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Production Network Features of Industrial Policy

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ABSTRACT: Industrial policy has gained popularity in recent years and across all regions and income levels. Consequently, it is increasingly important to understand how governments choose the sectors they target. This analysis explores the role of domestic production networks in sector targeting, while controlling for other sector and global value chain characteristics. Combining datasets on industrial policy (Global Trade Alert) and input-output linkages (ICIO, OECD) provides novel insight into the network features of industrial policy. In particular, a sector's 'centrality'—i.e., its degree of connectedness - within the domestic production network is an important and significant predictor of sector intervention. The results indicate that industrial policy is used differently across regions, income groups, time periods, and types of policy tools. Notably, emerging economies tend to target more central sectors, while advanced economies target less central ones, on average. However, there has been a global shift toward more central sectors over time. Lastly, subsidies are deployed on more central sectors, while tariffs are used on less central ones.

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WORKING PAPERS

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Production Network Features of Industrial Policy

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Abstract

Industrial policy has gained popularity in recent years and across all regions and income levels. Consequently, it is increasingly important to understand how governments choose the sectors they target. This analysis explores the role of domestic production networks in sector targeting, while controlling for other sector and global value chain characteristics. Combining datasets on industrial policy (Global Trade Alert) and input-output linkages (ICIO, OECD) provides novel insight into the network features of industrial policy. In particular, a sector's 'centrality'—i.e., its degree of connectedness - within the domestic production network is an important and significant predictor of sector intervention. The results indicate that industrial policy is used differently across regions, income groups, time periods, and types of policy tools. Notably, emerging economies tend to target more central sectors, while advanced economies target less central ones, on average. However, there has been a global shift toward more central sectors over time. Lastly, subsidies are deployed on more central sectors, while tariffs are used on less central ones.

1 Introduction

Industrial policy has been significantly on the rise in recent years. As such, it has garnered the attention of policy makers and researchers, leading to a rapidly growing body of work on its impacts. In the presence of complex value chains, industrial policy (IP) has the potential for far-reaching effects. Indeed, the literature underscores the importance of production networks for the propagation of IP through the domestic (Liu & Tsyvinski, 2024; Liu, 2019) and global (Rotunno & Ruta, 2023, 2024; Barattieri et al., 2024) economies. This paper contributes to the discussion by first systematically placing recent industrial policy in its domestic and global production network context, then establishing the sector's network positioning as a determinant of IP targeting.

Toward the first objective, this paper merges two datasets - the Global Trade Alert (GTA) database (Evenett & Fritz, 2020) and the OECD's Inter-Country Input-Output (ICIO) tables (OECD, 2023). The GTA database covers IP announcements, including information on targeted sectors. These sectors are then placed in a production network context using the ICIO tables. Specifically, measures of sector centrality - the degree of connectedness to other sectors in the production network - are computed at the domestic and global levels. The second objective employs a panel logistic regression to examine how a sector's centrality, as well as other sector and GVC characteristics, affect the likelihood of IP announcements.

Results indicate different targeting patterns across income levels, regions, time periods and policy tools. Emerging markets and Asian countries tend to prioritize central sectors throughout the sample period, 2009 to 2023. By contrast, advanced economies and European countries target less central ones, on average, and only begin to shift toward central sectors later in the sample period. Analogously, IP across all regions and income groups is increasingly focused on more central sectors over time. Finally, the choice of policy tools also varies: subsidies, export restrictions, and export support policies are typically used for central sectors, while import tariffs and antidumping measures are applied to less central sectors. Importantly, these observations are intended to characterize the determinants of IP, rather than its results. While IP can be used in an attempt to alter the production network, such structural transformation is unlikely to materialize within the fifteen-year time horizon of the data.

Sector-level control variables reveal other salient characteristics and GVC considerations. First, large sectors and those with higher final demand are less likely to receive IP support. Second, sectors reliant on imported inputs are more frequently targeted. Third, there are differences between advanced and emerging economies in the most relevant export metrics. Advanced economies appear to be mainly targeting sectors with high exports for intermediate use. Emerging markets, on the other hand, target sectors with high export share out of global trade.

2 Literature Review

This work draws on two strands of literature in industrial policy. The first has concerned itself with documenting the recent increase in industrial policy (Evenett et al., 2024; Rotunno & Ruta, 2023; Juhász et al., 2024, 2023) and analyzing its effects on trade (Rotunno & Ruta, 2023, 2024; Barattieri et al., 2024). The second is a structural analysis of the propagation of policy through a production networks (Liu, 2019; Liu & Tsyvinski, 2024). The principal contribution of this paper is to bring the theoretical insights into an empirical analysis using current and multi-country data.

At present there is little consensus on the types of policies and policy objectives that constitute industrial policy. This analysis will rely on a comparatively broad definition set forth in the surveillance guidelines of the International Monetary Fund (2024):

> "IP refers to targeted government interventions aimed at supporting specific domestic firms, industries, or narrowly defined economic activities to achieve certain national (economic or non-economic) objectives."

This definition is preferred as it does not take a strong stance on specific policy objectives, which are unobservable in the data.

The principle data source is provided by the Global Trade Alert initiative, founded at the University of St. Gallen. Thanks to this comprehensive data on policy announcements, a new literature paints a detailed and nuanced picture of the recent increase in industrial policy. Descriptive evidence suggests that 'new' IP differs from that of the late-twentieth century. It is more technocratic and targeted instead of relying on broad-scope tariffs (Juhász et al., 2024). Recent IP has been driven substantially by subsidies in advanced economies, and to a lesser degree by trade restrictions in emerging and developing economies (Evenett et al., 2024). In exploring the determinants of IP, research points to a number of motivations [1] and targeted products [2] (Juhász et al., 2024; Evenett et al., 2024).

Further research links IP to trade outcomes. Rotunno and Ruta (2024) show that domestic subsidies promote both imports and exports. In earlier work, the authors show that Chinese subsidies promoted Chinese exports in downstream industries (Rotunno & Ruta, 2023). Similarly, Chinese subsidies to shipbuilding have been linked to subsequent rise in exports (Barwick et al., 2024). In addition, Barattieri and co-authors (2024) find that preferential trade agreements limit the trade effects of IP.

In the context of industrial policy, a natural line of inquiry is the degree of propagation or spillover across the production network. Intuitively, propagation will affect the policy's costs and benefits, and who bears or receives them. Liu (2019) shows that, in the presence of market distortions[3], shocks propagate 'down' the production network. In particular, the author demonstrates that small sectors with high 'distortion centrality'[4] offer the higher opportunity for externality correction with smaller fiscal outlays (Liu, 2019). Later work by Liu & Tsyvinski, that in the presence of adjustment costs to changing inputs, shocks to upstream sectors propagate down the production chain (2024). Finally, a key paper in this literature provides measures of sector upstreamness (Antràs et al., 2012).

This paper contributes to the discussion in three main ways. First, it places

[1] Frequently cited motives are strategic competitiveness, climate change mitigation, economic resilience, and national security

[2] IP targeting products such as semiconductors, critical minerals, green technology, civilian-military use products

[3] The author remains agnostic on the source of the distortions, modeling them instead as reduced-form wedges (Liu, 2019).

[4] Sectors with high distortion centrality "tend to be upstream sectors that supply inputs, directly or indirectly, to many distorted downstream sectors" (Liu, 2019).

recent IP in its production network context, which is not yet been performed in a systematic way with up-to-date, multi-country data. Second, it emphasizes the role of a sector's centrality within the domestic production network as a key determinant of IP targeting, while controlling for GVC positioning. Third, it borrows insights from structural work and empirically applies them to a broad set of countries using the most recent data available.

This paper draws from the insights in Liu (2019), as the rationale for network analysis of recent IP. However, it does not take a stance on the specific motivations for these policies. While important, investigating the sources and magnitudes of market distortions is beyond the scope of the project. Instead, this paper focuses on situating the 'targeted sectors'[5] within the domestic and global production networks using related, but distinct, empirical measures of centrality. As such, results should be interpreted as positive statements.

3 Data

This project combines two datasets to form a novel comparison: policy announcements from Global Trade Alert and the OECD's Inter-Country Input-Output tables. Combining these two datasets allows for important insights into production network features of recent IP. As of yet, this dimension of recent IP (policies announced since 2008) has not been systematically documented. Further, this analysis takes a larger geographic scope with data on 76 countries.

3.1 Global Trade Alert Database

The Global Trade Alert (GTA) database consists of a collection of individual announcements of policies affecting trade relationships. GTA is an initiative originally launched at University of St. Gallen and is currently housed at the St.Gallen Endowment for Prosperity through Trade. The data compiles announcements and analyzes the text to extract information such as implementing jurisdiction, announcement date, type

[5] In the language of this paper, a 'targeted' sector is simply a sector that is the direct 'recipient' of an IP measure.

of intervention, and affected sector. The data covers policies from 195 countries ('Implementing Jurisdictions'), of which 31 are in Asia and Pacific. The temporal coverage is between November 2008 and May 2024. The data includes information on affected sector. In total, there are 329 CPC (Rev. 2.1) 3-digit sector codes[6].

Table 3.1: Global Trade Alert, Data Coverage

Number of Countries	195
Number of Sectors	329
Number of Policy Tools	29
First Announcement Date	6/20/2008
Last Announcement Date	5/31/2024

Details on country and region coverage in Appendix 1.
Source: Global Trade Alert (2024)

In total, the database includes 29 types of policies, including tariff and non-tariff measures[7]. Globally, the most common type of policies deployed are subsidies (46.8 percent), followed by import tariffs (15.8 percent), export support measures (11.0 percent), antidumping measures (4.6 percent), and export restrictions (3.1 percent). In accordance with the IP definition in Section 2 (International Monetary Fund, 2024), the analysis to follow does not place any restriction on the types of policies or policy tools. The frequency of all policy tools is available in Appendix 1.

Table A1.2 (Appendix 1) ranks the most used interventions by region. While there are some differences in the most used tools across regions, the aforementioned five tools are frequently used in all regions. Additionally, subsidies are the most used tool in every year, between 2009 and 2024. Import tariffs are the second most used tool in all years except 2012-2013. Tool use by income group is shown in Table A1.3 (Appendix 1). Subsidies are the most frequently used tool in both advanced and emerging economies. Other commonly used tools, by both income groups, are import tariffs, export supports and export restrictions. Low income countries make more use of import tariffs and export restrictions, likely due to lower fiscal capacity. Still, subsidies rank third in their most used tools.

[6]Some policies also contain more granular 6-digit HS2012 codes. They are not used in this analysis in order to match the level of aggregation of the input-output tables.

[7]Non-tariff measures are classified according to the MAST chapter from the UN Conference on Trade and Development.

Table 3.2: Global Trade Alert, Policy Counts for Top 5 Tools

Intervention Type	Count	Percent
Subsidies	27117	46.8
Import Tariffs	9144	15.8
Export Support	6373	11.0
Antidumping	2675	4.6
Export Restriction	1777	3.1
Other	10864	18.7
Total	57950	

Count is number of unique policy announcements that use given tool.
More details on counts by policy tool and 'Other' category in Appendix 1.
Source: Global Trade Alert (2024)

Data Limitations

An important limitation of the GTA dataset, and all resulting research, is that metrics from this dataset is based on counts of policies. As of yet, there is no available data on the magnitude of IP. In an attempt to remedy this, the analysis to follow focuses on the extensive margin only, using binary variables rather than the count of policies. That is, if a policy is implemented in a given country-sector-year, the binary variable takes the value one. Note that a policy can target multiple sectors. Without further information on the magnitudes, all listed sectors are treated equally.

The sector information is available for most policies, with 19.3 percent of policies missing sector information. Since sector analysis is integral to this exercise, observations without a CPC code are dropped. Table A1.4 (Appendix 1) breaks this down by intervention for the top tools. The highest share of missing sector information is in subsidies (15.3 percent) and export support measures (14.1 percent).

3.2 OECD Inter-Country Input-Output Tables

The OECD provides input-output tables that include links between countries. The data includes input-output links for 76 countries and 49 sectors, annually between 1996 and 2020, as per Table 3.3 below.

The main section of the I-O tables is the transaction matrix, showing the value of transactions between country-sector pairs. Further, the table includes measures for

Table 3.3: Inter-Country Input-Output Data, OECD, Coverage

Number of Countries	76
Number of Sectors	45
Frequency	Annual
Year Available	1996-2020

Details on country, region, sector coverage in Appendix 1
Source: OECD (2023)

each country-sector's final demand, value added and total output[8].

Country, and sector coverage in OECD Input-Output Tables

Country coverage is extensive in Asia (19 countries) and in Europe (36 countries), but less comprehensive in the Western Hemisphere (9 countries), Middle East and Central Asia (7 countries), and Africa (5 countries). In terms of income, there are 36 advanced economies, 33 emerging economies, and 7 low-income economies. The table below shows the counts by both region and income dimensions.

Table 3.4: ICIO Data, OECD, Coverage by Income Group and Region

	Advanced	Emerging	Low-Income	Total
Africa	0	2	3	5
Asia Pacific	7	8	4	19
Europe	27	9	0	36
Middle East, Central Asia	0	7	0	0
Western Hemisphere	2	7	0	9
Total	36	33	7	76

Details on country and region coverage in Appendix 1.
Source: OECD (2023)

This IO table was chosen over other alternatives due to its balance of sector and country coverage. Other commonly used input-output tables are MRIO EORA26 and WIOD. EORA26 has slightly higher country coverage in some regions (e.g., Asia with 28 countries), but are limited to 26 sectors. On the other hand, the coverage from WIOD has better sector disaggregation (56 sectors), but low country coverage, which is especially reduced in Asia (7 countries). As an additional advantage, the

[8]Final demand is available by country and broken down into six sub-categories. The analysis aggregates final demand into domestic and foreign.

ICIO table facilitates the link to the GTA data. First, the concordance between the ICIO sectors and ISIC Rev.4 is provided by OECD. Second, there is a standard concordance table between ISIC and CPC codes from the UN Statistics Division.

3.3 Merged dataset

GTA and OECD data are combined based on standard correspondence tables[9]. The merged dataset consists of policy announcement information (e.g. Implementing Jurisdiction, announcement date, policy tool), the affected sector code, and other (country-)sector variables (sector production centrality measures and control variables).Due to the lower country and sector coverage in the I-O table compared to the GTA, the resulting merged data has the following coverage:

Table 3.5: Merged Dataset, Coverage

Number of Countries	76
Number of Asian Countries	19
Number of Sectors	43
Year Available	2009-2023

Details on country, region, sector coverage in Appendix 1.
Source: OECD (2023), Global Trade Alert (2024), Author calculation

Data Limitations

Also, note that the ICIO tables are available until 2020. However, in the context of IP, it is important to capture recent trends. To do this, the input-output structure from 2019 is imposed on 2021 to 2023. This abstracts from possible changes in the input-output linkages post-covid. However, at this level of aggregation, linkages are less likely to change in the short-run. Instead, the interpretation of the results for 2021 to 2023 should be interpreted as "holding constant the input-output structure".

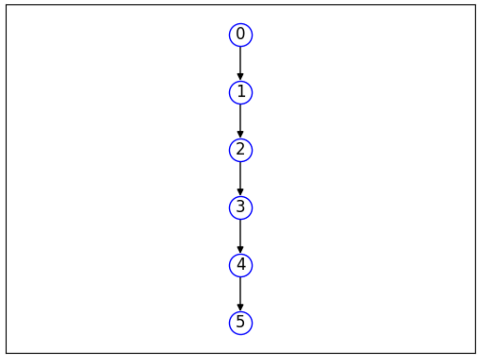
[9] Note that the OECD sector codes can be expressed in ISIC Rev.4, using the conversion provided in the documentation. Additionally, GTA sector codes are converted from CPC Rev 2.1 to ISIC Rev 4 using a standard correspondence table from the UN Statistics Division (United Nations Statistics Division, 2015).

4 Sector Centrality Measures

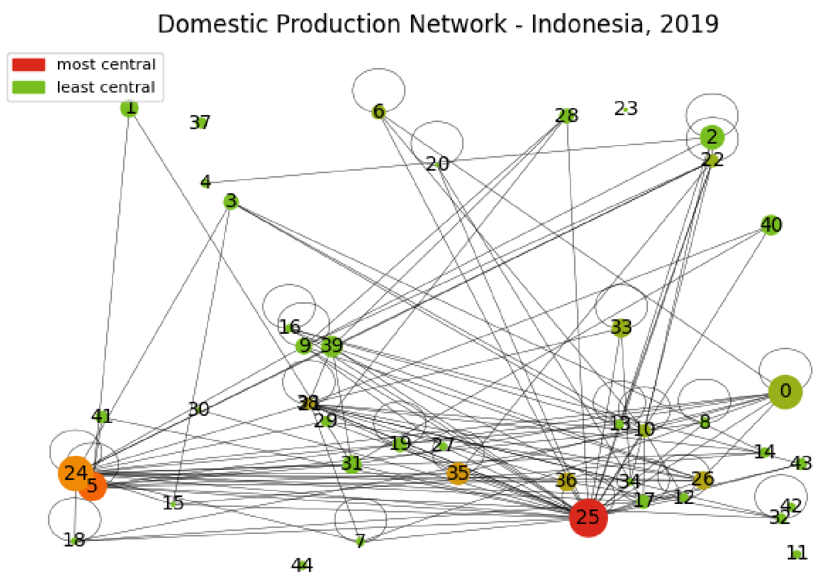
Previous work has empirically and theoretically demonstrated that, in the presence of distortions or adjustment costs, policy interventions propagate 'down' the production chain (Liu & Tsyvinski, 2024; Liu, 2019). As previously discussed, Liu 2019 derives a measure of 'distortion centrality' and relates it to upstreamness. Hence, IP that targets upstream sectors (ie. closer to the "beginning" of a production chain) also have effects to downstream sectors.

In a simple, linear production chain (a.k.a. snake network), the concepts of upstream and downstream are easily defined and observed (Fig 4.1a); however, in a real-world setting, many of these chains are superimposed, forming production networks (Fig 4.1b). This makes upstream and downstream more difficult to define. A related but distinct concept is network centrality, which captures the relative position of a sector within the production network. This can be defined at the domestic (section 4.1) and global (section 4.2) levels. Appendix A1.6 describes technical aspects of these measures. The comparison between centrality and upstreamness is further explored in section 4.3.

Figure 4.1: Examples of Production Networks



(a). An example of a linear production chain. Sector 0 is most upstream. Sector 5 is most downstream.



(b). Indonesia's domestic production network in 2019. Links <0.1 percent of GDP not pictured. Size of node is proportional to sector size. Color of node indicates the sector's centrality. Sector names found in Table A1.6, Appendix 1.

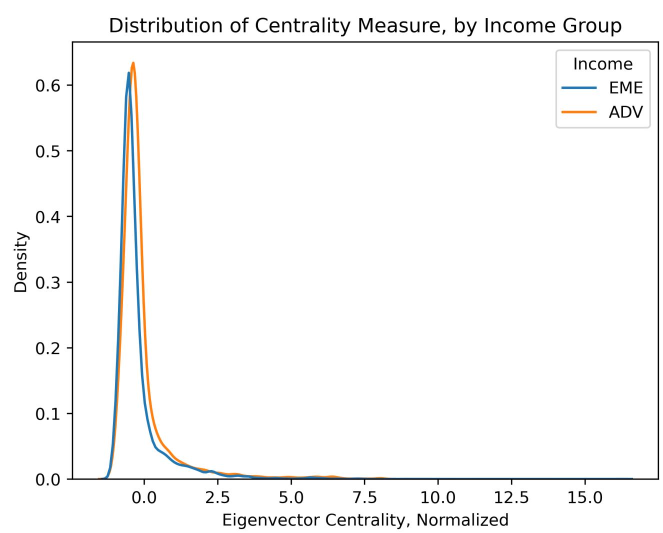
4.1 Domestic Production Centrality

To better represent the complexity of production, this analysis uses the domestic input-output linkages to compute the sector's degree of 'centrality'. This is a measure of the relative position of a sector within the domestic production network.

While there are many measures of centrality, the preferred measure here, eigenvector centrality, has two main advantages. Eigenvector centrality captures all indirect sector linkages and does not require additional parameters to be estimated[10]. Under eigenvector centrality, a sector is more central if it has more connections to other highly connected sectors. Hence, the measure goes beyond the number of first-line input-output links and incorporates indirect connections. In practice, eigenvector centrality consists of a single number for each sector. It is then normalized such that, within country, the measure has zero mean and unit variance.

Importantly, the centrality measure per sector is specific to the country: a given sector can be central to one country's production and not to another. This reflects countries' comparative advantage, degree of specialization, level of production development, among other factors. Figure 4.2 plots the distribution of normalized Eigenvector centrality for emerging and advanced economies. The two distributions are strikingly similar, except a small right-ward shift for the advanced economies.

Figure 4.2: Distribution of normalized eigenvector centralities for country-sectors, by income group.



[10] Bloch et. al. (2023) demonstrate that Eigenvector centrality is an appropriate measure for networks involving 'cycles', which is the case with input-output linkages. Unlike other measures suited to cycles, such as diffusion or Katz-Bonacich centrality, it does not require the estimation of a parameter governing the probability of shock pass-through.

Taking a look within the distribution reveals both differences and similarities in sector centrality between income groups. Table 4.1 shows the ten most central sectors in emerging and advanced economies, on average. The full tables are included in Appendix 1, Tables A1.7a through A1.7c. Differing sector centrality reflects certain anticipated differences in specialization and production methods. For example, in advanced economies, services sectors (such as professional, financial, and real-estate services) are central. Whereas in emerging markets food products and agriculture are, on average, more central. On the other hand, some sectors, such as construction, transportation and financial services, occupy a central position in both income groups. Perhaps surprisingly, food products (though not agriculture) remains central even in advanced economies, albeit less so.

Table 4.1: Average Sector Centrality, by Income Group

Rank	Advanced Economies	Emerging Economies
1	Construction	Food products, beverages and tobacco
2	Professional, scientific and technical activities	Construction
3	Financial and insurance activities	Agriculture, hunting, forestry
4	Real estate activities	Financial and insurance activities
5	Food products, beverages and tobacco	Land transport and transport via pipelines
6	Administrative and support services	Professional, scientific and technical activities
7	Electricity, gas, steam and AC	Electricity, gas, steam and AC
8	Warehousing and support for transportation	Real estate activities
9	Land transport and transport via pipelines	Administrative and support services
10	Motor vehicles, trailers and semi-trailers	Coke and refined petroleum products

Ranking based on mean value of the normalized domestic eigenvector centrality taken for all countries in the income group across all years. Full tables available in Appendix 1, Tables A1.7a - A1.7c.
Source: OECD (2023), Author calculations

Furthermore, eigenvector centrality measure does not have to be related to sector size. To illustrate, Figure 4.1b depicts the domestic production links for Indonesia in 2019. Each node is a sector. The color of the node indicates the sector's centrality. The size of the node is proportional to the sector's size (total sector value-added out of GDP). Consider, sector 5 (Food products, beverages and tobacco) and sector 0 (Agriculture, hunting, forestry) which are similarly sized. Sector 5 is, however, more connected than sector 0. Therefore, centrality provides additional information, over-and-above sector size.

4.2 Global Production Centrality

While the main variable of interest is domestic sector centrality, as an additional check, the same centrality measure is also computed using the global I-O matrix (ie. using all available country-sector linkages). This measure captures the relative position of the country-sector within the global value chain. The global sector centrality is also normalized to have mean zero and unit variance[11]. The inclusion of this variable allows for international considerations in the IP sector choice.

Figure 4.3 compares the (scaled) ranks of country-sectors domestically versus internationally, highlighting select countries. The most central sectors take value one, least central take value zero. The x-axis shows the domestic ranking and the y-axis shows the global ranking. Notably, the size of the economy is an important determinant of global centrality, because the I-O links are weighted by the value of the transactions. Hence, for large economies, even domestically peripheral sectors can still be globally relevant (ie. sectors in the top-right corner). The opposite is the case for small economies. In the regression analysis to follow, differences in size of an economy are captured by the country fixed effects. Finally, export and import variables are controlled for, as described in section 5.

4.3 Sector Centrality Versus Upstreamness

To better understand the distinction between upstreamness and centrality, consider Figure 4.4. This figure plots a measure of average sector upstreamness (Antràs et al., 2012) against the domestic centrality of each country-sector. There is no direct relationship between sector centrality and upstreamness: a highly connected (ie. 'central') sector can be upstream or downstream in the value chain. A sector with many outward (or forward) links can be considered upstream. Conversely, a sector with many inward (or backward) links can be considered downstream. Centrality is informative on the overall importance of a sector, as highly connected sectors have more potential for spillovers and propagation of shocks and policy.

[11] This normalization further ensures that the global and domestic centralities are not co-linear.

Figure 4.3: Domestic vs. global sector centrality, scaled ranks. Ranks are scaled, with most central taking value 1 and least central taking value 0. Domestic centrality is ranked within country. Global centrality is ranked among the full sample. Centrality measures based on ICIO tables (OECD, 2023) and author calculations.

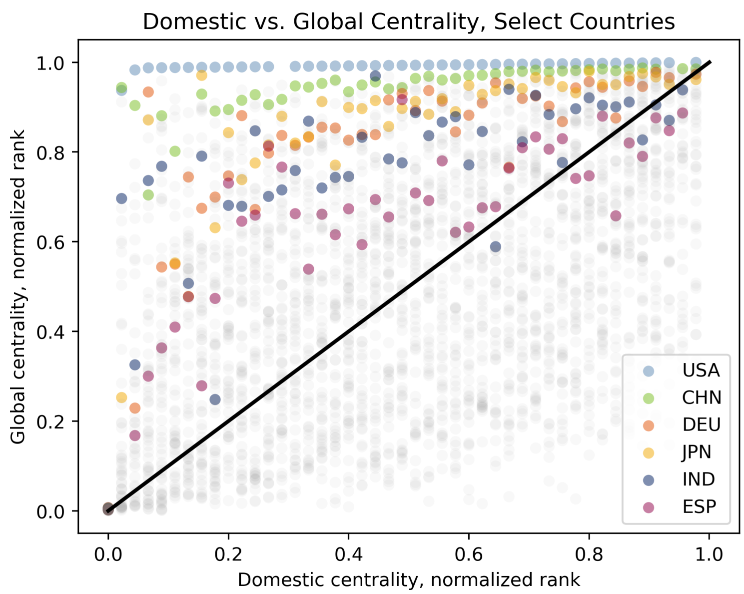
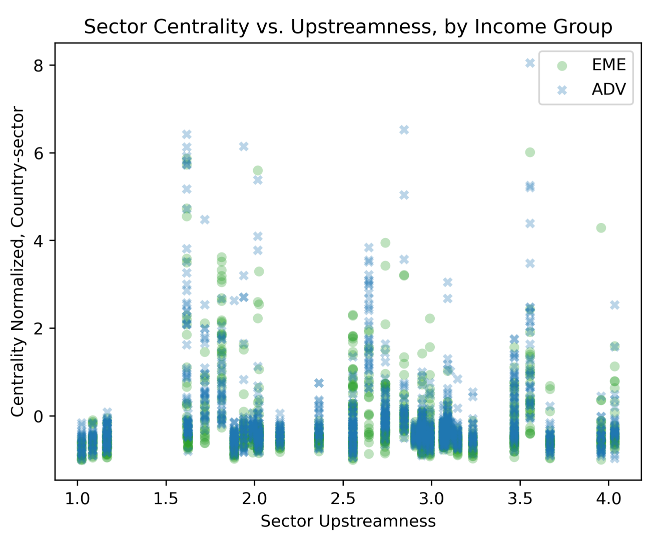


Figure 4.4: Plot of sector upstreamness against country-sector centrality. Upstreamness measure is provided by Antràs (2012), the mean across available countries is computed to obtain a sector-level measure. Centrality measure based on ICIO tables (OECD, 2023) and author calculations.



5 Empirical Methodology

As noted earlier, the objective is to understand whether an IP intervention is more likely to be directed to more central sectors in the domestic economy. The main empirical method is a panel logistic regression in equation 1. The dependent variable, $Logit(IP_{c,s,t})$, is the logit transformation of a binary variable for any IP announced in the given country-sector-year. The key independent variable is the normalized domestic eigenvector centrality, also at the country-sector-year level, $(C^D_{c,s,t})$. To capture global value chain positioning, the regression specification also includes a measure of global sector centrality, $(C^G_{c,s,t})$. Further, a measure of sector upstreamness [12],(U_s), is included. This variable aims to capture inherent upstream or downstream nature of a sector. Next, the specification uses a series of lagged country-sector control variables$(\boldsymbol{X_{c,s,t-2}})$. Finally, country and year fixed effects are included.

$$Logit(IP_{c,s,t}) = \beta_0 + \beta_1 C^D_{c,s,t} + \beta_2 C^G_{c,s,t} + \beta_3 U_s + \boldsymbol{\beta X_{c,s,t-2}} + \delta_t + \delta_c + \epsilon_{c,s,t} \quad (1)$$

Where $C^D_{c,s,t}$ is the sector centrality for the domestic economy, $C^G_{c,s,t}$ is the sector centrality for the global economy, as described in the previous section, U_s is sector upstreamness, and $\boldsymbol{X_{c,s,t-2}}$ is the vector of controls described below.

$$\boldsymbol{X_{c,s,t-2}} = \left[\frac{VA_{c,s,t-2}}{GDP_{c,t-2}}, \frac{FD_{c,s,t-2}}{GDP_{c,t-2}}, \frac{M_{c,s,t-2}}{GDP_{c,t-2}}, \frac{X^F_{c,s,t-2}D}{GDP_{c,t-2}}, \frac{X^Z_{c,s,t-2}}{GDP_{c,t-2}}, \frac{X_{c,s,t-2}}{X_{s,t-2}} \right]$$

(i) value added of domestic industry as share of GDP, $\left(\frac{VA_{c,s,t-2}}{GDP_{c,t-2}}\right)$

(ii) domestic final demand as share of GDP, $\left(\frac{FD_{c,s,t-2}}{GDP_{c,t-2}}\right)$

(iii) Imports used in production of sector s as share of GDP, $\left(\frac{M_{c,s,t-2}}{GDP_{c,t-2}}\right)$

(iv) industry exports for final demand as share of GDP, $\left(\frac{X^F_{c,s,t-2}D}{GDP_{c,t-2}}\right)$

(v) industry exports for intermediate uses as share of GDP, $\left(\frac{X^Z_{c,s,t-2}}{GDP_{c,t-2}}\right)$

[12] Specifically, the sector-level upstreamness measures is computed by taking the average (mean) upstreamness for the set of countries covered in Antràs (2012).

(vi) industry exports as a share of global industry exports, $\left(\frac{X_{c,s,t-2}}{X_{s,t-2}}\right)$.

All the controls use a 2-year lag[13]. This addresses endogeneity concerns and establishes the right-hand-side as the determinants of IP, rather than its results. Control variables (i)-(v) are scaled by country GDP in the lagged period. Control (vi) is scaled by the global value of exports in the sector. Each of these variables is derived from the OECD's Inter-Country Input Output tables.

The variables are used to control for economic size (variable i), domestic consumption (ii), exposure to intermediate inputs in production (iii), and export exposure (iv-vi). Notice that control variables (iii)-(vi) control for the sector's positioning in the global value chain. They reflect the importance of imports for production, exports of intermediate goods and exports of final goods relative to the domestic economy size. Finally, variable (vi) captures the sector's overall importance to global trade through its share of global exports. The regression in equation (1) is first performed on the complete sample. The estimation is repeated for the sub-samples by income level, region, and time-period. Lastly, the use of specific tools and tool combinations is assessed. In this case, the IP variable takes value of one if IP of that tool type is implemented.

Intuitively, if β_1 is positive, IP tends to target more (domestically) central sectors. If the coefficient is negative, IP tends to target less central sectors. More precisely, the interpretation of the key centrality variable is: "a one standard deviation increase in sector centrality results in IP being $100(e^{\beta_1} - 1)$ percent more (less) likely in the same sector". An insignificant coefficient would indicate that domestic sector centrality is unrelated to sector IP choice.

[13] The centrality and upstreamness measures are not lagged because it is unlikely that newly-announced IP can immediately impact the production structure, especially at a relatively high level of aggregation.

A further specification includes interactions with dummy variable of the form:

$$Logit(IP_{c,s,t}) = \beta_0+\beta_1 C^D_{c,s,t}+\beta_D D+\beta_I C^D_{c,s,t}*D+\beta_2 C^G_{c,s,t}*D+\beta_3 U_s+\boldsymbol{\beta X_{c,s,t-2}}+\delta_t+\delta_c+\epsilon_{c,s,t} \tag{2}$$

Where D is a dummy variable for (i) region, (ii) income level, or (iii) time period.

The specifications above suggest that, in practice, policymakers may seek for industrial policy to target sectors with high potential propagation (or "cascading") effects by selecting highly connected (or "central") sectors. While it is outside the scope of this paper to assess the presence of market distortions along the production network, it is worth noting that targeting central sectors would constitute optimal policy if such central sectors were to present market distortions/failures. As pointed out by Liu (2019), sectors with high distortion centrality and small size are good candidates for intervention, offering high policy influence and low fiscal commitment. Finally, while Liu (2019) ultimately relates distortion centrality to upstreamness, a concept better suited to simpler "snake" value chains, this analysis includes measures of both centrality and upstreamness. By retaining the features of the full production network, it offers a broader, more encompassing view on how these spillovers could take place, through both forward and backward linkages. The specification captures these three factors - centrality $\left(C^D_{c,s,t}\right)$, size $\left(\frac{VA_{c,s,t-2}}{GDP_{c,t-2}}\right)$, and upstreamness (U_s) - among other relevant sector characteristics.

6 Results

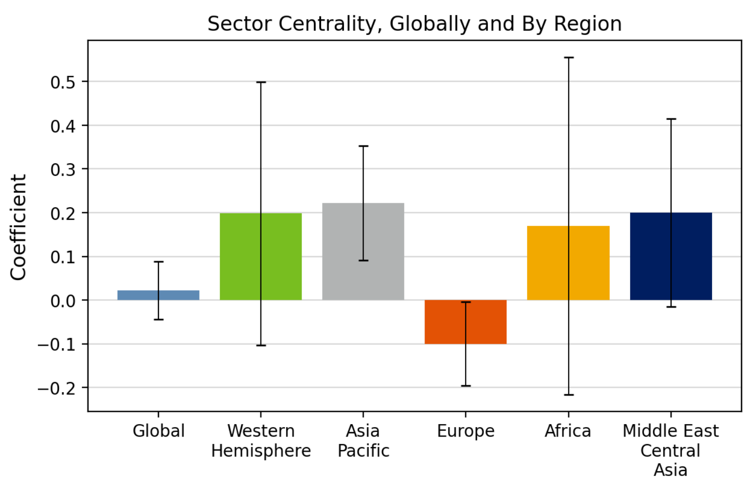
Figures 6.1 through 6.5 show key regression results on sector centrality. Tables A2.1 through A2.5 in Appendix 2 show the full regression results. Appendix 3 presents additional results. All specifications include control variables, country and year fixed effects, as described in the previous section. Errors are clustered at the country-sector level.

At first glance—including the full sample—domestic production centrality appears unimportant to IP choice. However, as subsequent results show, the relevance of centrality is masked by differences across regions, income groups[14], and specific policy tools—and it has evolved over time.

6.1 Results globally and by region

The key results for the global sample and regional subsamples are presented in Figure 6.1. The full regression results can be found in Table A2.1 in Appendix 2.

Figure 6.1: Sector Centrality Globally and By Region - Presents coefficients and 95 percent confidence intervals for Eigenvector Centrality, Domestic, Normalized, from the regressions in Appendix 2. 'Global' refers to the full sample. Regional subsamples are used in the remaining specifications.



As seen in Figure 6.1, in the global sample, there is a small positive but statistically insignificant effect. Strikingly, Asia Pacific is the only region that tends to target central sectors. In particular, a one standard deviation increase in centrality makes a sector 25 percent more likely to receive IP. This result is significant at the one percent level, even after the inclusion of the control variables. By contrast, Europe tends to target less central sectors, where one standard deviation increase in centrality makes a sector 10 percent less likely to receive IP. This effect is significant at the 5 percent level. Finally, the remaining regions, Western Hemisphere, Africa and the Middle East, all show weak positive relationship between IP and centrality. Notably, data coverage is best in Asia and Europe, possibly resulting in a lack of power for the

[14] Regions and income groupings follow IMF classification.

remaining regions. Nevertheless, the opposite relationships of IP and centrality in Asia Pacific versus Europe warrant further analysis[15].

A brief inspection of the control variables (Appendix 2, Table A2.1) show a number of patterns. First, in the full sample, global production centrality is not significant, but it is positive in Asia and negative in Europe[16]. Second, sector upstreamness is not significantly related to IP use, except in Middle East and Central Asia, where it is highly significant and positive. Third, IP tends to target smaller sectors (in terms of value added out of GDP) with lower domestic final demand. Fourth, exposure to imports is a predictor of IP use in the full sample, as well as in Europe and in the Middle East and Central Asia. This could be indicative of governments' attempts to lower the effective cost of imported inputs for domestic producers. Lastly, exports for intermediate use have a small positive association with IP globally and in Europe.

Combining the results on sector centrality with the controls, it is revealed that domestic and global production placement are important determinants to IP in Europe and Asia. Interestingly, a regional difference arises: Asia targets more central sectors, while Europe targets less central sectors, with respect to both domestic and global production. Subsidies (or IP more generally) to large sectors or those with high final demand are less prevalent. In the full sample, exposure to imported inputs is highly predictive of IP.

6.2 Results by income

Figures 6.2a and 6.2b present regression results by country income level. The full regression tables are found in Table A2.2 in Appendix 2. Since there are few low-income countries in the input-output data, the main regression excludes these jurisdictions. Results with all income groups are included in Appendix 3. Further, the results presented below are robust to the exclusion of China from the sample (Appendix 3,

[15] Europe is composed of predominantly advanced economies, while Asia has a significant number of emerging economies. Income level differences are explored in Section 6.2.

[16] Care should be taken when interpreting the coefficients, because a one standard deviation increase in global sector centrality is very meaningful in a tight distribution.

Table A3.4).

There are clear differences in the role of sector centrality as a determinant of IP across income levels[17]. In Figure 6.2a the income level is interacted with centrality, revealing different targeting patterns. First, advanced economies (the reference group) tend to target less central sectors. Second, the interaction term reveals that emerging markets target much more centrally-placed sectors than advanced economies. In fact, by combining the effect for reference group (Fig. 6.2a, left bar) with the interaction (Fig. 6.2a, right bar), in net, emerging markets target more central sectors. These results are echoed in Figure 6.2b, which uses sub-samples for advanced and emerging economies. Advanced economies target less central sectors: a one standard deviation increase in centrality makes IP in that sector 10 percent less likely. Conversely, emerging economies target more central sectors. A one standard deviation increase in centrality makes IP 19 percent more likely. The magnitudes in Figures 6.2a and 6.2b are very comparable.

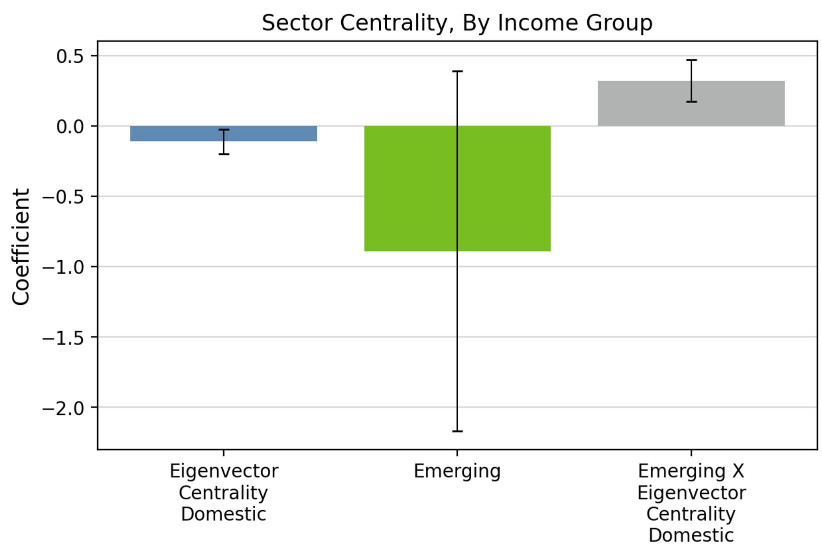
Consider the most commonly targeted sectors in advanced and emerging economies, as shown in Table 6.1[18]. Noticeably, emerging markets and advanced economies target very similar sectors. However, as discussed in Section 4.1, these sectors occupy a different position in their production networks. Namely, they are more central in the production of emerging economies than advanced ones. As a result, the targeting strategy of emerging markets is more consistent with theoretical predictions.

The control variables (see Appendix 2, Table A2.2) show some patterns by income level, which are broadly consistent with those discussed in section 6.1. First, for both income levels, sectors with high domestic final demand or large share of GDP are less likely to be the targets of IP. Second, again for both income levels, large exposure to imported intermediates increases the probability of IP in that sector. Third, the role of exports differs between income groups. Advanced economies are more likely to target sectors with high exports for intermediate uses and less likely to target sectors

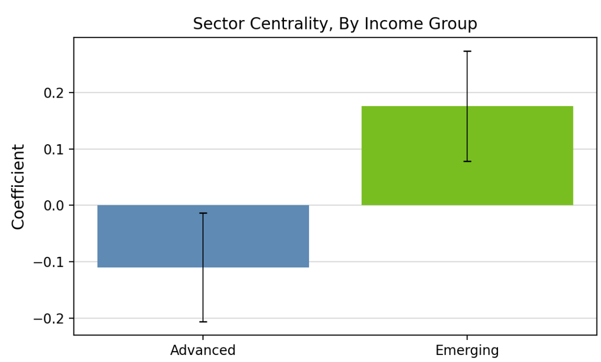
[17]This is inherently related to the regional analysis in Section 6.1, due to the regional composition of advanced and emerging economies

[18]The full tables are included in Appendix 1, Tables A1.8a through A1.8c.

Figure 6.2: IP and Sector Centrality - Results by Income Group



(a). Specifications uses interaction for income status, with advanced economies as the reference group. Figure presents coefficients and 95 percent confidence intervals. Full regression results in Appendix 2.



(b). Specifications use income group subsamples. Figure presents coefficients and 95 percent confidence intervals for domestic eigenvector centrality. Full regression results in Appendix 2.

Table 6.1: Top 10 Most Targeted Sectors, by Income Group

Rank	Advanced Economies	Emerging Economies
1	Agriculture, hunting, forestry	Agriculture, hunting, forestry
2	Fishing and aquaculture	Food products, beverages and tobacco
3	Chemical and chemical products	Fishing and aquaculture
4	Food products, beverages and tobacco	Chemical and chemical products
5	Textiles, leather and footwear	Basic metals
6	Computer, electronic and optical equipment	Computer, electronic and optical equipment
7	Basic metals	Textiles, leather and footwear
8	Electrical equipment	Rubber and plastics products
9	Other non-metallic mineral products	Other non-metallic mineral products
10	Rubber and plastics products	Electrical equipment

Ranking based on count of country-years for which each sector received at least one intervention. Total count across all years used. Full counts and by period, available in Appendix 1, Tables A1.8a-c.
Source: GTA (2024), Author calculations

with high exports of final goods. In emerging markets, the dominant factor is the country-sector's share out of global exports. Fourth, global centrality is only weakly positive for advanced economies, but is a strong (positive) predictor of IP in emerging markets. Finally, IP is positively associated with upstreamness in emerging markets, but it is not a significant predictor for advanced economies.

6.3 Results by time period

To further exploit the time dimension of the data, Figures 6.3a and 6.3b present results by two periods: 2009-2016 and 2017-2023. This break in the series was chosen to represent the broad shift in geopolitical and trade relations—as well as the document surge in IP. Full regression results are presented in Table A2.3, Appendix 2. Additional robustness checks were conducted with time-period split in 2018, 2019 and 2020. Results are consistent with the discussion below (see Table A3.2, Appendix 3).

Specification (1) interact the centrality measure with a dummy variable that takes value one for years 2017 and onward. The reference group is the early period (2009-2016). Three main conclusions result from this exercise. First, in the reference period (2009-2016) centrality is not significantly related to IP use. Second, the recent period is associated with significantly more IP interventions. Lastly, and importantly, the interaction term of post-2016 and centrality is positive, substantial in magnitude, and highly significant. That is to say, all countries are targeting more central sectors since 2017, compared to the early period.

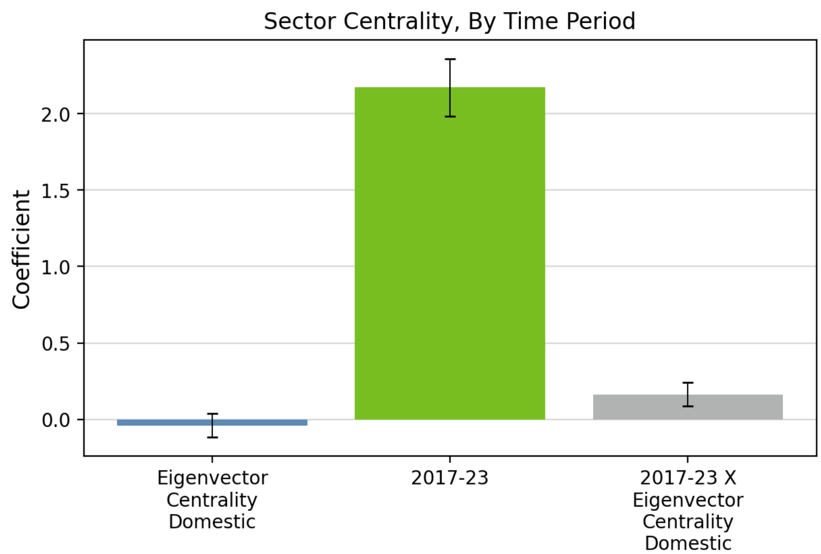
To take a deeper look at the targeted strategies, consider Tables A1.8a and A1.8b in Appendix 1. These tables show the count of country-sector-years that have received at least one policy intervention, broken down by income group, sector, and time-period. Consider first the emerging economies. The ranking of the most targeted sectors remains largely consistent across time, indicating little change in the targeting strategy. By contrast, advanced economies show a significant increase in targeting of sectors such as energy (electricity and gas), transportation (land, water, and pipeline), construction, as well as services (professional, research, administrative, financial). These sectors, as described in Section 4.1, are among the most central to the domestic production in advanced economies. This is a key driver of the shift toward central sectors in IP, as documented above.

The patterns revealed by the controls are consistent over time. In both time periods, domestic final demand and sector VA are negatively related to IP use. Reliance on imported inputs is highly associated with IP. Export variables are, however, only weakly associated with IP use. In both periods, upstreamness and global centrality are not significantly associated with IP.

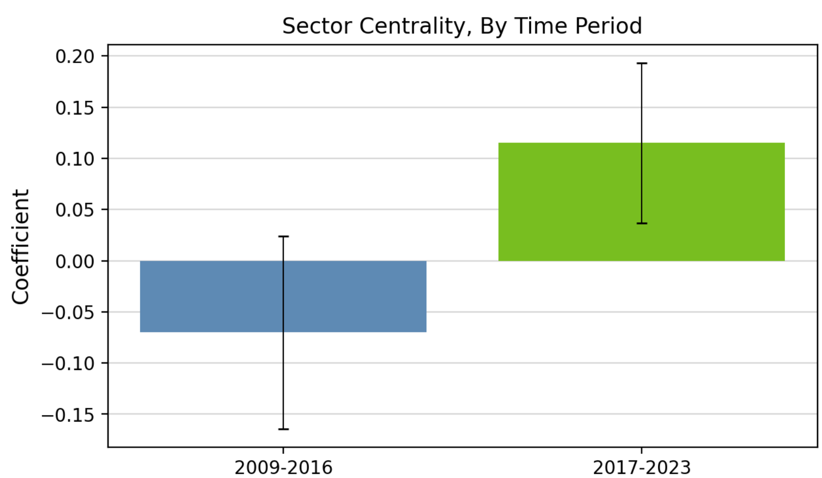
6.4 Results by type of intervention

The final dimension distinguishing the effects of centrality is the type of tool used. Recall that the five most used tools, in order, are: subsidies, import tariffs, export support, antidumping, and export restrictions. The results in Figures 6.4a and 6.4b explore the use of each of these tools. To investigate the joint use of tools, for each of the five top tools, the first specification includes this tool and possibly others. The second specification uses only the given tool. Full regression results are presented in

Figure 6.3: IP and Sector Centrality - Results by Time Period



(a). Specifications uses interaction for time period, with 2009-16 as the reference group. Figure presents coefficients and 95 percent confidence intervals. Full regression results in Appendix 2.



(b). Specifications use time period sub-samples. Figure presents coefficients and 95 percent confidence intervals for domestic eigenvector centrality. Full regression results in Appendix 2.

Tables A2.4a and A2.4b in Appendix 2.

Subsidies, export restrictions, and export support measures all tend to target more central sectors. One standard deviation increase in centrality makes targeting 8 percent, 18 percent, 15 percent more likely, respectively. Import tariffs and antidumping measures tend to target less central sectors. One standard deviation increase in centrality makes targeting 15 percent and 23 percent less likely, respectively. In all cases, the results are larger in magnitude when a single tool is considered. In particular, the import tariff result is only significant when used alone or in conjunction with subsidies. That is, sectors that are subject to both subsidies and import tariffs are negatively associated with centrality.

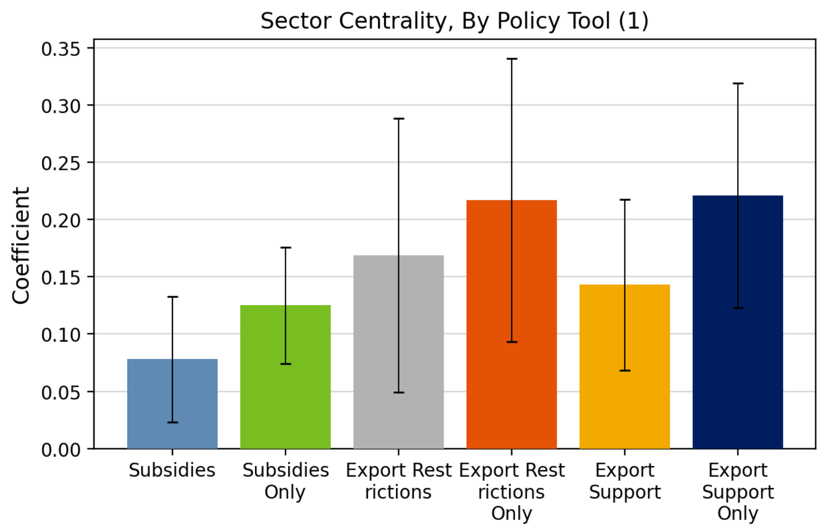
Overall, a sector's centrality within the global value chain is not a strong predictor of the type of policy tool. There is some evidence that subsidies and import tariffs are more targeted toward globally central sectors, though the magnitude of the effect is small. On the other hand, export restrictions are targeted toward less globally central sectors. Export support and anti-dumping measures do not show any relationship to global sector centrality.

Table 6 in Appendix X, extends this policy tool analysis by period, showing some changes over time. Subsidies start targeting central sectors in the latter period. Export restrictions target centrally in the first period, but not the second. Export support measures target centrally in both periods, but more so in the earlier one. Import tariffs and Antidumping measures consistently target less central sectors.

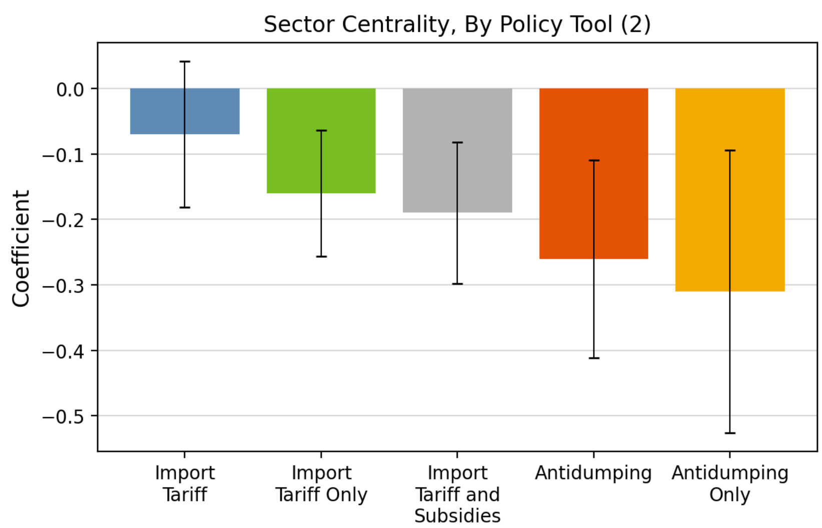
6.5 Zooming in on Asia

IP has a long history in Asia, commanding substantial attention. While there are competing views about the impact of IP in the region vis-à-vis other factors, many have argued that IP have been marked with considerably more success in Asia than elsewhere (Juhász et al., 2024). While the data does not span the so-called "East Asian Miracle" growth episodes of 1965 to 1990, this paper explores recent Asian IP. The analyses by income group, time period, and tool use are repeated within Asia. Key results are shown in Figures 6.5a and 6.5b. Full regression results are presented

Figure 6.4: IP and Sector Centrality - Results by Policy Tool



(a). Figure presents coefficients and 95 percent confidence intervals for domestic eigenvector centrality by type of policy intervention. Full regression results in Appendix 2.



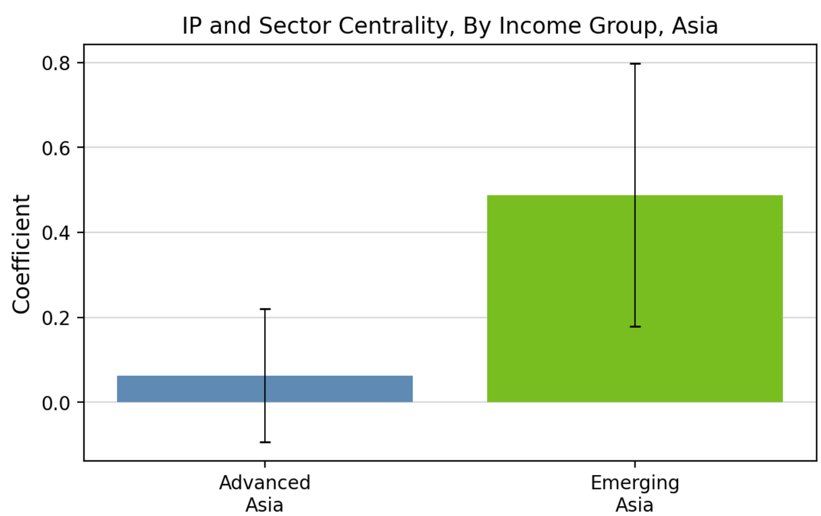
(b). Figure presents coefficients and 95 percent confidence intervals for domestic eigenvector centrality for additional types of policy intervention. Full regression results in Appendix 2.

in Tables A2.5a and A2.5b, in Appendix 2.

6.5.1 Asia by income group

Asia shows a smaller distinction between advanced and emerging economies, with respect to domestic centrality and IP targeting. As shown in Figure 6.5a, both income groups tend to target more central sectors over the whole sample period. This result is smaller and weaker (significant only at 10 percent level) for advanced economies. It has higher magnitude and high significance for emerging markets: a one standard deviation increase in centrality makes a sector 63 percent more likely to be targeted. Global sector centrality is only significantly, positively associated with IP in emerging countries.

Figure 6.5a: Presents coefficients and 95 percent confidence intervals for Eigenvector Centrality, Normalized, for Income Groups in Asia. Full regression results in Appendix 2.

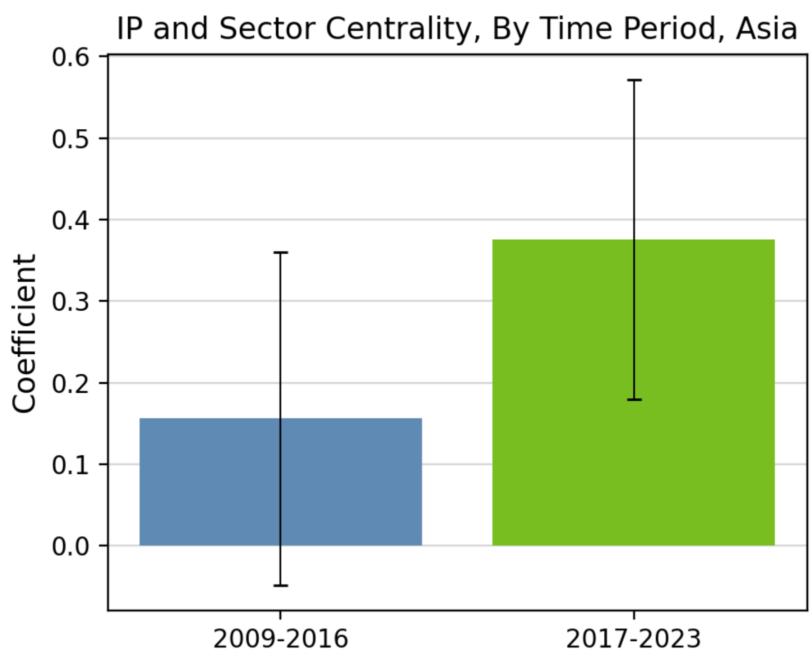


Notably, the advanced economies in Asia differ from the overall sample of advanced economies. In the global sample (Figure 6.2), advanced economies target less central sectors (negative and significant coefficient). In Asia, they (weakly) target more central sectors (Figure 6.5a). These results are robust to excluding China from the sample (see Appendix 3, Table A3.5).

6.5.2 Asia by time period

Asian economies targeted more central sectors over the full span of the data, 2009-2023. Consistent with global trends, this relationship is stronger in the later period. Differing from global results, Asia was targeting more centrally located sectors even in the early period, 2009-16. Where other regions begin targeting central sectors in the later period, Asian economies have targeted centrally placed sectors in both periods.

Figure 6.5b: Specifications use time period sub-samples. Figure presents coefficients and 95 percent confidence intervals for Eigenvector Centrality, Normalized, for Income Groups in Asia. Full regression results in Appendix 2.



When China is excluded from the sample (Appendix 3, Table A3.5), both periods are significant and positive. That is, all other Asia countries have been strongly targeting central sectors for the full time horizon available (2009-2023).

6.5.3 Asia by tool use

As shown in Figures 5.5c-5.5e, there are some differences in tool use in Asia and by income group. In Asia as a whole, four of the five main tools (subsidies, import tariffs, export restrictions, and export supports) are estimated to (weakly) target central sectors. Only antidumping is (weakly) targeted to less central sectors. When broken down by income group, emerging economies have a higher tendency to target central sectors, especially using tariffs, export restrictions, and export support. Notably, Asian emerging markets use import tariffs on more central sectors, unlike the global sample. Evidence for the advanced economies is mixed and not significant.

Figure 6.5c: Presents coefficients and 95 percent confidence intervals for Eigenvector Centrality, Normalized, by policy tool in Asia. Full regression results in Appendix 2.

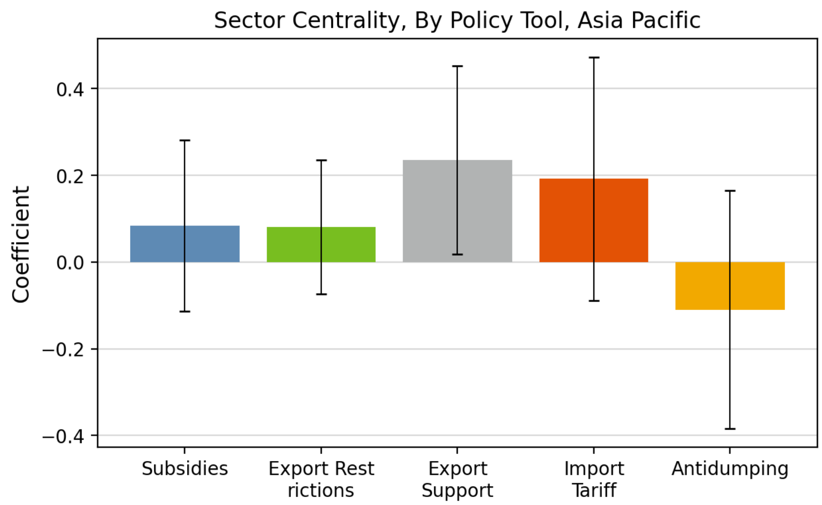


Figure 6.5d: Presents coefficients and 95 percent confidence intervals for Eigenvector Centrality, Normalized, by policy tool in emerging Asian economies. Full regression results in Appendix 2.

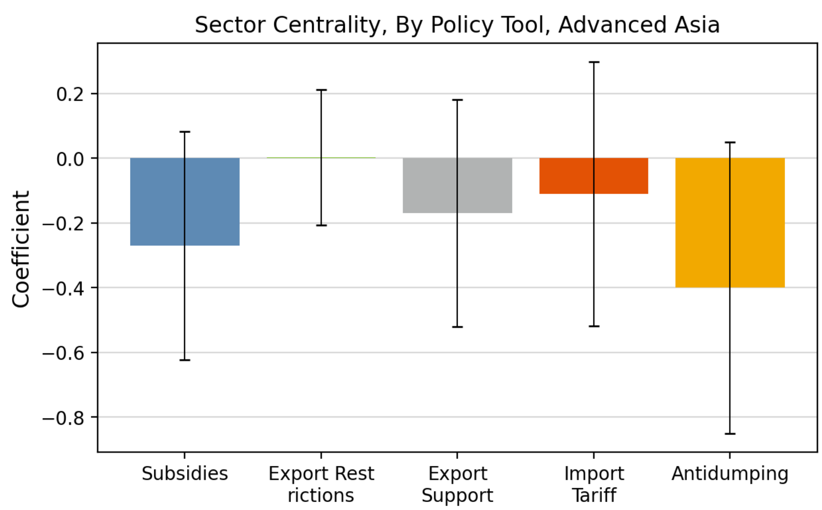
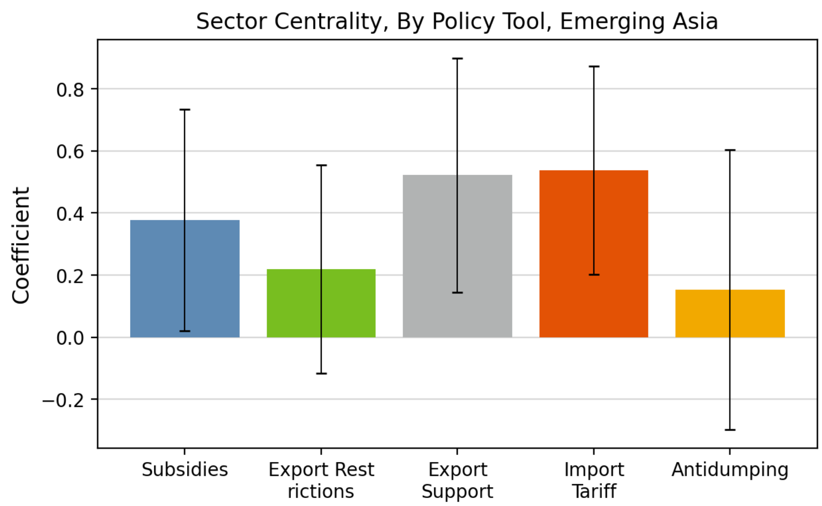


Figure 6.5e: Presents coefficients for Eigenvector Centrality, Normalized, by policy tool in advanced Asian economies. Full regression results in Appendix 2.



6.6 Summary of Results and Discussion

The findings here indicate that IP is heterogenous and changing over time. The role of domestic sector centrality in the governments' IP choice differs across regions, income groups, time periods, and policy tools. In addition, there is evidence that Asia is different. Lastly, the control variables reveal other relevant sector characteristics, including that GVC placement matters.

Overall, the results presented here demonstrate the following relationships between domestic sector centrality and industrial policy use. The role of domestic centrality:

1. *Differs by region.* In Asia, IP tends to target more central sectors, while in Europe it tends to target less central sectors. Due to the composition of the regions, this could reflect differences between income groups.

2. *Differs by income.* Emerging markets target centrally positioned sectors, while advanced economies target less centrally, when considering the full time horizon. In fact, both income groups target strikingly similar set of sectors; however, these sectors tend to be more central to emerging economies than advanced ones. This could reflect different policy objectives behind IP, the former being

more consistent with capacity or export development.

3. *Changes over time.* Since 2017, there is global shift toward targeting central sectors, for both advanced and emerging economies. Prior to 2017, globally, production centrality was not a significant predictor of IP. Beginning in 2017, all governments are more likely to target central sectors. The shift is driven by advanced economies' increased interest in central sectors, such as energy, construction and transportation. This could reflect the changing sentiment among many policy makers, who are more inclined to intervene in market outcomes and pursue other strategic objectives. Frequently cited motives include increased domestic capacity in high-importance sectors, de-risking global value chains, promotion of green technologies, among others.

4. *Differs by policy tool.* IP that targets central sectors relies on subsidies, export restrictions and export supports. IP that targets less central sectors relies on import tariffs and anti-dumping policies. The former is more consistent with objectives such as capacity development, export-driven growth, and externality correction. The latter could reflect more protectionist motives.

5. *Is consistent in Asia.* Asian economies, emerging and advanced, tend to target more central sectors for the entire time horizon. Importantly, while this data does not span the so-called 'East Asian Miracle' of high growth between 1965 and 1990, it could reflect practices inherited from that period.

In addition, the following patterns emerge from the sector-level control variables:

1. IP tends to target smaller sectors, consistent with the fiscal implications of IP.

2. In the global sample, high import reliance is a stronger predictor of IP than high exports. In Europe, both imports and exports of intermediate goods are positive predictors of IP.

3. In terms of the role of exports, in advanced economies, IP targets sectors with high exports for intermediate use. In emerging markets, the overall share of

global trade is more relevant. This could reflect a higher focus on commodities (or sectors early in the value chain) among emerging economies.

4. IP tends to target sectors with less (domestic or foreign) final demand. However, policy-makers may be using tools other than IP (ex. taxation and rebates) to subsidize domestic demand, which are unobserved.

5. These patterns are consistent over the two time periods.

7 Conclusion

While much attention has been devoted to the international spillovers of IP - including vulnerabilities of supply-chains, economic and political fragmentation - the discussion on the rise of industrial policy and protectionism would be incomplete without a discussion on domestic objectives. This analysis aims to contribute here. This article demonstrates that a sector's position in the domestic production network significantly affects its likelihood to be targeted by industrial policy. Moreover, the context (the income and time-period) of the IP can inverse the targeting strategy completely. Only in Asia is the targeting consistent: more central sectors are more likely to 'receive' industrial policy.

As an important caveat, this analysis and the various extensions described, are informed by existing production network features. It is however conceivable that governments would use IP in an attempt to alter the production network. This would be a slow-moving process. From an econometric perspective, it is unlikely to lead to endogeneity between IP and centrality measures due to the relatively short time horizon of 15 years. Nevertheless, it is worth noting that governments may target sectors not because they are central but because they wish those sectors to become central. Inherently, this cannot be captured by the data.

A number of new questions arise from this research. More work is needed to better understand the distinction between emerging and advanced economies. For instance, it would be expected that the level of development directly influences which sectors are more connected in production. Understanding other features of targeted sectors such as tradeable/non-tradeable and country-sector comparative advantages would help to interpret the results. Further, this analysis can be enriched by comparing multiple centrality measures. Lastly, the analysis would benefit from a structural model to apply theoretical underpinning to the centrality measure and aid in interpretation. The results presented here are, at present, positive statements. Further research is needed to draw policy recommendations.

References

Antràs, P., Chor, D., Fally, T., & Hillberry, R. (2012). Measuring the upstreamness of production and trade flows. *American Economic Review: Papers & Proceedings 2012*, *102*, 412–416.

Banerjee, A., Chandrasekhar, A. G., Duflo, E., & Jackson, M. O. (2013). Diffusion of microfinance. *Science*, *341*.

Banerjee, A., Chandrasekhar, A. G., Duflo, E., & Jackson, M. O. (2019). Using gossips to spread information: Theory and evidence from two randomized controlled trials. *The Review of Economic Studies*, *86*.

Barattieri, A., Mattoo, A., & Taglioni, D. (2024). Trade effects of industrial policies, are preferential agreements a shield? *World Bank Group, Policy Research Working Paper 10806.*.

Barwick, P. J., Kalouptsidi, M., & Zahur, N. (2024). Industrial policy implementation: Empirical evidence from China's shipbuilding industry. *Review of Economic Studies, Forthcoming*.

Bloch, F., Jackson, M., & Tebaldi, P. (2023). Centrality measures in networks. *Social Choice and Welfare*, *61*, 413–453.

Evenett, S., & Fritz, J. (2020). The global trade alert database handbook. *St.Gallen Endowment for Prosperity through Trade*.

Evenett, S., Jakubik, A., Martín, F., & Ruta, M. (2024). The return of industrial policy in data. *International Monetary Fund, Working Paper No. 2024/001*.

International Monetary Fund (2024). Industrial policy coverage in imf surveillance—broad considerations. *IMF Policy Paper Series*.

Juhász, R., Lane, N., Oehlsen, E., & Pérez, V. C. (2023). The who, what, when, and how of industrial policy: A text-based approach. *STEG WORKING PAPER, WP050*.

Juhász, R., Lane, N., & Rodrik, D. (2024). The new economics of industrial policy. *Annual Review of Economics*, *16*, 213–242.

Liu, E. (2019). Industrial policies in production networks. *The Quarterly Journal of Economics*, *134*, 1883–1948.

Liu, E., & Tsyvinski, A. (2024). A dynamic model of input–output networks. *The Review of Economic Studies*.

OECD (2023). Inter-country input-output tables. *16*, 213–242.

Rotunno, L., & Ruta, M. (2023). Trade implications of China's subsidies. *IMF Working Papers, Working Paper No. 2024/180*, *180*.

Rotunno, L., & Ruta, M. (2024). Trade spillovers of domestic subsidies. *IMF Working Papers, Working Paper No. 2024/041*, *180*.

United Nations Statistics Division (2015). Classifications on economic statistics, correspondence tables. `https://unstats.un.org/unsd/classifications/EconCorrespondences`, Last accessed on July 30, 2024.

8 Appendix

8.1 Appendix 1: Additional Information on Data and Methodology

8.1.1 Appendix 1a: Calculation of Centrality Measures

The particular measure of centrality used is the Eigenvector centrality. This is measure of placement in a network that has many applications in production networks, social networks, and search. It's most famous use is Google's PageRank algorithm. A key feature of this centrality measure is its recursive nature: a sector is central if it is connected to other central sectors. The basic definition is given by

$$\lambda C = MC$$
$$(\lambda I - M)C = 0$$

Where C is the centrality measure of interest and corresponds to the largest Eigenvalue (λ) of the adjacency (input-output) matrix (M). The actual measure used is computed using the widely-accepted Python package 'networkx'. It's construction includes bi-directional input-output links that are weighted by the transaction value.

Bloch et al. (2023) demonstrate that this measure is appropriate for networks with 'cycles'. In the context of production, a cycle occurs when a sector's output is used in its own production, either directly or after being processed by other sectors. This is clearly the case, since the main diagonal of the I-O matrix is non-zero.

Furthermore, Bloch et al. (2023) relate this measure to others in the same family: diffusion centrality and Katz-Bonacich centrality. All three of these measures have a recursive structure, where first-order connections are worth the most and more distant connections are discounted. Diffusion centrality involves a finite number of relevant levels of connection and a discount factor that represents the likelihood of transmission. Banerjee et al. (2013, 2019) use this measure to study the transmission of gossip within a community after finite number of rounds of communication. If the discount parameter is sufficiently small and all indirect connections in the network are included (ie. the number of rounds is infinity), diffusion centrality is equal to Katz-Bonacich centrality (Bloch et al., 2023). Similarly, if all indirect links are considered and the parameter is large[19], diffusion centrality becomes Eigenvector centrality (Bloch et al., 2023). This is a very useful measure because it does not require estimating the discounting parameter.

8.1.2 Appendix 1b: Additional Descriptions of the Data

Tables A1.1 through A1.8c provide additional descriptions of the datasets.

[19]Specifically, the discount factor is larger than than the inverse of the largest eigenvalue of the adjacency matrix. At this threshold, the Bonacich-Katz and Eigenvector centralities converge.

Table A1.1: Countries by Region

Africa	Asia-Pacific	Europe	Middle East, Central Asia	West. Hemisphere	Other
Zambia	*Indonesia	*Ukraine	Iraq	*Argentina	US Virgin Islands
*South Africa	*Japan	*Russia	Kuwait	*United States of America	Puerto Rico
Eswatini	*India	*France	United Arab Emirates	Ecuador	Cuba
Botswana	*Philippines	*Latvia	*Saudi Arabia	*Canada	Cayman Islands
Namibia	*Vietnam	*Ireland	*Kazakhstan	*Mexico	Falkland Islands
Ghana	*Korea	*Romania	*Egypt	Brazil	Montserrat
*Nigeria	*Malaysia	*Finland	*Jordan	*Peru	Anguilla
*Côte d'Ivoire	*Thailand	*Germany	*Pakistan	Dominican Republic	Bermuda
Kenya	*China	*Poland	Kyrgyz Republic	*Colombia	New Caledonia
Tanzania	*Taiwan (Province of China)	*Greece	*Morocco	Paraguay	State of Palestine
Uganda	*Australia	*United Kingdom	Algeria	*Chile	Faeroe Islands
Rwanda	Mongolia	*Denmark	Sudan	*Costa Rica	Turks & Caicos Islands
Zimbabwe	*New Zealand	*Portugal	Iran	Jamaica	
Lesotho	*Bangladesh	*Italy	Mauritania	Bolivia	
Sierra Leone	Sri Lanka	*Belgium	*Tunisia	Venezuela	
Gabon	*Singapore	*Austria	Uzbekistan	Trinidad and Tobago	
*Cameroon	*Brunei Darussalam	*Spain	Armenia	Uruguay	
Angola	Fiji	*Sweden	Afghanistan	El Salvador	
Togo	Maldives	*Czech Republic	Bahrain	Panama	
Liberia	Nepal	*Lithuania	Qatar	Honduras	
Mozambique	Papua New Guinea	*Cyprus	Oman	Guatemala	
Gambia, The	Tonga	*Hungary	Georgia	Belize	
Mauritius	*Myanmar	*Netherlands	Azerbaijan	Guyana	
Chad	*Hong Kong SAR	*Bulgaria	Tajikistan	Haiti	
Ethiopia	*Cambodia	*Slovak Republic	Djibouti	Nicaragua	
Malawi	Samoa	*Estonia	Yemen	Antigua and Barbuda	
Burundi	Solomon Islands	*Slovenia	Lebanon	Grenada	
Guinea	Vanuatu	Bosnia and Herzegovina	Libya	St. Kitts and Nevis	
Madagascar	*Lao P.D.R.	*Switzerland	Syria	Suriname	
Benin	Nauru	*Belarus	Somalia	Barbados	
Burkina Faso	Bhutan	*Turkey	Turkmenistan	Dominica	
Cabo Verde		*Croatia		St. Lucia	
Democratic Republic of the Congo		*Malta		St. Vincent and the Grenadines	
Guinea-Bissau		*Luxembourg		Bahamas, The	
Mali		*Israel			
Niger		North Macedonia			
*Senegal		*Iceland			
Congo, Republic of		Albania			
Central African Republic		*Norway			
Seychelles		Serbia			
Comoros		Montenegro, Rep. of			
South Sudan		Moldova			
Eritrea					
Equatorial Guinea					
São Tomé and Príncipe					

* Country is included in OECD ICIO table and merged dataset.
Regions follow official IMF categorization. Countries in 'Other' are included in regressions using global sample, but not in region or income sub-samples.
Source: Global Trade Alert (2024), OECD (2023)

Table A1.2: Global Trade Alert, Top Tools by Region

	Rank 1	Rank 2	Rank 3	Rank 4	Rank 5
Asia Pacific	Subsidy	Import Tariff	Export Support	Anti-dumping	Export Restriction
Africa	Import Tariff	Subsidy	Export Restriction	Prohibition	Local Content Measure
Europe	Subsidy	Export Support	Import Tariff	Anti-dumping	Export Restriction
Middle East, Central Asia	Import Tariff	Subsidy	Export Restriction	Anti-dumping	Export Support
West. Hemisphere	Subsidy	Import Tariff	Export Restriction	Anti-dumping	Gov. Local Content

Source: Global Trade Alert (2024)

Table A1.3: Global Trade Alert, Top Tools by Income Group

	Rank 1	Rank 2	Rank 3	Rank 4	Rank 5
Advanced	Subsidy	Export Support	Import Tariff	Export Measures, Other	Gov. Local Content Requirement
Emerging	Subsidy	Import Tariff	Anti-dumping	Export Price Controls	Export Licenses
Low-Income	Import Tariff	Export Restriction	Subsidy	Internal taxes/charges on Imports	Tariff Rate Quotas

Source: Global Trade Alert (2024)

Table A1.4: Global Trade Alert, Sector Codes for Top 5 Tools

Intervention Type	Known Sector	Missing Sector	Total	Percent Missing
Overall	57950	13 895	71845	19.3
Subsidies	27117	4899	32016	15.3
Import Tariffs	9144	841	9985	8.4
Export Support	6373	1049	7422	14.1
Antidumping	2675	261	2936	8.9
Export Restriction	1777	100	1877	5.3

Count is number of unique policy announcements that use given tool.
Source: Global Trade Alert (2024)

Table A1.5: Count of Interventions by Policy Tool

Policy Tool: MAST Chapter	Unique Policies
L Subsidies (excluding export subsidies)	27117
Tariff measures	9144
P6 Export-support measures	6373
D1 Antidumping	2675
P3 Export licences, quotas, prohibition and other restrictions	1777
P9 Export measures, n.e.s.	1556
P4 Export price-control measures, including additional taxes and charges	1341
M3 Government Procurement Local Content Requirement	1335
E6 Tariff-rate quotas (TRQ)	1084
I1 Local content measures	766
FDI measures	759
E1 Non-automatic import-licensing procedures	724
F7 Internal taxes and charges levied on imports	721
E3 Prohibitions other than for SPS and TBT reasons	537
D2 Countervailing measure	436
Instrument unclear	425
D31 General (multilateral) safeguard	332
E2 Quotas	330
Capital control measures	109
Migration measures	93
M5 Government Procurement Tendering Process	86
M1 Government Procurement Market Access Restrictions	66
M2 Government Procurement Domestic Price Preference	65
G Finance measures	53
D32 Agricultural special safeguard	20
C4 Import monitoring, surveillance and automatic licensing measures	17
B Technical barriers to trade	4
I2 Trade-balancing measures	3
N Intellectual Property	2

Source: Global Trade Alert (2024)
Non-tariff measures are classified according to the MAST chapter from the UN Conference on Trade and Development.

Table A1.6: Count of Interventions by Sector

Industry	ICIO Sector Code	Sector Num. in Figures	Unique Interventions
Agriculture, hunting, forestry	A01_02	0	20442.0
Fishing and aquaculture	A03	1	19908.0
Chemical products	C20	10	15309.0
Computer, electronic and optical equipment	C26	16	10912.0
Basic metals	C24	14	9701.0
Food products, beverages and tobacco	C10T12	5	9232.0
Other non-metallic mineral products	C23	13	7555.0
Electrical equipment	C27	17	7489.0
Textiles, leather and footwear	C13T15	6	6395.0
Rubber and plastics products	C22	12	5952.0
Pharmaceuticals	C21	11	5779.0
Electricity, gas, steam and AC	D	22	4738.0
Fabricated metal products	C25	15	4157.0
Coke and refined petroleum products	C19	9	3948.0
Publishing, audiovisual and broadcasting activities	J58T60	32	3867.0
Other transport equipment	C30	20	3748.0
Wood and products of wood and cork	C16	7	3187.0
Machinery and equipment, nec	C28	18	3047.0
Mining and quarrying, energy	B05_06	2	2967.0
Motor vehicles, trailers and semi-trailers	C29	19	2295.0
Manufacturing nec	C31T33	21	2040.0
Paper products and printing	C17_18	8	1814.0
Transport via land and pipelines	H49	26	1726.0
Construction	F	24	1580.0
Financial and insurance activities	K	35	1531.0
Telecommunications	J61	33	1318.0
Professional, scientific and technical activities	M	37	1317.0
Warehousing and support activities for transportation	H52	29	1168.0
Accommodation and food service activities	I	31	1017.0
Administrative and support services	N	38	959.0
Health and social work activities	Q	41	817.0
Water transport	H50	27	770.0
Arts, entertainment and recreation	R	42	738.0
Air transport	H51	28	698.0
Mining and quarrying, non-energy	B07_08	3	612.0
IT and other information services	J62_63	34	582.0
Water supply; sewerage, waste management	E	23	468.0
Real estate activities	L	36	451.0
Education	P	40	383.0
Other service activities	S	43	372.0
Postal and courier activities	H53	30	314.0
Public administration and defence	O	39	217.0
Activities of households as employers	T	44	199.0
*Mining support service activities	-	4	-
*Wholesale and retail trade; repair of motor vehicles	-	25	-

*Mining support services and Wholesale/Retail Trade sectors not included after data merge.
Certain sectors (ISIC 45, 46, 47) are not yet included in the conversion tables.
A policy intervention can target multiple sectors, hence the count in this table exceeds the number of policies.
This count differs from the main regression analysis, which use a binary variable for IP in a country-sector-year.
Source: Global Trade Alert (2024), OECD (2023), Author calculations

Table A1.7a: Average Sector Centrality, Advanced Economies by Time Period

Industry	Average Domestic Eigenvector Centrality		
	All years	2009-2016	2017-2023
Construction	2.686	2.573	2.815
Professional, scientific and technical activities	2.025	2.034	2.016
Financial and insurance activities	1.682	1.921	1.409
Real estate activities	0.795	0.802	0.787
Food products, beverages and tobacco	0.687	0.718	0.65
Administrative and support services	0.655	0.614	0.702
Electricity, gas, steam and AC	0.495	0.587	0.389
Warehousing and support for transportation	0.276	0.316	0.232
Land transport and transport via pipelines	0.168	0.203	0.128
Motor vehicles, trailers and semi-trailers	0.155	0.052	0.274
Computer, electronic and optical equipment	0.101	0.117	0.084
Agriculture, hunting, forestry	-0.019	-0.007	-0.033
IT and other information services	-0.08	-0.093	-0.064
Chemical and chemical products	-0.128	-0.112	-0.146
Machinery and equipment, nec	-0.196	-0.21	-0.179
Basic metals	-0.212	-0.151	-0.28
Telecommunications	-0.267	-0.243	-0.295
Pharmaceuticals	-0.272	-0.306	-0.234
Manufacturing nec	-0.286	-0.309	-0.26
Accommodation and food service activities	-0.287	-0.301	-0.272
Fabricated metal products	-0.305	-0.315	-0.294
Coke and refined petroleum products	-0.316	-0.315	-0.317
Public administration and defence	-0.344	-0.344	-0.345
Paper products and printing	-0.348	-0.334	-0.364
Publishing, AV and broadcasting	-0.35	-0.345	-0.355
Water supply; sewerage, waste management	-0.399	-0.407	-0.391
Rubber and plastics products	-0.407	-0.421	-0.392
Electrical equipment	-0.414	-0.425	-0.401
Water transport	-0.424	-0.4	-0.452
Textiles, leather and footwear	-0.424	-0.439	-0.407
Wood and products of wood and cork	-0.435	-0.445	-0.422
Other non-metallic mineral products	-0.438	-0.445	-0.429
Arts, entertainment and recreation	-0.457	-0.551	-0.35
Other service activities	-0.483	-0.479	-0.488
Air transport	-0.493	-0.497	-0.489
Postal and courier activities	-0.504	-0.51	-0.497
Education	-0.513	-0.51	-0.517
Other transport equipment	-0.523	-0.535	-0.51
Mining and quarrying, energy	-0.525	-0.528	-0.521
Mining and quarrying, non-energy	-0.559	-0.568	-0.548
Human health and social work activities	-0.56	-0.568	-0.55
Fishing and aquaculture	-0.576	-0.583	-0.568
Activities of households	-0.638	-0.644	-0.63

Mean value of the normalized domestic eigenvector centrality taken for all countries in the income group across years, as indicated. Observations ordered by average for all years.
Source: OECD (2023), Author calculations

Table A1.7b: Average Sector Centrality, Emerging Markets by Time Period

Industry	Average Domestic Eigenvector Centrality		
	All years	2009-2016	2017-2023
Food products, beverages and tobacco	1.625	1.683	1.558
Construction	1.494	1.385	1.618
Agriculture, hunting, forestry	0.828	0.846	0.808
Financial and insurance activities	0.731	0.779	0.676
Land transport and transport via pipelines	0.499	0.467	0.536
Professional, scientific and technical activities	0.371	0.302	0.449
Electricity, gas, steam and AC	0.279	0.347	0.2
Real estate activities	0.13	0.136	0.124
Administrative and support services	0.065	-0.002	0.142
Coke and refined petroleum products	-0.052	-0.009	-0.101
Chemical and chemical products	-0.113	-0.083	-0.146
Textiles, leather and footwear	-0.137	-0.145	-0.127
Computer, electronic and optical equipment	-0.165	-0.242	-0.078
Basic metals	-0.221	-0.223	-0.218
Warehousing and support for transportation	-0.223	-0.256	-0.185
Motor vehicles, trailers and semi-trailers	-0.279	-0.307	-0.246
Mining and quarrying, energy	-0.303	-0.243	-0.372
Telecommunications	-0.351	-0.318	-0.388
Rubber and plastics products	-0.441	-0.44	-0.441
Fabricated metal products	-0.445	-0.445	-0.444
IT and other information services	-0.458	-0.506	-0.403
Other non-metallic mineral products	-0.46	-0.449	-0.473
Paper products and printing	-0.476	-0.475	-0.477
Manufacturing nec;	-0.478	-0.481	-0.474
Machinery and equipment, nec	-0.504	-0.498	-0.511
Mining and quarrying, non-energy	-0.513	-0.534	-0.489
Accommodation and food service activities	-0.517	-0.497	-0.539
Electrical equipment	-0.534	-0.543	-0.523
Public admin. and defence	-0.561	-0.58	-0.54
Water supply; sewerage, waste management	-0.568	-0.562	-0.575
Human health and social work	-0.572	-0.576	-0.567
Publishing, AV and broadcasting	-0.58	-0.568	-0.594
Pharmaceuticals	-0.602	-0.596	-0.609
Air transport	-0.602	-0.602	-0.601
Wood and products of wood and cork	-0.605	-0.605	-0.605
Fishing and aquaculture	-0.633	-0.624	-0.644
Education	-0.637	-0.64	-0.635
Other transport equipment	-0.645	-0.641	-0.648
Water transport	-0.658	-0.657	-0.658
Other service activities	-0.666	-0.661	-0.672
Postal and courier activities	-0.666	-0.682	-0.647
Arts, entertainment	-0.699	-0.686	-0.714
Activities of households	-0.781	-0.771	-0.792

Mean value of the normalized domestic eigenvector centrality taken for all countries in the income group across years, as indicated. Observations ordered by average for all years.
Source: OECD (2023), Author calculations

Table A1.7c: Average Sector Centrality, Low-Income Countries by Time Period

Industry	Average Domestic Eigenvector Centrality		
	All years	2009-2016	2017-2023
Food products, beverages and tobacco	1.765	1.806	1.719
Textiles, leather and footwear	0.969	0.983	0.954
Agriculture, hunting, forestry	0.894	0.883	0.906
Warehousing and support for transportation	0.64	0.636	0.645
Land transport and transport via pipelines	0.262	0.279	0.244
Administrative and support services	0.025	0.046	0.0
Financial and insurance activities	0.015	0.006	0.026
Construction	-0.097	-0.047	-0.155
Accommodation and food service activities	-0.139	-0.151	-0.126
Professional, scientific and technical activities	-0.173	-0.111	-0.243
Electricity, gas, steam and AC	-0.291	-0.249	-0.338
Real estate activities	-0.32	-0.319	-0.322
Chemical and chemical products	-0.33	-0.339	-0.32
Coke and refined petroleum products	-0.359	-0.347	-0.373
Water supply; sewerage, waste management	-0.424	-0.394	-0.458
Wood and products of wood and cork	-0.434	-0.429	-0.439
Public administration and defence	-0.437	-0.411	-0.468
Other non-metallic mineral products	-0.457	-0.456	-0.457
Rubber and plastics products	-0.462	-0.463	-0.46
Fishing and aquaculture	-0.505	-0.501	-0.51
IT and other information services	-0.505	-0.5	-0.51
Education	-0.505	-0.501	-0.51
Fabricated metal products	-0.51	-0.483	-0.54
Mining and quarrying, non-energy	-0.512	-0.51	-0.514
Other service activities	-0.513	-0.498	-0.53
Paper products and printing	-0.518	-0.505	-0.533
Mining and quarrying, energy	-0.521	-0.525	-0.516
Manufacturing nec	-0.528	-0.522	-0.535
Water transport	-0.537	-0.536	-0.537
Postal and courier activities	-0.554	-0.544	-0.566
Basic metals	-0.554	-0.549	-0.561
Human health and social work activities	-0.558	-0.549	-0.568
Activities of households	-0.582	-0.575	-0.59
Computer, electronic and optical equipment	-0.582	-0.593	-0.57
Air transport	-0.591	-0.593	-0.59
Electrical equipment	-0.593	-0.591	-0.595
Machinery and equipment, nec	-0.601	-0.611	-0.59
Pharmaceuticals	-0.604	-0.615	-0.592
Publishing, AV and broadcasting activities	-0.613	-0.605	-0.623
Motor vehicles, trailers and semi-trailers	-0.649	-0.646	-0.653
Arts, entertainment and recreation	-0.655	-0.648	-0.662
Other transport equipment	-0.662	-0.657	-0.667

Mean value of the normalized domestic eigenvector centrality taken for all countries in the income group across years, as indicated. Observations ordered by average for all years.
Source: OECD (2023), Author calculations

Table A1.8a: Count of Affected Country-Periods, Advanced Economies by Time Period

Industry	Count of affected country-periods		
	All years	2009-2016	2017-2023
Agriculture, hunting, forestry	498.0	269.0	229.0
Fishing and aquaculture	485.0	254.0	231.0
Chemical and chemical products	480.0	253.0	227.0
Food products, beverages and tobacco	478.0	254.0	224.0
Textiles, leather and footwear	468.0	247.0	221.0
Computer, electronic and optical equipment	468.0	240.0	228.0
Basic metals	460.0	243.0	217.0
Electrical equipment	460.0	238.0	222.0
Other non-metallic mineral products	455.0	234.0	221.0
Rubber and plastics products	452.0	235.0	217.0
Fabricated metal products	447.0	238.0	209.0
Pharmaceuticals	432.0	217.0	215.0
Coke and refined petroleum products	420.0	223.0	197.0
Wood and products of wood and cork	418.0	219.0	199.0
Other transport equipment	405.0	208.0	197.0
Electricity, gas, steam and AC	405.0	195.0	210.0
Machinery and equipment, nec	389.0	193.0	196.0
Publishing, AV and broadcasting activities	385.0	189.0	196.0
Motor vehicles, trailers and semi-trailers	379.0	197.0	182.0
Manufacturing nec	352.0	196.0	156.0
Mining and quarrying, energy	339.0	166.0	173.0
Paper products and printing	336.0	179.0	157.0
Telecommunications	225.0	90.0	135.0
Land transport and transport via pipelines	213.0	68.0	145.0
Professional, scientific and technical activities	208.0	80.0	128.0
Warehousing and support for transportation	194.0	65.0	129.0
Construction	188.0	47.0	141.0
Water transport	173.0	60.0	113.0
Administrative and support services	166.0	51.0	115.0
Financial and insurance activities	165.0	51.0	114.0
Air transport	158.0	48.0	110.0
Human health and social work activities	153.0	52.0	101.0
Accommodation and food service activities	149.0	48.0	101.0
Arts, entertainment and recreation	146.0	41.0	105.0
IT and other information services	126.0	42.0	84.0
Other service activities	106.0	37.0	69.0
Water supply; sewerage, waste management	102.0	17.0	85.0
Postal and courier activities	97.0	37.0	60.0
Real estate activities	94.0	14.0	80.0
Mining and quarrying, non-energy	93.0	7.0	86.0
Education	89.0	18.0	71.0
Public administration and defence	59.0	3.0	56.0
Activities of households	53.0	0.0	53.0

Count of country-sector-year that have at least one intervention, by sector and time-period as indicated. Sectors ordered by total count across all years.
Source: GTA (2024), Author calculations

Table A1.8b: Count of Affected Country-Periods, Emerging Markets by Time Period

Industry	Count of affected country-periods		
	All years	2009-2016	2017-2023
Agriculture, hunting, forestry	443.0	238.0	205.0
Food products, beverages and tobacco	409.0	211.0	198.0
Fishing and aquaculture	408.0	216.0	192.0
Chemical and chemical products	406.0	221.0	185.0
Basic metals	383.0	209.0	174.0
Computer, electronic and optical equipment	373.0	189.0	184.0
Textiles, leather and footwear	370.0	195.0	175.0
Rubber and plastics products	366.0	196.0	170.0
Other non-metallic mineral products	363.0	198.0	165.0
Electrical equipment	338.0	180.0	158.0
Pharmaceuticals	329.0	170.0	159.0
Fabricated metal products	309.0	163.0	146.0
Coke and refined petroleum products	300.0	159.0	141.0
Machinery and equipment, nec	269.0	138.0	131.0
Wood and products of wood and cork	266.0	133.0	133.0
Publishing, AV and broadcasting activities	264.0	117.0	147.0
Motor vehicles, trailers and semi-trailers	258.0	125.0	133.0
Mining and quarrying, energy	256.0	118.0	138.0
Other transport equipment	235.0	113.0	122.0
Manufacturing nec	228.0	109.0	119.0
Electricity, gas, steam and AC	216.0	83.0	133.0
Paper products and printing	214.0	99.0	115.0
Land transport and transport via pipelines	167.0	55.0	112.0
Financial and insurance activities	156.0	65.0	91.0
Telecommunications	140.0	55.0	85.0
Construction	139.0	52.0	87.0
Warehousing and support for transportation	130.0	42.0	88.0
Administrative and support services	125.0	32.0	93.0
Accommodation and food service activities	123.0	33.0	90.0
Professional, scientific and technical activities	123.0	46.0	77.0
Air transport	116.0	41.0	75.0
Water transport	110.0	35.0	75.0
IT and other information services	106.0	44.0	62.0
Arts, entertainment and recreation	101.0	20.0	81.0
Mining and quarrying, non-energy	94.0	18.0	76.0
Human health and social work activities	94.0	31.0	63.0
Education	68.0	17.0	51.0
Real estate activities	67.0	24.0	43.0
Water supply; sewerage, waste management	64.0	18.0	46.0
Other service activities	57.0	19.0	38.0
Postal and courier activities	50.0	11.0	39.0
Public administration and defence	41.0	9.0	32.0
Activities of households	32.0	4.0	28.0

Count of country-sector-year that have at least one intervention, by sector and time-period as indicated. Sectors ordered by total count across all years.
Source: GTA (2024), Author calculations

Table A1.8c: Count of Affected Country-Periods, Low-Income Countries by Time Period

Industry	Count of affected country-periods		
	All years	2009-2016	2017-2023
Agriculture, hunting, forestry	44.0	22.0	22.0
Food products, beverages and tobacco	30.0	14.0	16.0
Fishing and aquaculture	29.0	11.0	18.0
Chemical and chemical products	29.0	11.0	18.0
Textiles, leather and footwear	27.0	11.0	16.0
Rubber and plastics products	24.0	11.0	13.0
Computer, electronic and optical equipment	22.0	10.0	12.0
Coke and refined petroleum products	20.0	11.0	9.0
Machinery and equipment, nec	19.0	8.0	11.0
Wood and products of wood and cork	19.0	8.0	11.0
Basic metals	19.0	6.0	13.0
Other non-metallic mineral products	17.0	5.0	12.0
Pharmaceuticals	17.0	6.0	11.0
Publishing, AV and broadcasting activities	16.0	5.0	11.0
Electrical equipment	15.0	5.0	10.0
Fabricated metal products	13.0	4.0	9.0
Motor vehicles, trailers and semi-trailers	12.0	3.0	9.0
Paper products and printing	12.0	3.0	9.0
Mining and quarrying, energy	11.0	4.0	7.0
Electricity, gas, steam and AC	10.0	3.0	7.0
Other transport equipment	10.0	1.0	9.0
Manufacturing nec	10.0	2.0	8.0
Financial and insurance activities	9.0	2.0	7.0
Arts, entertainment and recreation	7.0	0.0	7.0
Accommodation and food service activities	6.0	1.0	5.0
Mining and quarrying, non-energy	6.0	0.0	6.0
Land transport and transport via pipelines	6.0	2.0	4.0
Warehousing and support for transportation	5.0	1.0	4.0
Real estate activities	5.0	3.0	2.0
Water transport	4.0	1.0	3.0
Administrative and support services	4.0	0.0	4.0
Education	2.0	0.0	2.0
Air transport	2.0	2.0	0.0
Construction	2.0	1.0	1.0
IT and other information services	2.0	1.0	1.0
Human health and social work activities	1.0	0.0	1.0
Professional, scientific and technical activities	1.0	0.0	1.0
Postal and courier activities	1.0	0.0	1.0
Activities of households	1.0	0.0	1.0
Water supply; sewerage, waste management	1.0	0.0	1.0
Other service activities	1.0	0.0	1.0
Public administration and defence	1.0	0.0	1.0

Count of country-sector-year that have at least one intervention, by sector and time-period as indicated. Sectors ordered by total count across all years.
Source: GTA (2024), Author calculations

8.2 Appendix 2: Main Empirical Results

Table A2.1: Sector Centrality, Globally and By Region

	(1) Global	(2) Global	(3) Western Hemisphere	(4) Asia Pacific	(5) Europe	(6) Africa	(7) Middle East, Central Asia
Interventions Binary							
Eigenvector Centrality, Domestic	0.025	0.022	0.198	0.222***	-0.102**	0.170	0.200*
	(0.035)	(0.034)	(0.154)	(0.067)	(0.049)	(0.197)	(0.116)
Eigenvector Centrality, Global		0.064	0.050	5.829**	-9.797***	40.833	10.944
		(0.044)	(0.047)	(2.835)	(2.390)	(75.323)	(34.504)
Upstreamness		0.085	-0.114	0.205	-0.223	-0.286	0.484***
		(0.083)	(0.250)	(0.146)	(0.143)	(0.341)	(0.179)
Final Demand, Domestic, 2nd Lag		-1.204***	-2.124***	-1.102***	-2.217***	-0.986	0.324
		(0.243)	(0.714)	(0.426)	(0.440)	(0.820)	(0.498)
Final Demand, Foreign, 2nd Lag		-0.708	0.666	-0.927	-1.574**	0.893	-1.605
		(0.486)	(2.274)	(0.808)	(0.765)	(2.358)	(1.085)
Export Intermediates, 2nd Lag		0.565*	-0.691	-0.708	1.173**	-0.405	-0.328
		(0.334)	(1.071)	(0.569)	(0.573)	(1.078)	(1.006)
Import Intermediates, Domestic, 2nd Lag		3.779***	2.149	0.572	5.116***	-0.573	3.514**
		(0.591)	(2.340)	(0.870)	(1.150)	(1.493)	(1.437)
Sector Size, Value Added, 2nd Lag		-2.596***	-3.459***	-2.266***	-3.462***	-1.328	-0.866
		(0.279)	(0.802)	(0.473)	(0.496)	(1.096)	(0.690)
Share of Global Exports, 2nd Lag		0.763	-2.846	4.618*	1.724	-16.014	3.918
		(1.589)	(3.777)	(2.635)	(2.810)	(14.843)	(5.165)
Constant	0.151	1.317**	2.939***	0.744	1.632**	0.238	-1.486
	(0.489)	(0.537)	(1.117)	(0.636)	(0.807)	(4.722)	(2.101)
Country FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
Observations	42345	39996	4341	8700	21075	2280	3600
Intra-class variance, ρ	0.594	0.492	0.494	0.359	0.582	0.415	0.393
Panel-level variance, $ln(\sigma_u^2)$	1.571***	1.157***	1.165***	0.610***	1.522***	0.848***	0.758***
	(0.036)	(0.043)	(0.135)	(0.095)	(0.064)	(0.197)	(0.146)
Clustering	robust	robust	robust	robust	robust	robust	robust

Standard errors in parentheses
Global specification uses the full sample.
Regional specifications use subsamples
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2.2: Sector Centrality, By Income Group

	(1) Advanced and Emerging	(2) Advanced	(3) Emerging
Interventions Binary			
Eigenvector Centrality, Domestic	-0.113^{**}	-0.116^{**}	0.176^{***}
	(0.044)	(0.049)	(0.059)
Emerging	-0.891		
	(0.653)		
Emerging×Eigenvector Centrality, Domestic	0.322^{***}		
	(0.075)		
Eigenvector Centrality, Global	0.081^{*}	0.089^{*}	10.066^{**}
	(0.045)	(0.048)	(4.825)
Upstreamness	0.082	-0.223	0.279^{***}
	(0.087)	(0.145)	(0.107)
Final Demand, Domestic, 2nd Lag	-1.288^{***}	-1.863^{***}	-1.041^{***}
	(0.259)	(0.434)	(0.314)
Final Demand, Foreign, 2nd Lag	-0.913^{*}	-1.598^{**}	-0.648
	(0.512)	(0.810)	(0.655)
Export Intermediates, 2nd Lag	0.549	1.485^{***}	-0.769^{*}
	(0.357)	(0.571)	(0.467)
Import Intermediates, Domestic, 2nd Lag	4.299^{***}	4.747^{***}	3.101^{***}
	(0.653)	(1.128)	(0.782)
Sector Size, Value Added, 2nd Lag	-2.622^{***}	-3.553^{***}	-2.074^{***}
	(0.296)	(0.506)	(0.359)
Share of Global Exports, 2nd Lag	0.995	-0.453	6.567^{**}
	(1.627)	(2.071)	(3.196)
Constant	2.304^{***}	1.769^{***}	1.288^{**}
	(0.633)	(0.649)	(0.648)
Country FE	✓	✓	✓
Year FE	✓	✓	✓
Observations	37431	20145	17286
Intra-class variance, ρ	0.503	0.570	0.440
Panel-level variance, $ln(\sigma_u^2)$	1.202^{***}	1.471^{***}	0.950^{***}
	(0.045)	(0.061)	(0.068)
Clustering	*robust*	*robust*	*robust*

Standard errors in parentheses
Advanced Economy as Reference group
Specifications (2)-(3) use subsamples
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2.3: Sector Centrality, By Time Period

	(1) 2009-2023	(2) 2009-2016	(3) 2017-2023
Interventions Binary			
Eigenvector Centrality, Domestic	-0.043	-0.071	0.115^{***}
	(0.040)	(0.048)	(0.040)
2017-23	2.172^{***}		
	(0.095)		
2017-23$\times$Eigenvector Centrality, Domestic	0.163^{***}		
	(0.040)		
Eigenvector Centrality, Global	0.063	0.094^{*}	0.044
	(0.045)	(0.055)	(0.041)
Upstreamness	0.096	-0.035	0.035
	(0.083)	(0.116)	(0.082)
Final Demand, Domestic, 2nd Lag	-1.161^{***}	-2.178^{***}	-0.905^{***}
	(0.242)	(0.333)	(0.258)
Final Demand, Foreign, 2nd Lag	-0.666	-1.121	-0.924^{*}
	(0.487)	(0.694)	(0.473)
Export Intermediates, 2nd Lag	0.576^{*}	1.030^{**}	0.645^{*}
	(0.333)	(0.460)	(0.350)
Import Intermediates, Domestic, 2nd Lag	3.769^{***}	5.842^{***}	3.194^{***}
	(0.588)	(0.799)	(0.608)
Sector Size, Value Added, 2nd Lag	-2.600^{***}	-4.033^{***}	-3.120^{***}
	(0.278)	(0.389)	(0.285)
Share of Global Exports, 2nd Lag	0.803	1.040	-0.954
	(1.589)	(2.223)	(1.875)
Constant	1.272^{**}	2.679^{***}	1.396^{***}
	(0.536)	(0.638)	(0.528)
Country FE	✓	✓	✓
Year FE	✓	✓	✓
Observations	39996	21334	18662
Intra-class variance, ρ	0.492	0.627	0.378
Panel-level variance, $ln(\sigma_u^2)$	1.158^{***}	1.710^{***}	0.693^{***}
	(0.043)	(0.054)	(0.059)
Clustering	*robust*	*robust*	*robust*

Standard errors in parentheses
Early period (2009-2016) as reference group
Specifications (2)-(3) use subsamples
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2.4a: Sector Centrality, By Policy Tool (1)

	(1) Subsidies	(2) Subsidies, Only	(3) Export Restrictions	(4) Export Restrict. Only	(5) Export Support	(6) Export Support Only
Eigenvector Centrality, Domestic	0.078***	0.125***	0.169***	0.217***	0.143***	0.221***
	(0.028)	(0.026)	(0.061)	(0.063)	(0.038)	(0.059)
Eigenvector Centrality, Global	0.001	0.051**	-0.382***	-1.862	-0.013	0.026
	(0.029)	(0.024)	(0.148)	(1.383)	(0.027)	(0.019)
Upstreamness	0.082	0.535***	-0.604***	-0.362*	-0.244***	0.012
	(0.063)	(0.061)	(0.139)	(0.193)	(0.087)	(0.110)
Final Demand, Domestic, 2nd Lag	-0.722***	0.669***	-2.059***	-1.742***	-0.990***	0.392
	(0.195)	(0.195)	(0.450)	(0.599)	(0.273)	(0.342)
Final Demand, Foreign, 2nd Lag	0.171	1.874***	-2.254***	-0.738	-1.712***	-1.551*
	(0.328)	(0.315)	(0.733)	(1.156)	(0.490)	(0.837)
Export Intermediates, 2nd Lag	-0.515**	-1.907***	2.053***	2.066***	0.402	-0.785
	(0.249)	(0.323)	(0.470)	(0.737)	(0.374)	(0.590)
Import Intermediates, Domestic, 2nd Lag	1.222***	-2.833***	3.827***	-0.900	1.397**	-1.037
	(0.433)	(0.569)	(0.796)	(1.269)	(0.567)	(0.843)
Sector Size, Value Added, 2nd Lag	-1.457***	0.833***	-3.245***	-1.513**	-2.304***	-0.658*
	(0.238)	(0.248)	(0.562)	(0.764)	(0.312)	(0.360)
Share of Global Exports, 2nd Lag	2.603*	2.213	-5.821**	1.370	-0.247	4.607**
	(1.378)	(1.564)	(2.291)	(4.608)	(1.609)	(2.087)
Constant	-1.098***	-5.373***	-2.145***	-5.232***	-0.605	-4.312***
	(0.376)	(0.418)	(0.710)	(1.256)	(0.405)	(0.579)
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	37851	37356	37200	16324	35055	22845
Intra-class variance, ρ	0.271	0.240	0.540	0.109	0.367	0.191
Panel-level variance, $ln(\sigma_u^2)$	0.201***	0.036	1.352***	-0.912	0.644***	-0.254
	(0.060)	(0.065)	(0.077)	(0.621)	(0.069)	(0.166)
Clustering	robust	robust	robust	robust	robust	robust

Standard errors in parentheses
Specifications (1),(3),(5) allow for the use of multiple tools in a country-sector-year.
Specifications (2),(4),(6) restrict to using only the specified tool, in the given country-sector-year
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2.4b: Sector Centrality, By Policy Tool (2)

	(1) Import Tariff	(2) Import Tariff, Only	(3) Import Tariff and Subsidies	(4) Antidumping	(5) Antidumping, Only
main					
Eigenvector Centrality, Domestic	−0.070	−0.168***	−0.192***	−0.265***	−0.310***
	(0.057)	(0.049)	(0.055)	(0.077)	(0.112)
Eigenvector Centrality, Global	−0.100	0.070**	−0.148	−0.183	0.052*
	(0.073)	(0.036)	(0.128)	(0.114)	(0.030)
Upstreamness	−0.155	−0.234**	−0.336***	−0.198	0.077
	(0.145)	(0.099)	(0.114)	(0.183)	(0.188)
Final Demand, Domestic, 2nd Lag	−2.511***	−1.711***	−1.809***	−2.068***	−2.131***
	(0.411)	(0.274)	(0.331)	(0.549)	(0.538)
Final Demand, Foreign, 2nd Lag	−1.704**	−0.236	−0.106	−4.345***	−3.330***
	(0.819)	(0.528)	(0.552)	(0.854)	(0.912)
Export Intermediates, 2nd Lag	1.904***	0.302	−0.296	3.020***	0.967*
	(0.535)	(0.360)	(0.397)	(0.546)	(0.567)
Import Intermediates, Domestic, 2nd Lag	1.792**	2.485***	2.707***	2.380***	2.173**
	(0.709)	(0.469)	(0.551)	(0.719)	(0.866)
Sector Size, Value Added, 2nd Lag	−5.029***	−3.215***	−3.291***	−4.950***	−4.212***
	(0.436)	(0.330)	(0.365)	(0.562)	(0.661)
Share of Global Exports, 2nd Lag	−8.423***	−8.212***	0.399	−2.035	−0.638
	(2.639)	(2.958)	(1.592)	(3.287)	(3.881)
Constant	0.674	−1.008*	−2.356***	1.402	−2.416**
	(0.869)	(0.530)	(0.568)	(0.972)	(0.994)
Country FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Observations	38286	38286	34761	32781	24786
Intra-class variance, ρ	0.781	0.425	0.386	0.672	0.265
Panel-level variance, $ln(\sigma_u^2)$	2.462***	0.888***	0.729***	1.906***	0.172
	(0.059)	(0.055)	(0.071)	(0.069)	(0.183)
Clustering	*robust*	*robust*	*robust*	*robust*	*robust*

Standard errors in parentheses
Specifications (1),(4) allow for the use of multiple tools in a country-sector-year.
Specifications (2),(5) restrict to using only the specified tool, in the given country-sector-year
Specification (3) restricts to joint use of tariffs and subsidies
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2.5a: Sector Centrality, By Time Period or Income Group, Asia Pacific

	(1) Advanced Asia	(2) Emerging Asia	(3) 2009-2016	(4) 2017-2023
Interventions Binary				
Eigenvector Centrality, Domestic	0.063	0.488***	0.156	0.376***
	(0.080)	(0.158)	(0.104)	(0.106)
Eigenvector Centrality, Global	1.538	12.726**	11.810***	−1.003
	(6.780)	(5.695)	(4.230)	(4.537)
Upstreamness	−0.273	0.455**	0.268	−0.002
	(0.252)	(0.230)	(0.193)	(0.152)
Final Demand, Domestic, 2nd Lag	−1.323*	−1.436**	−1.252**	−1.451***
	(0.739)	(0.661)	(0.556)	(0.459)
Final Demand, Foreign, 2nd Lag	−3.252**	−0.124	−2.638**	−1.266
	(1.565)	(1.211)	(1.144)	(0.887)
Export Intermediates, 2nd Lag	1.165	−1.728**	−1.078	−0.743
	(1.282)	(0.771)	(0.755)	(0.590)
Import Intermediates, Domestic, 2nd Lag	2.012	0.789	2.068*	−0.151
	(1.688)	(1.236)	(1.080)	(0.968)
Sector Size, Value Added, 2nd Lag	−3.305***	−1.322**	−3.159***	−2.631***
	(0.974)	(0.641)	(0.663)	(0.498)
Share of Global Exports, 2nd Lag	0.555	10.158*	7.443**	6.877
	(3.823)	(5.483)	(3.591)	(4.865)
Constant	1.992*	−1.562	0.732	1.889***
	(1.110)	(1.017)	(0.835)	(0.698)
Country FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Observations	3240	4170	4640	4060
Intra-class variance, ρ	0.387	0.383	0.458	0.278
Panel-level variance, $ln(\sigma_u^2)$	0.731***	0.714***	1.024***	0.239*
	(0.147)	(0.145)	(0.119)	(0.138)
Clustering	*robust*	*robust*	*robust*	*robust*

Standard errors in parentheses
Specifications (1) and (2) use subsamples by income group, for 2009-23
Specifications (3)-(4) use subsamples by time period for advanced and emerging economies
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2.5b: Sector Centrality, By Policy Tool, Asia Pacific

	(1) Subsidies	(2) Export Restrictions	(3) Export Support	(4) Import Tariff	(5) Antidumping
main					
Eigenvector Centrality, Domestic	0.084	0.081	0.235**	0.192	−0.118
	(0.101)	(0.079)	(0.111)	(0.143)	(0.145)
Eigenvector Centrality, Global	2.313	8.620***	5.024***	−0.844	5.290***
	(1.679)	(2.792)	(1.631)	(0.931)	(1.529)
Upstreamness	−0.274	0.129	−0.955***	0.146	−0.328
	(0.296)	(0.149)	(0.323)	(0.293)	(0.439)
Final Demand, Domestic, 2nd Lag	−3.026***	−0.602	−4.576***	0.019	−4.679***
	(0.794)	(0.445)	(0.937)	(0.818)	(1.218)
Final Demand, Foreign, 2nd Lag	−5.240***	0.002	−1.866	−1.880	−14.430***
	(1.842)	(0.828)	(1.856)	(1.988)	(3.610)
Export Intermediates, 2nd Lag	−0.755	−1.478**	1.516	−0.200	0.636
	(0.913)	(0.596)	(1.081)	(1.302)	(1.661)
Import Intermediates, Domestic, 2nd Lag	5.471***	−0.004	−0.497	2.526	6.208***
	(1.495)	(1.297)	(2.276)	(2.094)	(2.407)
Sector Size, Value Added, 2nd Lag	−2.994***	−0.797	−1.536	−2.669***	−1.706
	(0.947)	(0.546)	(1.159)	(0.968)	(1.549)
Share of Global Exports, 2nd Lag	9.557**	6.107**	−3.546	3.238*	5.600
	(3.759)	(2.540)	(2.562)	(1.861)	(4.393)
Constant	0.587	−2.628***	−0.360	−2.983**	−0.627
	(1.210)	(0.634)	(1.233)	(1.160)	(1.726)
Country FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Observations	6735	6720	6540	5400	6045
Intra-class variance, ρ	0.651	0.237	0.531	0.498	0.690
Panel-level variance, $ln(\sigma_u^2)$	1.814***	0.024	1.316***	1.183***	1.989***
	(0.132)	(0.149)	(0.198)	(0.172)	(0.162)
Clustering	*robust*	*robust*	*robust*	*robust*	*robust*

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

8.3 Appendix 3: Additional Empirical Results

Table A3.1: Sector Centrality, By Income Group, Including Low-Income

	(1) All	(2) Advanced	(3) Emerging	(4) Low Income
Interventions Binary				
Eigenvector Centrality, Domestic	-0.114^{***}	-0.116^{**}	0.176^{***}	0.377^{***}
	(0.043)	(0.049)	(0.059)	(0.126)
Emerging	-0.870			
	(0.646)			
Low Income	-4.839^{***}			
	(0.558)			
Emerging×Eigenvector Centrality, Domestic	0.325^{***}			
	(0.074)			
Low Income×Eigenvector Centrality, Domestic	0.500^{***}			
	(0.144)			
Eigenvector Centrality, Global	0.081^{*}	0.089^{*}	10.066^{**}	-93.904
	(0.044)	(0.048)	(4.825)	(223.989)
Upstreamness	0.094	-0.223	0.279^{***}	0.184
	(0.082)	(0.145)	(0.107)	(0.211)
Final Demand, Domestic, 2nd Lag	-1.184^{***}	-1.863^{***}	-1.041^{***}	-0.087
	(0.242)	(0.434)	(0.314)	(0.552)
Final Demand, Foreign, 2nd Lag	-0.767	-1.598^{**}	-0.648	-2.107
	(0.485)	(0.810)	(0.655)	(1.552)
Export Intermediates, 2nd Lag	0.555^{*}	1.485^{***}	-0.769^{*}	-1.437^{**}
	(0.332)	(0.571)	(0.467)	(0.710)
Import Intermediates, Domestic, 2nd Lag	3.822^{***}	4.747^{***}	3.101^{***}	-1.709
	(0.589)	(1.128)	(0.782)	(1.088)
Sector Size, Value Added, 2nd Lag	-2.588^{***}	-3.553^{***}	-2.074^{***}	-2.161^{***}
	(0.277)	(0.506)	(0.359)	(0.748)
Share of Global Exports, 2nd Lag	0.961	-0.453	6.567^{**}	69.494^{**}
	(1.599)	(2.071)	(3.196)	(29.108)
Constant	2.216^{***}	1.769^{***}	1.288^{**}	-5.816
	(0.614)	(0.649)	(0.648)	(13.657)
Country FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Observations	39996	20145	17286	2565
Intra-class variance, ρ	0.486	0.570	0.440	0.175
Panel-level variance, $ln(\sigma_u^2)$	1.135^{***}	1.471^{***}	0.950^{***}	-0.362
	(0.043)	(0.061)	(0.068)	(0.224)
Clustering	*robust*	*robust*	*robust*	*robust*

Standard errors in parentheses
Advanced Economy as Reference group
Specifications (2)-(4) use subsamples
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3.2: Sector Centrality, By Time Period, Robustness

	(1) 2018 split	(2) 2019 split	(3) 2020 split
Interventions Binary			
Eigenvector Centrality, Domestic	-0.041	-0.037	-0.039
	(0.040)	(0.039)	(0.040)
2018-23	2.176^{***}		
	(0.095)		
2018-23×Eigenvector Centrality, Domestic	0.191^{***}		
	(0.041)		
2019-23		2.181^{***}	
		(0.095)	
2019-23×Eigenvector Centrality, Domestic		0.219^{***}	
		(0.044)	
2020-23			2.194^{***}
			(0.096)
2020-23×Eigenvector Centrality, Domestic			0.293^{***}
			(0.057)
Eigenvector Centrality, Global	0.063	0.064	0.066
	(0.046)	(0.046)	(0.045)
Upstreamness	0.096	0.095	0.094
	(0.083)	(0.083)	(0.082)
Final Demand, Domestic, 2nd Lag	-1.158^{***}	-1.158^{***}	-1.155^{***}
	(0.242)	(0.242)	(0.242)
Final Demand, Foreign, 2nd Lag	-0.659	-0.665	-0.675
	(0.487)	(0.487)	(0.487)
Export Intermediates, 2nd Lag	0.579^{*}	0.585^{*}	0.591^{*}
	(0.333)	(0.333)	(0.332)
Import Intermediates, Domestic, 2nd Lag	3.773^{***}	3.780^{***}	3.777^{***}
	(0.588)	(0.588)	(0.589)
Sector Size, Value Added, 2nd Lag	-2.598^{***}	-2.596^{***}	-2.600^{***}
	(0.278)	(0.278)	(0.278)
Share of Global Exports, 2nd Lag	0.824	0.848	0.887
	(1.590)	(1.592)	(1.596)
Constant	1.270^{**}	1.272^{**}	1.278^{**}
	(0.536)	(0.536)	(0.536)
Country FE	✓	✓	✓
Year FE	✓	✓	✓
Observations	39996	39996	39996
Intra-class variance, ρ	0.492	0.492	0.492
Panel-level variance, $ln(\sigma_u^2)$	1.158^{***}	1.158^{***}	1.158^{***}
	(0.043)	(0.043)	(0.043)
Clustering	*robust*	*robust*	*robust*

Standard errors in parentheses
Early period as reference group
Specification (1) periods: 2008-2017, 2018-2023
Specification (2) periods: 2008-2018, 2019-2023
Specification (3) periods: 2008-2019, 2020-2023
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3.3: Sector Centrality, By Policy Tool Over TIme

	(1) Subsidies	(2) Export Restrictions	(3) Export Support	(4) Import Tariff	(5) Antidumping
main					
Eigenvector Centrality, Domestic	0.000	0.408***	0.214***	−0.058	−0.227***
	(0.038)	(0.074)	(0.043)	(0.061)	(0.080)
2017-23	3.001***	4.566***	1.903***	−0.037	−2.045***
	(0.090)	(0.257)	(0.124)	(0.120)	(0.152)
2017-23×Eigenvector Centrality, Domestic	0.165***	−0.433***	−0.143***	−0.033	−0.157*
	(0.040)	(0.095)	(0.054)	(0.057)	(0.088)
Eigenvector Centrality, Global	0.003	−0.372**	−0.014	−0.100	−0.186
	(0.029)	(0.149)	(0.026)	(0.073)	(0.114)
Upstreamness	0.092	−0.649***	−0.252***	−0.158	−0.199
	(0.063)	(0.140)	(0.088)	(0.145)	(0.182)
Final Demand, Domestic, 2nd Lag	−0.691***	−2.193***	−1.018***	−2.522***	−2.084***
	(0.194)	(0.455)	(0.275)	(0.411)	(0.547)
Final Demand, Foreign, 2nd Lag	0.187	−2.373***	−1.735***	−1.711**	−4.302***
	(0.329)	(0.721)	(0.490)	(0.819)	(0.854)
Export Intermediates, 2nd Lag	−0.501**	1.994***	0.373	1.896***	2.987***
	(0.249)	(0.467)	(0.374)	(0.536)	(0.547)
Import Intermediates, Domestic, 2nd Lag	1.208***	3.701***	1.400**	1.783**	2.371***
	(0.432)	(0.797)	(0.568)	(0.710)	(0.717)
Sector Size, Value Added, 2nd Lag	−1.461***	−3.294***	−2.306***	−5.027***	−4.942***
	(0.238)	(0.565)	(0.312)	(0.436)	(0.561)
Share of Global Exports, 2nd Lag	2.601*	−5.548**	−0.150	−8.394***	−1.856
	(1.378)	(2.300)	(1.613)	(2.635)	(3.299)
Constant	−1.135***	−2.034***	−0.582	0.687	1.408
	(0.376)	(0.711)	(0.406)	(0.869)	(0.971)
Country FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Observations	37851	37200	35055	38286	32781
Intra-class variance, ρ	0.272	0.538	0.367	0.781	0.672
Panel-level variance, $ln(\sigma_u^2)$	0.204***	1.345***	0.647***	2.462***	1.907***
	(0.060)	(0.076)	(0.069)	(0.059)	(0.069)
Clustering	*robust*	*robust*	*robust*	*robust*	*robust*

Standard errors in parentheses
Early period (2009-2016) as reference group
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3.4: Sector Centrality, By Income Group, Excluding China

	(1) Advanced and Emerging	(2) Advanced	(3) Emerging
Interventions Binary			
Eigenvector Centrality, Domestic	-0.110^{**}	-0.116^{**}	0.179^{***}
	(0.044)	(0.049)	(0.060)
Emerging	-0.981		
	(0.657)		
Emerging×Eigenvector Centrality, Domestic	0.312^{***}		
	(0.075)		
Eigenvector Centrality, Global	0.082^{*}	0.089^{*}	7.507
	(0.044)	(0.048)	(6.332)
Upstreamness	0.067	-0.223	0.254^{**}
	(0.088)	(0.145)	(0.107)
Final Demand, Domestic, 2nd Lag	-1.287^{***}	-1.863^{***}	-1.048^{***}
	(0.260)	(0.434)	(0.317)
Final Demand, Foreign, 2nd Lag	-0.925^{*}	-1.598^{**}	-0.638
	(0.512)	(0.810)	(0.654)
Export Intermediates, 2nd Lag	0.598^{*}	1.485^{***}	-0.703
	(0.358)	(0.571)	(0.475)
Import Intermediates, Domestic, 2nd Lag	4.319^{***}	4.747^{***}	3.117^{***}
	(0.654)	(1.128)	(0.784)
Sector Size, Value Added, 2nd Lag	-2.626^{***}	-3.553^{***}	-2.113^{***}
	(0.299)	(0.506)	(0.364)
Share of Global Exports, 2nd Lag	0.211	-0.453	5.480
	(1.743)	(2.071)	(3.689)
Constant	2.446^{***}	1.769^{***}	1.246^{*}
	(0.638)	(0.649)	(0.696)
Country FE	✓	✓	✓
Year FE	✓	✓	✓
Observations	36831	20145	16686
Intra-class variance, ρ	0.502	0.570	0.439
Panel-level variance, $ln(\sigma_u^2)$	1.198^{***}	1.471^{***}	0.944^{***}
	(0.045)	(0.061)	(0.069)
Clustering	*robust*	*robust*	*robust*

Standard errors in parentheses
Advanced Economy as Reference group
Specifications (2)-(3) use subsamples
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3.5: Sector Centrality, By Time Period or Income Group, Asia Pacific Excluding China

	(1) Advanced Asia	(2) Emerging Asia	(3) 2009-2016	(4) 2017-2023
Interventions Binary				
Eigenvector Centrality, Domestic	0.063	0.548^{***}	0.236^{**}	0.380^{***}
	(0.080)	(0.172)	(0.115)	(0.117)
Eigenvector Centrality, Global	1.538	-6.365	-1.851	-0.539
	(6.780)	(13.520)	(7.372)	(8.065)
Upstreamness	-0.273	0.378	0.155	0.001
	(0.252)	(0.240)	(0.195)	(0.156)
Final Demand, Domestic, 2nd Lag	-1.323^{*}	-1.555^{**}	-1.303^{**}	-1.395^{***}
	(0.739)	(0.696)	(0.574)	(0.470)
Final Demand, Foreign, 2nd Lag	-3.252^{**}	-0.233	-2.911^{**}	-1.227
	(1.565)	(1.219)	(1.138)	(0.893)
Export Intermediates, 2nd Lag	1.165	-1.846^{**}	-0.844	-0.594
	(1.282)	(0.804)	(0.778)	(0.607)
Import Intermediates, Domestic, 2nd Lag	2.012	0.925	2.507^{**}	-0.285
	(1.688)	(1.225)	(1.090)	(0.991)
Sector Size, Value Added, 2nd Lag	-3.305^{***}	-1.436^{**}	-3.033^{***}	-2.741^{***}
	(0.974)	(0.678)	(0.685)	(0.519)
Share of Global Exports, 2nd Lag	0.555	12.306	7.957^{*}	5.511
	(3.823)	(8.161)	(4.517)	(5.055)
Constant	1.992^{*}	-2.315^{*}	0.242	1.971^{**}
	(1.110)	(1.320)	(0.933)	(0.841)
Country FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Observations	3240	3570	4320	3780
Intra-class variance, ρ	0.387	0.381	0.454	0.284
Panel-level variance, $ln(\sigma_u^2)$	0.731^{***}	0.706^{***}	1.005^{***}	0.268^{*}
	(0.147)	(0.151)	(0.123)	(0.137)
Clustering	*robust*	*robust*	*robust*	*robust*

Standard errors in parentheses
Specifications (1) and (2) use subsamples by income group, for 2009-23
Specifications (3)-(4) use subsamples by time period for advanced and emerging economies
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

PUBLICATIONS

Production Network Features of Industrial Policy
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