarking approach: Given that both import shocks and real exchange rate misalignments are clear predictors of the initiation and the success rate of anti-dumping petitions (Broz and Werfel, 2014), we can assess how much stronger than these variables an omitted variable would have to be as a predictor of petition success to invalidate our results.

We present the results, based on our base models that we reported throughout the paper, in Table D1 for import shocks and in Table D2 for the real exchange rate. The tables indicate in the first column the maximum considered strength of the unobserved confounder as a predictor of the outcome, relative to the benchmark variable (import shocks and the real exchange rate); in the second column the resulting lower bound on the coefficient estimate of our key measure (η, η^T, and η^M, respectively); and the 95% confidence interval for the coefficient estimate in the last column. Note that these are linear models, and the coefficient estimates should therefore be compared to the linear probability model estimates reported above. The results indicate that even an unobserved confounder that is a ten times stronger predictor of petition success than import shocks, and that has the same correlation with import shocks as our key measures, would be insufficient to invalidate our results. We obtain similar results for other predictors from our base models, such as status as a non-market economy and whether the petition was filed in a Presidential election year.

Table C2 Production Networks and Indirect Exposure of Swing States

DV: Indirect Employment Swing States (log)	(1)	(2)	(3)
η	.60		
	(.000)		
η^T		.28	
		(.000)	
η^M			3.34
			(.000)
MNC	.33	.32	.34
	(.000)	(.000)	(.000)
Stock-listed	-.22	-.20	-.12
	(.002)	(.002)	(.075)
Real Exchange Rate	1.22	1.26	1.29
	(.000)	(.000)	(.000)
Fixed Assets	-.29	-.29	-.23
	(.000)	(.000)	(.003)
Steel Products	.25	.14	-.38
	(.288)	(.531)	(.010)
Industry Output (log)	.73	.68	.21
	(.000)	(.000)	(.026)
Percentage Change Imports	.34	.41	-.001
	(.066)	(.021)	(.994)
Non-Market Economy	-.062	-.048	-.015
	(.526)	(.614)	(.862)
Campaign Contributions	.0082	.029	.16
	(.863)	(.535)	(.001)
Presidential Election	.39	.40	.39
	(.000)	(.000)	(.000)
Constant	-.70	-.59	5.25
	(.665)	(.703)	(.001)
Number Obs.	3,592	3,592	3,592
Time trend	✓	✓	✓
NAICS 3-digit FE	✓	✓	✓

Columns 1-3: Linear models with robust standard errors, clustered on petition. p-values in parentheses.

Table D1 Sensitivity Analysis: Import Shocks as Benchmark

η		
multiple	coef.	95% CI
1	.053	(.034, .072)
5	.034	(.017, .052)
10	.019	(.004, .036)
η^T		
multiple	coef.	95% CI
1	.026	(.018, .033)
5	.019	(.012, .026)
10	.014	(.007, .020)
η^M		
multiple	coef.	95% CI
1	.376	(.303, .449)
5	.371	(.301, .440)
10	.367	(.302, .432)

Sensitivity analysis with benchmarking relative to import shocks: unobserved confounder with same correlation with η and 1x, 5x, and 10x stronger predictor of the success rate of anti-dumping petitions compared to import shocks. Table shows coefficients on η and 95% confidence intervals. Model specification follows the base model as described in the main text.

Table D2 Sensitivity Analysis: Real exchange rate as Benchmark

η		
multiple	coef.	95% CI
1	.068	(.050, .088)
5	.064	(.045, .083)
10	.061	(.042, .079)
η^T		
multiple	coef.	95% CI
1	.031	(.024, .039)
5	.029	(.022, .037)
10	.028	(.020, .035)
η^M		
multiple	coef.	95% CI
1	.380	(.304, .455)
5	.357	(.282, .432)
10	.340	(.266, .414)

Sensitivity analysis with benchmarking relative to real exchange rate: unobserved confounder with same correlation with η and 1x, 5x, and 10x stronger predictor of the success rate of anti-dumping petitions compared to real exchange rate. Table shows coefficients on η and 95% confidence intervals. Model specification follows the base model as described in the main text.

E Imports across Industries: Construction

To account for imports of inputs and changes in those patterns over time, we combine data from the input-output tables with product-level data on U.S. imports. To hold constant changes in production technology and industry classifications, we use data from the 2012 version of the input-output tables. This ensures that the driver of differences over time in our measure are changes in trade flows. We then concord these data to BEA I-O codes and match them with the 2012 Use Table to adjust for imported inputs.

We match U.S. product-level trade data from 1996 to 2020 to NAICS codes, using the concordance from Schott (2008), to obtain imports at the level of NAICS six-digit industries. We deflate imports, to account for price changes, by scaling them to the 2012 benchmark year.

Because no publicly available data track the usage of imports of specific commodities across industries, we follow BEA guidelines and allocate imports across industries based on a proportionality assumption: an industry's reliance on imports of a commodity is proportional to the ratio of total imports to domestic supply of that commodity. While it is unlikely that the proportionality assumption holds exactly, Feenstra and Jensen (2012) demonstrate that it is a good approximation: the correlation coefficient with a similarly constructed measure based on confidential transaction-level data is between .68 and .87, and most deviations fall within a relatively narrow band.

The proportionality assumption has an attractive implication for our research design: changes over time in imports, and therefore in our measure, are based on (1) changes in industry size, which we control for in our empirical models; and (2) changes in *total* imports of that commodity, which are not specific to the industry in question.[124]

We then concord these data to BEA I-O codes and match them with the 2012 Use Table to adjust for imported inputs. With $m^*_{i,j}$ denoting industry i's purchases of imported inputs j, we calculate analogously to above

$$\sigma^*_{i,j} = \frac{m_{i,j} - m^*_{i,j}}{q_j} = \sigma_{i,j} - \frac{m^*_{i,j}}{q_j}, \tag{6}$$

resulting in our third measure as

$$\eta_i^M = \sum_{j=1}^{N} \sigma^*_{i,j}. \tag{7}$$

[124] The import matrices published by the BEA use the same proportionality assumption. See, for example, `https://www.bea.gov/help/faq/453`, last accessed March 14, 2024, where the BEA notes that "[because] source data are not available that show the imported share of intermediate inputs by industry, the estimates must be imputed" using a proportionality assumption.

F Imports across Industries: Sensitivity

In calculating η^M, we followed guidance from the BEA in allocating imports across industries uing a proportionality assumption. To assess whether the resulting measurement error could result in substantial bias, we lean on Feenstra and Jensen (2012), who compare the import allocation derived from the proportionality assumption to an import allocation derived from confidential, transaction-level data and find that (i) on average, the two measures are highly correlated, (ii) deviations are centered around zero, and (iii) deviations fall within a relatively narrow range, of about a quarter of a percentage point. In the following, we discuss the proportionality assumption, and we show that the results remain robust when allowing for arbitrary random perturbations of the industry share of imports.

The construction of η^M requires us to allocate imports of commodities across industries. To do so, we follow the BEA's proportionality assumption, such that an industry's use of a commodity as a share of total usage of that commodity corresponds to imports of that commodity as a share of total supply of that commodity. This assumption is unlikely to hold *exactly*, even though it is a reasonable approximation and corresponds to common practices. For example, the BEA provides import matrices as part of its input-output tables, and these import tables are based on the same proportionality assumption.

Feenstra and Jensen (2012) use confidential transaction-level data to evaluate the plausibility of this proportionality assumption. They report a correlation ranging from .68 to .87 when comparing a measure constructed from transaction-level data to a measure constructed using the proportionality assumption. Additionally, they report a histogram, showing that deviations are centered on zero, and that at the level of NAICS three-digit industries, almost all deviations fall within a range of 25 percentage points – with the vast majority being smaller than 10 percentage points.

To evaluate the robustness of our results to violations of the proportionality assumption, we create random perturbations of our import shares. To do so, we draw a random variable from a uniform distribution, with bounds $-t$ and t. We then add these perturbations to the import shares derived from the proportionality assumption, and allocate these perturbations across NAICS six-digit industries within each NAICS three-digit industry. We consider, in steps of $.025$, bounds for the uniform distribution between $t = .025$ and $t = .975$, exceeding significantly the range reported in Feenstra and Jensen (2012): at the upper end of the scenarios we consider, the *median* deviation is allowed to be as large as 50 percentage points. At each of the steps between $.025$ and $.975$, we create $1,000$ data sets based on perturbed import shares, calculate accordingly $1,000$ perturbed versions of η^M, estimate our baseline model $1,000$ times, and save the coefficient estimates and t-statistics for η^M.

Figure F1 reports the range of coefficient estimates and t-statistics, across the deviations we consider (on the horizontal axis, which depicts the parameter t ranging from .025 to .975), for each of the $1,000$ variants of η^M at each step – the Figure thus represents data from $39,000$ estimations. The estimates remain similar in size and statistically significant in every single case, corroborating that our results are robust to deviations from the proportionality assumption.

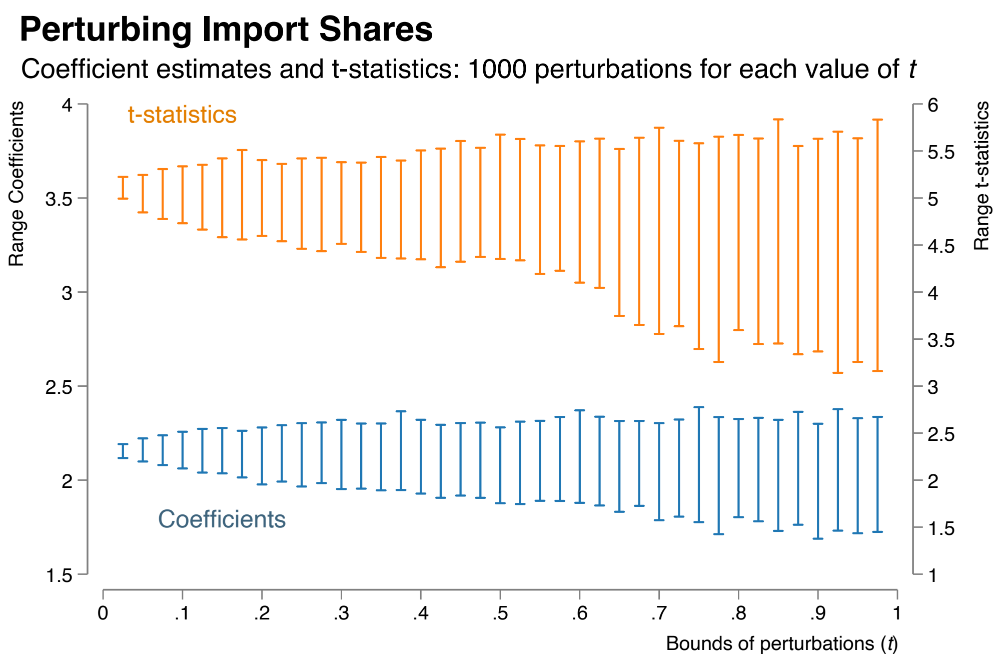

Figure F1 Range of coefficient estimates (capped bars, in blue, left axis) and t-statistics (capped bars, in red, right axis), when perturbing import shares with errors drawn from a uniform distribution of varying bounds (horizontal axis), across $1,000$ perturbations at each level of perturbations.

G Withdrawn Cases: Permuting the Outcome Variable

A small proportion of anti-dumping petitions were terminated or withdrawn without final or negative preliminary ruling. Unfortunately, these cases are difficult to allocate as either wins or losses. On the one hand, a withdrawn case may indicate that the petitioner lost faith in a positive outcome, deciding to no longer spend (political and financial) capital on a petition. On the other hand, Prusa (1992) shows that withdrawn cases frequently are the result of private bargaining between a petitioner and the foreign counterpart, resulting in a settlement that often benefits the petitioner.

In the main models in the text, we omit these cases from the data set. Here, we consider an alternative approach. Instead of enumerating all possible distributions of wins and losses across terminated and withdrawn cases, we consider random permutations. We proceed in four steps. First, we determine a fixed probability p of a case being a win for the petitioner, ranging from 0.05 to .95, in steps of .05. We will consider the probability of wins and losses as synonymously with the proportion of wins and losses: at the lower end of the scale, most cases are considered losses, and the upper end, most cases are considered wins for the petitioner. Second, at each of these steps, we randomly allocate wins and losses across terminated and withdrawn cases, according to this fixed probability. For example, for $p = .05$, each terminated or withdrawn case is coded as a win with a probability of 5%, and as a loss with a probability of 95%. Third, we repeat step 2 $5,000$ times, to obtain $5,000$ permutations of wins and losses across terminated and withdrawn cases, for each fixed probability of wins and losses. Fourth, we estimate our baseline model with an outcome variable that incorporates these imputed wins and losses, which results in $5,000$ coefficient estimates of η at each probability of wins and losses.

None of these estimates are statistically significantly different from the original coefficient estimate. Additionally, we report two sets of results. Figure G1 reports the range of coefficient estimates and the proportion of statistically insignificant coefficient estimates at the 5% level. The horizontal axis reports the proportion of terminated and withdrawn cases that we considered wins, and each bar represent the upper and lower end of the distribution of $5,000$ estimates. The dashed horizontal line represents the original coefficient estimate. Figure G2 reports, similarly, the t-statistics and again the proportion of statistically insignificant coefficient estimates at the 5% level. As before, the horizontal axis reports the proportion of unobserved cases that we considered wins, and each bar represent the upper and lower ends of the distribution of $5,000$ estimates. The dashed horizontal line represents the critical value for the t-statistic for a test at the 5% significance level.

As Figures G1 and G2 demonstrate, our results are robust to making any assumptions about lost and won cases. In total, each Figure represents the results from $95,000$ estimations: $5,000$ estimates for each bar, at 19 values for the proportion of cases we consider wins. Among the unobserved (terminated or withdrawn) petition outcomes, private bargaining would result in our coefficient estimates losing statistical significance in none of the scenarios we considered. Moreover, the coefficient estimate remains stable across permutations and within a relatively narrow range around the original estimate.

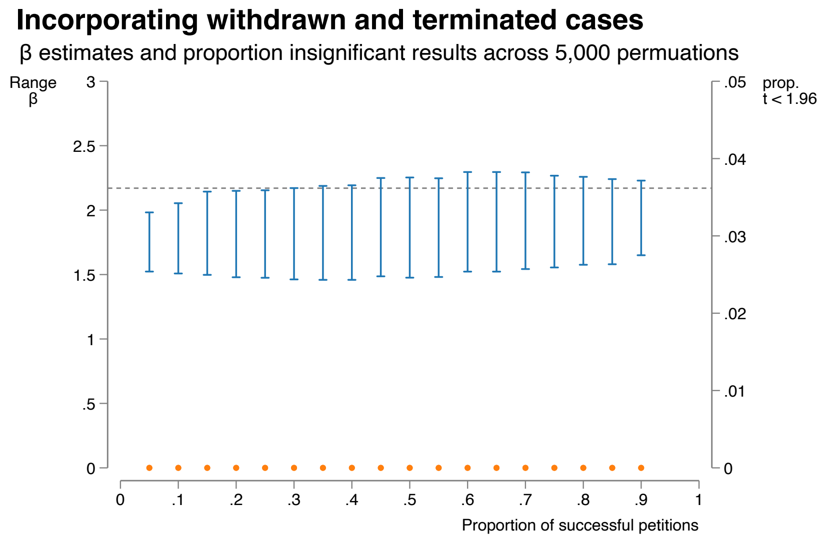

Figure G1 Range of coefficient estimates (capped bars, in blue, left axis) and proportion of statistically insignificant coefficient estimates at the 5% level (circles, in orange, right axis), at different levels of the proportion of petitioner wins among unobserved outcomes (horizontal axis), across $5,000$ permutations of wins and losses at each level.

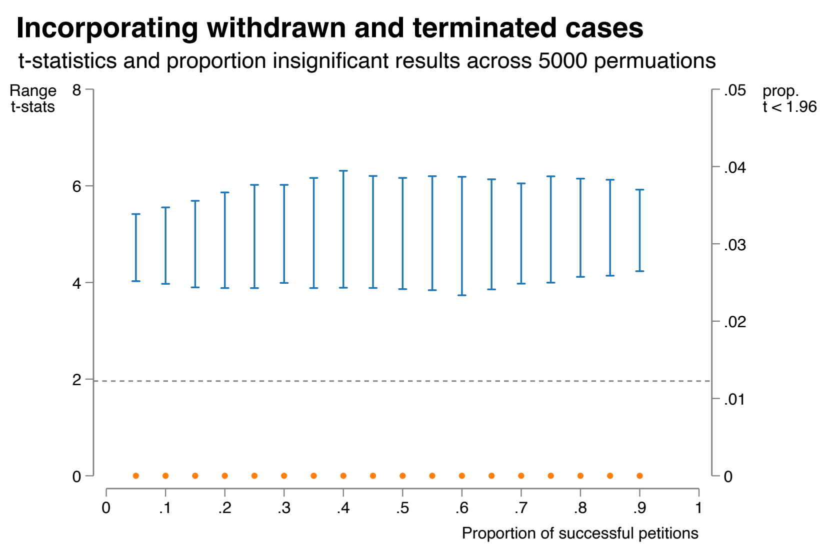

Figure G2 Range of t-statistics (capped bars, in blue, left axis) and proportion of statistically insignificant coefficient estimates at the 5% level (circles, in orange, right axis), at different levels of the proportion of petitioner wins among unobserved outcomes (horizontal axis), across $5,000$ permutations of wins and losses at each level.

H Additional Results

In Table H1, in the first two columns we report results when using η derived from the input-output tables in a single year, 2012. This ensures that differences in η are only driven by cross-industry differences, not by differences in industry aggregations and disaggregations over time.

In the third and fourth column, we report results when distinguishing between related-party trade and arms-length transactions. A substantial portion of U.S. imports constitutes related-party trade: imports that are sourced from U.S.-owned firms abroad. Our measure η^M stripped these out, as part of overall import volumes. We construct an alternative measure that retains related-party imports and only strips out arms-length imports. To do so, we obtain data on related-party trade by industry from the Census Bureau's annual reports.[125] These data provide us with a measure of the share of imports that are sourced from U.S.-owned firms abroad and the share of imports that are sourced from foreign firms through arms-length transactions. We then re-construct our measure, resulting in a variable η^F, which only adjusts for imports sourced through arms-length transactions.

In columns 5 and 6, we provide results for using (logged) total domestic inputs sourced by an industry. This presents an alternative – and simpler – measure of importance to upstream industries. Unlike our main measures, this variable does not take into account the distribution across industries or the importance to upstream industries relative to their size. It does, however, reflect a transparent metric to what extent production of a good draws on domestic suppliers, and it incorporates that sourcing a large amount of inputs might be economically and politically meaningful, even if it only accounts for a small portion of an upstream supplier's output. We leave a more complete exploration of the role of industry size of customers relative to suppliers to future work.

In Table H2-H4, we consider standard errors clustered by (1) firms, by (2) industries, and by (3) petitions and industries simultaneously. In Table H5, we estimate weighted logistic regression models, with weights corresponding to the number of observations belonging to each petition. In Table H6, we collapse the data by the petition, averaging observations across products and firms using firm employment shares as weights; in Table H7, we similarly collapse the data by the petition, but use simple averages instead. In Table H8, we include year fixed effects instead of a year polynomial. In Table H9, we estimate linear probability models.

We consider additional control variables in Tables H10-H17. For all of these, we replicate the extended baseline model with industry fixed effects, adding control variables. In Table H10, we include in odd columns a control variable for imports of an industry's inputs, to account for total foreign sourcing of an industry. Including this variable isolates differences in the extent of the domestic production network in our main variable of interest. Put differently, this variable allows us to hold constant total foreign sourcing, thus focusing on differences in the domestic production network and the distribution of sourcing across industries, as reflected in η, η^M, and η^T. In even columns, we include the upstreamness measure from Antràs et al. (2012), which identifies the vertical position of a product in the production network. Including this variable distinguishes our results from an argument that downstream industries might receive more trade protection in a variant of tariff escalation.

[125] For 2000 to 2005, we obtain the data from the pdf reports. For years after 2005, we can use the data files provided by the Census Bureau. For 1998 and 1999, where the data are not available, we use information from 2000, given that related-party trade varies little year-to-year.

In Table H11, in odd columns we include a measure of vertical integration derived from the Orbis firm-level data. To obtain this measure, we use the data from the input-output tables to identify, for each NAICS six-digit industry, the NAICS six-digit industries that account for at least 1% of an industry's inputs. We obtain these data from the 2012 input-output tables to hold constant industry classifications. We then match these with the Orbis ownership data to identify, for each firm, whether at any point in time between 2007 and 2019 (the range of the Orbis data) it held a direct or indirect ownership stake in a firm from a supplying industry. We then calculate for each firm the sum of firms in supplying industries in which it holds such an ownership stake. In even columns, we include a measure of whether a firm has a subsidiary in the counter-party of the anti-dumping investigation. We first identified for each anti-dumping petition the target market against which the petition was filed. We then identified, for each firm in our data set that we were able to match with the Orbis data base, whether that firm had a subsidiary in the target market or whether a parent in the petitioner's corporate family had a subsidiary in the target market. The results for our main measures remain statistically significant at the 5% level in all models. Vertically integrated firms are more likely to have their anti-dumping petitions approved, consistent with the notion that these firms are likely to solve collective action problems within the boundaries of the firm.

In Table H12, in odd columns we include log Employees, obtained from the Orbis data base and from Refinitiv; where both data sources report the number of employees, we take the larger of the two values, because the Orbis data in some cases reports an implausibly small number of employees (e.g., fewer than 10 employees when the Refinitiv data reports over 700 employees). Including this variable cuts down our number of observations considerably, and likely biases our sample toward larger firms which report these data. In even columns, we therefore include log Employees at the industry-level. The results remain statistically significant at the 5% level in all models.

In Table H13, we include several industry-level control variables: In odd columns, we add an industry's contribution to GDP growth; in even columns, we include industry value added as a share of GDP and the capital-labor ratio, following Broz and Werfel (2014), obtained from the BEA. The coefficients on our core measures remain positive and statistically significant.

In Table H14, we include two control variables for political attributes. In odd columns, we include the (logged) number of counties in which an industry has at least 250 employees, following the cut-off used by Hansen (1990). In even columns, we include the share of counties with at least 250 employees in an industry that are represented by a Democratic member in the House of Representatives, which over most of the sample period were perceived as more protectionist on average than Republicans. We obtain data on industry employment across counties from the County Business Patterns, compiled and standardized by Eckert et al. (2020).

In Table H15, we examine the role of swing states. We define swing states as those that were won by a vote margin of five percent or less in the past Presidential election. In odd columns, we include total (log-transformed) employment in swing states by an industry involved in an anti-dumping petitition (we obtain similar results when using a dummy variable for whether an industry employed at least 250 employees in swing states). In even columns, we identify whether a petitioner is located in a swing state using information from the Global Anti-Dumping Database, company directories (include Orbis and Dun&Bradstreet), and information from anti-dumping petitions and press releases.

In Table H16, we control for a firm's political involvement, which might be a substitute or a complement to the structural attribute we identify. We match the company names with data on campaign contributions from DIME (Bonica, 2024) and lobbying data from LobbyView (Kim, 2017). For 1998, where LobbyView provides no data yet, we manually supplement the LobbyView data with lobbying data from opensecrets.org, which – like LobbyView – draws on the Lobbying Disclosure Act reports. We include whether a firm provided campaign contributions or lobbied in the two years before or after an anti-dumping investigation in odd columns, and measures of whether a firm provided campaign contributions or lobbied at any given point during the sample period in even columns.

In Table H17, we include import volumes in odd columns as an alternative measure of import penetration. In even columns, we include exporting market fixed effects. These capture all time-invariant differences across countries that are the target markets of anti-dumping investigations – including, for example, political relations with the U.S. (beyond what is captured by the variable for non-market economies).

In Table H18, we split the sample, reporting results for market economies in odd columns and for non-market economies in even columns. We derive the variable of whether a country is classified as a non-market economy from the U.S. Federal Register. The results indicate that the results are confined to market economies. In cases directed against non-market economies, the effect disappears. This is consistent with an interpretation that domestic politics plays less of a role in cases against non-market economies.

In Table H19, we report results from negative binomial regression models with the total number of signatories of submissions by Members of Congress as the dependent variable.

Table H1 Success of AD Petitions: Alternative Predictors

	(1)	(2)	(3)	(4)	(5)	(6)
η^{2012}	.96	1.12				
	(.001)	(.000)				
η^{F}			1.36	1.65		
			(.004)	(.001)		
total domestic Inputs (log)					.57	.67
					(.002)	(.001)
Steel Products	-1.19	-1.45	-1.04	-1.40	-.50	-.92
	(.005)	(.043)	(.009)	(.050)	(.099)	(.170)
Industry Output (log)	-.14	.0051	-.14	-.00061	-.39	-.17
	(.388)	(.982)	(.398)	(.998)	(.076)	(.506)
Percentage Change Imports	1.74	2.77	1.63	2.63	1.83	2.85
	(.043)	(.000)	(.047)	(.000)	(.025)	(.000)
Non-Market Economy	.51	.83	.51	.84	.57	.87
	(.144)	(.018)	(.142)	(.017)	(.104)	(.013)
Campaign Contributions	-.42	-.41	-.40	-.40	-.43	-.41
	(.006)	(.001)	(.008)	(.001)	(.004)	(.001)
Presidential Election	2.23	2.61	2.22	2.60	2.26	2.59
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
MNC		-.31		-.31		-.32
		(.050)		(.054)		(.043)
Stock-listed		-.071		-.063		-.074
		(.728)		(.754)		(.708)
Real Exchange Rate		1.89		2.03		1.85
		(.003)		(.002)		(.004)
Fixed Assets		-.016		-.0091		-.032
		(.894)		(.938)		(.782)
Constant	9.68	6.30	8.96	5.02	7.29	2.57
	(.002)	(.087)	(.004)	(.166)	(.006)	(.421)
Number Obs.	3,850	3,370	3,850	3,370	3,850	3,370
Time trend	✓	✓	✓	✓	✓	✓
NAICS 3-digit FE		✓		✓		✓

Columns 1-6: Logit models with robust standard errors, clustered on petition. p-values in parentheses.

Table H2 Success of AD Petitions: Clustered by Firm

	(1)	(2)	(3)	(4)	(5)	(6)
η	.43	.48				
	(.002)	(.001)				
η^T			.19	.23		
			(.000)	(.000)		
η^M					2.17	2.30
					(.000)	(.000)
Steel Products	-.93	-1.36	-1.08	-1.32	-1.30	-1.49
	(.005)	(.033)	(.002)	(.029)	(.000)	(.025)
Industry Output (log)	.027	.30	.012	.23	-.28	-.11
	(.833)	(.068)	(.927)	(.160)	(.077)	(.580)
Percentage Change Imports	1.91	2.95	1.96	3.12	1.69	2.68
	(.003)	(.000)	(.003)	(.000)	(.006)	(.000)
Non-Market Economy	.50	.79	.50	.81	.50	.85
	(.007)	(.000)	(.007)	(.000)	(.006)	(.000)
Campaign Contributions	-.48	-.49	-.47	-.48	-.38	-.38
	(.057)	(.030)	(.065)	(.032)	(.136)	(.091)
Presidential Election	2.23	2.61	2.23	2.61	2.23	2.62
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
MNC		-.31		-.32		-.30
		(.245)		(.241)		(.257)
Stock-listed		-.11		-.11		-.040
		(.683)		(.701)		(.883)
Real Exchange Rate		2.10		2.19		2.07
		(.000)		(.000)		(.000)
Fixed Assets		-.036		-.036		-.0067
		(.848)		(.850)		(.972)
Constant	6.98	1.81	6.92	2.05	10.6	6.34
	(.004)	(.534)	(.004)	(.476)	(.000)	(.049)
Number Obs.	3,850	3,370	3,850	3,370	3,850	3,370
Time trend	✓	✓	✓	✓	✓	✓
NAICS 3-digit FE		✓		✓		✓

Logit models with robust standard errors, clustered by firm. p-values in parentheses.

Table H3 Success of AD Petitions: Clustered by Industry

	(1)	(2)	(3)	(4)	(5)	(6)
η	.43	.48				
	(.010)	(.032)				
η^T			.19	.23		
			(.002)	(.004)		
η^M					2.17	2.30
					(.000)	(.000)
Steel Products	-.93	-1.36	-1.08	-1.32	-1.30	-1.49
	(.016)	(.081)	(.005)	(.073)	(.000)	(.066)
Industry Output (log)	.027	.30	.012	.23	-.28	-.11
	(.872)	(.313)	(.943)	(.403)	(.160)	(.738)
Percentage Change Imports	1.91	2.95	1.96	3.12	1.69	2.68
	(.004)	(.000)	(.008)	(.000)	(.002)	(.000)
Non-Market Economy	.50	.79	.50	.81	.50	.85
	(.003)	(.000)	(.003)	(.000)	(.003)	(.000)
Campaign Contributions	-.48	-.49	-.47	-.48	-.38	-.38
	(.037)	(.001)	(.057)	(.004)	(.084)	(.016)
Presidential Election	2.23	2.61	2.23	2.61	2.23	2.62
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
MNC		-.31		-.32		-.30
		(.032)		(.029)		(.037)
Stock-listed		-.11		-.11		-.040
		(.696)		(.722)		(.885)
Real Exchange Rate		2.10		2.19		2.07
		(.005)		(.005)		(.003)
Fixed Assets		-.036		-.036		-.0067
		(.740)		(.741)		(.952)
Constant	6.98	1.81	6.92	2.05	10.6	6.34
	(.019)	(.585)	(.026)	(.550)	(.008)	(.162)
Number Obs.	3,850	3,370	3,850	3,370	3,850	3,370
Time trend	✓	✓	✓	✓	✓	✓
NAICS 3-digit FE		✓		✓		✓

Logit models with robust standard errors, clustered by industry. p-values in parentheses.

Table H4 Success of AD Petitions: Clustered by Petitions and Industries

	(1)	(2)	(3)	(4)	(5)	(6)
η	.43	.48				
	(.028)	(.044)				
η^T			.19	.23		
			(.007)	(.006)		
η^M					2.17	2.30
					(.000)	(.000)
Steel Products	-.93	-1.36	-1.08	-1.32	-1.30	-1.49
	(.049)	(.083)	(.022)	(.075)	(.001)	(.065)
Industry Output (log)	.027	.30	.012	.23	-.28	-.11
	(.882)	(.324)	(.948)	(.415)	(.191)	(.743)
Percentage Change Imports	1.91	2.95	1.96	3.12	1.69	2.68
	(.051)	(.000)	(.057)	(.000)	(.050)	(.000)
Non-Market Economy	.50	.79	.50	.81	.50	.85
	(.111)	(.007)	(.112)	(.007)	(.112)	(.006)
Campaign Contributions	-.48	-.49	-.47	-.48	-.38	-.38
	(.057)	(.003)	(.079)	(.008)	(.122)	(.027)
Presidential Election	2.23	2.61	2.23	2.61	2.23	2.62
	(.001)	(.003)	(.001)	(.002)	(.001)	(.002)
MNC		-.31		-.32		-.30
		(.101)		(.099)		(.113)
Stock-listed		-.11		-.11		-.040
		(.732)		(.752)		(.899)
Real Exchange Rate		2.10		2.19		2.07
		(.009)		(.008)		(.005)
Fixed Assets		-.036		-.036		-.0067
		(.797)		(.798)		(.963)
Constant	6.98	1.81	6.92	2.05	10.6	6.34
	(.044)	(.603)	(.053)	(.567)	(.016)	(.177)
Number Obs.	3,850	3,370	3,850	3,370	3,850	3,370
Time trend	✓	✓	✓	✓	✓	✓
NAICS 3-digit FE		✓		✓		✓

Logit models with robust standard errors, clustered by petitions and industries. p-values in parentheses.

Table H5 Success of AD Petitions: Weighted Logit

	(1)	(2)	(3)	(4)	(5)	(6)
η	.57	.87				
	(.008)	(.003)				
η^T			.22	.36		
			(.004)	(.001)		
η^M					2.22	2.93
					(.000)	(.001)
Steel Products	-.56	-.29	-.61	-.33	-.80	-.72
	(.319)	(.768)	(.273)	(.707)	(.116)	(.479)
Industry Output (log)	-.062	.10	-.019	.13	-.20	-.094
	(.790)	(.724)	(.936)	(.626)	(.388)	(.768)
Percentage Change Imports	.48	3.61	.45	3.66	.35	3.30
	(.805)	(.007)	(.816)	(.006)	(.853)	(.015)
Non-Market Economy	.093	1.25	.11	1.32	.15	1.37
	(.893)	(.048)	(.874)	(.039)	(.829)	(.039)
Campaign Contributions	-.52	-.62	-.51	-.59	-.48	-.51
	(.115)	(.002)	(.127)	(.003)	(.161)	(.008)
Presidential Election	5.03	4.92	5.02	4.88	4.91	4.94
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
MNC		-.47		-.48		-.45
		(.269)		(.272)		(.303)
Stock-listed		-.093		-.072		-.013
		(.842)		(.874)		(.977)
Real Exchange Rate		1.79		1.93		1.83
		(.029)		(.020)		(.023)
Fixed Assets		-.11		-.10		-.074
		(.523)		(.548)		(.670)
Constant	9.91	6.88	9.63	6.33	12.6	10.5
	(.012)	(.139)	(.015)	(.173)	(.003)	(.047)
Number Obs.	3,850	3,370	3,850	3,370	3,850	3,370
Time trend	✓	✓	✓	✓	✓	✓
NAICS 3-digit FE		✓		✓		✓

Logit models with robust standard errors, clustered by petition. p-values in parentheses. Weighted by number of observations per petition.

Table H6 Success of AD Petitions: Collapse by Petition, Weighted Average

	(1)	(2)	(3)	(4)	(5)	(6)
η	.26	.31				
	(.074)	(.032)				
η^T			.11	.14		
			(.057)	(.020)		
η^M					1.05	1.36
					(.121)	(.040)
Steel Products	-.18	-.34	-.25	-.43	-.29	-.50
	(.630)	(.421)	(.530)	(.331)	(.521)	(.294)
Industry Output (log)	-.23	-.14	-.23	-.15	-.34	-.30
	(.189)	(.500)	(.173)	(.482)	(.118)	(.221)
Percentage Change Imports	1.37	1.53	1.37	1.54	1.15	1.27
	(.007)	(.004)	(.007)	(.003)	(.023)	(.017)
Non-Market Economy	.91	.91	.91	.92	.91	.91
	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
Campaign Contributions	-.19	-.11	-.19	-.088	-.16	-.043
	(.443)	(.712)	(.464)	(.761)	(.531)	(.879)
Presidential Election	1.18	1.19	1.19	1.20	1.22	1.24
	(.000)	(.001)	(.000)	(.001)	(.000)	(.000)
MNC		-.47		-.50		-.48
		(.168)		(.145)		(.162)
Stock-listed		-.17		-.16		-.21
		(.588)		(.592)		(.493)
Real Exchange Rate		.76		.74		.74
		(.235)		(.249)		(.251)
Fixed Assets		.24		.23		.27
		(.262)		(.282)		(.220)
Constant	4.92	2.10	4.81	2.02	6.14	3.70
	(.043)	(.500)	(.045)	(.514)	(.029)	(.257)
Number Obs.	553	540	553	540	553	540
Time trend	✓	✓	✓	✓	✓	✓

Logit models with robust standard errors, clustered by petition. p-values in parentheses.

Table H7 Success of AD Petitions: Collapse by Petition, Simple Average

	(1)	(2)	(3)	(4)	(5)	(6)
η	.30	.35				
	(.027)	(.014)				
η^T			.11	.13		
			(.062)	(.026)		
η^M					.96	1.40
					(.143)	(.026)
Steel Products	-.20	-.60	-.17	-.60	-.19	-.74
	(.561)	(.134)	(.653)	(.162)	(.668)	(.106)
Industry Output (log)	-.20	-.023	-.19	-.0086	-.27	-.17
	(.206)	(.909)	(.234)	(.965)	(.164)	(.456)
Percentage Change Imports	1.01	1.07	.94	1.01	.77	.79
	(.030)	(.030)	(.043)	(.041)	(.099)	(.113)
Non-Market Economy	.91	1.08	.92	1.09	.92	1.09
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Campaign Contributions	-.76	-.47	-.73	-.43	-.64	-.29
	(.018)	(.186)	(.023)	(.229)	(.043)	(.402)
Presidential Election	1.18	1.16	1.19	1.17	1.22	1.20
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
MNC		-.50		-.53		-.57
		(.186)		(.163)		(.119)
Stock-listed		-.0077		-.00063		.021
		(.984)		(.999)		(.957)
Real Exchange Rate		1.34		1.31		1.32
		(.032)		(.038)		(.035)
Fixed Assets		.25		.23		.27
		(.239)		(.272)		(.190)
Constant	4.29	.26	3.98	.056	5.02	1.74
	(.059)	(.927)	(.074)	(.984)	(.053)	(.563)
Number Obs.	630	574	630	574	630	574
Time trend	✓	✓	✓	✓	✓	✓
NAICS 3-digit FE		✓		✓		✓

Logit models with robust standard errors, clustered by petition. p-values in parentheses.

Table H8 Success of AD Petitions: Year Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)
η	.77	.74				
	(.000)	(.000)				
η^T			.33	.34		
			(.000)	(.000)		
η^M					3.41	3.17
					(.000)	(.000)
Steel Products	-1.57	-1.91	-1.75	-1.75	-2.05	-2.07
	(.001)	(.065)	(.000)	(.072)	(.000)	(.061)
Industry Output (log)	-.092	.28	-.087	.20	-.48	-.16
	(.622)	(.194)	(.607)	(.332)	(.025)	(.527)
Percentage Change Imports	2.23	3.61	2.17	3.60	1.86	3.19
	(.003)	(.000)	(.002)	(.000)	(.007)	(.000)
Non-Market Economy	.55	.72	.57	.75	.59	.77
	(.120)	(.047)	(.108)	(.036)	(.086)	(.033)
Campaign Contributions	-.29	-.35	-.27	-.33	-.24	-.31
	(.056)	(.008)	(.072)	(.012)	(.097)	(.015)
MNC		-.36		-.37		-.36
		(.031)		(.028)		(.031)
Stock-listed		.12		.13		.17
		(.567)		(.530)		(.403)
Real Exchange Rate		2.13		2.25		2.25
		(.006)		(.003)		(.002)
Fixed Assets		.11		.11		.14
		(.413)		(.426)		(.283)
Constant	537.2	649.4	514.2	632.0	483.2	624.1
	(.003)	(.001)	(.004)	(.002)	(.006)	(.002)
Number Obs.	3,597	2,974	3,597	2,974	3,597	2,974
Year FE	✓	✓	✓	✓	✓	✓
NAICS 3-digit FE		✓		✓		✓

Logit models with robust standard errors, clustered by petition. p-values in parentheses. Weighted by number of observations per petition.

Table H9 Success of AD Petitions: Linear Probability Model

	(1)	(2)	(3)	(4)	(5)	(6)
η	.069	.063				
	(.015)	(.036)				
η^T			.031	.032		
			(.003)	(.003)		
η^M					.38	.35
					(.000)	(.001)
Steel Products	-.17	-.22	-.20	-.24	-.26	-.29
	(.010)	(.026)	(.003)	(.014)	(.000)	(.007)
Industry Output (log)	.0088	.047	.0066	.039	-.041	-.0077
	(.667)	(.061)	(.739)	(.101)	(.074)	(.773)
Percentage Change Imports	.34	.44	.34	.45	.31	.41
	(.002)	(.000)	(.002)	(.000)	(.004)	(.000)
Non-Market Economy	.084	.092	.084	.094	.084	.096
	(.109)	(.044)	(.110)	(.040)	(.112)	(.034)
Campaign Contributions	-.089	-.084	-.087	-.082	-.072	-.069
	(.001)	(.000)	(.001)	(.000)	(.005)	(.000)
Presidential Election	.29	.28	.29	.28	.29	.28
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
MNC		-.040		-.041		-.039
		(.114)		(.103)		(.119)
Stock-listed		-.028		-.027		-.017
		(.379)		(.397)		(.586)
Real Exchange Rate		.25		.26		.26
		(.003)		(.003)		(.003)
Fixed Assets		-.013		-.013		-.0076
		(.465)		(.459)		(.669)
Constant	1.81	1.14	1.80	1.18	2.42	1.76
	(.000)	(.017)	(.000)	(.011)	(.000)	(.000)
Number Obs.	3,850	3,414	3,850	3,414	3,850	3,414
Time trend	✓	✓	✓	✓	✓	✓
NAICS 3-digit FE		✓		✓		✓

Linear regression models with robust standard errors, clustered on NAICS industry, in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table H10 Success of AD Petitions: Upstream Controls

	(1)	(2)	(3)	(4)	(5)	(6)
η	.51	.52				
	(.010)	(.004)				
η^T			.26	.25		
			(.001)	(.000)		
η^M					2.55	2.39
					(.000)	(.000)
Supplier Imports (log)	-.16		-.33		-.30	
	(.532)		(.245)		(.257)	
Upstreamness		.62		.70		.61
		(.063)		(.041)		(.082)
MNC	-.30	-.31	-.31	-.31	-.29	-.30
	(.056)	(.055)	(.058)	(.057)	(.073)	(.068)
Stock-listed	-.11	-.10	-.11	-.095	-.033	-.024
	(.596)	(.633)	(.620)	(.648)	(.873)	(.903)
Real Exchange Rate	2.04	1.96	2.08	2.04	1.95	1.93
	(.003)	(.003)	(.002)	(.002)	(.003)	(.002)
Fixed Assets	-.032	-.012	-.028	-.011	.0053	.015
	(.788)	(.917)	(.819)	(.924)	(.965)	(.894)
Steel Products	-1.22	-1.33	-1.03	-1.28	-1.23	-1.46
	(.115)	(.072)	(.171)	(.065)	(.113)	(.045)
Industry Output (log)	.27	.23	.15	.16	-.22	-.17
	(.219)	(.257)	(.501)	(.442)	(.410)	(.472)
Percentage Change Imports	2.98	3.12	3.22	3.30	2.72	2.81
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Non-Market Economy	.77	.82	.77	.85	.81	.88
	(.025)	(.020)	(.027)	(.017)	(.022)	(.014)
Campaign Contributions	-.49	-.51	-.49	-.50	-.38	-.40
	(.000)	(.000)	(.000)	(.000)	(.003)	(.002)
Presidential Election	2.62	2.48	2.63	2.49	2.64	2.51
	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
Constant	5.65	1.56	10.1	1.74	14.2	6.19
	(.449)	(.622)	(.214)	(.574)	(.098)	(.079)
Number Obs.	3,370	3,325	3,370	3,325	3,370	3,325
Time trend	✓	✓	✓	✓	✓	✓
NAICS 3-digit FE	✓	✓	✓	✓	✓	✓

Logit models with robust standard errors, clustered by petition. p-values in parentheses.

Table H11 Success of AD Petitions: Vertical Integration

	(1)	(2)	(3)	(4)	(5)	(6)
η	.49	.49				
	(.007)	(.007)				
η^T			.23	.23		
			(.000)	(.000)		
η^M					2.32	2.28
					(.000)	(.000)
Vertical Integration	.28		.27		.31	
	(.001)		(.001)		(.000)	
Subsidiaries in Target Market		.22		.23		.21
		(.256)		(.247)		(.285)
MNC	-.34	-.31	-.35	-.31	-.34	-.30
	(.036)	(.042)	(.036)	(.039)	(.042)	(.049)
Stock-listed	-.20	-.15	-.19	-.14	-.13	-.072
	(.368)	(.500)	(.381)	(.514)	(.538)	(.727)
Real Exchange Rate	2.07	2.12	2.17	2.21	2.05	2.08
	(.003)	(.002)	(.001)	(.001)	(.002)	(.001)
Fixed Assets	-.040	-.010	-.041	-.013	-.012	.019
	(.735)	(.931)	(.736)	(.917)	(.922)	(.872)
Steel Products	-1.40	-1.29	-1.37	-1.24	-1.54	-1.41
	(.056)	(.086)	(.050)	(.083)	(.034)	(.059)
Industry Output (log)	.30	.32	.23	.25	-.11	-.086
	(.137)	(.127)	(.238)	(.223)	(.637)	(.708)
Percentage Change Imports	2.97	2.91	3.14	3.07	2.70	2.63
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Non-Market Economy	.80	.81	.82	.83	.85	.86
	(.022)	(.022)	(.020)	(.020)	(.016)	(.016)
Campaign Contributions	-.56	-.48	-.55	-.47	-.46	-.38
	(.000)	(.000)	(.000)	(.000)	(.001)	(.003)
Presidential Election	2.57	2.62	2.57	2.63	2.58	2.63
	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
Constant	1.90	1.40	2.13	1.68	6.47	5.94
	(.556)	(.662)	(.503)	(.595)	(.068)	(.094)
Number Obs.	3,370	3,322	3,370	3,322	3,370	3,322
Time trend	✓	✓	✓	✓	✓	✓
NAICS 3-digit FE	✓	✓	✓	✓	✓	✓

Logit models with robust standard errors, clustered by petition. p-values in parentheses.

Table H12 Success of AD Petitions: Employment

	(1)	(2)	(3)	(4)	(5)	(6)
η	.49	.42				
	(.009)	(.022)				
η^T			.24	.22		
			(.000)	(.002)		
η^M					2.44	2.01
					(.000)	(.001)
log Employees (firm)	-.046		-.052		-.045	
	(.094)		(.064)		(.108)	
log Employees (industry)		.10		.035		.062
		(.365)		(.754)		(.585)
MNC	-.25	-.33	-.26	-.33	-.28	-.32
	(.129)	(.036)	(.129)	(.039)	(.097)	(.042)
Stock-listed	-.026	-.20	-.0075	-.20	.075	-.13
	(.905)	(.350)	(.972)	(.358)	(.718)	(.513)
Real Exchange Rate	2.18	1.31	2.30	1.40	2.15	1.29
	(.002)	(.052)	(.001)	(.037)	(.001)	(.047)
Fixed Assets	-.11	-.074	-.12	-.079	-.098	-.041
	(.463)	(.583)	(.458)	(.562)	(.512)	(.759)
Steel Products	-1.00	-1.30	-.94	-1.20	-1.10	-1.37
	(.185)	(.106)	(.184)	(.117)	(.143)	(.085)
Industry Output (log)	.24	.22	.14	.17	-.23	-.12
	(.242)	(.339)	(.487)	(.434)	(.326)	(.622)
Percentage Change Imports	3.11	2.88	3.36	3.06	2.94	2.66
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Non-Market Economy	.75	.79	.76	.80	.80	.84
	(.038)	(.030)	(.035)	(.029)	(.028)	(.022)
Campaign Contributions	-.35	-.52	-.34	-.52	-.23	-.43
	(.023)	(.000)	(.029)	(.000)	(.153)	(.001)
Presidential Election	2.44	2.34	2.47	2.35	2.47	2.37
	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)
Constant	1.49	.23	1.83	.75	7.15	4.56
	(.638)	(.948)	(.559)	(.824)	(.040)	(.238)
Number Obs.	2,705	3,290	2,705	3,290	2,705	3,290
Time trend	✓	✓	✓	✓	✓	✓
NAICS 3-digit FE	✓	✓	✓	✓	✓	✓

Logit models with robust standard errors, clustered by petition. p-values in parentheses.

Table H13 **Success of AD Petitions: Industry-Level Controls**

	(1)	(2)	(3)	(4)	(5)	(6)
η	.56	.40				
	(.012)	(.049)				
η^T			.26	.20		
			(.001)	(.008)		
η^M					2.48	1.93
					(.000)	(.001)
GDP Growth added	5.32		5.52		4.66	
	(.002)		(.001)		(.007)	
Value Added (%GDP)		.30		.29		.28
		(.000)		(.000)		(.000)
Capital-Labor Ratio		3.36		3.23		3.10
		(.002)		(.002)		(.003)
MNC	-.33	-.35	-.34	-.36	-.32	-.35
	(.014)	(.020)	(.014)	(.017)	(.019)	(.020)
Stock-listed	-.21	-.039	-.20	-.035	-.12	.032
	(.433)	(.895)	(.469)	(.908)	(.633)	(.908)
Real Exchange Rate	2.19	2.07	2.30	2.15	2.07	2.02
	(.001)	(.004)	(.001)	(.004)	(.001)	(.003)
Fixed Assets	-.057	-.56	-.059	-.54	-.025	-.50
	(.596)	(.004)	(.583)	(.004)	(.823)	(.007)
Steel Products	-1.43	-.99	-1.38	-.98	-1.55	-1.14
	(.065)	(.134)	(.058)	(.126)	(.056)	(.105)
Industry Output (log)	.25	.27	.18	.21	-.16	-.067
	(.377)	(.310)	(.502)	(.398)	(.611)	(.818)
Percentage Change Imports	2.87	2.68	3.01	2.84	2.54	2.48
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Non-Market Economy	.82	.84	.85	.85	.87	.88
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Campaign Contributions	-.53	-.54	-.52	-.53	-.40	-.44
	(.000)	(.001)	(.003)	(.004)	(.012)	(.009)
Presidential Election	2.56	2.53	2.56	2.54	2.59	2.56
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Constant	1.92	3.01	2.09	3.17	7.15	6.97
	(.594)	(.446)	(.576)	(.435)	(.191)	(.186)
Number Obs.	3,327	3,244	3,327	3,244	3,327	3,244
Time trend	✓	✓	✓	✓	✓	✓
NAICS 3-digit FE	✓	✓	✓	✓	✓	✓

Logit models with robust standard errors, clustered by petition. p-values in parentheses.

Table H14 Success of AD Petitions: Political Controls

	(1)	(2)	(3)	(4)	(5)	(6)
η	.34	.49				
	(.082)	(.006)				
η^T			.18	.23		
			(.015)	(.000)		
η^M					1.76	2.30
					(.014)	(.000)
Counties > 250 employees	.21		.18		.17	
	(.053)		(.109)		(.131)	
Democratic Representation		-.24		-.23		-.00031
		(.804)		(.810)		(1.000)
MNC	-.37	-.31	-.36	-.31	-.35	-.30
	(.020)	(.054)	(.023)	(.053)	(.027)	(.062)
Stock-listed	-.083	-.12	-.085	-.11	-.032	-.040
	(.691)	(.564)	(.684)	(.581)	(.873)	(.840)
Real Exchange Rate	1.84	2.09	1.96	2.18	1.86	2.07
	(.007)	(.002)	(.003)	(.001)	(.004)	(.001)
Fixed Assets	.0073	-.034	.0021	-.034	.025	-.0067
	(.952)	(.775)	(.986)	(.775)	(.835)	(.955)
Steel Products	-1.38	-1.37	-1.35	-1.33	-1.48	-1.49
	(.065)	(.063)	(.060)	(.057)	(.048)	(.042)
Industry Output (log)	.036	.30	.021	.23	-.23	-.11
	(.878)	(.144)	(.929)	(.250)	(.319)	(.637)
Percentage Change Imports	2.90	2.93	3.05	3.10	2.72	2.68
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Non-Market Economy	.81	.80	.82	.82	.85	.85
	(.020)	(.021)	(.020)	(.019)	(.017)	(.016)
Campaign Contributions	-.48	-.49	-.48	-.48	-.40	-.38
	(.000)	(.000)	(.000)	(.000)	(.001)	(.002)
Presidential Election	2.52	2.59	2.54	2.60	2.55	2.62
	(.001)	(.001)	(.001)	(.000)	(.001)	(.001)
Constant	4.26	1.74	4.05	1.97	7.27	6.34
	(.215)	(.597)	(.233)	(.543)	(.040)	(.080)
Number Obs.	3,370	3,370	3,370	3,370	3,370	3,370
Time trend	✓	✓	✓	✓	✓	✓
NAICS 3-digit FE	✓	✓	✓	✓	✓	✓

Logit models with robust standard errors, clustered by petition. p-values in parentheses.

Table H15 Success of AD Petitions: Swing States

	(1)	(2)	(3)	(4)	(5)	(6)
η	.48	.49				
	(.008)	(.006)				
η^T			.23	.24		
			(.003)	(.002)		
η^M					2.27	2.31
					(.000)	(.000)
Industry employment in swing states (log)	.19		.12		.12	
	(.419)		(.703)		(.692)	
Firm in swing state		.007		.003		.043
		(.961)		(.971)		(.676)
MNC	-.31	-.32	-.32	-.33	-.31	-.32
	(.048)	(.042)	(.030)	(.012)	(.038)	(.016)
Stock-listed	-.12	-.099	-.11	-.093	-.045	-.028
	(.568)	(.640)	(.716)	(.764)	(.874)	(.921)
Real Exchange Rate	2.06	2.17	2.16	2.27	2.04	2.08
	(.002)	(.002)	(.004)	(.005)	(.003)	(.004)
Fixed Assets	-.023	-.12	-.027	-.12	.0017	-.087
	(.848)	(.344)	(.811)	(.354)	(.989)	(.497)
Steel Products	-1.36	-1.31	-1.32	-1.28	-1.49	-1.43
	(.066)	(.083)	(.077)	(.099)	(.069)	(.094)
Industry Output (log)	.28	.32	.22	.25	-.11	-.087
	(.177)	(.117)	(.421)	(.366)	(.724)	(.787)
Percentage Change Imports	2.92	3.12	3.10	3.31	2.67	2.83
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Non-Market Economy	.80	.82	.82	.84	.85	.88
	(.022)	(.018)	(.000)	(.000)	(.000)	(.000)
Campaign Contributions	-.49	-.51	-.48	-.50	-.39	-.41
	(.000)	(.000)	(.004)	(.002)	(.016)	(.009)
Presidential Election	2.57	2.72	2.59	2.72	2.59	2.72
	(.001)	(.001)	(.000)	(.000)	(.000)	(.000)
Constant	1.84	1.29	2.05	1.56	6.27	5.98
	(.569)	(.686)	(.555)	(.644)	(.171)	(.183)
Number Obs.	3,370	3,272	3,370	3,272	3,370	3,272
Time trend	✓	✓	✓	✓	✓	✓
NAICS 3-digit FE	✓	✓	✓	✓	✓	✓

Logit models with robust standard errors, clustered by petition. p-values in parentheses.

Table H16 Success of AD Petitions: Campaign Contributions and Lobbying

	(1)	(2)	(3)	(4)	(5)	(6)
η	.50	.46				
	(.023)	(.035)				
η^T			.24	.22		
			(.004)	(.004)		
η^M					2.29	2.35
					(.000)	(.000)
Campaign Contributions	-.48		-.47		-.39	
	(.000)		(.001)		(.002)	
Lobbying	-.078		-.089		.039	
	(.754)		(.754)		(.888)	
Any Campaign Contributions		.061		.043		.11
		(.743)		(.832)		(.575)
Any Lobbying		.022		.015		.082
		(.930)		(.956)		(.769)
MNC	-.31	-.32	-.31	-.32	-.31	-.32
	(.026)	(.017)	(.023)	(.014)	(.027)	(.016)
Stock-listed	-.092	-.28	-.083	-.26	-.051	-.21
	(.704)	(.203)	(.736)	(.243)	(.833)	(.319)
Real Exchange Rate	2.10	1.96	2.20	2.07	2.07	1.98
	(.005)	(.007)	(.005)	(.007)	(.003)	(.003)
Fixed Assets	-.037	-.022	-.038	-.022	-.0062	.0065
	(.724)	(.845)	(.719)	(.838)	(.955)	(.955)
Steel Products	-1.37	-1.52	-1.33	-1.48	-1.49	-1.66
	(.082)	(.055)	(.075)	(.044)	(.068)	(.041)
Industry Output (log)	.29	.33	.22	.26	-.11	-.10
	(.308)	(.253)	(.401)	(.334)	(.738)	(.741)
Percentage Change Imports	2.95	2.96	3.12	3.14	2.69	2.74
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Non-Market Economy	.79	.83	.81	.85	.85	.88
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Presidential Election	2.62	2.58	2.63	2.59	2.62	2.60
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Constant	1.94	1.64	2.19	1.93	6.27	6.32
	(.572)	(.623)	(.539)	(.574)	(.177)	(.163)
Number Obs.	3,370	3,370	3,370	3,370	3,370	3,370
Time trend	✓	✓	✓	✓	✓	✓
NAICS 3-digit FE	✓	✓	✓	✓	✓	✓

Logit models with robust standard errors, clustered by petition. p-values in parentheses.

Table H17 Success of AD Petitions: Export Market FE and Import Volumes

	(1)	(2)	(3)	(4)	(5)	(6)
η	.44	.54				
	(.015)	(.007)				
η^T			.21	.26		
			(.002)	(.000)		
η^M					2.12	2.79
					(.001)	(.000)
Import volume (log)	.16		.13		.092	
	(.116)		(.212)		(.374)	
MNC	-.31	-.30	-.31	-.31	-.30	-.31
	(.057)	(.074)	(.055)	(.072)	(.064)	(.077)
Stock-listed	-.13	-.083	-.12	-.078	-.054	.0027
	(.547)	(.711)	(.570)	(.727)	(.792)	(.990)
Real Exchange Rate	2.13	2.02	2.21	2.11	2.08	2.05
	(.001)	(.005)	(.001)	(.003)	(.001)	(.003)
Fixed Assets	-.019	-.069	-.022	-.071	.00093	-.036
	(.870)	(.566)	(.851)	(.559)	(.994)	(.766)
Steel Products	-1.53	-1.87	-1.47	-1.85	-1.59	-2.13
	(.035)	(.019)	(.034)	(.016)	(.029)	(.006)
Industry Output (log)	.21	.32	.16	.25	-.12	-.17
	(.320)	(.136)	(.442)	(.224)	(.611)	(.495)
Percentage Change Imports	2.85	2.82	3.02	2.99	2.63	2.57
	(.000)	(.000)	(.000)	(.000)	(.001)	(.001)
Non-Market Economy	.82	2.03	.83	2.10	.86	2.14
	(.020)	(.101)	(.018)	(.082)	(.016)	(.095)
Campaign Contributions	-.49	-.53	-.48	-.52	-.39	-.42
	(.000)	(.000)	(.000)	(.000)	(.002)	(.001)
Presidential Election	2.61	2.89	2.62	2.91	2.61	2.97
	(.000)	(.001)	(.000)	(.001)	(.000)	(.001)
Constant	-.75	1.75	-.055	1.98	4.47	7.11
	(.825)	(.649)	(.987)	(.603)	(.241)	(.105)
Number Obs.	3,370	3,202	3,370	3,202	3,370	3,202
Time trend	✓	✓	✓	✓	✓	✓
Export Market FE		✓		✓		✓
NAICS 3-digit FE	✓	✓	✓	✓	✓	✓

Logit models with robust standard errors, clustered by petition. p-values in parentheses.

Table H18 Success of AD Petitions: NME Split Samples

	(1) ME	(2) NME	(3) ME	(4) NME	(5) ME	(6) NME
η	.82	.12				
	(.000)	(.748)				
η^T			.35	.14		
			(.000)	(.256)		
η^M					3.38	1.35
					(.000)	(.196)
MNC	-.45	.049	-.44	.024	-.42	.045
	(.004)	(.894)	(.005)	(.949)	(.007)	(.904)
Stock-listed	-.15	.042	-.14	.034	-.077	.077
	(.433)	(.936)	(.449)	(.947)	(.675)	(.880)
Real Exchange Rate	4.07	.72	4.13	.87	3.80	.79
	(.000)	(.401)	(.000)	(.302)	(.000)	(.363)
Fixed Assets	.12	-.089	.11	-.11	.13	-.082
	(.549)	(.717)	(.564)	(.662)	(.483)	(.748)
Steel Products	-1.05	-1.54	-.89	-1.80	-.67	-1.99
	(.336)	(.228)	(.370)	(.131)	(.560)	(.099)
Industry Output (log)	.32	.11	.23	.055	-.36	-.11
	(.262)	(.714)	(.418)	(.842)	(.228)	(.732)
Percentage Change Imports	3.60	2.58	3.73	2.76	2.93	2.59
	(.000)	(.062)	(.000)	(.041)	(.000)	(.062)
Non-Market Economy	0	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)	(.)
Campaign Contributions	-.45	-.71	-.42	-.70	-.25	-.66
	(.001)	(.005)	(.003)	(.006)	(.088)	(.009)
Presidential Election	3.37	1.56	3.39	1.49	3.31	1.55
	(.000)	(.209)	(.000)	(.228)	(.000)	(.223)
Constant	-.17	-5.46	.11	-6.38	7.52	-3.54
	(.967)	(.521)	(.978)	(.454)	(.079)	(.682)
Number Obs.	2,107	1,134	2,107	1,134	2,107	1,134
Time trend	✓	✓	✓	✓	✓	✓
NAICS 3-digit FE	✓	✓	✓	✓	✓	✓

Logit models with robust standard errors, clustered by petition. p-values in parentheses.

Table H19 U.S. Congress: Briefs in Support of Petitioners

	(1)	(2)	(3)	(4)	(5)	(6)
η	1.19	1.69				
	(.002)	(.003)				
η^T			.27	.38		
			(.004)	(.012)		
η^M					2.19	2.81
					(.001)	(.006)
Steel Products	-.39	-1.26	-.23	-1.06	-.56	-1.18
	(.193)	(.045)	(.467)	(.131)	(.090)	(.068)
Industry Output (log)	-.22	-.13	-.093	.060	-.28	-.21
	(.364)	(.597)	(.664)	(.818)	(.264)	(.528)
Percentage Change Imports	-2.31	-2.54	-2.38	-2.71	-2.53	-2.89
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Non-Market Economy	1.26	1.27	1.27	1.23	1.28	1.31
	(.002)	(.000)	(.002)	(.001)	(.002)	(.000)
Campaign Contributions	-.032	.0044	-.026	.0029	-.016	.012
	(.757)	(.964)	(.802)	(.976)	(.882)	(.895)
Presidential Election	-.15	.69	-.18	.69	-.20	.69
	(.791)	(.230)	(.747)	(.240)	(.719)	(.235)
MNC		.19		.21		.19
		(.214)		(.196)		(.229)
Stock-listed		-.16		-.19		-.16
		(.331)		(.296)		(.374)
Real Exchange Rate		1.09		1.20		.81
		(.156)		(.126)		(.332)
Fixed Assets		-.16		-.17		-.17
		(.135)		(.107)		(.109)
Constant	-341.6	-210.7	-367.9	-249.4	-349.5	-215.0
	(.002)	(.106)	(.001)	(.051)	(.001)	(.106)
Number Obs.	1,407	1,254	1,407	1,254	1,407	1,254
Time trend	✓	✓	✓	✓	✓	✓
NAICS 3-digit FE		✓		✓		✓

Negative binomial models with robust standard errors, clustered by petition. p-values in parentheses.