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Dynamic Network Determinants of Economic Growth

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Abstract

This study investigates how the structure of national production networks influences long-run economic growth. Using data from the EORA26 Multi-Region Input-Output Database for 187 countries (1991–2017), we reconstruct annual upstream and downstream sectoral networks and extract detailed topological metrics. We combine machine learning (XGBoost) with SHAP-based interpretability and two-way fixed effects panel regressions to identify and validate key structural determinants. The results show that growth is driven primarily by sector-specific network positions rather than aggregate network geometry at the country level. A pronounced bottleneck effect emerges in the transport sector, where insufficient mediation severely constrains growth. More broadly, strong outbound supply connectivity in key sectors promotes growth, whereas excessive input dependence in certain service sectors is associated with weaker performance. Our findings highlight the importance of structural positioning within production networks for understanding cross-country growth heterogeneity.

Keywords: Production Networks; Economic Growth; Network Topology; Machine Learning; Input–Output Analysis

JEL Codes*:* C67; E23; L14; L16.

1. Introduction

We examine how the dynamic structure of national production networks shapes economic growth. Using detailed inter-industry data from the EORA26 Multi-Region Input-Output Database for 187 countries over 26 years, we reconstruct the evolving architecture of sectoral interactions within each economy. Rather than treating growth as the outcome of aggregate factor accumulation alone, we focus on how the relative positioning of industrial sectors within supply and demand chains conditions macroeconomic performance at the country level.

Traditional macroeconomic models postulate a single aggregate production function in which sectoral heterogeneity and inter-industry linkages are largely abstracted away. Within this framework, idiosyncratic disturbances are assumed to wash out in the aggregate. This view has been fundamentally challenged. Gabaix (2011) showed that shocks to large firms can generate aggregate fluctuations, questioning the traditional "law of large numbers" intuition. Acemoglu et al. (2012) formalized this insight by modeling the economy as a network of sectoral interdependencies embedded in the input–output matrix, demonstrating that shocks to highly connected "hub" sectors propagate across the production web and can produce sizable aggregate effects. Extending the theoretical frontier, Baqaee and Farhi (2019) showed that non-linearities and substitution elasticities further amplify microeconomic shocks.

A growing empirical literature has validated these propagation mechanisms. Acemoglu et al. (2016) documented how supply-side and demand-side disturbances travel downstream and upstream through U.S. production networks. Barrot and Sauvagnat (2016) highlighted the role of input specificity in amplifying firm-level shocks, while Atalay (2017) quantified the aggregate importance of sectoral disturbances. Together, these contributions establish that network topology is central to understanding macroeconomic volatility.

Beyond short-run fluctuations, recent research links production networks to long-run growth and development. Jones (2011) introduced the concept of "weak links," arguing that distortions in critical intermediate inputs can depress aggregate productivity. McNerney et al. (2021) showed that longer production chains amplify productivity improvements, accelerating GDP growth. In parallel, Hidalgo et al. (2007) conceptualized development as movement through a network of productive capabilities, where countries located in dense regions of the product space experience stronger growth dynamics. Collectively, this

literature demonstrates that the structure of inter-sectoral linkages shapes both macroeconomic instability and development paths.

Despite these advances, an important limitation remains. Most existing studies treat the production network as a fixed and exogenous topology—a static snapshot in which the matrix of inter-sectoral linkages is assumed constant over time. While this assumption is analytically convenient and well suited to the study of short-run cascades, it abstracts from the dynamic nature of real-world production systems. In practice, firms and sectors continuously adjust their supplier and customer relationships in response to relative prices, technological change, trade integration, and geopolitical risk. The production network is therefore not merely a conduit for shocks, but an evolving structure shaped by endogenous economic decisions.

This study departs from the tradition by adopting a dynamic perspective on network topology. Rather than assuming rigid input–output coefficients, we treat the observed production structure as the outcome of ongoing sectoral reallocation and adjustment processes. Empirically, we reconstruct annual network configurations and link their structural properties to macroeconomic performance over time. In doing so, we shift the focus of network macroeconomics from volatility—how networks transmit recessions—to future performance—how network structure influences sustained growth trajectories.

More specifically, we provide systematic cross-country evidence linking detailed topological properties of national production networks to long-run macroeconomic performance, measured by annual real GDP growth rates. By distinguishing between sectoral bottlenecks, supply intensity, and input dependence, and by allowing for non-linear and threshold effects, we show that the shape of a nation's production web is not a secondary descriptive feature but a primary determinant of its economic trajectory. Structural positioning within the network emerges as a core driver of productivity dynamics and long-run development.

Our empirical strategy proceeds sequentially, integrating network science, machine learning, and econometric analysis. First, we construct dual national production topologies for each country-year observation. A downstream network, grounded in the Leontief framework, captures the propagation of supply-side shocks from producers to users. An upstream network, derived from the Ghosh allocation structure, traces how demand-side shocks travel backward through supplier linkages. This representation enables us to assess the production structure of the countries in a systematic fashion.

Second, to address the high dimensionality and (potential) non-linearities of the network statistics, we implement an Extreme Gradient Boosting (XGBoost) model. This approach helps us to rank the structural features according to their predictive contribution to GDP growth, uncovering complex interactions and threshold effects that may be obscured in conventional linear models. Rather than imposing functional forms *ex ante*, our algorithm allows the data to reveal the most influential sectoral network indicators.

Third, we apply SHAP (Shapley Additive Explanations) values to open the predictive "black box," decomposing growth predictions into variable-level contributions and identifying which sectoral network positions act as growth drivers and which function as bottlenecks. Finally, we subject the machine learning results to econometric scrutiny through a simple two-way fixed effects panel regression. By controlling for time-invariant country characteristics and common global shocks, this step provides additional validation for the expected average effect of the main determinants identified in the predictive framework.

Our results demonstrate that growth dynamics are shaped less by the overall geometry of national production networks and more by the structural positioning of specific industries/sectors within supply and demand chains. Although we considered aggregate topological indicators—such as average path length, diameter, and modularity—in our models, the most influential determinants of growth were exclusively node-level metrics.

Growth is therefore sector-specific rather than aggregate in nature: macroeconomic performance depends primarily on how individual sectors are embedded and function within the production web. In particular, the evidence supports a bottleneck hypothesis centered on transport connectivity. Downstream transport betweenness exhibits a pronounced non-linear threshold effect: when logistical intermediation falls below a critical level, the economy enters a negative regime characterized by severe contractionary pressure. Once a minimum level of connectivity is secured, however, additional centrality yields limited marginal gains. More broadly, we document a structural asymmetry between supply intensity and input dependence. Strong outward-oriented supplier roles in key sectors such as electricity and construction are consistently growth-enhancing, whereas excessive reliance on concentrated inputs—especially in services such as finance, post, and education—tends to dampen performance. These relationships are highly non-linear, often displaying L-shaped profiles and threshold dynamics rather than smooth proportional effects.

The policy implications of our findings follow directly from the structural patterns identified in the analysis. Effective development strategies should prioritize the removal of sectoral bottlenecks and the strategic repositioning of keystone industries, rather than pursuing uniform increases in connectivity across production networks. Infrastructure policy should ensure adequate transport intermediation, as even modest improvements in fragmented logistical systems can yield disproportionately large growth gains, especially in low-income and developing economies, as is the case of Central American and Mexico economies.

Strengthening the electricity sector's role as a reliable and outward-oriented supplier can further amplify economy-wide multiplier effects. This is particularly salient given the central role of electricity in enabling technological upgrading and supporting the ecological transformation of production systems. Agricultural policy should promote deeper integration into domestic value chains and foster upstream value addition, reducing structural isolation in primary activities. At the same time, policymakers must carefully manage excessive input concentration in sectors such as education and finance to prevent structural imbalances that may constrain growth. Finally, trade and industrial strategies should facilitate a gradual shift away from dependence on low value-added intermediation and primary resource extraction. Sustained economic expansion thus arises not from generalized network expansion, but from addressing critical structural weaknesses and enabling key sectors to transition from input dependence to supply leadership within the production network.

The relevance of our results for Central American countries and Mexico is particularly strong given their structural position within regional and global value chains. Economies such as Mexico, Guatemala, El Salvador, Honduras, Nicaragua, Costa Rica, and Panama are characterized by relatively concentrated export structures, strong dependence on a limited number of strategic sectors, and high exposure to external shocks—particularly through trade integration with the United States and global supply chains. In such contexts, the internal configuration of production networks becomes a decisive determinant of resilience and long-run growth. Transport infrastructure, electricity provision, and key service sectors often function as structural bottlenecks that can either amplify or constrain economy-wide performance. Moreover, many of these countries remain positioned in lower value-added segments of global production, with limited upstream supply leadership. By identifying how sectoral positioning, bottlenecks, and input dependence shape growth trajectories over time, this study provides a framework for understanding why some economies in the region achieve sustained expansion while others risk remaining vulnerable to volatility and low

growth dynamics. The dynamic network perspective is especially relevant for these countries as they navigate nearshoring opportunities, changes in global supply-chain configurations, energy and ecological transitions, and regional integration. In this sense, our findings offer actionable guidance for development strategies aimed at strengthening keystone sectors, reducing structural fragilities, and fostering a transition from input dependence toward more central and growth-enhancing roles within national and international production networks.

The rest of this document is organized as follows. In section 2 we describe our methodology, which blends Network Science, Machine Learning and Explainable Artificial Intelligence. In section 3 we present our main results, while section 4 concludes with some policy implications and discussion of our main findings.

2. Methodology

In this section, we describe the methodological framework used to identify the network-based structural determinants of economic growth. Our methodology integrates statistics from Network Science, Machine Learning models (in particular, Extreme Gradient Boosting), and Econometric Panel Data Analysis in a sequential architecture that moves from high-dimensional structural extraction to algorithmic discovery and finally to causal validation. The framework is grounded in the theoretical perspective of production networks as amplification mechanisms of shocks, as formalized by Acemoglu et al (2010, 2012, 2015, 2016,2020).

2.1. Data and Network Topologies

The empirical foundation of the analysis is the EORA26 Multi-Region Input-Output Database, which provides harmonized multi-region input-output (MRIO) tables for 187 countries over the period 1991–2017. Each country-year observation contains a 26-sector inter-industry transaction structure, enabling the reconstruction of national production networks. For each country-year, two distinct directed weighted network topologies are constructed aiming to capture the bidirectional propagation of shocks within the production system.

2.1.1. Downstream Networks

The downstream topology is derived from the Leontief inverse matrix:

$$L = (I - A)^{-1}, \tag{1}$$

where A is the matrix of technical coefficients. The Leontief inverse captures total (direct and indirect) input requirements necessary to satisfy one unit of final demand. In network terms, edges represent the cumulative propagation of supply-side shocks from upstream producers toward downstream users. The resulting graph reflects how shocks originating in one sector diffuse throughout the economy via production linkages.

2.1.2. Upstream Networks

The upstream topology is constructed from the Allocation (or Ghosh) matrix, which redistributes sectoral output across purchasing industries. This representation captures how demand-side shocks propagate backward from final users toward input suppliers. While the Leontief structure models cost-push transmission (e.g., productivity shocks, TFP shocks), the allocation structure captures demand-pull amplification (e.g., fiscal policy shocks, trade shocks). Together, these two kinds of topologies provide a dual representation of national production architectures, allowing the identification of asymmetric propagation mechanisms in each economy.

2.2. Structural Feature Extraction

Each network consists of 26 nodes representing harmonized economic sectors and weighted directed edges capturing inter-sectoral flows. From these structures, a high-dimensional feature space is extracted at two levels of aggregation: global (country-wide) and node-level (sector-specific).

2.2.1. Global Network Metrics

Country-level structural indicators describe the overall topology of the production system. We construct the full set of indicators permitted by the available data. These metrics capture structural efficiency, redundancy, and fragmentation—features that theory links to shock propagation and aggregate volatility including: i) *Average Path Length*, measuring the average number of steps required for shocks to traverse the network. ii) *Diameter,* capturing the maximum shortest-path distance and thus the network's structural extent. iii) *Modularity,* identifying the extent of community clustering or sectoral compartmentalization. iv) *Transitivity (Clustering Coefficient),* measuring the density of triadic closures and local interconnectedness. See Table A1 of the Appendix for a summary of the main indicators constructed.

2.2.2. Node-Level Centrality Measures

Sector-level statistics measure the relative position of each sector within the national network structure of each country. At the sectoral level, five classes of centrality measures are computed for each of the 26 sectors. i) *Strength Centrality* (Total, In, and Out), capturing weighted degree and overall transactional importance. ii) *Betweenness Centrality,* identifying sectors acting as structural bottlenecks controlling flow between otherwise disconnected sectors. iii) *Closeness Centrality,* measuring proximity to all other sectors in terms of shortest paths. iv) *Eigenvector Centrality,* capturing influence derived from connections to other influential sectors. v) *PageRank,* evaluating recursive importance under a stochastic flow interpretation.

This process generates a high-dimensional space of variables reflecting both *systemic density* and *sectoral dominance* patterns across countries and over the time. This constitutes the second step of our methodology and paves the way for an exhaustive exploration of the determinants of economic growth rooted in the network structure of the economies.

Given the high dimensionality of this structural feature space and the likely presence of non-linear and interaction effects among these correlated variables, our analysis leverages machine learning models alongside recent tools from explainable artificial intelligence to extract robust signals from the variables tat can be used to anticipate economic growth.

2.3. Machine Learning Framework: Extreme Gradient Boosting

In the third stage of our empirical strategy, we employ a non-causal machine learning approach to evaluate the relative predictive importance of production-network characteristics for economic growth. At this stage, the objective is not to estimate structural causal parameters, but rather to assess how strongly network-based indicators contribute to out-of-sample predictive performance when considered jointly. This predictive exercise allows us to rank structural features according to their explanatory power and take at first step in the exploration of the network's origins of long-run economic growth.

To this end, we leverage Extreme Gradient Boosting (XGBoost), introduced by Chen and Guestrin (2016), as an optimized and regularized implementation of Gradient Tree Boosting originally developed by Friedman (2001). XGBoost is particularly well suited for structured panel data with high-dimensional feature spaces and potentially complex non-linear relationships—precisely the context generated by our network-based feature extraction procedure.

Within our broader methodological framework, XGBoost plays a diagnostic and exploratory role. It processes our high-dimensional network feature space, detects non-linear and interaction effects, and ranks structural determinants according to predictive importance. The insights obtained at this stage guide the selection of variables and the identification of candidate thresholds that are later tested in a fixed-effects panel setting.

2.3.1. Model Structure

Let Y_{it} denote the annual real GDP growth rate for country $i$at time t. The predictive model can be written as:

$$\hat{Y}_{it} = \Phi(X_{it}) = \sum_{k=1}^{K} f_k\,(X_{it}), f_k \in \mathcal{F}, \tag{2}$$

where X_{it} is the vector of predictors, including global and sector-level network metrics, $\mathcal{F}$ denotes the space of regression trees, $f_k(\cdot)$ represents an individual decision tree, K is the total number of trees in the ensemble.

The model therefore approximates the unknown mapping between network structure and economic growth through an additive expansion of regression trees. Each tree partitions the predictor space into regions defined by recursive binary splits and assigns a constant prediction to each region.

2.3.2. Gradient Boosting

The core idea of Gradient Tree Boosting is sequential error correction. Rather than estimating a single large tree, the algorithm builds an ensemble of shallow trees (weak learners) in a forward stagewise manner. At each iteration k, a new tree is fitted to the residuals of the previous ensemble. More formally, each tree approximates the negative gradient of the loss function evaluated at the current prediction. In our application, we minimize the standard squared error loss:

$$\mathcal{L} = \sum_{i,t}(Y_{it} - \hat{Y}_{it})^2. \tag{3}$$

The boosting procedure proceeds as follows: (i) initialize predictions with a constant value; (ii) compute the residuals (negative gradients); (iii) fit a regression tree to these residuals; (iv) update the predictions by adding the scaled contribution of the new tree; and (v) repeat the process until convergence or until the optimal number of trees is reached. This iterative structure enables the model to capture complex non-linearities and higher-order interactions among network metrics—features that would be difficult to specify parametrically in a traditional regression framework.

2.3.3. Regularization and Treatment of Overfitting

A key advantage of XGBoost over standard boosting algorithms lies in its explicit regularization framework. The objective function combines goodness-of-fit with a penalty on model complexity:

$$\mathcal{L}^* = \sum_{i,t} \ell(Y_{it}, \hat{Y}_{it}) + \sum_{k=1}^{K} \Omega(f_k)\,, \tag{4}$$

where the penalty term $\Omega(f_k)$ constrains tree depth, the number of leaves, and leaf weights. This regularization discourages overly complex trees and mitigates overfitting—an important concern given the high dimensionality of sector-level centrality measures relative to the time dimension of our panel.

Hyperparameters such as maximum tree depth, learning rate (shrinkage parameter), minimum child weight, subsampling ratio, and column sampling rate are tuned using a *Racing ANOVA* procedure. This approach iteratively eliminates poorly performing configurations based on cross-validation, thereby concentrating computational effort on the most promising regions of the hyperparameter space. The resulting model balances predictive accuracy with parsimony.

XGBoost is particularly appropriate for our context because our dataset consists of tabular panel observations with engineered structural features rather than raw unstructured inputs. Moreover, the algorithm internally learns optimal splitting directions for missing observations, reducing the need for *ad hoc* imputation strategies if required. Production networks exhibit inherently interactive effects (e.g., the joint role of sectoral centrality and overall modularity), which tree-based ensembles capture naturally.

Finally, compared with neural networks, which typically require very large samples to exploit deep architectures effectively, or support vector machines that rely on kernel approximations, XGBoost provides a robust balance between flexibility and stability in moderate-sized macroeconomic panels as the one we constructed in the second step of this methodology.

2.3.4. Explainable AI and SHAP Decomposition

Although ensemble tree methods are often characterized as “black-box” predictors, we recover interpretability using SHAP (SHapley Additive exPlanations), introduced by Lundberg and Lee (2017). SHAP values are grounded in cooperative game theory and decompose each prediction into additive contributions from individual variables. For each country-year observation, the predicted growth rate can be written as:

$$\hat{Y}_{it} = \phi_0 + \sum_{j=1}^{J} \phi_{j,it} \,, \tag{5}$$

where, ϕ_0 is the average prediction across the sample, $\phi_{j,it}$ is the SHAP value associated with variable j. Each SHAP value measures the marginal contribution of a variable/feature to the prediction, averaged across all possible coalitions of other variables/features. This ensures consistency and accounts for interaction effects between network characteristics.

In our application, the SHAP analysis serves three purposes. Namely, as a variable ranking, where mean absolute SHAP values identify the most influential network metrics in predicting growth. Second, for directionality assessment, as the sign of SHAP contributions reveals whether higher centrality, density, or modularity enhances or dampens growth predictions. Finally, for non-Linearity detection, because SHAP dependence plots uncover threshold effects and regime changes in the structural-growth relationship.

This interpretability layer transforms the predictive model into a discovery tool. The variables identified as most influential by SHAP are subsequently subjected to a fixed-effects panel estimation, ensuring that the machine learning stage informs—but does not replace—econometric inference.

2.4. Panel Model

To validate the top network determinants identified by SHAP importance, we use a fixed effects panel regression implemented according to the following equation:

$$\text{Growth}_{it} = \sum_{k=1}^{5} \beta_k X_{k,it} + \alpha_i + \delta_t + \epsilon_{it}, \tag{7}$$

where, $X_{k,it}$ are the selected network metrics, α_i denote country fixed effects controlling for time-invariant heterogeneity (geography, institutions, historical factors), δ_t capture global time shocks, ϵ_{it} is the idiosyncratic error term.

3. Results

Figure 1 presents the SHAP summary plot derived from the application of SHAP values as explained in equation 5 before. These SHAP decomposition is based upon the XGBoost model presented in equation 4. Figure 1 provides a non-linear ranking of the sectoral and global network characteristics (see Table A1) that shape Real GDP growth trajectories in the countries of our sample.

Note that, importantly, although both global and node-level measures were included in the variable space for our ranking, the top 20 determinants that we analyzed in what follows, turned out to be exclusively node-level statistics. This finding indicates that growth

dynamics are mostly driven by sector-specific relative positions within the production network of each country, rather than by aggregate topological properties of the national economy, which is an interesting result by itself.

The SHAP visualization enables a joint assessment of (i) variable importance, (ii) directionality of impact, and (iii) structural asymmetries across sectors. Based on the position of high variable values (dark purple observations) relative to the zero axis, the top-ranked variables can be classified into two broad groups: growth facilitators and structural drags or bottlenecks.

A. *Growth Enablers:*

The first group consists of sectoral network characteristics for which *higher values are systematically associated with positive SHAP contributions* (purple points concentrated on the right-hand side of the distribution). These variables reflect network configurations that enhance productive capacity and inter-sectoral transmission. A clear example in this category is the upstream *Electricity strength_out statistic*. High outbound strength in the electricity sector—measuring the intensity with which electricity supplies other industries—appears as a robust growth driver. Economies where electricity functions as a concentrated and reliable supplier to the rest of the production system benefit from amplified multiplier effects and industrial scalability.

Similarly, *upstream Construction strength_out* is positively associated with growth. Strong outbound connections from construction reflect infrastructure-led expansion, where investment in physical capital propagates through supply chains and stimulates complementary sectors.

Downstream Agriculture PageRank also emerges as a facilitator. High centrality of agriculture within the demand network suggests that the primary sector is deeply integrated into domestic production chains, allowing upstream value addition rather than remaining isolated at the raw-material stage.

In the service domain, downstream *Hotels strength_total* and *strength_in* display positive clustering on the right side of the zero axis. This indicates that integration of the hospitality sector into demand networks contributes positively to growth, or is a natural consequence of it, potentially reflecting tourism-driven multiplier effects and domestic consumption linkages. Notice that, interestingly, the negative effects of this indicator are more notable than the positive effects on the right of the plot, cautioning on the limited upside potential of a growth strategy based on tourisms and consumption based (hotel and restaurants).

Finally, downstream Private eigenvector centrality—capturing influence within private consumption flows of households—acts as a strong positive signal. When the private sector occupies a structurally influential position, it reflects diversified and interconnected domestic demand, reinforcing expansionary dynamics.

Collectively, these findings suggest that ***growth is facilitated when foundational utility and infrastructure sectors operate as strong suppliers*** (high out-degree strength) and when consumption-linked services occupy influential central positions within demand chains.

B. *Structural Drags and Bottlenecks*

The second group comprises two types of variables: (i) those for which high values are associated with negative SHAP contributions (purple points concentrated on the left), and (ii) those for which low values (yellow points) exhibit pronounced negative tails, interpretable as growth bottlenecks. These patterns point to structural frictions, either in the form of excessive input dependence or systemic bottlenecks, respectively.

The most important variable in the ranking is *downstream Transport betweenness centrality*. Although high values of transport betweenness tend to cluster near zero, low values exhibit an extreme negative tail. This asymmetric distribution identifies the *transport sector as the primary systemic bottleneck in the model*. When transport fails to function as an intermediary bridging otherwise disconnected sectors, the entire production system experiences fragmentation, resulting in disproportionately large negative growth effects. The evidence suggests that insufficient bridging capacity is far more damaging than excess centrality is beneficial.

Upstream Agriculture strength_total exhibits a similar mechanism. Low overall connectivity of agriculture is associated with negative growth contributions, reflected in the extremely long left tail of yellow dots. This finding is particularly relevant for developing or structurally transforming economies. It suggests that excessive isolation of the primary sector from the rest of the production network may constitute a bottleneck to long-run growth. At the same time, while greater integration through stronger linkages is necessary—especially integration into higher value-added activities—its marginal impact appears bounded, as indicated by the short right tail of the distribution and the dark purple points clustered close to zero

A recurring negative configuration emerges for in-degree measures (strength_in). *Downstream Post strength_in* and *Financial strength_in*, as well as upstream *Electricity*

strength_in and Financial strength_in, show that high input reliance or customer concentration often exerts contractionary pressure. These sectors appear vulnerable when they depend excessively on intermediate inputs or a narrow customer base, potentially increasing operational costs and systemic fragility.

Education strength_in and strength_total also display pronounced negative clustering. High systemic reliance on education inputs may signal transitional frictions, skill mismatches, or elevated human capital costs during phases of structural upgrading. This interpretation aligns with the literature on intangible investment and economic complexity (Uribe, et al., 2025), which emphasizes that avoiding costly human capital mismatches requires coordinated upgrades in both human and physical capital. Absent complementary structural and industrial transformation, such imbalances can become a drag on growth.

Additional negative contributors include *upstream Maintenance closeness*, where high centrality may signal aging infrastructure burdens, *upstream Re-export strength_total*, indicating concentration in low value-added trade intermediation, and *downstream Mining strength_total*, where dependence on primary resource demand acts as a structural weight on long-term growth.

Taken together, these variables reveal that excessive input dependence, customer concentration, and primary-sector dominance constitute recurring structural drags within national production networks.

C. *Structural Patterns Across Network Metrics*

Beyond sectoral interpretation, the composition of the top 20 variables reveals systematic structural regularities in the model. First, the distribution between network types shows a slight predominance of supply-side dynamics: 11 upstream (allocation matrix) variables compared to 9 downstream (Leontief-based) variables. This suggests that growth sensitivity is marginally stronger with respect to output allocation and supplier positioning than to pure input requirements.

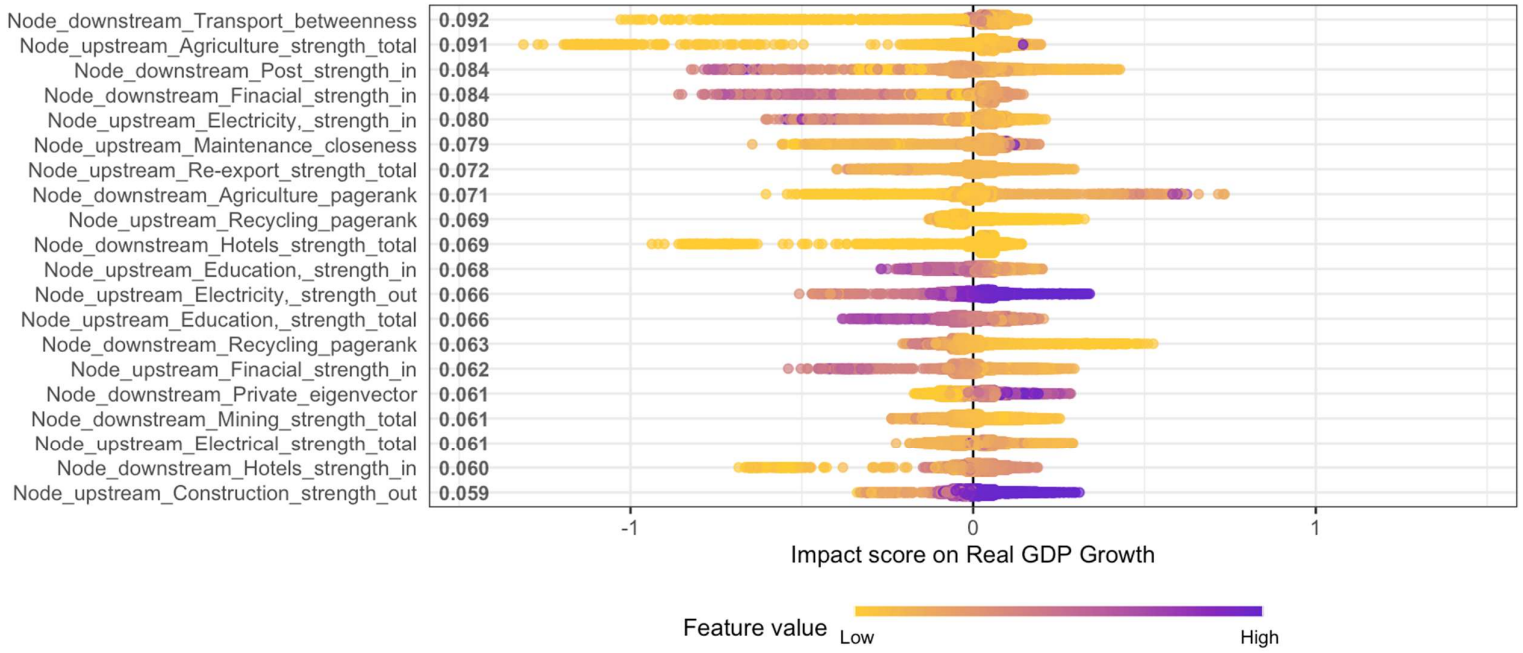
Second, strength (degree-based) measures dominate the ranking, accounting for 14 of the top 20 variables. In contrast, purely topological centrality metrics such as PageRank, eigenvector centrality, and betweenness appear only six times. This pattern indicates that the absolute volume and concentration of flows—how much a sector buys or sells—are more predictive of growth outcomes than the abstract geometric shape of the network. Structural intensity outweighs structural topology.

Third, a consistent asymmetry emerges between in-degree and out-degree measures. Out-degree strength (sales concentration to the rest of the economy) is typically associated with growth contributions. In contrast, in-degree strength (input reliance or customer concentration) is predominantly associated with negative effects. This directional asymmetry suggests that becoming a strong supplier is expansionary, whereas remaining a heavy input-dependent consumer is contractionary.

The recurrence of specific sectors across different metrics highlights the economy's "keystone" components. **Agriculture, Electricity, Financial Services, Education, Hotels, and Recycling** each appear multiple times, underscoring their multi-faceted influence across both upstream and downstream configurations.

Transport appears only once among the top 20, yet it is the single most influential variable. Its betweenness centrality captures its role as the physical mediator of inter-sectoral flows. The severe negative tail associated with low transport centrality confirms that inadequate logistical intermediation constitutes the largest systemic vulnerability in the network.

Figure 1. SHAP Global Importance and Distribution of Network Determinants on Real GDP Growth



Note: The figure displays the SHAP (SHapley Additive exPlanations) summary plot for the top 20 network structural characteristics derived from the XGBoost model. Features are ranked vertically by their global predictive importance, measured by the mean absolute SHAP value (indicated by the bold numerical values on the left). Each point represents a single country-year observation. The horizontal axis quantifies the impact of a specific feature on the model's prediction of Real GDP growth, where positive values indicate an expansionary effect and negative values indicate a contractionary effect. The color gradient represents the feature's relative value (yellow for low, purple for high). Network metrics are calculated based on downstream (Leontief Inverse) and upstream (Allocation) matrices following the methodology of Acemoglu et al. (2016) using EORA26 MRIO data (1991–2017).

Figure 2 presents SHAP dependence plots for the most relevant sectoral network metrics. These plots offer a detailed representation of the marginal effects of the top predictors on Real GDP growth dynamics. While the SHAP summary plot presented in Figure 1 establishes a hierarchical ranking of variable importance, the dependence plots allow us to examine the functional form of each relationship. In particular, they reveal pronounced non-linearities, tipping points, and saturation phenomena that would remain difficult to identify under a linear and parametric specification. The evidence presented in this new figure confirms that sectoral network positions affect growth through threshold mechanisms rather than smooth proportional changes.

A first interesting result concerns the downstream *Transport betweenness* measure. The plot displays a steep vertical increment in predicted growth contributions within a narrow interval close to zero (approximately between 0.00 and 0.03). Below this minimal level of bridging connectivity, the SHAP values fall sharply into strongly negative territory, in some cases below −1.0, indicating severe contractionary pressure. However, once this threshold is reached, the marginal effect stabilizes and flattens. This pattern substantiates the bottleneck hypothesis: insufficient transport intermediation imposes disproportionately large growth penalties, whereas additional centrality beyond a minimum viable level does not generate equivalent gains. The growth process thus appears highly sensitive to transport *critical failures* rather than sensitive to transport dominance.

A closely related non-linearity emerges for upstream *Agriculture total strength*. At near-zero levels of connectivity, the model predicts extreme negative contributions to growth. Yet as agricultural integration into upstream production chains increases, the marginal penalty declines rapidly and the curve levels off. This L-shaped pattern suggests that the primary sector must reach a minimum degree of systemic integration to avoid acting as a structural drag. Beyond that threshold, further increases in connectivity yield limited additional benefits.

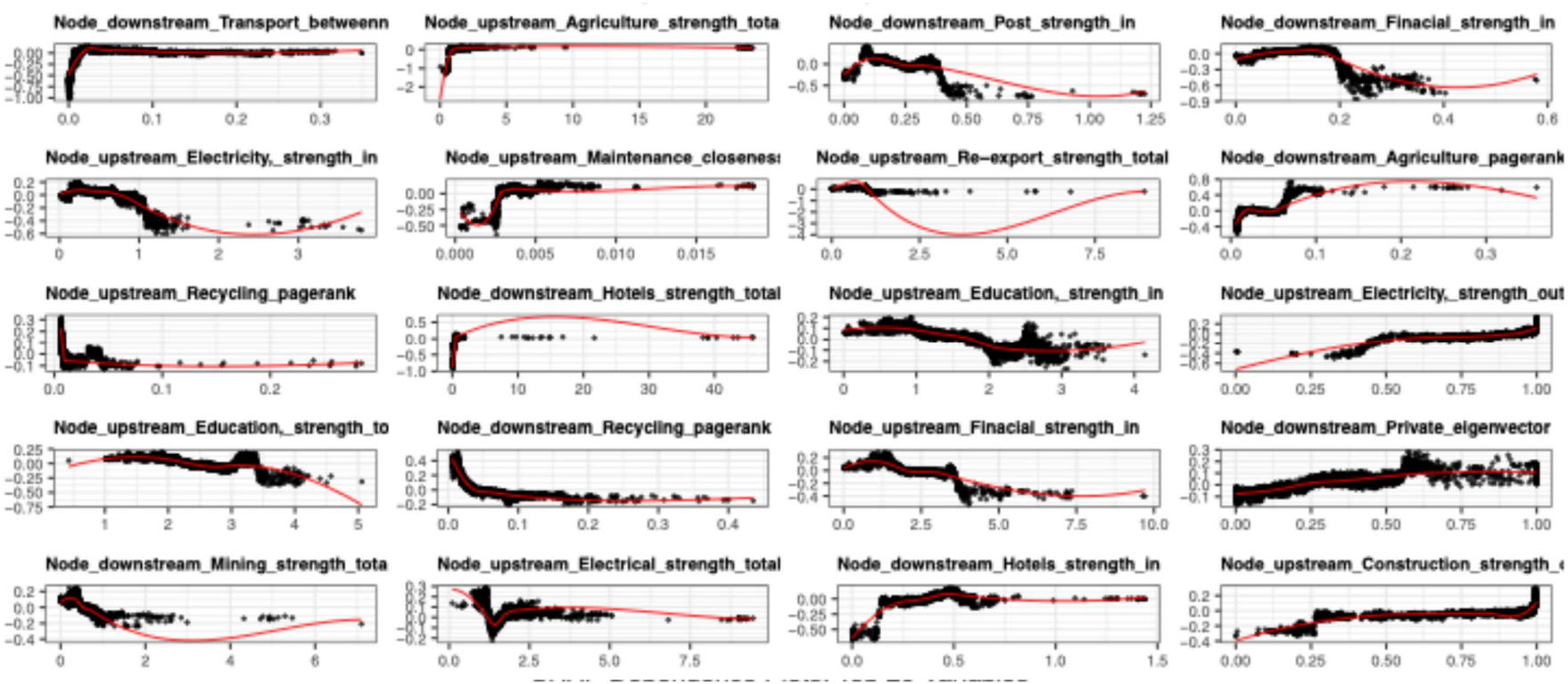
A different form of non-linearity characterizes service-sector input dependence. For downstream *Post strength_in* and *Financial strength_in,* the marginal contribution is mildly positive or neutral at low-to-moderate levels of input reliance. However, after a visible kink—around 0.4 in the case of Post and 0.2 for Financial—the SHAP values trend downward. This indicates diminishing returns and eventual negative effects from excessive dependence on intermediate service inputs. Moderate integration may facilitate coordination and financial intermediation, but over-reliance appears to increase costs or signal structural imbalances that weigh on growth performance.

Across the full set of dependence plots, three recurring structural configurations can be identified. The first is an “L-shaped” leap-frogging profile, observed for Transport betweenness, Agriculture total strength, and Hotels total strength. These variables exhibit a sharp upward movement from strongly negative values followed by a flat plateau. Economically, they represent prerequisite sectors. The economy does not gain proportionally from extremely high connectivity in these domains, but it suffers severely when connectivity falls below a critical minimum. Growth is therefore constrained by bottleneck removal rather than enhanced by continuous marginal improvements.

The second configuration is a steady upward slope, characteristic of upstream *Electricity strength_out* and *Construction strength_out*. These plots show an approximately monotonic positive relationship between outbound supply intensity and growth. Unlike bottleneck sectors, these foundational supply industries generate incremental benefits as their sales concentration to the rest of the economy increases. Strong outbound linkages in utilities and infrastructure amplify multiplier effects, supporting sustained expansion.

The third configuration resembles a persistent negative slope at higher values, particularly for upstream *Electricity strength_in*, *Education strength_in*, and *Financial strength_in*. After an initial neutral or slightly positive range, greater customer concentration correlates with declining growth contributions. This pattern suggests that excessive upstream in-degree reflects supply-chain vulnerability or over-specialization. When sectors depend too heavily on a narrow customer base or concentrated input channels, systemic fragility increases, and the model associates this structure with weaker growth trajectories. Also, these dynamics may reflect a lack of coordinated structural upgrading, with costly unbalances in terms of growth.

Figure 2. SHAP Dependence Plots of Top 20 Network Determinants of Real Growth



Note: Each panel illustrates the marginal effect of a specific network metric on the model's prediction for Real GDP growth. The x-axis represents the normalized value of the network metric, while the y-axis represents the SHAP value (impact on growth). The red line indicates a smoothed trend to highlight non-linearities. Metrics are categorized by their origin in the Downstream (Leontief) or Upstream (Allocation) matrices. Data covers 187 countries from 1991–2017 using EORA26 MRIO sectoral classifications.

Finally, centrality-based metrics such as *Agriculture PageRank* or *Private eigenvector centrality* display comparatively greater dispersion and volatility in their dependence plots. Their marginal effects appear more conditional and sensitive to interactions with other structural characteristics. In contrast, strength-based measures—capturing the absolute volume and concentration of flows—exhibit clearer and more stable functional forms. This reinforces the broader finding that growth dynamics are more directly tied to flow intensity and sectoral dependence structures than to purely topological centrality positions.

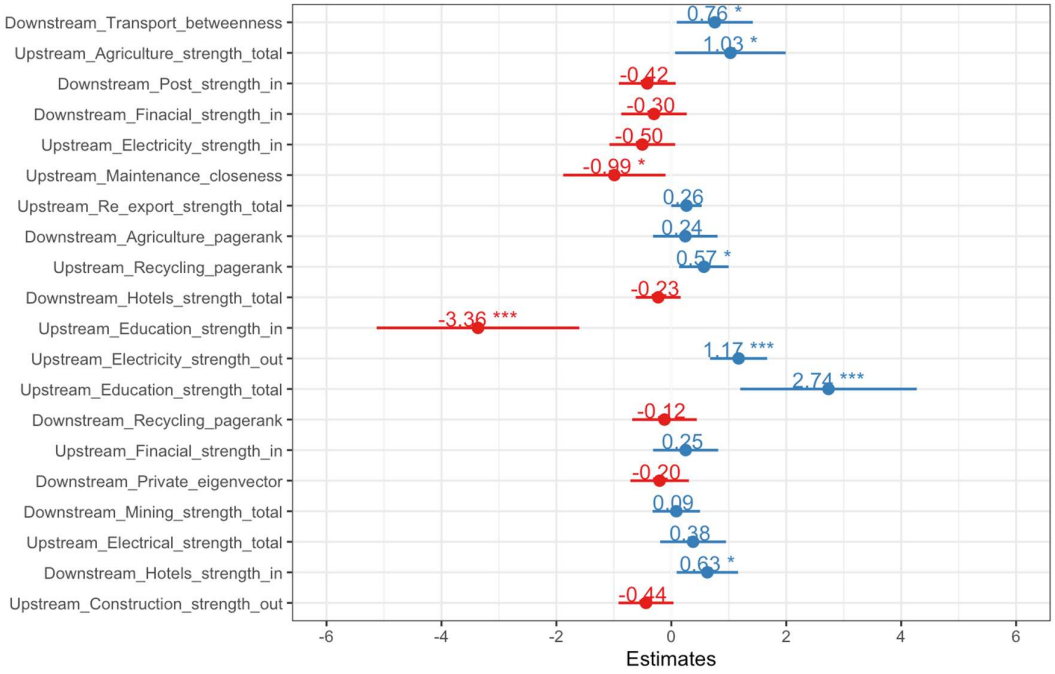
Figure 3 reports the estimates from a two-way fixed effects panel regression designed to assess the statistical significance of the leading network variables identified through the XGBoost model and their corresponding SHAP values. The specification includes both country and year fixed effects, thereby controlling for time-invariant national characteristics and common global shocks.

It is important to emphasize that the figure reflects the statistical significance of *average marginal effects*. As demonstrated in the SHAP dependence analysis, the relationship between network structure metrics and growth is frequently non-linear and characterized by thresholds or regime-dependent behavior. Consequently, a variable that exerts strong effects in specific regions of its distribution may display a statistically weak or insignificant average coefficient in a linear panel specification. In other words, statistical insignificance in this context does not necessarily imply economic irrelevance, but may instead reflect heterogeneity in marginal effects across observations. Nonetheless, the fixed effects framework provides a complementary validation exercise. By evaluating the mean within-country association between network characteristics and growth, it allows us to rank the previously identified determinants according to conventional measures of statistical significance. This step therefore bridges the machine learning–based importance ranking with standard econometric inference, reinforcing the robustness and interpretability of the results.

Figure 3 displays the standardized effects of the top 20 network variables on GDP growth, as estimated by your two-way fixed effects panel regression. Since the variables are standardized, the estimates represent the change in GDP growth (in percentage points) associated with a one-standard-deviation increase in each network metric. Variables shown in blue represent positive associations with growth, while those in red indicate negative associations, with horizontal lines depicting the confidence intervals. Notably, *Upstream Education strength total* (2.74) and *Upstream Electricity strength out* (1.17) emerge as the most significant positive drivers, both statistically significant at the 0.1%

level. Conversely, *Upstream Education strength in* (-3.36) shows a substantial and significant negative impact. Other significant predictors include *Upstream Agriculture strength total* (1.03), *Downstream Transport betweenness* (0.76), and *Upstream Maintenance closeness* (-0.99). Several other variables, such as *Downstream Hotels strength in* and *Upstream Recycling pagerank*, show smaller but statistically significant positive effects, while many remaining variables do not reach standard levels of statistical significance, suggesting their individual impacts are less robust within this specific panel framework.

Figure 3: Standardized Determinants of Real GDP Growth – Two-Way Fixed Effects Panel Regression



*Note: The figure shows point estimates and 95% confidence intervals from a two-way fixed effects panel regression (within-estimator) using data from 1991 to 2017. The dependent variable is Real GDP growth. Predictors include the top 20 network variables identified by mean absolute SHAP values from a tuned XGBoost model. All explanatory variables are standardized (mean = 0, sd = 1) to allow for direct comparison of effect magnitudes. Significance levels are denoted by: *** p < 0.01, ** p < 0.05, * p < 0.1.*

It is important to acknowledge that the fixed effects specification is subject to substantial multicollinearity, given the high degree of correlation among network metrics derived from the same underlying input–output structures. Many of the centrality and strength measures capture closely related dimensions of sectoral connectivity, which inflates standard errors and complicates the isolation of independent partial effects. Consequently, while the regression provides useful information on average associations and broad directional patterns, it should not be interpreted as delivering definitive estimates of the causal impact of individual network characteristics in the presence of strong interdependence among regressors.

4. Conclusions

This study reveals that growth dynamics are shaped less by the overall geometry of a given economy production network and more by the structural positioning of industries within supply and demand chains in such network.

A first central conclusion of our study is that growth is fundamentally sector-specific rather than aggregate in nature. Despite the inclusion of global network measures—such as average path length, diameter, and modularity—the top-ranked determinants of Real GDP growth in our ML model were exclusively node-level metrics. This finding implies that macroeconomic performance depends primarily on how individual sectors are embedded within the production network, rather than on broad systemic topological characteristics of the production network structures. In other words, it is the relative position and functional role of specific industries, not the abstract density of the network, that drives expansion.

Second, the evidence strongly supports a bottleneck hypothesis regarding some relevant sectors. The transport sector emerges as the single most influential determinant of growth. The SHAP dependence analysis reveals a pronounced non-linear threshold effect in downstream transport betweenness. When transport connectivity falls below a critical minimum level of intermediation, the economy experiences severe contractionary pressure—a “critical failure” regime in which fragmented logistics disrupt inter-sectoral flows. However, once a baseline level of connectivity is achieved, additional centrality yields limited marginal gains. Growth is therefore highly sensitive to the removal of infrastructural deficiencies but relatively insensitive to incremental improvements beyond adequacy.

Third, the results reveal a systematic asymmetry between supply intensity and input dependence. High out-degree strength—reflecting a sector’s capacity to act as a

concentrated supplier to the rest of the economy—consistently emerges as growth-enhancing in foundational industries such as electricity and construction. These sectors amplify multiplier effects when they function as robust outward-oriented providers of essential inputs. In contrast, high in-degree strength—indicating heavy reliance on specific upstream inputs or a narrow customer base—tends to exert contractionary pressure, particularly in services such as post, finance, and education. Excessive input concentration appears to signal structural fragility or cost burdens that dampen growth. The distinction between being a strong supplier and being a dependent consumer thus constitutes a central structural axis of economic performance.

Fourth, the relationship between network structure and growth is rarely linear. Many sectors exhibit L-shaped marginal profiles: economies are heavily penalized when connectivity in these sectors is insufficient yet experience diminishing returns once an relatively high integration is achieved. Such patterns confirm that production networks operate through regime shifts and threshold dynamics rather than smooth proportional effects. Linear models that ignore these non-linearities risk understating the economic relevance of structural bottlenecks.

Taken together, these findings suggest that strategic policy should focus on structural positioning rather than on uniform increases in connectivity. Infrastructure policy should prioritize logistical intermediation, particularly transport connectivity, as small improvements in fragmented systems may yield disproportionately large growth gains. In the domain of utilities, strengthening the electricity sector's role as a reliable and concentrated supplier can enhance multiplier effects and industrial scalability. Agricultural policy should facilitate deeper integration of the primary sector into domestic production chains, promoting upstream value addition rather than raw-material isolation—an especially critical transition for developing economies.

In the area of human capital and financial intermediation, policymakers should carefully manage the concentration and cost structure of education and financial inputs. While these sectors are essential, excessive reliance without coordinated upgrades in complementary physical capital may reflect imbalances that weigh on aggregate performance. Finally, trade and industrial strategies should encourage movement away from dependence on low value-added trade intermediation (re-exports) and primary resource demand (mining), both of which appear as structural drags in the network configuration.

Overall, the results indicate that economic growth is shaped by the elimination of critical bottlenecks and by the transition from input dependence to supply leadership in some key sectors. Effective policy for development, therefore, requires identifying and repositioning keystone sectors within the production network rather than pursuing generalized connectivity or indiscriminate expansion.

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Table A1: Summary of the Network Statistics

Statistic	Description	Economic Interpretation	Level
Betweenness Centrality	The frequency with which a sector sits on the shortest path between any two other sectors.	Identifies "choke points" or critical intermediaries that control the flow of supply/demand shocks.	Node (Sector)
Aggregate Volatility Contribution- C_k	A metric quantifying a sector's predicted impact on total macroeconomic volatility.	Measures "granularity"; shocks to these sectors have a disproportionately large impact on aggregate GDP.	Node (Sector)
Eigenvector Centrality	A measure of influence based on being connected to other highly connected sectors.	Highlights sectors that are influential because they trade with other influential sectors of the economy.	Node (Sector)
PageRank	A ranking of importance where links from other important sectors carry more weight.	A robust measure of systemic relevance and global importance within the production hierarchy.	Node (Sector)
Total Strength (In- and Out-)	The sum of weighted intermediate inputs (In) and weighted output sales (Out).	Measures a sector's total scale of intermediate dependence and its role as a primary supplier.	Node (Sector)
Average Strength	The arithmetic mean of all sector strengths within a specific country.	Captures the overall intensity of connectivity and intermediate trade volume in the national economy.	Country (Global)
Average Path Length (APL)	The average number of steps required to travel between any two sectors.	Indicates network integration; lower values mean shocks spread faster across fewer hierarchical layers.	Country (Global)
Diameter (D)	The longest of all shortest paths between any two sectors in the network.	Measures network compactness; a small diameter allows shocks to traverse the entire system quickly.	Country (Global)
Modularity (Q)	The strength of the network's division into distinct, independent communities.	Indicates segregation; high modularity can limit shock spread by containing it within specific production blocs.	Country (Global)

Note: The table summarizes the network and centrality statistics used to evaluate production structures in the region. It divides indicators into node-level metrics, which identify the systemic importance and influence of individual sectors, and country-level global metrics, which characterize the overall connectivity, integration, and structural segregation of the national economy. Additional details are provided in the Appendix, Section A.