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

Drawing on input-output data, 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 ($MA2$). Market and competition policy reforms are discussed from a network perspective in such a way as to enhance the productivity of the manufacturing sector.

Together, these algorithms automate the analysis of $MA2$ from a production network perspective. Applications may focus on a single sector or multiple sectors. The automated sector analysis starts with targeting $MA2$ by extracting pathways of critical backward binary links, all of which represent the upstream network of $MA2$. The analysis continues with the identification of cascade of layers of critical backward binary links in $MA2$'s upstream network. Understanding the cascading structure of sectors in its 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 from pathways of individual sectors to the interaction of the layers (or groups) of sectors. The former analysis characterizes the role of the 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 upstream network is measured using edge betweenness centralities of the edges in between the communities. (The evolution of these communities over the period 2005-2018 is explored in the following sections.) 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 the network is assumed to approximate the degree of the connectedness of the network.

The methodology developed provides critical information on the key network characteristics of $MA2$, and hence, can be regarded in general as an ex-ante policy design tool for assessing economic growth policy alternatives. From a network perspective, policy design is a multi-sectorial challenge, and is key for enhancing the quality and effectiveness of policies and strategies, and for increasing return on public and private investments. Many developing countries adopt policies to selectively target economic sectors to facilitate economic growth. Targeting a specific sector is desirable especially for a government with limited fiscal space as it needs to intervene and support its sectoral production. The methodology introduced is applied to systematically analyze the production environment of $MA2$, uncovering its network properties that can be exploited in the design of economic growth policy interventions. Industrial policy design, for example, can be informed of the characteristics of the backward and forward linkages of $MA2$ and their relations with the rest of the production network.

A growing number of studies in the literature models 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 (inefficiencies) and then the process works backward resulting in additional distortions in the upstream sectors (Acemoglu, Carvalho, Ozdaglar, & Tahbaz-Salehi, 2012; Carvalho, 2008, 2014). Interactions between sources of distortions and sinks where they land represent the mechanisms that need better understanding. Those studies fall short of developing methods to identify the critical pathways of interactions among industries, although they highlight the key role that highly central industries play in the creation of shocks at the macro level. In the present paper, we develop an automated computational method to uncover hidden patterns of industry or sector interactions in relation to a targeted (prioritized or central) sector, further dig into those patterns to characterize cascades of the interactions, and propose a measure of network resilience based on the centrality scores of linkages along the cascade. The logical extension of our paper is that, once identified and characterized, the pathways and cascade can be managed by policy reforms targeting specific pathways or cascade of links, as well as network constructs such as communities. More specifically, given the production network of the targeted sector or industry, the communities and their interactions represent units of investigation for policy reforms aimed to avoid the cascading effects of distortions on aggregate output. Such a thinking process assumes that the dynamics of a production network are endogenous to institutional arrangements and type and effectiveness of the policies implemented. The framework explained in what follows is a mere conceptualization of the idea that institutions and policies have the power to influence the dynamics of the production 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 acquisition of sector- and network-specific productive capacities, as well as the implementation of right policies. **Table** 1 presents a logical framework (mathematically expressed in Equ. 1) to motivate the relation between network constructs (such as upstream/downstream pathways, cascades of layers, community structure, etc.) and their potential productivity effects on the targeted sector i as a response to network-based policy reforms. Examples of regulatory arrangements 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 sector i. To describe it formally, the production of sector i 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 (exogenous to sector i) evolving network construct (such as a pathway of sector links, or a cascade of links, or a community where sector i is a member of) implied by targeting sector i; $N_i = n(P_i)$ assumes that market institutions and competition policy reforms (P_i), which are related to binary links in the upstream network of sector i, can influence the dynamics of the network construct; C, general purpose productive capacity that augments 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 the use of its own output as input). Y_{-i} denotes an exogenous vector of outputs of the rest of the economy, influencing the output of sector i through pathways of sector linkages. Note that technological change is embodied in productive capacities.

Unfortunately, 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 focuses on the implications of market reforms and competition law (or anti-trust law) and policy (henceforth, *policy reforms*) for the efficiency of sectoral productions. We conjecture that the efficiency depends not only the implementation of good policies promoting competition but also the properties of the production network. Competition law and policy aims to create an enabling environment - a level playing field - that facilitates the meeting of (topologically) distant, and possibly disadvantaged, producers, and in doing so, increases their production possibilities. In other words, 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. (Network connectedness is measured as the ratio of the number of actual binary links to total number of potential links in the network.) The higher the degree of network connectedness, the

Table 1: A framework for linking network structure and policy reforms

Network construct $n(.)$	Markets and competition policy (P)	Productivity effects	Regulatory barriers
Identify critical upstream and downstream networks of a targeted sector to enhance its productivity;	– **To improve network structure** through free entry of firms; effective mechanisms & increased capacity for input-output flow; promoting new binary links; strengthening weak links along the pathways between an intervention and 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), business (EST), construction (CST) and transport-ICT (TSC), etc.	**Sector specific anti-competitive regulations** and **lack or ineffective enforcement of anti-trust law** would reduce total factor productivity (TFP) of sectors along the upstream pathways and supply of output along the downstream pathways. Examples of related reforms include entry liberalization and deregulation of the TSC, the removal of price control on legal services in professional services (EST), and pro-competition regulatory reforms to increase labor productivity in retail sector (WHS).
Uncover the community structure 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 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, **competition law are be complemented by ex-ante sector regulations to** avoid failure in the input-output flow; and prevent potentially **anti-competitive links to exercise dominance**;

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. This line of argument suggests that connectedness should promote competition. Since competition calls for markets to be connected, network-based reforms and policies that this paper advocates should facilitate the connectedness of the production network.

Competition policy affects the dynamics of production network through removing anti-competitive regulations - enabling contestability, firm entry, and rivalry - 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, 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). More 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 professional services and energy provision (EST, EGW) increases value added, productivity, and export growth in downstream service intensive industries.

Most empirical research focused on the competition-productivity link within a sector (or market). Yet, expected rents from innovation or technology adoption and the corresponding within-sector 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 sectors (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 sectors, 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 sectors as well, further reducing pressures to improve efficiency in these sectors. 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, takes a broader view from a network perspective that the structure of production network 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 promoting productivity. The network structure can change over time through PMR and regulations to the extent that they affect three processes (which are used in Atalay, Hortacsu, Roberts, and Syverson (2011)'s model of network formation). 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 and regulation to influence the three processes described. The current study does not predict such probabilities but give an assessment of PMR with respect to their potential impact on the performance of sectors in the production network.

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 then illustrates how to study the implications of these properties for aggregate production, elaborates on the design of network-based policies that improve the existing network architect for increasing productivity and reducing the risk of disruptions (Schweitzer et al., 2009). Our conceptual framework given in Equ. 1 is a mere summary of what we aim to achieve in this paper.

Recent theoretical 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 production units (Acemoglu et al., 2012; Acemoglu, Ozdaglar, & Tahbaz-Salehi, 2010; Bigio & Laâo, 2020; Carvalho, 2008, 2014; Jovanovic, 1987). The promise of production networks is to view aggregate shock as the endogenous outcome of micro shocks propagating across input linkages. Production 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 dynamic interaction between endogenous credit limits and asset prices as a powerful transmission mechanism through which cascading liquidity shocks spill over to other sectors (Kiyotaki & Moore, 1997). (This is important for the stable link between FIN and $MA2$ along which the effects of a distortionary interaction between sub-optimal credit limits and inefficient asset prices will lead to misallocation of resources in $MA2$.) 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 methodology is one-little contribution to the stock of computational data analysis methods, with an application to economic policy design motivated by the production network dynamics. Graph-theoretic principles and 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 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). 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.

Our conceptual framework specified by Equ. 1 conjectures that pro-competitive PMR and regulations can reshape the production network by minimizing 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. Such regulations also aim to remove regulatory barriers to competition, including, but not limited to, minimum capital requirements, increased cost of doing business, protection of incumbents, excessive restrictions on the expansion of and potential discrimination against more-efficient firm, and burdensome requirements to obtain operating permits. 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 (Gal & Hijzen, 2016). 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 (Barone & Cingano, 2011). 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 reform replacing heterogeneous tax rates by a single VAT rate applicable to all sectors 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 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 (such as $MA2$). 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 and regulations aimed to reform a priority 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 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

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

		users						
		A	**B**	**C**	**D**	**E**	Y	X_D
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		

is an intermediate consumption sub-matrix ($\mathbf{X}$) with five sectors, {**A**, **B**, **C**, **D**, **E**}, as users and suppliers:

The second is a column-vector of final consumption ($\mathbf{Y}$); the third, a column-vector of total demand ($\mathbf{X}_D$); the fourth, a row-vector of value-added ($\mathbf{VA}$); and the fifth, a row-vector of total supply ($\mathbf{X}_S$). Sub-matrix $\mathbf{X}$ and total output supply $\mathbf{X}_S$ are used to calculate the backward technical coefficients matrix, $A_b = [\mathbf{X_{ij}}/\mathbf{X_S^j}]$ (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)).[1] 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 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

[1]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

of output produced by supplier sector **A**); that is, to identify the entire chain of **downstream** sectors of supplier **A**.[2]

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.[3]

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 $B \to A$), and another is from **D** to **A** with a coefficient of 0.41 (denoted by $D \to A$).[4]

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

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

[4]The technical terms used throughout the report 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 target sector. For example, given

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

Then, moving to the 2^{nd} column associated with user sector **B**, we observe that **A** also provides input to **B** (denoted by $A \to B$) with a strength level of 0.34, and that **D** provides input to **B** (denoted by $D \to B$) 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 $B \to D$ and $C \to D$ 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 $B \to C$ and 0.33 for the 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

a 2-edge pathway of three sectors, $\{MA1 \to CST \to EST\}$, there are two binary links, $\{MA1 \to CST, CST \to EST\}$, each one of which shows a link ($\to$) established between two sectors only. Along this 2-edge pathway, $MA1$ represents a source, and EST a target. These definitions distinguish a pathway from a binary link. These definitions imply that the minimum length of a pathway is 2 edges. A directed arrow ($\to$) indicates the direction of flow of either money or material or influence. In the context of an upstream (downstream) pathway, a binary link $MA1 \to CST$ 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, $\{MA1 \to CST$, $CST \to EST$, $EST \to WHS\}$, and a *3-edge* pathway, $\{MA1 \to CST \to EST \to WHS\}$.

targeted:

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

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:

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

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:

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

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[5] denoted by $C_{g_i^u}$. Identify the set of between-community edges in $C_{g_i^u}$ (denoted by $BCE(C_{g_i^u})$);

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:

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

[5] 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.

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.[6] The OECD IO matrices with 36 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). The aggregation allows for a comparative analysis of the IO systems across countries. The first column in **Table** 6 shows the individual sectors in OECD IO database; the second column shows the aggregated sectors used in this study. 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 activities in the manufacturing sub-sectors. $MA2$ is an important sector as it represents the agglomeration of several inter-connected industrial sectors and that it is a high-priority sector in Turkiye. Bilateral linkages between the manufacturing and the service sectors, including wholesale, retail, finance, real estate, hotels-tourism, etc. are important, and in this paper, we elaborate on the linkages between the manufacturing and the service sectors.

5.2 Qualitative network 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

[6] 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.

Table 6: Sector aggregation

Sectors in the OECD Input-Output matrices	**Sector aggregation in this study**
01T03: Agriculture/forestry/fishing	AGF: Agriculture, forestry and fishing
05T06: Mining/extraction of energy products	CO12: Crude oil/mining
07T08: Mining/quarrying of non-energy products 09: Mining support service activities	MA1: Manufacturing/petroleum refining
10T12: Food products/beverages/tobacco 13T15: Textiles/wearing apparel/leather/others 16: Wood/products of wood/cork (except furniture) 17T18: Paper products and printing 19: Coke and refined petroleum products 20T21: Chemicals and pharmaceutical products 22: Rubber and plastics products 23: Other non-metallic mineral products 24: Manufacture of basic metals 25: Fabricated metal products except machines 26: Computer, electronic and optical products 27: Electrical equipment 28: Machinery and equipment n.e.c. 29: Motor vehicles, trailers and semi-trailers 30: Other transport equipment 31T33: Other manufac./repair-installation/equipment	MA2: Manufacturing-other
35T39: Electricity/gas/water supply/waste etc	EGW: Electricity/gas/water supply
41T43: Construction	CST: Construction
45T47: Wholesale/retail trade; motor repairs	WHS: Wholesale-retail trade
55T56: Accommodation and food services	HOT: Hotels/restaurants
58T60: Publishing/audiovisual/broadcasting activities 49T53: Transportation and storage 61: Telecommunications 62T63: IT and other information services	TSC: Transport/storage/communication
64T66: Financial and insurance activities	FIN: Financial intermediation
69T82: Other business sector services	EST: Real estate/business activities
84: Public adm/defense/compulsory social security	ADM: Public adm./defense/social sec.
85: Education	EDU: Education
86T88: Human health and social work	HLT: Health/social work
90T96: Arts/entertainment/recreation/other services 97T98: Private households with employed persons	ART: Art/entertainment

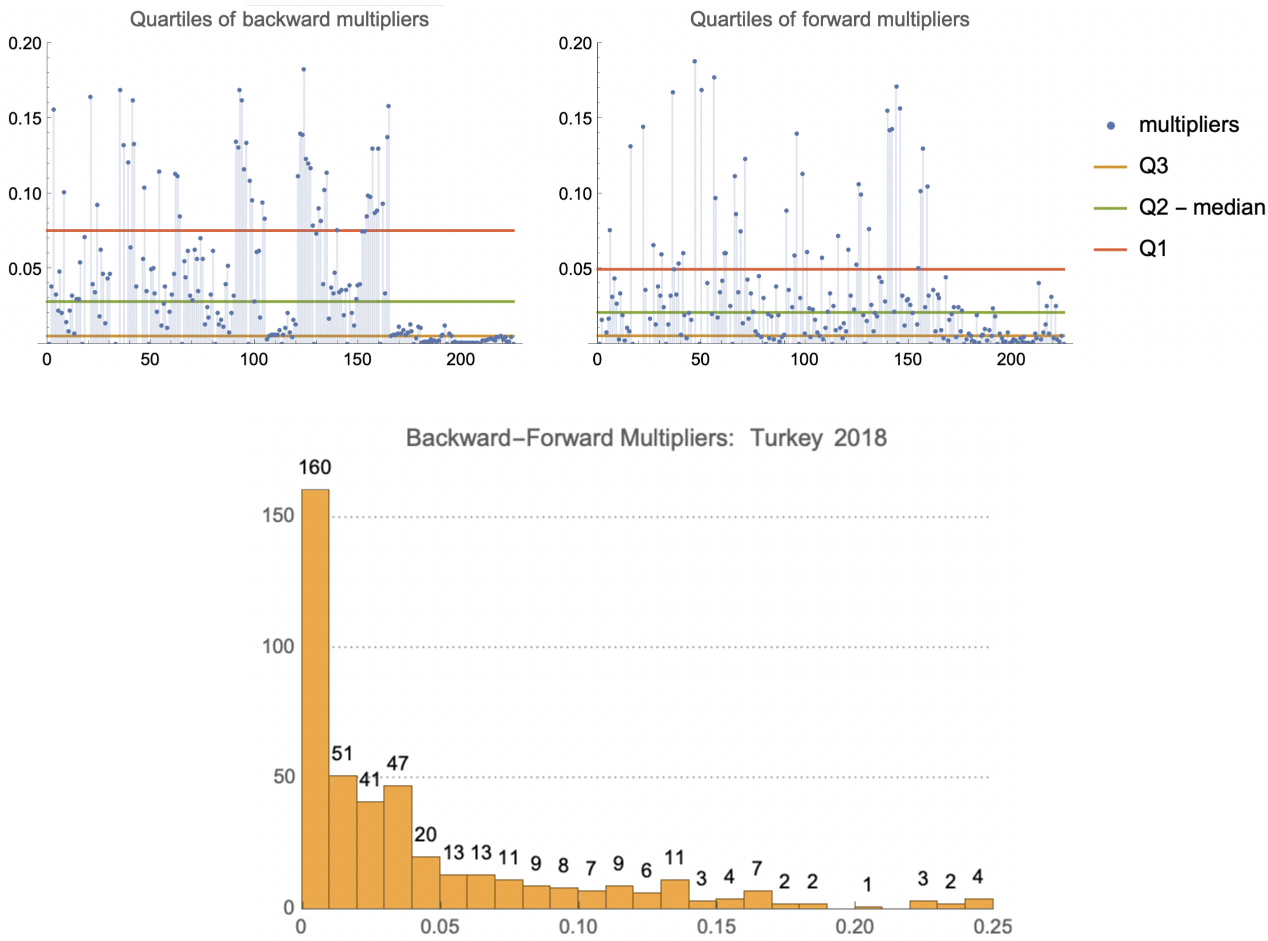


Figure 1: Quartile distribution and histogram of multipliers

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, the current study focuses on the multiplier interval $[Q1 - Q3]$ (see **Fig.** 1). Those linkages with multipliers that fall in that interval are selected, and then, a threshold significance level is applied to further select from each sector those multipliers that account for at least 20 percent of their multiplier sum. This two-stage selection procedure accounts for differences in the supply-use size of each sector. The quartile distribution of the multipliers selected account for about 80 percent of the interactions in the production network (see the histogram in **Fig.** 1).

Several properties are noteworthy. The first property is critical for modeling the 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 production 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 characterizing the 2018 production network by applying graph-theoretic concepts should provide critical information for evidence-based policy design.

The second property gives information about a sector's linkage preference. Sectoral eigenvector centrality[7] scores (see **Table** 7) suggest that linkages originating from high-scoring sectors contribute more to the score of a sector than linkages from low-scoring sectors. A high (low) eigenvector centrality score means that a sector is connected to many sectors with high 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. 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 also 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)" (out-degree links) and "effect (e)" (in-degree links), representing the sum of the multipliers of links from i and the sum of the multipliers of links into i, respectively. The "cause" and "effect" of i serve as one measure of the size of IO flow in the network, and the centrality, on the other hand, serves as an indication of where that flow in the network is most likely to end up. The centrality measure indicates the limiting probability distribution of the flow across sectors.

Nine different cases are shown in **Table** 8. There is a striking difference between the list of sectors with the largest IO flow and the list of most central sectors, suggesting 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. The most important case (case 1: large-high) is that a sector is dominant (with large flow size) and highly central (with high flow absorption), suggesting 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 such sectors is expected to lead to the largest reduction in aggregate output (Acemoglu et al., 2010). $MA2$ is the most dominant sector (case 1) that is expected to significantly drive aggregate output, followed by CST and EGW (case 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

[7]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 - positive assortativity: tendency for sectors to connect to other sectors with similar properties - eigenvector centralization will be high.

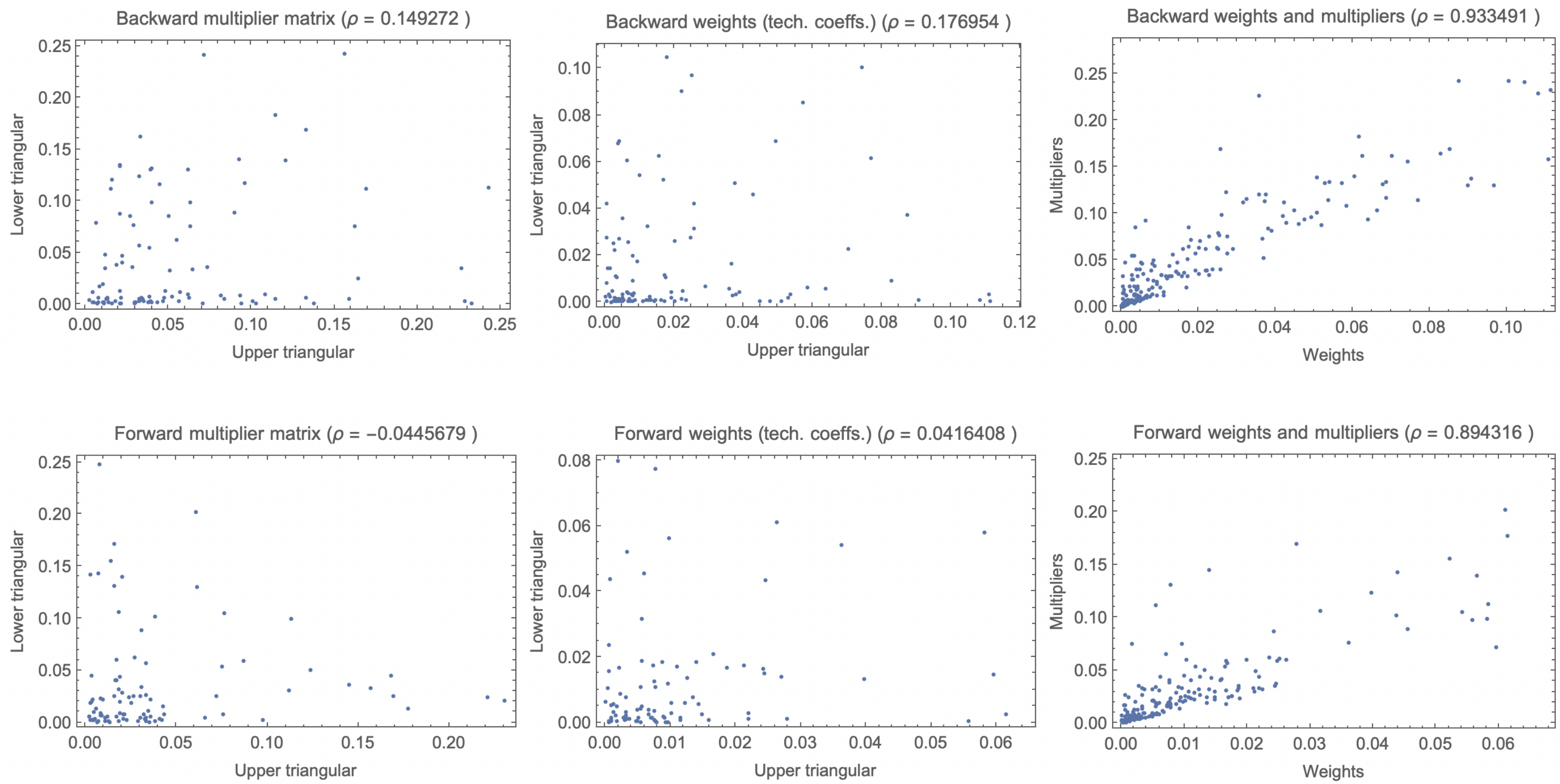


Figure 2: Properties of Turkiye's 2018 production network

Table 7: Sectoral eigenvector centrality scores and (c, e) - coordinates of g^U_{MA2}

Communities	Sectors	(cause, effect)	Dominance	Centrality
C_1	$MA2$	(0.16, 0.11)	large	0.18 - high
	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
C_3	AGF	(0.12, 0.11)	medium	0.12 - moderate
	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

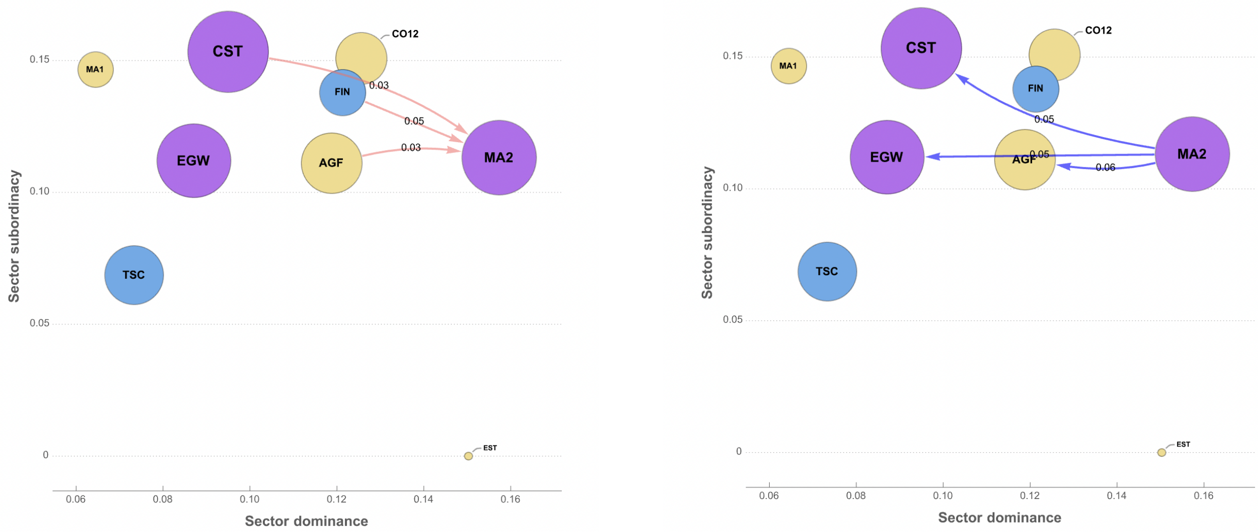
Table 8: The extent of impact on aggregate output through $MA2$'s upstream network: g^U_{MA2}

		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 ($MA1$)

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.

Fig. 3 provides additional information critical for the design of policy reforms. 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. $MA2$, the most dominant sector, is fed by inputs from general purpose service sectors $\{FIN, AGF, CST\}$, while providing inputs to $\{AGF, CST\}$ and a regulated general purpose service sector, EGW. Lastly, 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, $C_2 = \{FIN, TSC\}$.

Sectoral indicators for pro-competitive PMR are available for four network sectors, including energy (EWG), transport-ICT (TSC), and the retail (WHS) and professional services (EST) (Alemani, Klein, Koske, Vitale, & Wanner, 2016; Koske, Wanner, Bitetti, & Barbiero, 2015). Together, these sectors 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. Regulations in EGW, TSC, WHS, and EST are mainly about the organization of network access to potential service providers. Regulation in WHS typically takes the form of entry barriers, specific restrictions for large firms and the flexibility of shops in terms of opening hours and prices. Regulation 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 PMR tend to materialize only over time, but yield somewhat conflicting insights with respect to the possible presence of short-term costs (Bassanini,



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

2015; Bouis et al., 2016). Furthermore, manufacturing sector ($MA2$) accounts for 0.6 percent of GDP and invests 11 cents per USD cost of labor. Similarly, financial sector (FIN) accounts for 3 percent of GDP and invests 5 cents per USD cost of labor.

6 An application

6.1 Algorithm I: Key findings and policy implications

Algorithm I generates four hierarchically layered graphs. **Fig.** 4(a) exhibits the network of input suppliers of targeted sector $MA2$ (henceforth, referred to as the upstream network of $MA2$); (b) the network of users of $MA2$'s output (henceforth, referred to as the downstream network of $MA2$); (c) the combined network of upstream and downstream linkages of $MA2$, identifying the complete network of $MA2$; and lastly, (d) the structural (one-edge links of $MA2$) and ancillary ($MA2$'s multiple-edge links) linkages in the combined network of $MA2$ shown in (c). The linkage patterns observed from the four graphs provides critical information for evidence-based policy design to improve $MA2$'s contribution to aggregate output growth.

The first pattern (see **Fig.** 4(a)) is that $MA2$ has two-way links to $CST$and AGF, followed by its single-edge link to FIN and EGW. More importantly, $MA2$'s operation is characterized by two cycle-pathways:

$$\{MA2 \rightarrow AGF \rightarrow CST \rightarrow MA2\} \; and \; \{MA2 \rightarrow EGW \rightarrow CST \rightarrow MA2\},$$

implying that any input from FIN into $MA2$'s production process would necessarily go through these cycle-pathways. AGF and EGW along these pathways act as intermediary sectors that have the power to control the flow of inputs into CST, which in turn create 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 supplies input to $MA2$ through:

$$\{MA1 \rightarrow FIN \rightarrow MA2\} \ and \ \{TSC \rightarrow FIN \rightarrow MA2\},$$

implying that FIN as an upstream sector to $MA2$ has power to influence $MA2$'s production.

Together, the first and second input flow patterns suggest that policy reforms should consider the following pathways of sectoral linkages:

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

to design effective policy reforms to promote $MA2$'s production not only by addressing $MA2$'s weak linkages but also by taking into account the weaknesses of the network concerned:

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

Network-based policy reforms targeting $MA2$'s productivity need to consider mechanisms causing a deviation from competitive prices "*distortions*" 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 (Atalay, 2017). Informed policy design based on the analysis of the upstream network of $MA2$ 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 flow "*absorbing*" sectors, $\{CST, MA2, EGW, AGF\}$, suggests that the largest flow absorbers $\{CST, EGW\}$ do not necessarily drive economic activities in 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. Policies should consider the peculiarities of EGW and $CO12$, both of which are regulated general service sectors. Pro-competitive PMR in these regulated industries are found to increase the productivity in the rest of the network as their general purpose outputs tend to be 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, $\{FIN \rightarrow MA2, EGW \rightarrow TSC\}$, to create a virtuous cycle between community 1 and 3.

So far, all was about input supply and use. 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 $MA2$:

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

Equ. 11 reveals that 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, and hence, the aggregate output. 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.[8] Knowing the output elasticities of the shock is a valuable information for policy design. The relation between the shock and output multipliers of the sectors concerned can be also investigated to identify those sectors experiencing little change in their output multipliers as a response to the shock. A low (high) shock elasticity of output multipliers in a sector would imply that the shock is not disrupting (disturbing) much the production process in that sector. This can be partially attributed to the resilience (vulnerability) of the sector hit with the shock.

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 or minimize the cost of the accumulated distortions in the upstream sectors. Two viable strategies exist. The first, mildly protective strategy is to regulate the links of input-suppliers of $MA2$, $\{AGF \rightarrow MA2, CST \rightarrow MA2, FIN \rightarrow MA2\}$, and $MA2$'s output supplies on the demand side, $\{MA2 \rightarrow HLT, MA2 \rightarrow ENT, MA2 \rightarrow HOT\}$. 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,

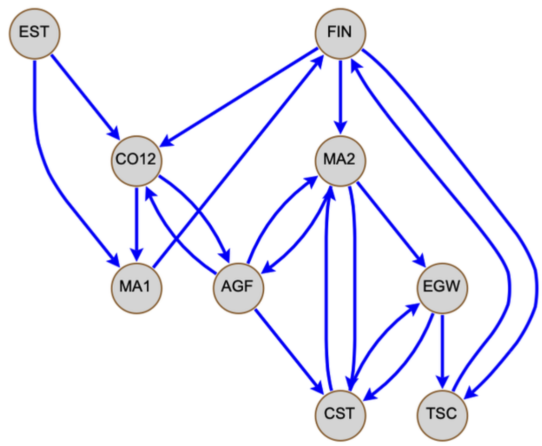
[8]Scenario analyses can be carried out using the RAS matrix balancing method, which is more practical compared to the cross-entropy method. See Holý and Šafr (2023) for the equivalence of the RAS method with the cross-entropy method for matrix balancing.

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)).

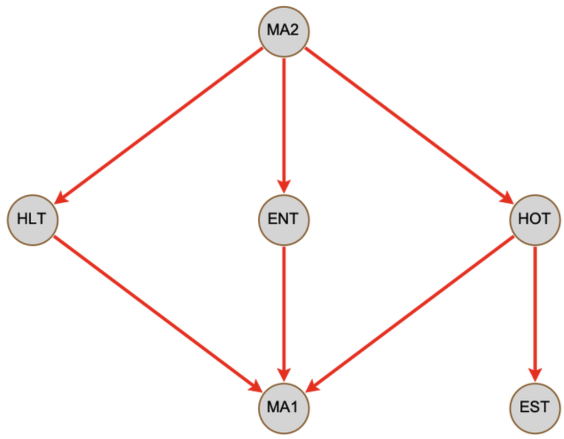
The longer the pathway, the higher the upstream sector's distortion centrality. Topologically, EST is an exogenous sector in the upstream network of $MA2$ as it has no in-coming links. Thus, it can only transmit its own distortions to two sectors $\{CO12, MA1\}$, the users of $EST's$ output. Conversely, 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 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),[9] we produce **Fig.** 4(a) representing the "*upstream*" network of $MA2$. We further refine that network to isolate the downward links from upward links in order to create purely hierarchical structures as tools for the analysis of ex-ante pro-competitive PMR design (see **Fig**. 5(a, b)). F**ig**. 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 hierarchical relation in the network: $\{MA1 \to FIN, TSC \to FIN, AGF \to MA2, CST \to MA2, AGF \to CO12, CST \to EGW\}$ (see **Fig.** 5(b)). The two isolated networks can be analyzed as an causal influence network to explore complex input-output linkages mapping functional dependencies across sectors (Ay & Polani, 2008). Adopting the pure hierarchical structure 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 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

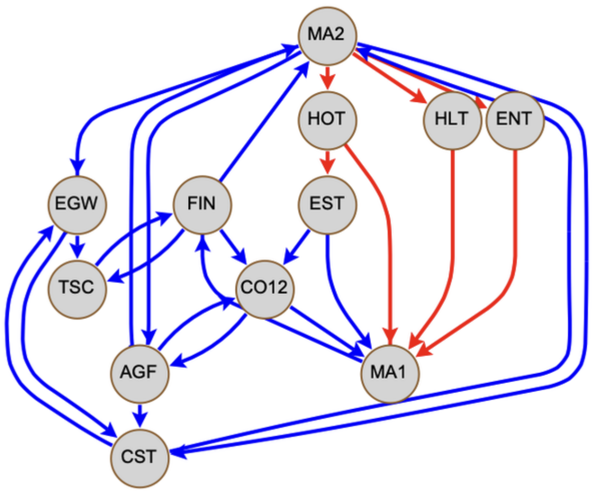
[9] A layered graph drawing algorithm - also known as hierarchical layout or Sugiyama algorithm - places the vertices of a graph into horizontal layers (virtual horizontal lines) such that the links, modeling the relationships, point in a uniform direction. This algorithm is based on an acyclic graph 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.



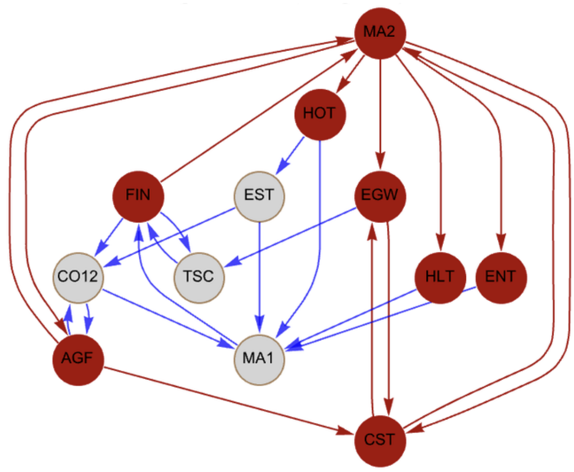
(a) Upstream network of $MA2$, g^{U}_{MA2}



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



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



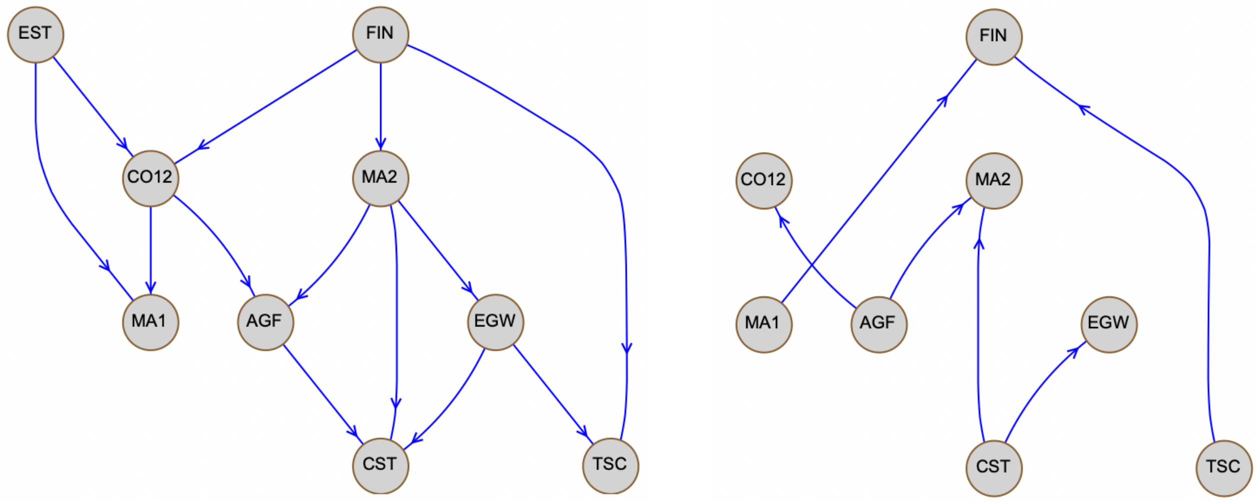
(d) Structural (red) and ancillary (blue) links in (c)

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

$MA2$ 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 is used to elaborate on the effects on $MA2$'s production of a shock to one of the critical input suppliers of $MA2$. The resulting effect is traced forward from the sector hit with the shock towards $MA2$ and from $MA2$ to the rest of the production network. The pathway through which the shock penetrates into downstream sectors would provide us with more information



(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}

that can be used to design layer-specific pro-competitive PMR and policy interventions.

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 aimed 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 (shortest distance) 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 ICT infrastructure included 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

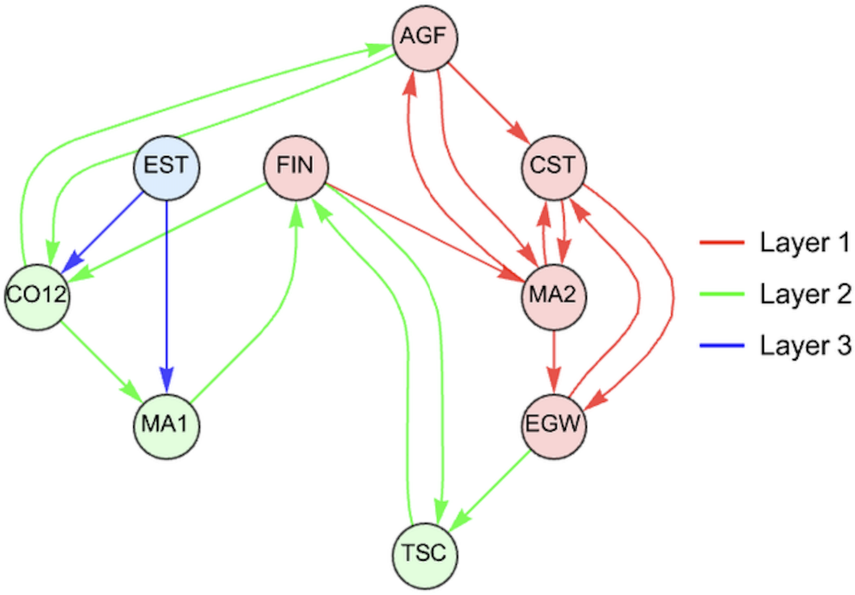


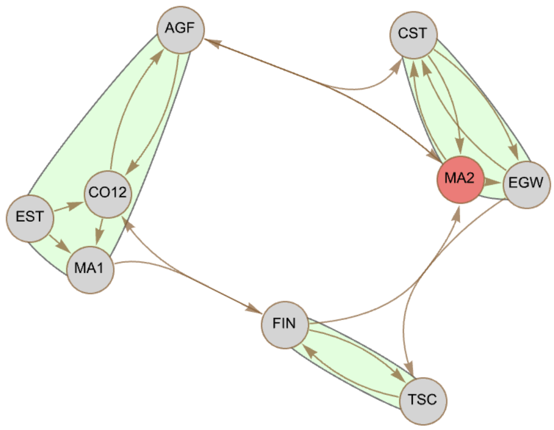
Figure 6: Turkiye 2018: Cascade of layers in the upstream network g^U_{MA2}

$CO12$ 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. In step 1, the community structure of $MA2$'s upstream network (see **Fig**. 4(a)) is derived; in step 2, all the edges in between communities are extracted; in step 3, edge betweenness centrality score of each edge in the upstream network is computed; and in step 4, the network resilience indicator given in Equ. 5 is computed using edge betweenness centrality (EBC) scores of the weighted "*upstream*" network. The idea is simple: the more connected a network is, the more resilient it is. Namely, if the communities are strongly 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 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



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

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

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,

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

are severely disrupted, in which case the measure of network resilience with respect to Layer 2 is calculated as $R_1(g^U_{MA2}, Layer\,2) = 0.27$. To improve the resilience of the network, policy interventions should selectively target those links which appear more often along the shortest paths, including

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

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

6.4 Evolution of the production network

By allowing a time-dependent resolution of the hierarchical networks (see **Fig.** 8) of $MA2$, we are able to move beyond the 2018 single-snapshot network. This allows us to identify the evolutionary path of the networks during the period 2005-2018. The time-series nature of the input-output data for Turkiye lets us track changes in $MA2$'s linkages over the period 2005-2018. Concentrating on the multipliers in between Q1 and Q3 and then selecting those binary links accounting for more than 20% of the variation in $MA2$, followed by other significant links in the rest of $MA2$'s network, we can identify upstream and downstream sectors in $MA2$'s network. **Fig.** 8 shows the time-series plots of the upstream networks of $MA2$ over 2005-2018. (These networks have been generated by a single-shot application of **Algorithm I** for each year.)

Few observations are noteworthy to assess the changes in the structure of $MA2$'s network. First, FIN has always been connected to $MA2$ during the entire period 2005-2018, followed by AGF's linkages to $MA2$ for the periods (2007-2011, 2016-2018), CST's linkages for the periods (2007-2011, 2016-2018), and EGW's for the periods (2009, 2015-2018). Second, during the period 2016-2018, a more pronounced structure arises: (1) $MA2$ is always linked to $\{FIN, AGF, CST, EGW\}$, (2) the set of sectors in each year remains constant at 9, including $MA2$, (3) in two of three networks, FIN and EST act as upstream sectors relative to $MA2$, which always remains to be a midstream relative to its own network. Third, in all these hierarchical networks, $MA2$ occupies a midstream position along the existing pathways. This suggests that policy reforms aimed to improve the productivity of $MA2$ need to primarily consider the potential expected impact of its immediate neighbors. Fourth, except 2005, the number of sectors in each network changes between 6-10, with average 8 sectors over the period concerned. The number of sectors remained stable especially during the last three years, 2016-2018, with 8 sectors surrounding $MA2$.

Likewise, the time evolution of community structures of the upstream networks of $MA2$ is explored to identify major changes in $MA2$'s network during the period 2005-2018. The identification has been carried out based on snapshots of the network data for each year as an independent community detection problem (see Granell et al. (2015) for an algorithmic implementation). Several observations are as follows. First, during the entire period 2005-2018, $MA2$ and FIN have remained connected through a stable, binary link from FIN to $MA2$. This reveals that the input from FIN is critical for $MA2$. Second, starting from 2011 until 2016, the upstream network of $MA2$ shows two communities; for 2017 and 2018, the number of communities have increased to three. Third, these two sectors have shared a common community during 2011-2015, while for 2016-2018, they shared different communities, implying that their linkage strength levels decreased compared to the level in 2011-2015. In other words, their commonalities in terms of linkage strength decreased in between 2011-2015 and 2016-2018. Fourth, for the latter period, FIN and TSC have always shared the same community, implying that TSC has been significantly and continuously financed and that financial resources potentially available for $MA2$ have slowly phased out. Fifth, during the latter period, EST made itself known as a a stable element of the upstream network of $MA2$, with its continuous binary link to $CO12$, and remained within the same community with $CO12$. Likewise, during the same period, $\{MA2, EGW, CST\}$ have always remained in the same community, pointing out that the strength of their binary linkages has remained as strong. That during the same period, $MA2$ has remained connected to $\{FIN, AGF, CST, EGW\}$ and that $\{MA2, EGW, CST\}$ have always remained in the same community suggest that the strength of their binary linkages has remained as strong.

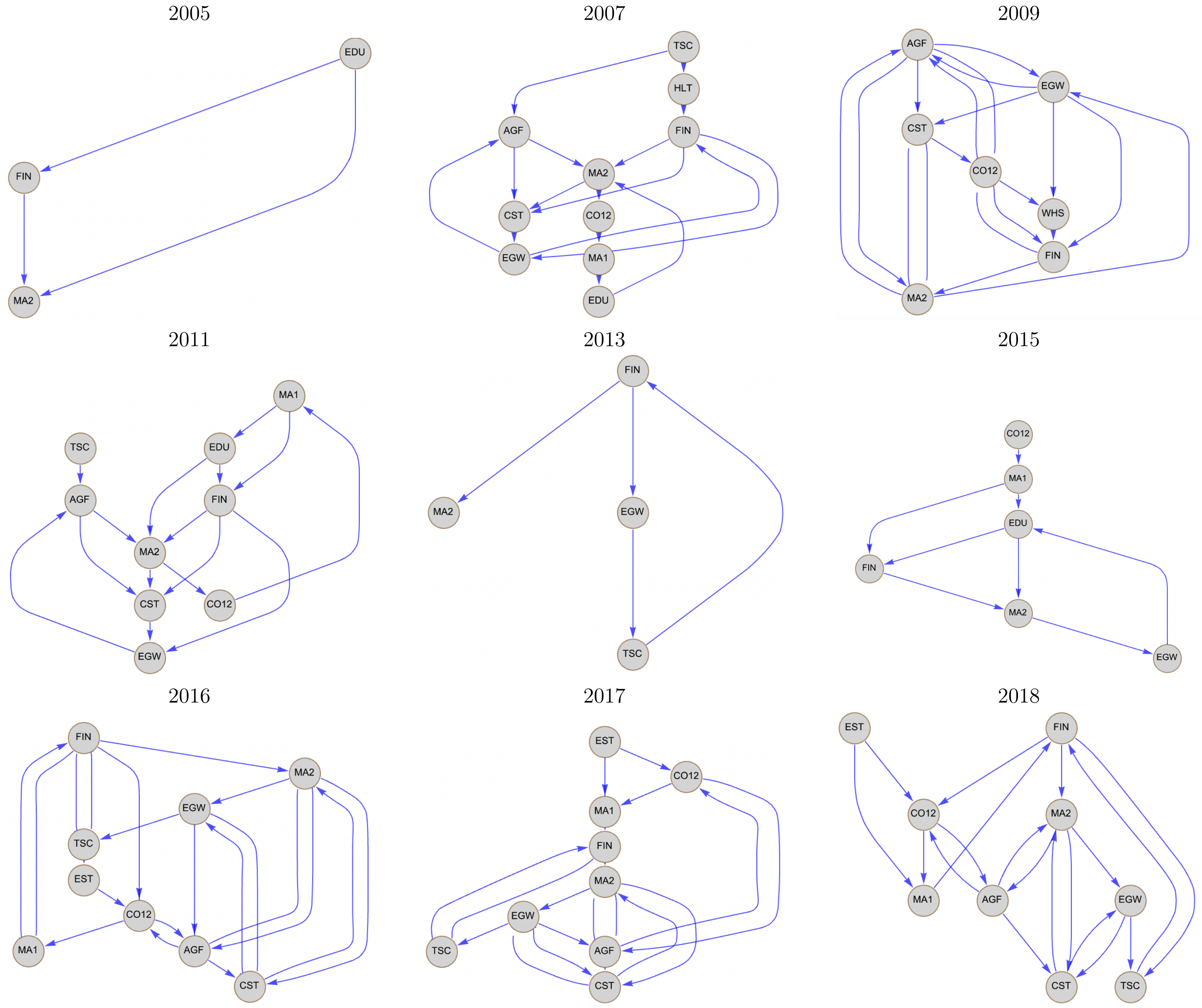


Figure 8: Time evolution of upstream networks of $g^U_{MA2}(t)$ in the (Q1 - Q3) interval of multipliers

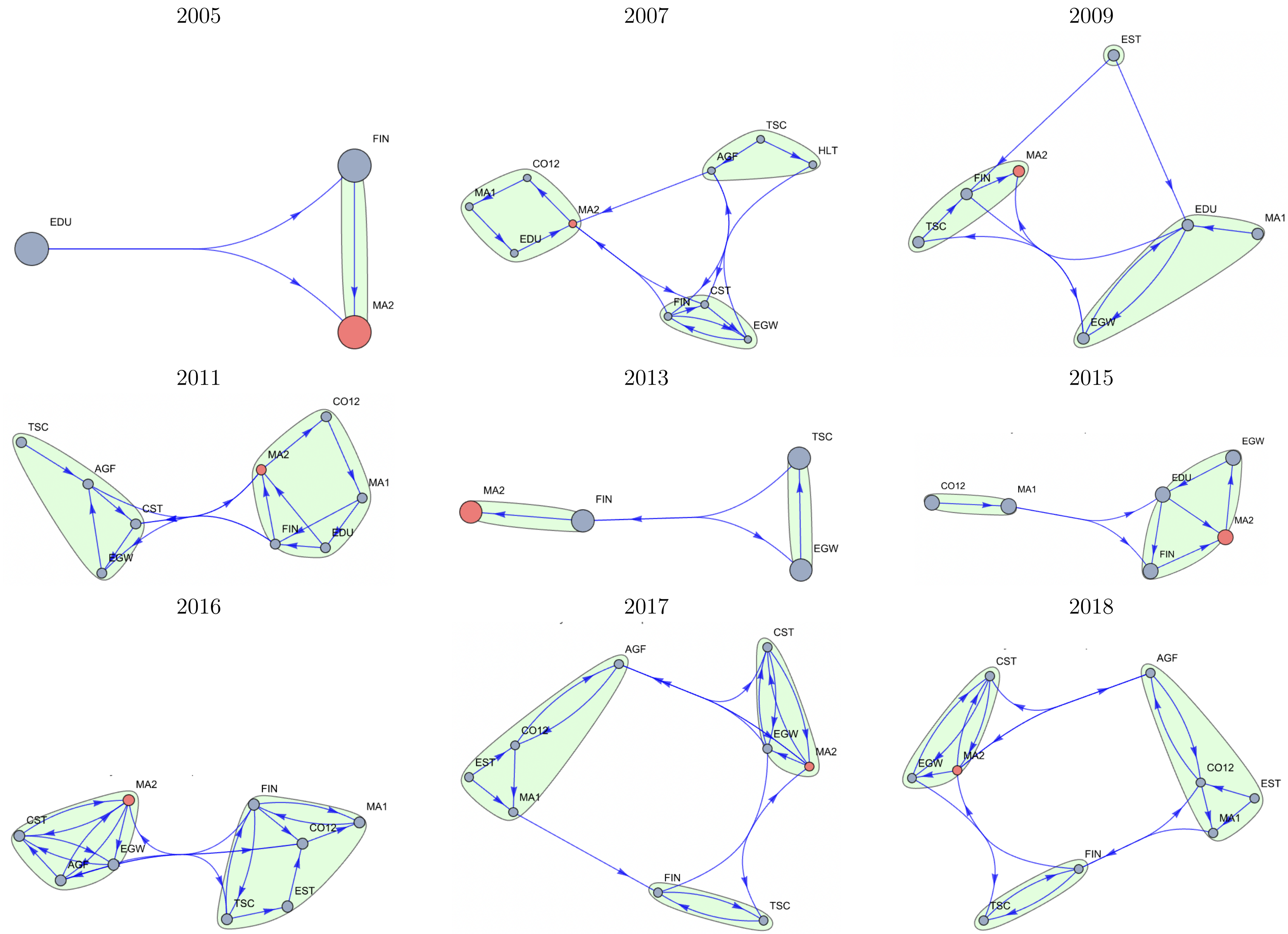


Figure 9: Time evolution of the community structure of $g^U_{MA2}(t)$ in the (Q1 - Q3) interval of multipliers

7 Discussion

During the period 2000-2022, Turkiye has gone through a series of political and economic crises. Several political conflicts triggered 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, resulted in capital outflow hoping to settle in safe heavens. 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 (Keyder, 2022). These cyclic crises seem to originate mainly from adverse developments in the monetary economy, however, it is undeniable that various political-economic factors deepened the crises. Fundamentals in the real economy were not as strong as expected to be to withstand the shocks that followed 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. 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.

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.[10] 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.

The 2008 global financial crisis was largely a making of three intertwined factors, among others, including 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. Finance, real estate, and construction sectors were the sources of troubles, which were catalyzed by the risk-taking behavior of global financial institutions. 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

[10]See Daron Acemoglu (2015) for a broader discussion of the political-economy and institutional developments that took place in Turkiye during 2002-2015.

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.

The 2018 production network of Turkiye demonstrates some important characteristics that have implications for the effective workings of $MA2$'s upstream network and the growth of aggregate output. The analysis of how $MA2$ influences is influenced by others in the network provides useful entry points for discussion (see **Fig**. 3). Identifying how **dominant and subordinate** sectors cluster with other sectors further provide an overview of potentially strategic partnerships. 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. A highly **subordinate** sector has the least control over its own issue area. Rather than surrendering to this fact, it should be a strong motivation to nurture relationships with the sectors that hold the key to its 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. A number of **dominant** sectors 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 and they have a lot of freedom to act independently. However, 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) and what is now perceived as important collaborations given shared or conflicting interests. Exploring communities can thus present an effective way to build strategic partnerships.

In general, sectors in a production network operate in a complex environment in which: (1) competitive and regulated producers engage in trade, (2) distortions and imperfections amplify the scale of a disruption or a shock, and (3) cascade of layers of sectoral links heightens the systemic risk. $MA2$, a priority sector of Turkiye's economy, and its upstream network have to survive in this challenging environment and increase aggregate output. Here are some suggestions based on the key findings of this paper, laying the ground for the design of sound policy reforms from a network perspective.

Here is an example of how the three properties of such a complex environment may lead to the breakdown of the upstream network of a prioritized sector. Take, for example, $MA2$. Suppose 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 (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 or FIN. 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.

Here is the most distorted pathway influencing the productivity of $MA2$:

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

suggesting 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 of $MA2$ would then lead to significant misallocation of resources in $MA2$, resulting in much reduced profits and the contraction of the industry as entry to market will be discouraged by sharply declining 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 derived, 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, $\{EGW \to TSC \to FIN\}$, should be prioritized to address potential adversities that might arise due to bottlenecks in TSC. 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.[11] All of the regulated sectors requires advanced 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.

What are the implications of pro-competitive PMR on the productivity of the upstream network of $MA2$? 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:

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

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. Removing restrictive government policies in international shipping services, such as restrictions on foreign shipping services, would lead to an average reduction in transport prices for goods shipped. Declining prices of services resulting from liberalization improves traffic and access, and hence, overall consumer welfare. Entry liberalization, deregulation of TSC, and deregulation of EGW are likely to create a particularly substantial positive impact on capital accumulation and therefore 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

[11] 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>.

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 in $MA2$) would substantially increase consumers' savings through the backward linkage from $MA2$ to HLT. Competition in social programs such as those relating to HLT would further offer various benefits to consumers through better functioning of health (HLT), education (EDU) and professional services (EST) markets.

8 Concluding remarks

This paper developed and demonstrated a practical computational methodology for gaining a systemic perspective on production networks by building on graph-theoretic concepts and a typology of interactions. The methodology can be applied in almost any country since many countries across the globe compile input-output tables of their economies. It is systemic as it analyzes network-wide effects of a policy intervention based on a structured interconnectedness between sectors. 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 in a highly aggregated way which is suitable in a policy context.

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, and elaborates on how the information obtained from the analysis can be used in policy design to address the challenges. The paper introduces three complementary algorithms that can be applied to generate information for evidence-based policy design to improve the productivity in $MA2$. The analysis employed the 2018 input-output data of Turkiye, and hence, the findings are limited in nature. However, the results help us derive lessons to guide future policy interventions at the network level.

The main results from this paper 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. This points out that the identification of significant sectoral links and their structural properties along the pathways of sectors in the network is vital for effective policy interventions. Improved competition in a single market may not generate the desired outcome even if competition policies perfectly support that market because benefits from competition will not be spread over the rest of the network due to the peculiarities of the interdependencies concerned. Second, from the practical policy design perspective, a network-based policy design should start with the identification of the "*dominant*" source and the "*subordinate*" sink sector(s), and those in between. Once identified, peculiarities of the sectors in the network should be studied to characterize the pathways of linkages and the outcomes expected from them. **Fig**. 3 maps the $source - sink$ structure of $MA2$, illustrating that $MA2$ is the most dominant, whereas EST, TSC, EGW, and CST are the potential sinks of input flow in the network. The other sectors, AGF, FIN, and $CO12$ seem to be interactive, that is, their influence on the rest of the network is comparable to the influence of the rest of the network. The last but not the least is the identification of the cascade of layers of links and the measurement of community or link-specific network resilience. This piece of information is of high importance to minimize the systemic risk, and design policies to avoid deleterious effects of a shock, such as the COVID-19 pandemic and the war in Ukraine, to the network.

The methodology proposed is neither final nor the most efficient one, but opening a new avenue for semi-quantitative computational analysis of a production network. Patterns of interactions in a network can be further refined using more complex algorithms to uncover the very core of interdependencies across sectors. However, the lack of a benchmark production network structure against which Turkiye's structure can be contrasted makes the current analysis more of an exploration of existing sectoral interdependencies and their policy implications because progress towards the productivity improvement cannot be assessed diligently.

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 to be addressed. 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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