Doctoral Thesis

The Dynamics of Innovation in Production Networks

Nurten KAYNARCA

A thesis submitted in fulfillment of the requirements
for the degree of Doctor of Philosophy
in the

École doctorale d'économie of Université Paris 1 Panthéon-Sorbonne,
Ph.D. School in Economics and Finance of Università Cattolica del Sacro Cuore

Defense Date
11 February 2026

Jury Members

Prof. Dr. Herbert DAWID, President	Bielefeld University
Prof. Dr. Ivan SAVIN, Referee	ESCP Business School
Prof. Dr. Domenic Delli GATTI, Member	Università Cattolica del Sacro Cuore
Asst. Prof. Dr. Vipin P. VEETIL, Member	Indian Institute of Management Kozhikode
Prof. Dr. Antoine MANDEL, Supervisor	Université Paris 1 Panthéon-Sorbonne
Prof. Dr. Maria Luisa MANCUSI, Supervisor	Università Cattolica del Sacro Cuore

Acknowledgements

I want to express my deepest gratitude to my supervisors, Antoine Mandel and Maria Luisa Mancusi, for their invaluable guidance, support, and patience throughout my doctoral studies.

I want to thank all the colleagues and friends I met during my PhD for the stimulating discussions, collaborations, and shared experiences. I am particularly grateful to all members of the EPOC network, including the doctoral fellows and professors. I specifically acknowledge Herbert Dawid, Agnieszka Rusinowska, Domenico Delli Gatti, and Ivan Savin for their valuable feedback and inspiring ideas.

I am profoundly grateful to my family for their support. I especially thank my parents, Hafize and Ayhan, for their constant encouragement and belief in me. I also thank my sisters, İknur, Ayla, and Cansu, whose love and support have always been a source of strength and motivation.

Finally, I would like to acknowledge my nephew, Artun, whose recent arrival brought joy and renewed motivation during the most demanding final phase of this doctoral journey.

Summary

The thesis examines how firms' input/technology choices drive the structural evolution of production networks and subsequent macroeconomic outcomes, and how industrial policies can be designed to account for endogenous production network formation. The thesis comprises research papers that employ new theoretical and empirical approaches to analyze production networks as outcomes of firms' input choices and key transmission channels within the macro-economy.

The first research paper proposes a production network formation model grounded on a general equilibrium economy in which technology is endogenous and determined by input combinations. In the model, the production network evolves through the entry of new firms, which choose input combinations that will determine their technology level. The objective is to gain a deeper understanding of how firms' openness to innovation in input choices shapes the structural evolution of production networks through computational simulations. The simulations highlight that the outcomes of innovation in input choices depend on where the innovation occurs within production networks. The main assumption is that new firms have limited information about all feasible input combinations within the production network and explore the technological landscape in a boundedly rational way. The dynamic interplay between firms' technology choices and the production network structure leads to a continuous process of network reconfiguration. The endogenous evolutions of the production network and idiosyncratic productivity levels induce a sequence of general equilibrium outcomes. The simulation results suggest that technological homogeneity within sectors and the innovative behavior of entrant firms are essential to achieve optimal firm-level productivity and aggregate outcomes.

The second research paper turns to firm-level empirical evidence from Turkey, with a conceptual framework that links firms' supplier linkages with their technological differentiation. The objective is to gain a micro-level un-

derstanding of the factors driving the adjustments of input-output linkages. The empirical analysis is based on Turkey's firm-to-firm transaction data. The regression analysis represents robust empirical findings regarding firms' supplier network adjustments: (i) Firms maintain more stable supplier linkages when their peers make significant adjustments to their own supplier linkages. (ii) High exposure to the 2018 currency shock in Turkey led to higher stability in domestic supplier sets. The main result is that firms with lower overall supplier-set relatedness (higher supplier-set differentiation) tend to perform better. These insights contribute to the literature on resource-based measures of firm diversification in explaining performance.

The third paper bridges the remarks from the first and second papers on the dynamic structure of production networks into the design and evaluation of industrial policies. Understanding the influence of industrial policies on production network formation is essential for understanding how their effects are amplified or attenuated as production networks evolve. The paper presents a structured literature review and a production network formation model grounded in a general equilibrium economy. The general equilibrium economy incorporates a policymaker designing a tax schema for firm-to-firm input transactions. The impacts of tax exemptions on the dynamics of production network formation are analyzed through computational simulations with different policy targeting strategies. Our findings show that production network-informed policy targeting strategies can improve the efficiency of industrial policies.

Contents

List of Figures

List of Tables

List of Abbreviations

GDP: Gross Domestic Product.
OLS : Ordinary Least Squares.
R&D: Research and Development.
TL : Turkish Lira.
USD : United States Dollar.

Chapter 1

General Introduction

As Wassily Leontief stated in the interview conducted by Foley (1998), "The first job of an economist is to understand the economic system. To understand the operation of the system, one figure is not enough. You want to see how it disaggregates." Leontief's call for disaggregation and his consideration of production processes as a network are gaining popularity in recent literature on how the structure of production networks influences macroeconomic dynamics (Acemoglu et al., 2012; Barrot and Sauvagnat, 2016; Carvalho et al., 2020). The literature models shock propagation through production networks relying on external shocks (Carvalho, 2014; Carvalho et al., 2020; Mandel and Veetil, 2021; Acemoglu and Tahbaz-Salehi, 2020). The interdependencies across disaggregated units amplify the effects of idiosyncratic shocks. The literature demonstrates remarkable progress in modeling the propagation of idiosyncratic shocks to aggregate effects through production networks, while accounting for market distortions (Gabaix, 2011; Acemoglu et al., 2012; Baqaee and Farhi, 2019a; Carvalho and Tahbaz Salehi, 2019; Baqaee and Farhi, 2019b; Bigio and La'O, 2020).

While this literature reinforces Leontief's insights, mechanisms of production network formation remain underexplored. Understanding these mechanisms is critical due to high potential contribution to the research on (i) supply chain disruptions, (ii) technological progress and innovation in production processes, and (iii) industrial policy design and evaluations.

(i) The supply chain disruption models explore the fragility of supply networks—the sensitivity to aggregate or micro-level disruptions—and the role of network complexity in amplifying shocks (Elliott et al., 2022; Elliott and Jackson, 2023). Through general equilibrium models incorporating production networks, shock propagation is explored for fixed networks. The internal decision-making process for forming links creates a new channel for robustly amplifying shocks (Elliott and Golub, 2022). Firms strategically adjust their supplier linkages to mitigate the adverse effects of external shocks. Further, there may be heterogeneity in their behaviors regarding supply network adjustments. Therefore, deeper theoretical and empirical analyses of those behavioral differences enable us to understand mechanisms of production network formation and their influence on aggregate outcomes.

(ii) Further, firms adjust their input linkages by seeking technological progress in production through the adoption of new inputs (i.e., Automation processes, robots, and AI). Technological progress driven by firms' endogenous input choice also spread through production networks (Oberfield, 2013; Acemoglu and Azar, 2020). The endogenous production network model by Acemoglu and Azar (2020) proposes that firms choose an optimal input combination by balancing the trade-off between higher production technology and higher production costs associated with adopting inputs. The model suggests that firms consider all possible input combinations to minimize unit cost through productivity gains and lower-priced inputs within an economy. However, searching all possible input combinations is not feasible for firms in a real-world economy. Firms behave boundedly rationally in the search spectrum of inputs. How firms differentiate their input choices from others determines the structural evolution of production networks. The common assumption in search of inputs is that productive units (i.e., firms, industries, countries) tend to adopt inputs that are technologically close to those they, their competitors, and suppliers already use (Hidalgo and Hausmann, 2009; Carvalho and Voigtländer, 2014).

(iii) The current resurgence of industrial policy implications, rationalized through market failures, coordination, or agglomeration failures, necessitates new theoretical and methodological approaches in their design and evaluations (Hausmann and Rodrik, 2003; Hidalgo and Hausmann, 2009; Cimoli and Dosi, 2016; Chang and Andreoni, 2020; Juhász et al., 2024). However, the design and evaluation of industrial policies are difficult due to the dynamic interactions among productive units and the heterogeneity of their behavior (Pack and Saggi, 2006). Further, industrial policies are criticized for unclear procedures for targeting sectors, regions, or economic activities for intervention, and for unclear criteria for choosing the right target group (Rodrik, 2009; Chang and Andreoni, 2020). Network theory provides a fresh perspective on the spillover effects of industrial policy and accounts for the heterogeneity of economic agents (Liu, 2019; Grassi and Sauvagnat, 2019; König et al., 2019; Liu and Ma, 2021; Lane, 2024; Georgieva, 2025). The growing literature on production networks highlights that production networks are not only outcomes of firms' input choices but also key transmission channels through which industrial policies may shape structural transformation in economies.

Despite these advances, the literature lacks empirical studies on production network formation and on how firms' input linkages influence their performance, due to a lack of firm-to-firm transaction data. Firm performance is empirically analysed through the product and patent portfolios as indicators of a firm's production technology and scope (Teece et al., 1994; Hidalgo et al., 2018; Breschi et al., 2003; Pugliese et al., 2019; Dosi et al., 2022; Juhász et al., 2021). This literature is based on relatedness measures, suggesting that two economic activities (technologies, industries, products, jobs) occur within the same productive units because they belong to the same technological field or share complementarities. Firm-level production technology is defined as the design and procedures, along with the necessary material inputs, machines, and services, to achieve final goals, implicitly or explicitly (Shell et al., 1999; Kauffman et al., 2000; Frenken, 2006). Firms' input choices state their production technology for achieving a final output. The strategic decisions on inputs stand out in supplier choices. Therefore, analysis of firm-level supplier-set scope and adjustments is critical for a better understanding of production network formation dynamics. Even industry-level analysis of input-output linkages through relatedness measures and methodology highlights the importance of firm-level analysis of supplier linkages (Fan and Lang, 2000; Bryce and Winter, 2009; Essletzbichler, 2015).

The mainstream literature on production networks assumes that production networks and firm-specific productivity levels vary due to external shocks. Moreover, the production network formation models assume that firms behave uniformly. Bringing production network formation models closer to real-world dynamics is difficult because of feedback loops among production technology, production costs, and the formation of input links. The choices of inputs determine production technology and production cost. While adopting additional inputs increases production technology, it also increases production costs. Balancing this trade-off requires searching for different input combinations. This search process depends on firm-specific characteristics such as innovation capabilities, position in production networks (i.e., existing suppliers and customers), and regulatory restrictions on access to specific inputs. A two-way causal relationship between production network formation and economic outcomes, mediated by firm-level productivity and prices, makes identification and interpretation difficult. Including all these characteristics in production network formation models increases their complexity. Still, studying network formation dynamics with some simplifications provides remarkable insights into the influence of production network formation patterns on aggregate outcomes.

The thesis suggests a framework that explicitly models firms' input choices and network formation as endogenous processes. The main research questions are as follows:

1. How do firms' input/technology choices drive the structural evolution of production networks and subsequent macroeconomic outcomes?

2. How can we measure technological differentiation and evolution through supplier linkages, and what firm-level factors explain network adjustments?

3. How can industrial policies be designed to account for endogenous network formation and the propagation of policy effects through input-output linkages?

The thesis comprises three research papers that encompass theory, empirical analysis, and policy simulations, using new theoretical and empirical approaches to examine production networks as outcomes of firms' input choices and as key transmission channels within the macroeconomy. The main idea of these papers is that technological change in production is embodied in firms' input combinations (Arrow and Debreu, 1954; Oberfield, 2013; Acemoglu and Azar, 2020). Endogenous technological choices shape production network structures at the micro-level, and these evolving structures influence macroeconomic outcomes.

I conceptualize input choices as technological choices. Further, firms sharing a common customer base influence each other in their input/technology choices. Thereby, technology and production network structure are jointly endogenized: Firms' input choices are influenced by current production network structures and determine subsequent production networks within the economy. This approach moves beyond the literature on production networks that considers exogenous productivity shocks and fixed production function parameters. This thesis contributes to the literature on production network theory, innovation economics, and Industrial policy.

The thesis's chapters are organized around the common object that input-output linkages are formed endogenously, and they examine production network formation through complementary theoretical, empirical, and policy-oriented approaches. The thesis chapters share a conceptual framework that the formation of input-output linkages embodies production technology, and they can serve as an empirical indicator of technology in the context of temporal firm-to-firm transactions. I progressively shift the level of analysis from theory to empirics and to policy design.

Chapter 2 develops a general equilibrium model of endogenous production network formation in which firms' technologies are determined by their input combinations. This chapter is primarily theoretical and methodological, and it introduces the mechanisms through which firms' input search behaviors and choices jointly shape the evolution of production networks and aggregate economic outcomes. The chapter is situated in the research stream on the micro-foundations of network formation and the dynamic interaction between technology and network structure. It focuses on the conditions under which technological differentiation increases firms' productivity, while accounting for the tension between technological differentiation and homogeneity within sectors. This network formation model establishes a relationship between firms' innovation behaviors and macroeconomic outcomes through production networks. The simulations highlight that the outcomes of innovation in input choices depend on where the innovation occurs within production networks.

The dynamic interplay between firms' technology choices and the production network structures leads to a continuous process of network reconfiguration. The endogenous evolutions of production networks and idiosyncratic productivity levels induce a sequence of general equilibrium outcomes.

Chapter 3 turns to firm-level empirical evidence on production network formation using detailed firm-to-firm transaction data from Turkey. As a complement to the conceptual framework introduced in Chapter 2, this chapter explores technological differentiation through firms' supplier sets. It empirically examines how firms adjust their supplier linkages in response to peer behavior, product diversification, and external shocks. Furthermore, the chapter empirically links supplier-set differentiation to firm performance. The chapter mainly focuses on empirical methods, identification challenges, and firm-level heterogeneity. Firm-level empirical analysis of supplier linkages is crucial for capturing heterogeneity in firms' differentiation and peer effects within production network formation.

Chapter 4 leverages the implications of endogenous production networks for industrial policy design and evaluation. Incorporating a policymaker into a general equilibrium production network model enables us to examine how tax exemptions influence production network formation and aggregate outcomes. The chapter links the theoretical mechanisms and empirical patterns represented in the earlier chapters to policy design and propagation effects within production networks.

The chapters jointly demonstrate how firm-level input and supplier choices aggregate into evolving production networks that determine firm-level productivity and aggregate outcomes. The models developed in the thesis consider production networks as outcomes of firms' technological choices and as central transmission channels through which economic shocks and policy interventions propagate.

The computational simulations and the firm-level empirical analysis demonstrate how input choices lead to significant structural network transformations. Transformation patterns within production networks determine innovation pathways, resilience to shocks, and the efficiency of industrial policies. Diversifying technologies through new input adoption or adjusting supplier linkages in response to external shocks does not remain localized. The decisions on linkage formation propagate through production networks, influencing other firms connected through input-output linkages and those sharing common neighbours. The spillover in the formation of input-output linkages is not instantaneous. The gradual standardization of input choices leads to gradual structural transformations in production networks. Unlike the creative destruction model of Aghion and Howitt (1992) — which does not incorporate diffusion lags by modeling innovation as a discrete replacement — the thesis considers the gradual diffusion of innovation arising from the interaction between firms in input choices.

Understanding network formation is crucial for predicting how industrial policies influence the economic structure. Policy interventions may propagate through existing linkages and trigger endogenous reconfigurations of supply chains - amplifying or softening their effects over time. Designing an industrial policy is challenging due to the dynamic behavioral rules of firms and the endogenous nature of production networks. Policies that target firms without accounting for how they adjust input-output linkages may generate limited spillovers or unintended network reconfigurations. The design of those policies must account for potential shifts in firms' decisions governing the formation of input-output linkages.

Network-informed policy design appears as a promising approach to optimize fiscal resources and improve structural outcomes. By recognizing production networks as key transmission channels, this approach allows policymakers to analyze how policy interventions propagate across firms and sectors over time. Overall, bridging micro-level input choices with macro outcomes offers tools usable beyond innovation, such as green transition, digital transformation, and precautionary policies for supply chain disruptions. For instance, green transition supply chain policies include instruments to encourage firms to link to green suppliers. Considering the positions of green suppliers and their technology and cost functions, policymakers may speed up the transition towards them.

As an example of industrial policy targeting structural transformation, the "Made in Europe" partnerships set local sourcing targets for parts in products such as cars and solar panels. Carmakers highlight potential issues arising from further supply chain disruptions and a slowdown in the transition to electric vehicles (Hancock et al., 2025). The success rate of this transition policy can be increased by supporting highly central local suppliers to enhance their attractiveness. Further, the local sourcing targets may be relaxed for non-European suppliers that are difficult to replace. The remainder of the thesis provides a structured investigation of production network formation and its macroeconomic and policy implications.

Chapter 2

Technological Evolution of Production Networks

Abstract

This chapter emphasizes the mutual evolution of production networks and technology and the significant impact of production network structures on macroeconomic dynamics. We propose a production network formation model grounded on a general equilibrium economy. Production networks evolve with continuous new-firm entries. The model examines how varying dimensions of openness to innovation influence the structural evolution of production networks. Our numerical simulations reveal varying structural evolution paths for production networks under 2 scenarios regarding new firms' input search processes. The varying correlation between technological homogeneity and new firms' productivity levels explains the varying evolutionary paths of production networks. We demonstrate the dispersed effects of innovation on economies, accounting for production network structure and behavioral factors.

Keywords: Endogenous technology, innovation, production networks.

Note: This chapter is a joint work with Antoine MANDEL.

2.1 Introduction

The recent literature has demonstrated that the structure of production networks can significantly influence macroeconomic dynamics (Acemoglu et al., 2012; Barrot and Sauvagnat, 2016; Carvalho et al., 2020). However, the mechanisms governing the evolution of these networks are less well understood. Acemoglu and Azar (2020) - which is a base for the present chapter- proposes that production networks are formed by firms' input choices that minimize production costs, considering the trade-off between high technology and high production cost from adopting inputs. This research aims to address the production network evolution by firms' technology choices with a model of production network formation grounded on a general equilibrium economy. Our model clearly illustrates how aggregated economic outcomes are affected by varying dimensions of openness to innovation, embodied in different input combinations and, in turn, different production network structures.

Building on Acemoglu and Azar (2020), the model contributes to the literature by incorporating a behavioral and simulation-based approach. Through the endogenous categorization of firms and the bounded rationality assumption, it explains the co-evolution of production networks and technology. In the model, the production network evolves through the entries of new firms, which choose input combinations that will determine their technology levels. New firms have limited information about all possible input combinations within the production network and explore the technological landscape in a boundedly rational way. To simplify this exploration, firms focus their search on inputs of specific target categories/sectors. Those categories are defined by the similarity of input sets among existing firms in the network. Firms that share many common inputs are grouped into the same category, and these inputs are considered essential to the firms within that category. In other words, the categories are shaped by the structure of the production network. New firms' decision-making processes depend on these categories and, in turn, the network structure. When a new firm enters, it selects its input combination by incorporating the essential inputs of its target category, along with some innovative additional inputs. After choosing its input set, the new firm competes with other firms in its target category to attract their customers. In this way, while the new firm's input choices are influenced by the existing structure of the production network, its entry and technology decisions also reshape the network's structure. This dynamic interplay between firms' innovation choices and the evolving production network leads to a continuous process of network reconfiguration. As the production network structure evolves, the categorization of firms evolves as well. We trace the evolution of technological proximity within categories and its influence on new-firm performance through endogenous categorization.

In this setting, how new firms are open to searching for more innovative additional input - beyond the essential inputs of their target category- is an important factor in determining production network evolution. As Dosi (1982) suggests, firms search for new technologies with some perceptions of a limited set of possible technological alternatives. Therefore, we consider two possible innovation processes concerning the new firm's search behaviors for innovative additional inputs. This analysis explores the varying evolutionary patterns under different behavioral rules governing the search for alternative technologies, drawing on the literature in evolutionary economics (Nelson and Winter, 1985). In Scenario A (Focused Search), the new firm searches for all possible combinations of the additional inputs of existing firms in its category. In Scenario B (Perturbative Search), the new firm searches for one additional input from the other inputs that were not used by the existing firms in its category before. Those scenarios represent different dimensions of openness to innovation through additional input search processes. Scenario A is the least innovative case in which new firms only look for optimal combinations within the target categories' additional inputs. Scenarios B is more innovative because firms search for one more input outside the category.

We simulate the evolution of a random production network that has highly homogeneous categories, indicating that category firms share a high number of essential inputs. In our simulation setting, a new firm tries to enter the economy every period. If the new firm is able to acquire at least one customer, the production network is updated by adding the new node and its input-output linkages. The endogenous evolution of the production network induces a sequence of general equilibrium outcomes. We illustrate how economic outcomes and the structure of the production network dynamically evolve through innovation and competition.

The simulation results reveal that the paths of structural evolution of production networks differ based on the varied input search processes of new firms. We explain this difference with variations in technological homogeneity within the categories that new firms enter over time. Technological homogeneity decreases in all scenarios but more significantly in highly innovative environments (Scenarios B). Decreasing technological homogeneity affects new firms' productivity differently under those scenarios. In the less innovative environment (Scenario A), we observe a negative correlation between technological homogeneity in the targeted category and new firms' productivity. This negative correlation suggests that entering less homogeneous categories benefits new firms and the economy more. Despite the gradual decrease in technological homogeneity in Scenario A, it benefits new firms requiring less homogeneity to achieve higher productivity over time. In contrast, in more innovative environments (Scenario B), we observe a positive correlation between technological homogeneity in the targeted category and the productivity of new firms. New firms achieve higher productivity by entering highly homogeneous categories, but that contradicts the significantly decreasing homogeneity due to the entry of more differentiating firms. Therefore, we observe an inverted U-shaped trend in the evolution of real GDP. These findings characterize the aspects of innovation that cause unsustained growth in real GDP under boundedly rational technology/input choices. As a future research direction, the model can be employed to simulate the potential outcomes of industrial policies that advocate innovative change or promote green transitions within the supply chain.

The remainder of this chapter is organized as follows: Section 2.2 reviews the related literature. Section 2.3 introduces an endogenous general equilibrium model that incorporates a process of technological evolution within production networks. Section 2.4 analyzes, through numerical simulations, how the varying innovation processes of firms influence the evolution of production networks and shape economic outcomes. Section 2.5 concludes.

2.2 Related Literature

Understanding the complex dynamics of production networks and their influence on economic outcomes has been a focal point in current economic literature. Since the pioneering paper by Leontief (1965), the production system is modeled through flows of goods and services from industry to industry by adding value in each transaction. Those flows create input-output tables. The industrial instructions for producing an output with different intermediary input combinations shape input-output tables. Currently, network theory is being used to study the formation of those complex input-output linkages that have also been introduced into endogenous technology models. Acemoglu and Azar (2020)'s endogenous production networks model explains the firms' technology levels with their input combinations. They demonstrate that sustained economic growth is achieved by allowing firms' choices of optimal input combinations to have higher technology levels. They define the direct and indirect effects of new input-output linkages. If a firm achieves a higher technology level by adopting new inputs, it can directly improve its productivity, indirectly benefiting downstream customers through price mechanisms. McNerney et al. (2022) show that production network structures influence long-term economic growth through price changes and productivity improvements accumulated along supply chains.

The literature also examines the propagation of idiosyncratic price or productivity changes through supply chains.

Mandel and Veetil (2021) define the price dynamics of production networks under a decentralized mechanism and analyze the impact of exogenous monetary shocks on prices. Carvalho (2014) and Carvalho et al. (2020) study the propagation mechanism for the case of the Japan earthquake that caused supply chain disruptions. Acemoglu and Tahbaz-Salehi (2020)'s study explores the impact of external shocks on firm failures and supply chain disruption. Their non-competitive model shows that the exit of a profitable firm can lead to additional exits. Gabaix (2011) shows that idiosyncratic shocks to firms may lead to aggregate volatility empirically by applying the theorem of Hulten (1978), which implies that individual shocks may not cancel out each other as deduced from the law of large numbers. Acemoglu et al. (2012) and Baqaee and Farhi (2019a) clarify the shock propagation from micro to macro by introducing input-output relations. The influence of firms in production networks is determined by their sales shares in the overall economy, as defined by centrality measures proposed by Bonacich (1987) and Ballester et al. (2006). Many of the models demonstrating shock propagation rely on external shocks. For instance, Gualdi and Mandel (2019) model technological diffusion regarding given innovations. However, technological progress driven by firms' endogenous innovative decisions, as in Acemoglu and Azar (2020), also spread through production networks in the economy.

There is also a growing empirical literature on the role of firms' input-output linkages in explaining firm performance and economic growth. Mundt et al. (2023) and Savin and Mundt (2022) highlight the importance of supply chain productivity in explaining output growth and labor productivity change empirically at the country-sector level. The latter compares the effects of supply chain productivity and idiosyncratic innovation levels. Even if most empirical papers on production networks are at the sector or regional level because of the lack of microdata, there are examples of papers that define production network characteristics with firm-level data, such as Atalay et al. (2011) for the US and di Giovanni et al. (2014) for France.

The literature on the strategic formation of production networks is relatively less developed than the literature on the propagation of shocks in production networks. Understanding how innovation decisions are related to input-output linkages is a complex issue because of the need to explain the decision processes of firms in detail. The explanation requires defining a search mechanism for input combinations that will give efficient production technology levels. In Acemoglu and Azar (2020), the firms' decision on input combinations results from a search through all possible input combinations. Other contributions consider alternative processes with imperfect information or bounded rationality. Elliott et al. (2022) explain that technological compatibility and geography can limit a firm's pool of potential suppliers. Firms multi-source inputs and invest in stronger industrial linkages against the risk of supply chain disruptions. Their paper does not include firms' link formations with the motivation to increase technology level, and the case of new firms' entries. Carvalho and Voigtländer (2014) constitute a network formation model in which firms restrict their search to the neighborhood of their existing suppliers. The steady state of production networks and the trade-off between technological progress and the cost of adopting new inputs determine firms' decisions. We extend the model of Acemoglu and Azar (2020) with the perspectives of Carvalho and Voigtländer (2014) on essential and potential inputs: Firms tend to adopt new inputs that are technologically close to those they or their competitors already use. Technological closeness refers to the similarity of input combinations. This perspective also builds on the pioneering paper of Hidalgo and Hausmann (2009) that studied the technological capabilities of countries by analyzing their export product portfolios and trade partners. They state that an extension in countries' export basket can be toward products technologically close to their current products because they require similar capabilities as before. Analogously, their approach to technological closeness inspired us. While Hidalgo and Hausmann (2009) suggest the technology level of countries at a period must be close to its technology level at the previous period, we suggest that a firm must make its input sets closer to its competitors' input sets to sell products to its customers. In other words, an extension of a firm's customer base can be toward customers of technologically close firms.

2.3 Model

We propose a model with discrete periods where a general equilibrium economy is formed through input-output relationships between a set of firms $N_t = \{1, 2, \ldots, n_t\}$ and a representative household at each period t.[1] The suggested model considers endogenous technology based on the firms' input choices. The firms' input choices shape the production network W_t, which captures the input-output linkages between the firms in N_t at time t. The model incorporates a process of production network formation with new-firm entry in each period t, building on the proposition that a firm chooses the most beneficial input combination by balancing the trade-off between high production cost and high productivity from adopting additional inputs Acemoglu and Azar (2020). This process is based on firms' input search behaviors. While Acemoglu and Azar (2020) assumes a fixed technological landscape, in which all firms choose the most beneficial input combinations as the outcome of a cost-minimizing optimization, our model allows firms to choose technologies determined by input combinations boundedly rationally within endogenously defined categories. Firms' input choices that determine their production technology are influenced by the production network structure from the previous period, $t - 1$. Therefore, the present production network structure at period t is also influenced by the previous period's

[1] In our assumption, each firm produces a product that is differentiated horizontally. Therefore, we may use the words "firm" and "product" interchangeably.

production networks through entrant firms' input choices.

The following section is structured into three parts: First, we outline the general equilibrium economy and the conditions that apply at any given period. Secondly, we present rules that explain how the production network evolves through the entry of a new firm at any given period. Finally, we propose a technology function that determines the productivity level of firms within a given production network.

2.3.1 The General Equilibrium Economy

Production Function and Utility Preferences

In each period t, the economy is characterized by the set of firms represented by N_t and a representative household. The representative household is endowed with one unit of labor and has the following preferences over the n_t different products with an equal share of consumption:

$$U(C_{1t}, C_{2t}, ..., C_{nt}) = n_t \prod_{i \in N_t} C_{it}^{1/n_t}. \tag{2.1}$$

where C_{it} is the consumption level of the product of firm i. Each firm i has a Cobb-Douglas production function with constant returns to scale such that

$$Y_{it} = A_{it}(Z_{it})\zeta_{it} L_{it}{}^{\alpha} \prod_{j \in Z_{it}} X_{ijt}^{(1-\alpha)w_{ijt}}, \tag{2.2}$$

where Y_{it} is the level of output, X_{ijt} is the amount of product j used by firm i, L_{it} is the amount of labor hired by the firm i, α is the labor share, and w_{ijt} is the share of intermediary input j in total intermediary input cost of firms; $w_{ijt} = \frac{X_{ijt}}{\sum_{k \in N_t} X_{ikt}}$. The production network, W_t, is defined by the weights of those intermediary inputs w_{ijt} at time t. In turn, the productivity parameter $A_{it}(Z_{it})$ is assumed to be determined by the network linkages of the firm: $Z_{it} = \{j \mid w_{ijt} \geq 0\}$. $\zeta_{it} = \alpha^{-\alpha} \prod_{j \in Z_{it}} (1-\alpha) w_{ijt}^{-(1-\alpha)w_{ijt}}$ is a normalization factor.

In the following, we shall only consider production networks where all intermediary input weights of a firm are equal. That is letting one has for all j, $w_{ijt} = \frac{1}{|Z_{it}|}$.

Definition of Equilibrium:

Within a given period t, the set of firms N_t and their input-output linkages are fixed. In this setting, we assume that agents' behavior is consistent with the general equilibrium of the corresponding economy by following Acemoglu and Azar (2020). The competitive equilibrium of the economy is determined as follows.

Definition 1. *A competitive equilibrium of the economy in period t is a combination of prices P^*, consumption plans of the household C^*, labor L^*, and intermediary inputs X^* of the firm, and output Y^* such that.*
1. The consumption plan C^* is a solution utility maximization problem of the representative household

$$\begin{aligned} \max_{C_t} \quad & U(C_{1t}, C_{2t}, ..., C_{nt}) \\ \text{s.t.} \quad & \sum_{i \in N_t} P_{it} C_{it} \leq 1, \end{aligned}$$

where $C_t = \{C_{it}\}_{i \in N_t}$.
***2. The price of each firm is equal to its production cost (assuming a contestable market structure)**, i.e.*

$$P_{it}^* = K_i(Z_{it}, A(Z_{it}), P_t^*)$$

where $K_i(Z_{it}, A(Z_{it}), P_t)$ is the cost function defined as the value of the prob-

lem

$$\begin{aligned}\min_{L_{it}, X_{it}} \quad & L_{it} + \sum_{j \in Z_{it}} X_{ijt} P_{jt} \\ \text{s.t.} \quad & A_{it}(Z_{it}) \zeta_{it} L_{it}{}^{\alpha} \prod_{j \in Z_{it}} X_{ijt}^{(1-\alpha) w_{ijt}} = 1.\end{aligned}$$

3. The Market clearing conditions hold:

$$\textit{For each } i \in N_t \; Y_{it}^* = C_{it}^* + \sum_{j \in N_t} X_{jit}^*,$$
$$\sum_{i \in N_t} L_{it}^* = 1.$$

Under the above setting, we obtain the conditional input demands for each firm $i \in N_t$:

$$L_{it}^* = \frac{\alpha \prod_{k \in Z_{it}} P_{kt}^{*\,(1-\alpha) w_{ikt}}}{A(Z_{it})},$$
$$X_{ijt}^* = \frac{(1-\alpha) w_{ijt} \prod_{k \in Z_{it}} P_{kt}^{*\,(1-\alpha) w_{ikt}}}{A(Z_{it}) P_{jt}^*},$$

by solving the first order conditions in the cost minimization problem for L_{it}^* and X_{ijt}^*, and by substituting those in the production function of each firm $i \in N_t$. Note that we assume the wage of the representative household is 1. To obtain the unit cost function, we substitute the above conditional input demands in the objective function of the cost minimization problem. The unit cost of any firm $i \in N_t$ is

$$K_i(Z_{it}, A(Z_{it}), P_t^*) = \frac{\prod_{j \in Z_{it}} P_{jt}^{*\,(1-\alpha) w_{ijt}}}{A_i(Z_{it})}. \tag{2.3}$$

By using the contestable market assumption and taking the logarithm of the unit cost function, we get

$$p_{it}^{*} = \sum_{j \in Z_{it}} (1-\alpha) w_{ijt} p_{jt}^{*} - a_{it},$$

where p_{it}^{*} is logarithm of the optimal price of the product $i \in N_t$.

Proposition 1. *After rearranging the system of equations for equilibrium price levels of each firm $i \in N_t$, we obtain*

$$p_t^{*} = -[\mathbf{I} - (1-\alpha)W_t]^{-1} a_t(Z_t), \tag{2.4}$$

where p_t^{*} is the vector of the log prices, $a_t(Z_t)$ is the vector of log productivities and W_t is weight matrix at period t.

Both the vector of log productivities and the weight matrix is obtained by the input sets of the firms $Z_t = \{Z_{it}\}_{i \in N_t}$. At each period t, the nominal GDP is total consumption by the representative household which is equal to the labor income: $GDP_t^N = \sum_{i \in N_t} P_{it}^{*} C_{it}^{*} = 1$. The real GDP is the total utility of the representative household. Note that the optimal consumption level of any product $i \in N_t$ is obtained from the utility maximization problem: $C_{it}^{*} = \frac{1}{n_t P_{it}^{*}}$. After substituting this into the utility function, we get the real GDP, GDP_t, which is the deflated nominal GDP:

$$GDP_t = \frac{1}{\prod_{i \in N_t} P_{it}^{*\frac{1}{n_t}}}.$$

Proposition 2. *The logarithm of real GDP in this economy is given as a function of the choices of input sets and log productivities of firms:*

$$g_t^{*} = \frac{1}{n_t} \mathbf{1}' [\mathbf{I} - (1-\alpha)W_t]^{-1} a_t(Z_t), \tag{2.5}$$

where $\mathbf{1}$ is the $n_t \times 1$ vector of ones.

2.3.2 Evolution of Production Network

In our setting, firm decisions on input combinations determine aggregate outcomes through production network structure. In this subsection, we propose a model of the evolution of the production network driven by the entry of a new firm at each period t. The network formation in each period t unfolds as follows: Given a specific production network and productivity distribution in the period $t-1$, a new firm e makes decisions about its input combination by evaluating a specific set of potential input combinations for the period t. Subsequently, existing firms determine whether to adopt the new firm e as a supplier for the period t. Decisions made by the new firm e and the existing firms about their input sets determine the subsequent production network structure and productivity levels. Given the input weights in production and productivity levels for each firm, the general equilibrium economy is defined for the period t.

Acemoglu and Azar (2020) proposes that each firm has $n_t - 1$ possible inputs to combine at any time t. That means firms have 2^{n_t-1} ways of combining those different inputs. This proposition is restricted by the assumption that firms behave boundedly rationally to explore all possible input combinations. Therefore, we restrict the technological possibilities of new firms on the basis of their category/sector of operation and their openness to new innovative inputs. Typically, firms operate with similar technologies as their competitors, differentiating themselves horizontally through a small set of incremental inputs. Carvalho and Voigtländer (2014) supports this viewpoint, suggesting that firms within the same sector share commonalities in their input portfolios essential for producing products of their sector. Each firm also incorporates optional and incremental inputs, distinguishing its products from others.

We define the categories within the production network endogenously. The categorization is based on the similarity in firms' input choices. Each category encompasses firms producing technologically similar products with shared inputs in their production processes. These shared inputs are essential for producing products technologically akin to those in the category.

At period t, the new firm e randomly chooses a category to enter the market in view of producing a product technologically aligned with that of firms in the category. The categorization of firms in the preceding period $t-1$ further guides the new firm e in exploring inputs by defining sets of essential and potential inputs corresponding to the targeted category.

Endogenous Categorization of Firms:

We employ an agglomerative categorization algorithm to organize the firms into distinct categories. This algorithm relies on proximity measures that assess the common characteristics of objects. Within this algorithm, firms can undergo hierarchical agglomeration until they are all consolidated into a single category. We halt the merging process once a predetermined number of categories is reached to prevent over-agglomeration. Agglomerative categorization algorithms utilize various proximity measures.[2] To specifically categorize firms based on similar technology, we adopt the proximity measure proposed by Chen et al. (1995), incorporating an extension that enables the measurement of similarity among more than two firms.

At any period t, we start the algorithm by categorizing the set of firms, N_t, into n_t singleton categories: $H_t(0) = \{\{1\}, \{2\}, ..., \{n_t\}\}$. Furthermore, utilizing the firms' input sets, we define an $n_t \times n_t$ adjacency matrix M_t such that the entry m_{ijt} of this matrix is 1 if the firm j 's product is used by the firm i in its production process at period t.

For all categories $K_0, S_0 \in H_t(0)$, we measure the proximity between their member firms $i \in K_0$ and $j \in S_0$:

$$\Phi_{K_0,S_0,t} = \min\left\{\frac{\sum_{k\in N_t} m_{ikt}m_{jkt}}{\sum_{b\in Z_{it}} m_{ibt}}, \frac{\sum_{k\in N_t} m_{ikt}m_{jkt}}{\sum_{b\in Z_{jt}} m_{jbt}}\right\}. \tag{2.6}$$

[2] For a comprehensive survey of the literature, refer to Day and Edelsbrunner (1984) and Xu and Wunsch (2005).

Let us say K_0 and S_0 are the categories with the highest proximity measure. We combine those two categories in a higher category, $G_1 = K_0 \cup S_0$ or $G_1 = \{i, j\}$. After that, we revise the set of categories as $H_t(1) = \{\{1\}, \{2\}, ..., \{G_1\}, ..., \{n_t - 1\}\}$. As for the second stage, we measure the proximity between the new category $G_1 = K_0 \cup S_0$ and the others, $H_t(1) \setminus G_1$. The present algorithm differs from the previous ones in measuring proximity between more than two firms. In order to find the proximity between G_1 and any other category $J_1 \in H_t(1) \setminus G_1$, we measure the proximity between the firms $i, j \in G_1$ and $l \in J_1$ in such a way that

$$\Phi_{G_1,J_1,t} = \min\left\{\frac{\sum_{k\in N_t} m_{ikt}m_{jkt}m_{lkt}}{\sum_{b\in Z_{it}} m_{ibt}}, \frac{\sum_{k\in N_t} m_{ikt}m_{jkt}m_{lkt}}{\sum_{b\in Z_{jt}} m_{jbt}}, \frac{\sum_{k\in N_t} m_{ikt}m_{jkt}m_{lkt}}{\sum_{b\in Z_{lt}} m_{lbt}}\right\}.$$

More formally, the proximity between any two categories K and S is the proximity between the firms in both categories such that

$$\Phi_{K,S,t} = \min\{\phi_{it} \ \forall \ i \in K \cup S\}, \tag{2.7}$$

where

$$\phi_{it} = \frac{\sum_{k\in N_t} \prod_{c\in K\cup S} m_{ckt}}{\sum_{b\in Z_{it}} m_{ibt}}. \tag{2.8}$$

This term enables us to compare the share of the common inputs in the input basket of each firm $i \in K \cup S$. Combining K and S into a higher category implies that the common inputs among its members are essential for producing similar products.

We iterate the process of agglomeration of categories $n_t - h$ times until we get h different categories. We partition the set of firms N_t into a set of categories $H_t(n_t - h) = \{1, 2, \ldots, h\}$. A $n_t \times h$ matrix is defined such that, each entry $h_{iK} = 1$ if the firm i is belong to any category $K \in H_t$.

Link Formation Process:

In this part, we describe how a new firm e determines its set of input suppliers and how existing firms decide whether to adopt e's product as an input. The process defines the input share parameters that characterize the new firm's production function. At the same time, the entry of firm e reshapes the production network by altering the input share parameters of its customers' production functions. The updated production networks and input shares lead to new general equilibrium economy.

At any period t, the new firm e randomly selects a category $K \in H_{t-1}$, formed in the preceding period $t-1$. The category K determines the choice set of firms which is a subset of all possible input combinations $2^{n_{t-1}-1}$. We consider 2 scenarios for the input choice process of the entrant firm. These scenarios aim at illustrating the impact of difference in innovation behavior on the formation of production networks and the resulting macro-economic dynamics. Scenario A represents the most focused/myopic innovation behavior as firms only search for inputs within the existing set of suppliers of their sector. Scenario B allows the search of an extended set of candidate input combinations with an input from the other suppliers that are not linked to the targeted category. In Scenario B, it is more possible to make more differentiating input combinations within the target categories. More precisely, each scenario is characterized as follows.

Scenario A "Focused Search": In this scenario, the new firm e searches for inputs exclusively from suppliers of firms belonging to the targeted category K without considering alternative sources. The new firm e decides on its input set by evaluating the union of the input sets of firms in the targeted category: $D = \bigcup_{i \in K} Z_{it-1}$. We characterize **the set of essential inputs** of the firms in the category K as the intersection of input sets of those firms at period $t-1$: $E = \bigcap_{i \in K} Z_{it-1}$. We propose that the new firm uses the essential inputs along with additional inputs from the set $F = D \setminus E$, where

D represents the union of input sets and E represents the essential input set. The choice set of potential input combinations for the new firm e is denoted as $\Omega_e^A = \{E \cup f \mid f \in 2^F\}$ where 2^F denotes the power set of the set F. The new firm chooses the most beneficiary input combination, Z_{et}^*:

$$Z_{et}^* \in \underset{Z_{et} \in \Omega_e^A}{\operatorname{argmin}} K_e(Z_{et}, A(Z_{et}), P_{t-1}^*)$$

where the unit cost function $K_e(Z_{et}, A(Z_{et}), P_{t-1}^*)$ is defined based on the Equation 2.3:

$$K_e(Z_{et}, A(Z_{et}), P_{t-1}^*) = \frac{\prod_{j \in Z_{et}} {P_{jt-1}^*}^{(1-\alpha)w_{ejt}}}{A_e(Z_{et})}.$$

The cost function $K_e(Z_{et}, A(Z_{et}), P_{t-1}^*)$ is defined as the ratio of the product of input prices P_{jt-1}^*, raised to the power of $(1-\alpha)w_{ejt}$ for all j in Z_{et}, divided by the new firm's productivity level $A(Z_{et}^*)$, which will be defined below in subsection 2.3.3. This implies that the choice of inputs influences the cost structure and, consequently, the productivity of the new firm e. It is important to note that we assume no firm utilizes its own product as input so the new firm needs price information for the existing firms.

Acquisition of Customers: After the new firm has made an input choice, customers of the firms within its targeted category evaluate the new firm as a potential supplier based on two key factors: the technology level, $A(Z_{et}^*)$ and the unit cost $K_e(Z_{et}^*, A(Z_{et}^*), P_{t-1}^*)$ which is an expected price for the new firm e, represented as P_{et}. Customers in the targeted category are then given the flexibility to either add the new firm to their set of suppliers or replace one of their existing suppliers in the targeted category with the new firm.

For any customer c of the firms in the targeted category, it updates its supplier set by considering the potential substitution or addition of the new firm. That is the firm aims to choose an updated set of suppliers in $\Omega^c =$

$\{C \subset Z_{ct-1} \cup \{e\} \mid |C| \geq |Z_{ct-1}|)\}$. It can either simply add the new firm to its current set of suppliers, substitute an old supplier by the new firm or leave the set of supplier unchanged. This choice is made by determining the most cost efficient input combination, that is:

$$Z^*_{ct} \in \underset{Z_{ct} \in \Omega^c}{\operatorname{argmin}} K_c(Z_{ct}, A(Z_{ct}), (P^*_{t-1}, P_{et})).$$

If the new firm e successfully acquires at least one customer, it integrates the production network.

Scenario B "Perturbative Search": In this scenario, the new firm e searches inputs among the suppliers of firms in its target sector but also broadens the technological landscape by searching for one additional input among other firms. In other words, the firm chooses either (i) an input combination in Ω^A_e (as in scenario A) or (ii) an input combination in Ω^A_e together with one additional input. Formally, the choice set of the firm is $\Omega^B_e = \Omega^A_e \cup \{G \cup \{f^B\} \mid G \in \Omega^A_e \wedge f^B \in D^B\}$ where $D^B = N_{t-1} \setminus D^A$. The behavioral rules regarding the new firm's choice of cost-efficient input combinations and the targeted category customers' evaluation of the firm remain as in Scenario A.

2.3.3 Productivity Function

Acemoglu and Azar (2020) suggests that the productivity of the firms depends on the given parameters of their inputs and a random term drawn from a Gumbel distribution. We propose a micro-founded perspective on productivity, where a spatial auto-regressive linear relationship determines a firm's productivity as a function of the productivity levels of its suppliers. This spatial auto-regressive model captures the spillover effects in the production network.

More precisely, we assume that the log-level technology of a firm i, $a_{it} =$

$\log(A_{it})$, depends explicitly on the productivity levels of its input suppliers. Formally, we define:

$$a_{it}(a_{jt} : j \in Z_{it}) = \lambda_0 + \lambda_1 \sum_{j \in Z_{it}} m_{ijt} a_{jt} + \epsilon_{it}, \tag{2.9}$$

where λ_0 is the constant technology parameter and λ_1 is the parameter that captures the strength of technological dependence among firms in the production network. The term ϵ_{it} is a random disturbance drawn from an exponential distribution. This productivity function formalize firms' productivity levels as considering their input suppliers and their productivity levels.

A Summary of the Model:

Before proceeding with the simulations, let us summarize the main assumptions of our model. The production network formation model is grounded on **the endogenous technology** definition in which firms' input combinations determine their production technology. Firms strategically consider different input combinations, facing a trade-off between higher productivity and higher production costs when adopting additional inputs. Firm entries trigger the evolution of the production network. Firms are **boundedly rational**: They have limited information about all possible input combinations and search the technological landscape, focusing on the inputs of their target categories. Those categories are groups of firms sharing highly similar input sets within the production network. **The categories are endogenously** defined: as production networks evolve with firm entries, those categories also evolve. **Technological proximity/homogeneity** - how firms are similar in their input combinations - within the categories also evolves with new production network reconfigurations. Evolving technological homogeneity within the categories influences the future entrants' input combinations and, in turn, their productivity levels.

The entrant firms may exhibit different behaviors in searching for additional inputs, thereby differentiating themselves from their target categories. To analyze this **behavioral mechanism in production network formation**, we define two scenarios regarding firm search behavior:(A) Focused search, and (B) Perturbative search. These scenarios differ in how far firms deviate from existing input sets of their target categories.

These assumptions create a dynamic feedback loop between firms' innovation decisions and the evolving network structure. We aim to capture how heterogeneous innovation behaviors generate distinct evolutionary patterns of technological homogeneity and how new-firm productivity levels are influenced by these patterns. In the model, log-real GDP evolves through continuous-form firm entries with endogenous productivity and production network structure.

2.4 Simulation Results

To simulate our model, we first generate an initial random network as follows.

- We consider a set of 250 firms and assign them into 5 categories of equal size (i.e. 50 firms per category).
- We first draw 1 to 5 random suppliers for each firm within each category.
- We then draw randomly between 20 and 30 essential input suppliers. Each firm in the category is connected to these suppliers. [3]

As described in the previous sections, the evolution of the network is driven by the following sequence of steps.

1. We apply the categorization algorithm to the production network[4]. This determines in particular the essential inputs as those used by all firms in the category.

[3] The number of such essential suppliers is first drawn uniformly between 20 and 30, and then the corresponding suppliers are drawn. This implies high homogeneity of initial input combinations within a category.

[4] As introduced in section 3.2.1, the categorization algorithm has a predefined number

2. We compute firms' productivity levels using the spatial auto-regressive model defined in the previous section and adding random errors from an exponential distribution.[5]

3. Given the productivity vector and the production network, we determined equilibrium prices and real-GDP. [6]

4. We then consider the entry of a new firm.

5. The new firm chooses its category at random.

6. The input choice set for the new firm is given by the essential inputs of the category together with the additional inputs specified by the link formation scenarios, i.e. "focused search", or "perturbative search". Input combination within this additional set are determined by choosing the combination that gives the lowest cost given the price vector P^*_{t-1} and the spatial auto-regressive model of technology.[7]

7. For each customer of the targeted category, define the choice set as defined in the previous section. If any input combination, including the new firm, enhances efficiency for the customers, adjust the production network by introducing the new firm and its corresponding input-output linkages.

---

of categories for any given period t. Initially, we start with 5 categories for 250 firms. As time progresses, we increase the number of categories proportionally to the number of firms (more precisely the number of categories corresponds to the quotient of the number of firms divided by 50). The partitioning of firms into categories evolves as technological change modifies the structure of the production network.

[5]We assume $\lambda_0 = 0$ and $\lambda_1 = 0.004$ for simplicity and keeping the effect of new input adaptation limited.

[6]We assume $\alpha = 0.6$ that is an approximation to labor share data of the US Bureau of Labor Statistics.

[7]The new firm's productivity is estimated for all potential input combinations using the existing firms' prices and productivity as a basis at time $t-1$.

8. Monitor firms losing all customers and remove them from the network. Iterate this process until all firms have at least one customer.[8]

9. Iterate this process for 1000 periods.

2.4.1 Evolution of Production Network Structure

Below, we report the result of an ensemble of 100 Monte-Carlo simulations for each scenario. We first analyze the impacts of the search scenarios on the evolution of the network structure.

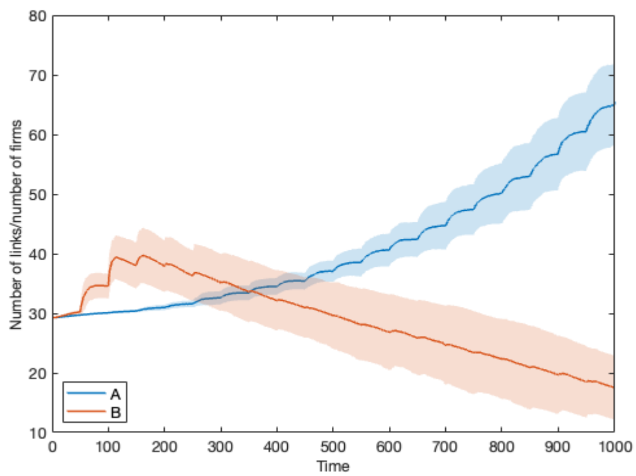

Figure 2.1: Evolution of the network density over time (mean and 1 Std.).

Figure 2.1 shows the evolution of network density. In the focused search scenario (A), network density grows monotonically. In the perturbative search scenario (B), the network density follows a non-monotonic path. It increases rapidly until period 150 and then decreases steadily.

[8]It is noteworthy that new firm entries may cause cascading exits in the economy because new firms get customers of the firms within their target category, subsequently leading to the exit of firms losing all their customers. This, in turn, causes their supplier linkages to disappear, potentially resulting in the exit of their suppliers if they are the sole customer.

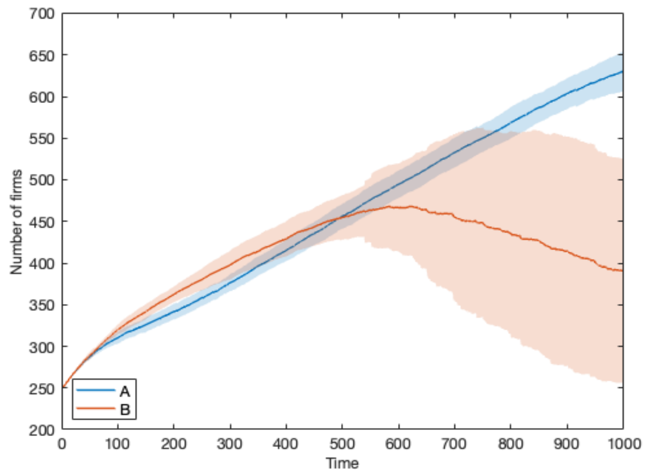

Figure 2.2: Evolution of the number of firms over time (mean and 1 Std.).

As for the evolution of the degree distribution, Figure 2.3 highlights that the in-degree distribution is initially highly homogeneous, highlighting the predominance of essential inputs in the network. The distribution becomes more heterogeneous over time. In particular, in the focused search scenario, nearly 50% of firms have less than 50 in-degrees, while 40% have more than 100 in-degrees.

Conversely, the initial predominance of essential inputs implies that the out-degree distribution is initially heterogeneous. There are 20-30 essential inputs for all firms in a category with 50 firms. Therefore, those essential input suppliers have at least 50 customers. That causes an unequal distribution of out-degrees in our initial network. This inequality in out-degrees decreases over time through new firm entries. In the perturbative search scenario (B), the extension of the input choice set reduces inequality between essential input suppliers and other suppliers. In the focused search scenario (A), where firms are restricted to searching within the category, some inequality persists, suggesting the continued presence of essential inputs.

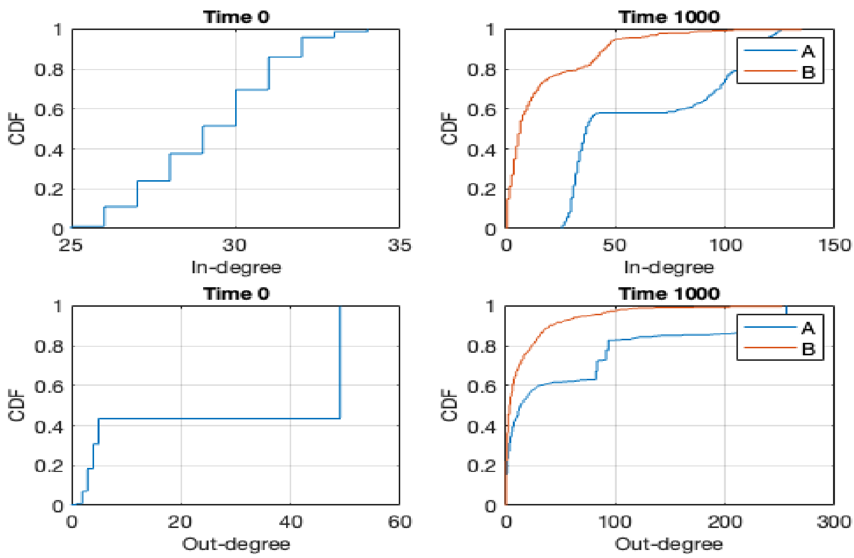

Figure 2.3: Degree distributions at Time-0 and Time-1000

2.4.2 Drivers of Production Network Evolution

In this subsection, we analyze in more detail the determinants of the structural evolution of the network. Technological homogeneity, i.e., the similarity of input combinations of firms within a category, will appear as a key characteristic of the network in this respect. In our setting, technological homogeneity can be measured through the notion of proximity of a category $\Phi_{K,t}$ that is defined as follows.

$$\Phi_{K,t} = \min \left\{ \phi_{it} \; \forall \; i \in K \right\}, \tag{2.10}$$

where

$$\phi_{it} = \frac{\sum_{k \in N_t} \prod_{c \in K} m_{ckt}}{\sum_{b \in Z_{it}} m_{ibt}}. \tag{2.11}$$

The technological homogeneity measure decreases with the number of essential inputs that are common in input sets of all the members. Initially, categories in the production network are the same size, and the technological homogeneity measures within the categories are high. Over time, homogeneity within the categories drops in both scenarios and more significantly in the perturbative search scenario (B). In other words, in the scenario where firms are more innovative in their input combinations, the economy becomes less homogeneous technologically. Accordingly, new firms enter less homogeneous categories over time.

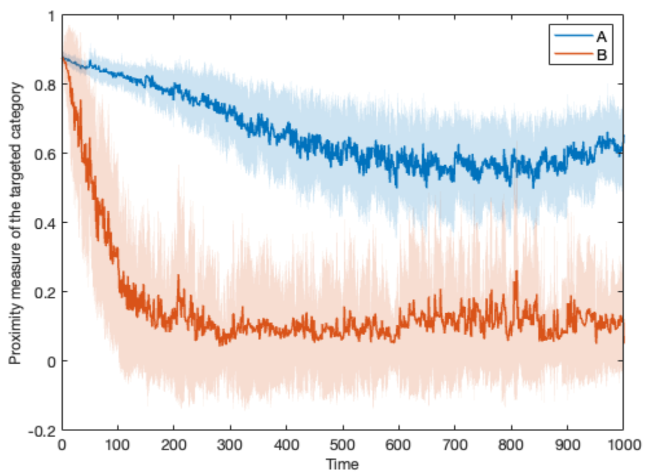

Figure 2.4: Evolution of the proximity measure of targeted categories (mean and 1 Std.).

Figure (2.4) highlights more specifically a rapid decrease in technological homogeneity until period 150 in the perturbative search scenario (B). This drastic decrease is related to the decrease in network density observed in these scenarios after period 150 (see Figure 2.1). The homogeneity of categories significantly influences the subsequent firms' decisions on input combinations, affecting their productivity and ability to acquire customers. The firms that enter less homogeneous categories have fewer inputs because less homogeneous categories have fewer essential inputs that all the firms in that category ought to use (See Figure 2.5). In the focused search scenario (A), the new firms always search for inputs as similar to the firms within the target category, and thus, technological homogeneity does not decrease substantially over time. On the contrary, new firms search for inputs outside of their category in the perturbative search scenario. The perturbative search reduces technological homogeneity and the number of essential inputs. In these scenarios, firms thus have fewer connections on average (see Figure 2.5).

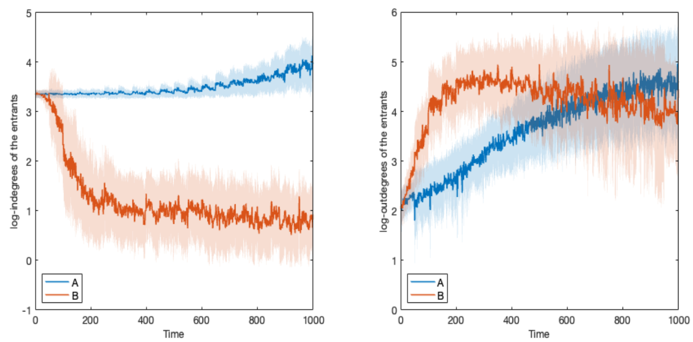

Figure 2.5: Evolution of log-degrees of the new firms (mean and 1 Std.).

Technological homogeneity within categories determines the productivity levels of new firms over time as a result of our defined behavioral rules on search input combinations. Figure 2.6 illustrates the correlation between the productivity of new firms and technological homogeneity within their targeted categories (Average values for 100 simulations). In the focused search scenario (A), there is a negative correlation between the new firms' productivity and the homogeneity of their target category. Since we restrict new firms to search only for incumbents' inputs in the category, they have fewer options to expand and differentiate their input combinations, leading to higher productivity. Therefore, new firms are more productive when they enter less homogeneous categories with more innovative/differentiating input combinations by existing firms. However, in a more innovative environment with less homogeneous categories (scenario B), the correlation between new firms' productivity and homogeneity within their target categories is positive.

That means new firms are more productive when they enter more homogeneous categories. However, entering more homogeneous categories becomes progressively more difficult with decreasing homogeneity.

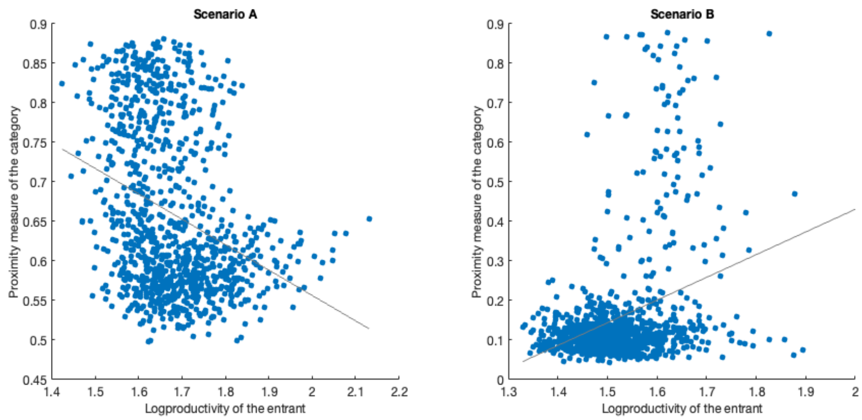

Figure 2.6: Correlation between new firms' log-productivity and the proximity measure of their target categories. Scenario A: -0.32; Scenario B: 0.33.

Notably, the innovative behaviors represented in our focused and perturbative search scenarios are related to firms' innovation capacity. If firms have limited capacity to adopt more differentiating inputs, they prefer to imitate their competitors. For instance, in scenario (A), the technological homogeneity of categories remains relatively high, with the entries of firms with lower innovation motivation. New firms with limited innovation motivation achieve higher productivity by entering less homogeneous categories, as this enables some differentiation in input combinations. Those firms benefit from using many additional inputs that incumbents already use and from combining them in an optimal way, resulting in a high level of differentiation. In the perturbative search scenario (B), the continuous flow of innovative/differentiating firm entry leads to a less technologically homogeneous economy. In this environment, where every firm is radically differentiated, standardization of production processes would benefit new firms by allowing them to adopt standardized essential inputs. Standardization in input combinations can be achieved by the diffusion of differentiating input combinations in prospective periods. However, in our setting, incumbent firms do not adjust their input choices. Therefore, as firms enter the relatively less homogeneous categories, they have fewer common inputs with the incumbent firms. Even if they search an extended set of input combinations in scenario (B), compared to scenario (A), they have fewer inputs with less technology flow from them. This process leads to lower productivity levels for the entrant firms over time. This result stems from our assumptions that input choices determine productivity and that input choices are boundedly rational, determined by the target categories.

2.4.3 Evolution of Macro-economic Outcomes

So far, we have explained how firms' input search behaviors determine the technological homogeneity within categories, which, in turn, affects subsequent firms' input combinations and productivity levels. The correlation between productivity and technological homogeneity varies depending on the innovative environment prevalent in the economy. In the less innovative environment, denoted as focused search scenario (A), there is a marginal decrease in homogeneity within categories. This scenario shows a negative correlation between technological homogeneity and productivity. Consequently, firms that enter less homogeneous categories attain higher productivity levels with additional inputs that differentiate more and with essential inputs of their target categories. Despite the modest decline in technological homogeneity, this trend positively affects the productivity of new firms over time in scenario (A). Therefore, there is an observable upward trend in evolution of average productivity levels and real GDP, as depicted in figures 2.7 and 2.8.

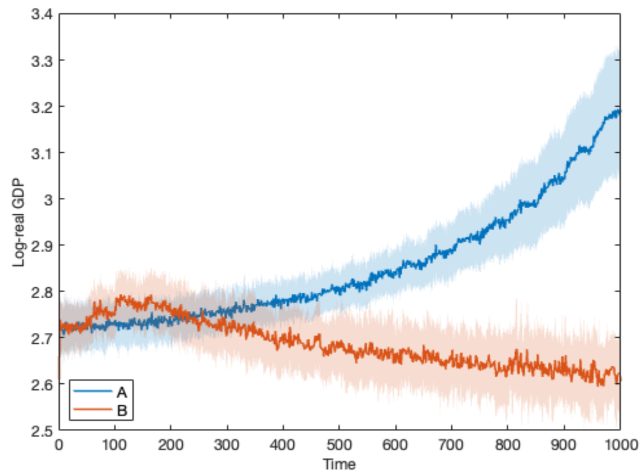

Figure 2.7: Evolution of real GDP under different scenarios (mean and 1 Std.).

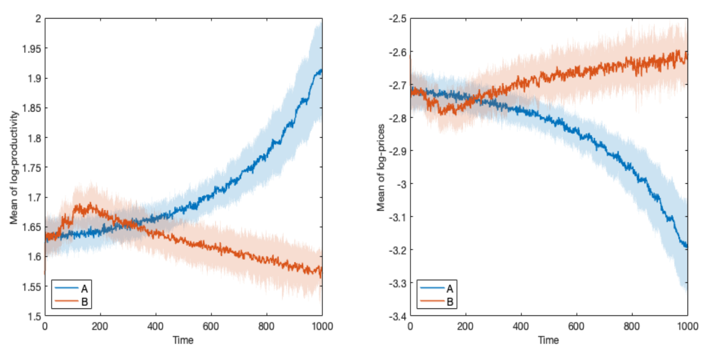

Figure 2.8: Evolution of the average log-productivity and log-prices over time (mean and 1 Std.).

Conversely, in the more innovative environment (scenario B), we observe that homogeneity within categories drops drastically, resulting in less homogeneous environments. The positive correlation between technological homogeneity within target categories and entrants' productivity levels is evident in this scenario. Despite firms seeking a broader, more differentiating set of inputs to adopt, as well as the essential inputs of their target categories, they have lower productivity levels. Increasing productivity with additional inputs becomes unattainable as technological homogeneity declines sharply (Figure 2.4). As a result, the economy experiences a short-term increase in log-real GDP and productivity, followed by a decline. The log-real GDP and average productivity trends are inverted-U shaped, with the peak point occurring when technological homogeneity approaches zero, as illustrated in figures 2.7 and 2.8.

Additionally, in the perturbative search scenario (B), new firms fail more frequently when entering the production network (319 firms fail out of 1000 trials on average across 100 simulations). In comparison, in the focused search scenario (A), only 5.3 firms fail to acquire a customer and to enter the network. Further new firm entries lead slightly more exits in scenario (A) than in scenario (B) (612.5 vs 540.7 on average). Therefore, the number of firms and the network density also have an inverted-U shape in scenario (B).

To sum up, the simulation results emphasize the importance of the mutual interaction between firms' innovative behaviors, represented by input search rules, and the production network structure, represented by firm categorization. Our scenarios regarding firms' innovation behaviors represent the two distinct innovative environments. In scenario A, as more firms enter the economy with less differentiation motivation, technological homogeneity within categories is sustained. However, in scenario B, as more firms enter the economy with more differentiated input combinations, technological homogeneity drops drastically. Those trends determine the environment for the subsequent firms and their performance. Understanding this mechanism is vital for understanding the significance of innovation behaviors at the micro-level in determining macroeconomic outcomes. Firms' search behaviors determine technological homogeneity across the economy, which, in turn, feeds back on the input search process of subsequent firms.

The results indicate that dispersed innovation in dynamic environments might have a negative impact on the economy, arising from decreasing technological homogeneity. This finding holds implications for the evaluation of innovation policies across different economies. In real economies, sectors/categories vary in technological homogeneity: while some are highly homogeneous in their production inputs, others are not. However, innovation policies mainly spur all firms toward more differentiated technologies. Our model suggests that innovation policies must consider sectors/categories as endogenous and technological homogeneity within those sectors/categories. Policymakers designing innovation policies should carefully consider technological homogeneity within sectors/categories and innovative behaviors of potential new firms. It's crucial to consider individual behavioral differences and innovative environments within the economy when formulating innovation strategies at the micro level and innovation policies at the macro level.

In cases where the economy exhibits heterogeneity in technology choice and features innovative firms, policymakers should explore avenues to standardize firms' production processes. This standardization can lead to improved input combinations and higher productivity levels for new firms. Achieving standardization necessitates the harmonization of existing firms' knowledge and experience. Therefore, policies oriented toward fostering open innovation processes can facilitate attaining an optimal level of technological homogeneity within the economy.

2.5 Conclusion

This chapter contributes to understanding the interplay between technology, production network structure, and economic dynamics. We argue that production technology is determined by input choices, and we develop a production network-formation model grounded in a general equilibrium economy. The input choices are influenced by firms' search behaviors and their target sectors/potential competitors. We employ a categorization algorithm, characterized by its fuzzy and dynamic nature, based on firms' common inputs to identify potential competitors, indicating technological proximity among firms.

Our network formation model involves scenarios that capture different dimensions of new firms' search for additional inputs, thereby indicating their innovation behavior. The primary objective of new firms is to produce a product closely aligned with the technology of existing firms within a randomly selected category. This is achieved by using essential inputs alongside additional inputs. In the focused search scenario (A), new firms explore all combinations of additional inputs from firms within the selected category. In the perturbative search scenario (B), new firms search for an additional input from the remaining firms, as well as the inputs in scenario (A).

The simulation results highlight that the paths of production networks' structural evolution differ based on the innovative behaviors of entering firms. This difference results from the dynamic interplay between technological homogeneity within categories and input/technology choices of entrant firms. Although technological homogeneity decreases in all scenarios, it is more pronounced in the highly innovative environment (Scenario B), as expected.

The impact of decreasing technological homogeneity on the productivity of entering firms varies significantly under these scenarios. In the focused search scenario (A), a negative correlation exists between technological homogeneity in the targeted category and new firms' productivity. Despite the gradual decrease in technological homogeneity, it benefits new firms that require less homogeneity to achieve higher productivity, thereby driving sustained growth in real GDP.

On the other hand, in the perturbative search scenario (B), there is a positive correlation between technological homogeneity in the targeted category and the productivity of new firms. New firms achieve higher productivity by entering highly homogeneous categories, contradicting the significant decrease in homogeneity due to the entry of more innovative firms. Consequently, the real GDP follows an inverted U-shaped trend, reaching its peak when technological homogeneity approaches almost zero. Given the low level of technological homogeneity and the presence of more disrupted categories, being innovative in input combinations does not lead to higher productivity. These findings illustrate the evolving effects of continuous disruptive innovation on economies.

The research findings have significant implications for policy-making. They indicate that economic policies must adapt and take into account the innovation environment and behavioral differences across economies. Policymakers should carefully evaluate technological homogeneity across sectors and firms' innovative behavior, recognizing that sustained radical innovation may not always lead to optimal economic outcomes. The study also highlights the importance of promoting open innovation processes and standardization in production, thereby increasing sectoral homogeneity.

In conclusion, this research enhances our comprehension of the complex relationship between innovation, production network structure, and economic dynamics, providing valuable insights for policymakers, researchers, and practitioners navigating the complexities of modern economies.

Chapter 3

Exploring Sources of Dynamism in Production Networks

Abstract

The study examines the dynamics of production network evolution, focusing on firms' strategic decisions on supplier choices and their impact on firm performance. We investigate the input-output relationships between firms and introduce two metrics to evaluate firms' supplier sets: (i) the overall supplier set relatedness metric, which measures how a firm's supplier set differs from others, and (ii) the Jaccard Distance Metric to measure how a firm's supplier set changes over time. These metrics enable us to analyze dynamism in production networks and firm performance variations, using firm-to-firm transaction data from Turkey (2010-2021). The empirical analysis provides meaningful insights into the factors driving supplier linkage formation and the relationship between firms' supplier-relatedness and performance. The findings contribute to the relatedness literature with a resource-based approach.

Keywords: Technological change, production networks, relatedness economics.

Note. This chapter is a joint work with Seyit Mumin CILASUN.

3.1 Introduction

The definition of the modern economy is a network of specialized production units that use intermediary inputs produced by other specialized units (Carvalho, 2014). Input-output linkages between those production units constitute production networks that evolve with firms' strategic decisions on product diversification, new technology adoption, or adaptation to external shocks. Their strategic decisions impact their performance and aggregated economic outcomes through production networks (Carvalho, 2014; Acemoglu et al., 2012; McNerney et al., 2022). Therefore, it is crucial to understand how firms' supplier choices, triggered by their strategic decisions on product and technology portfolios, affect their performance and, in turn, macro-economic outcomes. In this chapter, we address the growing literature on endogenous production networks, arguing that technological change occurs through the adoption of different inputs (Oberfield, 2013; Carvalho and Voigtländer, 2014; Acemoglu and Azar, 2020). This technological change can be driven by product or process innovation, but both lead to the evolution of inputs and, in some ways, to changes in firms' supplier linkages.

We aim to contribute to the literature by focusing on the micro-level interactions between firms through technology/input choices. Building on the technology definitions of Arrow and Debreu (1954) and Elliott and Jackson (2023), we conceptualize a framework in which firms' technology sets influence their supplier sets, thereby influencing the structure of production networks. We have developed two primary measures to evaluate firms' supplier set differentiation and evolution: (i) the overall supplier set relatedness, which indicates the differentiation of firms' supplier sets within production networks, and (ii) the Jaccard Distance metric for two consecutive periods' supplier sets, which implies the changes in supplier composition over time. These measures enable us to analyze firms' differentiation across technology sets and to examine firm performance. The measure of overall supplier set relatedness is systematic and depends on the entire production network at a given period. It is the average relatedness between each pair of suppliers within a firm's supplier set. This measure indicates how frequently a firm's suppliers are linked to the common customers.

We empirically analyze Turkey's firm-to-firm transaction data, which was provided by the Entrepreneur Information System (EIS) of the Ministry of Industry and Technology of Turkey. This data set contains administrative records of firm-to-firm transactions exceeding 5000 TL (about 375 USD in 2021) for the period 2010-2021. We merge this data with the balance sheet and the foreign trade data.

The empirical analysis starts with an exploration of the factors triggering firms' supplier adjustments over time: Product portfolio changes, supplier adjustments of peer firms, and Turkey's 2018 currency shock as an external factor. Later, we empirically test the relationship between firms' overall supplier set relatedness and their performance. Our findings suggest that supplier linkage adjustments are associated with adjustments in the product portfolios. We propose a Supplier Adjustment Propagation Measure (SAPM) that captures supplier adjustments across peer firms. The regression results indicate a negative association between supplier adjustments of firms and their structurally related peers. Further, we explore the role of the currency shock that Turkey experienced in 2018 in firms' supplier adjustments. Firms—highly dependent on imports—exhibited significantly lower variation in their supplier compositions. Our findings reveal a significant negative relationship between supplier differentiation and performance indicators, including net sales and labor productivity. Firms with less relatedness (i.e., highly differentiated) supplier compositions exhibit higher net sales and labor productivity.

The remainder of this chapter is organized as follows. Section 3.2 reviews the related literature and discusses the relationship between production networks and technology. Section 3.3 introduces a conceptual framework and measures regarding firms' supplier sets. Section 3.4 presents the data and variables, along with descriptive statistics. In section 3.5, we test our empirical models on production network formation dynamics and firm performance.

3.2 Related literature

3.2.1 Technology and Input-Output Relationships

Dosi and Nelson (2010) defines **Technology**: *"In the most general terms, technology can be seen as a human-designed means for achieving a particular end-being it a way of making steel like the oxygen process, a device to process information, such as a computer, or the ensemble of operations involved in heart surgery. These means often entail particular knowledge, procedures, and artifacts. These different aspects offer different but complementary ways of describing technologies."* As they suggest, technology may appear in different aspects as a recipe, a routine, and an artifact. Technology as a recipe involves a sequence of cognitive and physical activities to achieve specific goals. Recipes outline the design and procedures with the necessary material inputs, machines, and services to achieve final goals, implicitly or explicitly. The procedural definition of technology focuses on the design of devices and procedures utilized to transform raw materials into the final product. Early micro-level models proposed to understand firms' technology through recipes corresponding to various input-output relationships. Shell et al. (1999) suggest that production recipes involve fundamental operations such as heating, mixing, shaping, and packaging, with input requirements contingent upon operation instructions and other factors. Similarly, Kauffman et al. (2000) view recipes as sets of discrete choices—whether qualitative (e.g., choosing between a conveyor belt or forklift for internal transport) or quantitative (e.g., adjusting settings on a machine). Firms seek optimal recipes and procedures to enhance productivity through innovation, repositioning themselves within the complex system of technology by altering its elements and interactions (Frenken, 2006).

Arrow and Debreu (1954) define technology as a production plan representing the list of inputs that are combined to produce a specific output. The neoclassical production theory proposes that firms are endowed with technologically feasible input combinations with some fixed parameters. Romer (1990) presents the variety of capital inputs as a crucial indicator of technology that promotes economic growth. The coherence of inputs in production is essential in defining firms' technological knowledge space. Therefore, evolution in those inputs also indicates the evolution of firms' technological knowledge space. In an economy, the variety of capital goods available for production indicates production technology (Frensch and Gaucaite Wittich, 2009).

Based on the technology's aspect of combinations of different inputs, those definitions of technology direct us to look at input-output relationships. Input-output relationships between producers constitute production networks in economies. Acemoglu and Azar (2020) incorporates production networks in general equilibrium models as a determiner of production technology. They propose that producers choose the most beneficial input combination among many different ways of combining different inputs. In this decision process, producers face a trade-off between high production technology and high production cost by adopting extra inputs in production processes. As Leontief (1965) and McNerney et al. (2022) highlight, production value is accumulated through input-output linkages between firms. At each transaction, firms buy a product produced by another firm and sell it to another firm by adding a value. For example, a semiconductor chip producer sells its products to a computer producer. The value of production of the computer producers is affected by the value added by the semiconductor chip producer. The propagation of technological changes along production networks causes cumulative value-added growth in the economy. Gualdi and Mandel (2019) suggests that technological change is embedded in the structure of production networks and models the effect of process innovation on the overall economy. Although theoretical insights into the interplay between technology and production networks are abundant, empirical studies remain limited due to the challenges of obtaining detailed firm-level data. Nevertheless, recent work by Oberfield and Raval (2021) provides a rare empirical analysis, examining cross-sectional plant data to assess capital-labor elasticity in production, with a view toward extending this approach to a broader range of production inputs. Furthermore, there is growing literature leveraging national firm-to-firm transaction datasets (Bacilieri et al., 2023; Criscuolo et al., 2024). The increasing availability of those data sets has led to reveal the structural properties of production networks across different economies and comparative analysis of firm-level factors.

3.2.2 Drivers of Production Network Evolution

In this part, we review the literature on Production network evolution triggered by changes in firms' input choices. Those changes may be sourced from (1) external shocks that firms have no control on, or (2) Internal dynamics: (2a) Product diversification by introducing new product lines and (2b) Introducing new production technologies.

External Shocks and Network Disruptions

External shocks are critical in influencing production network evolution. Exogenous shocks (e.g., natural disasters, pandemics, political crises, or failures in logistics infrastructure) can hinder a firm's ability to obtain its necessary production inputs. Since firms are embedded in complex production networks, a shock to a firm can propagate through the network, affecting numerous downstream firms and, ultimately, the broader economy.

For instance, the pioneering paper by Carvalho et al. (2020) demonstrates how the shock to the firms that are influenced by the Great East Japan earthquake of 2011 propagates through their customers. Elliott et al. (2022) study the potential disruptive effects of idiosyncratic supply chain failures and conceptualize "supply network fragility" as the sensitivity of aggregate output to small aggregate shocks. Acemoglu and Tahbaz-Salehi (2024) demonstrate that distortions to relationship-specific investments and productivity levels in the normal functioning production networks may have severe macroeconomic consequences.

Potential macro-economic risks sourced from distortions in production networks are also discussed from the policy perspectives (Grossman et al., 2023a,b). The information regarding the entire structure of supply networks is necessary to foresee disruption risks and design prudential policies (Bimpikis et al., 2018).

Internal Dynamics: Firm-Level Product Diversification and Technological Innovation.

Firms also experience internally driven evolution through their diversification and innovation efforts. These internal dynamics play a vital role in reshaping the structure of production networks by altering input combinations.

Product diversification requires new inputs to produce new product lines, potentially leading to changes in firms' supplier linkages. Product diversification is widely studied through measures of relatedness and coherence, beginning with the pioneering paper by Teece et al. (1994). They argue that the similarity of product lines is based on shared resource and capability requirements. They propose a measure of relatedness grounded in the idea that new product lines often resemble existing ones due to similar capability requirements. Therefore, the presence of products within the same firm's product portfolio indicates that those products are related. Diversifying product portfolios is a strategic decision closely tied to the firm's technological capabilities. Expanding product lines requires diversification in technology (Dosi et al., 2022). Technological knowledge accumulates over time and is linked to the current knowledge base used for existing product lines. Firm performance is influenced by the interactions between the product lines.

The relatedness measures are also applied to other indicators regarding firms' diversification, such as technology portfolios, as represented by patent data, and resource compositions, as represented by labor skill sets and intermediary inputs. Those indicators are more efficient for measuring firm diversification in technology portfolios. Diversification in firms' patent portfolios and resource compositions may stem from **new production technology** adoption to produce existing product lines, as well as from altering product portfolios.

Breschi et al. (2003) and Pugliese et al. (2019) study firms' patent portfolios to monitor their technological diversification. According to Breschi et al. (2003), the relatedness of knowledge between different patent technology fields determines technological diversification. On the other hand, the resource-based approach considers technological necessities for production. The resource-based approach states that firms must diversify their resources — such as labor skills or intermediary inputs — to facilitate the production of different products or to adopt different production methods. Fan and Lang (2000), Bryce and Winter (2009), and Essletzbichler (2015) employ industry space mapping, using industry-level input-output relationships to study firm diversification, an approach akin to ours.

Input-output linkages are generally available at transaction values, but there is no explicit identification of the inputs/resources. However, suppliers remain a practical source of information for analyzing firm diversification, as supplier selection is a strategic decision closely intertwined with innovation strategies. Firms seek technological knowledge through supplier relationships (Roy et al., 2004; Hora and Klassen, 2013; Bellamy et al., 2014; Sharma et al., 2020). Therefore, we present a conceptual framework in the next section for how firms' supplier linkages indicate their technology sets based on the technology definition of Arrow and Debreu (1954). Later, we define supplier-set-based measures of relatedness and Jaccard Distance to trace firms' differentiation through their supplier linkages and the evolution of those linkages over time.[1]

3.3 Conceptual Framework

This section outlines the conceptual framework and measurement strategy that links firms' technology sets to their supplier sets. Although it is not a formal equilibrium model, this framework provides the theoretical basis for our empirical measures of firm differentiation in production networks.

We sketch an economy to argue that supplier-set variations indicate technology set variations across firms and over time. Let us assume a set of firms $N_t = 1, ..., n_t$ as productive units at time t. Those firms may produce one or more products. Those products are represented by the set $L_t = 1, ..., l_t$. The set of products produced by a firm $f \in N_t$ is represented by $O_{ft} \subset L_t$. Firms have the necessary technological knowledge to produce those products.

Technologies as Production Plans. In this economy, each product corresponds to a technology as defined by Arrow and Debreu (1954). A technology is a production plan to produce a product k represented by the vector of τ_k. Any production plan τ_k is the list of inputs and a recipe used in the production process of the product k. A recipe is a firm-specific ability, know-how, and procedures to achieve the final product k. Inputs are the other products within L_t that are produced by different production plans. The definition of a technology considers the transformation of inputs into an output. The technological feasibility defines the possibilities within this

[1] We use the term "differentiation" instead of "diversification" because the relatedness measures are systematic, which evolve with firms' decisions as the lowest micro-level productive unit (Juhász et al., 2021; Kuusk and Martynovich, 2021). Those measures indicate how a firm differentiates at a given period. Even if a firm does not change its supplier combinations, its differentiation level may change due to variations in the relatedness of supplier pairs. We will explain this circumstance in more detail in the next section.

transformation process and limits potential input combinations in production processes.

Each technology is capable of producing one product, but each firm can produce multiple products. Therefore, we define the set of technologies assigned to any firm $f \in N_t$ as $T_{ft} = \{\tau_k : k \in O_{ft}\}$. Note that the technology set is a set of sets whose elements are production plans for different products. The economy is endowed with the union of technology sets of firms represented by $T_t = \bigcup_{f \in N_t} T_{ft}$, at any period t.

Assumption 1. *In the defined economy, there are no duplicate technologies:* $\tau_k \neq \tau_l$ *for any* $\tau_k, \tau_l \in T_t$.

This assumption implies that firms never produce exactly the same products, even if any two firms have the same product lines. They use differentiated technology/production plans on some levels. This differentiation may be sourced from their input choices and/or recipes. Firms could produce the same product lines but with different efficiency levels or input intensities. As a real economy example, any two phone producers use different inputs like screens, camera lenses, and recipes by bringing those inputs together in different ways. Those differences correspond to different technology sets.

On the micro level, as firms change their technology sets, those changes affect their technological differentiation and heterogeneity within the overall economy. Input-output relationships between firms represented by firm-level production networks provide insightful information on technological heterogeneity sourced from technology set differentiations across the firms within the economy.

From Technology Sets to Production Networks. Firms' technology choices influence their input requirements and supplier relationships. A firm's technology set, defined by its product sets, necessitates the use of some inputs produced by other firms. The input-output relationships constitute the supplier-buyer linkages between firms. Let's define the production network

$A_t \in \mathbb{R}^N \times \mathbb{R}^N$ which is a $n_t \times n_t$ matrix: each entry $A_{fit} = 1$ if any product $k \in O_{ft}$ (produced by firm f) is relied on any input $l \in O_i$ (produced by firm i) such that the technology τ_k include the input $l \in \tau_k$. In other words, at least one of the products of firm i is used to produce at least one product of firm f. The list of all suppliers of firm f constitutes its supplier set: $Z_{ft} = \{i : A_{fit} = 1\}$.

The above technology and production network definitions highlight that supplier sets relate to technology sets. The first condition of a firm f to be linked to a supplier i is that the firm i produces an input that is necessary for firm f's technology set T_{ft}. The inputs that determine a firm's technology set are sourced from other firms' technologies.

Proposition 3 (Supplier Sets Reflect Technology Sets)**.** *Under the assumption 1, two different supplier sets $Z_{ft} \neq Z_{ct}$ implies two different technology sets: $T_{ft} \neq T_{ct}$. However, the reverse is not true: two different technology sets $T_{ft} \neq T_{ct}$ may source from the same supplier sets: $Z_{ft} = Z_{ct}$.*

The above proposition implies that if any two firms have different supplier sets, it also indicates they have different technology sets. However, firms may have different technology sets even if they do have the same supplier linkages. That is because suppliers may have different products used in different technologies. Despite this complication, differentiation in firms' supplier sets provides information on differentiation in technology sets. Therefore, the present chapter suggests tracing how firms differentiate from others in terms of supplier sets that will indicate technology set differentiations.

3.3.1 Measures of Supplier Set Differentiation and Evolution

We propose to measure how firms frequently supply to the same customers, which indicates their relatedness to other firms' technology/ production plans. Our approach is based on the relatedness literature discussed in Hidalgo et al.

(2018) in detail. This literature suggests that related economic activities co-locate in the same productive units, such as firms, industries, and countries, because they share common skills, technology, and knowledge.

Our measure of differentiation considers the production network as a system of technology flows. In a given network, while some firms combine suppliers that are mostly combined together, others choose more differentiated supplier sets. We trace distances between firms in their supplier sets in the given production network.

Supplier relatedness measure: We measure the relatedness of each supplier pair within the production network A_t. We construct a symmetric network B_t: Each element B_{ijt} represents the relatedness between suppliers $i, j \in N_t$. It is a measure for common customers of suppliers i and j normalized by the out-degree of those firms and the in-degree of the common customers:

$$B_{ijt} = \frac{\sum_{f \in N_t} \frac{A_{fit} A_{fjt}}{d_f^{in}}}{max(d_i^{out}, d_j^{out})} \tag{3.1}$$

where $d_f^{in} = \sum_{i \in N_t} A_{fit}$ denotes the in-degree or number of suppliers of firm f and $d_i^{out} = \sum_{f \in N_t} A_{ift}$ represents the out-degree or number of customers of firm i. This measure indicates the extent of relatedness between the products of these firms as inputs of the common firms. It effectively ranks supplier pairs based on their proximity in technology sets of common customers.

Two suppliers may be related for two reasons: (i) Their products are used in the same technology/production plans of their common customers. (ii) Their products are used in two different technology/production plans that are in the technology sets of one common firm. In this case, even if these two suppliers' products are not in the same technology/production plan, they are somehow related because they are used in two related technology/production plans of one common firm. We assume those technology/production plans are related, apart from the literature on product diversification (Teece et al., 1994). The literature suggests that firms' product portfolios are constituted by related product lines sharing common technological capabilities. Therefore, even if the products supplied by different firms are used for different products, they must be related because the output products are related in terms of technological capabilities.

Overall supplier set relatedness: After we measure how each supplier pair is related in the production network at time t, we can infer how a firm's supplier set is differentiated in the production network. We measure how firm f's supplier set is related overall by the relatedness measure for each pair of suppliers in its supplier set Z_{ft}:

$$R^s_{ft} = \frac{\sum_{i \in Z_{ft}} \sum_{j \in Z_{ft}} Q_{fit} Q_{fjt} B_{ijt}}{\sum_{i \in Z_{ft}} \sum_{j \in Z_{ft}} Q_{fit} Q_{fjt}} \tag{3.2}$$

where Q_{fit} represents the value of the input transaction from firm i to firm f. This measure serves as an indicator of firm supplier set differentiation at time t. A low (high) level of overall supplier set relatedness indicates a high (low) level of differentiation. We prefer the term "differentiation" because it is a systematic measure and depends on the current production network structure. It measures how the representative firm differentiated within the given supplier-buyer relationships. As we suggest, technological feasibility defines possibilities in technology/production plans within the economy. As technological feasibility changes over time, so do production networks and firms' levels of differentiation. For example, while the use of automated robotics in manufacturing was quite new and highly differentiating in the 2000s, it has become quite popular nowadays and less differentiating for manufacturers.

Temporal Dynamics and Supplier Set Change.

At any given time t, a production network reflects the technological possibilities available for all products and firms. These production networks evolve as technological possibilities change over time. The measures of relatedness within these networks also evolve as the connections between suppliers and customers shift. As certain inputs become more popular, others may decrease in usage within production processes. Adopting popular inputs allows firms to increase the overall relatedness of their supplier sets. Conversely, firms become more differentiated if they choose not to use popular inputs. At any time t, the change in the overall supplier set relatedness of any firm f,

$$\Delta R^s_{ft} = R^s_{ft} - R^s_{ft-1}, \tag{3.3}$$

can result either from changes in firm f's own supplier linkage adjustments, or from adjustments made by other firms that share similar suppliers with firm f. Firms adjust their supplier sets based on internal decisions or external shocks, as mentioned in the previous section. In summary, we can identify three reasons for updating supplier sets:

1. Changing production plan/s of products in their product portfolios.
2. Changing product portfolios by adding new product lines requiring new production plans and/or dropping some product lines.
3. To adopt an external shock such as price shocks, natural disasters, industrial regulations, etc.

The first two reasons stem from firms' internal decisions on technological progress or product portfolio diversification. On the other hand, external shocks are the factors the firms cannot control. Firms update their supplier sets to avoid the potential negative effects of those external shocks. For example, a natural disaster or a new industrial regulation may prevent a firm from accessing its current suppliers and spur it to look for substitutes.

Proposition 4. *Under the assumption 1, if a firms changes its supplier set from period* $t-1$ *to* t, $Z_{ft} \neq Z_{ft-1}$, *it means this firm changed its technology set:* $T_{ft} \neq T_{ft-1}$. *However, the reverse is not true: a firm may have changed its technology set* $T_{ft} \neq T_{ft-1}$ *even if it does not change its supplier set:* $Z_{ft} = Z_{ft-1}$.

Any change in supplier linkages of a firm indicates that the firm has changed its technology set because there is no duplicate technology assumption in the economy. A new production plan for existing or new product lines may trigger this change. A buyer firm may change its supplier set by producing an existing product line with another supplier's product and/or by introducing a new product line that necessitates a new technology/production plan. However, it is also possible to introduce a new product line or a new production process for firms without changing its supplier set. The proposition 4 underlines that firms might change their technology/production plans without changing their supplier sets.

Measuring supplier set change over time: In any case, we can capture a proportion of technology set change by measuring supplier set changes over time by utilizing a Jaccard Distance metric. The Jaccard Distance metric quantifies the change in a firm f's set of suppliers Z_{ft} at period t compared to the previous period $t-1$. It is calculated as follows:

$$JD^s_{ft} = \frac{|Z_{ft} \cup Z_{ft-1}| - |Z_{ft} \cap Z_{ft-1}|}{|Z_{ft} \cup Z_{ft-1}|}. \tag{3.4}$$

The Jaccard Distance measure captures the distance between the two supplier sets from one period to another. A non-zero Jaccard Distance measure implies that firm f altered its supplier set at time t. As firms adjust their supplier linkages due to changes in their technology sets or external shocks, production networks' overall structure and relatedness continuously change. This evolution results in varying degrees of differentiation between firms' supplier sets, which we can measure over time. In the following part, we interpret these time-varying relationships, exploring how dynamic and stable firms contribute to the ongoing changes in network structure and supplier set differentiation.

Interpretation and Limitations

The present chapter suggests that Overall Supplier Set Relatedness - referring to the extent to which a firm's supplier relationships differ from those of other firms- indicates technology set differentiation under Proposition 3. As production networks evolve due to firms' updates of their supplier linkages, the relatedness between suppliers changes. Firms update their supplier sets due to technological changes or to adapt to external shocks.

In this evolutionary process, firms can be analyzed in two different groups: **Dynamic Firms**, which update their supplier sets, and **Stable Firms**, which maintain the same supplier set from the period $t-1$ to t. The **Dynamic Firms** drive the evolution of production networks by altering their supplier sets, which triggers changes across the relatedness matrix B_{t-1}, even for the **Stable Firms** that do not directly update their suppliers. Their supplier set changes affect them and their peers' Overall Supplier Set Relatedness because it is a systematic measure depending on the distance between firms' supplier linkages. A firm's peers are the firms whose supplier sets intersect with its supplier set. The behavior of dynamic firms influences the evolution of the relatedness matrix, making it complex to analyze with only supplier set relatedness measures. The broader network trends affect the relatedness measures of supplier sets. A firm's supplier set may appear more (less) differentiated by decreasing relatedness among its suppliers triggered by the peer firms' actions.

When a firm's suppliers become more related by being connected to the same customers more frequently, its overall supplier set relatedness increases, even if it does not change its suppliers. Conversely, if the suppliers become less related by being linked to the common customers less frequently, the overall supplier set relatedness decreases. Table 3.1 presents a potential interpretation of the evolution of supplier sets and the overall relatedness measures to understand the differentiation patterns of dynamic and stable firms. Dynamic firms, which modify their supplier linkages $JD^s_{ft} > 0$, along

Table 3.1: Interpretation of the Jaccard distance and the overall relatedness measures.

	$\Delta R^s_{ft} > 0$	$\Delta R^s_{ft} < 0$
Dynamic Firms		
($JD^s_{ft} \neq 0$)	Firm f converges to stable firms.	Firm f diverges from stable firms.
Stable Firms		
($JD^s_{ft} = 0$)	Dynamic firms converge to firm f.	Dynamic firms diverge from firm f.

with new firms, are sources of dynamism in production networks. If these dynamic firms reduce the overall relatedness of their supplier sets, $\Delta R^s_{ft} < 0$, it indicates that they have chosen less related suppliers, differentiating themselves from other firms compared to the previous period. This suggests that their current supplier choices are less common/popular than those made in the past. Conversely, if dynamic firms increase their supplier set relatedness $\Delta R^s_{ft} > 0$ by selecting more closely related suppliers, aligning more with other firms, resulting in more common/popular supplier sets than in the previous period. In this case, their supplier linkages converge with those of other firms.

Stable firms, which have not changed their supplier sets, $JD^s_{ft} = 0$, are indirectly affected by the actions of dynamic firms. If a stable firm's overall relatedness decreases ($\Delta R^s_{ft} < 0$), it suggests that dynamic firms have diverged from stable firms' supplier sets by adopting a less related supplier composition. On the other hand, if its overall relatedness increases $\Delta R^s_{ft} > 0$, this implies that dynamic firms are converging towards the stable firm's supplier set. This distinction between dynamic and stable firms underscores the interconnectedness of production networks such that firms' differentiation is a systematic issue. [2]

3.4 Data and descriptive statistics

In the previous section, we propose that supplier set differences across firms are sourced from technology set differences. Therefore, supplier-based measures across firms and over time are remarkable indicators of firm performance and dynamism in economies. We use Turkey's national firm-to-firm transactions data covering the period 2010-2021 to analyze firms' supplier linkage formation dynamics and its influence on firm performance. This data set covers all firm-to-firm transactions exceeding 5000 TL (about 375 USD in 2021) provided by the Ministry of Industry and Technology of the Republic of Turkey. We limit the data to manufacturing firms because those firms rely more on inputs than other firms. We define time intervals annually. For each year, we create a production network representing firm-to-firm transactions, and create a symmetric relatedness matrix that shows relatedness for each supplier pair as defined in the equation 3.1. Later, we compute the overall supplier set relatedness by the measure defined in the equation 3.2 for each firm with two or more suppliers (multi-supplier firms). In order to measure supplier set adjustments of firms, we use the formula in the equation 3.4 in annual intervals.

To show the dynamism in production network evolution, we define some extra variables: (i) Jaccard Distance Metric to measure product portfolio adjustments of firms, (ii) a supplier adjustment propagation measure (SAPM) capturing supplier adjustment of peer firms and (iii) an exposure variable for importer firms that are expected to be influenced by the 2018 Currency

[2]Discussions on the dynamism of relatedness measures are relatively new (Juhász et al., 2021; Kuusk and Martynovich, 2021). See Appendix A for a simple case study incorporating different products and technology definitions.

shock in Turkey. We use those variables to analyze supplier set adjustments of firms. The first and third variables are created by integrating foreign trade data of Turkey.

Product set adjustments: In order to demonstrate the relationship between supplier-set evolution and product portfolio evolution, we measure **Jaccard Distance (JD^p) for firms' product portfolio** adjustments over time. We have detailed data on the product codes of exporter firms only, so we have the product-based Jaccard Distance measure (JD^p) exclusively for these firms. We use this measure to test whether our supplier set-evolution measure is in a relationship with the product set-evolution measure for the sample of exporter firms.[3]

We measure firms' product portfolio changes using a Jaccard Distance metric, similar to the one used for supplier set changes:

$$JD^p_{ft} = \frac{|PS_{ft} \cup PS_{ft-1}| - |PS_{ft} \cap PS_{ft-1}|}{|PS_{ft} \cup PS_{ft-1}|}. \tag{3.5}$$

Here, JD^p_{ft} measures the distance between the sets of products exported by firm f from time $t-1$ to t.

Co-movements in supplier sets: As production networks evolve, firms may respond to their counterparts' actions: Firms sharing the same customer base/market may change their supplier sets as response to the actions of each other. $B_{ijt} > 0$ reflecting the structural similarity between firms i and j, based on shared customer relationships, is used to analyze co-movements in firms' supplier linkage updates. If B_{ijt} is high, firms i and j share many common customers, indicating that they operate in a similar market or play a similar role in the production network. We propose a **Supplier Adjustment**

[3] Our overall supplier set relatedness metric is based on the relatedness literature, which is mostly studied on product level (Hidalgo et al., 2018). Therefore, analyzing the relationship between supplier set evolution and product set evolution is important.

Propagation Measure (SAPM) for the firm i:

$$SAPM_{it} = \sum_{j \in N_t} B_{ij} JD_j^s \tag{3.6}$$

which captures the supplier set variations of firm i's related firms. The summation aggregates how the supplier sets of all related firms have changed. A high value of $SAPM$ suggests that firm i's related firms have undergone significant changes in their supplier sets, which could indicate a structural shift in the production network.

External shocks: We test whether external shocks significantly affect firms' supplier set adjustment decisions. To do so, we consider the currency shock experienced by importer firms in 2018. Turkey experienced a sharp currency depreciation, with the exchange rates nearly doubling in 2018. This shock increased the cost of imported inputs, potentially forcing firms to disconnect their foreign suppliers. We aim to test whether this shock, which influences their foreign supplier linkages, also impacts their domestic supplier compositions.

To define the shock exposure ($Exposure$), we first define the share of imports in the sum of import purchases and input purchases from the domestic firms, SI, for each year t:

$$SI_t = \frac{Import_{ft}}{Import_{ft} + D\_Purchases_{ft}}.$$

where $Import_{ft}$ is the purchases from foreign suppliers and $D\_Purchases_{ft}$ is the input purchases from domestic suppliers of firm f at year t.

The exposure variable is zero for all firms prior to the shock (in 2017 and earlier). After the shock (2018 and beyond), exposure is calculated based on the import share from 2017. The exposure of any firm f to the currency shock in 2018 is defined as their share of input purchases just before the shock occurred:

$$Exposure_f = \begin{cases} SI_{f-2017}, & \text{if } year \geq 2018. \\ 0, & \text{otherwise.} \end{cases}$$

This approach reflects how firms— highly reliant on foreign inputs —adjust their supplier linkages in response to a currency shock. A higher exposure value indicates greater dependence on imported inputs, which increases the firm's vulnerability to exchange rate fluctuations in 2018 and thereafter.

We merge all the measures above with the balance sheet data: net sales, R&D spending, and number of employees. We compute firms' labor productivity as value added per hour worked annually. We deflated the relevant balance sheet data using the Producer Price Index (PPI) and the Consumer Price Index (CPI). We use net sales and labor productivity as an indicator of firm performance. Table 3.2) demonstrates the list of all variables.

Table 3.2: List of Variables and Explanations

Variable	Description
1. R^s	Overall relatedness measure of the firms in suppliers as defined in the equation 3.2.
2. JD^s	Jaccard Distance measure of supplier set change as defined in the equation 3.4.
3. JD^p	Jaccard Distance measure of product set change as defined in the equation 3.5.
4. $SAPM$	This measure captures the supplier set variations of a firm's related firms as defined in the equation 3.6.
5. d^{in}	Number of suppliers of the firms.
6. d^{out}	Number of customers of the firms.
7. NS	Net sales revenue generated by the firm (deflated by PPI).
8. LP	Value added per hour worked.
9. RD	Total expenditure on research and development deflated by Producer Price Index (PPI).
10. SI	The share of imports in the sum of import purchases and input purchases from the other domestic firms.
11. $Exposure$	The share of imports in 2017 for the years 2018-2021 and 0 for the other years.
12. Age	The number of years since the establishment.
13. $Size$	Number of employees.

3.4.1 Descriptive Statistics

Table 3.3 shows the number of observations from 2010 to 2021 for our main sample of manufacturing firms with multi-suppliers. We have unbalanced panel data, in which observations increase over the years. The average number of suppliers (in-degrees - d^{in}) and the number of customers (out-degrees - d^{out}) increases continuously over time.

Table 3.3: Summary Statistics of d^{in} and d^{out}

Year	d^{in}					d^{out}				
	Obs.	Mean	Std.	Min.	Max.	Obs.	Mean	Std.	Min.	Max.
2010	57387	10.201	18.036	2	822	46555	11.450	24.808	1	1130
2011	64110	10.748	18.928	2	851	52641	12.058	26.366	1	1167
2012	68132	10.866	19.347	2	884	56205	12.167	26.535	1	1193
2013	73748	11.033	19.741	2	911	61222	12.260	27.001	1	1327
2014	80904	11.492	20.875	2	940	67829	12.689	28.431	1	1492
2015	86526	11.546	21.309	2	984	72640	12.735	28.703	1	1539
2016	89031	11.760	21.912	2	1010	75125	12.925	28.942	1	1377
2017	93934	12.237	22.964	2	924	79197	13.514	30.472	1	1335
2018	103195	12.666	24.444	2	937	87305	14.014	32.137	1	1429
2019	103984	12.822	25.085	2	885	88242	14.106	32.744	1	1494
2020	110890	13.288	25.561	2	935	94094	14.808	34.461	1	1555
2021	132490	14.930	29.312	2	1298	114373	16.616	39.655	1	1739

Table 3.4 presents summary statistics for our produced measures for firms' supplier and product sets. The mean of the overall relatedness measures decreases over the years 2010-2021, except for 2015 and 2019. The increase in 2015 is ignorable, but in 2019, the increase may be economically remarkable due to the currency shock that began in 2018, as we mentioned. The mean of supplier-based and product-based Jaccard distance measures demonstrates minor variations over time. Note that we ignore the firms with zero Jaccard Distance metrics in their supplier and product sets.

Table 3.4: Summary Statistics of Overall Relatedness, Jaccard Distance Metrics for suppliers and products, and SAPM

Year	R^s			JD^s			JD^p			SAPM		
	Obs.	Mean	Std.	Obs.	Mean	Std.	Obs.	Mean	Std.	Obs.	Mean	Std.
2010	57387	0.0159	0.0303	45736	0.7023	0.1760	13061	0.6699	0.1918	45923	0.1975	0.1245
2011	64110	0.0144	0.0281	53846	0.6770	0.1792	13793	0.6685	0.1933	52040	0.2003	0.1246
2012	68132	0.0143	0.0283	57485	0.6706	0.1781	14384	0.6715	0.1909	55569	0.2012	0.1248
2013	73748	0.0140	0.0267	56044	0.6981	0.1731	15362	0.6664	0.1944	60520	0.1906	0.1204
2014	80904	0.0134	0.0259	61360	0.6948	0.1733	16717	0.6600	0.1962	67085	0.1899	0.1201
2015	86526	0.0136	0.0267	69655	0.6789	0.1766	17220	0.6577	0.1966	71938	0.1947	0.1225
2016	89031	0.0132	0.0262	73250	0.6795	0.1766	17679	0.6538	0.1980	74410	0.1970	0.1232
2017	93934	0.0125	0.0258	76119	0.6837	0.1763	17094	0.6577	0.1971	78443	0.1950	0.1238
2018	103195	0.0123	0.0260	84481	0.6664	0.1766	17598	0.6524	0.1992	86479	0.1903	0.1220
2019	103984	0.0128	0.0276	88772	0.6739	0.1768	18634	0.6469	0.2061	87427	0.1976	0.1254
2020	110890	0.0111	0.0245	92067	0.6804	0.1772	19336	0.6547	0.2074	93233	0.1946	0.1262
2021	132490	0.0097	0.0225	106569	0.6908	0.1742	20816	0.6333	0.2094	113554	0.1887	0.1258

The average net sales and labor productivity slightly decrease with the increasing sample size over time. We do not observe significant variations in the standard deviations of net sales and labor productivity. The number of firms with R&D activity increased from 2036 to 3132; the mean of those firms' R&D spending did not change significantly from 2010 to 2021. The mean of the variable SI significantly decreases from 2010 to 2021, indicating that firms rely less on imports for their input purchases on average.

Table 3.5: Summary Statistics for performance, innovation, import share variables.

Year	NS			LP			RD			SI		
	Obs.	Mean	Std.	Obs.	Mean	Std.	Obs.	Mean	Std.	Obs.	Mean	Std.
2010	57302	14.005	1.681	46687	9.287	1.680	2036	10.529	2.560	16433	0.271	0.277
2011	64015	13.966	1.786	52365	9.251	1.675	2128	10.599	2.518	17728	0.260	0.272
2012	68007	13.994	1.771	55827	9.281	1.661	2147	10.720	2.591	17924	0.244	0.267
2013	73612	13.950	1.716	59565	9.170	1.627	2303	10.781	2.618	18645	0.238	0.263
2014	80755	13.928	1.734	65153	9.185	1.655	2428	10.855	2.526	19628	0.218	0.253
2015	86378	13.864	1.749	67630	9.134	1.650	2481	10.825	2.639	20177	0.199	0.242
2016	88860	13.836	1.728	68157	9.088	1.625	2518	10.886	2.635	19800	0.186	0.234
2017	93777	13.811	1.718	73046	9.063	1.648	2585	10.856	2.633	19133	0.167	0.222
2018	102961	13.600	1.801	76603	8.957	1.713	2727	10.828	2.619	19829	0.148	0.209
2019	103699	13.623	1.787	74729	9.001	1.715	2860	10.980	2.649	21361	0.131	0.198
2020	110579	13.443	1.881	76171	8.872	1.788	2920	10.890	2.702	21300	0.120	0.186
2021	132011	13.185	1.941	82783	8.594	1.774	3132	10.668	2.745	24469	0.094	0.163

Correlation Analysis: Table 3.6 demonstrates the correlation analysis for the list of variables in Table 3.2. The variations in supplier sets (JD^s) and product sets (JD^p) of firms are positively correlated. The negative and significant correlation between firms' JD^s and $SAPM$ measures suggests that firms' supplier linkages may be influenced by their related firms sharing the same customer base.

The variable representing the share of imports, denoted as SI, is positively correlated with both supplier set relatedness and the Jaccard Distance in supplier sets. This indicates that importing firms tend to have more closely related domestic supplier relationships and experience greater changes in their supplier sets over time. Conversely, our defined variable for the currency shock exposure shows a negative correlation with overall supplier set relatedness and Jaccard Distance. This means that firms with high exposure to the currency shock have less related supplier sets and exhibit a smaller distance within their supplier sets.

Additionally, the innovation indicator RD is negatively correlated with the overall supplier set relatedness measure (R^s), suggesting that firms with some innovation activity have more differentiated supplier sets. The negative correlation between JD^s and RD suggests that firms with higher R&D expenditure experience lower supplier turnover, possibly reflecting more stable input sourcing strategies.

Finally, firms' performance indicators: net sales (NS) and labor productivity (LP) are negatively correlated with the overall supplier set relatedness measure (R^s). Firms with higher distance in their supplier sets (JD^s) tend to have less net sales and more labor productivity. Furthermore, there are strong positive correlations between firms' supplier/customer linkages (d^{in} and d^{out}) and their performance indicators (NP and LP).

Table 3.6: Correlation Coefficients

	R^s	JD^s	JD^p	$SAPM$	d^{in}	d^{out}	NS	LP	RD	SI	$Exposure$	age
JD^s	0.066***											
JD^p	0.037***	0.177***										
$SAPM$	-0.201***	-0.041***	-0.070***									
d^{in}	-0.161***	-0.115***	-0.096***	0.449***								
d^{out}	-0.117***	-0.040***	-0.071***	0.583***	0.553***							
NS	-0.203***	-0.091***	-0.138***	0.537***	0.585***	0.400***						
LP	-0.111***	-0.030***	-0.089***	0.327***	0.410***	0.286***	0.575***					
RD	-0.145***	-0.249***	-0.021**	0.314***	0.451***	0.224***	0.563***	0.396***				
SI	0.148***	0.141***	0.027***	0.018***	-0.094***	0.063***	0.020***	0.118***	0.133***			
$Exposure$	-0.046***	-0.017***	-0.056***	0.146***	0.187***	0.191***	0.176***	0.152***	0.152***	0.165***		
age	0.012***	-0.127***	-0.081***	0.030***	0.025***	0.036***	0.009***	0.007***	0.157***	0.046***	-0.002*	
$size$	-0.170***	-0.070***	-0.093***	0.352***	0.403***	0.231***	0.576***	-0.058***	0.274***	-0.067***	0.112***	-0.012***

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

3.5 Empirical Analysis

In this section, we empirically analyze the dynamics of firm-level production network formation and the relationship between firm performance and the overall supplier set's relatedness. The empirical analysis in the section estimates all regression specifications using ordinary least squares (OLS).

3.5.1 Network formation dynamics

To analyze firms' supplier network formation behavior, we estimate linear models that incorporate key indicators for product portfolios, peer effects, and external shocks identified in the prior part. Specifically, we assess how product portfolio adjustments (JD^p), the measure for propagation of supplier adjustments of peers ($SAPM$), and the 2018 currency shock exposure ($Exposure$) influence supplier set updates (JD^s) at the firm level. Our main explanatory variables (JD^p, $SAPM$, $Exposure$) might be endogenous: For instance, firms exposed to currency shocks might need to update their export product offerings. Consequently, we will analyze the impacts of these variables individually.

Model 1: Our first empirical model is formulated to analyze the influence of the product portfolio adjustments on supplier linkage adjustments. Therefore, we empirically test the following linear model:

$$JD^{s}_{ft} = \lambda_0 + \lambda_1 JD^{p}_{ft} + FE_f + FE_t + FE_{t-ind} + FE_{t-reg} + \epsilon_{ft}, \qquad (3.7)$$

where

- JD^{s}_{ft} represents Supplier set change (Jaccard Distance) of firm f at time t.
- JD^{p}_{ft} represents Product portfolio change of firm f.
- FE_f, FE_t, FE_{t-ind}, FE_{t-reg} represent firm, year, year-industry, and year-region fixed effects, respectively.

Table 3.7: Regression Results: Adjustments in Supplier Sets and Product Portfolios

Variables	**(1)** JD^s	**(2)** JD^s $(\Delta d^{in} > 0)$	**(3)** JD^s $(\Delta d^{in} \leq 0)$
JD^p	0.0336***	0.0283***	0.0373***
	(0.0017)	(0.0023)	(0.0036)
Constant	0.6410***	0.6357***	0.6320***
	(0.0011)	(0.0015)	(0.0024)
Year Fixed Effects	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes
Year-Nace Fixed Effects	Yes	Yes	Yes
Year-Region Fixed Effects	Yes	Yes	Yes
Number of observations	180,969	91,202	58,175
Adjusted R^2	0.4708	0.5090	0.4417

Note: Standard errors are in parentheses. $*p < 0.1, **p < 0.05, ***p < 0.01$.

Fact 1: Supplier relationships adjustments are associated with product portfolio adjustments. Table 3.7 reports regression results examining the relationship between changes in firms' product portfolios (JD^p)

and their supplier sets (JD^s). Across all model specifications, we find a positive and statistically significant relationship, indicating that firms that update their product portfolios also tend to adjust their supplier linkages.

Specifically, a Jaccard Distance metric in product portfolios, which equals one, indicating that completely updating the relevant product set, is associated with approximately a 3.4 basis-point increase in supplier set distance (JD^s), holding firm, year, industry, and region fixed effects constant. Although the magnitude of this coefficient is modest, it is statistically significant. This finding is consistent with the proposition that firms extend their product portfolios through product lines that share common technological requirements (Teece et al., 1994).

To investigate whether this alignment differs depending on the direction of supplier network change, we split the sample based on whether the firm increases its number of suppliers ($\Delta d^{in} > 0$) or not ($\Delta d^{in} \leq 0$). While the estimated coefficients remain positive and significant in both groups of firms, the magnitude is slightly higher for firms with fewer or the same supplier linkages (0.0283 vs. 0.0373). This indicates that the changes in product sets are systematically associated with changes in supplier linkages, even among firms not expanding their supplier base.

Model 2: We further formulate an empirical model for co-movements in production network evolution:

$$JD^s_{ft} = \lambda_0 + \lambda_4 SAPM_{ft} + FE_f + FE_t + FE_{t-ind} + FE_{t-reg} + \epsilon_{ft}, \quad (3.8)$$

where $SAPM_{ft}$ represents the Supplier Adjustment Propagation Measure (SAPM) capturing changes in supplier linkages of related firms of firm f. FE_f, FE_t, FE_{t-ind}, and FE_{t-reg} represent firm, year, year-industry, and year-region fixed effects, respectively.

Table 3.8: Regression Results: Adjustments in Supplier Sets and Supplier Adjustment Propagation Measure (SAPM)

Variables	**(1)** JD^s	**(2)** JD^s ($\Delta d^{in} > 0$)	**(3)** JD^s ($\Delta d^{in} \leq 0$)	**(4)** JD^s	**(5)** JD^s ($\Delta d^{in} > 0$)	**(6)** JD^s ($\Delta d^{in} \leq 0$)
SAPM	-0.0606***	-0.0178***	-0.1037***	-0.0467***	0.0235***	-0.1176***
	(0.0031)	(0.0048)	(0.0056)	(0.0035)	(0.0052)	(0.0060)
L1.SAPM				-0.0451***	-0.0939***	0.0170***
				(0.0035)	(0.0049)	(0.0061)
Constant	0.6942***	0.6756***	0.6895***	0.6928***	0.6867***	0.6896***
	(0.0007)	(0.0012)	(0.0012)	(0.0009)	(0.0014)	(0.0016)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-Nace Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-Region Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	696,267	294,143	254,074	566,874	276,858	238,396
Adjusted R^2	0.3569	0.3949	0.3440	0.3849	0.4044	0.3506

Note: Standard errors are in parentheses. $*p < 0.1, **p < 0.05, ***p < 0.01$.

Fact 2: There is a statistically significant association between supplier set adjustments of firms and their structurally related peers. Table 3.8 presents the estimates from the empirical model above. Across all specifications, we find a statistically significant association between $SAPM$ and firms' idiosyncratic supplier set adjustments, denoted as JD^s. In Column (1), the contemporaneous coefficient of $SAPM$ is negative and significant (-0.0606), suggesting that a higher supplier adjustments by a firm is associated with a limited supplier adjustments by its structurally related firms in a given year. We observe a similar relationship when we introduce a one-period lag of $SAPM$ in Column (4): The lagged $SAPM$ has a negative and significant coefficient (-0.0451), indicating that higher lagged supplier adjustments by peer firms are associated with limited supplier adjustments. This lagged contagion pattern suggest that the co-movements in supplier adjustments are valid over time.

We further analyze the relationship between supplier adjustments by structurally related peers for firms expanding their supplier linkages and others. For firms expanding their supplier linkages ($\Delta d^{in} > 0$), the initial correlation—reflected in the contemporaneous $SAPM$—is in the same direction as their peers (0.0235 in Column 5). Those firms tend to exhibit larger supplier linkage adjustments in periods in which their structurally related peers make radical shifts in their supplier compositions. However, the effect of the lagged $SAPM$ is negative (-0.0939 in Column 5).

For firms with stable or fewer supplier linkages ($\Delta d^{in} \leq 0$), the association pattern diverges from those expanding their networks. In Column (6), the contemporaneous effect of $SAPM$ is significantly negative (-0.1176), indicating that these firms are less likely to adjust their own supplier linkages in period in which their peers heavily restructure their supplier sets. However, the lagged $SAPM$ effect is significantly positive (0.0170), indicating a delayed co-movement with their peers' prior adjustments.

Model 3: We analyze the impact of the currency shock in 2018 on supplier adjustment decisions of firms. We analyze the impact of the 2018 currency depreciation on firms' supplier adjustments using a difference-in-differences (DiD) approach. Our *Exposure* variable is set to zero for 2017 and earlier, and to the import shares in 2017 for the years 2018 and beyond. This method ensures that exposure is determined based on firms' import dependency prior to the 2018 shock, which helps alleviate concerns regarding endogeneity in the treatment assignment. We expect firms' supplier adjustments to vary with their dependency on imported inputs in the pre-shock period. The empirical model for the effect of the currency shock on firms' supplier set adjustments is formulated as follows:

$$JD^{s}_{ft} = \lambda_0 + \lambda_1 Exposure_{ft} + FE_f + FE_t + FE_{t-ind} + FE_{t-reg} + \epsilon_{ft}, \quad (3.9)$$

where $Exposure_{ft}$ represents Firm f's exposure to the 2018 currency shock. FE_f, FE_t, FE_{t-ind}, and FE_{t-reg} represent firm, year, year-industry, and year-region fixed effects, respectively.

Supplier Set Evolution and Relatedness Trends in 2019: Before proceeding to the regression results of Model 3, let us to analyze how firms' supplier linkages have changed from 2018 to 2019 for different groups descriptively. We observe an increase in the mean of the overall supplier set relatedness measure (R^s) in 2019 (Table 3.4). The increase in R^s applies mainly to dynamic firms that adjust their supplier compositions ($JD^s > 0$). For those firms, the change in R^s has distinct directions for non-importer and importer firms. As seen in Table 3.9, non-importer firms exhibit a positive change in R^s (0.0005), while importer firms show a decline (-0.0003) on average. The measure JD^s, which captures the distance in supplier sets from 2018 to 2019, is higher for the non-importer firms (0.6797 vs. 0.6539). Importer firms experienced a significant increase in their supplier linkages (Δd^{in} = 1.5098), whereas non-importer firms had a minor reduction (Δd^{in} = -0.0363) on average.

Table 3.9: Descriptive Analysis of Dynamic Firms in 2019

Mean values	**Dynamic Firms (88,772)**	
	Non-importer firms (68,713)	**Importer firms (20,059)**
R^s	0.0130	0.0047
ΔR^s	0.0005	-0.0003
JD^s	0.6797	0.6539
Δd^{in}	-0.0363	1.5098

These descriptive patterns are consistent with importer firms exhibit larger expansions in their supplier sets through less related domestic suppliers, while non-importer firms disrupt some of their supplier linkages and keep their more related suppliers. This pattern is consistent with importer firms exhibiting dynamic adjustments in their supplier linkages by linking to new less related domestic suppliers. On the other hand, non-importer firms disconnect from their differentiating suppliers and keep their highly related subset of suppliers. Importer firms mainly have more related domestic supplier sets as demonstrated in Table 3.6 (The correlation between SI and R^s is 0.148 and statistically significant). The analysis of this correlation and the descriptive statistics for importer firms in 2019 suggest that the currency shock is associated with differentiating supplier sets by linking to more domestic suppliers while keeping their existing domestic suppliers more stable.

Table 3.10: Regression Results: Adjustments in Supplier Sets and the 2018 Currency Shock Exposure

Variables	**(1)** JD^s	**(2)** JD^s ($\Delta d^{in} > 0$)	**(3)** JD^s ($\Delta d^{in} \leq 0$)
Exposure	-0.0077**	-0.0019	-0.0150***
	(0.0032)	(0.0041)	(0.0057)
Constant	0.6790***	0.6683***	0.6657***
	(0.0002)	(0.0002)	(0.0003)
Year Fixed Effects	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes
Year-Nace Fixed Effects	Yes	Yes	Yes
Year-Region Fixed Effects	Yes	Yes	Yes
Number of observations	817,272	327,602	306,803
Adjusted R^2	0.3415	0.3852	0.3303

Note: Standard errors are in parentheses. $*p < 0.1, **\,p < 0.05, ***p < 0.01$.

Fact 3: High exposure to the 2018 currency shock is associated with more stable domestic supplier linkages. Firms with high import dependency in 2017 exhibited significantly less supplier set adjustments JD^s in response to the 2018 currency depreciation (-0.0077). For firms expanding their supplier base (Column (2) - $\Delta d^{in} > 0$), the coefficient is small and not significant indicating that no significant association between exposure and supplier adjustments. For firms with stable or fewer supplier linkages ($\Delta d^{in} \leq 0$), the magnitude of the coefficient is higher and significant (-0.0150). This indicates that the negative association between the shock exposure and supplier set adjustments is valid for firms with stable or fewer supplier linkages. Firms that were highly dependent on imports before the 2018 currency shock tend to maintain their domestic supplier linkages. In contrast, non-importer firms and those with lower import dependency exhibit higher levels of supplier adjustments.

Model 4: The above regression results indicates a strong asscoation between the 2018 currency shock exposure and supplier linkage adjustments. Therefore, we also test a model to analyze the relationship between the 2018 currency shock exposure and the Supplier Adjustment Propagation Measure (SAPM), capturing supplier adjustments of firms with a similar customer base. We expect an association between the currency shock exposure and supplier adjustments by structurally related peers. The empirical model is as follows:

$$SAPM_{ft} = \lambda_0 + \lambda_1 Exposure_{ft} + FE_f + FE_t + FE_{t-ind} + FE_{t-reg} + \epsilon_{ft}, \quad (3.10)$$

where $Exposure_{ft}$ represents Firm f's exposure to the 2018 currency shock. FE_f, FE_t, FE_{t-ind}, and FE_{t-reg} represent firm, year, year-industry, and year-region fixed effects, respectively.

Table 3.11: Regression Results: Supplier Adjustment Propagation Measure (SAPM) and the 2018 Currency Shock Exposure

Variables	**(1)** *SAPM*
Exposure	0.0049***
	(0.0013)
Constant	0.2004***
	(0.00007)
Year Fixed Effects	Yes
Firm Fixed Effects	Yes
Year-Nace Fixed Effects	Yes
Year-Region Fixed Effects	Yes
Number of observations	825,342
Adjusted R^2	0.7781

Note: Standard errors are in parentheses.
$*p < 0.1, **p < 0.05, ***p < 0.01$.

Fact 4: High exposure to the 2018 currency shock is associated with adjustments of supplier linkages by structurally related peer

firms. Peer firms with high exposure to the 2018 currency shock exhibit significantly higher supplier set adjustments. For firms with a shared customer base, a shock to one affects the other. This finding is consistent with the regression results for Models 2 and 3: There is a statistically significant and negative association between supplier set adjustments of firms and their structurally related peers. Firms with high exposure to the 2018 currency shock tend to maintain stable domestic supplier linkages. Therefore, supplier adjustments of structurally related firms are positively and significantly associated with the 2018 currency shock exposure. Importer firms exhibit supplier adjustments involving less related domestic suppliers, while their structurally related peers display more pronounced adjustment patterns in post-shock periods.

3.5.2 Firm performance

Building on the descriptive analysis of our production network based measures and regression analysis of firms supplier adjustments, we extend the analysis to examine whether overall supplier set relatedness is associated with firm performance. As we conceptualized in the previous section, supplier set compositions are closely related to the technology sets of firms. A firm's ability to source from a diverse set of suppliers with lower relatedness reflects its technological differentiation and adaptability. Such firms have different motivations for adjusting supplier linkages, such as diversifying their product lines, integrating novel technologies, or adapting to external shocks. Those strategic behaviors are systematically correlated with firm performance. Therefore, we hypothesize a negative association between firm performance and overall supplier set-relatedness measure R^s, indicating greater differentiation within the relevant year's production network. To test this hypothesis, we estimate the following regression models:

$$Y_{it} = \beta_0 + \beta_1 R^s_{it} + \beta_c X_c + FE_f + FE_t + FE_{t-ind} + FE_{t-reg} + \epsilon_{it} \quad (3.11)$$

where Y_{it} is net sales or labor productivity, which are indicators of firm performance. R^s_{it} is the overall supplier set relatedness measure. We added firm size (number of employees) as a control. The model also controls for firm (FE_f), year (FE_t), year-industry (FE_{t-ind}) and year-region FE_{t-reg} fixed effects.

Fact 5: Lower overall supplier set relatedness (higher supplier set differentiation) is associated with higher firm performance. The negative and significant coefficient on R^s suggests that firms with lower supplier relatedness exhibit higher labor productivity. This finding is consistent with the proposition that firms linked to a more diverse range of suppliers also benefit from a broader technology base with more varied products and/or innovations.

Table 3.12: Regression Results: Labor Productivity/Net Sales and the Overall Supplier Set Relatedness Measure

Variables	**(1) Labor Productivity**	**(2) Net Sales**
R^s	-1.8792***	-2.6030***
	(0.0693)	(0.0488)
Size	-0.8271***	0.1790***
	(0.0015)	(0.0012)
Constant	10.8479***	13.5353***
	(0.0035)	(0.0026)
Year Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes
Year-Nace Fixed Effects	Yes	Yes
Year-Region Fixed Effects	Yes	Yes
Number of Observations	745,320	946,985
Adjusted R^2	0.7386	0.8159

Note: Standard errors are in parentheses. $*p < 0.1, **p < 0.05, ***p < 0.01$.

3.6 Conclusion

This chapter empirically contributes to theoretical insights into the dynamics of production network formation and its relationship with firm performance, drawing on a resource-based perspective from the literature on firm diversification. We discuss conceptually why supplier compositions of firms may explain their performance by suggesting that supplier set choices indicate the technological sets to which it belongs.

We quantify firm supplier-set differentiation and adjustments using the overall supplier-set-relatedness metric (R^s), the Jaccard Distance metric for supplier sets (JD^s), and the Supplier Adjustment Propagation Measure (SAPM). We use firm-to-firm transaction data of Turkey for the years 2010-2021. We merged this data with the firm-level balance sheet and foreign trade data. In addition to the supplier-based measures, we introduce a variable for the adjustments in product portfolios (JD^p).

We start the empirical analysis by exploring the factors that are associated with supplier linkage adjustments. The first finding is that supplier network adjustments are associated with adjustments in the product portfolios. Specifically, firms restructure their supplier linkages in periods in which they modify product lines. Secondly, firms' supplier set adjustments are negatively associated with their structurally related peers' supplier set adjustments, which share the common customer base. Supplier linkage adjustments exhibits a significant negative relationship with the Supplier Adjustment Propagation Measure (SAPM), underscoring the interconnected nature of production networks. Further, high exposure to the 2018 currency shock is associated with higher stability in domestic supplier sets. Firms with high exposure to the currency shock maintain stable supplier sets in their domestic production networks, while firms with less or no exposure adjust their supplier sets more. Lastly, we find a significant positive relationship between firms' exposure to the 2018 currency shock and supplier adjustments of their structurally related firms (SAPM).

After we explain the dynamics in supplier linkage adjustments, we analyze how their supplier set differentiation relates to their performance. The linear model linking the overall supplier set relatedness metric to net sales and labor productivity as performance indicators suggests that firms with lower supplier-relatedness tend to perform better. This empirical finding contributes to the literature on resource-based measures of firm diversification in explaining performance. This research offers a comprehensive approach to measuring firm scope through supplier linkages. The overall supplier set relatedness measure is as effective as the other approaches to measure firm diversification, such as product portfolios, patent portfolios, or labor skills, in exploring firm performance.

Chapter 4

Production Networks and Industrial Policy: A General Equilibrium Framework with Endogenous Link Formation

Abstract
This chapter presents a structured review of recent literature that intersects industrial policy and production network theory. We complement the literature review with a production network formation model grounded in a general equilibrium economy to analyze how industrial policies may alter the evolutionary patterns of production networks. We simulate the model across scenarios with different targeting strategies for tax policy interventions. The simulations demonstrate that the efficiency of tax policy varies with respect to the static and temporal centrality of target industries. The model provides a flexible tool for designing and evaluating industrial policies.

Keywords: Industrial policy, production networks, endogenous network formation.

4.1 Introduction

Economic policy is the art of influencing the behaviors of economic agents using varying policy tools. For policymakers, understanding the sensitivity of agents' responses to these tools and evaluating the broader economic impact, including spill-over effects, is a challenging task. Among these policies, industrial policy—which involves strategic efforts to transform industrial systems to foster economic growth—is particularly difficult due to the dynamic interactions between productive units and the heterogeneity in their behaviors (Pack and Saggi, 2006).

In this chapter, we present a structured literature review on industrial policy and production networks. Economists have approached industrial policies more ideologically for a long time. Currently, the discussion is more systematic and focuses on design rather than debating its necessity. The emerging literature on production networks has considerable potential to inform discussions of the implications of industrial policies.

The literature review is complemented by a production network formation model grounded in a general equilibrium economy incorporating a policymaker. The defined economy has two key fundamentals: (i) Firm productivity levels depend on input use. (ii) Production network structure, along with firm-level productivity and tax wedges, jointly determine equilibrium prices and real GDP. In our production network formation model, firms aim to replace a proportion of their labor use with an automation input. The decision of firms to increase the use of automation input depends on the productivity gains from substituting labor with automation input and its effect on production costs.

We simulate our model by using "The Use Table (Supply-Use Framework), 2017" from the Bureau of Economic Analysis (BEA), focused on 6-digit manufacturing industries in the US. We consider tax exemptions as an industrial policy tool inspired by real-world subsidy programs in the US and Turkey, where firms conducting R&D are exempted from tax payments for machinery and equipment purchases. We consider five different scenarios in simulations: Scenario A - No Intervention: In this scenario, the policy-maker does not implement any tax exemptions, and the production network evolves based solely on the ordinary decisions of firms/industries. Scenario B - Random Targeting: This scenario involves providing full exemptions from tax payments on input transactions of a random industry. Scenario C - High Centrality Targeting: This scenario involves providing full exemptions from tax payments on input transactions to the industry with the highest network centrality. Scenario D - Low Centrality Targeting: This scenario involves providing full exemptions from tax payments on input transactions to the industry with the least network centrality. Scenario E - Temporal Centrality Targeting: In this case, the industry with the highest potential centrality gains from adopting the automation-enhancing input receives tax exemptions. We run 1000 simulations for random labor-substitution shares for each scenario.

The simulation results demonstrate the clear impact of tax-based industrial policies on the dynamics of production network formation. Our research indicates that targeted tax-based industrial policies can enhance overall economic performance by strategically reshaping the production network. While no industry achieves automation in Scenario A (No interventions), all industries automate after some periods in the scenarios for targeted policy interventions. The number of periods until all industries automate - automation completion time- is shorter in Scenario E, where the industry with the highest potential to increase centrality through automation is supported. The variations in automation completion time across scenarios stem from differences in spill-over effects due to industry prioritization. As productivity gains and price decreases in target industries influence the automation input supplier's price and productivity more, the automation input supplier becomes more feasible for other industries over time.

The remainder of this chapter is organized as follows. Section 4.2 reviews the related literature on production networks and industrial policy. Section 4.3 introduces an endogenous general equilibrium model that incorporates a policymaker designing a tax system. The second part of section 4.3 presents a production network formation model and decomposes the potential effects of tax-based industrial policies. Section 4.4 analyzes, through numerical simulations, the evolution of the production network structure and economic outcomes under the scenarios we define. Section 4.5 concludes.

4.2 Literature Review

In this section, we first review the literature on production networks, bringing new perspectives on industrial policy. Later, we turn to the recent resurgence of industrial policy in both academic and policy circles, and examine how theoretical and empirical advances—often inspired by network thinking—are reshaping our understanding of its rationale, implementation, and evaluation.

4.2.1 Literature on production networks

A growing body of research emphasizes the importance of production networks in the design of industrial policy. In a seminal contribution, Liu (2019) models a general equilibrium economy shaped by input-output linkages and that incorporates a policymaker and market imperfections. This work establishes a formal rationale for industrial policy rooted in production network theory through three main research lines:

1. Propagation Mechanisms and Fragility in Production Networks: Broadly, the production network literature studies how external shocks propagate through input-output relationships (Long and Plosser, 1983; Carvalho et al., 2020; Acemoglu et al., 2012; Baqaee and Rubbo, 2023; Acemoglu and Tahbaz-Salehi, 2020). Technological improvements also propagate along supply chains, leading to faster price reductions and economic growth (McNerney et al., 2022). Understanding shock propagation mechanisms is crucial because it helps us to explain how production cost and productivity changes -triggered by industrial policy- cascade through production networks, influencing aggregate outcomes. Research on shock propagation can also inform precautionary industrial policies addressing potential external shocks such as natural disasters or pandemics (Barrot and Sauvagnat, 2016; Boehm et al., 2019; Carvalho et al., 2020). Atalay (2017) estimates almost two-thirds of the variations in aggregate outputs sourced from industry-specific shocks by emphasizing the role of limited substitution across inputs in the short run. Other studies, such as Elliott et al. (2022) and Elliott and Jackson (2023), explore the fragility of supply networks—the sensitivity to aggregate or micro-level disruptions—and the role of network complexity in amplifying shocks. Elliott and Golub (2022) focuses on the economic fragility resulting from the internal decision-making process regarding the formation of links between nodes.

These contributions offer a valuable toolkit for assessing how effects of industrial policy propagate and amplify across the economy, facilitating more accurate welfare analysis. Moreover, this body of literature aids policymakers in anticipating the potential effects of external shocks and in designing precautionary policies.

2. Distortions in Production Networks: There is generally room for government intervention in inefficient economies with market distortions (Pack and Saggi, 2006). Baqaee and Farhi (2019b), Liu (2019), and Bigio and La'O (2020) model inefficient economies incorporating some form of distortions or wedges. The framework proposed by Baqaee and Farhi (2019b) aims to analyze aggregate productivity and distortion wedge (such as markups, taxes, etc.) shocks in a general economy. This framework decomposes the shocks into a pure technology effect and an allocative efficiency effect. Their key insight is that the allocative efficiency effect—arising from the reallocation of resources—can be as important as the pure technology effect in driving productivity changes. Bigio and La'O (2020) demonstrates how an economy's production structure affects its response to micro-level distortions, using a static, multi-sector framework. Dhyne et al. (2022) develop a model where firms charge buyer–supplier-specific markups that depend on the bilateral input shares and find that markup dispersion across buyer firms creates remarkable welfare loss.

The above studies guide policy targeting such as firms or sectors where correcting distortions yields larger efficiency gains.

3. Production Network Formation: An emerging area in production network theory concerns the endogeneity of network structure—how firms form and adjust their linkages based on strategic and technological considerations. Carvalho and Voigtländer (2014), Oberfield (2018), Acemoglu and Azar (2020), and Taschereau-Dumouchel (2022) are examples of production network formation models in which productive units search and make decisions on their supplier linkages. The existing production networks have a remarkable impact on the diffusion of inputs, analogous to social network formation models (Jackson and Rogers, 2007; Carvalho and Voigtländer, 2014). Firms search for potentially useful inputs from the upstream firms of their current suppliers. Firms' input combinations determine their production technologies (Acemoglu and Azar, 2020). Firms' input choices determine both individual productivity and, in turn, aggregate productivity through the economy's equilibrium input-output structure (Oberfield, 2018). There are also complementarities between firms' decisions, leading to production being organized in tightly connected clusters. These complementarities in firms' decisions cause cascades in firm failures (Taschereau-Dumouchel, 2022). Firms' decisions affect production network structures as well as levels and volatility of macroeconomic aggregates (Kopytov et al., 2024). Baqaee and Farhi (2024) define the presence and strength of input-output links by minimizing cost subject to a smooth production technology. They provide a flexible toolbox to analyze how input-output linkages, domestic complementarities, limited factor mobility, and nominal rigidities can amplify welfare losses from trade disruptions. Production network formation models are also used in the context of open economies where firms endogenously and dynamically search for new foreign markets and trade partners (Chaney, 2014; Lim, 2017; Dhyne et al., 2021). All these research on how production networks are formed by firm decisions have potential to guide industrial policies considering the network formation effects.

4.2.2 Theoretical Foundations and Practical Considerations.

Before proceeding to how networks can guide industrial policies, we discuss industrial policies theoretically and practically. Since the 2008 financial crisis and the pandemics, numerous economies initiated substantial industrial programs, including the United States "CHIPS Act," the European Union's "Green Deal," and China's "Made in China 2025" (UNIDO, 2024). These programs exemplify the scale of contemporary industrial policies that are mainly designed considering supply chain disruptions.

As industrial policy gains popularity, there is a growing need for more productive discussions on industrial policy, noting the diverse motivations behind its implementation in different economies (Chang and Andreoni, 2020). While developing economies utilize industrial policies as a means to bypass poverty and the middle-income trap, developed countries implement them to address productivity slowdowns, regional inequalities, and climate change (Lee, 2013; Lebdioui, 2020). Juhász et al. (2024) summarize the rationales behind the industrial policy in 3 main categories:

1. Market failures: Any economic activity may produce positive or negative externalities that affect different groups rather than the economic agent carrying out that activity. Learning externalities —such as gains from R&D, experience, and inter-firm spillovers— are among the most cited market failures justifying industrial policy. The future capabilities are built upon, refined, and modified existing ones at the national level (Hausmann and Rodrik, 2003; Hidalgo and Hausmann, 2009; Cimoli and Dosi, 2016). Therefore, industrial policies should consider path dependencies in the learning process.

National security externalities, such as dependence on foreign inputs and the need for domestic production, are broadly recognized by policymakers (The White House, 2025). Green industrial policies incorporating climate change mitigation strategies appear within the broader objective of social welfare policies (Tagliapietra, 2022).

2. Coordination (or agglomeration) failures refer to situations in which the individual profitability of a producer may be possible with the appearance of related economic activities undertaken by others. Two economic activities are considered related if they complement each other in the final consumption by households or in firms' production processes. The fundamental coordination issue is the matching between the decentralized behaviors of economic agents (Cimoli and Dosi, 2016). For instance, a well-functioning charging infrastructure is crucial for the development of the electric vehicle market.

3. The provision of activity-specific public inputs: Each industrial structure requires corresponding infrastructure to facilitate its operations and transactions (Lin, 2010). Production by private companies frequently depends on public goods, including tangible (hard) infrastructure such as transportation and communication systems, as well as intangible (soft) infrastructure such as institutions, regulations, social capital, value systems, and various social and economic arrangements. Policymakers prioritize some private sector entities in allocating investments in public goods based on the type and location.

Criticisms and Political Economy Challenges

The critique of industrial policy is based on the lack of information that policymakers need to select which sectors, regions, or economic activities to target for intervention. The question is: what criteria should be followed to choose the right target group, considering externalities that require coordination or public input? Policymakers should manage conflicts between target groups that may appear by intervention (Chang and Andreoni, 2020). Politics may influence policymakers' target-group choices, leading to inefficiencies from resource misallocation and rent-seeking (Rodrik, 2009). For example, governments are more likely to use industrial policies in countries with upcoming elections (Evenett et al., 2024). That suggests that governments seek to poll from industrial policy target groups.

The boosters of industrial policy agree with this criticism that politics may cause the misallocation of resources and rent-seeking and highlight that governments need to strengthen their institutional capabilities (Rodrik, 2004). High-income countries made some progress in developing the fiscal and administrative capacity to design modern industrial policies; however, lower-income countries still need to develop industrial policy capabilities (Juhász et al., 2023). Developing countries should overcome limited financial and institutional capacities and need innovative strategies to boost industrialization (Santiago et al., 2024).

Instruments of industrial policy

Industrial policy includes various instruments, such as tax incentives, subsidies, social security relief, financial grants, loans, government venture capital, government guarantees, and public procurement schemes. It also includes regulatory and institutional mechanisms such as intellectual property rights regimes and international trade measures, including tariffs and export restrictions. In addition to these tools, policymakers may coordinate by providing forward-looking guidance or shaping expectations to influence individual decision-making under uncertainty.

Trade protectionism that supports domestic infant industries is one of the most common examples of industrial policy measures widely applied and discussed in the literature (Chang, 2002; Mazzucato, 2018). Domestic producers in infant industries -where established foreign competitors operate- may have higher production costs than foreign competitors. Therefore, it may be a good strategy for policymakers to protect those domestic producers until they gain efficiency through a learning process (Bardhan, 1971; Succar, 1987).

Modern industrial policies primarily focus on outward orientation and promoting exports (Juhász et al., 2024). For instance, resource-based sectors — those that have been the engines of growth in Malaysia and Chile — achieved sustained growth through specific industrial policy measures, such as R&D support, fiscal incentives, export assistance, and quality control (Lebdioui et al., 2021). While Rodrik (2004) advocate strategic collaboration between private sector entities and governments, Aghion et al. (2015) argue that tax holidays or other tax subsidies as more efficient tools in enhancing innovation and competition in targeted sectors by attracting new firms.

New trends in evaluating industrial policy efficiency and network theory

The literature moves toward micro-level analysis of industrial policies, enabling us to detect heterogeneity in firm responses (Juhász et al., 2024). Additionally, the diverse characteristics of firms—such as age, size, and levels of physical and human capital—can influence the success of industrial policies (Criscuolo et al., 2022). Specifically, the effects of place-based policies on firms' output growth, employment, investment, or productivity tend to be heterogeneous across firms and over time (Millot and Rawdanowicz, 2024). Empirical research on the evaluation of industrial policies uses mainly causal econometric analysis (Criscuolo et al., 2019). However, the causal analyses may not account for spillover effects from policies or their heterogeneous impacts unless anticipated by researchers. There is a growing body of literature on "spatial causal analysis," which aims to capture spatial spillover effects, meaning that untreated neighbor units may be indirectly affected by the treatment (Akbari et al., 2023; Kolak and Anselin, 2020). However, this literature mainly focuses on the geographical neighborhood of productive units.

Network theory provides a fresh perspective on studying the spillover effects of industrial policy. It investigates how the impacts of industrial policies spread from targeted units to non-targeted ones, using various definitions of neighborhood between them (i.e., input-output relationships, collaboration in R&D projects, and patent citations) (König et al., 2019; Liu and Ma, 2021).

Industrial policies influence the allocation and accumulation of resources, as well as the choice of technologies (Noman and Stiglitz, 2016). Lane (2024) find that industrial policies benefit the output and productivity of targeted sectors and indirectly benefit downstream users of targeted intermediates using the input-output network in South Korea. Liu and Tsyvinski (2024) model shock propagation through input-output networks and analyze its welfare consequences.

Liu (2019) propose that the measure of distortion centrality - capturing how a sector and its direct or indirect downstream sectors are distorted- may be a useful indicator in the determination of target sectors. Grassi and Sauvagnat (2019) provide a framework for combining input-output table data and insights from the theory of production networks in order to inform policy. Georgieva (2025) study empirically the model of Liu (2019). They find that industrial policies target the most central sectors in Asia and emerging economies, while less central sectors are targeted in Europe and advanced economies.

Building on the insights from the production network and industrial policy literatures, this chapter develops a theoretical model to study how tax-based industrial policies—specifically tax exemptions on intermediate input purchases—affect firm-level input use decisions and, in turn, the evolution of production networks. While a central strand of the literature focuses on the propagation of shocks and/or the distortional effects of market imperfections, limited research explicitly examines how industrial policy implications shape patterns of production network formation. The model captures how industrial policy not only influences micro-level efficiency but also reshapes the structure of production networks and, in turn, macroeconomic outcomes.

4.3 Model

In this section, we define a general equilibrium economy that incorporates production networks and a policymaker. Later, we will define a simple network formation model in which firms' input use decisions determine their production cost and technology. The policymaker may influence firms' decisions to use a specific automation input by offering tax exemptions to a targeted group of firms.

4.3.1 The General Equilibrium Economy

Production Function and Utility Preferences

The economy is characterized by a set of firms represented by the set $N_t = \{1, 2, \ldots, n_t\}$ and a representative household at each period t. Each firm produces a horizontally differentiated single product.

Consumer: The representative household supplies one unit of labor and has logarithmic preferences on n_t different products that are consumed equally:

$$u(C_{1t}, C_{2t}, ..., C_{nt}, R_t) = \sum_{i \in N_t} \frac{1}{n_t} log(n_t C_{it}) + \chi log(R_t), \tag{4.1}$$

where C_{it} is the consumption level of the product i. $\chi log(R_t)$ states the utility from the provision of public goods, which is an increasing function of policymaker revenue R_t.

Producers: Firms have Cobb-Douglas form production functions with constant returns to scale such that

$$Y_{it} = A_{it}(Z_{it})\zeta_{it}{L_{it}}^{\alpha_{it}} \prod_{j \in Z_{it}} X_{ijt}^{w_{ijt}}, \tag{4.2}$$

where Y_{it} is the level of output of firm $i \in N_t$. L_{it} is the amount of labor and X_{ijt} is the amount of input j used in production of the firm i. $\alpha_{it} = \frac{L_{it}}{L_{it}+\sum_{k \in N_t} X_{ikt}}$ is the labor share and $w_{ijt} = \frac{X_{ijt}}{L_{it}+\sum_{k \in N_t} X_{ikt}}$ is the share of input j in the production cost of firm i. $Z_{it} = \{j \mid w_{ijt} \geq 0\}$ is the set of inputs of firm i supplied by the other firms. W_t is the production network such that its entries are w_{ijt} at time t. Note that $\sum_{j \in Z_{it}} w_{ijt} < 1$ for all firms $i \in N_t$. This statement implies that the labor share of firm i is always greater than zero, $\alpha_{it} > 0$. The productivity $A_{it}(Z_{it})$ is a function of the input set of the firm i, Z_{it}. $\zeta_{it} = \alpha_{it}^{-\alpha_{it}} \prod_{j \in Z_{it}} w_{ijt}^{-w_{ijt}}$ is a normalization factor.

Policymaker: We incorporate a policymaker into the model that designs an indirect tax scheme E_t for the input purchases such that the entries of the tax schema E_t are e_{ijt} - the tax rates for input purchase of firm i from firm j. A firm i has a vector of tax rates for each input $j \in N_t$; $e_{it} = \{e_{i1t}, ..., e_{int}\}$. The policymaker has a total revenue that is collected from firm-to-firm transactions:

$$R_t = \sum_{i \in N_t} \sum_{j \in Z_i t} e_{ijt} P_{jt} X_{ijt}. \tag{4.3}$$

Note that there is no tax on final consumption. Total revenue R_t is completely spent to cover the cost of public goods.

Definition of equilibrium

At each period t, there is a fixed set of firms N_t. Each firm has a fixed set of inputs Z_{it}. Under this setting, firms minimize their production cost, and the household maximizes its utility. The competitive equilibrium of the economy is determined as follows.

Definition 2. *At each period t, the economy has a competitive equilibrium that is denoted as a combination of equilibrium levels of the household consumption C^*, the use of labor L^*, and intermediary inputs X^* by the firms, prices P^*, and output Y^* such that.*
1. The consumption plan C^* is a solution to the following utility maximization problem of the representative household:

$$\begin{aligned} \max_{C_t} \quad & U(C_{1t}, C_{2t}, ..., C_{nt}, R_t) \\ \text{s.t.} \quad & \sum_{i \in N_t} P_{it} C_{it} \leq 1, \end{aligned}$$

where $C_t = \{C_{it}\}_{i \in N_t}$.
2. Firms has the unit cost function $K_i(Z_{it}, A_{it}(Z_{it}), P)$ defined by the solution of the following cost-minimization problem:

$$\begin{aligned} \min_{L_{it}, X_{it}} \quad & L_{it} + \sum_{j \in Z_{it}} X_{ijt} P_{jt} (1 + e_{ijt}) \\ \text{s.t.} \quad & A_{it}(Z_{it}) \zeta_{it} {L_{it}}^{\alpha_{it}} \prod_{j \in Z_{it}} X_{ijt}^{w_{ijt}} = 1. \end{aligned}$$

We assume that firms operate in a contestable market structure, implying the price of each firm is equal to its production cost:

$$P_{it}^* = K_i(Z_{it}, A_{it}(Z_{it}), P_t^*).$$

3. The market-clearing conditions hold:

In equilibrium,

$$\sum_{i \in N_t} L_{it}^* = 1,$$

and for each $i \in N_t$,

$$Y_{it}^* = C_{it}^* + \sum_{j \in N_t} X_{jit}^*.$$

After solving the utility maximization problem, we obtain the optimal consumption level of any product $i \in N_t$ by the representative household: $C_{it}^* = \frac{1}{n_t P_{it}^*}$. We obtain the conditional labor and input demands by solving the cost minimization problem and substituting those in the production function of each firm $i \in N_t$:

$$L_{it}^* = \frac{\alpha_{it} \prod_{k \in Z_{it}} \left(P_{kt}^*(1+e_{ikt})\right)^{w_{ikt}}}{A_{it}(Z_{it})},$$

$$X_{ijt}^* = \frac{w_{ijt} \prod_{k \in Z_{it}} \left(P_{kt}^*(1+e_{ikt})\right)^{w_{ikt}}}{A_{it}(Z_{it}) P_{jt}^*(1+e_{ijt})}.$$

We assume the labor wage is 1. We obtain the cost function $K_i(Z_{it}, A_{it}(Z_{it}), P_t^*)$ by substituting the conditional labor and input demands in the objective function of the cost minimization problem:

$$K_i(Z_{it}, A_{it}(Z_{it}), P_t^*) = \frac{\prod_{j \in Z_{it}} \left(P_{jt}^*(1+e_{ijt})\right)^{w_{ijt}}}{A_i(Z_{it})}. \tag{4.4}$$

The contestable market assumption enables us to derive log-prices from the unit cost function above:

$$p_{it}^* = \sum_{j \in Z_{it}} w_{ijt} p_{jt}^* + \sum_{j \in Z_{it}} w_{ijt} log(1+e_{ijt}) - a_{it},$$

where p_{it}^* is logarithm of the equilibrium price of the product $i \in N_t$.

Proposition 5. *After rearranging the system of equilibrium price levels for all firms, we obtain*

$$p_t^* = -[\mathbf{I} - W_t]^{-1}(a_t(Z_t) - T_t), \tag{4.5}$$

where p_t^* is the vector of the log prices, W_t is the matrix representing the production network with w_{ijt} as its ij-th entry. $a_t(Z_t)$ is the vector of log productivities. T_t is an $n_t \times 1$ vector: The i-th entry is $\tau_{it} = \sum_{j \in Z_{it}} w_{ijt} log(1 + e_{ijt})$ that combine the weights from the production network and tax wedges.

The equation 4.5 emphasizes that prices are determined by firms' input-output linkages, productivity levels, and the tax schema designed by the policymaker.

In our setting, the nominal GDP is the total consumption of the representative household and the government spending, which equals to the total revenue of the policymaker R_t. The consumption level is equal to the labor income: $\sum_{i \in N_t} P_{it}^* C_{it}^* = 1$. The total utility of the representative household from the consumption and the provision of the public goods is the real GDP. After substituting the optimal consumption level of any product $i \in N_t$, C_{it}^*, into the logarithmic utility function, we get the equilibrium log-real GDP:

Proposition 6. *The equilibrium log-real GDP in this economy is*

$$g_t^* = \frac{1}{n_t}\mathbf{1}'[\mathbf{I} - W_t]^{-1}(a_t(Z_t) - T_t) + \chi log(R_t), \tag{4.6}$$

where $\mathbf{1}$ is the $n_t \times 1$ vector of ones.

The equation 4.6 emphasizes that the equilibrium log-real GDP is a function of production network structure, firm-level productivity, tax wedges, and utility from public good provisions. The effect and propagation of productivity shocks on the real GDP are often analyzed through the structure of production networks. The structure determines how variations in production costs and prices propagate through the economy. Analysis of tax schema design represents a promising area of growth research, offering different perspectives on the formation of production networks and industrial policy. The tax schema, E_t, directly affects the economy through production costs and the provision of utility from public goods. Further, it may influence firms' input use decisions by prompting them to adjust their intermediary input weights and labor share out of equilibrium.

In the next part, we discuss the potential network formation effects of altering the tax schema. We bring together the researches of Liu (2019), Baqaee and Farhi (2019b), Bigio and La'O (2020), and Acemoglu and Azar (2020) to develop an endogenous production network formation model with industrial policy implications.

4.3.2 Production Network Evolution

The general equilibrium economy defined above has two key fundamentals: (i) The productivity levels of firms depend on their input combinations which are denoted as $Z_{it} = \{j \mid w_{ijt} > 0\}$, where w_{ijt} represents the cost share of input j used by firm i at time t. (ii) The production network structure, represented by the matrix $W_t = [w_{ijt}]$, along with firm-level productivity and tax wedges, jointly determine equilibrium prices and real GDP.

In this section, we present a network formation model in which firms seek to increase the use of a specific automation input k, which substitutes for a proportion of labor used in production. This process alters both the firms' productivity levels and the overall structure of the production network over time. Firms' decisions are driven by the flow of technological efficiency and the relative price of the automation input.

Input share adjustment process: In our model, each firm $i \in N_t$ evaluates the marginal benefit of substituting a fraction of its labor use L_{it-1}

for the automation input k at time t. Firm i considers replace the fraction $s_{it} \in (0,1)$ of its labor use L_{it-1} by input k, leading to potential shares of input k and labor for firm i at time t:

$$\widehat{w_{ikt}} = w_{ikt-1} + s_{it}\alpha_{it-1} \quad \text{and} \quad \widehat{\alpha_{it}} = (1 - s_{it})\alpha_{it-1}.$$

The shares of other inputs remain unchanged to maintain tractability and preserve the relative composition of other inputs: $w_{ijt} = w_{ijt-1}$ for all $j \in Z_{it-1} \setminus \{k\}$. The potential cost shares satisfy the accounting identity:

$$\widehat{\alpha_{it}} + \sum_{j \in Z_{it-1} \setminus \{k\}} w_{ijt} + \widehat{w_{ikt}} = 1.$$

Input set and cost minimization: Given the adjusted automation share s_{it} and the current period's input shares, $\{w_{ijt-1}\}_{j \in Z_{it-1}}$, firm i evaluates whether to increase the weight of input k to $\widehat{w_{ikt}}$. Let's define the candidate input combination as $\widehat{Z_{it}} = \{Z_{it-1} \cup \{k\} \bigm| w_{ikt} = \widehat{w_{ikt}}\}$: If the input k is already used by firm i ($k \in Z_{it-1}$), this represents a reallocation rather than an expansion of the input set. If $k \notin Z_{it-1}$, the inclusion of k is a switching decision. Firm i compares unit costs before and after the adjustment using the unit cost function:

$$K_i(Z_{it}, A_i(Z_{it}), P^*_{t-1}) = \frac{\prod_{j \in Z_{it}} \left(P^*_{jt-1}(1 + e_{ijt})\right)^{w_{ijt}}}{A_i(Z_{it})},$$

where: P^*_{jt-1} is the equilibrium price of input j at time $t-1$, e_{ijt} is the tax rate on the firm i's purchase from the firm j. $A_i(Z_{it})$ is the productivity level associated with the input set Z_{it}. The evaluation of the unit cost is based on the equilibrium price levels of the previous period and the tax rates of the current period. Firm i accepts the candidate input set $\widehat{Z_{it}}$ if the productivity gain from increasing the use of automation outweighs the cost increase determined by the automation input's price and tax wedge:

$$w_{ikt} = \widehat{w_{ikt}} \quad \text{iff} \quad \frac{A_i(\widehat{Z_{it}(s_{it})})}{A_i(Z_{it-1})} > \left(P^*_{kt-1}(1+e_{ikt})\right)^{s_{it}\alpha_{it-1}}. \tag{4.7}$$

This condition ensures that the productivity improvement from reallocating labor to the automation input k exceeds the proportional increase in unit cost.

The evolution of the weighted production network $W_t = [w_{ijt}]$ over time is governed by firm-level adjustments. For each firm i, the input shares evolve according to:

$$w_{ijt} = \begin{cases} w_{ijt-1} + s_{it}\alpha_{it-1}, & j = k \text{ and } \frac{A_i(\widehat{Z_{it}(s_{it})})}{A_i(Z_{it-1})} > (P^*_{kt-1}(1+e_{ikt}))^{s_{it}\alpha_{it-1}} \\ w_{ijt-1}, & j \in Z_{it-1} \setminus \{k\} \\ 0, & j \notin Z_{it-1} \cup \{k\} \end{cases}$$

with the labor share α_{it} ensuring that:

$$\alpha_{it} + \sum_{j \in Z_{it}} w_{ijt} = 1.$$

Thus, the production network W_t evolves endogenously as firms adjust their input allocations based on relative prices, tax wedges, and productivity gains from automation.

4.3.3 Using Tax Exemptions as a Tool for Fostering Automation

The decision regarding the use of an automation input is fundamentally driven by the firm's evaluation of the trade-off between its cost and the potential productivity gains from the update of its weight in the production process. Notably, the decision is based on the cost of the input k - determined by its previous period equilibrium price P^*_{kt-1} and the current tax rate e_{ikt}-, and the firm's own (private) assessment of productivity improvements.

Tax rates are controllable industrial policy tools by the policymaker that may influence firms' input use decision processes. Governments frequently use tax exemptions to enhance innovation in R&D conducting firms. For example, the United States offers a sales and use tax exemption for manufacturers investing in qualifying machinery and equipment used in production or R&D activities (Department of Revenue Washington State, 2024). Similarly, Turkey provides VAT exemptions on R&D conducting firms' machinery and equipment purchases through its Technology Development Zones (TDZs). These incentives reduce the cost of technology adoption for target firms, thereby increasing their likelihood of adopting new, productivity-enhancing inputs into their production processes. In our framework, this corresponds to a lower effective tax rate e_{ikt} on input purchases for targeted firms.

Identifying the potential impacts of these policies is challenging because tax exemptions can be transmitted through multiple channels to aggregated economies. To clarify the effect of tax policies on aggregated outcomes, we analyze the equilibrium real GDP:

$$g^*_t = \frac{1}{n_t}\mathbf{1}'\mathcal{L}_t(a_t(Z_t) - T_t) + \chi log(R_t),$$

where $\mathcal{L}_t = [\mathbf{I} - W_t]^{-1}$ is the Leontief inverse whose ij'th element shows the influence of firm j on firm i as a direct and/or an indirect supplier. Its aggregation by final consumption shares of firms gives an influence vector for the firms within the economy: $V_t = \frac{1}{n_t}\mathbf{1}'\mathcal{L}_t$.

Decomposition of the Effects of Tax-exemption Policies:

1. Direct effects - variations in production cost and policymaker revenue: Changes in tax rates directly influence the equilibrium real GDP through two main channels: (i) variations in production costs due to tax wedges (T_t), and (ii) changes in government revenue (R_t), which influence household utility from public goods provision ($\chi log(R_t)$).

If the policymaker exempts certain firms from input taxes, their unit costs decrease, which in turn leads to lower prices. The lower prices propagate downstream for the given influence vector V_t. Furthermore, such exemptions also impact government tax revenue (R_t). Because those firms do not pay any tax on their input purchases, the revenue decreases. Decreasing revenue also reduces the household's utility by lowering the resources available for public goods spending. The parameter χ determines the magnitude of the negative influence of tax exemptions.

2. Indirect effects - production network formation dynamics: The second mechanism of transmission of tax exemptions to aggregated outcomes is shifts in the evolution of production networks. Tax-exemption increases the probability of automation through the use of more input k as defined in the condition 4.7. As firms use more input k, this causes a change in the evolution pattern of the weight matrix W_t. The weight matrix influences the productivity levels and the Leontief inverse:

(2a) The productivity levels: As explained earlier, a firm's productivity depends on its use of intermediary inputs. Therefore, shifts in network formation patterns influence firms' productivity levels. Let us assume a spatial auto-regressive linear relationship between a firm's productivity and the productivity levels of its suppliers. This functional relationship captures the spillover effects in production networks. Formally, we define:

$$a_{it}(w_{ijt}, a_{jt} : j \in Z_{it}) = \lambda_0 + \lambda_1 \sum_{j \in Z_{it}} w_{ijt} a_{jt}, \tag{4.8}$$

where the log-productivity of firm i, $a_{it} = \log\left(A_{it}(Z_{it})\right)$, is a linear function of the productivity levels of its input suppliers. λ_0 is the constant technology parameter, and λ_1 is the parameter that captures the strength of technological dependence among firms in the production network. Spillover effects imply that firms enhance their productivity by sourcing inputs from more productive suppliers. This linear formulation leads to the productivity vector:

$$a_t = [\mathbf{I} - \lambda_1 W_t]^{-1}\mathbf{1}\lambda_0, \tag{4.9}$$

where $\mathbf{1}$ is the $n_t \times 1$ vector of ones. The above formula indicates that a change in a firm's input use weights affects both its own productivity and that of its downstream customers. Consequently, the vector of log-productivity levels $a_t(Z_t)$ evolves with the structure of the production network, and productivity spillovers from automation propagate through downstream linkages.

Notably, the productivity gains from automation are known only to individual firms and cannot be fully anticipated or observed by policymakers. Therefore, policymakers cannot design a tax-exemption policy that ensures firms will adjust their input use accordingly. Considering the infeasibility of predicting firms' input use decisions, policymakers can design tax policies that systematically influence the broader structure of the production network by shifting cost-benefit calculations in favor of automation.

(2b) The Temporal Leontief inverse: Lastly, tax exemptions may alter the equilibrium real GDP through the variations in firms' influence within the production network defined through the Leontief inverse. As the production network evolves, the influence between pairs of firms also evolves. To understand the effect of production network formation on firms' influence within the network, we draw on the literature on the Temporal Leontief Inverse, which examines how changes in input-output relationships between firms/sectors affect the overall state of the economy (Sonis and Hewings, 1998; Okuyama et al., 2006; Avelino et al., 2021). Temporal Leontief inverse formulation enables us to trace the impact of production network evolution on aggregated outcomes.

Let's say the production network denoted as W_t at period t is resulted from a change in W_{t-1} by K_t^{ik} that is a $n_t \times n_t$ matrix whose ik'th element is the change in the weight of input k in production of firm i $w_{ikt} - w_{ikt-1}$ and other elements are zero:

$$W_t = W_{t-1} + K_t^{ik}.$$

So, the Leontief inverse can be written as

$$\mathcal{L}_t = [\mathbf{I} - (W_{t-1} + K_t^{ik})]^{-1}$$

or

$$\mathcal{L}_t = [\mathbf{I} - \mathcal{L}_{t-1} K_t^{ik}]^{-1} \mathcal{L}_{t-1}.$$

$M_t = [\mathbf{I} - \mathcal{L}_{t-1} K_t^{ik}]^{-1}$ is called as left Leontief inverse multiplier as defined in Sonis and Hewings (1998). It denotes the change in influences of each firms on other firms as direct and/or indirect suppliers due to K_t^{ik}. We can also decompose the change in Leontief inverse additively:

$$\mathcal{L}_t = \mathcal{L}_{t-1} + [M_t - \mathbf{I}]\mathcal{L}_{t-1}.$$

The second term in the above expression is called a Temporal Increment Matrix, which also captures the Leontief inverse changes.

The change in the Leontief inverse triggered by a tax exemption policy influences spillover effects in the economy. How variations in the productivity levels a_t or tax wedges T_t spillover through the economy depends on how the Leontief inverse evolves with the tax exemption policies.

Policy Design and Targeting Scenarios

Let us consider a case in which a policymaker aims to achieve the replacement of s share of labor use to be replaced by the automation input k by all the firms. As all firms adjust their automation input use, the policymaker stops considering tax-exemption implications. In designing tax-exemption policy, the policymaker has information on the equilibrium input prices in the previous period. However, it is difficult to know how productivity levels exactly change with automation. Thus, the policymaker can not certainly determine a threshold at which firms' input use decisions may be altered through tax exemptions. Hypothetically, we define the condition of adjusting the use of input k for firm i for a given productivity function as defined in the equation 4.8 through the input use adjustment condition 4.7:

$$\frac{\lambda_1 a_{kt-1}}{p_{kt-1} + log(1 + e_{ikt})} > 1. \tag{4.10}$$

This ratio serves as an indicator of the feasibility of increasing the weight of automation input k in production. As this ratio is below one, no firm adjusts the use of automation input.

However, this ratio can be altered for specific firms by adjusting tax rates for their input purchases (e_{it}). For the policymaker, it is costly to exempt all firms from their tax payments to achieve complete automation by all firms. Therefore, the policymaker should prioritize some firms to adjust their use of automation input. As prioritized firms automate over time, the productivity and price levels within the economy change. That may make the automation feasible for all firms at some point with decreasing price and increasing productivity of the automation input due to spillover effects. Let us consider different scenarios in which the policymaker targets a group of firms for tax exemption policies for their input purchases. The determination of target groups is a question that is difficult to answer, considering one factor. In general policy implications, target groups are determined based on sectors, regions, or types of firms, such as young, small or R&D conducting firms. In this chapter, we will analyze *network-informed targeting scenarios* that focus on firms with strong propagation potential—which may lead to shorter time to reach complete automation.

- Our base **Scenario A (No Intervention)** represents the case that the policymaker does not impose any tax exemptions, and the production network evolves with the ordinary decisions of firms.

- The **Scenario B (Random Targeting)** represents the case that the policymaker randomly targets a group of firms to be exempted from tax payments.

- In **Scenario C (Static Centrality Targeting - High Centrality):** The policymaker gives tax exemptions to firms with the strongest influence in the production network. The influence vector of the economy is $V_t = \frac{1}{n_t}\mathbf{1}'\mathcal{L}_t$. This vector implies the importance of each firm as a supplier within the production network.

- In **Scenario D (Static Centrality Targeting - Low Centrality):** The policymaker gives tax exemptions to firms with the least influence in the production network.

- In **Scenario E (Temporal Centrality Targeting):** The policymaker targets the firms with the highest potential to increase their influence with the update of their input use: We create an index for potential change in influence of firms by using the Temporal Leontief Inverse multiplier matrix for the supply set update of each of the firms:

  - For each firm i, compute the potential change in the influence vector, assuming that they adopt the innovative input k:

  $$\Delta V_t^{ik} = \frac{1}{n_t}\mathbf{1}' M_t^{ik}$$

  where $M_t^{ik} = [\mathbf{I} - \mathcal{L}_{t-1} K_t^{ik}]^{-1}\mathcal{L}_{t-1}$ is the Temporal Leontief Inverse multiplier if only firm i extend its input use with input k.

  - ΔV_t^{ik} is a vector of potential change in influences of all firms with firm i's expansion of use of input k.

– The i'th element of ΔV_t^{ik} is the potential change in influence of firm i by its decision in favor of automation.

– Target the firms with the highest potential increase in their influence by input use decision.

Our approach to designing industrial policy takes into account the impact of network formation. We leverage the structure of production networks in our policy design by considering both propagation and network formation effects. The next section presents a simulation setup to analyze effects of tax exemption policies.

4.4 Simulation Results

This section demonstrates the varying production network formation effect of tax-based industrial policies across the different targeting approaches. We simulate five scenarios using "The Use Table (Supply-Use Framework), 2017" from the Bureau of Economic Analysis (BEA), focused on 6-digit U.S. manufacturing industries. Because our data are at the industry level, we treat industries as the target productive units. We construct a 231×231 matrix representing industry-level input use, with each industry able to endogenously adopt inputs from the "Relay and Industrial Control Manufacturing" industry, which serves as a stylized automation-enhancing input supplier.

We run 1000 Monte Carlo Simulations for random Labor-Substitution Shares, denoted as $s \in (0, 0.5)$, to capture the uncertainty in the proportion of labor that can be substituted with the automation input. Further, we analyze in detail the variations in productivity and price levels of the automation input for a given labor substitution rate, $s = 0.25$. In reality, this value depends on technological characteristic of the automation input and the industries' capabilities. However, we assume labor-substitution rate is identical for all industries and given. The purpose of this chapter is to show the production network formation effect of tax exemption policies: In all scenarios except Scenario A, one industry is exempt from taxes on its input purchases for just one period.

4.4.1 Simulation Setup

The simulation proceeds in the following steps for random Labor-Substitution Shares - $s \in (0, 0.5)$:

1. Construct the input use matrix $A_t = [A_{ijt}]$ capturing the value of transactions between supplier (columns) and buyer (rows) industries.[1]

2. Construct the labor compensation vector L_t representing total labor payments for each industry.

3. Compute labor share α_{it} for each industry i as:

$$\alpha_{it} = \frac{L_{it}}{L_{it} + \sum_{m \in N_t} A_{imt}}$$

   which is the share of labor compensation to total production cost.

4. Construct the input weight matrix W_t, where the w_{ijt} represents the share of industry j in industry i's production cost:

$$w_{ijt} = \frac{A_{ijt}}{L_{it} + \sum_{m \in N_t} A_{imt}}$$

5. Assume the productivity function parameters $\lambda_0 = 0.1$ and $\lambda_1 = 0.5$, and compute productivity vector a_t as:

$$a_t = [\mathbf{I} - \lambda_1 W_t]^{-1} \mathbf{1} \lambda_0.$$

6. Compute equilibrium prices p_t^* and log real GDP g_t^* (Assume the parameter $\chi = 0.2$).

[1] We assume there is no self-loop in the production network.

7. Set a tax schema E_t: the input transaction tax rate $e_{ij} = 0.2$ is unform for all industry pairs $(i, j) \subset N_t$.
8. Adjust the tax schema if there is a target industry that will be exempted from tax payments, considering the policy regimes:
   - Scenario A (No Intervention).
   - Scenario B (Random Targeting).
   - Scenario C (High Centrality Targeting).
   - Scenario D (Low Centrality Targeting).
   - Scenario E (Temporal Centrality Targeting).
9. Determine the industries replacing s_t share of labor use with the automation-enhancing industry inputs by considering the feasibility condition 4.7.
10. Identify industries that will continue to pursue automation, excluding those already automated.
11. The simulation iterates until either all industries automate or no further automation occurs.

4.4.2 Results and Interpretation

Figure 4.1 illustrates the distributions of productivity and price levels for both the initial production network and the hypothetical production network in which all industries substitute 25% of their labor with automation inputs from the "Relay and Industrial Control Manufacturing" industry (complete automation).

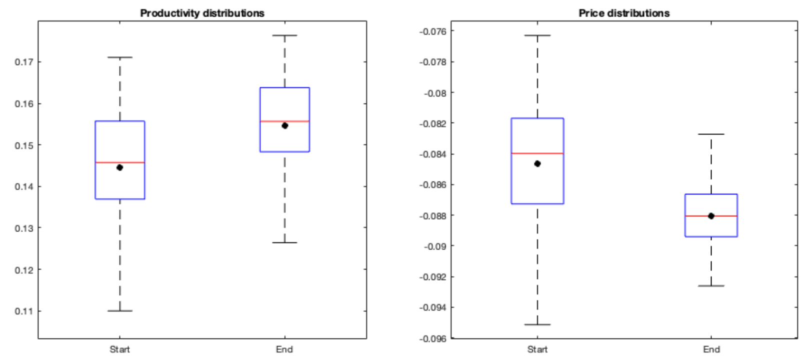

Figure 4.1: Productivity and price distributions initially and after all industries substitute 25% of their labor with the automation input

The hypothetical production network with complete automation provides a valuable reference point (Complete automation states that $w_{ikt} > 0$ for all $i \in N_t$). When all industries automate, the average log-productivity rises by one basis point (from 0.1445 to 0.1546). The average log-level price also decreases from -0.0847 to -0.0880. After complete automation, the centrality level of the automation input supplier radically rises from 0.0163 to 0.3086. The log-level real value added increases from 2.6773 to 2.7038.

For given values for the automation input productivity and price levels, the parameter $\lambda_1 = 0.5$ and the tax rate $e_{ikt} = 0.2$ for all $i \in N_t$, the feasibility ratio is

$$\frac{\lambda_1 a_{kt-1}}{p_{kt-1} + log(1 + e_{ikt})} = 0.7387.$$

Since the feasibility ratio is less than 1, no industry chooses to adjust its automation input use in scenario (A), where there is no tax exemption policy. Therefore, we analyze automation patterns in other scenarios in which an industry is exempt from tax payments at each period.

The automation completion time, which is the number of simulation periods needed until all industries automate, is the indicator to analyze the efficiency of target strategies across scenarios. The automation completion time varies across scenarios due to the varying spillover effects within the network. It depends on the targeted industries' positions in the production network and on how their automation choices influence downstream industries. The automation decision made by an industry directly increases its productivity and reduces its price. The productivity increase and price decrease in the adopter industry indirectly influence its downstream industries. This indirect effect reaches the automation input supplier to some extent. Therefore, while supporting certain industries may lead to faster automation across the economy, it may be slower in others due to varying influences on the price and productivity levels of the automation input supplier. If the feasibility ratio exceeds one due to increasing productivity and/or decreasing prices, automation becomes feasible across all industries.

Longer automation completion times require the policymaker to support more industries through tax exemptions, thereby generating higher fiscal costs. We define the fiscal cost of tax exemptions as the difference between the revenue from tax payments for input purchases with and without the target industry m:

$$\sum_{i \in N_t} \sum_{j \in Z_{it}} e_{ijt} A_{ijt} - \sum_{i \in N_t \setminus m} \sum_{j \in Z_{it}} e_{ijt} A_{ijt},$$

at a period t. This value represents the tax revenue foregone at time t for the given transaction values. The total value of tax exemptions is the sum of the value of tax exemptions until all industries automate. Table 4.1 demonstrates these outcomes across five different policy regimes.

Table 4.1: Automation completion time and the total value of tax exemptions

Scenario	**Automation Completion Time**		**Total Value of Tax-Exemptions**	
	Mean	**Std.**	**Mean**	**Std.**
Scenario A	-	-	-	-
Scenario B	86.47	57.03	591.78	395.96
Scenario C	3.30	1.48	16.69	10.09
Scenario D	228.40	0.73	1572.75	4.71
Scenario E	2.87	0.99	13.43	6.37

Scenario-A (No interventions): When there is no policy intervention, no industry chooses to automate. That highlights the role of policy in shifting industries' idiosyncratic cost-benefit trade-off in input adoption processes.

Scenario - B (Random Targeting): Randomly supporting industries requires 86.47 tax exemption periods on average. This scenario serves as an unbiased benchmark that reflects the network's average diffusion capacity. The total value of tax exemptions provided by the policymaker across the average 86.47 simulation steps is 591.78.

Scenario - C (High Centrality Targeting): Targeting the most central industry requires 3.30 exemption periods on average. On average, the total value of tax exemptions amounts to 16.69.

Scenario - D (Low Centrality Targeting): This is the least efficient targeting strategy, with 228.40 simulation periods for complete automation. Peripheral industries have limited propagation effects, so they yield little spillover toward the rest of the network. The average of the total value of tax exemptions is 1572.75 across 1000 simulations.

Scenario - E (Temporal Centrality Targeting): This strategy identifies industries with the highest potential to increase their centrality after automation. It is the most efficient, requiring 2,87 exemption periods until all industries choose to automate. This result suggests that the marginal change in centrality due to automation, rather than current centrality, may govern the greater propagation of automation. The average of the total value of tax exemptions is 13.43 across 1000 simulations.

The table 4.1 helps us understand which policy regime is better for faster automation across all industries in the economy. Let us analyze how the feasibility of the automation input and macroeconomic indicators vary across the policy targeting scenarios (B-E) until all industries automate, for a given labor-substitution rate $s = 0.25$. As we mentioned before, all industries choose to automate if the feasibility condition 4.10 is satisfied. The price and productivity levels of the automation input, along with the tax rate, determine this condition.

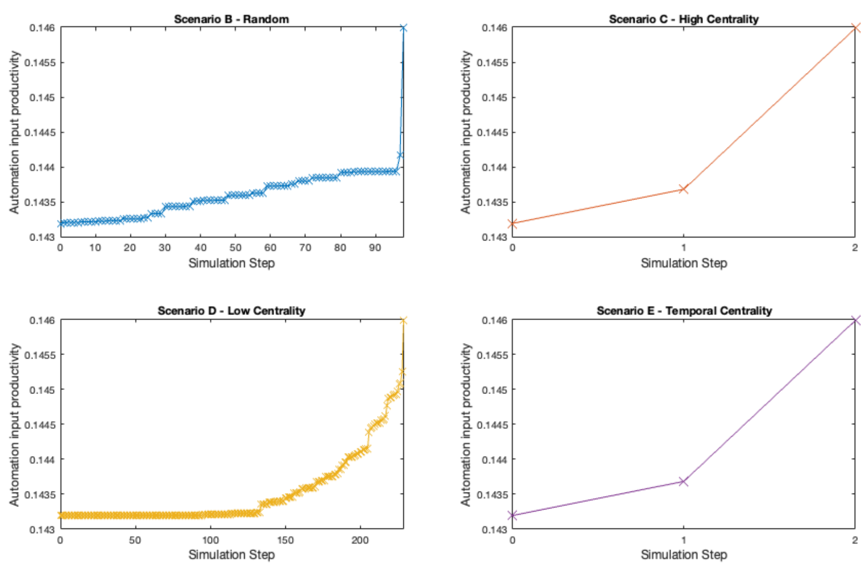

Figure 4.2: Evolution of the Productivity Level of the Automation Input Supplier.

Figure 4.2 demonstrates the evolution of the productivity level of the automation input supplier. In all scenarios, the productivity level of the automation input suppliers increases. That trend stems from the definition of the productivity function in Equation 4.8. As adopter industries increase their productivity, their downstream industries also gain productivity. These spillover effects increase the productivity level of the automation input supplier.

Figure 4.3 demonstrates fluctuating patterns in the automation input price. The high volatility in prices stems from the implications of tax exemptions for a single period for each target industry. As targeted industries automate in the current period, they pay taxes in subsequent periods. The price decrease at each simulation step is corrected. However, it still has a downward trend.

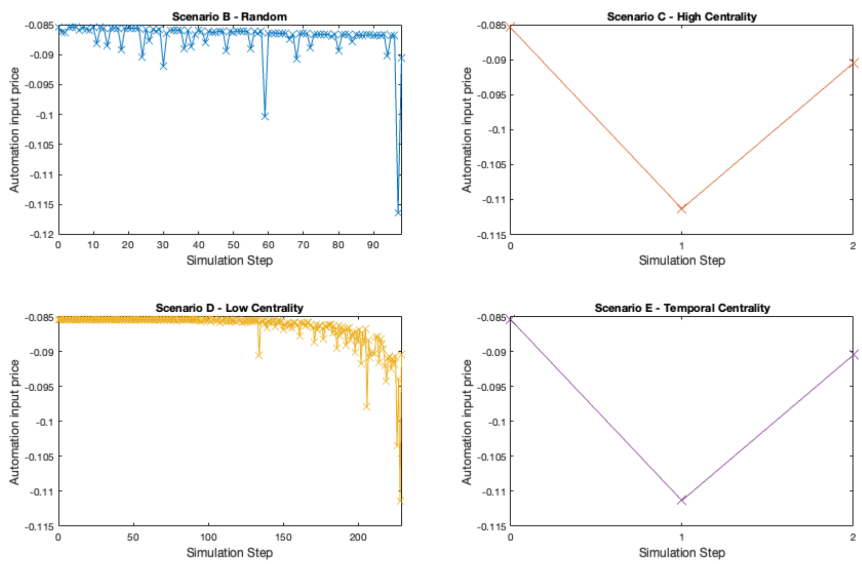

Figure 4.3: Evolution of the Price Level of the Automation Input Supplier.

Variations in the productivity and price levels of the automation input supplier lead to fluctuations in the feasibility ratio (Figure 4.4). As the feasibility ratio exceeds the threshold value of 1, all industries adjust their automation input use, and the policymaker ends the tax-exemption policy. In 2 simulation steps, all industries adjust their automation input use in Scenario (C) and (E) when the labor-substitution rate is 25%. As the policymaker withdraws tax exemptions, prices rise again, leading to a feasibility ratio below one after all industries automate.

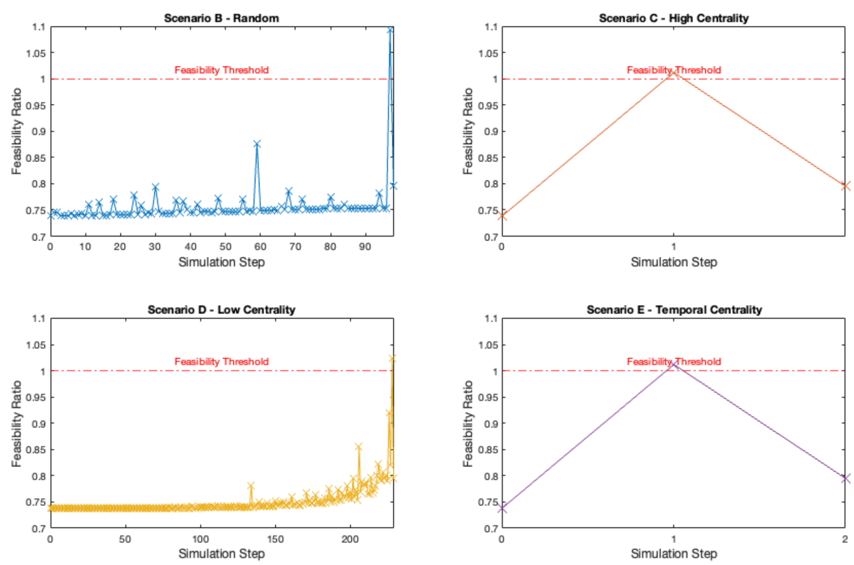

Figure 4.4: Feasibility ratio for automation

Figure 4.5 demonstrates the fluctuations in real value added until all industries choose to automate. As we mentioned before, the start and end period real value added are the same across all scenarios, as all industries adjust their use of automation inputs. As seen in Figure 4.6, the policy maker's revenue is also highly fluctuating because target industries are exempted from tax payments just for one period. However, it increases after all industries automate, driven by higher purchases from the automation input supplier.

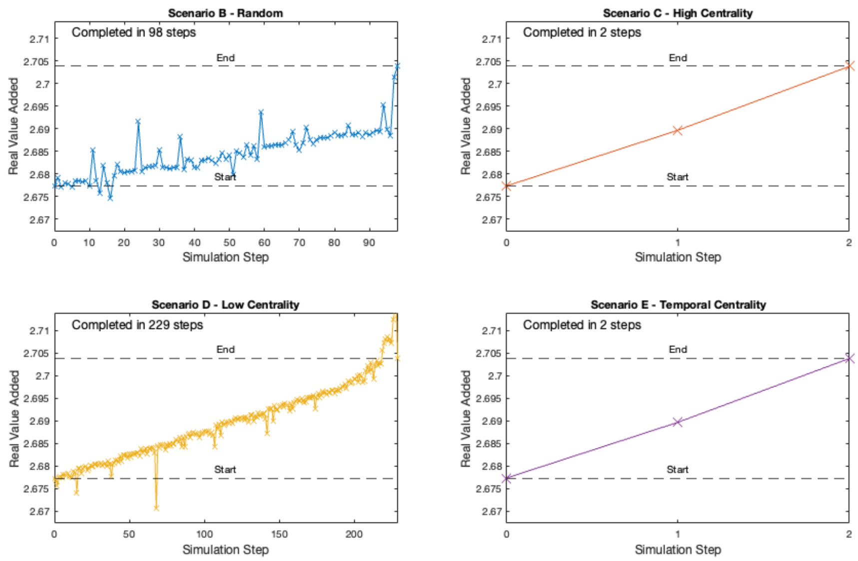

Figure 4.5: Evolution of real value added until complete automation

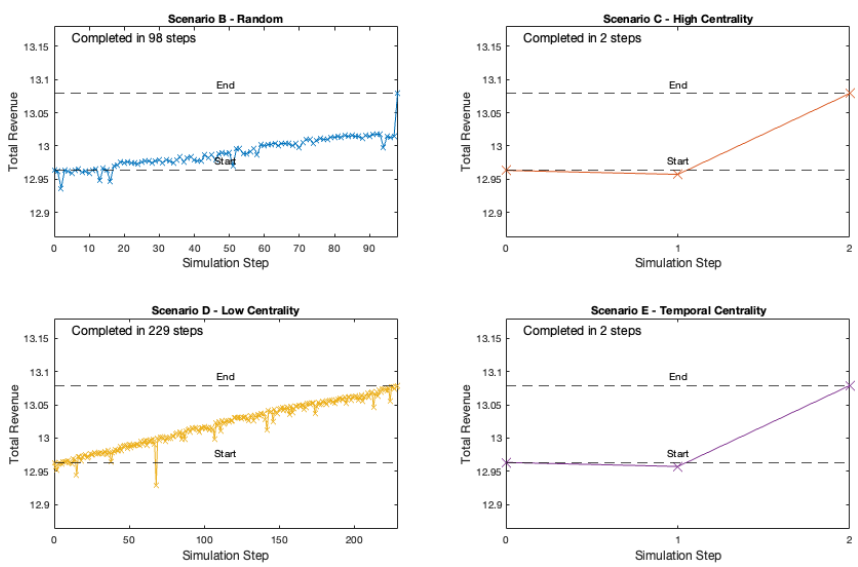

Figure 4.6: Evolution of total policymaker revenue until complete automation

Scenarios (C) and (E) outperform the others due to more substantial spillover effects within the production network. Table 4.1 demonstrates that targeting industries with high marginal centrality increases potential (Scenario-E) and results in slightly shorter average automation completion time across 1000 simulations. This strategy accounts for the industry with the most remarkable marginal change in centrality triggered by a higher automation input share. This targeting strategy creates spillovers that accelerate economy-wide transformation while efficiently using fiscal resources.

This basic model helps us understand the effects of tax exemptions on the formation of production networks. As we mentioned before, those policies apply to certain R&D-conducting producers for specific periods and to all machinery and equipment purchases in many countries. In reality, firms search for multiple alternative technologies from different suppliers and select an optimal combination of inputs by considering the trade-off between high production costs and higher productivity from additional inputs. Firms exempt from tax payments are more flexible in their search for alternative technologies and in forming supplier links. Our simulation results highlight the need to study tax exemption policies in greater detail in the context of production network formation dynamics.

4.5 Conclusion

This chapter explores the intersection of industrial policy and production network theory. We provide a structured review of recent literature on production network theory, which has the potential to enhance the research on industrial policy. Industrial policy is now being discussed more systematically, moving away from the previous ideological debates.

Building on the structural review of production networks and industrial policy, we develop a general equilibrium framework with a production network formation model. In the formation model, firms decide whether to replace a proportion of labor with an automation input. The primary goal is to analyze how industrial policies shape the evolution of production networks through tax exemptions, drawing on real-world tax relief programs in the US and Turkey.

The model is simulated using the industry-level Use Table from the Bureau of Economic Analysis (BEA), and industries are therefore treated as the productive units. We consider five different scenarios: Scenario A - No Interventions. Scenario B - Random Targeting: a randomly selected industry is supported by tax-exemptions. Scenario C - High Centrality Targeting: The industry with the highest centrality is targeted. Scenario D - Low Centrality Targeting: The industry with the least centrality is targeted. Scenario E - Temporal Centrality Targeting: The industry with the highest potential centrality gains from adopting the automation input receives tax exemptions. We run 1000 simulations for random labor-subsitution shares for each scenario. Our findings show that targeted tax-based industrial policies can influence overall economic performance by strategically transforming production networks. While there are no interventions (Scenario A), no industry can automate. On the other hand, scenarios including policy interventions lead to automation across all industries over time. When firms with the highest marginal influence potential are exempted from tax payments (Scenario E), the shortest average automation completion time (the number of periods until all industries automate) is observed. The variations in automation completion time across scenarios are explained by differences in the propagation effects, amplified by strategic targeting.

The network-informed policy targeting strategies are feasible to implement because they require only input-output tables and firm-level tax records to approximate potential propagation metrics. Optimizing the timing for targeting a group of firms may be a valuable area for future research. Additionally, exploring alternative input search rules, such as inputs that either substitute for or complement existing intermediary inputs instead of labor, could be a valuable future contribution.

Statements and Declarations

Funding declaration

This work has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No 956107, "Economic Policy in Complex Environments (EPOC)."

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used [ChatGPT and Grammarly] in order to improve language and readability. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Bibliography

Acemoglu, D. and Azar, P. D. (2020). Endogenous production networks. *Econometrica*, 88(1):33–82.

Acemoglu, D., Carvalho, V. M., Ozdaglar, A., and Tahbaz-Salehi, A. (2012). The network origins of aggregate fluctuations. *Econometrica*, 80(5):1977–2016.

Acemoglu, D. and Tahbaz-Salehi, A. (2020). Firms, failures, and fluctuations: The macroeconomics of supply chain disruptions. Working Paper 27565, National Bureau of Economic Research.

Acemoglu, D. and Tahbaz-Salehi, A. (2024). The Macroeconomics of Supply Chain Disruptions. *The Review of Economic Studies*, page rdae038.

Aghion, P., Cai, J., Dewatripont, M., Du, L., Harrison, A., and Legros, P. (2015). Industrial policy and competition. *American Economic Journal: Macroeconomics*, 7(4):1–32.

Aghion, P. and Howitt, P. (1992). A model of growth through creative destruction. *Econometrica*, 60(2):323–351.

Akbari, K., Winter, S., and Tomko, M. (2023). Spatial causality: A systematic review on spatial causal inference. *Geographical Analysis*, 55(1):56–89.

Arrow, K. J. and Debreu, G. (1954). Existence of an equilibrium for a competitive economy. *Econometrica*, 22(3):265–290.

Atalay, E. (2017). How important are sectoral shocks? *American Economic Journal: Macroeconomics*, 9(4):254–80.

Atalay, E., Hortaçsu, A., Roberts, J., and Syverson, C. (2011). Network structure of production. *Proceedings of the National Academy of Sciences*, 108(13):5199–5202.

Avelino, A. F., Franco-Solís, A., and Carrascal-Incera, A. (2021). Revisiting the temporal leontief inverse: New insights on the analysis of regional technological economic change. *Structural Change and Economic Dynamics*, 59:79–89.

Bacilieri, A., Borsos, A., Astudillo-Estevez, P., Hoefer, M., and Lafond, F. (2023). Firm-level production networks: what do we (really) know? INET Oxford Working Papers 2023-08, Institute for New Economic Thinking at the Oxford Martin School, University of Oxford.

Ballester, C., Calvó-Armengol, A., and Zenou, Y. (2006). Who's who in networks. wanted: The key player. *Econometrica*, 74(5):1403–1417.

Baqaee, D. and Rubbo, E. (2023). Micro propagation and macro aggregation. *Annual Review of Economics*, 15(Volume 15, 2023):91–123.

Baqaee, D. R. and Farhi, E. (2019a). The macroeconomic impact of microeconomic shocks: Beyond hulten's theorem. *Econometrica*, 87(4):1155–1203.

Baqaee, D. R. and Farhi, E. (2019b). Productivity and Misallocation in General Equilibrium*. *The Quarterly Journal of Economics*, 135(1):105–163.

Baqaee, D. R. and Farhi, E. (2024). Networks, barriers, and trade. *Econometrica*, 92(2):505–541.

Bardhan, P. K. (1971). On optimum subsidy to a learning industry: An aspect of the theory of infant-industry protection. *International Economic Review*, 12(1):54–70.

Barrot, J.-N. and Sauvagnat, J. (2016). Input Specificity and the Propagation of Idiosyncratic Shocks in Production Networks. *The Quarterly Journal of Economics*, 131(3):1543–1592.

Bellamy, M. A., Ghosh, S., and Hora, M. (2014). The influence of supply network structure on firm innovation. *Journal of Operations Management*, 32(6):357–373.

Bigio, S. and La'O, J. (2020). Distortions in Production Networks*. *The Quarterly Journal of Economics*, 135(4):2187–2253.

Bimpikis, K., Fearing, D., and Tahbaz-Salehi, A. (2018). Multisourcing and miscoordination in supply chain networks. *Operations Research*, 66(4):1023–1039.

Boehm, C. E., Flaaen, A., and Pandalai-Nayar, N. (2019). Input Linkages and the Transmission of Shocks: Firm-Level Evidence from the 2011 Tōhoku Earthquake. *The Review of Economics and Statistics*, 101(1):60–75.

Bonacich, P. (1987). Power and centrality: A family of measures. *American Journal of Sociology*, 92(5):1170–1182.

Breschi, S., Lissoni, F., and Malerba, F. (2003). Knowledge-relatedness in firm technological diversification. *Research Policy*, 32(1):69–87.

Bryce, D. J. and Winter, S. G. (2009). A general interindustry relatedness index. *Management Science*, 55(9):1570–1585.

Carvalho, V., Nirei, M., Saito, Y., and Tahbaz-Salehi, A. (2020). Supply chain disruptions: Evidence from the great east japan earthquake*. *The Quarterly Journal of Economics*, 136.

Carvalho, V. M. (2014). From micro to macro via production networks. *Journal of Economic Perspectives*, 28(4):23–48.

Carvalho, V. M. and Tahbaz Salehi, A. (2019). Production networks: A primer. *Annual Review of Economics*, 11(1):635–663.

Carvalho, V. M. and Voigtländer, N. (2014). Input diffusion and the evolution of production networks. Working Paper 20025, National Bureau of Economic Research.

Chaney, T. (2014). The network structure of international trade. *American Economic Review*, 104(11):3600–3634.

Chang, H.-J. (2002). *Kicking Away the Ladder: Development Strategy in Historical Perspective*. Anthem Press.

Chang, H.-J. and Andreoni, A. (2020). Industrial policy in the 21st century. *Development and Change*, 51(2):324–351.

Chen, S.-M., Yeh, M.-S., and Hsiao, P.-Y. (1995). A comparison of similarity measures of fuzzy values. *Fuzzy Sets and Systems*, 72(1):79–89.

Cimoli, M. and Dosi, G. (2016). *Efficiency, Finance, and Varieties of Industrial Policy : Guiding Resources, Learning, and Technology for Sustained Growth*, chapter 2. Industrial Policies in Learning Economies, pages 23–64. Columbia University Press, New York, UNITED STATES.

Criscuolo, C., Dechezlepretre, A., Guillouet, L., Lalanne, G., and Manaresi, F. (2024). Estonia's firm-level production network: Lessons for industrial policy. OECD Science, Technology and Industry Working Papers 2024/13, OECD Publishing.

Criscuolo, C. et al. (2022). An industrial policy framework for oecd countries: Old debates, new perspectives. OECD Science, Technology and Industry Policy Papers 127, OECD Publishing, Paris.

Criscuolo, C., Martin, R., Overman, H. G., and Van Reenen, J. (2019). Some causal effects of an industrial policy. *American Economic Review*, 109(1):48–85.

Day, W. H. E. and Edelsbrunner, H. (1984). Efficient algorithms for agglomerative hierarchical clustering methods. *Journal of Classification*, 1(26):7–24.

Department of Revenue Washington State (accessed on October 9, 2024). Manufacturer's sales/use tax exemption for machinery and equipment (m&e). `https://dor.wa.gov/education/industry-guides/manufacturing-guide/manufacturers-salesuse-tax-exemption-machinery-and-equipment-me`.

Dhyne, E., Kikkawa, A. K., and Magerman, G. (2022). Imperfect competition in firm-to-firm trade. *Journal of the European Economic Association*, 20(5):1933–1970.

Dhyne, E., Kikkawa, A. K., Mogstad, M., and Tintelnot, F. (2021). Trade and domestic production networks. *The Review of Economic Studies*, 88(2 (319)):pp. 643–668.

di Giovanni, J., Levchenko, A. A., and Mejean, I. (2014). Firms, destinations, and aggregate fluctuations. *Econometrica*, 82(4):1303–1340.

Dosi, G. (1982). Technological paradigms and technological trajectories: A suggested interpretation of the determinants and directions of technical change. *Research Policy*, 11(3):147–162.

Dosi, G., Mathew, N., and Pugliese, E. (2022). What a firm produces matters: Processes of diversification, coherence and performances of indian manufacturing firms. *Research Policy*, 51(8):104152. Special Issue on Economic Complexity.

Dosi, G. and Nelson, R. R. (2010). Chapter 3 - technical change and industrial dynamics as evolutionary processes. In Hall, B. H. and Rosenberg, N., editors, *Handbook of The Economics of Innovation, Vol. 1*, volume 1 of *Handbook of the Economics of Innovation*, pages 51–127. North-Holland.

Elliott, M. and Golub, B. (2022). Networks and economic fragility. *Annual Review of Economics*, 14(Volume 14, 2022):665–696.

Elliott, M., Golub, B., and Leduc, M. V. (2022). Supply network formation and fragility. *American Economic Review*, 112(8):2701–47.

Elliott, M. and Jackson, M. O. (2023). Supply chain disruptions, the structure of production networks, and the impact of globalization.

Essletzbichler, J. (2015). Relatedness, industrial branching and technological cohesion in us metropolitan areas. *Regional Studies*, 49(5):752–766.

Evenett, S., Jakubik, A., Martín, F., and Ruta, M. (2024). The return of industrial policy in data. *The World Economy*, 47(7):2762–2788.

Fan, J. P. H. and Lang, L. H. P. (2000). The measurement of relatedness: An application to corporate diversification. *The Journal of Business*, 73(4):629–660.

Foley, I. b. D. K. (1998). An interview with wassily leontief. *Macroeconomic Dynamics*, 2(1):116–140.

Frenken, K. (2006). Technological innovation and complexity theory. *Economics of Innovation and New Technology*, 15:137–155.

Frensch, R. and Gaucaite Wittich, V. (2009). Product variety and technical change. *Journal of Development Economics*, 88(2):242–257.

Gabaix, X. (2011). The granular origins of aggregate fluctuations. *Econometrica*, 79(3):733–772.

Georgieva, V. (2025). Production Network Features of Industrial Policy. *IMF Working Papers*, 2025(023):1.

Grassi, B. and Sauvagnat, J. (2019). Production networks and economic policy. *Oxford Review of Economic Policy*, 35(4):638–677.

Grossman, G. M., Helpman, E., and Lhuillier, H. (2023a). Supply chain resilience: Should policy promote international diversification or reshoring? *Journal of Political Economy*, 131(12):3462–3496.

Grossman, G. M., Helpman, E., and Sabal, A. (2023b). Resilience in vertical supply chains. Working Paper 31739, National Bureau of Economic Research.

Gualdi, S. and Mandel, A. (2019). Endogenous growth in production networks. *Journal of Evolutionary Economics*, 29(1):91–117.

Hancock, A., Inagaki, K., and Millard, R. (2025). Carmakers sound warning over eu's 'very dangerous' local sourcing rules. Financial Times.

Hausmann, R. and Rodrik, D. (2003). Economic development as self-discovery. *Journal of Development Economics*, 72(2):603–633. 14th Inter-American Seminar on Economics.

Hidalgo, C., Balland, P.-A., Boschma, R., Delgado, M., Feldma, M., Frenken, K., Glaeser, E., He, C., Kogler, D. F., Morrison, A., Neffke, F., and Rigby, D. (2018). The Principle of Relatedness. Papers in Evolutionary Economic Geography (PEEG) 1830, Utrecht University, Department of Human Geography and Spatial Planning, Group Economic Geography.

Hidalgo, C. A. and Hausmann, R. (2009). The building blocks of economic complexity. *Proceedings of the National Academy of Sciences*, 106(26):10570–10575.

Hora, M. and Klassen, R. D. (2013). Learning from others' misfortune: Factors influencing knowledge acquisition to reduce operational risk. *Journal of Operations Management*, 31(1-2):52–61.

Hulten, C. R. (1978). Growth Accounting with Intermediate Inputs. *The Review of Economic Studies*, 45(3):511–518.

Jackson, M. O. and Rogers, B. W. (2007). Meeting strangers and friends of friends: How random are social networks? *American Economic Review*, 97(3):890–915.

Juhász, R., Lane, N., Oehlsen, E., and Pérez, V. C. (2023). Global industrial policy: Measurement and results. Policy Brief 1, United Nations Industrial Development Organization (UNIDO). Accessed: 2025-04-15.

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

Juhász, S., Broekel, T., and Boschma, R. (2021). Explaining the dynamics of relatedness: The role of co-location and complexity. *Papers in Regional Science*, 100(1):3–21.

Kauffman, S., Lobo, J., and Macready, W. (2000). Optimal search on a technology landscape. *Journal of Economic Behavior and Organization*, 43:141–166.

Kolak, M. and Anselin, L. (2020). A spatial perspective on the econometrics of program evaluation. *International Regional Science Review*, 43(1-2):128–153.

Kopytov, A., Mishra, B., Nimark, K., and Taschereau-Dumouchel, M. (2024). Endogenous production networks under supply chain uncertainty. *Econometrica*, 92(5):1621–1659.

Kuusk, K. and Martynovich, M. (2021). Dynamic nature of relatedness, or what kind of related variety for long-term regional growth. *Tijdschrift voor Economische en Sociale Geografie*, 112(1):81–96.

König, M. D., Liu, X., and Zenou, Y. (2019). R&D networks: Theory, empirics, and policy implications. *The Review of Economics and Statistics*, 101(3):476–491.

Lane, N. (2024). Manufacturing revolutions: Industrial policy and industrialization in south korea.

Lebdioui, A. (2020). Economic diversification, oil revenue management, and industrial policy in the middle east and north africa. Working Paper 1416, Economic Research Forum. Revised November 2020.

Lebdioui, A., Lee, K., and Pietrobelli, C. (2021). Local-foreign technology interface, resource-based development, and industrial policy: How chile and malaysia are escaping the middle-income trap. *The Journal of Technology Transfer*, 46(3):660–685.

Lee, K. (2013). *Knowledge and country-level catch-up*, page 45–71. Cambridge University Press.

Leontief, W. W. (1965). The structure of the u.s. economy. *Scientific American*, 212(4):25–35.

Lim, K. (2017). Firm-to-firm Trade in Sticky Production Networks. 2017 Meeting Papers 280, Society for Economic Dynamics.

Lin, J. Y. (2010). New structural economics : A framework for rethinking development.

Liu, E. (2019). Industrial Policies in Production Networks*. *The Quarterly Journal of Economics*, 134(4):1883–1948.

Liu, E. and Ma, S. (2021). Innovation networks and r&d allocation. Working Paper 29607, National Bureau of Economic Research.

Liu, E. and Tsyvinski, A. (2024). A dynamic model of input–output networks. *The Review of Economic Studies*, 91(6):3608–3644.

Long, J. B. and Plosser, C. I. (1983). Real business cycles. *Journal of Political Economy*, 91(1):39–69.

Mandel, A. and Veetil, V. P. (2021). Monetary dynamics in a network economy. *Journal of Economic Dynamics and Control*, 125:104084.

Mazzucato, M. (2018). *Entrepreneurial State Debunking Public Vs. Private Sector Myths*. Penguin Books.

McNerney, J., Savoie, C., Caravelli, F., Carvalho, V. M., and Farmer, J. D. (2022). How production networks amplify economic growth. *Proceedings of the National Academy of Sciences*, 119(1):e2106031118.

Millot, V. and Rawdanowicz, L. (2024). The return of industrial policies: Policy considerations in the current context. OECD Economic Policy Papers 34, OECD Publishing, Paris.

Mundt, P., Savin, I., Cantner, U., Inoue, H., and Vannuccini, S. (2023). Peer Effects in Productivity and Differential Growth: A Global Value-Chain Perspective. *Industrial and Corporate Change*, page dtad022.

Nelson, R. R. and Winter, S. G. (1985). *An Evolutionary theory of economic change*. Belknap Press.

Noman, A. and Stiglitz, J. E. (2016). *Efficiency, Finance, and Varieties of Industrial Policy : Guiding Resources, Learning, and Technology for Sustained Growth*, chapter 1. Learning, Industrial, and Technology Policies, pages 1–20. Columbia University Press, New York, UNITED STATES.

Oberfield, E. (2013). Business networks, production chains, and productivity: A theory of input-output architecture. 2013 Meeting Papers 120, Society for Economic Dynamics.

Oberfield, E. (2018). A theory of input–output architecture. *Econometrica*, 86(2):559–589.

Oberfield, E. and Raval, D. (2021). Micro data and macro technology. *Econometrica*, 89(2):pp. 703–732.

Okuyama, Y., Sonis, M., and Hewings, G. J. (2006). Typology of structural change in a regional economy: a temporal inverse analysis. *Economic Systems Research*, 18(2):133–153.

Pack, H. and Saggi, K. (2006). The case for industrial policy : a critical survey. Policy Research Working Paper Series 3839, The World Bank.

Pugliese, E., Napolitano, L., Zaccaria, A., and Pietronero, L. (2019). Coherent diversification in corporate technological portfolios. *PLOS ONE*, 14(10):1–22.

Rodrik, D. (2004). Industrial policy for the twenty-first century. *KSG Faculty Research Working Paper Series*, RWP04(047).

Rodrik, D. (2009). Industrial policy: Don't ask why, ask how. *Middle East Development Journal*, 1(1):1–29.

Romer, P. M. (1990). Endogenous Technological Change. *Journal of Political Economy*, 98(5):71–102.

Roy, S., Sivakumar, K., and Wilkinson, I. (2004). Innovation generation in supply chain relationships: A conceptual model and research propositions. *Journal of The Academy of Marketing Science - J ACAD MARK SCI*, 32:61–79.

Santiago, F., Haraguchi, N., and Lavopa, A. (2024). Global trends and world order: Implications for new industrial policies in developing countries. *Journal of Industry, Competition and Trade*, 24(1):5.

Savin, I. and Mundt, P. (2022). Drivers of productivity change in global value chains: Reallocation vs. innovation. *Economics Letters*, 220:110878.

Sharma, A., Pathak, S., Borah, S. B., and Adhikary, A. (2020). Is it too complex? the curious case of supply network complexity and focal firm innovation. *Journal of Operations Management*, 66(7-8):839–865.

Shell, K., Auerswald, P., Shelly, K., Ghiglino, C., Goenka, A., Gomory, R., Guckenheimer, J., Holmes, T., Volgelsang, T., Wan, H., Antinol, W., Keister, T., and Gave, W. (1999). The production recipes approach to modeling technological innovation: An application to learning by doing.

Sonis, M. and Hewings, G. J. (1998). Temporal leontief inverse. *Macroeconomic Dynamics*, 2(1):89–114.

Succar, P. (1987). The need for industrial policy in ldc's-a re-statement of the infant industry argument. *International Economic Review*, 28(2):521–534.

Tagliapietra, S. (2022). Green industrial policy: A global perspective. Technical report, United Nations Department for Economic and Social Affairs.

Taschereau-Dumouchel, M. (Jun 7, 2022). Cascades and fluctuations in an economy with an endogenous production network.

Teece, D. J., Rumelt, R., Dosi, G., and Winter, S. (1994). Understanding corporate coherence: Theory and evidence. *Journal of Economic Behavior and Organization*, 23(1):1–30.

The White House (2025). Fact sheet: President donald j. trump declares national emergency to increase our competitive edge, protect our sovereignty, and strengthen our national and economic security. Accessed: 2025-04-14.

UNIDO (2024). Industrial development report 2024: Turning challenges into sustainable solutions—the new era of industrial policy. Report 24.II.B.2, United Nations Industrial Development Organization (UNIDO), Vienna. Accessed: 2025-04-15.

Xu, R. and Wunsch, D. (2005). Survey of clustering algorithms. *IEEE Transactions on neural networks*, 16(3):645–678.

Appendix A

Appendix to Chapter 3

A.1 Case Study

For clear comprehension of network-based relatedness and Jaccard Distance metrics, let us consider a basic scenario with 2 final products and their intermediary inputs as represented in Figure A.1. Production plan of the product A is $\tau_A = \{X, Y, Z, T, Recipe_A\}$ and the production plan of the product B is $\tau_B = \{X, Y, Z, U, P, Recipe_B\}$. Given these production plans, we analyze different cases regarding the status of firms' differentiation in supplier linkages.

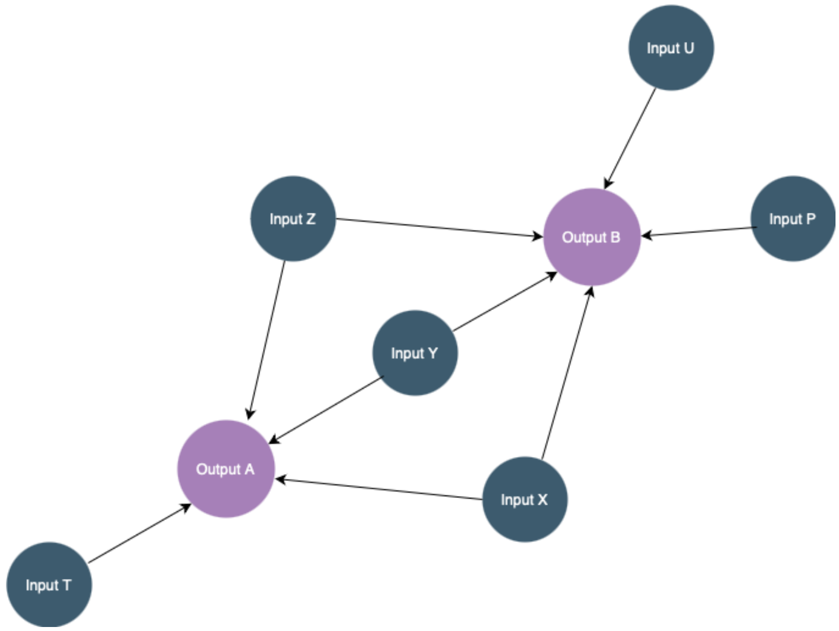

Figure A.1: Illustration of two production plans for the final products A and B.

Case 1a - Differentiation by production plans: Figure A.2 illustrates a case in which all firms produce a single product. Intermediary inputs $\{X, Y, Z, T, U, P\}$ are supplied by 6 different firms, and products $\{A, B\}$ are produced by Firm 1 and Firm 2. Those firms buy each necessary input defined in production plans τ_A and τ_B from different suppliers. The relatedness measures 3.1 between those 6 suppliers over their co-occurrence in Firm 1 and Firm 2 supplier sets are demonstrated in Table A.1. Given these relatedness measures, Firm 1's overall supplier set relatedness is 0.175, and Firm 2's overall supplier set relatedness is 0.1475. Firm 2 is more differentiated in its supplier set because it uses 2 additional inputs $\{U, P\}$ while Firm 1 differentiates by using only $\{T\}$ as well as their common inputs $\{X, Y, Z\}$. The differentiation between these two producers stems from having different production plans for A and B.

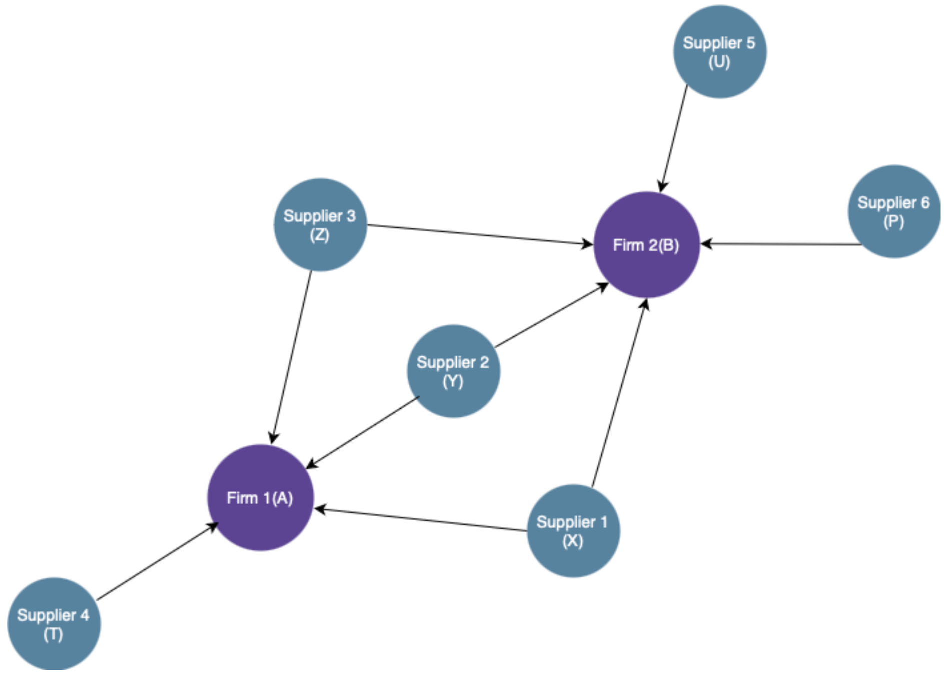

Figure A.2: Illustration of a production network between single-product firms.

Table A.1: Case 1a - Relatedness between supplier pairs.

	Supplier 1 (X)	Supplier 2 (Y)	Supplier 3 (Z)	Supplier 4 (T)	Supplier 5 (U)
Supplier 2 (Y)	0.225				
Supplier 3 (Z)	0.225	0.225			
Supplier 4 (T)	0.125	0.125	0.125		
Supplier 5 (U)	0.100	0.100	0.100	0.000	
Supplier 6 (P)	0.100	0.100	0.100	0.000	0.200

Case 1b - Multi-product suppliers: Let us consider a case in two intermediary inputs, T and U, are supplied by the same supplier 4 (Supplier 5 is out of the network) as demonstrated in Figure A.3. Firm 1 and Firm 2 still produce products A and B, respectively, with the same production plans as in case 1. In this case, Firm 2 remains more differentiated: Firm 1's overall supplier set relatedness is 0.225, while Firm 2's is 0.175. Compared

Table A.2: Case 1b - Relatedness between supplier pairs.

	Supplier 1 (X)	Supplier 2 (Y)	Supplier 3 (Z)	Supplier 4 (TU)
Supplier 2 (Y)	0.225			
Supplier 3 (Z)	0.225	0.225		
Supplier 4 (TU)	0.225	0.225	0.225	
Supplier 6 (P)	0.100	0.100	0.100	0.1

with Case 1a, both firms have more related supplier sets. Production of two inputs, T, and U -used in different production plans for A and B-, increases the overall relatedness of Firm 1 and 2's supplier sets.

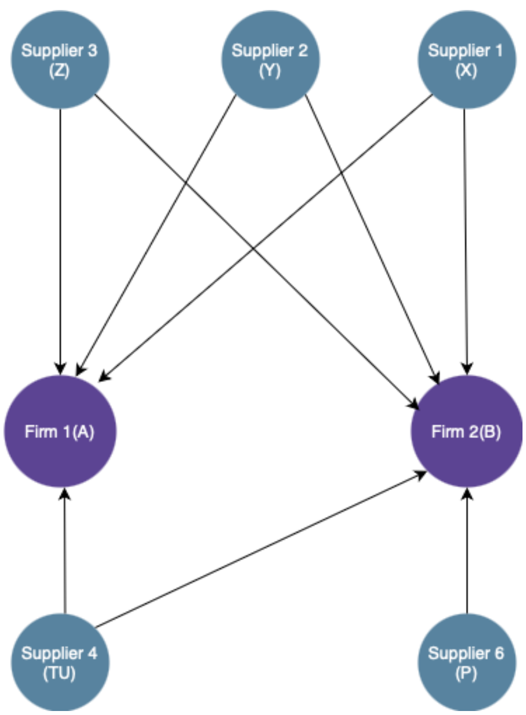

Figure A.3: Illustration of a production network including single-product firms (4 supplier firms and 2 buyer firms) and one multi-product firm (Supplier 4 produces products T and U).

Case 2 - Supplier set differentiation by product diversification: Let us consider a case where firm 1 also started to produce a product C with a technology $\tau_C = \{E, F, Recipe_C\}$. In this case, there are eight different inputs produced by 8 different firms (Figure A.4). In this case, the overall supplier-set relatedness measures for Firm 1 and Firm 2 are 0.12 and 0.135, respectively. Firm 1's technology set $T_1 = \{\tau_A, \tau_C\}$ is extended by product C. Firm 1's product diversification decreases the overall relatedness of the supplier sets of both firms.

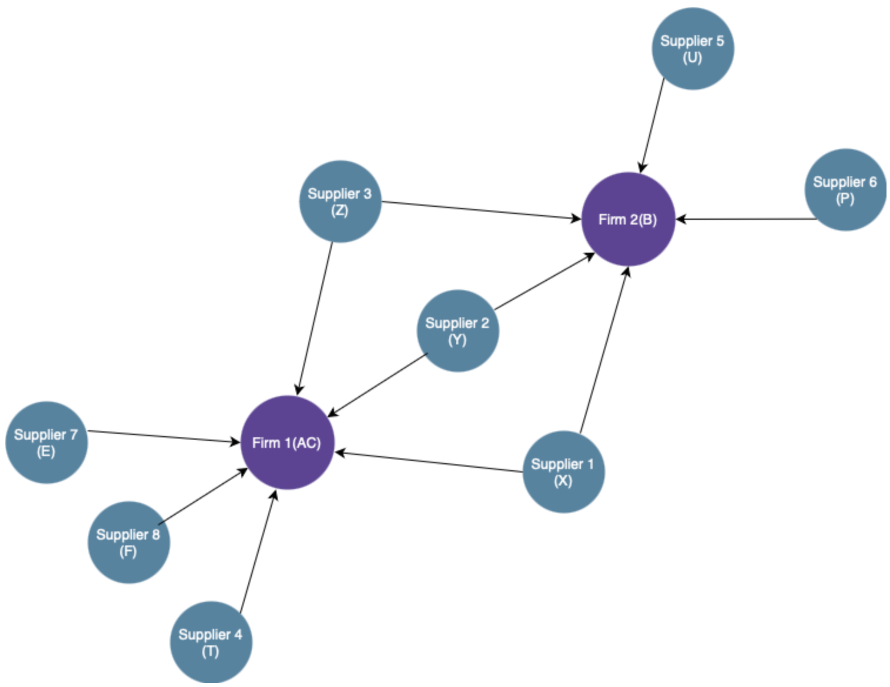

Figure A.4: Illustration of a production network including single-product firms (8 supplier firms and 1 buyer firm) and one multi-product firm (Firm 1 produces products A and C).

The cases above consider variations in firms' supplier set differentiation that may stem from differences in firms' product-level production plans and from product diversification leading to technology set diversification. Case 1b highlights that we cannot capture all technology set differentiation among

Table A.3: Case 2 - Relatedness between supplier pairs.

	Supplier 1 (X)	Supplier 2 (Y)	Supplier 3 (Z)	Supplier 4 (T)	Supplier 5 (U)	Supplier 6 (P)	Supplier 7 (E)
Supplier 2 (Y)	0.183						
Supplier 3 (Z)	0.183	0.183					
Supplier 4 (T)	0.083	0.083	0.083				
Supplier 5 (U)	0.100	0.100	0.100	0.000			
Supplier 6 (P)	0.100	0.100	0.100	0.000	0.200		
Supplier 7 (E)	0.083	0.083	0.083	0.167	0.000	0.000	
Supplier 8 (F)	0.083	0.083	0.083	0.167	0.000	0.000	0.167

firms when their suppliers have multiple products. As we indicate in Proposition 3, supplier-set differences imply technology set differences, but firms may have different technology sets even if they share the same supplier sets. Therefore, the overall supplier set-relatedness measure cannot fully capture technology set differentiation across firms. Supplier-set differentiation measures underestimate technology set differentiation. Even if we cannot fully account for technology set differentiation across firms with the same supplier linkages, we can make inferences for those with different supplier linkages.