Policy Design from a Network Perspective: Targeting a Sector, Cascade of Links, Network Resilience

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Abstract

A computational methodology is proposed to: (i) characterize the upstream and/or downstream network of a targeted sector i, (ii) uncover the cascade of layers of links in the network, and (iii) measure the degree of network resilience. The methodology is implemented using Turkiye's 2018 input-output data to characterize the gaps and the type of policy reforms required to address them in the context of the targeted manufacturing sector. Market and competition policy reforms are discussed from a network perspective in such a way as to enhance the productivity of the manufacturing sector. Three findings are noteworthy. First, production activities of the manufacturing sector have strong links with regulated general purpose service sectors, including financial, energy-water-gas, and transport and ICT. Therefore, improved competition in the manufacturing sector will not necessarily increase its productivity even if competition policies perfectly support the market for manufacturing products. Second, the $source - sink$ structure of Turkiye's manufacturing network illustrates that the manufacturing sector is the most dominant, whereas transport-ICT, energy-water-gas, and construction sectors are the potential sinks where large chunk of input flow ends up. Third, the cascade of three layers of links suggests that the upstream network of the manufacturing sector has a moderate level of resilience against the complete disruption of the intermediate layer.

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1 Introduction

A growing number of studies in the literature model production networks to investigate the mechanisms that create shocks to aggregate output. Most suggest that distortions at upstream firms or industries create cascade of avalanches hitting the key downstream sectors characterized by substantial resource misallocation and then the process works backward resulting in additional distortions in the upstream industries.[1] Interactions between sources of distortions and sinks where they land need better understanding. Those studies fall short of characterizing the critical pathways of interactions among industries, although they recognize the key role that highly central industries and their interactions along the pathways play in the creation of shocks at the macro level.

This study aims to contribute to the literature by proposing a computational methodology - three complementary algorithms - designed in such a way as to characterize a production network represented by an input-output matrix. For illustrative purposes, the methodology is applied using Turkiye's 2018 input-output data: (i) to identify the upstream and/or downstream networks of the targeted (or prioritized) manufacturing sector ($MA2$), (ii) to uncover the cascade of layers of links in the networks, and (iii) to measure the degree of network resilience based on a graph-theoretic concept of community (or cluster). Therefore, it serves as an *ex-ante* policy diagnostic tool for assessing alternative policy reforms concerning the network of the targeted sector. With this methodology, we can extract critical information on the key network characteristics of $MA2$, allowing for the identification of the gaps in the production network and the design of effective market and policy reforms required to address them. Addressing them through policy reforms necessarily implies improvements in network structure that is expected to increase the productivity of $MA2$. More specifically, given the production network of $MA2$, specific pathways and/or communities of sectors and their interactions are explored for policy reforms to avoid the cascading effects of distortions in the network of $MA2$ on aggregate output. In other words, the study assumes that the dynamics of a production network are endogenous to policies and institutional arrangements.

The implementation starts with the extraction of the pathways of critical backward (input-demand) and forward (output-supply) binary links, all of which represent $MA2$'s production network.[2] It continues with the identification of cascade of layers of critical input-demand linkages of $MA2$. Understanding the cascading structure of sectors in $MA2$'s "*upstream*" network is important as it provides a different approach to analyzing the interaction between the layers of sectors in its network. Here, the focus shifts away from an isolated pathway of individual sectors to the interaction of the layers (or groups) of sectors. The former analysis stresses the role of binary sectoral links and their importance along each pathway for productivity improvement in $MA2$. However, the latter analysis characterizes the role of layers of links and their importance for improving the productivity in $MA2$. In the final stage, the resilience of $MA2$'s network is measured by using edge betweenness centrality scores of those edges in between communities implied by $MA2$'s network. We make use of the idea that the more connected a network is, the more resilient it is. In line with this idea, the average of edge betweenness centralities over between-community edges of $MA2$'s network is assumed to approximate the degree

[1] See Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012); Acemoglu, Ozdaglar, and Tahbaz-Salehi (2010); Carvalho (2008, 2014) among others.

[2] The methodology is flexible in that any sector can be targeted at will, and the outputs from the implementation of the three algorithms will be available instantly.

of the connectedness of the network.

The key findings are three-fold. First, in network-based policy design, it is highly critical to consider the interdependencies of regulated and seemingly competitive sectors. Efficiencies gained in liberalized markets via pro-competitive PMR can easily be wasted before final consumers benefit from them as regulated industries may exercise their market power to confiscate part of the efficiency gain created in competitive markets. Improved competition in a single market may not generate the desired outcome even if competition policies perfectly support that market because benefits from competition may not spread over the rest of the network due to disruptions in the cascade of interdependencies concerned. Second, a network-based policy design should start with the identification of the "*dominant*" source and the "*subordinate*" sink sector(s), and those in between. The $source - sink$ structure of Turkiye's manufacturing network illustrates that the manufacturing sector is the most dominant, whereas telecommunications and transport, energy and construction sectors are the potential sinks where large chunk of input flow ends up. Agriculture, finance and oil extraction-mining seem to be interactive sectors. Third, the cascade of three layers of links are identified, and the upstream network of the manufacturing sector is found to have a mediocre level of resilience against the complete disruption of the intermediate layer of the network.

The remainder of this paper is structured as follows. Section 2 proposes a conceptual framework for exploring how pro-competitive product market reforms (PMR) can affect the structure of a production network is such a way as to deliver the desired outcomes. Section 3 provides a critical overview of recent studies in policy design from a network perspective. Section 4 develops a computational methodology based on the application of three complementary algorithms aimed to characterize the network of a targeted sector. We show how to identify the upstream network of a targeted sector $MA2$, construct the cascade of layers of links in the network, and measure the network resilience against disruptions. Section 5 overviews the properties of the 2018 input-output production network of Turkiye. Section 6 implements the algorithms and discusses the key findings in relation to potential productivity effects of pro-competitive PMR in Turkiye. Section 7 discusses how to use the findings in the formulation of network-based PMR to improve the efficiency of the upstream network of $MA2$. Finally, Section 8 concludes the paper with some suggestions for future research.

2 A framework for network-based policy design

From a network perspective, production is considered as the culmination of the dynamic interaction of various sectors along pathways of links. The realization of a given pathway depends on the implementation of right policies and the availability of productive capacities required by the sector linkages along that pathway. Therefore, an insufficient or a missing capacity and/or a distortionary policy will hinder, if not block, the realization of the entire pathway. The focus should, therefore, be on the simultaneous development of sector- and network-specific productive capacities, as well as the implementation of right policies and institutional arrangements. **Table** 1 presents a conceptual framework, which is mathematically specified in Equ. 1, to motivate the relation between network constructs (such as pathways, cascade of layers, community structure, etc.) and their potential effects on the productivity of the targeted sector as a response to network-based policy and institutional reforms.

We conjecture that the dynamics of the production network is endogenous to policy and institutional reforms. Examples of such reforms are also given to show how to improve the productivity of a targeted sector.

In our context, the key question is the identification of markets and policy reforms that are likely to enhance most the network dynamics of a targeted sector i. To describe it formally, sector i's production within an input-output production network, denoted by N, depends on changes in five factors:

$$Y_i = N_i \, f(K_i(C), L_i(C), M_i(C) \,|\, Y_{-i}). \tag{1}$$

N_i denotes an exogenously evolving network of sector i, such as a pathway of sector links, or a cascade of links, or a community where sector i is a member of; $N_i = n(P_i)$ assumes that market institutions and competition policy reforms concerning sector i, denoted by P_i, influence the dynamics of sector i's network; C, general purpose productive capacity that augments primary production inputs, capital K_i and labor L_i. M_{-i} denotes a vector of intermediate inputs that sector i purchases from the rest of the economy (including its own output). Y_{-i} denotes an exogenous vector of outputs of the rest of the economy, influencing sector i's production through pathways of sector linkages. Note that technological change is embodied in productive capacities C.

There is no shortage of economic policies that directly or indirectly affect the quality of sectoral interactions, and hence, the dynamics of production network. This paper considers the implications of market and competition policy reforms (henceforth, *policy reforms*) for the efficiency of sectoral production. We conjecture that the efficiency depends not only the implementation of good policies promoting competition but also the intrinsic properties of the production network. Competition law and policy aims to create an enabling environment - a level playing field - that facilitates the connectedness of (topologically) distant, and possibly disadvantaged, producers, and in doing so, increases their production possibilities. Competition process works effectively if new producers enter the market, compete on the merits and do not benefit from undue advantages. Regarding the network properties, connectedness of producers is only one of the properties that improves efficiency. The higher the degree of network connectedness, the faster the flow of price and quantity information and the easier sectors in the market concerned will be able to meet their input suppliers to trade. Since, in a connected network, the flow of information and sector interaction take place in a speedy manner, the likelihood of a sector to meet its input supplier is high. To sum up, a competitive environment improves connectedness, and in return, connectedness further promotes competition.

Competition policy affects the dynamics of production network through removing anti-competitive regulations (see examples of regulatory barriers in **Table** 1), enforcing anti-trust laws to regulate cartel agreements that raise the costs of key inputs and final products . Preventing anti-competitive mergers, abuse of dominance, and ensuring competitive neutrality are among other policy options that benefit consumers through competitive pricing. Pro-competitive product market reforms (PMR) are designed to achieve public policy objectives by minimizing dominance or entry restrictions or rules that are conducive to collusive outcomes or costs to compete in the market, as well as by removing the conditions that create favorable environment for certain sectors or distortions at the level playing field. Such reforms also aim to remove regulatory barriers to competition, including, but not limited to, minimum capital requirements, increased cost of doing business, protection of incumbents,

Table 1: A framework for linking policy reforms with network dynamics

Network construct $n(.)$	Markets and competition policy (P)	Productivity effects	Examples of regulatory barriers
Identify critical upstream and downstream networks of a targeted sector to enhance its productivity;	– **To improve network dynamics** through free entry of firms; effective mechanisms & increased capacity for input-output flow; promote new links; strengthen weak links along the pathways between an intervention & a targeted sector; – **To improve allocative efficiency** by allowing for efficient firms to enter/gain market share;	Competitive product markets for essential inputs to other industries would yield spillover effects across the economy. **Upstream regulatory improvements** would generate growth in downstream industries using those inputs through a reduction in the restrictiveness of such upstream input services, i.e., finance (FIN), professional services (EST), construction (CST), transport-ICT (TSC), etc.	**Sector specific** a**nti-competitive regulations** and **lack or ineffective enforcement of anti-trust law** would reduce total factor productivity of sectors along the upstream pathways and supply of output along the downstream pathways. Examples of related reforms include entry liberalization and deregulation of TSC, the removal of price control on legal services in EST, and pro-competition regulatory reforms to increase labor productivity in retail sector (WHS).
Uncover community structures of the upstream and downstream networks;	– **To increase connectedness within and between communities** through promoting the development of new links and linkage capacities;	Avoiding bottlenecks or disruptions along the pathways of sectoral interactions is conducive to positive spillover effects from between-community interactions.	**Community specific anti-competitive regulations** reduce coherence of sectoral interactions within a community, leading to its disintegration; Biased regulations against more efficient firms and protecting incumbents promote resource mis-allocation across sectors and communities;
Identify layers of binary links around a sector critical for aggregate productivity;	– **To avoid or reduce the spreading of adverse effects of a shock** to a binary link and/or respective sectors;	Sectors along the first layer surrounding the targeted sector and **upstream regulations across that layer** would ensure continuity of critical production links.	**Layer specific anti-competitive regulations** would risk the survival of the targeted sector in case of a shock to structural (first layer) and facilitating links and/or the sectors involved;
Characterize binary links and/or the involved sectors along the upstream and downstream pathways/layers/communities;	– **To promote the creation of an enabling environment** in which those critical links/sectors cannot take advantage of their positions along a pathway or within a community or a layer;	Improved understanding of the roles of structural, ancillary, facilitating, and restrictive links in a production network allows for effective design of **competition policy to avoid dominance of weak links/sectors** along a pathway/community/layer;	Along pathways/communities with weak links/purely complementary links, c**ompetition law are to be complemented by ex-ante sector regulations to** avoid failure in the input-output flow; and prevent potentially **anti-competitive links to exercise dominance**;

excessive restrictions on the expansion of and potential discrimination against more-efficient firm, and burdensome requirements to obtain operating permits.

In recent empirical research, competition and the institutional set up behind it have been found to be an important determinant of total factor productivity growth at the industry and firm levels (Acemoglu et al., 2012; Aghion & Schankerman, 2004; Barone & Cingano, 2011; Bouis, Duval, & Eugster, 2016; Buccirossi, Ciari, Duso, Spagnolo, & Vitale, 2013; Gal & Hijzen, 2016). Specifically, pro-competitive PMR - policies and institutions that intensify product market competition - are found to increase productivity by reducing the market share of less efficient firms, increasing the incentive of firms to reduce costs, and stimulating entry by new low-cost firms. PMR that reduce barriers to entry in regulated industries (EGW, TSC, WHS, EST) are also found to increase the productivity as their general purpose outputs tend to be widely used as inputs elsewhere in the economy. There are systematic and plausible differences in the effects of PMR across firms of different size across the different industries. In network industries, small firms tend to benefit most from pro-competitive PMR, while larger ones downsize to reduce costs and maintain market share. Deregulation yields positive spillovers on firms in downstream industries through input-output linkages. Research also finds that lower service regulation in EST and EGW increases value added, productivity, and export growth in downstream service intensive industries.

Most empirical research focus on the competition-productivity link within an industry. Yet, expected rents from innovation or technology adoption and the corresponding within-industry incentives to improve productivity may be reduced by lack of competition in upstream sectors that sell intermediate inputs that are necessary to production in downstream industries (Bourles, Cette, Lopez, Mairesse, & Nicoletti, 2010; Carvalho, 2008, 2014). In other words, if there is market power in upstream sectors and if firms in downstream industries have to negotiate terms of their contracts with suppliers, part of the rents expected downstream from adopting best-practice techniques will be confiscated by intermediate input suppliers. This will in turn reduce incentives to improve efficiency and curb productivity in downstream industries, even if competition may be thriving there. Moreover, lack of competition in upstream sectors can also generate barriers to entry that curb competition in downstream industries as well, further reducing pressures to improve efficiency in these industries. For example, overly restrictive regulation in banking and finance (FIN) can reduce the range of available sources of financing for all firms in the economy.

The first line of empirical research suggests from a single sector perspective that productivity improvement is merely an outcome of pro-competitive PMR. The second line of research, however, considers a broader view from a network perspective that network dynamics is important to determine the productivity effects of PMR. By stressing the role of intermediary network mechanisms between policy reforms and productivity, the current study adopts the latter perspective to characterize endogenous network constructs. Namely, it conjectures that the network structure would change over time through pro-competitive PMR.[3]

[3] Atalay, Hortacsu, Roberts, and Syverson (2011) models network formation by assuming three processes. The first is the permanent bankruptcy of a firm; the second, reconnecting of surviving firms; and the third, emergence of new firms. The structure of a production network with these growth and decay features in which links and firms appear and disappear probabilistically can be approximated using the model network. Here, the important point is to predict the probabilities for each ex-ante PMR to influence the three processes described. The current study does not predict such probabilities but give a qualitative assessment of PMR as to their potential impact on the performance of sectors in a

3 Related literature

This paper contributes to the growing toolbox of policy analysts, developing an automated, computational methodology to explore the dynamics of an input-output production network. Drawing on the properties of the network constructs given in **Table** 1, it illustrates how to study the implications of these properties for aggregate production, elaborates on the design of network-based policies aimed to improve the performance of the existing network architect and reduce the risk of disruptions along the critical pathways of sectors (Schweitzer et al., 2009). Equ. 1 is a mere summary of what we aim to achieve in this paper.

Recent studies elaborate on how pathways of input-output linkages in a production network are likely to amplify the adverse effects of distortions in upstream industries and their cascading effects sooner or later hit downstream industries (Acemoglu et al., 2012, 2010; Bigio & Laâo, 2020; Carvalho, 2008, 2014; Jovanovic, 1987). Production network approach views aggregate shock as an endogenous outcome of micro shocks propagating across input linkages. These networks have also been studied to analyze the economy-wide effects of disruptions in value and supply chains (Kim, Chen, & Linderman, 2015; Perera, Perera, & Kasthurirathna, 2017; Steiner & Ali, 2009; Xiao, Sun, Meng, & Cheng, 2017), to design innovation policies to promote technology, innovation and knowledge communities (Ahrweiler, Pyka, & Gilbert, 2004; Breschi & Malerba, 2005; Coe & Bunnell, 2003; Judge, Fryxell, & Dooley, 1997; Lynn, Aram, & Reddy, 1997; Pyka, 2014), and to better understand the systemic risk from cascading liquidity shocks spilling over to other sectors (Kiyotaki & Moore, 1997). Although the objectives of these studies vary somewhat, their main focus has been on developing policy diagnostic tools to identify network-wide systemic problems/inefficiencies and design polices to encounter them. In essence, our methodology is similar in purpose to some of these studies but also differs from them in that we develop an automated, computational method to uncover hidden patterns in a production network and develop a measure of network resilience with respect to disruptions in the linkages of a given sector (Wagner & Neshat, 2010).

Our point of departure from conventional statistical methods is the shift from the significance of relations between factors to the significance of relational patterns, such as community, clique, shortest path among others (Fortunato, 2010; Hric, Darst, & Fortunato, 2014; Newman & Girvan, 2004; Porter, Onnela, & Mucha, 2009; Sugiyama, Tagawa, & Toda, 1981). Graph-theoretic concepts serve as the core elements of our algorithms to learn from large data sets (Bollobás, 2012; Newman, 2004; Newman & Girvan, 2004). Production network data is one such dataset that is often exploited to identify complex patterns of critical relations and learn from them to improve policy design (Atalay et al., 2011; Carvalho, 2014; Liu, 2019). The community detection algorithms have been widely applied to identify technology, innovation, knowledge, and production communities (Fichter, 2009; Kandylas, Upham, & Ungar, 2008; Lynn et al., 1997). Weitz, Carlsen, Nilsson, and Skånberg (2018) apply network analysis to assess contextual interactions of Sustainable Development targets of the 2030 Agenda of the UN with a view to designing economic development policies. The analysis derives information on targets with the most and least positive influence on the development process, guiding policy efforts towards more productive areas.

Equ. 1 conjectures that pro-competitive PMR can reshape the production network by minimizing

production network.

dominance or entry restrictions or rules that are conducive to collusive outcomes, as well as by removing the conditions that create favorable environment for certain sectors or distortions at the level playing field. Using firm-level data and sectoral information on input-output linkages, Gal and Hijzen (2016) analyze the productivity effects of pro-competitive PMR in regulated industries (EGW, TSC, WHS, EST). PMR are found to increase the productivity as their general purpose outputs tend to be widely used as inputs elsewhere in the economy . There are systematic and plausible differences in the effects of PMR across firms of different size across the different industries. More specifically, in network industries, small firms tend to benefit most from pro-competitive PMR, while larger ones downsize to reduce costs and maintain market share. The findings confirm the positive effect of PMR on downstream firms through backward linkages within the same country, but also provide some indication that these effects also extend to firms abroad. Likewise, the economic effects of major PMR are also studied by Bouis et al. (2016) in some of the historically most protected non-manufacturing industries (electricity and gas, land transport, air transport, postal services, and telecommunications). They find that reductions in barriers to entry yield large increases in output and labor productivity over a five-year horizon. Providing a clear case for intensifying PMR efforts in economies with weak growth prospects, these findings also rationalize the potential emergence of new network constructs to further affect aggregate output growth.

Product market imperfections, such as legal barriers to entry in some non-manufacturing markets, that curb competition in upstream sectors will negatively affect the productivity of downstream sectors (Bourles et al., 2010). Trickle-down effects work through two main channels. Firstly, anticompetitive regulations in an upstream sector can reduce competition downstream if access to downstream markets requires using intermediate inputs produced upstream. For example, if financial market regulations narrow the range of available financial instruments, access to finance by downstream sectors can be made difficult, thereby curbing new entry and firm growth. Secondly, even if anticompetitive upstream regulations do not restrict market access downstream, they can still curb incentives to improve efficiency in downstream sectors. If markets for intermediate inputs are imperfect, downstream sectors may have to negotiate with suppliers. In this case, regulations that increase suppliers market power can reduce incentives to improve efficiency downstream, as part of the rents that downstream firms expect from such improvements will have to be shared with suppliers of the intermediate inputs that are necessary for downstream production. While most analyses of this issue have focused on the effects of these regulations on the productivity of the sectors directly concerned, the main point is that such regulations can also have powerful indirect depressing effects on the productivity of other sectors through input-output linkages. Barone and Cingano (2011) study the effects of anti-competitive service regulation by examining whether OECD countries with less anti-competitive regulation see better economic performance in manufacturing industries that use less-regulated services more intensively. They find that lower service regulation increases value added, productivity, and export growth in downstream service intensive industries. The regulation of professional services and energy provision (EST, EGW) has particularly strong negative growth effects in service dependent industries.

Delalibera, Ferreira, Gomes, and Soares (2023) is closely related to our paper in that they analyze the effects of economic policy reform - tax policy reforms in Brazil - from a production network perspective. The structure of production network is shown to deliver some relevant results that would be impossible to observe in a standard model. The upstreamness metric developed by Antràs, Chor, Fally, and Hillberry (2012) is used to understand how the tax reform changes the distance of sectors to final demand, that is, the tax reform changes the structure of the network. The complete tax reform is reevaluated taking into account some cases where groups of sectors - communities - can be subsidized or taxed more heavily. For example, the sectors with the highest carbon emissions can be taxed more heavily for the reason that the most important sectors of the economy are those with a strong link within the production pathway, that is, those with a high demand for inputs and which are critical suppliers to other sectors. Atalay et al. (2011) develops a model of network formation that better matches the attributes, such as the connectivity distribution, of an actual economic network. Using processes for firm death, reattachment of its links among surviving firms, and a mix of the preferential attachment mechanisms and random attachment, the model matches observed macro distribution of firm connectedness. Comparing the model and actual networks provides information on how much the actual network is away from the model network. Knowing the differences and/or similarities between the two networks is important for designing PMR aimed to reform a targeted sector or a community of sectors that are in its immediate neighborhood.

4 A computational methodology

In what follows, we explain the steps involved in the development of three complementary algorithms. We start with the extraction of pathways based on backward binary links (Algorithm I), continuing with the extraction of cascade of layers of groups of binary links (Algorithm II), and ending with the measurement of network resilience (Algorithm III), that is, the stability of the connectedness of binary links. Information derived from the implementation of the algorithms is an important input for the analysis of a targeted (usually prioritized) sector's production network. Summarized in **Table** 2, the key features of three algorithms should provide us with information for evidence-based policy design.

4.1 Algorithm I. Targeting a sector

This algorithm establishes a subgraph in which targeted sector i's upstream (backward or supply) and downstream (forward or demand) linkages are combined to analyze sector i's input and output structure. The Leontief inverse matrix represents backward linkages of a production system of an economy, derived from the proportion of input purchases in total output. Likewise, the Ghosh inverse matrix represents forward linkages of an intermediate consumption system of an economy, derived from the proportion of output sales in total final demand. Forward linkages measure changes in output values in response to changes in primary input prices (Dietzenbacher, 1997; Ghosh, 1958). Following Loviscek (1982), both backward and forward linkages are concurrently used in order to obtain an accurate picture of interindustry input-output structure (Loviscek, 1982). In case of sector i, for example, this algorithm identifies the pathways of input providers to sector i (i.e., upstream to sector i) and of consumers of sector i's output (i.e., downstream to sector i). By integrating supply and demand-side information, the Algorithm establishes a unified network of sector i.

The link-wise cascading structure constructed by *Algorithm I* starts with targeting sector i. In the first step, the immediate input providers of sector i are identified. In the second step, the input

Table 2: Interrelationships among three Algorithms and information for policy analysis

	Inputs	**Computations**	**Outputs**	**Information for evidence-based policy analysis**
Algorithm I	A national input-output (IO) matrix	• Leontief inverse matrix (M_b); • Output multiplier matrix, $M_b(\alpha_1, \alpha_2)$, in the multiplier range ($\alpha_1 \leq m_b \leq \alpha_2$) with $m_b \in M_b$; • Ghosh inverse matrix (M_f); • Demand multiplier matrix, $M_f(\alpha_1, \alpha_2)$, in the multiplier range ($\alpha_1 \leq m_f \leq \alpha_2$) with $m_f \in M_f$; • Targeting sector i by using $M_b(\alpha_1, \alpha_2)$ and $M_f(\alpha_1, \alpha_2)$;	• Upstream network of sector i, $g_i^U(\alpha_1, \alpha_2) \equiv g_i^U$, obtained from $M_b(\alpha_1, \alpha_2)$; • Downstream network of sector i, $g_i^D(\alpha_1, \alpha_2) \equiv g_i^D$, obtained from $M_f(\alpha_1, \alpha_2)$;	• Characterize the two networks, g_i^U and g_i^D, to uncover the key properties of the IO matrix by exploring community structures, between-community linkage patterns, shortest paths between policy reform (source sector j) and policy impact (sink sector i), dominant & subordinate sectors, strong & weak linkages, etc.
Algorithm II	Directed subgraph g_i^U	• Disentangle layers of links from g_i^U by implementing *Mathematica NeighborhoodGraph* [g_i^U, i]; • Construct a cascade of layers: $\{L_i^1, L_i^2, L_i^3, ...\}$;	• A hierarchical, directed network of the cascade;	• Design policy interventions to avoid network disruptions in case of a shock to a given layer; • Develop strategies to manage network volatility in case of extreme events;
Algorithm III	Directed subgraph g_i^U	• Identify community structure and between-community edges (BCE) of g_i^U; • For each BCE, compute the proportion of shortest paths in g_i^U;	• A measurement of resilience of g_i^U based on individual links and the group of between-community links;	• Design policy interventions to avoid network disruptions in case of a shock to g_i^U; • Develop strategies to manage network volatility against community-specific extreme events;

Table 3: An example input-output matrix

		A	B	C	D	E	Y	X_D
		users						
suppliers	**A**	10	60	5	9	12	4	100
	B	20	30	40	30	30	50	200
	C	10	20	20	90	60	200	400
	D	30	12	24	120	90	324	600
	E	6	24	12	21	15	222	300
	VA	24	54	299	330	93		
	X_S	100	200	400	600	300		

providers of sector i's immediate input providers are identified and so on. This process would result in layers of binary links, and each layer be associated with a sector that has bearing on sector i's production. From the graph-theoretic perspective, one-edge links of sector i to its immediate input providers define upstream links, which are regarded as sector i's structural connections. The upstream cascading arises when sector i is connected to immediate input providers of its own immediate input providers through two-edge pathways (i.e., two steps away from sector i). Such a cascading behavior may extend to three-edge, four-edge or higher order links between sector i and the rest of the network.

For purposes of clarity, an example input-output (IO) matrix in **Table** 3 is used to demonstrate step-by-step the implementation of Algorithm I. This matrix consists of five components. The first is an intermediate consumption sub-matrix (**X**) with five sectors, {**A**, **B**, **C**, **D**, **E**}, as users and suppliers. The second is a column-vector of final consumption (**Y**); the third, a column-vector of total demand ($\mathbf{X}_D$); the fourth, a row-vector of value-added (**VA**); and the fifth, a row-vector of total supply ($\mathbf{X}_S$).

Sub-matrix **X** and total output supply $\mathbf{X}_S$ are used to calculate the backward technical coefficients matrix, $A_b = [\mathbf{X_{ij}}/\mathbf{X^j_S}]$ (see **Table** 4(2)). The Leontief inverse matrix, $\mathbf{M}_b[m] \equiv (I - A_b)^{-1}$, defines the so-called backward multiplier matrix with m denoting elements of this matrix, where I stands for an identity matrix with dimension$(5, 5)$ (see **Table** 4(3)). For notational simplicity, we denote $\mathbf{M}_b[m] \equiv \mathbf{M}_b$. In order to focus on the analysis of inter-sectoral connectivity, the diagonal cells in $\mathbf{M}_b[m]$ are replaced with zeros; that is, $\mathbf{M}_b - diag[\mathbf{M}_b]$ (see **Table** 4(4)).[4] The matrix, $\overline{\mathbf{M}}_b[x]$, in **Table** 4(5) is obtained through column-wise standardization of $\mathbf{M}_b - diag[\mathbf{M}_b]$. In doing so, individual multipliers of a user sector are adjusted to reflect the relative importance of a supplier in the output multiplier of the user sector. The standardized matrix $\overline{\mathbf{M}}_b[x]$ is the only input used in targeting a sector by setting an arbitrary threshold significance level (for example, $0.25 \leq x$) with x being matrix elements greater than or equal to 0.25. The matrix $\overline{\mathbf{M}}_b(0.25 \leqslant x)$ given in **Table** 4(6) is a reduced form of $\overline{\mathbf{M}}_b[x]$, which includes only the cells greater than or equal to 0.25. Suppose that a user sector **A** is targeted to identify the entire chain of its direct and indirect suppliers (i.,e input suppliers of user sector **A**) side; that is, to identify the entire pathway (or chain) of **upstream** sectors of user **A**.

Using backward multipliers in $\mathbf{M}_b$ represents half through the targeting exercise because a backward

[4]The diagonal elements of the multiplier matrix are set to be equal to zero, in order to focus on the inter-sectoral connectivity. An empirical regularity is that a large majority of IO multiplier matrices are diagonally dominant as their diagonal multipliers are larger than one. The reason is that a sector produces part of its total input demand in addition to the production of inputs demanded by the rest of the sectors in the economy. Miller and Blair (2009, pp. 90-96) explain this within inter-regional IO framework, and Henderson and Evans (2017) explains the same issue with an example IO matrix <https://www.fwrc.msstate.edu/pubs/implan_2017.pdf>.

Table 4: Input-output matrix: Backward multipliers

[1] X

	A	B	C	D	E
A	10	60	5	9	12
B	20	30	40	30	30
C	10	20	20	90	60
D	30	12	24	120	90
E	6	24	12	21	15

[4] $M_b - diag[M_b]$

	A	B	C	D	E
A	0	0.48	0.08	0.07	0.14
B	0.38	0	0.17	0.13	0.24
C	0.30	0.30	0	0.25	0.36
D	0.58	0.39	0.15	0	0.52
E	0.16	0.23	0.07	0.08	0
Total	**1.43**	**1.40**	**0.46**	**0.54**	**1.26**

[2] $A_b = [X/X_S]$

	A	B	C	D	E
A	0.10	0.30	0.01	0.02	0.04
B	0.20	0.15	0.10	0.05	0.10
C	0.10	0.10	0.05	0.15	0.20
D	0.30	0.06	0.06	0.20	0.30
E	0.06	0.12	0.03	0.04	0.05

[5] $\overline{M}_b[x]$

	A	B	C	D	E
A	0	0.34	0.17	0.14	0.11
B	0.27	0	0.36	0.25	0.19
C	0.21	0.22	0	0.46	0.28
D	0.41	0.28	0.33	0	0.41
E	0.11	0.16	0.15	0.15	0

[3] $M_b[m] = (I - A_b)^{-1}$

	A	B	C	D	E
A	1.26	0.48	0.08	0.07	0.14
B	0.38	1.37	0.17	0.13	0.24
C	0.30	0.30	1.12	0.25	0.36
D	0.58	0.39	0.15	1.34	0.52
E	0.16	0.23	0.07	0.08	1.12

[6] $\overline{M}_b[0.25 \leq x]$

	A	B	C	D	E
A	0	0.34	0	0	0
B	0.27	0	0.36	0.25	0
C	0	0	0	0.46	0.28
D	0.41	0.28	0.33	0	0.41
E	0	0	0	0	0

linkage defines only the input providers of a targeted sector. To be complete, other half should be based on forward multipliers in $\mathbf{M}_f[m] \equiv (I - A_f)^{-1}$ (the so-called Ghosh inverse matrix) as a forward linkage defines the output linkage of the targeted sector (see **Table** 5(3)). For notational simplicity, we use $\mathbf{M}_f$. The only difference between the derivation of backward and forward multipliers is that the latter uses the forward coefficients matrix, $A_f = [\mathbf{X_{ji}}/\mathbf{X_D^j}]$, given in **Table** 5(2) to calculate the row-wise standardized matrix, $\overline{\mathbf{M}}_f[x]$ (see **Table** 5(5)). The matrix $\overline{\mathbf{M}}_f(0.25 \leqslant x)$ in **Table** 5(6) is a reduced form of $\overline{\mathbf{M}}_f$, which includes only the cells greater than or equal to 0.25. Suppose that a supplier sector **A** is targeted to identify the entire pathway (or chain) of its direct and indirect users (i.,e consumers of output produced by supplier sector **A**); that is, to identify the entire chain of **downstream** sectors of supplier **A**.[5]

Having derived the backward and forward reduced forms, $\overline{\mathbf{M}}_b(0.25 \leqslant x)$ and $\overline{\mathbf{M}}_f(0.25 \leqslant x)$, the next step is to combine them to identify the upstream and downstream pathways of targeted sector **A**, and map these pathways as a single network with a view to examining the connectivity of the upstream and downstream sectors of **A**. Replicating the targeting exercise for the rest of the sectors in the IO matrix would generate five networks, one for each sector. In what follows, the algorithm for computing and mapping the upstream and downstream networks of **A** is described in three steps using the example IO matrix.[6]

[5]The reader is referred to Miller and Blair (2009) for an extensive description of how to use input-output matrices in policy analysis.

[6]The *Algorithms* have been developed by the authors. *Mathematica* Codes developed at <https://mathematica.stackexchange.com/questions/210169/how-can-i-generate-a-tailor-made-directed-graph-from-a-given-matrix> have been extended to identify cascades of links and compute network resilience. The extended

Table 5: Input-output matrix: Forward multipliers

[1] X

	A	B	C	D	E
A	10	60	5	9	12
B	20	30	40	30	30
C	10	20	20	90	60
D	30	12	24	120	90
E	6	24	12	21	15

[4] $M_f - diag[M_f]$

	A	B	C	D	E	Total
A	0	0.96	0.30	0.44	0.43	**2.14**
B	0.19	0	0.33	0.40	0.36	**1.29**
C	0.08	0.15	0	0.37	0.27	**0.87**
D	0.10	0.13	0.10	0	0.26	**0.59**
E	0.05	0.15	0.079	0.16	0	**0.45**

[2] $A_f = [X/X_D]$

	A	B	C	D	E
A	0.10	0.60	0.05	0.09	0.12
B	0.10	0.15	0.20	0.15	0.15
C	0.025	0.05	0.05	0.225	0.15
D	0.05	0.02	0.04	0.20	0.15
E	0.02	0.08	0.04	0.07	0.05

[5] $\overline{M}_f[x]$

	A	B	C	D	E
A	0	0.45	0.14	0.21	0.20
B	0.15	0	0.26	0.31	0.28
C	0.09	0.18	0	0.43	0.31
D	0.17	0.22	0.17	0	0.44
E	0.12	0.34	0.20	0.35	0

[3] $M_f[m] = (I - A_f)^{-1}$

	A	B	C	D	E
A	1.26	0.96	0.30	0.44	0.43
B	0.19	1.37	0.33	0.40	0.36
C	0.08	0.15	1.12	0.37	0.27
D	0.10	0.13	0.10	1.34	0.26
E	0.05	0.15	0.079	0.16	1.12

[6] $\overline{M}_f[0.25 \leq x]$

	A	B	C	D	E
A	0	0.45	0	0	0
B	0	0	0.326	0.31	0.28
C	0	0	0	0.43	0.31
D	0	0.34	0	0	0.44
E	0	0	0	0.35	0

Step 1 (using $\overline{\mathbf{M}}_b(0.25 \leqslant x)$: At an arbitrarily set significance level, 0.25, **from input side**, we target user sector **A** associated with the 1^{st} column of $\overline{\mathbf{M}}_b(0.25 \leqslant x)$. This means that those numbers equal to or greater than 0.25 in the 1^{st} column are considered as significant enough from the user perspective, in which case there are two significant linkages. One is from **B** to **A** with a coefficient of 0.27 (denoted as $B \rightarrow A$), and another is from **D** to **A** with a coefficient of 0.41 (denoted by $D \rightarrow A$).[7] Then, moving to the 2^{nd} column associated with user sector **B**, we observe that **A** also provides input to **B** (denoted by $A \rightarrow B$) with a strength level of 0.34, and that **D** provides input to **B** (denoted by $D \rightarrow B$) with a strength level of 0.28. We then move on to identify the significant suppliers of user sector **D** associated with the 4^{th} column. Suppliers **B** and **C** provide input to user **D** through the two linkages denoted by $B \rightarrow D$ and $C \rightarrow D$ with the strength levels of 0.25 and 0.46, respectively. Finally, we identify suppliers of user sector **C** by moving to the 3^{rd} column, in which case suppliers **B** and **D** are observed as significant with the strength levels of 0.36 for the linkage $B \rightarrow C$ and 0.33 for the

Algorithms will be available upon request. Many thanks go to *@kglr* in *Mathematica* forum for his valuable programming support.

[7] The technical terms used throughout the paper warrant clarifications. A pathway of sectors is used to mean a set of directed binary links (one-to-one), connection of which generates a flow from a source to sink sector. For example, given a 2-edge pathway of three sectors, $\{MA1 \rightarrow CST \rightarrow EST\}$, there are two binary links, $\{MA1 \rightarrow CST, CST \rightarrow EST\}$, each one of which shows a directed link ($\rightarrow$) established between two sectors only. Along this 2-edge pathway, $MA1$ represents a source, and EST a sink. These definitions distinguish a pathway from a binary link. The minimum length of a pathway is 2 edges. A directed link indicates the direction of flow of either money or material or influence. In the context of an upstream (downstream) pathway, a binary link $MA1 \rightarrow CST$ implies that CST receives material inputs (outputs) from $MA1$ or that $MA1$ supplies the inputs (output) that CST uses (consumes) in its production process. The terms, supply network and production network, are used interchangeably to refer to a collection of sectors that exchange material inputs used in their production processes. A *k-edge* pathway refers to a pathway consisting of k binary links. For example, *k=3* implies a set of binary links, $\{MA1 \rightarrow CST$, $CST \rightarrow EST$, $EST \rightarrow WHS\}$, and a *3-edge* pathway, $\{MA1 \rightarrow CST \rightarrow EST \rightarrow WHS\}$.

linkage $D \to C$. This completes the search of significant direct and indirect suppliers of the targeted user sector **A**. Important to note is that, although the IO matrix has five sectors, the search for the suppliers of user **A** results in a directed network of four sectors, implying that, at the preset threshold level, sector **E** is irrelevant for sector **A**. Combining all of the binary linkages identified in this step generates the directed network, which consists of a set of eight binary linkages when user sector **A** is targeted:

$$\mathbf{A_{input}} = \{B \to A,\, D \to A,\, A \to B,\, D \to B,\, B \to D,\, C \to D,\, B \to C,\, D \to C\}. \quad (2)$$

Step 2 (using $\overline{\mathbf{M}}_f(0.25 \leqslant x)$: At the same significance level, 0.25, **from output side**, we target supplier sector **A** associated with the 1^{st} row of $\overline{\mathbf{M}}_f(0.25 \leqslant x)$. This means that those numbers equal to or greater than 0.25 in the 1^{st} row are considered as significant enough from the supplier perspective, in which case there is one significant linkage from **A** to **B** with the strength level of 0.45 (denoted as $A \to B$). Then, moving to the 2^{nd} row associated with supplier sector **B**, we observe three linkages from **B**: $B \to C$ with a strength level of 0.26, $B \to D$ with a strength level of 0.31, and $B \to E$ with a strength level of 0.28. We then move on to identify the significant users of supplier sector **C** associated with the 3^{rd} row. Supplier **C** provides output to users **D** and **E**, which are respectively denoted by $C \to D$ and $C \to E$ with the strength levels of 0.43 and 0.31. Supplier **D** associated with the 4^{th} row provides output to user **E** (denoted by $D \to E$) with the strength level of 0.44. Finally, supplier **E** associated with the 5^{th} row provides output to users **B** and **D**, which are denoted by $E \to B$ and $E \to D$ with the strength levels of 0.34 and 0.35, respectively. This completes the search of significant direct and indirect users of the targeted supplier sector **A**. Combining all of the binary output linkages identified in this step generates the directed network, which consists of a set of nine binary linkages when supplier sector **A** is targeted:

$$\mathbf{A_{output}} = \{A \to B,\, B \to C,\, B \to D,\, B \to E,\, C \to D,\, C \to E,\, D \to E,\, E \to B,\, E \to D\}. \quad (3)$$

Step 3: It should be noted that, $\mathbf{A_{input}}$ network in 2 and $\mathbf{A_{output}}$ network in 3 have four common linkages given in Equ. 4:

$$\mathbf{A_{input}} \cap \mathbf{A_{output}} = \{A \to B,\, B \to C,\, B \to D,\, C \to D\}, \quad (4)$$

which simultaneously carry both input (denoted by solid blue arrows) and output (denoted by solid red arrows).

To sum up, when sector **A** is targeted in input markets, its upstream linkages represent the input supply network; when it is targeted in output markets, its downstream linkages represent the output supply network. Combining the two networks fully characterizes sector **A**'s connectivity (i.e., all the linkages that matter for **A** at the given threshold strength level of 0.25) both in input and output markets. In the next step, community structure of the combined network and edges bridging the communities are extracted to examine the connectivity of the network. As an illustration of the outputs generated by Algorithm I, see **Fig.** 4.

4.2 Algorithm II. Constructing cascade of layers of links

This algorithm extends the link-wise cascading structure constructed by Algorithm I to uncover layers of links surrounding sector i. Using a directed network, g_i, constructed by *Algorithm I*, *Algorithm II* extracts cascade of layers of links in g_i by repeatedly implementing *Mathematica*'s **NeighborhoodGraph[g_i, i]** code. This code gives the graph neighborhood of a targeted sector i in the graph g.

1. Let L_i^1 denote first-order layer of the targeted sector i, which is constructed by one-edge (both In- and Out- edges are included) neighborhood graph, N_i^1, of i using NeighborhoodGraph[g_i, i], where $N_i^1 = \{S_i^1, E_i^1\}$ with S_i^1 being the set of sectors and E_i^1 being the set of links between sectors in N_i^1. By definition, layer 2 is:
$$L_i^1 = E_i^1.$$

2. Suppose $S_i^1 = \{j, k, m\}$ and for each sector in S_i^1, one-edge neighborhood graph is constructed: N_j^1, N_k^1, N_m^1. Define layer 2 as:
$$L_i^2 = \bigcup_{z=j,k,m} (E_z^2 \backslash E_i^1) \equiv E_i^2, \;\; where\, N_i^2 = \{S_i^2, E_i^2\}.$$

3. Suppose $S_i^2 = \{s, u, t\}$ and for each sector in S_i^2, one-edge neighborhood graph is constructed: N_s^2, N_u^2, N_t^2. Define layer 3 as:
$$L_i^3 = \bigcup_{z=s,u,t} (E_z^2 \backslash E_i^2) \equiv E_i^3, \;\; where\, N_i^3 = \{S_i^3, E_i^3\}.$$

   This process is repeated until all the sectors in g_i are exhausted. By construction, the following identity holds:
$$g_i \equiv \bigcup_{n=1,2,3} L_i^n.$$

4.3 Algorithm III. Measuring network resilience

Using graph-theoretic measures of community and edge betweenness centrality (EBC), this algorithm approximates the average network resilience by a 4-step procedure:

1. Given a multiplier threshold interval (α_1, α_2), implement Algorithm I to construct sector i's upstream network, denoted by $g_i^U(\alpha_1, \alpha_2) \equiv g_i^U$;

2. Suppose that g_i^U has communities[8] denoted by $C_{g_i^u}$. Identify the set of between-community edges in $C_{g_i^u}$ (denoted by $BCE(C_{g_i^u})$);

[8] A community or cluster is a grouping of sectors that interact through a relatively large number of binary links while minimizing the number of binary links with other communities. Consider, for example, the community structure in **Fig.** 7(a). Three communities are connected through seven binary links. All the communities are linked with two-sided complex interaction. Community 1 including $MA2$ carries its effect on AGF in Community 2, which in turn carries its influence on FIN in Community 3. It is a cyclic community structure. See Fortunato (2010); Fortunato, Latora, and Marchiori (2004); Granell, Darst, Arenas, Fortunato, and Gomez (2015); Hric et al. (2014) for community detection algorithms.

3. For each edge $e(k,l) \in BCE(C_{g_i^u})$, compute the resilience level of edge $e(k,l)$ in g_i^U by:

$$R_{g_i^u}(e(k,l)) = 1 - \left(\frac{\# \, of \, shortest \, paths \, from \, j \, to \, i \, that \, pass \, through \, e(k,l)}{\# \, of \, shortest \, paths \, from \, j \, to \, i} \right) \equiv R(e).$$

4. Compute the average resilience level of the network g_i^U by:

$$R_1(g_i^U) = \left(\frac{\sum_e R(e)}{\# \, of \, edges \, in \, BCE(C_{g_i^u})} \right). \tag{5}$$

5. Suppose that g_i^U has no community. The network resilience level is then computed by:

$$R_2(g_i^U) = 1 - \left(\frac{sum \, of \, centrality \, scores \, of \, in/out \, edges \, of \, the \, sector \, hit \, with \, shock}{sum \, of \, centrality \, scores \, of \, all \, edges \, in \, the \, network} \right). \tag{6}$$

The EBC measure given in item 3 describes the frequency at which an edge lies on the shortest path between pairs of nodes in a network. A production network is said to have community structure if the sectors of the network can be grouped into sets of sectors such that each set of sectors is densely connected internally and sparsely connected between groups.

5 Properties of input-output data

5.1 Input-output data

The input-output (IO) data used in the implementation are obtained from OECD's IO database for the most recent available year 2018.[9] The OECD IO matrices with 35 sectors have been aggregated to 15 sectors by using the 2008 UN definitions for sector aggregation (United Nations, European Commission, International Monetary Fund, Organisation for Economic Co-operation and Development, and World Bank, 2009).[10] The aggregation allows for a comparative analysis of the IO systems across countries. Our aggregation divides "Manufacturing sector" into two sub-sectors: $MA1$ in our analysis covers the petroleum and refinery activities, while $MA2$ captures the rest of the 16 manufacturing sub-sectors. $MA2$ is an important sector as it represents the agglomeration of 16 inter-connected industrial sub-sectors and that it is a high-priority sector in Turkiye.

5.2 Qualitative graph-theoretic properties

Under the Leontief production function, all inputs are critical and every input creates an input bottleneck if it is missing. Since input-output networks at the industry level are extremely dense, under the Leontief function, almost any industry can cause substantial downstream disruptions. The linear production function, in contrast, assumes no critical inputs at all. Downstream shock propagation only occurs when the total input level is insufficient. In reality, some of the inputs an industry employs are in fact not critical for production (Pichler, Pangallo, del Rio-Chanona, Lafond, & Farmer, 2022), and in the short-run, the associated technical coefficients can be scaled down or set to be equal to

[9] see <https://stats.oecd.org/Index.aspx?DataSetCode=IOTSI4_2018> for OECD input-output data for 64 countries over 14 years from 2005 through 2018.

[10] Information on sector aggregation from 35 to 15 sectors is available upon request.

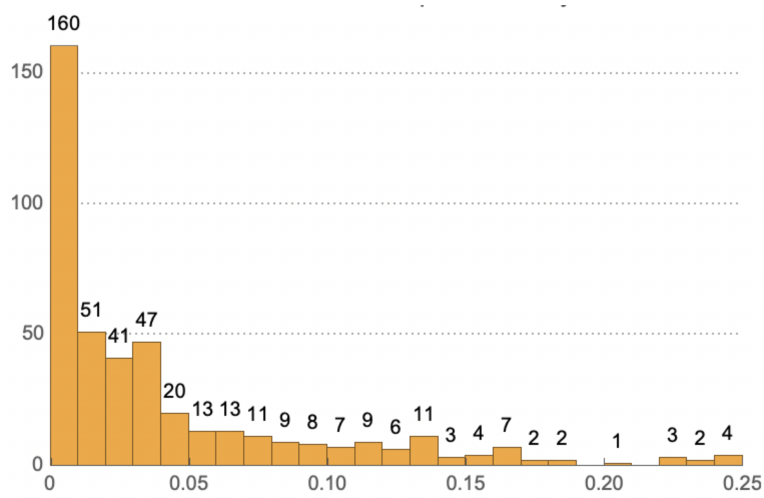


Figure 1: Distribution of backward and forward multipliers in 2018

zero, while the industry continues its production. Therefore, scaling down some of the technical coefficients because of non-critical input use is not in contradiction with the analysis based on the adjusted input-output linkages. Selectively focusing on the midrange multipliers, for example, those that fall in between 1st Quartile ($Q1$) and 3rd Quartile ($Q3$) , conjectures that the production function in play is between the Leontief and the linear specifications. The choice of multiplier interval can be changed at will if the targeting analysis aims to characterize those sectors with a given multiplier size.

To better understand the structure of Turkey's 2018 production network, we first select the multipliers in the interval between Quartile 1 ($Q1 = 0.005$) and Quartile 3 ($Q3 = 0.08$), and then apply a threshold significance level to further narrow down the interval. For each sector, those multipliers that account for at least 20 percent of their multiplier sum are used in the construction of the upstream and downstream networks. This two-stage selection procedure accounts for differences in the supply-use size of each sector. The multipliers selected account for about 80 percent of the interactions in the production network (see **Fig.** 1).

Several properties are noteworthy. The first property is critical for modeling the production network as a weighted, directed graph. If the multiplier matrix is strongly asymmetric (symmetric), a directed (undirected) graph configuration will be suitable for the representation of Turkiye's production network. A low (high) correlation coefficient (ρ) between the upper and lower triangular multipliers rationalizes the formulation of the network as a directed (undirected) graph. The correlation coefficients of backward and forward multipliers shown in **Fig.** 2, which are respectively $\rho_B = 0.14$ and $\rho_F = -0.04$, suggest that Turkiye's production network in 2018 can be analyzed by using a directed graph configuration. Regarding backward and forward weights (or technical coefficients), the correlation coefficients between upper and lower triangular elements are not significant either, which are $\rho_B = 0.17$ and $\rho_F = 0.04$, respectively (see the figures in the 2nd column of **Fig.** 2). This is natural because sector i's input demand from sector j is not necessarily equal to sector j's demand for the output of sector i. As to the correlation between multipliers and weights implied by the 2018 production network, a much stronger positive correlation is observed in the case of input supply (backward) as opposed to output demand (forward), which are $\rho_B = 0.93$ and $\rho_F = 0.89$, respectively (see the figures in the 3rd column of **Fig.** 2). Altogether, these statistics suggest that the 2018 production network

Table 6: Sectoral eigenvector centrality scores and (c, e) - coordinates of g^U_{MA2}

Communities	Sectors	(cause, effect)	Dominance	Centrality
	$MA2$	(0.16, 0.11)	large	0.18 - high
C_1	CST	(0.10, 0.15)	medium	0.22 - high
	EGW	(0.09, 0.11)	medium	0.18 - high
C_2	FIN	(0.12, 0.14)	medium	0.07 - low
	TSC	(0.07, 0.07)	small	0.11 - moderate
	AGF	(0.12, 0.11)	medium	0.12 - moderate
C_3	EST	(0.15, 0.00)	medium	0.001 - very low
	$CO12$	(0.13, 0.15)	medium	0.08 - low
	$MA1$	(0.07, 0.15)	small	0.04 - low

can be modeled as a weighted, directed graph, and hence, critical information for evidence-based policy reforms can be obtained by applying graph-theoretic concepts.

The second property provides information about a sector's linkage preference that directly affects its productivity. Sectoral eigenvector centrality scores suggest that linkages originating from high-scoring sectors contribute more to the score of a sector than linkages from low-scoring sectors.[11] A high (low) eigenvector centrality score means that a sector is connected to many sectors with high scores, and that most (least) of the input flow in the network is likely to end up with. In other words, the centrality measure indicates the limiting probability distribution of the flow across sectors. The eigenvector centrality score of $MA2$, 0.18, follows that of CST, 0.22, while $MA1$, FIN, and $CO12$ have scores on the lower end (**Table** 6). This property reveals that CST and $MA2$ do business with those sectors with high centrality, as opposed to FIN doing business mostly with non-central sectors. This observation points to the need for increasing policy efforts to strengthen the linkage between FIN and $MA2$. This finding further implies that FIN should innovate new financial instruments to fund investment in $MA2$ in particular and in the rest of the economy in general.

The third property concerns the degree of sector i's dominance. In a directed graph, sector i has both "cause (c)" (sum of sector i's out-degree multipliers) and "effect (e)" (sum of sector i's in-degree multipliers). The "cause" and "effect" of sector i serve as one measure of the flow size, while the centrality serves as an indication of where that flow ends up. The relation between dominance and centrality can be analyzed under nine different cases (**Table** 7). A striking difference between sectors with the largest flow and sectors that absorb that flow suggests the presence of a non-trivial structure to flows that do not necessarily drive economic activity towards the largest sectors. Each case demonstrates a distinct feature of the network. For productivity improvement, case 1 (large-high) represents the most desirable situation in which case a sector is dominant (with large flow size) and highly central (with high flow absorption). This suggests that that sector causes the largest impact (measured by multipliers), while at the same time absorbing the largest flow in the rest of the network. Under these conditions, a disruption or a shock to that sector is expected to lead to the largest reduction in aggregate output (Acemoglu et al., 2010). $MA2$ is found to be the most dominant sector (case 1) that is expected to significantly drive aggregate output, followed by CST and EGW (case

[11] Eigenvector centrality of a sector increases by connections to high degree sectors. When high degree sectors are preferentially directly connected to one another, and low degree sectors are preferentially connected to one another - tendency for sectors to connect to other sectors with similar properties "*positive assortativity*" - eigenvector centralization will be high.

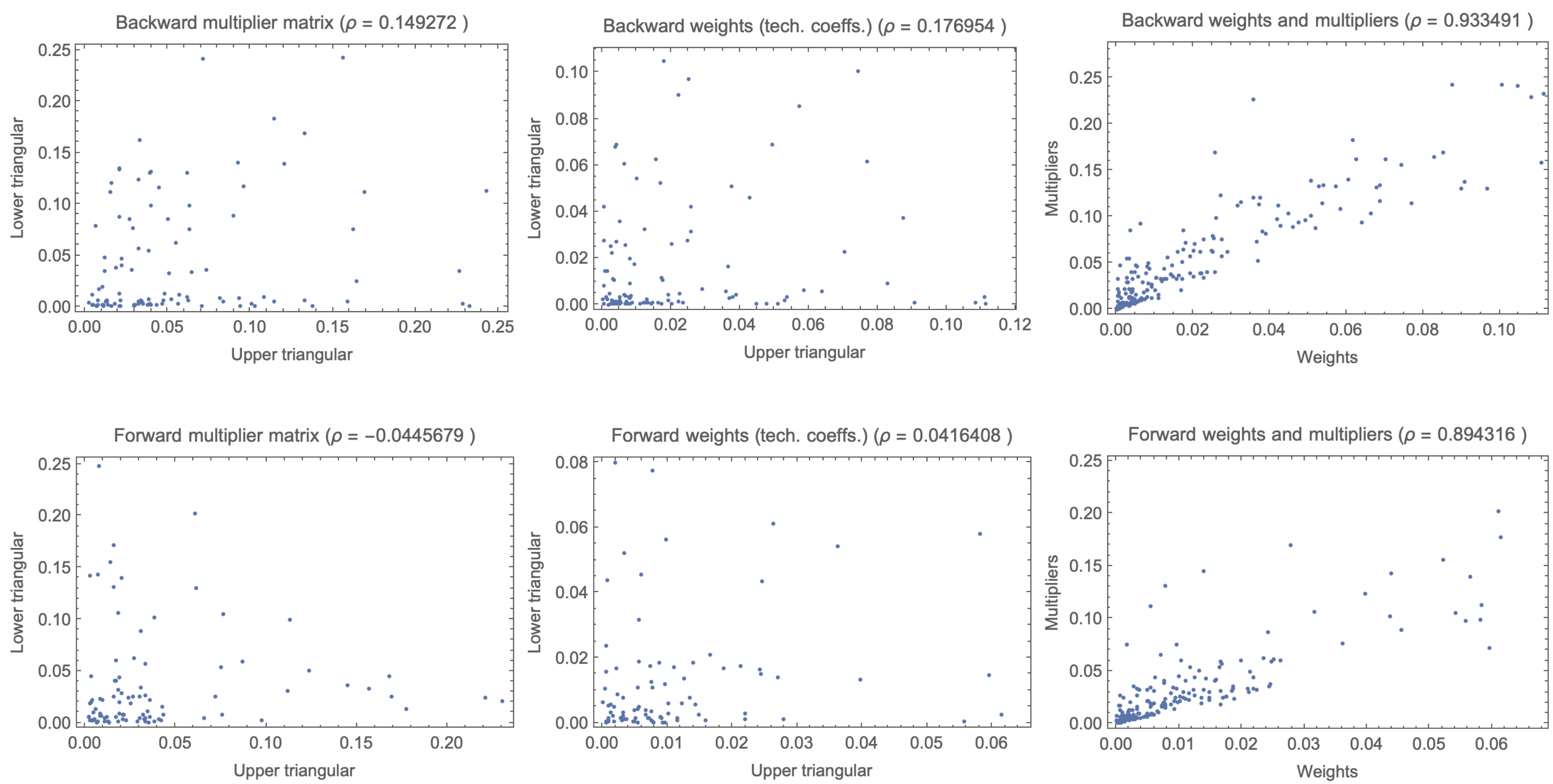


Figure 2: Properties of Turkiye's 2018 production network

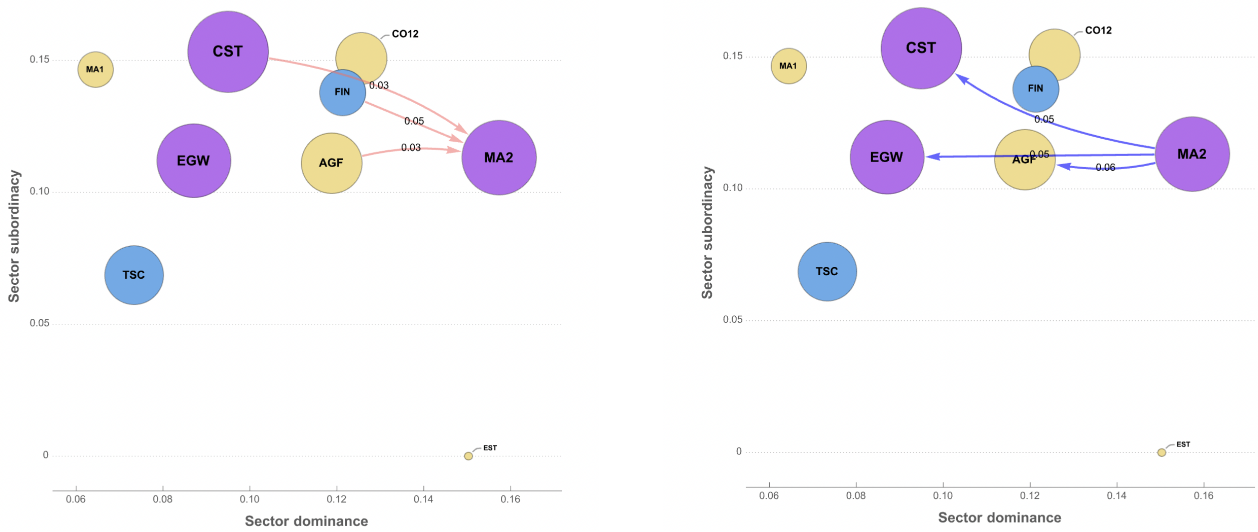
Table 7: The extent of impact on aggregate output through $MA2$'s upstream network: g^U_{MA2}

		Dominance		
		large	medium	small
Centrality	high	case1: significant ($MA2$)	case2: substantial (CST, EGW)	case3: small
	moderate	case4: substantial	case5: average (AGF)	case6: tiny (TSC)
	low	case7: small ($CO12$, FIN)	case8: negligible (EST)	case9: insignificant ($MA1$)

2). $\{MA2, EGW, CST\}$ are the most influential and the most central sectors in which case most flow ends up with these sectors shown as large circles (see **Fig.** 3). AGF under case 5 follows case 2. $\{CO12, FIN\}$ under case 7 are less impactful compared to AGF because of their low centrality. EST under case 7 has a negligible impactful compared to case 7 because a very tiny flow ends up this this sector. The rest of the sectors, $\{EST, TSC, MA1\}$, that respectively fall under under cases (6, 8, 9) are not expected to drive the variability in aggregate output.

The second and third properties are illustrated using a visual diagnostic tool for characterizing the network (**Fig.** 3). This figure also illustrates the fourth property *community structure*" of the network. The hard-core sectors all belong to the same community (as indicated by the same color, which is purple), implying that these sectors have more interactions among themselves than their interactions with others in the network. Community 1, $C_1 = \{MA2, CST, EGW\}$, has the largest average centrality, followed by Community 3, $C_3 = \{EST, CO12, AGF, MA1\}$, and Community 2, $C_2 = \{FIN, TSC\}$. Community 1 generates the largest flow through $MA2$ while absorbing the highest flow through CST and EGW, and they are all connected within the same community. Therefore, community 1 is to be prioritized for policy reforms to increase aggregate output. Although critical for overall economic growth, community 2 remains weak both in terms of flow size and flow absorption. Policy reforms should also prioritize this community as they produce general purpose services widely used in the rest of the economy. The figure also shows critical input suppliers of $MA2$, $\{FIN, AGF, CST\}$, and users of its output, $\{AGF, CST, EGW\}$.Therefore, it should also be a priority for policy reforms to create an enabling environment for $MA2$'s suppliers and users.

The final property of Turkiye's production network concerns the implementation of pro-competitive PMR. Research shows that most of sectoral indicators of pro-competitive PMR relate to four network sectors, $\{EGW$, TSC, WHS, $EST\}$ (Alemani, Klein, Koske, Vitale, & Wanner, 2016; Koske, Wanner, Bitetti, & Barbiero, 2015). Regulations in these sectors are mainly about the organization of network access to potential service providers. For example, regulations in WHS typically take the form of entry barriers, specific restrictions for large firms and the flexibility of shops in terms of opening hours and prices; those in EST relates to barriers to entry and the way services are delivered and includes, amongst others, rules governing the recognition of qualifications and the determination of fees and prices. Recent empirical studies provide some evidence that the benefits of pro-competitive regulations tend to materialize only over time, but yield somewhat conflicting insights with respect to the possible presence of short-term costs (Bassanini, 2015; Bouis et al., 2016). In the context of Turkiye, the four network sectors concerned account for about 41 percent of GDP in 2018. Their economic significance is wide since most of their output is heavily used as inputs in production elsewhere in the economy. Per USD cost of labor, these sectors invest 2 cents, 43 cents, 59 cents, and 14 cents, respectively. In other words, TSC and WHS have received relatively large investments per labor cost. However,



Bubble Properties: (1) **Position**: Coordinates of dominancy (row-wise sum) and subordinacy (column-wise sum of multipliers); (2) **Shape**: Size of eigenvector centrality score; (3) **Color**: Communities of sectors; (4) **Arrows**: In-degree (red) or Out-degree (blue) edges with edge weights.

Figure 3: Sector dominance, eigenvector centrality, degree, and community structure

regarding the targeted sector $MA2$, accounting for 0.6 percent of GDP, only 11 percent of labor cost has been invested. FIN, the main input supplier of $MA2$, accounts for 3 percent of GDP and invests 5 percent of labor cost. These observations suggest that successfully implementing pro-competitive PMR in $MA2$ and FIN calls for a stable political environment and a strong fiscal space to ensure the continuity of the reforms that are likely to yield short-term costs. Otherwise, for political economy reasons, incumbents are likely to fall on the short-term, less-productive policy reform.

6 An application

6.1 Algorithm I: Key findings and policy implications

Algorithm I generates four hierarchically layered graphs. **Fig.** 4(a) exhibits the "*upstream*"network of input suppliers of $MA2$; (b) the "*downstream*" network of users of $MA2$'s output; (c) the combined network of "*upstream*" and "*downstream*" linkages of $MA2$; and lastly, (d) the structural and ancillary links of $MA2$ from the combined network in (c). The linkage patterns embedded in the four graphs provide critical information for evidence-based policy design to improve $MA2$'s contribution to aggregate output.

The first pattern observed from **Fig.** 4(a) is that $MA2$ has two-way links to $CST$and AGF, followed by its binary links to FIN and EGW. $MA2$ also operates within two cycle-pathways, $\{MA2 \rightarrow AGF \rightarrow CST \rightarrow MA2\}$ and $\{MA2 \rightarrow EGW \rightarrow CST \rightarrow MA2\}$, implying that any input $MA2$ receives from FIN would necessarily go through these cycle-pathways. AGF and EGW along these pathways act as intermediary sectors that can control the flow of inputs into CST, which in turn creates a multiplier effect back on $MA2$. A similar multiplier effect on $MA2$ can also be established by any input into AGF's production process through, $\{CO12 \rightarrow AGF \rightarrow CST \rightarrow MA2 \rightarrow AGF\}$.

The second pattern concerns the impact of $MA1$'s and TSC's input supply to FIN, which in turn provides inputs to $MA2$ through, $\{MA1 \rightarrow FIN \rightarrow MA2\}$ and $\{TSC \rightarrow FIN \rightarrow MA2\}$. In the sense of hierarchy, this implies that FIN is the source and the upstream sector to $MA2$. Therefore, distortions accumulating in FIN would have substantial negative effect on the productivity of $MA2$. In case that financial market regulations narrow the range of available financial instruments, $MA2$'s access to finance would be risked, thereby curbing new entry and market growth. In this case, $MA2$ may have to negotiate with FIN, and that can result in loss of rents that $MA2$ expects to earn. Together, the first and second patterns suggest that policy reforms should consider the following pathways:

$$\{MA1, TSC\} \rightarrow FIN \rightarrow \mathbf{MA2} \leftrightarrow \{CST \leftarrow \{AGF, EGW\}\}, \tag{7}$$

to design effective policy reforms to promote $MA2$'s production. This requires not only to address $MA2$'s weak linkages but also to consider the weaknesses of the network itself:

$$\{MA1, TSC, FIN, \mathbf{MA2}, AGF, EGW, CST\}. \tag{8}$$

Network-based policy reforms targeting $MA2$'s productivity need to identify mechanisms causing "*distortions*" (sub-optimal prices) in $MA2$'s market, as well as the distortions in markets of sectors in Equ. 8. Having said that, a particular attention should be paid to distortions and misallocation of resources taking place along the pathways in Equ. 7. The convoluted distortions and misallocations created by backward input demand linkages cause the "*upstream*" network of $MA2$ to become cluttered with imperfections. Ultimately, $MA2$ becomes the sink for accumulated distortionary effects, experiencing the highest distortion level (Liu, 2019). At some point in time, the distortions accumulated in $MA2$ can burst if it goes beyond its carrying capacity, playing a much larger role in generating aggregate volatility in the economy-wide production network. Informed policy reforms should ease the wider diffusion of effects of the shock before it reaches back at $MA2$.

Centralities of sectors along the pathways in 7 call attention to two potential bottlenecks originating from FIN and AGF that absorb a relatively small size of inputs flowing in the rest of the production network. This is in turn likely to cause contraction in $MA2$'s production. On the positive side, CST has a facilitating linkage with $MA2$ as it absorbs a very large flow of input and redirects it to $MA2$, which would improve $MA2$'s production. These findings point to the need for increased policy efforts to strengthen the linkage between FIN and $MA2$ and efforts promoting financial innovations to expand $MA2$'s production possibilities.

The difference between input "*generating*" sectors, $\{MA2, CO12, FIN, AGF\}$, and input "*absorbing*" sectors, $\{CST, MA2, EGW, AGF\}$, suggests that the largest flow absorbers $\{CST, EGW\}$ do not necessarily drive economic activities of the largest input generators $\{MA2, CO12\}$. That is, there is a linkage gap between absorbers and generators:

$$\underbrace{\{CST, EGW\}}_{absorbers} \rightarrow \underbrace{\{MA2, CO12\}}_{generators}, \tag{9}$$

pointing out the need to design policy reforms to promote the discharging of the accumulated input in the absorbing sectors. This can be achieved either by establishing new channels between the absorbing and generating sectors or by investing in areas to promote new activities that will close the gap. Pro-competitive PMR should consider the peculiarities of EGW and $CO12$, both of which are regulated general service sectors, outputs of which are widely used as inputs elsewhere in the economy (Gal & Hijzen, 2016). TSC, another highly regulated general purpose service sector, is also critical for productivity improvement especially in FIN that serves as an important input supplier of $MA2$. Reductions in barriers to entry to most protected non-manufacturing network industries, $\{EGW, TSC\}$, lead small firms to benefit most from pro-competitive PMR (Bouis et al., 2016). Therefor, intensifying PMR efforts in these sectors should strengthen Turkiye's growth prospects.

More interestingly, these regulated and protected industries are spread across the three communities embedded in $MA2$'s upstream network:

$$\underbrace{\{MA2, EGW, CST\}}_{community\,1} > \underbrace{\{CO12, AGF, MA1\}}_{community\,2} > \underbrace{\{TSC, FIN\}}_{community\,3}, \tag{10}$$

which are ranked with respect to the average community centrality. The ranked communities also suggest that reductions in barriers to entry to community 3 promises the largest productivity gains from pro-competitive PMR, followed by community 2. Since every community includes at least one regulated industry, PMR related to regulated industries in general will strengthen growth prospects for $MA2$. For productivity growth in the upstream network of $MA2$, policy reforms should further target, $\{FIN \to MA2, EGW \to TSC\}$, to create a virtuous cycle between community 1 and 3.

Pro-competitive PMR also have substantial bearing for the immediate consumers, $\{HLT, ENT, HOT\}$, of $MA2$'s output. Their output demand and $MA1$'s and EST's demand from them (red links in **Fig.** 4(b)) are translated to input requirements for $MA2$ to meet the new demand (red links ending up with EST and $MA1$ in **Fig.** 4(c)). This new demand triggers a whole bunch of backward linkages in $MA2$'s production network, with the shortest pathway transmitting the input requirement signal to $MA2$:

$$\underbrace{\{EST, MA1\}}_{signal\,entry\,points} \to FIN \to MA2. \tag{11}$$

Pro-competitive PMR should guide the "*signal entry points*" in such a way as to improve their signal transmission mechanisms. For example, subsidies to strengthen competitive neutrality in $MA1$'s market would create opportunities for small disadvantaged firms to enter the market, increasing the flow of price-quantity information across firms and opportunities for FIN to design new financial instruments that would be available for $MA2$. Since FIN operates in a non-competitive environment, competition policy reforms should concurrently ensure the enforcement of competition law in FIN.

As seen from the combined upstream and downstream networks in **Fig.** 4(d), the immediate environment of $MA2$ includes only $MA2$'s direct links to its neighbors, as well as the links between its neighbors denoted by the red links in **Fig.** 4(d). This environment is called "*structural*" cluster as the interactions taking place in this environment are immediately passing on to $MA2$. The figure also shows that $\{EST, TSC, CO12, MA1\}$ fall in the "*ancillary*" cluster as the interactions in this cluster will take time to influence the structural cluster. Such a layered structure suggests that policy priority should be given to the structural cluster to sustain $MA2$'s production at least in the short run. In the long-run, however, policies that influence the interactions in the ancillary cluster be developed to avoid a collapse of the production network of $MA2$ in case of a shock to its critical sectors.

Research conjectures that upstream sectors in a given production network play an important role in the amplification of exogenous shocks (Pichler et al., 2022). In the context of input supply-input use "*upstream*" network, the amplification of an input-use "*demand*" shock to $MA2$ would depend on which sectors, $\{AGF,\ CST,\ FIN\}$, are involved in spreading the shock. The elasticity of aggregate output to the shock to a given sector depends on the linkage strength of that sector. That the three sectors have one-edge links with $MA2$ implies that, depending on the linkage strength, the shock to any of these sectors would have deleterious effect on $MA2$'s production. To generate critical information for evidence-based design of policy interventions, some of the properties of $\{MA2,\ AGF,\ CST,\ FIN\}$ can be uncovered ex-ante to know how systemic the shock is. For example, as proposed by Pichler et al. (2022), scenario analyses can be carried to measure the impact on the aggregate output of a single shock (i.e., by computing the output elasticity of that shock) to a single sector.[12] Knowing the relation between the shock and output multipliers of the sectors concerned is a valuable information for policy design. A low (high) shock elasticity of output multipliers in a sector would imply that the shock is not disrupting much the production process in that sector.

Furthermore, in the context of $MA2$'s "*upstream*" network, the distortions accumulated in $\{AGF,\ CST,\ FIN\}$ would lead to resource misallocation in $MA2$, resulting in a sub-optimal production, the effects of which would pass on the "*downstream*" network of consumers of $MA2$'s output (Atalay, 2017). Through $MA2$'s direct binary links to its customers, $\{HLT, ENT, HOT\}$, the effects of the shock will be observed across all the sectors in the "*downstream*" network of $MA2$ (see **Fig.** 4(b)). Eventually, through the connections of consumers to input-suppliers of $MA2$ in the "*upstream*" network, aggregate output growth in Turkiye will be at risk. The question is how to avoid the spread of the shock. Two viable strategies exist. The first, mildly protective strategy is to regulate the links of input-suppliers of $MA2$, $\{AGF \to MA2, CST \to MA2, FIN \to MA2\}$, and $MA2$'s output supplies on the demand side, $\{MA2 \to HLT, MA2 \to ENT, MA2 \to HOT\}$. Policy design would be relatively less troubling and less costly as the number of links considered gets smaller. Therefore, for government facing limited fiscal capacity, the identified sets of links should further be prioritized. The second, strongly protective strategy is to regulate not only the links of input suppliers and customers of $MA2$ but also those links among the neighbors of $MA2$. Prioritization of the links is more relevant under this strategy as the number of links can quickly and exponentially increase with the inclusion of the neighboring sectors of $MA2$ (see the structural (red colored) links in **Fig.** 4(d)).

The longer the pathway, the higher the upstream sector's distortion centrality. Topologically, EST is an exogenous sector in the upstream network of $MA2$ as it has no in-coming links at the implemented threshold multiplier level. Thus, it can only transmit its own distortions to two sectors $\{CO12, MA1\}$, the users of $EST's$ output. Conversely, CST is influenced by an accumulated amount of distortions as it has multiple links to $\{MA2, EGW, AGF\}$. The larger the distortions in its upstream sectors, the larger the resource misallocation in CST as it takes its price-quantity information from the upstream distorted markets. The large (small) bubble size of CST (EST) shown in **Fig.** 3 is an indication of this conjecture. A policy implication for $MA2$ of this conjecture is that pro-competitive

[12] Scenario analyses can be carried out using the RAS matrix balancing method, which is more practical compared to the cross-entropy method. See Holý and Šafr (2023) for the equivalence of the RAS method with the cross-entropy method for matrix balancing.

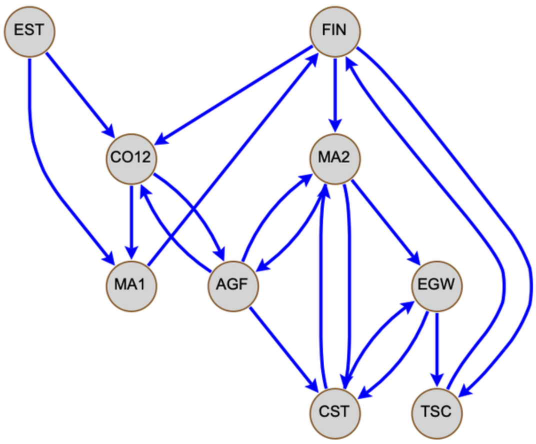
PMR should target upstream sectors, $\{CST, AGF, FIN\}$, to mitigate the distortions. Investing in markets where most-dominant and most-distorted upstream sectors interact would improve efficiency and reduce aggregate losses because an inefficient economy allocates too few factor inputs upstream and too many downstream. Policy interventions would improve efficiency only if they redirect the factor input to the dominant and distorted upstream sectors. In hierarchical production networks (the generalization of vertical networks), similar to networks in **Fig.** 4(a, b), upstream sectors tend to have higher distortion centrality because imperfections accumulate through backward linkages.

Applying Sugiyama's layered graph algorithm (Sugiyama et al., 1981),[13] we refine the "*upstream*" network of $MA2$ (**Fig.** 4(a)). The vertical links are isolated from the the upward links (see **Fig**. 5(a, b)). **Fig**. 5(a) shows that $\{EST, FIN\}$ occupy top of the hierarchy, while $\{CST, TSC\}$ bottom of the hierarchy and $MA2$ functions as a midstream sector. The distortion centrality in $MA2$ is expected to be smaller than that in the upstream sectors and larger than that in the downstream sectors. There are 6 binary links working against the vertical hierarchy in the network: $\{MA1 \rightarrow FIN, TSC \rightarrow FIN, AGF \rightarrow MA2, CST \rightarrow MA2, AGF \rightarrow CO12, CST \rightarrow EGW\}$ (see **Fig.** 5(b)). The two isolated networks can be analyzed as a causal influence network to explore functional dependencies across sectors (Ay & Polani, 2008). Adopting the pure hierarchical structures described, we conjecture that, with only one link from FIN to $MA2$, the priority for public support should be given to FIN in order to reduce the distortion in FIN, which would in turn reduce the misallocation in $MA2$ and then in the downstream sectors $\{AGF, EGW, CST, TSC\}$. From policy design perspective, and the observation that CST and TSC are at the bottom of the hierarchy, EST and FIN are to be supported to minimize the distortions that cause misallocation of resource use in $MA2$ and in AGF, EGW, CST, and TSC. CST and AGF work as counteracting forces through their upward links affecting the misallocation in $MA2$. This all points out that there is a potential aggregate productivity gain if $MA2$, AGF, and CST collaborate on a common cause. Since $MA2$ and CST are members of the same community, the collaboration concerned can be justified more easily on the grounds that these two sectors have already been interacting strongly. The second type of collaboration concerns the collaboration of sectors from two different communities, which are, by definition, connected through low-strength links. Hence, the second collaboration between AGF and $MA2$ would require more efforts to strengthen their interactions.

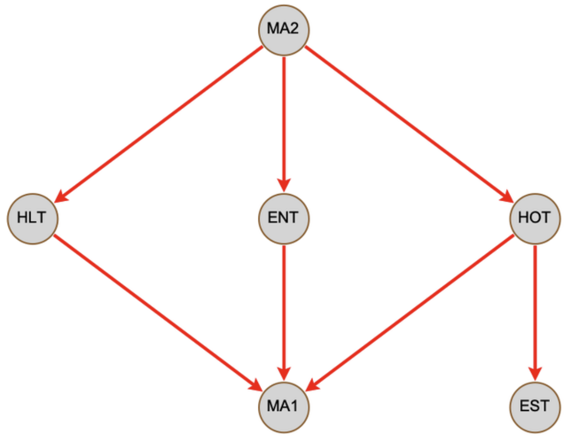
6.2 Algorithm II: Key findings and policy implications

Algorithm II identifies potential amplification mechanisms by uncovering cascades of layers of sectoral linkages. If a single sector fails, it may force other sectors to fail as well, which may eventually lead to failure cascades and the breakdown of the production network, referred to in the literature as systemic risk. This algorithm reshapes the "*upstream*" network of $MA2$ as a cascade of layers of links (see **Fig.** 6). The resulting layered network can be used to elaborate on the effects on $MA2$'s production of a shock to one of the critical input suppliers of $MA2$. The pathway through which the

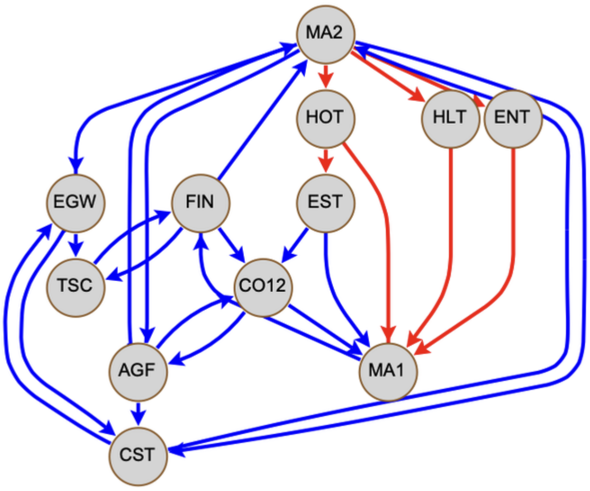
[13] A layered graph drawing algorithm - also known as hierarchical layout or Sugiyama algorithm - places the vertices of a graph into horizontal layers (virtual horizontal lines) such that the links, modeling the relationships, point in a uniform direction. This algorithm is based on an acyclic graph structure and works with an unweighted adjacency matrix in which existing links take on score 1, non-existing links score 0. This implies that the layering does not consider the actual edge weights which may take on values other than 1 and 0.



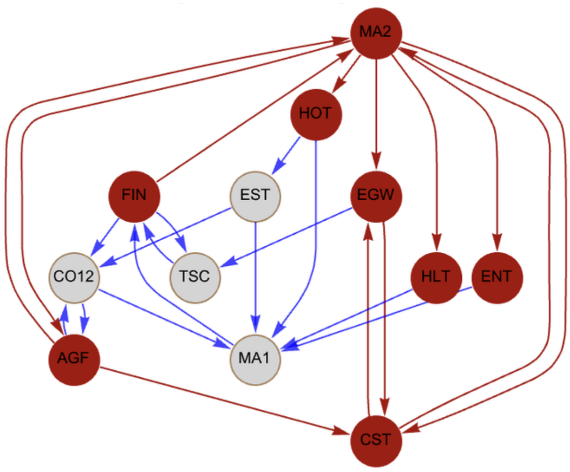
(a) Upstream network of $MA2$, g^U_{MA2}



(b) Downstream network of $MA2$, g^D_{MA2}

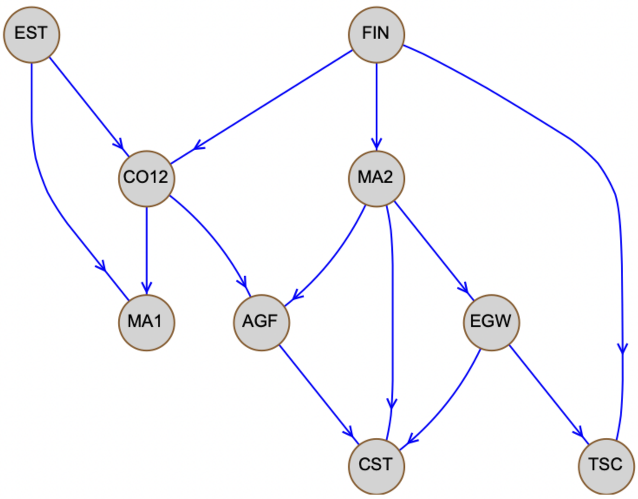


(c) Networks in (a) and (b) combined

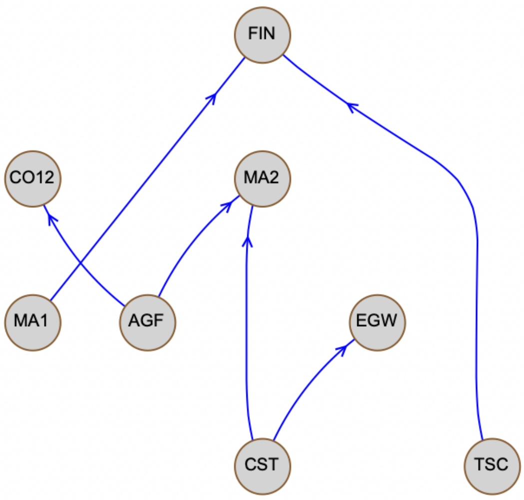


(d) Structural (red) and ancillary (blue) links in (c)

Figure 4: Turkiye 2018: Targeting sector $MA2$ using IO matrix with 15 sectors



(a) Downward network in **Fig.**4(a)



(b) Upward network in **Fig.**4(a)

Figure 5: Downward and upward hierarchical structure of g^U_{MA2}

shock penetrates into downstream sectors would provide us with more information that can be used to design layer-specific pro-competitive PMR.

Fig. 6, a policy diagnostic tool, shows three layers of links uncovered from a hierarchical network in **Fig**. 4(a). EST occupies the outmost Layer 3 (blue colored circle with blue arrows), implying that it is the single furthest sector that indirectly supplies input to $MA2$. The midstream Layer 2 (green colored circles with green arrows) includes three sectors, $\{CO12, MA1, TSC\}$, that provide inputs to two sectors, $\{FIN, AGF\}$, placed in the innermost Layer 1 (red colored circles with red arrows) centered around $MA2$. Layer 1 includes five sectors, $\{FIN, AGF, CST, EGW, MA2\}$. This cascade structure offers a new perspective for designing pro-competitive PMR to improve the productivity of $MA2$. In case of a shock to the economy-wide production network, there are alternative policies to minimize the adversities that $MA2$ is likely to encounter. From the point of maximizing $MA2$'s production, public policy should target Layer 1 to correct the accumulated distortions in $\{FIN, AGF\}$, which have direct bearing for the productivity of $MA2$. Depending on the sectors inflicted by the shock, policies should also target them individually and the layer they belong to. For example, if $MA1$ is hit by a shock, FIN should be the sector of interest to policy makers because $MA1$ is only two linkages away from $MA2$, $\{MA1 \rightarrow FIN \rightarrow MA2\}$, through which the effects of the shock will penetrate into $MA2$ in Layer 1. The effect of the shock to $MA1$ will also penetrate into $MA2$ through a delayed effect along the pathway, $\{MA1 \rightarrow FIN \rightarrow CO12 \rightarrow AGF \rightarrow MA2\}$. Public support to improve the resilience of FIN and AGF should slow down the penetration, and hence, in the short run, Layer 1 will buy time to improve the resilience of the sectors in it.

Competition policy enforcement, market reforms and institutions need to be elaborated to identify the areas that need to be strengthened to promote the productivity of $MA2$. Investment strategies can be designed. An obvious one is to invest in infrastructure to strengthen the resilience of FIN and AGF through improved market connectivity and access (i.e., investments in TSC) so that the penetration from Layer 2 to 1 of the effects of the shock can be minimized. Renewed investments in ICT would help catalyze the connectedness in the upstream network of $MA2$. Furthermore, two-way flows of inputs, $\{CO12 \leftrightarrow AGF, TSC \leftrightarrow FIN\}$, also justify public support to $CO12$ and TSC to reduce the distortionary effects on sectors in Layer 1 since the effects of the shock would amplify due to the two-way flow of inputs.

6.3 Algorithm III: Key findings and policy implications

Algorithm III measures the resilience of the "*upstream*" network of $MA2$. Two measures of network resilience are proposed: one for a network with communities, another for a network without communities. In the case of communities, the resilience indicator is constructed at four steps explained in Section 4.3. The idea is simple: the more connected a network is, the more resilient it is. Namely, if the communities are connected with a large number of links, it is more likely that the upstream network is more resilient against shocks because severely hit links can be quickly replaced with others.

$MA2$'s upstream network has a total of 19 links (see **Fig**. 7(b)), 7 of which are in between communities, $\{FIN \rightarrow CO12, MA1 \rightarrow FIN, FIN \rightarrow MA2, MA2 \leftrightarrow AGF, AGF \rightarrow CST, EGW \rightarrow TSC\}$ (see **Fig**. 7(a)). In other words, more than one-third of the links in the network should be hit severely for the entire network to breakdown. The centrality scores in our case are calculated using the

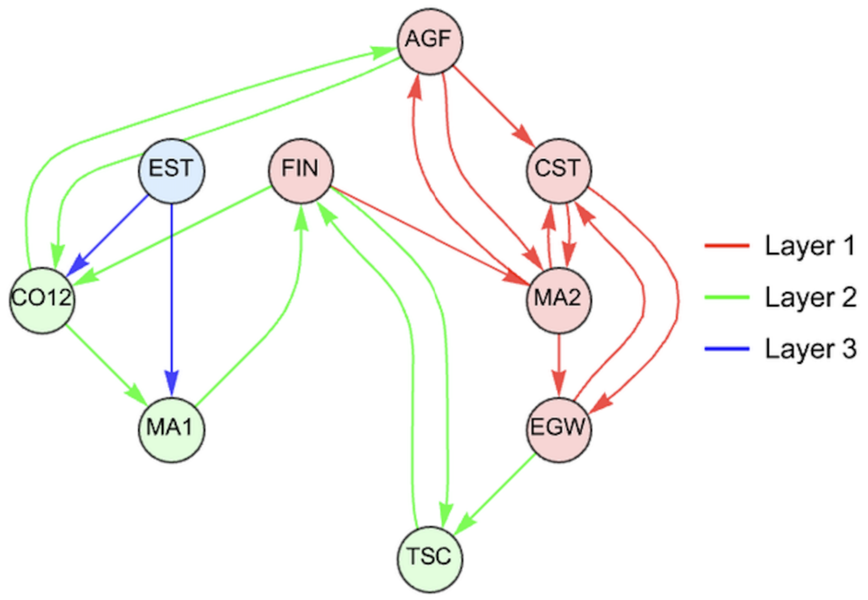


Figure 6: Turkiye 2018: Cascade of layers in the upstream network g^U_{MA2}

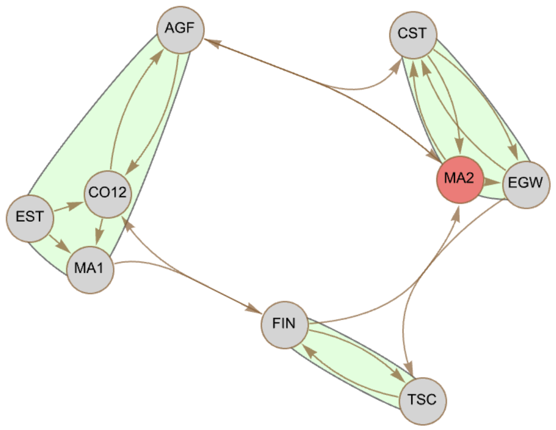
link weights (i.e., multipliers), considering that links have different multipliers. The indicator given in Equ. 5 approximates the degree of resilience of $MA2$'s network as $R_1(g^U_{MA2}) = 0.43$, implying a moderate resilience level based on the centrality scores of the relevant links (see **Fig**. 7(b)). The higher the score of a link is, the lower the network resilience with respect to that link is. If one link in between communities is disrupted completely, and if that link has a large edge-betweenness centrality score, then the resilience of the network with respect to that link will be low. The point of departure of this measure is that the connectedness of communities relies on the importance (i.e., edge betweenness centrality score) of between-community edges.

In the case of a network with no community, the importance of all incoming and outgoing links of a disrupted sector(s) is considered to measure the network resilience by Equ. 6. Here, the focus is on the connectedness of the entire network concerned with respect to the disrupted sector(s). If, for example, FIN and AGF are disrupted in an isolated manner, the network resilience will be $R_2(g^U_{MA2}, FIN) = (1 - 0.33) = 0.67$ and $R_2(g^U_{MA2}, AGF) = (1 - 0.27) = 0.73$, respectively. The average resilience level over the two disrupted links is 0.70 ($= (0.67 + 73)/2$). Assuming the complete breakdown of Layer 2 in the cascade analyzed in Section 6.2 means that all the links in that layer become non-operative due to a shock. That is, the following set of links,

$$\{CO12 \leftrightarrow AGF, FIN \rightarrow CO12, CO12 \rightarrow MA1, MA1 \rightarrow FIN, TSC \leftrightarrow FIN\},$$

are severely disrupted, in which case the measure of network resilience with respect to Layer 2 is calculated as $R_2(g^U_{MA2}, Layer\,2) = 0.27$. To improve the resilience of the network, policy interventions should selectively target those links which appear more often along the shortest paths, including

$$\underbrace{\{R(CO12 \rightarrow AGF)}_{0.35}, \underbrace{R(TSC \rightarrow FIN)}_{0.35}, \underbrace{R(MA1 \rightarrow FIN)\}}_{0.32},$$



(a) Community structure of g^U_{MA2} in **Fig.** 4(a)

Normalized eigenvector centrality scores (edge resilience measure)			
Edges / Scores		Edges / Scores	
$TSC \rightarrow FIN$	0.35	$AGF \rightarrow CO12$	0.20
$CO12 \rightarrow AGF$	0.35	$CST \rightarrow MA2$	0.18
$MA2 \rightarrow EGW$	0.32	$EST \rightarrow CO12$	0.15
MA1 → FIN	**0.32**	$MA2 \rightarrow CST$	0.12
FIN → CO12	**0.29**	$FIN \rightarrow TSC$	0.09
EGW → TSC	**0.29**	$EST \rightarrow MA1$	0.09
FIN → MA2	**0.26**	$EGW \rightarrow CST$	0.09
$CO12 \rightarrow MA1$	0.26	$CST \rightarrow EGW$	0.09
AGF → MA2	**0.23**	**AGF → CST**	**0.09**
MA2 → AGF	**0.20**		

(b) EBC scores of edges in g^U_{MA2} in **Fig.** 4(a)
Note: Emboldened edges link communities.

Figure 7: Community structure and EBCs of g^U_{MA2}

where the numbers below each link, e, represent the resilience level, $R(e)$, associated with that link.

6.4 Evolution of the production network

We move beyond the 2018 single-snapshot network of $MA2$ by allowing a time-dependent resolution of the network. This allows us to characterize the evolutionary path of $MA2$'s network during the period 2005-2018. Using the multipliers in between Q1 and Q3 and then selecting those binary links accounting for more than 20% of the variation in $MA2$'s output multiplier, we identify a time-series map of $MA2$'s network by a single-shot application of *Algorithm I* for each year from 2005 through 2018 (**Fig.** 8).

Few observations are noteworthy to assess the changes in the structure of $MA2$'s network. First, FIN is observed to be connected to $MA2$ during the entire period 2005-2018, followed by AGF's and CST's linkages to $MA2$ during 2007-2011 and 2016-2018, and EGW's linkages in 2009 and during 2015-2018. Second, during the most recent period 2016-2018, a more pronounced structure arises in which case $MA2$ is always linked to $\{FIN, AGF, CST, EGW\}$; the set of sectors in the network remains constant at 9; and in two of three networks, FIN and EST act as upstream sectors relative to $MA2$. Third, in all these hierarchical networks, $MA2$ occupies a midstream position along the existing pathways. This suggests that policy reforms to improve the productivity of $MA2$ need to primarily consider the potential expected impact of its immediate neighbors.

Likewise, the time evolution of community structures of $MA2$'s networks reveals that $MA2$ and FIN have shared a common community during 2011-2015 while sharing different communities during 2016-2018. This suggests that their linkage strength levels decreased during the latter period. Moreover, during the latter period, FIN and TSC have always shared the same community, implying that their links got stronger during 2016-2018. This may partly imply a weakening linkage between FIN and $MA2$. Finally, during 2016-2018, $\{MA2, EGW, CST\}$ have always remained in the same community, pointing out that the strength of their binary linkages has remained as strong.

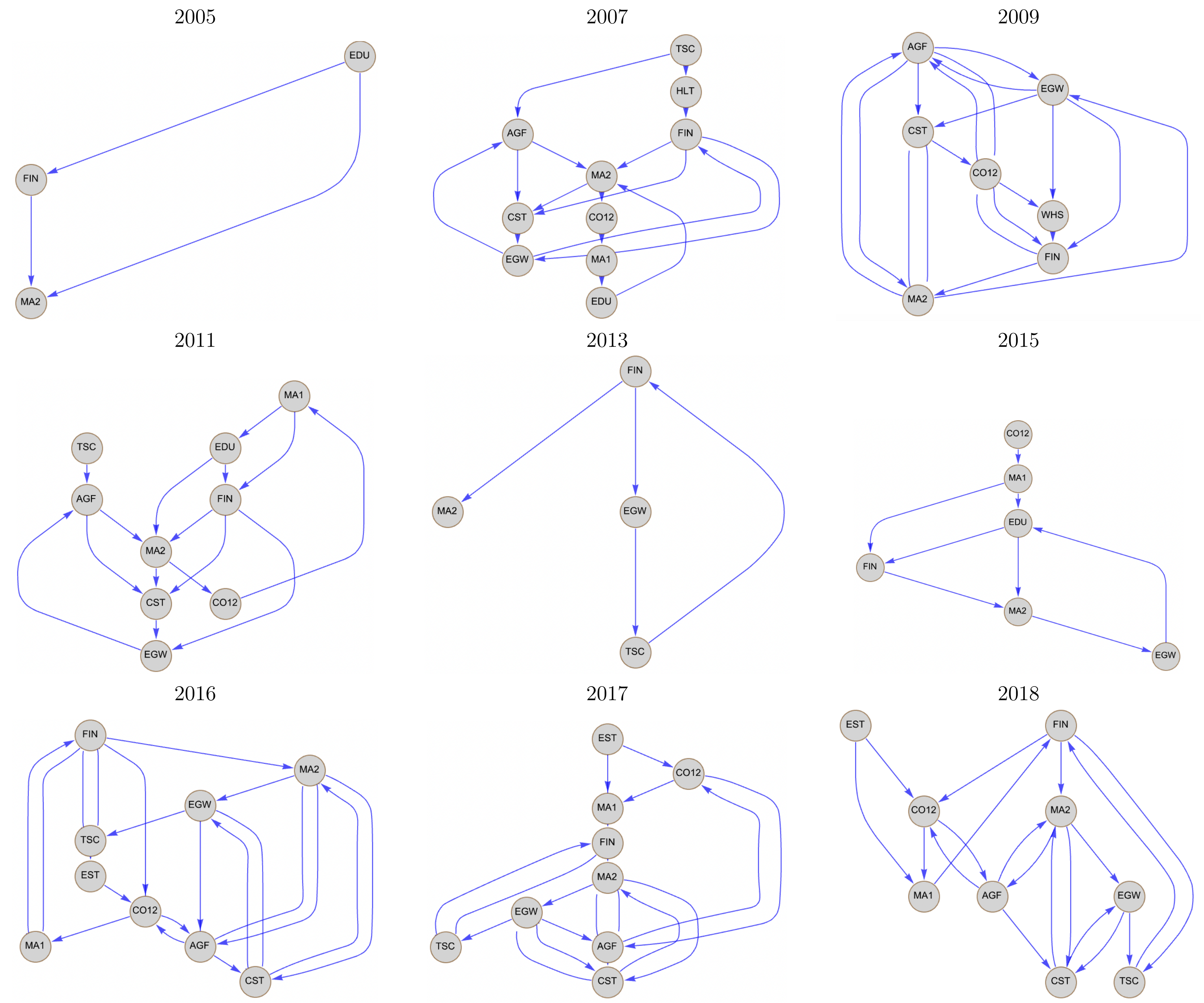


Figure 8: Time evolution of upstream networks of $g^U_{MA2}(t)$ in the (Q1 - Q3) interval of multipliers

7 Discussion

The period 2000-2022 has been especially tough for Turkiye due to a series of political and economic crises combined with the global financial crisis. Turkiye has gone through the 2000- 2001 financial crisis, followed by the 2008-2009 crisis that took place due to the global spreading of mortgage crisis in the US. The most recent 2018-2022 crisis emerged from the deteriorating investment environment both in domestic and international markets. On top of this, the COVID-19 pandemic and the war in Ukraine increased the severity of the crisis. These crises seem to originate mainly from adverse developments in the monetary economy, however, it is undeniable that various political-economic factors deepened the crises. The needed reforms to strengthen government fiscal space were not undertaken, including, among others, reforms in tax schemes, agricultural support, financial intermediation, and investment programs (Keyder, 2022). The delay increased the burden on the real side of the economy, putting a heavy strain on the long-time prioritized manufacturing sector in particular and the production economy in general.

As analyzed in more detail by Acemoglu and Ucer (2015), Turkiye experienced reasonably high-quality growth during the 2002-2006 period in between the 2001 and 2008 crises. With almost 6% per capita (per annum), the Turkish economy experienced its fastest per capita growth since the 1960s. Turkey's growth performance during this period was notable because it came with relatively high productivity growth. About half of the growth in per capita GDP during this period stemmed from total factor productivity (TFP) growth, which increased by about 3% per annum between 2002 and 2006. Much of this TFP growth was driven by the "structural" shift in employment from agriculture to manufacturing and service sectors. The share of manufacturing in GDP in constant prices increased from around 22% in 2001 to almost 24% in 2007. On the political account, a new government formed in 2002 started with the legacy of an enabling institutional-economic environment facilitated by the previous government, capitalized on the already-existing strong relations with the EU, and promised a more democratic and socially inclusive process of development. A new jump-start got the economy running again, catalyzing the establishment of growth-generating interactions in the production economy.

In 2008, adversities due to the global financial crisis arrested global economic growth. Predatory lending arising from the lack of competition in loan markets, the bursting of the US housing bubble, and excessive risk-taking in global financial institutions resulted in the bursting of the financial bubble. Finance, real estate, and construction sectors were the sources of troubles. It started in the financial sector but quickly spread over the real economy. In Turkiye, the 2008 growth rate was 1.1%, and in 2009, it was -4.7%. In May 2009, capacity utilization in the manufacturing sector declined to 62%.(Keyder, 2022)

The 2018-2022 crisis grew out of a combination of factors: high indebtedness, current account deficit, and appreciation of Turkish Lira. The period of cheap credit and public sector's support to the construction sector ended, halting the construction-based economic growth. During 2018-2020, GDP growth was 2.8%, 0.9% and 1.8% , respectively (Keyder, 2022). With the COVID-19 pandemic, the situation got worse with disruptions in the global value chains that adversely affected many firms, leading to increasing unemployment and decreasing consumption. To protect firms and consumers, the government provided direct financial support to businesses and income support to the most needy population groups. This has further increased the budget deficit, leading to expansion of money supply and hence high inflation.

Against this short background of the crises Turkiye has gone through, $MA2$'s network structure demonstrated in **Fig**. 3 helps us to better assess the existing structural inefficiencies (as of 2018) and develop potentially strategic partnerships across sectors to address them. Progress in the most subordinate sectors is more uncertain, and high dependency on other sectors can delay progress in the sector in question, even if the measures aimed directly to the sector are successful. Highly subordinate sectors (CST, EGW, TSC) have the least control over their own issues. Rather than surrendering to this fact, it should be a strong motivation to nurture relationships with the sectors (such as $MA2$) that hold the key to their productivity. Because of uncertainty, selecting a highly subordinate sector as a flagship sector would not be very strategic, even if the potential influence is strong. On the other hand, dominant sectors (such as $MA2$, $CO12$) receive very little support from other sectors or are weakly connected to the rest of the network. Their dependence on progress in other sectors is low. Not benefitting from network effects, they may need more targeted support.

Network perspective to policy design may guide the formation of cross-sector collaboration. In many networks, the distribution of links is unevenly distributed; they form communities of high concentrations of links with low concentrations of links in-between the communities. The identification of such communities within the upstream network of $MA2$ can help policy makers to develop comprehensive implementation strategies and organize implementation beyond just a ranking of individual sectors. Sectors forming a community can make a good coalition; they influence each other positively; and they have a shared interest in handling the links to other communities. The set of sectors in a community may be different from the present logic of how responsibility is divided (e.g., across ministries by policy area or topic). Exploring communities can thus present an effective way to build strategic partnerships.

In general, sectors in a production network operate in a complex environment where competitive and regulated producers engage in trade, distortions and imperfections amplify the scale of a disruption, and cascade of sectoral links heightens the systemic risk. $MA2$, a priority sector for Turkiye, and its upstream network have to survive in this challenging environment while pushing aggregate output towards the frontier. To accomplish this, policy reforms should take into account the defining characteristics of the key pathways of sectoral interactions. Suppose, for example, that $MA2$ sells its competitively-priced output to regulated monopolistic sector, EGW, which will lead to higher rents in EGW as its regulated input price will be higher than its competitively-priced input. EGW would gain from pro-competitive PMR in $MA2$. An opposite price incompatibility arises when FIN sells at the regulated price to $MA2$ operating in a competitive market. This will raise the competitive price of $MA2$'s output and hence lower the demand, which would subsequently lead to misallocation of resources in $MA2$'s production process. This mechanism is important when studying distortions in the upstream network (input suppliers) of $MA2$ that may cause $MA2$ to use the wrong suppliers, leading $MA2$ to use lower-productivity techniques or higher-cost inputs (Oberfield, 2018). The transmission mechanism reveals that, along a pathway of sectoral links,

$$\{\underbrace{competitive}_{MA2} \rightarrow \underbrace{regulated}_{EGW} \rightarrow \underbrace{competitive}_{MA2}\} \Longrightarrow MA2's\,profit \downarrow, \tag{12}$$

part of the profit of $MA2$ will be confiscated by the regulated industry, EGW. It further reveals:

$$\{\underbrace{regulated}_{FIN} \rightarrow \underbrace{competitive}_{MA2} \rightarrow \underbrace{regulated}_{EGW}\} \Longrightarrow EGW's\, profit \downarrow, \tag{13}$$

that high prices in FIN raise the cost of $MA2$'s production and depress the demand for its output, which would subsequently reduce $MA2$'s profits. In this case, regulated industry price would be rising due to price distortions in $MA2$ as input supplier of EGW. This time, misallocation of resources would take place in the regulated industry EGW. Such dynamic sectoral interactions along a pathway are harmful not only for the source but also for the sink sectors. It is also harmful for the entire upstream network of $MA2$ as such the accumulated price distortions would lead to a wider scale of resource misallocation and lower the productivity of the network. The effects of disruptions would amplify through backward linkages in the production network, increasing the systemic risk and the likelihood of the breakdown of the entire network. To minimize the welfare loss due to misallocation of resources in $MA2$ and improve network resilience to disruptions, pro-competitive PMR can target FIN and EGW to remove dominance and blockades to firms's entry to market, as well as to enforce competition policy and institutional changes supporting competitive neutrality. All these efforts should enhance $MA2'$s productivity and aggregate output growth.

The productivity of $MA2$ will be severely affected along:

$$\{\underbrace{regulated}_{TSC} \leftrightarrow \underbrace{regulated}_{FIN} \rightarrow \underbrace{competitive}_{MA2}\} \Longrightarrow MA2's\, profit \downarrow, \tag{14}$$

including two regulated sectors as upstream input suppliers of $MA2$. This suggests that pro-competitive PMR should target TSC and FIN, both of which are subject to severe market imperfections. Imperfect competition in the two heavily regulated upstream sectors would first amplify resource misallocation in their own activities. The accumulated distortions in these upstream sectors would then lead to significant misallocation of resources in $MA2$, resulting in much reduced profits. In order to unlock the productivity of $MA2$, PMR and institutional reforms should be undertaken to reduce price distortions in TSC and FIN.

The resilience of $MA2$'s production network relates to the level of systemic risk embodied in the cascade structure of the network. With the information obtained from the analysis of $MA2$'s network, layer-specific regulations and/or institutional structures can be designed to control the penetration of detrimental effects of a disruption in the production process of $MA2$. For example, in the case of disruptions in TSC, the regulated pathway, $\{EGW \rightarrow TSC \rightarrow FIN\}$, should be prioritized to address potential adversities that might arise due to bottlenecks in TSC (**Fig.** 6). However, the main issue is much wider than the disruptions in TSC. It is the concentration of regulated sectors or markets along that pathway, laying the ground for the conditions that are cohesive to cartel creation. In this case, systemic risk would elevate to a level that can result in the breakdown of the production network of $MA2$. In practice, the resilience of the network is also about whether or not the involved sectors along the pathway have sufficient productive capacities.[14] All of the regulated sectors requires advanced

[14]Productive capacities are defined as the productive resources, entrepreneurial capabilities and production linkages that together determine a country's ability to produce goods and services that will help it grow and develop, see <https://unctad.org/topic/least-developed-countries/productive-capacities-index>.

technology and skilled labor, and meeting the demand for the skilled labor and new technology takes time and requires resources. At the network level, the resilience can be strengthened not only by PMR and institutional reforms but also by investing in productive capacity development to meet the demand for new capacities in FIN and TSC.

Critical backward linkages of a mix of regulated and competitive sectors, $\{EGW, TSC, FIN\}$ being regulated and $\{MA2, AGF, CST\}$ being competitive, have been characterized in the previous sections as:

$$\{EGW \to TSC \to FIN\},\ \{MA2 \to AGF, MA2 \to CST\},\ \{FIN \to MA2, MA2 \to EGW\}.$$

The impact on $MA2$ of pro-competitive PMR along these pathways should be reassessed. Take, for example. the first pathway $\{EGW \to TSC \to FIN\}$. Energy market liberalization relating to EGW, such as privatization, competition, and regulation in both gas and electricity, is expected to lead to lower prices, but industrial consumers are likely to gain disproportionately. Opening transport markets to competition in TSC reduces the prices of transportation services, a key input for producers and traders in general. Entry liberalization and deregulation of TSC and EGW are likely to create a particularly substantial positive impact on growth because their general purpose services are widely used in the rest of the economy. Competition among service providers, such as firms in FIN, can help to increase the effectiveness of cash transfers, the functioning of voucher systems for agriculture subsidies, and reduce information asymmetry on quality of services. Reforms and regulations to promote competition in FIN would also reduce hidden costs of transactions and rules that increase discriminatory treatment, as well as improve SMEs' access to financial instruments and encourage firms in FIN to innovate financial intermediation instruments. In Turkiye, the direct linkage, $FIN \to EST$, is particularly weak (see **Fig**. 4(a)), representing an area for pro-competitive PMR interventions. The availability and pricing of credit is key to support SMEs and low-income individuals to start and develop new SMEs. On the other hand, removing price floors and other restrictions on legal services under EST is positively associated with greater productivity in professional services.

Competition among processors would benefit farmers ($MA2 \to AGF$) by increasing the farm gate price of the crop and therefore improve their livelihood. For instance, in the case where the firm with the largest market shares splits, an average income of producing households can increase. Although it could be argued that lower prices for producers could be passed on to lower prices for end consumers, the presence of buyer power coupled with high market power in selling to customers limits this pass-through to consumers, as implied by Equ. 12, it is instead monopsony intermediaries who would benefit from lower prices. Enabling widespread use of generic drugs through elimination of anti-substitution laws (i.e., pro-competitive PMR in pharmaceutical industry under $MA2$) would substantially increase consumers' savings through the linkage ($MA2 \to HLT$) (see **Fig**. 4(b)).

8 Concluding remarks

This paper developed and demonstrated a computational methodology for gaining a systemic insight into policy design from a production network perspective. It builds on graph-theoretic concepts and a typology of sectoral interaction patterns. It is systemic as it analyzes potential network-wide effects of a policy intervention. As a policy diagnostic tool, the key strength of the methodology is to support policy making, with a high degree of transparency and opportunity for engagement compared to modeling approaches. It induces policy decision makers to look outside their turf and think systematically about how they influence, and are influenced, by others. It also brings scientific knowledge into the evidence-based policy-making process.

Across many economies, $MA2$ has been a priority sector expected to catalyze the productivity in the rest of the economy. Turkiye has also prioritized $MA2$ hoping to promote the productivity. However, except for a limited period, $MA2$ has not met expectations due to various domestic and global adversities. This paper proposes a methodology to identify the gaps, bottlenecks, and weaknesses in a production network. Using the 2018 input-output data of Turkiye, the paper uncovered some of the challenges facing the upstream network of $MA2$ and presented ways to design policy reforms to address them.

The key findings are three-fold. First, in network-based policy design, it is highly critical to consider the interdependencies of regulated and seemingly competitive sectors. Efficiencies gained in liberalized markets via pro-competitive PMR can easily be wasted before final consumers benefit from them as regulated industries may exercise their market power to confiscate part of the efficiency gain created in competitive markets. Improved competition in a single market may not generate the desired outcome even if competition policies perfectly support that market because benefits from competition may not spread over the rest of the network due to disruptions in the cascade of interdependencies concerned. Second, a network-based policy design should start with the identification of the "*dominant*" source and the "*subordinate*" sink sector(s), and those in between. The $source - sink$ structure of Turkiye's manufacturing network illustrates that the manufacturing sector is the most dominant, whereas telecommunications and transport, energy and construction sectors are the potential sinks where large chunk of input flow ends up. Agriculture, finance and oil extraction-mining seem to be interactive sectors. Third, the cascade of three layers of links are identified, and the upstream network of the manufacturing sector is found to have a mediocre level of resilience against the complete disruption of the intermediate layer of the network.

The methodology proposed is by no means final, but opens up a new avenue for computational analysis of a production network with a view to designing policy reforms to promote an efficient upstream network of a targeted sector. However, the lack of a benchmark production network structure against which the network structure of the targeted sector can be contrasted makes the current analysis more of an exploration of existing sectoral interdependencies and their policy implications.

Future research is desirable in two broad areas. On the theoretical account, the complexities of interacting market structures (including competitive, monopolist, oligopolist), the speed and size of price transmission between interacting markets, the measurement of resource misallocation in downstream sectors due to distortions in the upstream sectors, and welfare effects comprise the challenges ahead. On the empirical account, there are more challenges concerning both data refinement and empirical market studies. First of all, using aggregate input-output data creates a completely connected production network as non-existent firm-level links are essentially ignored by the aggregation at the sectoral level. Refined firm-level data would be more appropriate to capture the effects at the micro level, which can deviate from the aggregate effects. Big data creation efforts are increasing, and our methodology can be applied to micro-level data to capture critical micro-level interdependencies. In the absence of firm-level data, a second best strategy would be to quantify how much of an input used by a sector is essential for its main production activity. As we observe at the aggregate level, ENT supplies not-so-small input to $MA1$'s production activity. This can be attributed to the catering input purchased by $MA1$, which is obviously not an essential production input used in $MA1$. By disentangling of essential input from non-essential input, the aggregate input-output production network can be adjusted to base the network analysis only on the use of essential inputs. With such adjustment, some links across sectors may disappear even at the aggregate level, giving rise a more realistic representation of input-output data. A similar adjustment can be pursued by distinguishing between easily substitutable inputs and crucial, hard-to-substitute inputs where firms are locked-in and switching costs are large. Alternative (or refined) network data can be then analyzed to paint a more realistic picture of interdependencies in the network concerned.

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