Doctoral Thesis

Agent-based models for macro-financial and climate economics

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Contents

Chapter 1

Introduction

The organization of international production and trade has undergone substantial transformation over the last few decades. The increasing interconnectedness of the global economy has been driven by a combination of technological progress, trade liberalization, and the reduction of transportation and communication costs. These revolutions paved the way for the *unbundling* of production (Baldwin, 2016), which, in turn, shaped modern economic geography and the structure of international trade.

As trade and capital barriers have decreased, firms gained flexibility in sourcing inputs and accessing foreign markets, leading to the emergence of global value chains (GVCs) and an increase in firm-to-firm trade relationships. While globalization has created new opportunities for efficiency gains through the exploitation of comparative advantages, economic interdependence has also heightened systemic vulnerabilities. The international fragmentation of production opened new channels for the propagation of shocks across borders. Recent global crises - such as the Great Financial Crisis, the COVID-19 pandemic, the escalating climate emergency - have exposed the susceptibility of the global economy to cascading effects triggered by disruptions in strategic areas. In addition, the structure of international trade is likely to further change under the influence of ever more stringent and asymmetric climate policies. This motivates the need for an in-depth analysis of international production networks, with particular attention to how their endogenous establishment interacts with asymmetric shocks and policies.

Rising to this challenge, the thesis proposes a micro-founded perspective on the emergence and evolution of international linkages, underpinned by the organizational choices of heterogeneous firms. It investigates how trade and production networks are shaped by asymmetric shocks and heterogeneous policy interventions, and how, in turn, these evolving linkages among firms and countries influence macroeconomic outcomes. The ultimate goal is to uncover the mechanisms through which firms rewire their international network in response to disruptive events - whether financial, environmental or geopolitical - and to assess how these adaptive dynamics generate complex, often non-linear, effects at the aggregate level. In doing so, the thesis aims at bridging the micro-level determinants of trade integration with the systemic consequences of network evolution in a globalized economy.

The analysis connects to the *New-new Trade Theory*, a branch of trade studies that emerged at the turn of the century to reflect the latest trends driving globalization. This stream of literature marked a paradigmatic change in the field, shifting the focus from countries and industries to firms, whose organizational choices shape patterns of international integration. Seminal contributions have focused on firms' exporting decisions (Melitz, 2003) and multinational activity (Helpman et al., 2004), sourcing strategies (Antras and Helpman, 2004), or the new geography of production (Antràs and Chor, 2013). These insights have deepened our understanding of the microeconomic foundations of global value chains, where firm-level heterogeneity and organizational decisions are key drivers of trade flows and cross-border activities.

This thesis is grounded into the microeconomics of international trade to build agent-based models, where aggregate patterns and dynamics emerge from the bottom-up (Delli Gatti et al., 2011). The resulting framework leverages the structural insights of static trade theory and embeds them within a dynamic, decentralized system populated by heterogeneous and boundedly rational agents. This approach is particularly suited to study complex adaptive systems, where agents interact with one another and with the environment, adjusting their strategies in response to evolving economic and policy conditions. Understanding the dynamics of globalization requires, indeed, close attention to its granular origins - namely, the behaviors, interactions, and constraints of heterogeneous firms embedded in evolving production and trade networks. Micro-level processes such as sourcing decisions, local frictions, and network reconfiguration play a critical role in shaping macroeconomic outcomes, particularly under asymmetric shocks and policy heterogeneity. The modelling strategy thus offers a novel contribution to the trade literature by capturing heterogeneity, endogenous network formation, and non-linear macroeconomic dynamics from the bottom up.

The thesis comprises *four essays in international economics*, each addressing a distinct dimension of trade. They do this by exploring the backward and forward trajectories of firms' boundaries, spanning from their decisions to outsource and establish supply chains to their choices with regard to export participation and market access. Despite focusing on different aspects of trade, all essays share a common analytical perspective. They emphasize the role of firm-level decision-making, the endogenous formation of international linkages and the cross-border propagation of shocks. From a methodological perspective, each chapter is grounded in a micro-founded model of international trade that incorporates asymmetric information and bounded rationality. These models are then simulated to uncover the aggregate and dynamic properties that emerge from individual interactions.

The first essay, "*Breaking bad: supply chain disruptions in a streamlined agent-based* *model*"- investigates the macro-financial consequences of supply chain disruptions. It develops an agent-based model featuring two interconnected networks: a credit network, linking banks and firms, and a production network, connecting upstream and downstream firms. With this setting, the study delves into the reorganization of supply chains triggered by localized and generalized shocks, such as those induced by the COVID-19 pandemic.

The second essay - *"Behind the international trade network: the role of heterogeneity and financial frictions"* - analyzes a different type of shock, i.e. a financial distress, and its effects on international trade. It focuses on the trade network and seeks to unravel the mechanisms that underpin its emergence and evolution. To this end, the paper develops a multi-country general equilibrium model of trade that incorporates firms and countries heterogeneity as well as asymmetric information and financial frictions in the credit market. Within this framework, exporting decisions of financially constrained firms give rise to an international trade network that mirrors the structure of real-world trade flows. The resulting model has been employed to study the effects of financial shocks on trade flows and their network-based spillovers. Incorporating a credit market into a trade model allows for a richer understanding of the role that monetary and financial conditions play in shaping international trade patterns.

The third essay - "*Carbon leakage in production networks under asymmetric climate policies*" - investigates the unbundling of production that follows the introduction of a carbon tax. The study develops and simulates an agent-based model in which firms endogenously form supply chain linkages based on sourcing strategies, while being subject to environmental policies. This framework enables a bottom-up analysis of how climate instruments, such as carbon pricing and border carbon adjustments, shape trade relationships by affecting firms' production decisions. The findings provide insight into the consequences of asymmetric climate policies and the effectiveness of border adjustment instruments, in mitigating carbon leakage and restoring economic competitiveness.

The fourth essay - "*A network approach to the environmental policy-trade nexus* "- delves deeper into the contentious relationship between trade and the environment. It presents a preliminary empirical exploration of the link between environmental policy stringency and trade flows, combining a traditional gravity model with elements of network analysis. Namely, the paper examines whether a country's centrality within the global trade network correlates with the stringency of its environmental policies. To complement this network-based perspective, the study also estimates a gravity model in which bilateral trade flows are explained by cross-country differences in environmental policy stringency. The chapter outlines initial insights and methodological directions that may serve as the foundation for future investigation and complements the theoretical analysis of the effects of environmental policies discussed in the preceding chapter.

Together, these essays contribute to the literature on international economics by offering novel insights into the effects of trade disruptions within a networked global economy, where aggregate outcomes emerge from the interactions of heterogeneous agents, subject to a variety of economic and climate policies.

Chapter 2

Breaking Bad: supply chain disruptions in a streamlined agent-based model

2.1 Introduction

International supply chains – also known as Global Value Chains (GVCs) – are key drivers of the present stage of globalization, which goes under the name of Great Convergence (Baldwin, 2016) or hyper-globalization (Rodrik, 2011). According to Antras (2020), p.3: "A global value chain consists of a series of stages involved in producing a product or service that is sold to consumers, with each stage adding value, and with at least two stages being produced in different countries." A stylized GVC consists of a downstream sector populated by firms located in an advanced economy and producing final goods and an upstream sector populated by firms located in an emerging country which supply intermediate inputs to downstream firms. GVCs therefore are first and foremost *production networks*.

However, there is more to a supply chain than a productive and organizational arrangement. Upstream suppliers are also lenders as they extend trade credit to downstream firms. Moreover, both types of firms need external finance, which is provided by financial intermediaries (banks for short). Hence GVCs are also *financial networks*. In this paper, therefore, conceive GVCs as networks of productive and financial interlinkages between U-firms, D-firms and banks.

Being complex webs of trade-credit-logistic arrangements, GVCs are vehicles for the transmission and amplifications of shocks. Real or financial shocks hitting a stage of production yield a *disruption* of the supply chain which reverberates on the other stages via backward and forward linkages. This is the *ripple effect*. Due to the interlinkages of a myriad of spatially dispersed heterogeneous firms international trade has become a

*This paper, co-authored with Prof. Domenico Delli Gatti, was developed during the first year of my PhD at Università Cattolica del Sacro Cuore (UCSC) and was subsequently published in *The European Journal of Finance*. The paper is included in the thesis in its original published version: Delli Gatti and Grugni (2021).

complex network characterized by high systemic risk (Goldin and Mariathasan, 2014).

For instance, an earthquake or the outbreak of a pandemic in an emerging country forces upstream firms to close down. Hence downstream firms face capacity constraints, being short of intermediate goods: the shock trickles down through productive edges. In parallel it percolates along firm-to-firm financial edges as the network of trade credit unravels. Last but not least the shock jeopardizes banks-firms financial relationships. The disruption of a supply chain is indeed a new type of *financial risk*. Firms experience liquidity shortfalls, leverage shoots up, banks will record non-performing loans and in the end there is a high risk of outright bankruptcy.

In this paper we explore the macro-financial consequences of the disruption of a supply chain in a *minimalistic* macroeconomic agent based framework based on Delli Gatti et al. (2006, 2010) characterized by two networks, a credit network connecting banks and firms and a production (and trade credit) network connecting upstream and downstream firms. We deem agent-based models particularly apt to explore supply chain disruptions, as they provide a natural framework to encompass productive and financial interactions among heterogeneous firms. Our agent based model is minimalistic, however, because we abstract from a number of relevant real world features (which are dealt with properly in more sophisticated macroeconomic agent based frameworks).[2] First of all we focus only on firms and banks, deliberately downplaying the role of households. Second, we abstract from the multi-stage input-output structure of real world supply chains, considering only two stages/sectors (downstream and upstream). Third, we assume that financial factors play an essential role in production decision at the downstream end of the supply chain and that the upstream sector accommodates the demand for intermediate inputs coming from downstream firms. As a consequence, in normal times firms in the downstream sector do not face demand constraints or capacity constraints.

In this setting, a low frequency/high impact disruptive event such as Covid-19 and the associated lockdown in the upstream end of the chain forces dowstream firms to face a sudden capacity constraint, with relevant macro-financial repercussions. We consider two scenarios. In the first one we assume that all the upstream firms are forced to cut production down with respect to the pre-pandemic level for a given time interval. This generalized contraction of the supply of intermediate inputs generates a huge downturn due to the direct and indirect effects of the shock. In fact, both upstream and downstream firms experience a contraction of profits and net worth while banks experience an increase in non-performing loans. The economy recovers only when the lockdown is lifted and goes back rapidly approximately to the pre-shock level of activity.

In the second scenario, we assume that only a fraction of upstream firms are forced to contract production, i.e., firms located in the "red zone", at the centre of the epidemic.

[2] See for instance Assenza et al. (2015, 2018). For an exhaustive survey of macroeconomic agent based model see Dawid and Delli Gatti (2018).

In this second scenario the recession is milder and less persistent than in the first one and the recovery begins earlier. In a sense, this is obvious since the localized shock is, by construction, less pervasive than the generalized one. The most interesting feature of the localized scenario, however, is the change in production interlinkages among downstream and upstream firms. Downstream firms usually supplied by firms located in the red zone, in fact, will switch to suppliers outside the red zone. This *diversification effect* is the main determinant of the mitigated impact of the shock in the localized type of lockdown. In this way in fact firms endogenously reconstruct (at least in part) the supply chain after disruption. In the managerial literature, it is often claimed that supply chains with "backups" may be less efficient but are more resilient to shocks than "lean" chains.[3] Our analysis, confirms this conjecture. Contrary to a generalized lockdown, red zoning allows downstream firms to find alternative suppliers and relax the capacity constraint due to the shock.

The chapter is organized as follows. Section 2.2 is a concise overview of the literature. In section 2.3 we present the model, describing the behavioural rules followed by each class of agents. In section 2.4 we discuss the mechanism for the selection of partners in the production and financial networks. We then pause briefly in section 2.5 to wrap up and describe the interrelation of markets at a given point in time. Section 2.6 is devoted to the definition of the law of motion of net worth – which drives the dynamics of the model – for each class of agents. In section 2.7 we present and discuss the results of simulations in the baseline (pre-pandemic) scenario. Section 2.8 is devoted to the discussion of the consequences of the pandemic shock to the upstream end of the supply chain under two scenarios: generalized lockdown and red zone. Section 2.9 concludes.

2.2 A concise review of the literature

GVCs have been extensively studied in the last decade. The canonical Krugman-Melitz framework used in this literature is characterized by monopolistic competition, cost differences across countries (affected by factor endowments), firms' heterogeneity (in terms of productivity), scale economies due to fixed cost of offshoring, imperfection/incompleteness of contracts; vertical and horizontal interactions shaping the configuration of the supply chain. The current literature conveys the following basic message: (a) only the most productive downstream firms are able to incur the fixed cost of outsourcing; (b) these firms outsource to upstream suppliers located in countries where the variable cost of production is lower; (c) they keep the upstream stages of production within the firm boundaries if transaction costs are high, i.e., if the quality of market institutions in the destination country is low.[4]

[3] See for instance Dolgui et al. (2018).

[4] For a insightful exhaustive overview of this literature, see Antras (2016) and the references therein.

Two (relatively) under-researched aspects of GVCs are worth exploring further: (i) the role of financial constraints in GVC participation; (ii) the macroeconomic repercussion of (changes in the) organization of GVCs following a disruptive event. The straightforward effect of the event is a sizable shortening of the GVC. This reshaping has profound and persistent consequences for the macroeconomic performance of countries participating in the GVC which must be duly recognized and explored.

There is already a wide range of models which analyze the effect of supply chain disruptions. We can group them in two classes: agent based input-output models (AB-IO) and production network models.

To the best of our knowledge, the first AB-IO model for this purpose was proposed by Hallegatte and co-authors a decade ago. Fanny et al. (2011) and Hallegatte (2014) employ a dynamic I-O framework in which firms follow adaptive rules to carry out production tasks (order, production, inventories) to study the effects of catastrophic events. Inoue and Todo (2019a,b, 2020) apply Hallegatte's framework to track the effects of supply chain disruptions in Japan. Pichler et al. (2020) employ an AB-IO model augmented with an epidemiological SIR component to assess demand and supply effects of Covid-19.

Production network models spring from the literature on the granular origins of macroeconomic fluctuations (Gabaix, 2011). Starting from an optimizing conceptual framework, Barrot and Sauvagnat, 2016; Baqaee and Fahri, 2020; Carvalho et al., 2020 employ I-O techniques to model a production network and study the effects of disruptive events. The analysis of the interlinkages between real and financial shocks is still in an early phase (Bigio and LaO, 2016; Luo, 2020; Altinoglu, 2018).

Central to both AB-IO models and models of production networks are the productive interlinkages among firms. A satisfactory mapping of the production network to the financial network associated to the supply chain (trade credit and finance) is still lacking.

As anticipated in the introduction we adopt an agent based perspective but propose a streamlined model with only downstream and upstream firms. We go (fairly) granular, however, in describing the productive and financial sides of GVCs. We adapt the approach of Delli Gatti et al. (2006, 2010) to GVCs.[5]

2.3 The Model

2.3.1 The environment

The economy under scrutiny is populated by four classes of agents: downstream and upstream firms (D-firms and U-firms hereafter), banks and households. Agents interact

[5]See Battiston et al. (2007, 2012) for previous work on the production/trade credit network among firms and for contagion in financial networks. Riccetti et al. (2013) have enriched the framework put forward by Delli Gatti et al. (2010) with a more sophisticated theory of leverage determination.

on five markets: intermediate goods, consumption goods, labour, credit and deposits. On the market for consumption goods, D-firms (indexed by $i = 1, 2..N_D$) sell final goods to households. To produce consumption goods, D-firms purchase intermediate goods from U-firms (indexed by $j = 1, 2, \dots N_U$). Banks (indexed by $z = 1, 2, ..N_B$) extend credit to firms and receive deposits from households. Finally, on the labour market firms hire workers.

2.3.2 Households

Households supply labour to firms, earn wages and spend on consumption goods. We assume that households play a passive role in the economy. They purchase all the output of D-firms, accommodating the supply of consumption goods. Hence the production decisions of D-firms are not constrained by households' consumption decisions. This (admittedly strong) assumption allows to focus on the financial determinants of D-firms' production. On the labour market households supply labour inelastically. We assume that labour supply is always abundant. Therefore, firms can obtain all the labour they need (at the given wage) to produce either intermediate or final goods. In a sense, labour supply always accommodates the demand. Labour shortages are ruled out by assumption.

2.3.3 Downstream firms

Technology and costs

In the following, in order to save on notation, all undated variables are referred to period t (the present). We will introduce the time suffix in section 2.6 when we will discuss the dynamics of net worth.

In order to produce, the generic i-th D-firm needs labour (N_i) and intermediate inputs (Q_i). For simplicity, the production function is of the Leontief type:

$$Y_i = \min\left(\frac{1}{\gamma_D}N_i, \frac{1}{q}Q_i\right) \tag{2.1}$$

The coefficients γ_D and q measure the labour and the intermediate input requirements (per unit of output). Since labour supply is "abundant" (labour shortages are ruled out by assumption), employment at firm i is linearly increasing in the scale of activity:

$$N_i = \gamma_D Y_i \tag{2.2}$$

Thanks to complementarity, also the intermediate input is linearly increasing with output:

$$Q_i = qY_i \tag{2.3}$$

We denote the real wage in the D-industry with w_D and the (real) price of intemediate inputs sold by the j-th supplier to the i-th firm with p_j^i. Both w_D and p_j^i are ratios of the corresponding nominal variable (the nominal wage and the price of intermediate input respectively) to the GDP deflator.

As we will show in section 2.3.4, the price of the intermediate input p_j^i has a "fundamental" component p_U – uniform across firms – and a firm-specific component which in turn will be affected by the interest rate on trade credit and by an idiosyncratic shock. We assume that the firm-specific component will be revealed *ex post*, i.e., after the firm has set the price and the quantity (see assumption 1 below). Therefore, when the i-th D-firm sets the quantity, it takes only the fundamental component of the price of intermediate inputs into account.

Thanks to Leontief technology, total real *ex ante* operating costs are: $TC_i = c_D Y_i$ where

$$c_D := w_D \gamma_D + p_U q \tag{2.4}$$

is the ex ante marginal operating cost.[6]

The financially constrained output function

For a given technology, the scale of activity of a firm can be constrained by: (i) the availability of productive inputs; (ii) the demand for the goods the firm produces; (iii) the availability of finance to purchase inputs and carry out production. In this model, for simplicity, we abstract from constraints (i) and (ii). In fact we assume that inputs are available in unlimited supply and households consume all the firm's output. We focus instead on constraint (iii). To simplify matters we will consider the following timing.

Assumption 1 ***Intra-period timing*** *At the beginning of period t, the firm's financial condition proxied by net worth A_i is made public. On this basis, financial resources $F_i = A_i + L_i$ available to fund production are determined, with $L_i \geq 0$ the amount of bank loans. We assume that D-firms have market power. The firm sets the price and the optimal scale of activity "ex ante", i.e., before the actual marginal cost will be revealed. In setting the price and the quantity, the firm employs the ex ante marginal cost. Once revealed, the actual marginal cost will determine ex post gains or losses.*

We show the sequence of events within period t in figure 2.1.

Assumption 2 ***Pricing (D-firms)*** *As far as pricing is concerned, ex ante firms are identical as they have the same technology and the same marginal cost c_D. Hence all the D-firms will set the same price. We assume they adopt a simple markup pricing rule: $P_D = C_D(1+\mu)$ where P_D is the price of D-goods (which coincide with the GDP deflator),*

[6] The ex post marginal cost for each D-firm will be based on the actual price of intermediate inputs the firm will pay, which has a firm-specific component. See subsection 2.3.4.

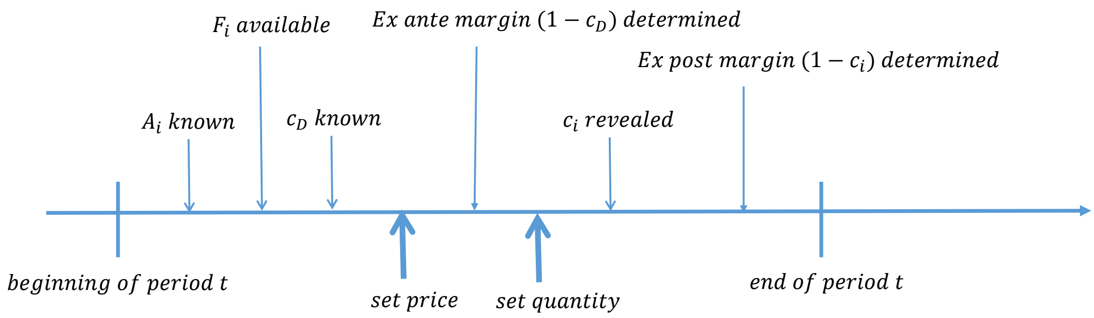

Figure 2.1: Timing

C_D is nominal (ex ante) marginal cost and μ is the markup. Since all the firms set the same price, the relative price *– i.e., the ratio of the individual price to the average price level – will be equal to 1. Dividing both sides of the pricing rule by the GDP deflator we get*

$$1 = c_D(1 + \mu) \tag{2.5}$$

where $c_D = \frac{C_D}{P_D}$ is the real ex ante marginal cost. Using equation (2.4) we can rewrite (2.5) as follows:

$$\frac{1}{1 + \mu} = w_D \gamma_D + p_U q \tag{2.6}$$

As a consequence, the ex ante price-cost margin is:

$$m := 1 - c_D = \frac{\mu}{1 + \mu} \tag{2.7}$$

From the previous assumption follows that the operating profit is an increasing linear function of output: $\pi_i = \frac{\mu}{1+\mu} Y_i$. In order to set production, the firm maximizes operating profits subject to the financial constraint: total costs must be covered by the liquidity F_i available to the firm. In symbols:

$$\max_{Y_i} \pi_i = \frac{\mu}{1 + \mu} Y_i$$
$$s.t.\ c_D Y_i \leq F_i$$

Thanks to the linearity of the profit function, in order to maximize profits the firm must maximize output. Since output is bounded by the availability of finance, the firm employs all the financial resources to produce. In other words, the financial constraint is binding: $c_D Y_i = F_i$ The (corner) solution of the problem is

$$Y_i = \frac{F_i}{c_D} = (1+\mu)F_i \tag{2.8}$$

Let's note now that the firm can either be self-financed or in need of external finance. We assume that, due to asymmetric information, sources of funds can be ordered in a financing hierarchy, in which internal finance A_i ranks first, i.e., it has the lowest cost.[7]

If in need of external finance, the firm applies to a bank to obtain a credit line. The bank employs human and computational resources to screen the applicant – i.e., to go through the books and collect data to assess the creditworthiness of the firm – in order to decide the size of the loan. There are benefits and costs of screening. We posit that the benefit – i.e., the accuracy and reliability of the evaluation of the firm's creditworthiness – is linear in the size of the loan L_i while the cost is quadratic. The objective function of the bank in screening the applicant is $Z^i = z(A_i)L_i - \frac{1}{2}L_i^2$ where $z(A_i)$ is the (average and) marginal benefit of screening, which is a function of the borrower's net worth. The bank maximizes this function with respect to L_i. The first order condition yields the optimal loan size: $L_i = z(A_i)$.

Let's suppose that the marginal benefit of screening is a hump shaped function : $z(A_i) = aA_i^\beta - A_i$ where $a > 0$ and $0 < \beta < 1$. The marginal benefit of screening is low when net worth is low because it is difficult to obtain reliable information on the financial conditions of a small firm. Reliability increases with size but beyond a certain threshold it decreases because big firms can obscure or hide important financial information. Sustituting this marginal benefit equation in the optimal loan size, we get

$$L_i = aA_i^\beta - A_i \tag{2.9}$$

The optimal size of the loan is therefore also hump shaped. Thanks to this assumption, total funds available to the borrowing firm are

$$F_i = L_i + A_i = aA_i^\beta \tag{2.10}$$

Total finance is an increasing concave function of net worth. Substituing this expression in (2.8) we get

$$Y_i = \alpha A_i^\beta \tag{2.11}$$

[7]The opportunity cost of internal finance is the risk free interest rate r which will be introduced below, see section 2.3.5.

with $\alpha = \frac{a}{c_D} = a(1+\mu)$. This is the *financially constrained output function* (hereafter FY) for a firm in need of external finance. The FY function is increasing and concave on the (A_i, Y_i) plane.[8] Delli Gatti et al. (2010) postulate a similar relationship but they do not provide a microeconomic foundation.[9]

If, on the contrary, the firm is self-financed, then $L_i = 0$. The firm becomes self-financed when $F_i = A_i$. Substituing this expression in (2.8) we get

$$Y_i = (1+\mu)A_i \tag{2.12}$$

This is the FY function for a self-financed D-firm. In this case, the FY function is linearly increasing on the (A_i, Y_i) plane.

We can compute a cut-off value of net worth $\hat{A}$ such that the firm can be either in need of external finance if it is relatively "poor" – i.e., if its net worth is smaller than the threshold – or self-financed if it is relatively "wealthy", i.e. with net worth bigger than (or equal to) the threshold. This cut-off value is determined by plugging (2.10) into the condition $F_i = A_i$. We get

$$\hat{A} := a^{\frac{1}{1-\beta}} \tag{2.13}$$

This threshold allows to divide the set Φ_D of D-firms into two subsets. The subset of self-financed D-firms is $\Phi_{SD} = \{i \in \Phi_D | A_i \geq \hat{A}\}$. As a consequence $\Phi_{BD} = \Phi_D - \Phi_{SD} = \{i \in \Phi_D | A_i < \hat{A}\}$ is the set of borrowing D-firms.

To sum up, the FY function can be written as follows :

$$Y_i = \begin{cases} \alpha A_i^{\beta} & \text{if } i \in \Phi_{BD}, \\ (1+\mu)A_i & \text{if } i \in \Phi_{SD} \end{cases} \tag{2.14}$$

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[8] If the marginal benefit of screening were linearly increasing with size, e.g. $z = \lambda A_i$, the first order condition would read $L_i = \lambda A_i$. This rule can be interpreted as follows: the bank sets the optimal size of the loan by applying a leverage target λ to the firm's net worth. In this case $F_i = (1+\lambda)A_i$. Substituting this expression in (2.8) we get the FY function: $Y_i = (1+\mu)(1+\lambda)A_i$. In this case the FY function of the borrowing firm would be linear.

[9] An alternative simple microfoundation of the concave FY function can be found following the approach pioneered by Greenwald and Stiglitz (1993). The problem of the firm consists in maximizing expected profits net of bankruptcy costs. Suppose that there are two states of the world. In the positive or favourable state – which occurs with probability $(1-\phi_i^b)$ – the firm earns operating profits $\pi_i^s = \frac{\mu}{1+\mu}Y_i$. In the negative or unfavourable state of the world – which occurs with probability ϕ_i^b – the firm goes bankrupt and earns profits $\pi_i^b = \pi_i^s - C_i^b$ where $C_i^b = \frac{1}{2}Y_i^2$ is the cost of bankruptcy. The firm maximizes the expected value of profits:

$$\max_{Y_i} V_i = \pi_i^s - C_i^b\ \phi_i^b = \frac{\mu}{1+\mu}Y_i - \frac{\phi_i^b}{2}Y_i^2$$

The (closed form) solution to this problem is $Y_i = \frac{\mu}{(1+\mu)\phi_i^b}$. Let's assume now that the probability of bankruptcy is a decreasing (convex) function of financial robustness captured by net worth: $\phi_i^b = A_i^{-\beta}; A_i \geq 1$. Substituing this expression into the solution above we get the FY function $Y_i = \frac{\mu}{(1+\mu)}A_i^{\beta}$. Also in this setting the FY function is increasing and concave.

Equation (2.14) can be interpreted in two ways. According to the first interpretation, it shows the optimal levels of ouput *an individual firm* should set depending on the levels of net worth it has. If the firm is relatively "poor" ($A_i < \hat{A}$), output is an increasing concave function of net worth; if it is "wealthy" ($A_i \geq \hat{A}$), output increases linearly with net worth.

Alternatively, the FY function can be interpreted as the optimal levels of output generated by *different firms*, with different levels of net worth. In this case, the domain of the function coincides with the support of the distribution of firms' net worth.

In figure 2.2 we draw the relationship between total financial resources available to the firm and net worth. It is the kinked bold line denoted with F_i. When the firm is not wealthy enough – i.e., when its net worth is lower than the cut off value – total finance is bigger than net worth because the firm resorts to bank loans. This is captured by the concave section of the line. When the firm is wealthy enough, it is self-financed and the line coincides with the 45 degree line. The kink is located at the threshold value of net worth. Therefore also the FY function is kinked. If the firm is borrowing, the FY function is represented by the concave section, while if it is wealthy, it is linear and steep. Therefore, we can define the demand for loans expressed by the generic i-th firm as:

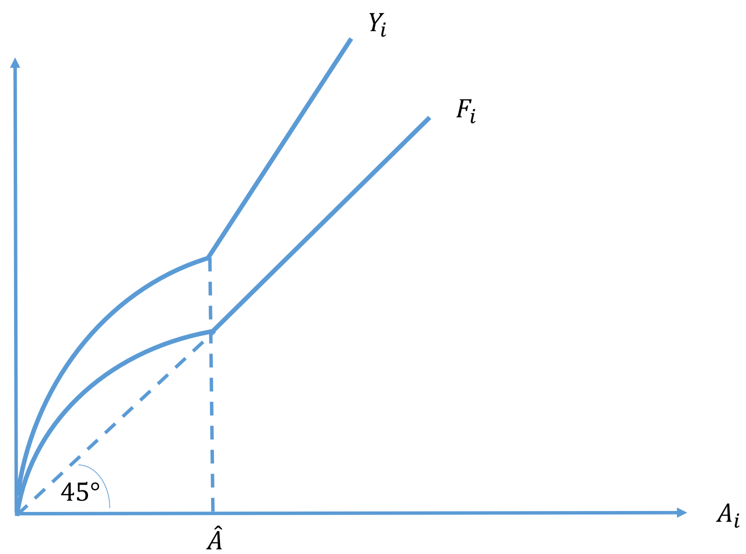


Figure 2.2: D-firms: output, finance and net worth

$$L_i = \mathbf{1}_{\Phi_{BD}} \left(aA_i^{\beta} - A_i \right) \tag{2.15}$$

where $\mathbf{1}_{\Phi_{BD}}$ is an indicator function which takes value 1 if the firm is borrowing (i.e., $A_i < \hat{A}$), 0 if the firm is self-financed. The leverage ratio of the i-th D-firm will be defined as the ratio of loans to net-worth. Rearranging one gets:

$$\lambda_i = \mathbf{1}_{\Phi_{BD}} \left(\frac{a}{A_i^{1-\beta}} - 1 \right) \tag{2.16}$$

Notice that the leverage of the D-firm is decreasing with its net worth.

D-firm is a borrower both in the credit market and in the intermediate goods market. Trade arrangements between the upstream supplier and the downstream costumer are, indeed, characterized by commercial credits since, as we will explain in details later on, we assume that D-firm can pay for the intermediate goods one period after the delivery. Hence, we can define the leverage on trade credits of the i-th firm as the ratio of commercial credit extended to the firm by the U-supplier – i.e. the amount of intermediate goods supplied – with respect to its net worth:

$$\lambda_i^U = \frac{qY_i}{A_i} \tag{2.17}$$

Using (2.14) and (2.2) we can express total labour requirement as follows:

$$N_i = \begin{cases} \gamma_D \alpha A_i^{\beta} & \text{if } i \in \Phi_{BD}, \\ \gamma_D (1+\mu) A_i & \text{if } i \in \Phi_{SD} \end{cases} \tag{2.18}$$

Analogously, using (2.14) and (2.3) the total requirement of intermediate inputs is:

$$qY_i = \begin{cases} q\alpha A_i^{\beta} & \text{if } i \in \Phi_{BD}, \\ q(1+\mu) A_i & \text{if } i \in \Phi_{SD} \end{cases} \tag{2.19}$$

Hence also the input requirements are kinked functions of net worth.

Using (2.19), the leverage on trade credits (2.17) can be rewritten as:

$$\lambda_i^U = \begin{cases} q\alpha A_i^{\beta-1} & \text{if } i \in \Phi_{BD}, \\ q(1+\mu) & \text{if } i \in \Phi_{SD} \end{cases} \tag{2.20}$$

Notice that all the downstream firms are borrowers in the intermediate goods market. The firms that do not rely on bank loans are characterized by a constant trade credts' leverage, while borrower D-firms have an higher level of leverage also in commercial credits; their leverage is decreasing with their financial soundness, proxied by the net worth.

Let's wrap up: the quantity produced by a generic D-firm is constrained and determined entirely by its financial robustness. Total production (GDP) will be $Y = \sum_{i=1}^{N_D} Y_i$. We assume that households absorb production. Hence $Y = C$.

2.3.4 Upstream firms

N_U U-firms produce intermediate goods on demand. We assume an asymmetric structure of the customer-supplier relationship. While each D-firm is attached to a single supplier, a U-firm can have more than one customer. We denote the set of downstream customers of the j-th U-firm with Φ_j. The scale of production of the j-th U-firm Q_j is demand constrained, i.e., it is determined only by the demand for intermediate goods expressed by partner D-firms. In symbols:

$$Q_j = \sum_{i \in \Phi_j} qY_i = q \left(\sum_{i \in \Phi_j | A_i < \hat{A}} \alpha A_i^{\beta} + \sum_{i \in \Phi_j | A_i > \hat{A}} (1+\mu) A_i \right) \tag{2.21}$$

From (2.21) follows that the financial conditions of the downstream customers determine the size of the upstream supplier.

In order to produce, the j-th U-firm employs only labour. For simplicity, the production function is linear: $Q_j = \frac{1}{\gamma_U} N_j$ where γ_U is the labour requirement per unit of U-output. Hence employment at firm j is linearly increasing in the scale of activity: $N_j = \gamma_U Q_j$. From (2.21) follows that also employment at the U-firm is determined by the financial conditions of its D-customers. Hence the financial conditions of D-firms are the drivers of production and employment not only in the downstream sector but also in the upstream sector.

Assumption 3 ***Pricing (U-firms)*** *The contract between the j-th supplier and its i-th customer envisages either payment "on delivery" at the so called* cash price $p^i_{j,c}$ *or payment one period after delivery, at the "post-shipment" price* p^i_j*. These prices*[10] *are connected as follows*

$$p^i_j = (1 + r^i_j) p^i_{j,c} \tag{2.22}$$

where r^i_j *is the interest rate on trade credit.*[11] *We postpone the discussion of the determinants of the interest rate on trade credit (see equation (2.34)). As to the determination of the cash price, we assume that U-firms do not have market power. Therefore, the cash price must be equal to the marginal cost:* $p^i_{j,c} = c_j$*. Moreover, we assume that the marginal cost is* $c_j = (1 + u_j) w_U \gamma_U$ *where* w_U *is the real wage in the U-industry and* u_j

[10] The prices in question are real prices, i.e., ratios of the corresponding nominal price of intermediate inputs to the GDP deflator.

[11] In real world contracts, if the customer pays on delivery, she will get a discount: $p^i_{j,c} = d^i_j p^i_j$ with $0 < d^i_j < 1$. It is straightforward to interpret the discount as the reciprocal of the gross interest rate on trade credit.

captures the idiosyncratic component of the marginal cost.[12] *In the end:*

$$p^i_{j,c} = (1 + u_j)p_U \tag{2.23}$$

with $p_U = c_U = w_U\gamma_U$. *In words: the cash price has a fundamental deterministic component* p_U *– equal to the average marginal cost, which in turn is equal to the unit labour cost in the upstream sector – and a random idiosyncratic component* u_j.[13] *In the end, therefore,* $p^i_{j,c}$ *is distributed normally with expected value equal to* p_U.

In order to make the argument simple and clear, we assume that all the transactions between D-firms and their U-suppliers are carried out at the post shipment price. Hence, using (2.23) and (2.22) the market price will be

$$p^i_j = (1 + r^i_j)(1 + u_j)p_U \tag{2.24}$$

The shock to the marginal cost of the upstream supplier translates into an unexpected change of the price of intermediate inputs and therefore generates a shock to the marginal cost of the downstream customer. Having specified the average price of intermediate inputs, equation (2.6) should be rewritten as follows.

$$\frac{1}{1+\mu} = w_D\gamma_D + w_U\gamma_U q \tag{2.25}$$

We will use this parameter restriction in the calibration of the model (see section 2.7).

The firm is self-financed if $A_j > W_j$ where $W_j = w_U\gamma_U Q_J$ is the wage bill and Q_j is determined by the financial conditions of D-customers as in (2.21). The wage bill is the cut-off value of net worth: $\hat{A}_j := w_U\gamma_U Q_J$. Notice that, contrary to the case of D-firms, the cut-off value of net worth is different from one U-firm to another (because the set of D-partners is different) and is time-varying because the set of D-customers changes over time (as we will show in section 2.4) and because the net worth of each D-firm also changes (see section 2.6).

In figure 2.3 the x-axis measures the net worth of the j-th U-firm. Output Q_j and the wage bill $w_U\gamma_U Q_J$ are represented by horizontal lines (being determined by the net worth of D-customers). The cut-off value of net worth is determined at the intersection of the wage bill line with the 45 degree line. When the firm is not wealthy enough – i.e., when its net worth is lower than the cut-off value – the firm resorts to bank loans. When the firm is rich, it is self-financed. Figure 2.3 depict the situation of *an individual firm.* It cannot be

[12]We assume that u_j has a normal distribution with zero mean and standard deviation $\sigma_u = 0.3$: $u_j \sim \mathcal{N}(0, 0.3)$. We set the standard deviation such that the realizations of the random variable fall in the interval $-0.9 < u_j < 0.9$ with probability 0.997.This assumption assures the non-negativity of the marginal cost c_j and therefore of the price $p^i_{j,c}$.

[13]The fundamental component of the cash price of intermediate inputs has been already introduced above. It contributes to the determination of the ex ante marginal cost for D-firms (see assumption 2).

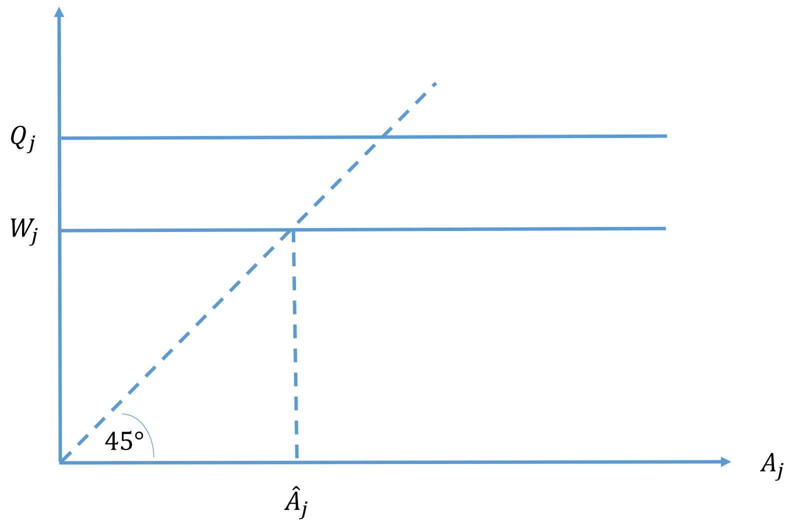


Figure 2.3: Output, the wage bill and net worth of the j-th U-firm.

interpreted as the levels of output associated to *different firms*, with different levels of net worth. While the relationship between the distribution of net worth and the distribution of output across D-firms is nicely and neatly determined by the upward sloping FY function, we cannot posit an analogous relationship for U-firms. The distribution of output across U-firms, in fact, is determined by the demand of intermediate inputs on the part of D-customers and is therefore disconnected from the distribution of net worth across U-firms.[14]

We can define the demand for loans expressed by the generic j-th U-firm as:

$$L_j = \mathbf{1}_{\Phi_{BU}} \left(w_U \gamma_U Q_j - A_j \right) \tag{2.26}$$

where $\mathbf{1}_{\Phi_{BU}}$ is an indicator function which takes value 1 if the firm is borrowing (i.e., $A_j < \hat{A}_j$), 0 if the firm is self-financed. Graphically, the size of the loan asked for by the firm when its net worth is at a given level is measured by the vertical distance between the wage bill line and the 45 degree line at the given level of net worth.

[14]The relationship could even be "downward sloping". Consider, for instance, two U-firms, say U1 and U2, with $A1 \ll A2$. Suppose the relatively "poor" U1 has many and/or rich D-customers such that Q_1 is "high" while the relatively rich U2 has few and/or poor D-customers so that Q_2 is "low". Hence it could be the case that $Q_1 > Q_2$.

The leverage ratio of the j-th U-firm is:

$$\lambda_j = \mathbf{1}_{\Phi_{BU}} \left(w_U \gamma_U \frac{Q_j}{A_j} - 1 \right) \tag{2.27}$$

Notice that the leverage of the U-firm is decreasing with its net worth and increasing with output. Output in turn is increasing with the net worth of D-customers. Hence, the higher the latter, the higher will be the output of the U-supplier and its leverage. In an expansion in which profits and net worth tend to increase in both sectors, leverage will decrease for D-firms (see equation (2.16)) but the effect on the leverage of U-firms is ambiguous: both output and net worth of the U-firm, in fact, will increase.

2.3.5 Banks

We assume an asymmetric structure of the firms-banks network: a single bank can be linked to many firms (both upstream and downstream), while each firm can ask loans to one bank only. The size of the loan extended by the z-th bank to the i-th D-firm is determined according to rule (2.9) while the loan received by the j-th U-firm is determined by (2.26).

Given the amount of loans extended to all connected firms, L_z, and net worth, A_z, the bank's liabilities (deposits) are:

$$D_z = \mathbf{1}_{\Phi_{BB}} \lambda_0 \left(L_z - A_z \right) \tag{2.28}$$

where $\lambda_0 := \frac{1}{1-d_R}$; $0 < d_R < 1$ is the ratio of bank reserves to deposits and $\mathbf{1}_{\Phi_{BB}}$ is an indicator function which takes value 1 if the bank is borrowing – i.e. if it is collecting deposits ($A_z < L_z$) – and zero if the bank is "wealthy" and therefore self-financed. Hence the bank's leverage is

$$\lambda_z = \mathbf{1}_{\Phi_{BB}} \lambda_0 \left(\frac{L_z}{A_z} - 1 \right) \tag{2.29}$$

Let's now turn to the interest rate. The bank should adapt the interest rate it charges to a specific firm to the latter's financial characteristics. We index the firms with $f = 1, 2, ...N_D, N_D + 1, ..N_F$ where $N_F = N_D + N_U$.[15] The general rule adopted by the z-th bank to set the interest rate for firm f is:

$$r_z^f = r + \rho \left(\lambda_z^\rho + \lambda_f^\rho \right) \tag{2.30}$$

where $\rho > 0$, λ_f is the leverage of firm f and λ_z is the leverage of bank z. In words: the interest rate is increasing with the financial fragility (measured by leverage) of both

[15] In words: firms indexed with $f \in [1, N_D]$ produce D-goods; firms indexed with $f \in [N_D + 1, N_F]$ produce intermediate goods.

the lender and the borrower. Taking into account the equations for leverage of D-firms, U-firms and the bank (equations (2.16), (2.27) and (2.29)) and abstracting from indicator functions for simplicity, we end up with the following interest rate equations:

$$r_z^f = \begin{cases} r + \rho \left\{ \left[\lambda_0 \left(\frac{L_z}{A_z} - 1 \right) \right]^\rho + \left(a A_f^{-(1-\beta)} - 1 \right)^\rho \right\} & \text{if } f \in [1, N_D], \\ r + \rho \left\{ \left[\lambda_0 \left(\frac{L_z}{A_z} - 1 \right) \right]^\rho + \left(w_U \gamma_U \frac{Q_f}{A_f} - 1 \right)^\rho \right\} & \text{if } f \in [N_D + 1, N_F] \end{cases} \tag{2.31}$$

The interest rate on bank loans has 3 components: (i) the risk free interest rate r (this is the instrument of monetary policy under the control of the central bank); (ii) a bank-specific component which is increasing with credit extended and decreasing with the bank's net worth; (iii) a firm-specific component which is increasing with the borrower's financial fragility.

Component (iii) is the *external finance premium*.[16] When the bank lends money to a firm, it requires a risk premium which depends on the leverage of the firm. Notice that the leverage of the borrowing D-firm is a function only of its net worth. The leverage of the borrowing U-firm is a function also of the net worth of the customer D-firms, which determines the scale of activity for the U-supplier. When the net worth of D-customers increases, they increase demand for intermediate inputs, borrowing U-firms increase the demand for loans, their leverage increases and leads to an increase of the interest rate they face. Hence the interest rate charged to the U-firm is decreasing with the net worth of the U-firm and increasing with the net worth of the D-customers.

Component (ii) is based on the notion that a financially robust bank (i.e., a bank with a relatively low leverage) will be eager to extend credit at favourable terms, in order to increase its market share. This component is key in shaping the credit network as we will show in the next section.

2.4 Networks

The macro-economy under scrutiny is characterized by two networks, a credit network connecting banks and firms and a production network connecting U-firms and D-firms. We assume an asymmetric structure of both networks. In the credit network, each bank – say the z-th bank – can be linked to several firms, which are the elements of the set of borrowers Φ_z, while each firm, either downstream or upstream, can ask for loans to one bank only.

In the production network, each upstream firm – say the j-th firm – can serve several downstream firms, which are the elements of the set of customers Φ_j, while a single D-firm buys intermediate goods from one supplier only.

[16] We adopt the wording of the literature on financial frictions. For the prioneering work, see Bernanke et al. (1999).

The credit and production networks interact as shown in the upper and intermediate layers of figure 2.4 where U_1 is an upstream firm, B_1 is a bank, D_i (i=1,2,3) are D-firms and H_h (h=1,. . . 5) are households. Links among agents are constantly changing, due to

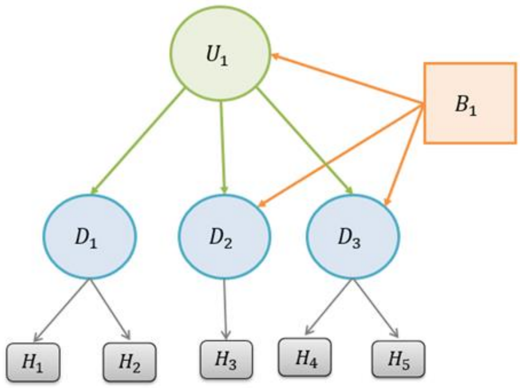


Figure 2.4: A simple example of links connecting D-firms to Households, U-firms to D-firms, Banks to firms

the partner's selection mechanism. In every period, in fact, on either network, agents can switch from one partner to another. On the credit network (downstream and upstream) firms look for the bank which is able to extend credit at the lowest interest rate. On the credit network, downstream firms search for the supplier (upstream firm) which can sell intermediate goods at the lowest price.

2.4.1 Partner selection in the credit network

Consider the credit network. At period zero (the initial condition), the credit network is randomly determined, i.e., the links among firms and banks are casually established. Following the "Strategic Link Formation" approach (Jackson (2008)), we assume that in each period $t > 0$ each borrower will consider the opportunity of changing partner (lender) by comparing interest rates. Firm f changes the lending bank in period t with a probability of switching ϕ_f^z which is an increasing function of the difference between the interest rate set by the previous bank partner z_0, $r_{z_0}^f$, and the interest rate set by the potential new partner z_1, chosen at random, $r_{z_1}^f$. We denote the ratio of the two with

$R^z_{0,1} = r^f_{z_0}/r^f_{z_1}$. We postulate the following law governing the probability of switching:

$$\phi^z_f = \begin{cases} 1 - e^{1-R^z_{0,1}} & \text{if } R^z_{0,1} > 1, \\ 0 & \text{if } R^z_{0,1} \leq 1 \end{cases} \tag{2.32}$$

This law states that the firm keeps the old borrowing/lending relationship if the new partner charges an interest rate higher than (or equal to) the old one (i.e., if $R^z_{0,1} < 1$), while it may switch to the new partner if the latter charges an interest rate lower than the old one (i.e., if $R^z_{0,1} > 1$), with the probability of switching increasing with the ratio and tending asymptotically to 1.

Notice now that, recalling (2.30) we can write:

$$R^z_{0,1} = \frac{r^f_{z_0}}{r^f_{z_1}} = \frac{r + \rho\left(\lambda^\rho_{z_0} + \lambda^\rho_f\right)}{r + \rho\left(\lambda^\rho_{z_1} + \lambda^\rho_f\right)} \tag{2.33}$$

It is easy to infer that $R^z_{0,1} > 1$ if $\lambda_{z1} < \lambda_{z0}$. In words: the firm will consider to switch to the new partner if the latter is more financially robust (has a lower leverage) than the old partner. Absent component (ii) of the interest rate (see again equation (2.30)), the old and new potential partners would be equivalent in the eyes of the firm. The bank-specific component of the interest rate on loans, therefore, plays a crucial role in partner selection on the credit network.[17]

The number of links among firms and banks changes over time, due to this partner selection mechanism, so that the topology of the network is constantly changing. By construction, however, the total number of nodes is constant. The network shows a pattern of increasing polarization because the above mentioned approach to link formation leads to Preferential attachment (Barabàsi (1999)). The most "prosperous" banks attract an ever increasing number of firms, increasing their profits. A self-reinforcing mechanism is at work: the more profitable a bank is, the higher will be the number of relationships it has and the more eager the bank will be to charge lower interest rates, attracting even more customers.

2.4.2 Partner selection in the production network

There is an analogous rule for partner selection in the production network. Notice that the production network is also a trade credit network. We assume in fact that the j-th supplier sells intermediate goods to its D-customers allowing payment either on delivery at a lower price or post shipment at a higher price. The difference between the two is the

[17]Notice that, if the old and the new partners were both "wealthy", i.e., if they did not have to collect funds in the form of deposits, the leverage of each bank would be zero so that the firm would be unable to make a decision. In this case, in simulating the model we assume that the firm will decide to switch to the new partner if the latter's net worth is bigger than the net worth of the old partner.

interest payment on trade credit, see equation (2.22). We assume that the interest rate on trade credit is:

$$r_j^i = \rho\left(\lambda_j^\rho + \lambda_i^{U\rho}\right) \tag{2.34}$$

Similarly to the interest rate on bank loans, the interest rate on trade credit is increasing with the lender's and the borrower's leverage, where the U-supplier is the lender and the D-customer is the borrower.

The i-th D-firm changes the U-partner with a probability of switching ϕ_i^j which is increasing with the difference between the post shipment price of the previous supplier/partner, p_{j0}^i, and decreasing with that of the potential new partner, p_{j1}^i. We denote the ratio of the two with $R_{0,1}^j$. In symbols:

$$\phi_i^j = \begin{cases} 1 - e^{1-R_{0,1}^j} & \text{if } R_{0,1}^j > 1, \\ 0 & \text{if } R_{0,1}^j \leq 1 \end{cases} \tag{2.35}$$

with $R_{0,1}^j = \frac{p_{j0}^i}{p_{j1}^i}$. Recalling (2.24) and (2.34), with a little algebra we can rewrite this expression as follows

$$R_{0,1}^j = \frac{1+\rho(\lambda_{j0}^\rho + \lambda_i^\rho)}{1+\rho(\lambda_{j1}^\rho + \lambda_i^\rho)} \times \frac{1+u_{j0}}{1+u_{j1}} \tag{2.36}$$

where u_{j0} and u_{j1} are realizations of the random variable u_j.[18]

The D-firm will switch to the new U-partner if the latter is less leveraged than the old one, because it will charge a lower post shipment price.[19]

[18]The crucial variable $R_{0,1}^j$ takes the form of "relative prices" and has two components, a deterministic time varying component (relative interest rates) which is characterized by the leverage of the borrower and the lender (new and old) and a stochastic component, i.e., the ratio of the idiosyncratic shocks of the post-shipment price. In running simulations we realized that, since interest rates have a low variability, the stochastic component overrides the relative interest rates and plays a major role in shaping the production network. Therefore, in this formulation, the allocation of links to nodes is distributed in an almost completely random way, with very little influence of financial considerations on partner choice. In our view, this makes the analysis not particularly interesting. Therefore, in the simulations we have used a simplified definition of the crucial variable, namely:

$$R_{0,1}^j = \frac{\lambda_{j0}^\rho + \lambda_i^\rho}{\lambda_{j1}^\rho + \lambda_i^\rho}$$

In other words, we assume that the D-firm will pierce and discard the veil of price noise and choose the U-firm which is in a better shape from the financial point of view, abstracting from the short run oscillations of the price. Financial robustness is proxied by leverage.

[19]Notice that, if the old and the new U-partners were both self-financed – i.e., if they had zero leverage – the D-firm would be unable to make a decision. In this case, in simulating the model we assume that the D-firm will decide to switch to the new U-partner if the latter's net worth is bigger than the net worth of the old U-partner.

2.5 Intermezzo

Let's now pause briefly to summarize the main features of the model. In this section, we "take a picture" of the macro-economy, as described by the model, at a certain point in time. By definition, aggregate GDP is equal to the aggregate production of D-firms and to the aggregate consumption of households. Since households absorb all the output of D-firms, the market for consumption goods is always in equilibrium. The aggregate production of D-firms is determined by the financial conditions of D-firms, captured by their net worth. Hence the fluctuations in aggregate output will be driven mainly by the variation of D-firms' net worth, as we will show in section 2.7.

Since U-firms produce on demand, the scale of activity of D-firms determines the amount of intermediate goods produced by U-firms. There will not be involuntary inventories of intermediate inputs because we assume that the U-supplier produces "just in time". In normal times – i.e., in the absence of disruptive events – the demand for intermediate inputs will be satisfied and D-firms will not face capacity constraints. Hence, also the output of U-firms depends ultimately on the net worth of D-firms.

On the market for labour, the demand coming from U-firms and D-firms is satisfied by assumption. Labour supply, in fact, does not constrain the employment decisions of firms. Hence aggregate employment, once again, ultimately depends on the net worth of D-firms. Due to real wage stickiness, there can be (and generally there is) involuntary unemployment: the market for labour, in other words, is characterized by persistent excess supply.

On the market for credit, banks accommodate demand, extending loans to relatively "poor" D-firms and to U-firms which register a financing gap. There will not be credit rationing.

This is simply a time frame of a "movie" which goes on during the simulation interval. In the following section we will describe the engine of change built in the model that allows the movie to proceed from one time frame to the following one, namely the accumulation of net worth.

2.6 Profits and the accumulation of net worth

In this section we describe the determination of profits and the law of motion of net worth for the banks and the different categories of firms. For each category of firms, retained profits are the difference between operating profits (i.e., earnings before interest and dividends) and the sum of interest payments (if the firm is borrowing) and dividends. Retained profits are employed to accumulate net worth.

2.6.1 Downstream firms

At this stage of the analys we introduce the time index. The operating profit of the self-financed i-th D firm (in real terms) is the difference between revenue Y_{it} and operating cost $c_{it}Y_{it}$ where c_{it} is the actual (ex post) marginal cost: $c_{it} := w_D\gamma_D + p^i_{jt}q$. Therefore the actual operating profit is $\pi_{it} = (1-c_{it})Y_{i,t}$. By definition, self-financed D-firms do not have debt commitments. However, they pay out dividends. We assume that dividends are a fraction $(1-\theta_D)$ (the dividend payout ratio) of operating profits, where $0 < \theta_D < 1$ is the retention ratio. Therefore, recalling that the FY function for self-financed D-firms is linear – see equation (2.12) – for each $i \in \Phi_{SD}$ retained profits are:

$$\pi^{SD}_{it} = \theta_D(1-c_{it})Y_{it} = \theta_D(1-c_{it})(1+\mu)A_{it} \tag{2.37}$$

Retained profits are re-invested in the firm. Net worth in period t+1 therefore will be:

$$A_{it+1} = (1-\delta)A_{it} + \pi^{SD}_{it} \tag{2.38}$$

where $0 < \delta < 1$ is the fraction of net worth that is appropriated by shareholders who "exit" and liquidate their shares. We introduce this parameter for a technical reason. In the absence of exit, net worth would grow "too fast" and make the model uninteresting because all the firms would become super-wealthy over time. In many financial friction models, therefore, it is assumed that a fraction of the population of entrepreneurs "exits". For example, in Bernanke et al. (1999) wording δ would be the "death rate" of entrepreneurs.

Recalling the definition of marginal cost, after substitution the law of motion of net worth becomes:

$$A_{it+1} = \left[1-\delta+\theta_D(1-w_D\gamma_D - p^i_{jt}q)(1+\mu)\right]A_{it} \tag{2.39}$$

where $p^i_{jt} = (1+r^i_{jt})(1+u_{jt})p_U$ and u_{jt} is an idiosyncratic shock. Notice that the accumulation of net worth of the self-financed D-firm is (i) non-linear because the leverage of the firm enters the interest rate on trade credit and (ii) affected by the evolution over time of the financial conditions of the U-supplier, because the net worth of the latter enters the definition of the interest rate on trade credit. The higher the net worth of the U-supplier, the lower the interest rate on trade credit and the higher the future net worth of the D-firm.

If the firm is borrowing, to determine retained profits we must subtract from operating profits not only dividends but also interest payments $r^i_{zt}L_{it}$. Recalling (2.14) and

(2.9), for each $i \in \Phi_{BD}$ the retained profit of the borrowing D-firm is:

$$\pi_{it}^{BD} = \theta_D(1 - c_{it})Y_{it} - r_{zt}^i L_{it} = \left[\theta_D(1 - c_{it})\alpha - r_{zt}^{it} a\right] A_{it}^{\beta} + r_{zt}^i A_{it} \quad (2.40)$$

Hence the law of motion of net worth is:

$$A_{it+1} = A_{it}(1 - \delta + r_{zt}^i) + \left[\theta_D(1 - w_D\gamma_D - p_{jt}^i q)\alpha - r_{zt}^i a\right] A_{it}^{\beta} \quad (2.41)$$

In the case of the borrowing D-firm, the law of motion of net worth is

- non-linear because of (i) the non-linearity of the FY function and (ii) the impact of the firm's leverage on the interest rates on loans and trade credit;
- coupled with the evolution of the net worth of the z-th bank and the net worth of the j-th U-supplier, which affect the interest rates.

The firm goes bankrupt (in periot t) if assets turn out to be lower than liabilities, i.e., if net worth becomes negative: $A_{it} \leq 0$. The bankrupt firm exits. It is insolvent, i.e., it will not reimburse bank loans and will not pay intermediate inputs. Hence the bank will register non performing loans on its balance sheets. Analogously, the upstream supplier will register a loss on its balance sheet. Bankrupt firms are replaced one-to-one by new entrants that are "small" relative to the average size of other agents in the market. The size of each agent is represented by its net worth. New entrants are endowed with a net worth which is drawn from a random variable, with mean equal to 1 and finite variance (uniform distribution between 0.5 and 1.5).

2.6.2 Upstream firms

The revenue of the generic j-th U-firm is equal to the sales of intermediate goods to all the solvent D firms in its production network. We will denote with Φ_j^s the subset of Φ_j consisting of solvent customers. Hence the complement of Φ_j^s is the set of defaulting customers: $\Phi_j^b = \Phi_j - \Phi_j^s = \{i \in \Phi_j | i \notin \Phi_j^s\}$. Operating costs consist of the wage bill only. Suppose firm j is self-financed: $j \in \Phi_{SU}$. In this case the firm does not have debt commitments. The firm, however, distribute as dividend the fraction $(1-\theta_U)$ of operating profits. Moreover, the U-firm (as a lender) has to take into account also the loss due to insolvent D-firms (non-performing loans or bad debt). Hence retained profits are

$$\pi_{jt}^{SU} = \theta_U \left(\sum_{i \in \Phi_j^s} p_{jt}^i q Y_{it} - w_U N_{jt} \right) - NP_{jt} \quad (2.42)$$

where non-performing loans are computed as

$$NP_{jt} = \sum_{i \in \Phi_j^b} qY_{it} \tag{2.43}$$

Hence net worth of the j-th U-firm is defined as follow:

$$A_{jt} = A_{jt-1}(1-\delta) + \pi_{jt}^{SU} \tag{2.44}$$

Consider now firm $j \in \Phi_{BU}$. In the case of borrowing U-firms, we must consider also the interest paid on bank loans. Hence retained profit will be

$$\pi_{jt}^{BU} = \theta_U \left(\sum_{i \in \Phi_j^s} p_{jt}^i qY_{it} - w_U N_{jt} \right) - r_{zt}^j L_{jt} - NP_{jt} \tag{2.45}$$

where: NP_{jt} is defined as in (2.43).

Adopting the same approach we used in the previous section, *mutatis mutandis*, we obtain the following law of motion of net worth:

$$A_{jt} = A_{jt-1}(1-\delta) + \pi_{jt}^{BU} \tag{2.46}$$

An upstream firm goes bankrupt if $A_{jt} \leq 0$. Bankrupt firms exit. They are insolvent, i.e., they will not reimburse bank loans. Hence banks will record non-performing loans. Bankrupt firms are replaced one-to-one by new entrants so that the total population of U-firms does not change. New entrants are endowed with an initial net worth which is drawn from a uniform distribution with finite variance and mean equal to 2.[20]

2.6.3 Banks

Consider the generic z-th bank. Let Φ_z denote the set of borrowing firms and Φ_z^s the subset of solvent (non-bankrupt) firms: $\Phi_z^s = \{f \in \Phi_z | A_f \geq 0\}$. The revenue of the z-th bank is equal to interest payments made by solvent firms. Costs consists of (i) interest payments on deposits (which are remunerated at the risk free rate) and (ii) operating costs, which are proportional to the size of the bank (measured by total assets). The second component comes from the "industrial organization approach to banking", i.e., the conception of the bank as a firm. In order to manage a given balance sheet the bank must incur operating costs (e.g., the cost of clerical workers), which are increasing with the "size" of the balance-sheet itself. The latter, in turn, is measured by total assets. In our setting the bank's assets consist of loans and bank reserves and are equal, by accounting identity, to the sum of deposits and net worth. Moreover, the bank has to

[20]This assumption is necessary to ensure the survival of new entrants.

take into account the losses from the insovent borrowers (non-performing loans). Hence the profits of the bank are

$$\pi_{zt} = \sum_{f \in \Phi_z^s} (1 + r_{zt}^f) L_{ft} - r D_{zt} - c_B (D_{zt} + A_{zt}) - NP_{zt} \tag{2.47}$$

where D_{zt} are deposits and $c_B > 0$ is the marginal cost of banking activity. The sum of deposits and net worth is equal – by accounting identity – to total assets. Non-performing bank loans are defined as

$$NP_{zt} = \sum_{f \in \Phi_z^b} L_{ft} \tag{2.48}$$

Assuming that the bank does not distribute dividends, the law of motion of the net worth is:

$$A_{zt} = A_{zt-1}(1 - \delta) + \pi_{zt} \tag{2.49}$$

where $\Phi_z^b = \Phi_z - \Phi_z^s = \{f \in \Phi_z | A_f < 0\}$. On the asset side of the balance sheet, the bank records loans extended to D-firms and U-firms. Bank reserves, equal to a fraction (the reserve coefficient $0 < d_R < 1$) of deposits, are liquid assets. Hence the balance sheet identity can be written as follows:

$$\sum_{f \in \Phi_z^s} L_{f,t} = (1 - d_R) D_{z,t} + A_{z,t} \tag{2.50}$$

Bad debts are an important channel of financial contagion in the network. When a firm f goes bankrupt, there will be a negative shock to the bank's net worth. The deterioration of bank's net worth makes the interest rate, set by the z-th bank, increase to all its borrowers, so that the financial conditions of the latter will deteriorate. Through this channel, the insolvency of a firm can affect also other firms not directly linked to the defaulted one.

A bank goes bankrupt if $A_{zt} \leq 0$. Bankrupt banks exit. They will be replaced one-to-one by new entrants whose net worth is drawn from a random variable with mean equal to 2 and finite variance.[21]

2.7 Simulations: the baseline scenario

In order to run the baseline version of the model we employ the numerical values of the parameters shown in table 4.1.

The economy is populated by households (not explicitly modelled) and three groups of heterogeneous agents: $N_D = 500$ downstream firms, $N_U = 250$ upstream firms and

[21] This is consistent with the fact that banks are characterized by higher average level of net worth, see table 2.2.

Table 2.1: **Numerical values of parameters**

Parameter	Description	Value
N_D	Number of D-firms	500
N_U	Number of U-firms	250
N_B	Number of banks	100
a	Multiplicative parameter (financially constrained output function)	3
β	Exponent (financially constrained output function)	0.4
γ_D	Labour requirement per unit of output (D-firms)	1/2
γ_U	Labour requirement per unit of output (U-firms)	3/4
q	Intermediate input requirement per unit of output (D-firms)	1/2
w_D	Real wage D-firm	1.3
w_U	Real wage U-firm	2/3
p_U	average price of intermediate inputs	1/2
u_j	Idiosyncratic component of the price of j-th U-firm	$\mathcal{N}(0, 0.3)$
r	Policy rate (risk-free interest rate)	0.02
ρ	Interest rate setting parameter	0.03
δ	Exit rate	0.1
θ_D	Retention ratio D-firms	0.8
θ_U	Retention ratio U-firms	1
d_R	Reserve requirement (per unit of deposit)	0.05
c_B	Bank's cost parameter	0.4

$N_B = 100$ banks. We ran 50 Montecarlo simulations over a time span of T=1000 periods. In the following we omit the initial 100-period interval, which represents the transient phase. Hence we show the time series generated by the simulations on the interval $1 < t < 900$, where the 1st period of this interval is the 101st period of the simulation.

We assume that when a firm or a bank goes bankrupt, it is replaced by another one. Therefore the size of each group is time invariant. We assume, moreover, that entrants are "small" relative to the average size of the incumbent in each group.

In order to capture a well known empirical stylized fact concerning GVCs, we assume that labour productivity and the real wage in the upstream sector (which is usually located in emerging countries in the real world) are remarkably smaller than the corresponding parameters in the downstream sector (located in advanced countries). With the current calibration, the unit labour cost in the upstream sector $w_U \gamma_U = 0.5$ is approximatly 75% of the unit labour cost in the downstream sector.

As argued above, the fundamental real price of intermediate inputs p_U is equal to the unit labour cost in the upstream sector. Therefore p_U turns out to be one half of the average price of D-goods (i.e., of the GDP deflator). With this calibration, from the parameter restriction (2.25) follows that the mark up in the downstream sector is $\mu = 1/9$. For each unit produced, the D-firm gets 1 unit of revenue and incurs average costs of intermediate inputs equal to 0.25 and labour cost equal to 0.65. This means that the wage bill represents 2/3 of GDP, an empirically plausible figure.

We assume "normal times". Hence the risk free interest rate is set at $r = 2\%$, slightly above the Zero Lower Bound. The reserve coefficients for banks is set at 5% to take into account not only mandatory but also free bank reserves. For simplicity we assume that all profits are retained in the upstream sector while in the dowstream sector firms distribute 20% of their profits as dividends.

In figure 2.5 we show the output of one (representative) simulation concerning the dowstream sector. The top left panel shows aggregate D-output (which coincides with GDP), computed "from the bottom up": $Y_t = \sum_{i=1}^{N_D} Y_{it}$ with $t = 1, ...900$. GDP fluctuates irregularly around a "long run mean" which we can characterize as a *quasi-equilibrium*. This pattern can be observed in all the Montecarlo simulations. In table 2.2 we report the long run mean and standard deviation computed on the average of the Montecarlo simulations.[22] The long run mean of GDP is approximately equal to $Y = 2278$, with very small volatility, captured by the standard deviation $\sigma^Y = 4.4$ i.e., 0.2% of the mean.

As we repeatedly said, since the scale of production of D firms is financially constrained, net worth is the main driver of output fluctuations. In fact, aggregate output fluctuates in synch with aggregate net worth $A_t^D = \sum_{i=1}^{N_D} A_{it}$ (see middle left panel). Table 2.3 shows the correlation index for a number of selected variables. Not surprisingly, the correlation index between D-firms aggregate output and net worth is close to 1 as shown in table 2.3.[23]

By construction – see equation (2.16) – the leverage of D-firms is a decreasing function of net worth and therefore it is countercyclical (middle right panel). The interest rate on loans charged by banks to D-firms is increasing with leverage, and therefore it shows the same countercyclical dynamic pattern (bottom left panel). Notice however that the range of oscillation of the interest rate is very small. The long run mean of the interest rate on loans is 5% (see table 2.2), so that on average the external finance premium is around 3%. As expected, the correlation between the interest rate on loans to D-firms and their net worth is negative and high in absolute value (see table 2.3). On the basis of equation (2.30) the correlation between the interest rate on loans and banks' net worth is negative.

Given the numerical values of a and β (see table 4.1), the cut-off value of net worth for D-firms is $\hat{A} = 6.2$. We have calibrated the model so as to generate a population of D-firms consisting primarily of borrowing firms. In fact, the average net worth of D-firms over the chosen time horizon is $\bar{A} = 1147/500 = 2.3$. Only a small subset of firms are rich enough to be self-financed as shown by the bottom right panel of figure 2.5. Not surprisingly, the number of self-financed D-firms is of procyclical.

In figure 2.6 we show the time series generated by the same simulation concerning the upstream sector. The top left panel shows aggregate output $Q_t = \sum_{j=1}^{N_U} Q_{jt}$. By

[22] For each variable, (i) we apply the HP filter to the time series generated by each simulation, (ii) we compute the average of the filtered time series and (iii) we use the averaged time series to compute the long run mean and standard deviation.

[23] The correlation indexes are computed on the same filtered and averaged data used for table 2.2.

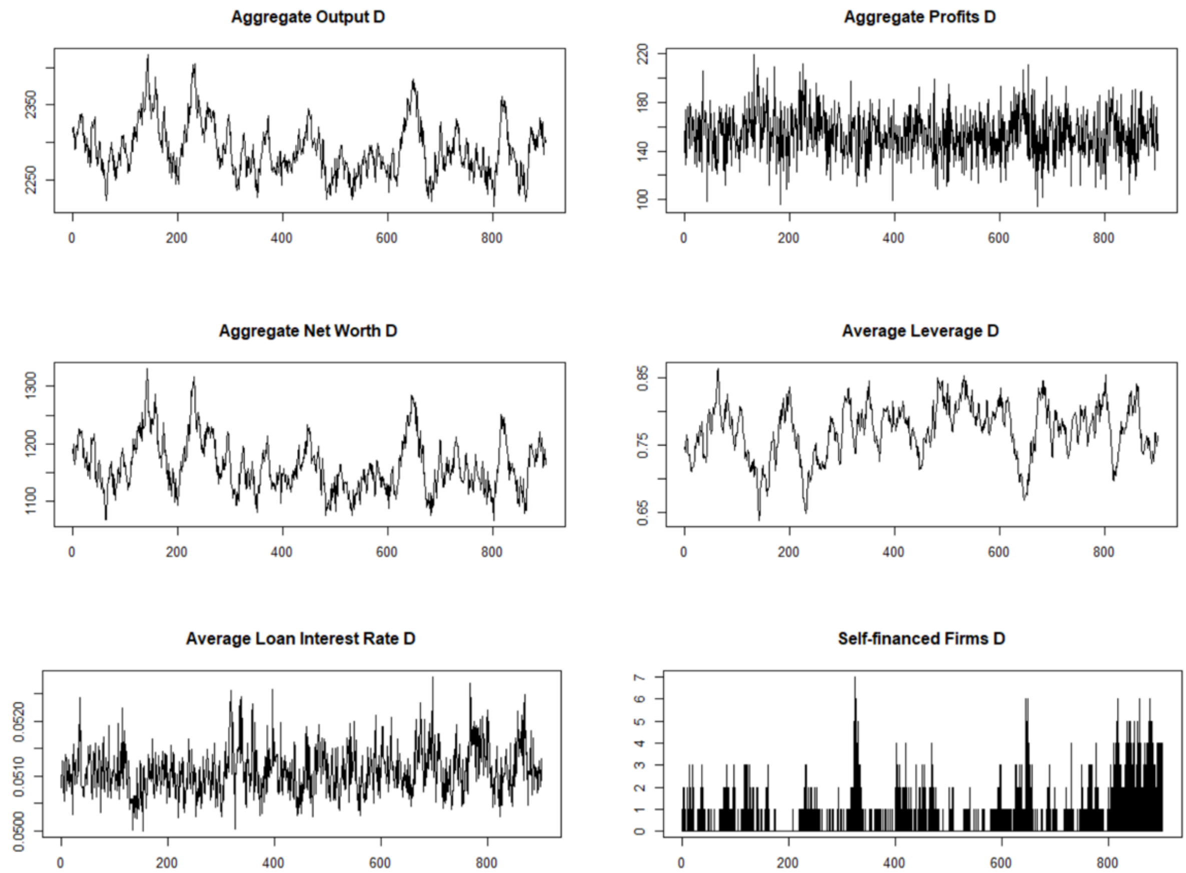


Figure 2.5: Baseline: D-firms (aggregate variables)

construction, the production decisions of D-firms determine the output of U-firms, since the latter produce on demand. Hence $Q_t = qY_t$ where, in the current calibration, $q = 1/2$. Therefore Q_t has the same dynamic pattern of GDP. The long run mean Q in table 2.2 is half the production of D-firms and half the volatility (so that the coefficient of variation is the same). Hence Q has the same correlations of Y.

The aggregate net worth of U-firms (middle left panel) is increasing with profits which scale up with production and therefore with GDP. In fact, as shown in table 2.3, the net worth of U-firms is strongly and positively correlated with the net worth of D-firms and GDP.

The interest rate on loans charged by banks to U-firms (bottom left panel) is countercyclical. Notice however that – as in the case of D-firms – the range of oscillation of the interest rate charged to U-firms is very small.

In the baseline scenario, around 10% of firms go bankrupt (and are replaced), most of them in the upstream sector. On average, 26 D-firms per period go bankrupt (5% of the population of D-firms) and 48 U-firms (around 20%). As expected, the number of defaults is strongly counter-cyclical.

Table 2.2: **Baseline: long run mean and standard deviation**

	Mean	**St. dev.**
Y	2.278,29	4,42
A^D	1.146,60	5,74
π^D	151,38	0,87
Q	1.139,15	2,21
A^U	479,32	2,15
π^U	-25,31	0,71
A^B	2.098,89	3,30
r^D	0,05	0,00
r^U	0,06	0,00
L^D	898,43	1,23
L^U	222,64	1,77

Note: We run 50 Montecarlo simulations over the interval (1-900). Then we apply the HP filter to the resulting time series and take the average of the filtered time series. Finally we use this series to compute the long run mean and standard deviation. **Legenda**: Y=aggregate production of D-firms (GDP); A^D=aggregate net worth of D-firms; π^D=aggregate profit of D-firms; Q=aggregate production of U-firms; A^U=aggregate net worth of U-firms; π^U=aggregate profit of U-firms; A^B=net worth of banks; r^D=average interest rate on loans to D-firms; r^U=average interest rate on loans to U-firms; L^D=bank loans extended to D-firms; L^U=bank loans extended to U-firms.

Table 2.3: **Correlations**

Note: The correlation indexes are computed on artificial data filtered and averaged as explained in table 2.2. Symbols represent aggregate variables (see legenda of table 2.2).

	Y	A^D	A^U	A^B	r^B	r^U	L^D	L^U
Y	1							
A^D	0.99	1						
A^U	0.98	0.97	1					
A^B	0.81	0.79	0.91	1				
r^D	-0.83	-0.80	-0,92	-0.99	1			
r^U	-0.44	-0.40	-0.59	-0.87	0.86	1		
L^D	-0.97	-0.98	-0.90	-0.64	0.66	0.20	1	
L^U	0.98	0.98	0.97	0.84	-0.86	-0.50	-0.93	1

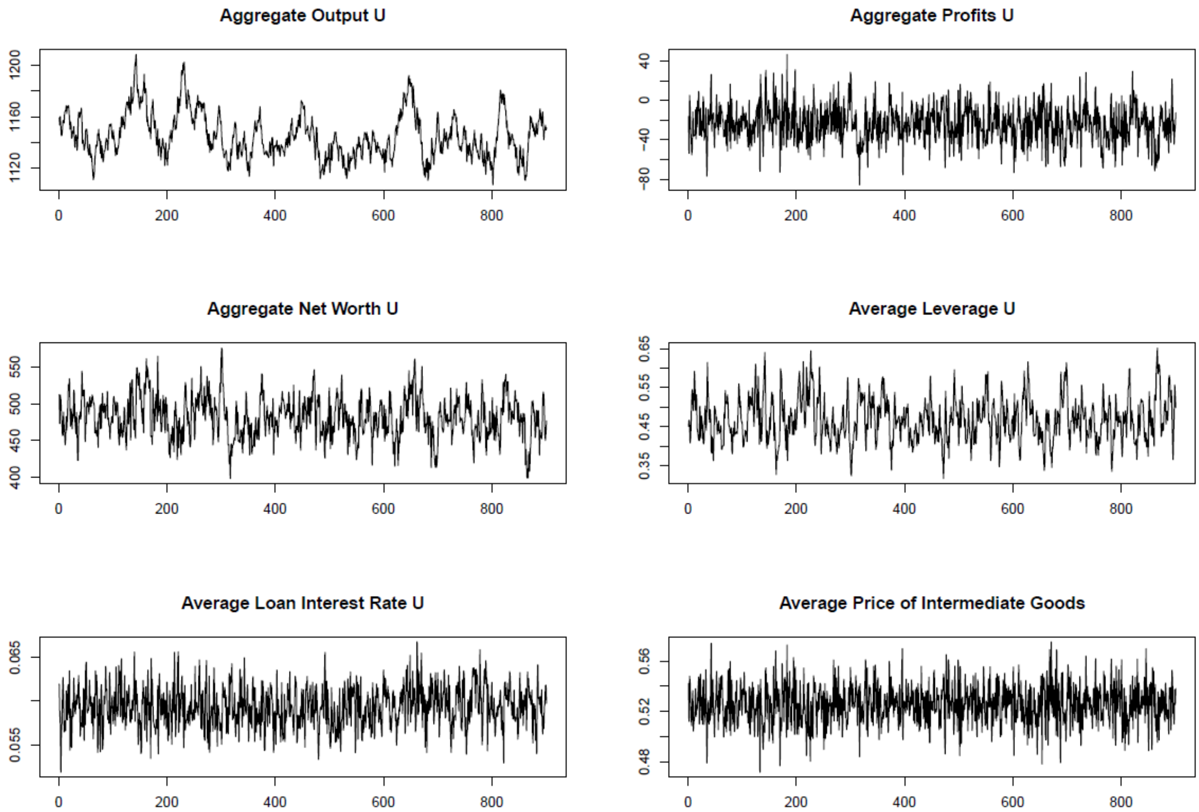


Figure 2.6: Baseline: U-firms (aggregate variables)

2.8 Supply chain disruptions

The production network which connects D-firms and U-firms can be conceived of as a web of supply chains. Each firm on the downstream side of the chain is linked, by assumption, to a single supplier (of intermediate inputs) on the upstream side. In the baseline model, the mechanism driving output fluctuations (for both D-firms and U-firms) is the accumulation of D-firms' net worth. Hence, a negative financial shock hitting the downstream side of a chain – e.g., a sudden increase of the interest rate charged to D-firms – would have repercussions on the upstream side and generate a contraction of the scale of activity of both the downstream firm and its upstream supplier. This transmission mechanism is straightforward and predictable.

In this section we analyse the macroeconomic effects of a disruption of the supply chain which occurs upstream because of a shock which impairs the capability of U-suppliers to respond to the demand for inputs coming from their downstream customers. A straightforward example comes to mind. Consider for instance a Global Value Chain whose downstream side is located in an advanced country – say, the United States – and the upstream side is located in an emerging country, China. If an epidemic erupts in China and U-firms are (temporarily) shut down during the ensuing lockdown, D-firms located in the USA will be unable to carry on production because of the interruption of the supply of intermediate inputs, independently of their net worth. In other words, D-firms will hit a sudden capacity constraint.

This shock may be captured in our model by assuming that U-firms suddenly contract their production at the moment of the lockdown, which will be lifted after a given number of periods. In the simulations discussed in this section, we divide the time horizon (900 periods) in three intervals: the pre-shock and pre-lockdown phase (phase 0) consists of the time interval [1-400); the lockdown phase (phase 1) consists of the interval [400-450) in which the lockdown is enforced; the post-lockdown phase (phase 2) consists of the interval [450-900) in which the lockdown is lifted. In the following subsections, we will consider two types of upstream-driven supply chain disruptions: (i) a generalized forced contraction of U-firms' production capabilities (generalized lockdown) and (ii) a targeted forced contraction which applies only to a subset of U-firms (localized lockdown or "red zone").

2.8.1 Generalized lockdown

For our first experiment, we assume that, due to the lockdown, there is a temporary shock that takes the form of a forced 30% reduction of the scale of activity of each and every U-firm which starts in period $T_0 = 400$ and lasts for 50 periods. In other words in each period between 400 and 450, each U-firm has a production cap equal to 70% of the orders of intermediate inputs it receives from downstream clients. The production constraint on U-firms forces downstream firms to revise their production schedule. In other words, the shock makes D-firms capacity constrained. In every period, each D-firm sets the production schedule, based on its financial condition (see equation (2.14)), and demand intermediate goods to the upstream firm (eq. (2.19)); since, during the lockdown, the U-supplier will be unable to fulfill all the demand coming from its customer, D-firm will have to cut on sales and reschedule the level of production, given the shortage of intermediate goods. D-firm will be affected by the capacity constraint through the net worth channel; D firm will experience a shrink in profits and net worth that forces it to downsizing. The reduction of net worth in one period determines a thighter financial constraint in the following one, which will imply a reduction in the scale of activity of the downstream firm. There is an amplification mechanism but the downsizing of the firm is not exponential, i.e. 0.7^{50}, because the firm still sets a production schedule which depends on its availability of funds; it is the worsening of its financial conditions that determines a lower level of production and, eventually, the downsizing.

In figure 2.7 we show artificial time series generated by one (representative) simulation concerning D-firms. Before the lockdown, the macro-economy behaves as in the baseline model. GDP fluctuates irregularly (top left panel) around a mean (computed over the interval of phase zero) which we can characterize as the *pre-shock* quasi-equilibrium.

The mean of GDP in phase zero is $Y_0 = 2275$ (see table 2.4).

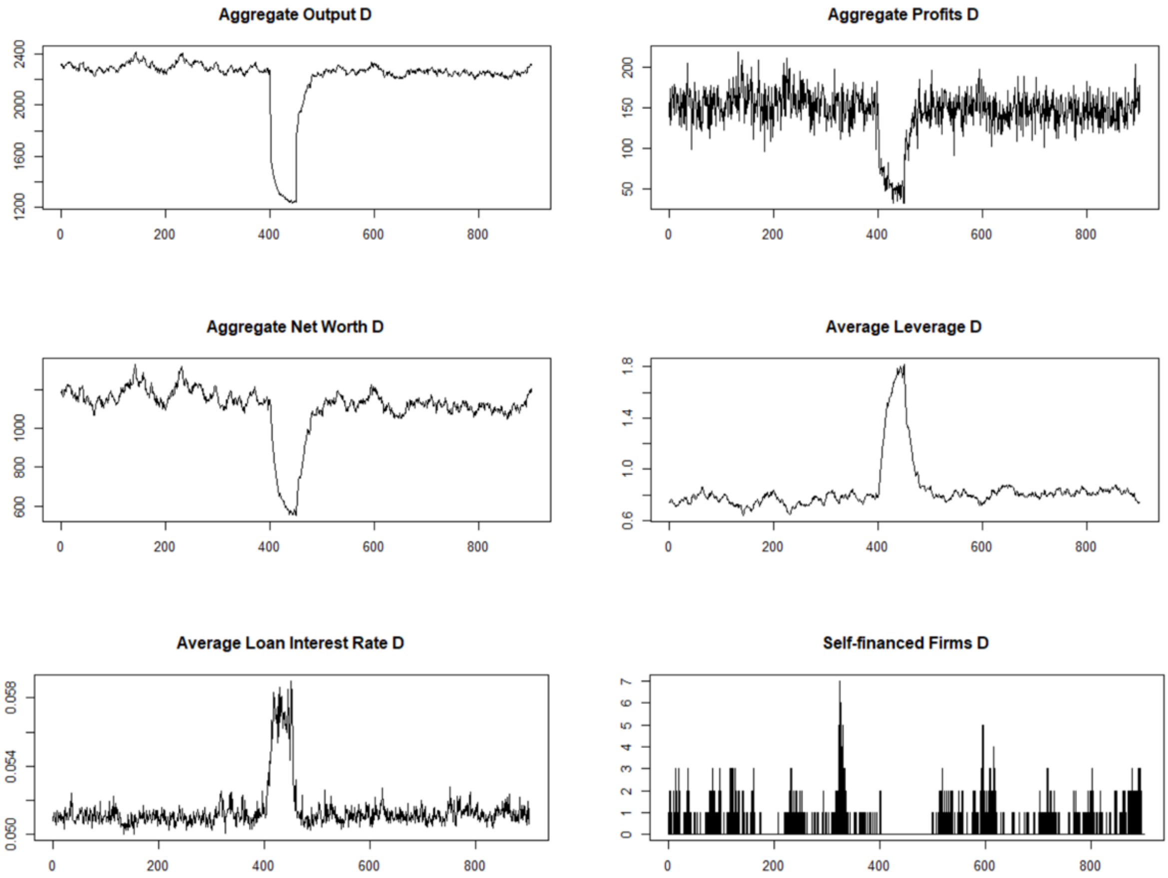


Figure 2.7: Generalized lockdown: D-firms

Macroeconomic volatility, captured by the standard deviation of GDP, is $\sigma_0^Y = 34$ i.e., 1.5% of the mean. Figure 2.8 shows the time series generated by the same simulation for U-firms. By construction, since $q = 1/2$, the average production of U-firms and volatility in phase zero is half the size of the corresponding indicators for D-firms: $Q_0 = 1138$ and $\sigma_0^Q = 17$.

Immediately after the shock the production of U-firms (see top left panel of figure 2.8) drops from a pre-shock level of 1100 to 790, and slides down further in the subsequent periods reaching a trough of at the end of phase 1. On average (see table 2.4), during the entire phase 1, U-production falls to $Q_1 = 693$ (-37% less than the pre-shock level) and volatility shoots up to $\sigma_1^Q = 87$. Also net worth shrinks approximately by the same amount. The overall reduction of production due to the lockdown is much bigger than the contraction forced on U-firms at the beginning of the lockdown (-30%). Not surprisingly, the fall of GDP is of the same size as that of U-production (top left panel of figure 2.7).

The magnification of the impact of the shock is due to the indirect effects of the lockdown. The reduction of upstream supply forces D-firms to cut back on production and sales. Therefore, also D-firms will experience a contraction of profits and net worth. As a consequence, D firms face an increase of their debt, which determines the rise

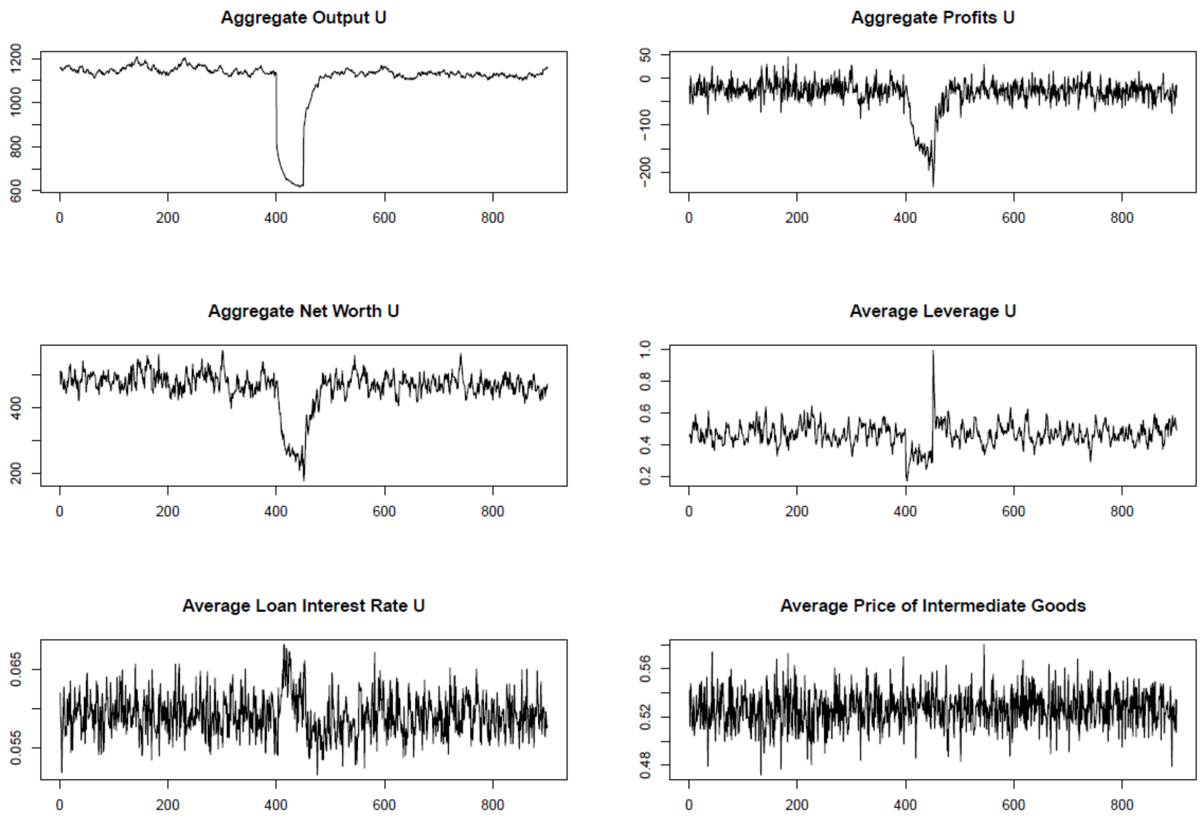


Figure 2.8: Generalized lockdown: U-firms

of leverage and of the risk premium on loans. Self-financed D-firms almost disappear during the lockdown. The initial contraction in D-profits, therefore, will trigger further contractionary effects on D-firms' net worth.

Some firms will go bankrupt. In the pre-lockdown phase (as in the baseline), on average 26 D-firms and 48 U-firms per period go bankrupt. Overall around 10% of the firms are exiting and replaced. In the lockdown phase on average 112 D-firms and 88 U-firms go bankrupt, 27% of the total population of firms.

After the removal of the lockdown the economy rebounds. The after-shock levels of GDP, production of U-firms, net worth of D-firms and U-firms are slightly below the pre-shock levels (see figures 2.7 and 2.8 and the average values for phase 2 as compared with phase 1 in table 2.4).

2.8.2 Red zone

In this section, we explore the consequences of a different type of lockdown, namely a contraction of production forced on a subset of upstream firms. This is the shock that occurs when the lockdown is imposed in a specific area ("red zone") which is at the centre of the epidemic. Only firms within the red zone are subject to the lockdown. We assume that 100 upstream firms (out of 250) are forced to contract production by 75% for 50 periods (phase 1). In Figures 2.9 and 2.10 we show artificial time series generated by one

Table 2.4: **Generalized lockdown: mean of selected variables**
Note: Mean of selected variables over three phases: Pre-lockdown interval (phase 0): periods 1-399; Lockdown (phase 1): periods 400-449; Post-lockdown (phase 2): periods 450-900. Each mean is computed on data filtered and averaged as explaned in the note of table 2.2. Symbols represent aggregate variables (see legenda of table 2.2).

	Pre-lockdown (0)	**Lockdown (1)**	**Post-lockdown (2)**
Y	2274.93	1389.47	2255.24
A^D	1146.68	692.33	1121.24
π^D	151.19	65.78	148.88
Q	1137.47	694.74	1127.62
A^U	479.84	300.74	470.28
π^U	-25.07	-117.05	-28.75
A^B	2099.13	1693.08	2097.38
r^D	0.05	0.06	0.05
r^U	0.06	0.06	0.06
L^D	898.53	986.08	905.48
L^U	221.88	100.79	220.17

(representative) simulation concerning D-firms and U-firms respectively in this scenario.

Before the lockdown, the macro-economy behaves as in the pre-shock period in the previous experiment. We remind that the mean of GDP is $Y_0 = 2275$ so that the corresponding descriptive statistics for U-firms is $Q_0 = 1138$. After the shock, the production of U-firms goes down (top left panel of figure 2.10). The mean of U-production during the lockdown is $Q_1 = 1011$ (see table 2.5): in the red zone case aggregate U-production goes down by 11%. The fall of GDP is of the same size as that of U-production. Also net worth of D-firms shrinks approximately by the same amount. The reduction of upstream supply, in fact, forces D-firms to cut back on production and sales.

Notice that, contrary to the generalized lockdown scenario, after the shock U-production does not keep falling until the removal of the lockdown but it begins to increase in the middle of the lockdown phase. In the red zone case, therefore, the magnitude of the macroeconomic downturn and its shape are markedly different from those of the generalized lockdown scenario: the economy takes less time to come back to the pre-shock level, after the removal of the supply restriction.

In part, this is obvious since the majority of firms are not subject to forced downsizing. But this is not the end of the story. In the localized case, in fact, the macroeconomic impact of the shock is affected by the change in production interlinkages among D-firms and U-firms.

U-firms hit by the shock will experience a contraction of their net worth. The interest rate on trade credit extended by these firms therefore will go up. As a consequence, their D-customers will switch to suppliers who can sell at more favourable terms, i.e. U-firms located outside the red zone. In figure 2.11 we show the number of downstream customers for each U-supplier (labelled from 1 to 250 on the x-axis) in a given period during the

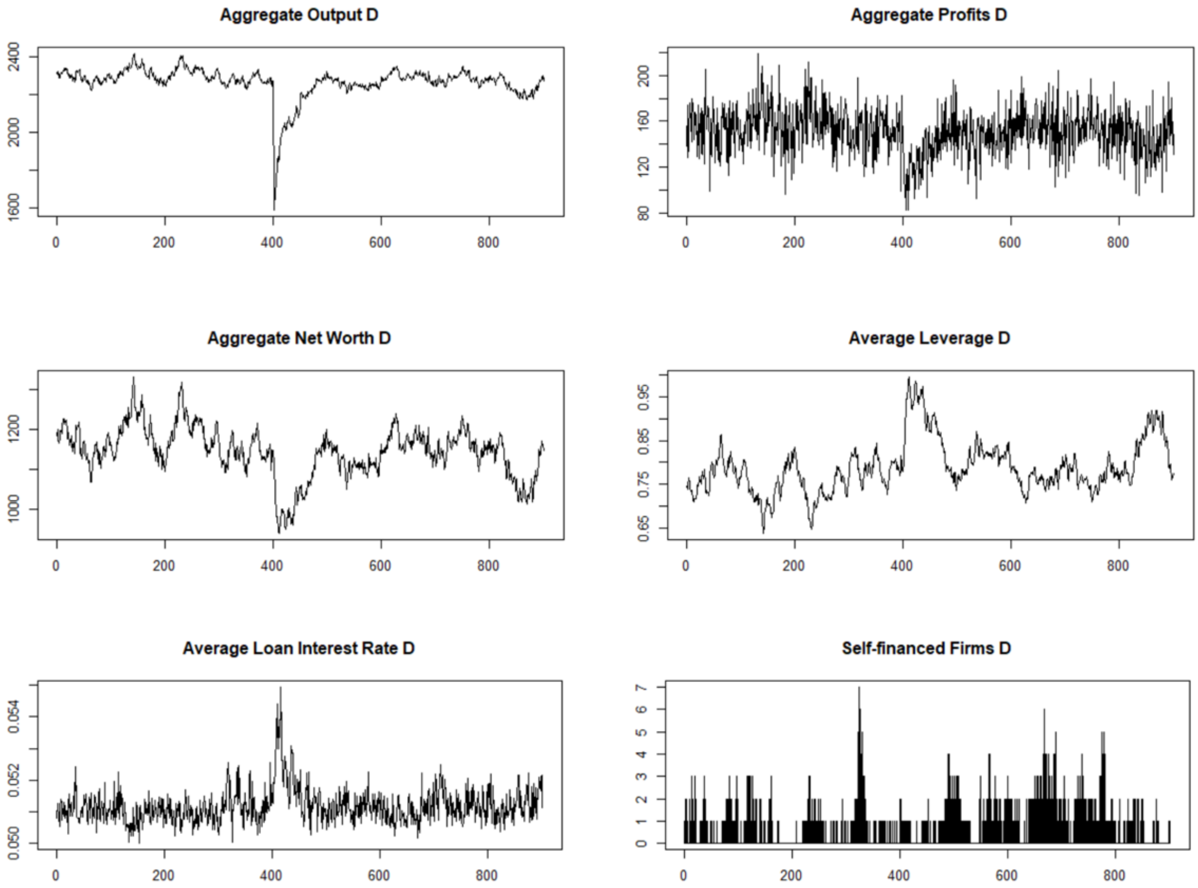


Figure 2.9: Red zone: D-firms

localized lockdown, compared with the same period in the baseline.[24]

Table 2.5: **Red zone: mean of selected variables**

	Pre-lockdown (0)	**Lockdown (1)**	**Post-lockdown (2)**
Y	2274.93	2022.07	2274.44
A^D	1146.68	1007.08	1142.37
π^D	151.19	125.39	150.93
Q	1137.47	1011.03	1137.22
A^U	479.84	411.57	477.02
π^U	-25.07	-50.17	-26.08
A^B	2099.13	1997.6	2098.1
r^D	0.05	0.05	0.05
r^U	0.06	0.06	0.06
L^D	898.53	927.68	899.51
L^U	221.88	220.64	222.60

See note of table 2.4.

In the red zone U-firms (the first 100 firms) lose customers in favour of U-firms

[24]We decided to take a picture of the connections in the production network in period t=449 of the baseline and of the red zone scenario. This is the last period of the localized lockdown (which goes from period 400 to period 450) in the red zone scenario.

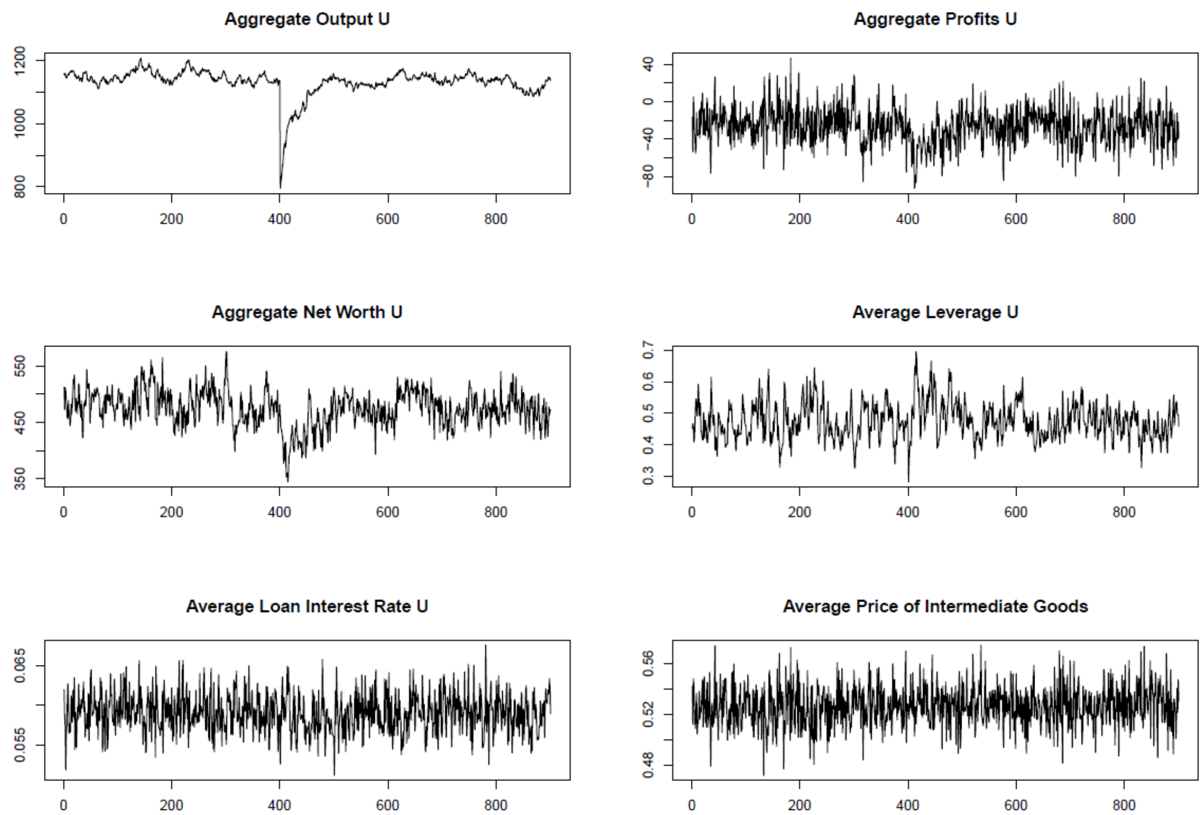


Figure 2.10: Red zone: U-firms

that are not subject to the lockdown. This diversification effect of the lockdown on the portfolio of suppliers available to D-firms is the main determinant of the mitigated impact of the shock in the red zone case.

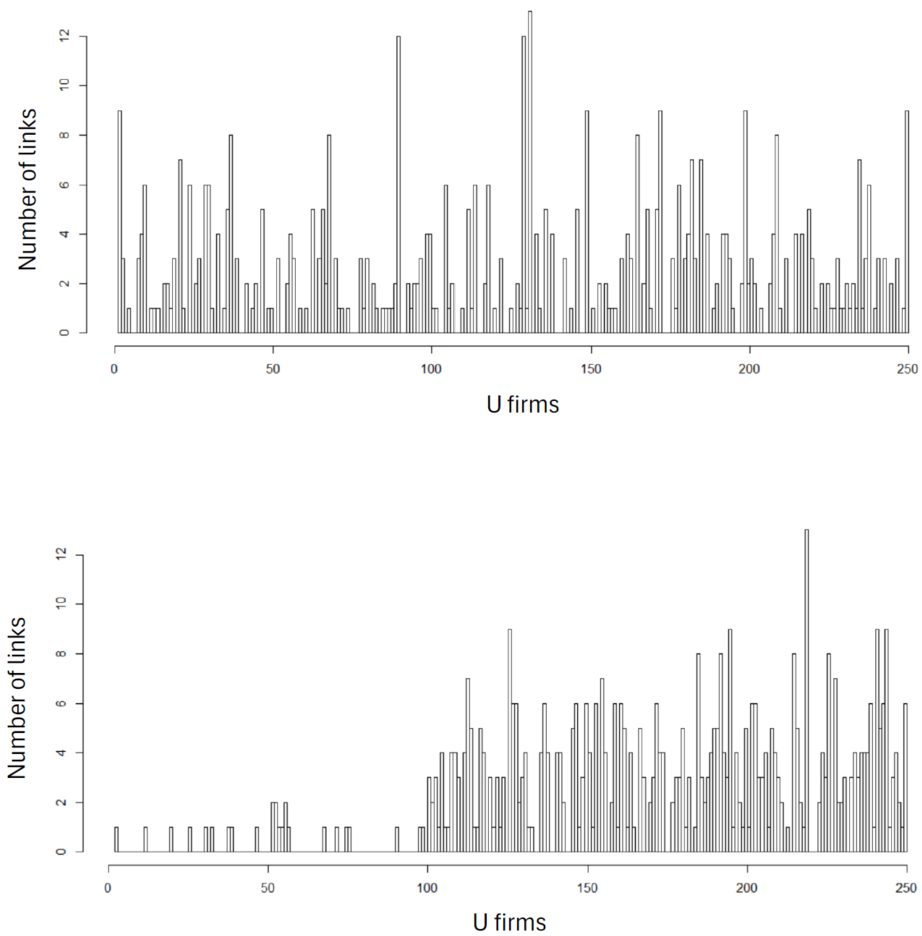


Figure 2.11: Number of links for each U-firm: baseline (upper panel) and red zone scenario (lower panel)

2.9 Conclusions

The disruptions of supply chains is generally recognized as one of the key economic consequences of Covid-19. In this paper we have investigated the macroeconomic and financial consequences of the disruption of a supply chain in a streamlined agent based framework characterized by a credit network connecting banks and firms and a production network connecting upstream and downstream firms. These networks propagate shocks through financial contagion.

We have experimented with two types of supply chain disruptions. In the first scenario we have assumed that the lockdown takes the form of a generalized contraction of the supply of upstream firms. This shock engenders a deep recession. The sudden reduction in the supply of intermediate goods leads to a generalized contraction of profits and net worth.

In the second scenario only some upstream firms are forced to cut on production, namely those located in the “red zone”. In the localized lockdown case, the recession is less persistent and the recovery begins earlier because downstream firms can switch to suppliers who are located outside the red zone. Hence they can limit the contraction of their production. The overall impact of the shock in the “red zone” case is therefore mitigated.

Our experiments shed light on the trade-off between lean production and resilience to shocks in GVCs. In normal, pre-pandemic times, since U-firms produce on demand, the scale of activity of the associated D-firm determines the amount of intermediate goods produced by U-firms. There will not be involuntary inventories of intermediate inputs because the U-supplier produces “just in time”. In normal times therefore, GVCs are “lean” and D-firms will not face capacity constraints. In the generalized lockdown case, the interruption of production at the upstream level leaves the downstream firms with no alternatives to a sizable downsizing. In the redzone case, on the contrary, the shock is mitigated because U-suppliers located outside the redzone operate as “backups”. From the managerial point of view GVCs with backups are less efficient than lean GVC. However when the likelyhood of a sizable disruptive event is high – as in the current situation – managers and policy makers should put more emphasis on resilience than on “leanness” of the production network and provide with the necessary alternative sources of inputs.

We are aware of the limitations of the model (highlighted in the discussion of the assumptions). These limitations notwithstanding, we deem these first results encouraging. The model can be further exploited to answer a wide range of related questions. For example, it would be interesting to study ways of re-organizing supply chains after the disruption or ways of responding by means of monetary/fiscal macro-stabilization tools. We leave these issues to future research.

Chapter 3

Behind the international trade network: the role of heterogeneity and financial frictions

3.1 Introduction

The deepening integration of global markets has amplified countries' exposure to cross-border shocks and systemic risks. International trade is a key driver of these spillovers: it delivers efficiency gains through specialization and expanded market access, yet simultaneously provides a powerful channel for the transmission of shocks. As trade is inherently a network activity - linking countries through a dense web of bilateral ties - localized shocks can quickly cascade across borders, shaping global production, trade flows, and macroeconomic performance.

Understanding how such interdependencies arise, and how they shape macroeconomic responses to shocks, requires moving *behind* aggregate representations of trade. This paper takes a micro-founded perspective, modeling international trade as a network, emerging from endogenous firm-level export decisions under asymmetric information. The goal is to uncover how the structure of trade linkages emerges and how it reacts to financial distress, leading to macroeconomic repercussions. This question is utterly relevant in light of the Great Trade Collapse that followed the Global Financial Crisis, where the sudden and synchronized contraction in trade was widely attributed to the high degree of interconnectedness within global production and trade networks (Baldwin, 2009)

In doing so, we build on the fundamental assumptions of the *New-New Trade Theory* (Melitz, 2003), which shifted the focus from countries and industries to firms. This paper expands the literature along three main threads. First, we introduce multiple layers of heterogeneity, both within and between countries, allowing us to capture differences

*This chapter, which is currently a working paper, has been developed under the supervision of *Prof. Giorgio Ricchiuti.*

across firms and economies. Second, we explicitly model the credit market, which enables the analysis of how monetary and financial conditions affect trade dynamics - a channel largely unexplored in general equilibrium trade frameworks (Antràs, 2023). Third, the interaction between heterogeneity and asymmetric information in the credit market generates financial frictions that constrain firms' access to external finance, ultimately shaping their ability to export. These frictions are empirically relevant, as previous studies have documented their impact on export participation, trade intensity, and resilience to shocks (Chor and Manova, 2012, Manova, 2008, Paravisini et al., 2015, Muûls, 2015). Together, these elements determine trade patterns and their responses to shocks, highlighting the mechanisms through which local disturbances can ripple across the global economy.

More specifically, the proposed framework builds on Feenstra et al. (2014), where exporting firms acquire capital under asymmetric information, establishing a link between financial access and trade participation. We extend this approach in two directions. First, we introduce a double layer of heterogeneity, i.e. across firms - in terms of productivity and financial robustness (as in Assenza et al., 2016) - and across countries, in terms of geography and financial conditions. These features allow us to better reflect observed cross-sectional variation in export behavior and credit conditions. Second, we embed the model within a multi-country framework where trade linkages emerge endogenously from the individual choices of firms. By aggregating these decentralized interactions, the model gives rise to a global trade network whose structure reflects salient empirical features, such as asymmetric and zero trade flows, as well as scale-free properties observed in real-world data.

The network-based perspective allows the study of both the formation of international trade linkages and the transmission of financial shocks. Namely, we evaluate the macroeconomic effects of a financial shock, modeled as an exogenous increase in the sovereign spread, conditional on both the characteristics of the affected country and its position within the international trade network. To this end, we simulate two scenarios: one in which the shock hits a central country, i.e., a node with high connectivity and influence in the trade network, and another in which it affects a randomly selected node. Due to the scale-free structure of the trade network, the two scenarios generate markedly different macroeconomic outcomes: shocks to central hubs cause widespread contagion and network reconfiguration, while shocks to peripheral countries remain largely contained. These findings underscore the importance of incorporating financial characteristics and network structure into models of international trade. By linking firm-level decisions to macroeconomic outcomes through an evolving network of trade relationships, the model provides new insights into the systemic consequences of financial shocks in an interdependent global economy.

The remainder of the chapter is organized as follows. Section 3.2 reviews the relevant literature. Section 3.3 presents the theoretical model. Section 3.4 describes the calibration strategy and discusses the main results. Section 3.5 concludes and suggests directions for future research.

3.2 Related literature

The paper proposes a static general equilibrium model with heterogeneous firms, in the vein of the *New-new Trade Theory*. Since the pioneering work of Melitz (2003), extensive research has examined modes of internationalization, considering productivity heterogeneity and market frictions. A stream of this literature investigates the effects of financial factors on firms' internationalization strategies (see, among others, Kohn et al., 2016, Kohn et al., 2020, Bergin et al., 2021). In this context, Manova (2013) proposes a model with heterogeneous firms subject to collateral constraints, while Chaney (2016) explores how liquidity constraints limit firms' exporting choices. Along the same line of research, Crinò and Ogliari (2017) study how financial frictions affect trade, through their impact on product quality.

The above-mentioned studies account for both fixed and variable costs, with exporters facing higher production expenses and tighter credit constraints. Feenstra et al. (2014) provides an in-depth explanation of this phenomenon, by showing that exporters encounter more stringent credit rationing as they are charged higher interest rates due to protracted debt repayment periods connected to the exporting activity. The relationship between interest rates and firm-level export is also central in Assenza et al. (2016), which accounts for the heterogeneity in both financial soundness and productivity. Our model builds on the microfoundation developed by Feenstra et al. (2014), in which firms operate under asymmetric information and face endogenous interest rates when borrowing capital to finance production. We extend this framework by incorporating a second layer of firm-level heterogeneity, as in Assenza et al. (2016), where differences in both productivity and financial soundness jointly determine firms' access to credit and export decisions. By embedding these elements within a general equilibrium setting, our model captures how the interaction between financial constraints and firm characteristics shapes the extensive and intensive margins of trade. This dual-layer heterogeneity proves essential for understanding the emergence of asymmetric trade patterns and the vulnerability of the trade network to shocks.

Furthermore, the current paper explores the intersection of financial frictions and monetary policies within a Melitz model framework, a relatively novel domain in the New-new Trade Theory. While research linking trade and interest rates exists, such as in Antràs (2023), who study trade in a two-country model with firm heterogeneity and time-dependent production cycles (following the Austrian approach of Boehm-Bawerk, 1896), our model differs by adopting a multi-country approach that considers both inter- and intra-country heterogeneity. This setup enables us to examine heterogeneous, network-based spillovers often overlooked in symmetric models. Multi-country Melitz models, such as Helpman et al. (2008) and Yeaple (2009), typically focus on country-pair relationships, whereas our model examines the structure of an entire system of interconnected firms and countries.

The proposed framework aims to bridge the *New-new Trade Theory* of firm heterogeneity with the *Old Trade Theory* of countries' comparative advantage. We propose a model in which both firms' heterogeneity and country-specific factors, especially financial robustness, shape the international trade network. This model relates to the Kletzer and Bardhan (1987), which augments the *Heckscher-Ohlin-Samuelson* model to show that credit market frictions affect comparative costs, favoring financially developed countries. However, unlike their model, we incorporate firm-level financial heterogeneity alongside country characteristics.

Our research also contributes to literature on the microeconomic origins of macroeconomic outcomes, notably Acemoglu et al. (2012) and Carvalho (2014), who first showed how sectoral linkages can propagate microeconomic shocks into aggregate fluctuations. Subsequent work, such as Barrot and Sauvagnat (2016) and Baqaee and Farhi (2020), models production networks using input-output analysis to assess disruptions, while Baqaee and Rubbo (2023) examines microeconomic shock transmission through general equilibrium. In the context of international linkages, studies like Taschereau-Dumouchel (2020) and Devereux et al. (2020) underscore the importance of network structure in propagating economic and policy shocks globally. Research on monetary policy in networked economies, as in La'O and Tahbaz-Salehi (2022) and Chen (2024), further highlights the role of input-output linkages across sectors and countries.

In contrast to much of the production network literature, which focuses on sectoral connections, we examine firm-level perspectives on shock propagation and the evolution of trade patterns. Our model, therefore, offers a unique contribution by blending financial frictions with the dynamics of international trade and firm-level heterogeneity, establishing a bridge between these intersecting areas of research and embodying the *Financial Accelerator View* of macroeconomic fluctuations through real shocks in a global trade network.

3.3 Theoretical framework

We develop a static multi-country general equilibrium model of international trade à la Melitz, in which heterogeneous firms endogenously choose their export destinations across N_c countries. Each country is populated by N_f firms. Firms are heterogeneous with respect to their level productivity, φ, and net worth a, both drawn from distinct distributions.

Firms finance production by borrowing liquidity from domestic banks. The market for loans is characterized by asymmetric information, wherein banks do not observe firms' true productivity levels. Instead, they offer loan contracts with interest rates that depend on the productivity levels announced by firms, φ_i'. Henceforth, banks design contracts that induce firms to reveal their true level of productivity. Firm productivity determines the expected profitability of a project and, consequently, the firm's ability to repay its loan. More productive firms generate higher revenue for a given level of input, which increases the expected return on the bank's loan. This approach of modeling financial frictions is grounded in the theoretical framework of Feenstra et al. (2014). We extend this model along two key dimensions. First, we allow firms to differ not only in productivity but also in their initial internal financial resources (net worth), which affects the amount of external credit they require to operate, even conditional on the same productivity level. Second, we embed the model in a multi-country environment in which sovereign spreads vary across countries, generating cross-country heterogeneity in borrowing conditions. These extensions allow us to study how both firm-level and country-level financial characteristics jointly shape export participation and the structure of the international trade network.

Once loans are issued, firms self-select into export markets according to a zero-profit cutoff condition: they serve only those — domestic or foreign — destinations where expected profits are non-negative.

After revenues are realized, firms repay principal and interest to the bank. As in Feenstra et al. (2014), export revenues are subject to a delay due to shipment lags. The timing of events is illustrated in Figure 3.1.

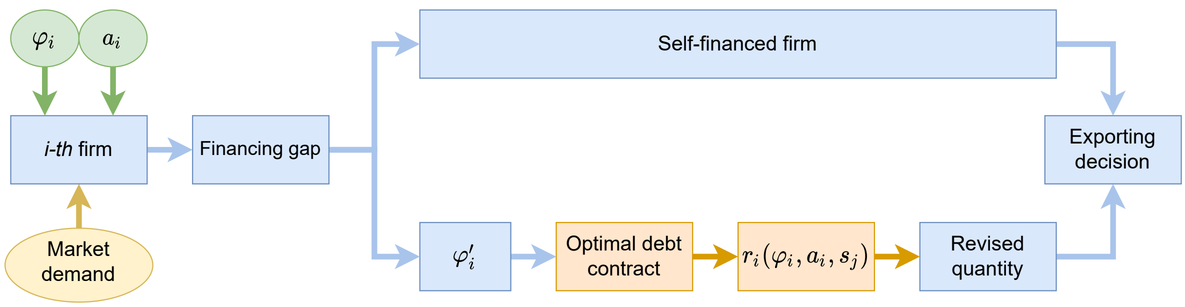


Figure 3.1: Sequence of events.

3.3.1 Households and firms

Each of the N_c countries (indexed with $j = 1, 2, ..., N_c$) is populated by a set, $Z^j = Z$, of homogeneous households and $N_f^j = N_f$ firms, each of them producing a differentiated variety, $i = 1, 2, ..., N_f$.[2] In line with the *Dixit-Stiglitz* setting, the representative house-

[2]Henceforth, superscripts shall denote the country, whereas subscripts shall indicate the firm.

hold's, z, utility function coincides with the CES aggregator of the quantities of each variety consumed, q_{iz} :

$$U_z^j = \left(\tilde{N^j}^{\frac{1}{1-\sigma}} \sum_{i=1}^{\tilde{N^j}} (q_{iz})^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}, \tag{3.1}$$

where $\tilde{N^j}$ is the equilibrium availability of varieties in an open economy, endogenously determined, which corresponds to the number of firms selling to market j. The latter is given by the sum of local producers, N_D^j, and the sum of foreign firms located in each $k \neq j$ country and exporting to the market j, N_E^k, such that: $\tilde{N^j} = N_D^j + \sum_{k=1}^{N_c-1} N_E^k$. The quantity of the *i-th* variety, q_{iz}, consumed by each z household, is the result of the following constrained maximization problem:

$$\max_{q_i z} \quad \left(\tilde{N^j}^{\frac{1}{1-\sigma}} \sum_{i=1}^{\tilde{N^j}} (q_{iz})^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}, \tag{3.2a}$$

$$\text{s.t.} \quad \sum_{i=1}^{\tilde{N^j}} p_i q_{iz} \leq R_z = w^j l_z + \Pi_z^j, \tag{3.2b}$$

$$\sum_{i=1}^{\tilde{N^j}} p_i q_{iz} = \tilde{P^j} C_z, \tag{3.2c}$$

where R_z denotes resources available to household - the wage bill, $w^j l_z$, and profits earned from firms' owning, Π_z - and $C_z = U_z$ is total consumption. Solving household's maximization problem and summing over the total population of households, we derive the market demand for the *i-th* variety in country j:

$$q_i^j = \left(\frac{p_i^j}{\tilde{P^j}}\right)^{-\sigma} \frac{\tilde{Q^j}}{\tilde{N^j}}, \tag{3.3}$$

which is an inverse function of the price of the variety produced by firm i and sold to country j. Market demand depends upon the characteristics of the market, as represented by the equilibrium price index, $\tilde{P^j}$, real GDP, $\tilde{Q^j}$, and equilibrium number of domestic producers and importers, $\tilde{N^j}$. The aggregate price index accounts for the price charged by the N_D^j domestic producers, p_i^j, and the price of the *m-th* variety produced in country $k \neq j$ and sold to j, p_m^j:

$$\tilde{P^j} = \left[\frac{1}{\tilde{N^j}}\left(\sum_{i}^{N_D^j} {p_i^j}^{(1-\sigma)} + \sum_{k=1}^{N_c-1} \sum_{m=1}^{N_E^k} {p_m^j}^{(1-\sigma)}\right)\right]^{\frac{1}{1-\sigma}}. \tag{3.4}$$

Similarly, real GDP, in the *j-th* country is computed as the inflation-adjusted sum of the value of all goods and services locally produced and sold by the N_D^j domestic producers, q_i^j, or shipped to the *k-th* foreign market by the N_E^j domestic exporters, q_i^k:

$$\tilde{Q}^j = \frac{\sum_{i=1}^{N_D^j} q_i^j p_i^j + \sum_{i=1}^{N_E^j} \sum_{k=1}^{N_c-1} q_i^k p_i^k}{\tilde{P}^j}. \tag{3.5}$$

To meet market demand, the i-th firm produces output using a linear technology in labor, l_i. Hence, the labor demand is:

$$l_i^j = \frac{q_i^j}{\varphi_i}, \tag{3.6}$$

where q_i^j is the quantity produced for country j and φ_i is the productivity of labor. Firms face a perfectly elastic supply of labor at a given nominal wage, $w^j = 1$, which represents the variable cost of production borne: $w^j l_i$. [3]
Moreover, firms, located in country j, pay fixed upfront costs for each market, k, they serves, F^{jk}. Consistent with the reference literature (Melitz, 2003), fixed costs of foreign sales are higher than those for domestic sales: $F^{jk} > F^{jj}$. In addition, firms face iceberg trade costs, denoted by τ^{jk}, which capture shipping fees, insurance premiums, and other expenses related to the geographical distance between the domestic country j, where production occurs, and the destination country k where output is sold. Iceberg costs are normalized to 1 for domestic sales, $\tau^{jj} = 1$, while exporting is assumed to involve higher costs ($\tau^{jk} > \tau^{jj}$ for $k \neq j$), capturing the additional expenses of longer shipment distances. As extensively discussed in the trade literature (Anderson, 1979), countries with greater proximity - both geographically and culturally - are more likely to engage in trade. Greater distances between trading partners, on the other hand, result in longer shipment times and extended lags between production and the realization of sales. This temporal dimension of trade costs has important implications for working capital requirements, as it will be discussed momentarily.

Hence, total production costs for the *i-th* firm selling to country j are:

$$PC_i^j = \frac{q_i^j}{\varphi_i}\tau^{jj} + F^{jj}. \tag{3.7}$$

Firms require working capital to finance production, which can be sourced from either internal equity or external bank loans. In the presence of asymmetric information, a financing hierarchy arises, consistent with the Pecking Order Theory (Myers and Majluf, 1984), whereby firms prioritize internal funds due to their lower cost. Consequently, production costs are initially covered by the firm's internal wealth (net worth); external financing through bank loans is used only when internal liquidity is insufficient to cover production costs.

[3]The nominal wage has been normalized to 1 and it will be omitted in the following to easy the notation.

We assume that firms allocate a constant fraction of their net worth, a_i, to production for each of the N_c potential destination markets. Accordingly, each firm is divided into $n = N_c$ divisions, with each division specialized in serving a specific country, either domestic or foreign. The division of firm i responsible for production for market k has access to internal resources up to a maximum of $a_i^k = \frac{a_i}{n}$.

If these internal funds are sufficient to cover production costs, the division is fully self-financed, and any remaining surplus is discarded.[4] Conversely, if internal resources are insufficient, a financing gap arises, and the firm must seek external funding from a bank.

Hence, the loan demand of firm i to serve the generic *k-th* country (with $k = j$ being the domestic market and $k \neq j$ the foreign ones) is:

$$M_i^k = PC_i^k - a_i^k = \frac{q_i^k}{\varphi_i}\tau^{jk} + F^{jk} - a_i^k. \tag{3.8}$$

Each division operates independently in deciding whether to serve a foreign market and sets production accordingly. In a multi-country model, this means that the *i-th* firm requests separate loans for each market served. Consequently, the firm's total exposure to the financial system is the sum of the loans obtained by its individual divisions:

$$M_i = \sum_{k=1}^{N_c} \left(\frac{q_i^k}{\varphi_i}\tau^{jk} + F^{jk} - a_i^k \right). \tag{3.9}$$

The firm applies for loans from the representative financial institution. Due to asymmetric information, the bank is unable to observe the true level of productivity of firm i, φ_i, and it will design a loan schedule, $M(\varphi_i')$, and interest payments, $I(\varphi_i') = r_i M(\varphi_i')$,contingent upon firm's announced productivity level, φ_i'. The contract designed by the bank should induce the firm to reveal the true level of productivity. Notice that asymmetric information pertains exclusively to firm-specific productivity. We assume that the bank knows firm's net worth, a_i, through its balance sheets. As a result, the bank determines the loan schedule solely as a function of the declared productivity level, $M(\varphi_i')$, taking net worth as given.

The firm sets the price to maximize profits, given the market demand and the loan schedule allotted by the bank, which, in turn, determines the interest rate. The overall profits of firm i will be given by the sum of all the profits realized in all the markets served: $\pi_i = \pi_i^{jj} + \sum_{k=1}^{N_c-1} \pi_i^{jk}$.

Due to the additive nature of the profit function, the maximization problem can be decomposed and solved separately for each market. Consequently, each division of

[4]From a managerial perspective, we assume that the Chief Financial Officer pre-allocates the firm's financial resources across divisions in the previous period, ruling out the possibility of intra-period reallocation.

the firm independently maximizes its profits, ensuring that the firm's total profit is also maximized. Focusing on the division of firm i serving market k, the optimization problem involves determining the price and the declared level of productivity that solve the following constrained maximization:

$$\max_{p_i^k,\varphi_i'} \quad \pi_i^k = {p^k}_i {q^k}_i - \left(\frac{q_i^k}{\varphi_i}\tau^{jk} + F^{jk}\right) - r_i^k M(\varphi_i'), \tag{3.10a}$$

$$\text{s.t.} \qquad q_i^k = (\frac{{p^k}_i}{\tilde{P}^k})^{-\sigma}\frac{\tilde{Q}^k}{\tilde{N}^k}, \tag{3.10b}$$

$$\pi_i^k(\varphi_i,\varphi_i) \geq \pi_i^k(\varphi_i,\varphi_i'), \tag{3.10c}$$

$$\pi_i^k(\varphi_i,\varphi_i) \geq 0, \tag{3.10d}$$

$$M^k(\varphi_i') \geq \frac{q_i^k}{\varphi_i}\tau^{kj} + F^{jk} - a_i^k, \tag{3.10e}$$

where (3.10b) is the market demand for the i-th variety; constraint (3.10c) ensures the revelation principle for the firm: profits must be greater when revealing the true level of productivity. They must also be positive according to constraint (3.10d). Furthermore, the loan schedule under asymmetric information (constraint (3.10e)) states that the external resources allotted should at least cover the financing gap. This happens whenever the firm declares a level of productivity that is lower than the true one: $\varphi_i' \leq \varphi_i$. In equilibrium, constraint (3.10e) must be binding; otherwise, the firm would pay higher interest payments by borrowing more than necessary. Since (3.10e) is binding, the quantity produced is a function of the loans schedule $M(\varphi_i')$:

$$q_i^k = (M(\varphi_i') - F^{jk} + a_i^k)\frac{\varphi_i}{\tau^{jk}}. \tag{3.11}$$

By substituting (3.11) and the inverse demand function obtained from (3.10b), we get:

$$\pi_i(\varphi_i,\varphi_i') = \left(\frac{\tilde{N}^k}{\tilde{Q}^k}\right)^{\frac{-1}{\sigma}} \tilde{P}^k\left[(M(\varphi_i') - F^{jk} + a_i^k)\frac{\varphi_i}{\tau^{jk}}\right]^{\frac{\sigma-1}{\sigma}} - a_i^k - (1+r_i^k)M(\varphi_i'). \tag{3.12}$$

By taking the first order derivative with respect to φ_i' under the revelation principle, we can find the declared level of productivity that maximizes firm's profits:

$$\frac{\partial\pi(\varphi_i,\varphi_i')}{\partial\varphi_i'}\,|_{\varphi_i'=\varphi_i}= 0,$$

$$M'(\varphi_i)\left[\tilde{P}^k\frac{\sigma-1}{\sigma}\left(\frac{\tilde{Q}^k}{\tilde{N}^k}\right)^{\frac{1}{\sigma}}\left(\frac{\varphi_i}{\tau^{jk}}\right)^{\frac{\sigma-1}{\sigma}}(M(\varphi_i) - F^{jk} + a_i^k)^{\frac{-1}{\sigma}}\right] - (1+r_i^k)M'(\varphi_i) = 0.$$

Given the strict monotonicity of the loans schedule, we can derive the inverse demand function as:

$$\Rightarrow r_i^k = \Phi(\varphi_i, M(\varphi_i)) - 1$$
$$where \quad \Phi(\varphi_i, M(\varphi_i)) = \tilde{P}^k \frac{\sigma - 1}{\sigma} \left(\frac{\tilde{Q}^k}{\tilde{N}^k}\right)^{\frac{1}{\sigma}} \left(\frac{\varphi_i}{\tau^{jk}}\right)^{\frac{\sigma-1}{\sigma}} (M^k(\varphi_i) - F^{jk} + a_i^k)^{\frac{-1}{\sigma}}. \tag{3.13}$$

The inverse demand function for loans exhibits the expected negative relationship between the interest rate and the quantity of credit demanded: as the interest rate increases, firms reduce their borrowing. This represents the *incentive-compatibility condition* for firm i: it characterizes the interest rate that induces the firm to truthfully reveal its productivity level, given the loan schedule. This constraint must be incorporated into the bank's profit-maximization problem.

Moreover, from the firm's maximization problem we get the optimal price charged by the *i-th* firm in the domestic market:

$$p_i^k = \frac{\sigma}{\sigma - 1} \frac{\tau^{jk}}{\varphi_i} (1 + r_i^k). \tag{3.14}$$

The optimal price is decreasing in the firm's productivity and increasing in the interest rate. The latter, which results from the bank's profit-maximization problem under asymmetric information, is itself a decreasing function of productivity, as will be shown below. Hence, more productive firms are able to charge lower prices and capture larger market shares, owing to both lower operational and financial costs.

3.3.2 Banks

Firms borrow working capital from a monopolistic bank, which sets the interests repayments to maximize profits. Bank's total revenues are given by the sum of the interests collected on loans whereas the total costs are represented by the opportunity cost of lending to the firm. The latter is computed as the interests the bank would have earned if the funds lent to the firm, $M(\varphi_i)$, would have been employed in a risk free asset paying an interest rate i^j, for τ periods. The distance between countries, proxied by iceberg costs, is assumed to reflect the time elapsed between production and realization of profits, thus indicating the maturity of debt. It follows that loans to exporting firms are characterized by longer maturity. The interest rate paid by the alternative asset, i^j, entails the risk free interest rate, i_{rf}^j, and a country-specific spread, s^j, reflecting the riskiness of the sovereign: $i^j = i_{rf}^j + s^j$.

The bank sets the interest rate by maximizing profits under the incentive compatibility constraint of the borrower:

$$\max_{r_i} \quad \sum_{i}^{N_j}\sum_{k}^{N_c}\Big(r_i^k M^k(\varphi_i) - i^j\tau^{jk}M^k(\varphi_i)\Big), \tag{3.15a}$$

$$\text{s.t.} \quad r_i^k = \Phi(\varphi_i, M^k(\varphi_i)) - 1, \tag{3.15b}$$

where N_j is the number of firm in country j, serving either the domestic market $(k = j)$ and the foreign countries $(k = 1, 2, ..., (N_c - 1) \neq j)$ and the incentive compatibility constraint 3.24b is defined according to Equation 3.13.

Given the additivity of the profits function, we can separately solve the maximization problem for each division-firm[5]:

$$\max_{r_i^k} \quad r_i^k M^k(\varphi_i) - i^j\tau^{jk}M^k(\varphi_i), \tag{3.16a}$$

$$\text{s.t.} \quad r_i^k = \Phi^k(\varphi_i, M(\varphi_i)) - 1, \tag{3.16b}$$

where: $\Phi^k(\varphi_i, M^k(\varphi_i)) = \tilde{P^k}\frac{\sigma-1}{\sigma}\left(\frac{\tilde{Q^k}}{\tilde{N^k}}\right)^{\frac{1}{\sigma}}\left(\frac{\varphi_i}{\tau^{jk}}\right)^{\frac{\sigma-1}{\sigma}}(M^k(\varphi_i) - F^k + a_i^k)^{\frac{-1}{\sigma}}$ & $M^k(\varphi_i) - F^k + a_i^k > 0$. From (3.16b), we get firm's demand of loans as a function of the interest rate:

$$r_i^k(M^k(\varphi_i)) = B(\tilde{P^k}, \tilde{Q^k}, \tilde{N^k}, \varphi_i)(M^k(\varphi_i) - F^k + a_i^k)^{\frac{-1}{\sigma}} - 1,$$

where:

$$B(\tilde{P^k}, \tilde{Q^k}, \tilde{N^k}, \varphi_i) = \tilde{P^k}\frac{\sigma-1}{\sigma}\left(\frac{\tilde{Q^k}}{\tilde{N^k}}\right)^{\frac{1}{\sigma}}\left(\frac{\varphi_i}{\tau^{jk}}\right)^{\frac{\sigma-1}{\sigma}}$$

and the direct loan demand function:

$$M^k(\varphi_i) = \left(\frac{B(\tilde{P^k}, \tilde{Q^k}, \tilde{N^k}, \varphi_i)}{1 + r_i^k}\right)^{\sigma} - a_i^k + F^k. \tag{3.17}$$

By substituting (3.17) into the bank's maximization problem, the optimal interest rate

[5] It is worth noticing that the firm will sign a contract for each k market she serves, paying differentiated interest rate, depending on the destination. Thus, the debt is designed as trade finance.

is derived as:

$$
\begin{aligned}
&\pi^B = \left(r_i^k - i^j\tau^{jk}\right)\left(\left(\frac{B(\tilde{P}^k, \tilde{Q}^k, \tilde{N}^k, \varphi_i)}{1+r_i^k}\right)^{\sigma} - a_i^k + F^{jk}\right),\\
&\frac{\partial \pi^B}{\partial r_i^k} = 0,\\
&\left(\left(\frac{B(\tilde{P}^k, \tilde{Q}^k, \tilde{N}^k, \varphi_i)}{1+r_i^k}\right)^{\sigma} - a_i^k + F^{jk}\right) + \left(r_i^k - i^j\tau^{jk}\right)\left(B(\tilde{P}^k, \tilde{Q}^k, \tilde{N}^k, \varphi_i)^{\sigma}(-\sigma)\big(\frac{1}{1+r_i^k}\big)^{\sigma+1}\right) = 0,\\
&\left(\frac{B(\tilde{P}^k, \tilde{Q}^k, \tilde{N}^k, \varphi_i)}{1+r_i^k}\right)^{\sigma}\left[1 - (r_i^k - i^j\tau^{jk})\sigma\big(\frac{1}{1+r_i^k}\big)\right] = a_i^k - F^{jk}.
\end{aligned}
\tag{3.18}
$$

The interest rate r_i^k, is implicitly defined by Equation (3.18) and will be numerically computed. By studying the sensitivities through the Implicit Function Theorem, we find that the interest rate is strictly decreasing in the net worth allocated to market k. Intuitively, firms with greater internal liquidity require smaller loans to meet their financing needs, thus posing lower risk to banks and being offered more favorable lending terms. This result is consistent with the balance sheet channel of credit frictions (Kiyotaki and Moore, 1997), where stronger financial positions improve access to external resources and reduce borrowing costs.

Once the interest rate charged by the bank, r_i^{k*}, is determined, the corresponding loan amount is derived from the direct demand function (Equation 3.17), and the quantity produced is set accordingly, as specified in Equation 3.11. A credit constraint emerges endogenously: the presence of asymmetric information in the loan market generates financial frictions that prevent some firms from reaching their first-best production level. Constrained firms borrow up to the maximum amount allowed by the loan schedule, $\bar{M} = M(r_i^{k*})$, and adjust their output based on the available funds: $q_i^k = \left(\bar{M} - F^{jk} + a_i^k\right)\frac{\varphi_i}{\tau^{jk}} < q_i^{k*}$. These firms are thus financially constrained and operate below their optimal scale.

3.3.3 The international trade network

Firms are assumed to have complete information and evaluate all potential export destinations. Hence, firms in country j export to a given destination k if expected profits from serving that market are positive. This yields a firm- and destination-specific productivity threshold, $\bar{\varphi}_i^k$, which depends on the firm's net worth a_i, the interest rate r_i^k, and destination fundamentals - aggregate price level $\tilde{P}^k$, market demand $\tilde{Q}^k$, and the number of competitors $\tilde{N}^k$:

$$\varphi_i \geq \bar{\varphi}_i^k(a_i, \tilde{P}^k, \tilde{Q}^k, \tilde{N}^k) = \Omega\, \tau^{jk} \left(\frac{\tilde{Q}^k}{\tilde{N}^k}\right)^{\frac{\sigma-1}{\sigma}} \left(\frac{1}{\tilde{P}^k}\right)^{\frac{\sigma}{\sigma-1}} \left[F^{jk}(1+r_i^k)^{\sigma} - a_i^k r_i^k (1+r_i^k)^{\sigma-1}\right]^{\frac{\sigma}{\sigma-1}}, \tag{3.19}$$

with $\Omega = \sigma^{\frac{\sigma}{\sigma-1}}(\sigma-1)^{-1}$.

The threshold reflects how both firm-specific characteristics (productivity, internal financial resources, credit costs) and market conditions jointly shape export decisions. Financial frictions enter through the interest rate r_i^k, which embeds both the firm's balance sheet and the sovereign spread s^j of the country of origin. Firms with stronger internal resources - and lower borrowing costs - face a lower threshold and are therefore more likely to access foreign markets. On the demand side, entry is facilitated by larger markets with stronger aggregate demand or by higher price indices, which mechanically reduce the participation threshold. Similarly, lower competitive pressure in the destination market further eases entry. In this framework, the productivity threshold constitutes the key selection margin governing access to international trade. Unlike the standard Melitz model, where the cutoff productivity is determined at the aggregate level and is independent of financial heterogeneity, in our framework financial frictions introduce a firm-level component to the participation threshold. As a result, shocks to credit conditions - such as a deterioration in the financial stability of the exporting country - shift the threshold and thereby affect the extensive margin of trade through the credit channel.

Macroeconomic trade flows emerge from the aggregation of firm-level decisions. The total exports from country j to country k are given by:

$$X^{jk} = \sum_{i=1}^{N_E^j} \mathbb{1}\left(\varphi_i \geq \bar{\varphi}_i^k\right) q_i^k, \tag{3.20}$$

where the indicator equals 1 if the firm clears the threshold, and q_i^k is the exported quantity. These bilateral flows define the entries of the trade network adjacency matrix G:

$$G = \begin{pmatrix} 0 & X^{12} & X^{13} & \cdots & X^{1N_c} \\ X^{21} & 0 & X^{23} & \cdots & X^{2N_c} \\ X^{31} & X^{32} & 0 & \cdots & X^{3N_c} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ X^{N_c1} & X^{N_c2} & X^{N_c3} & \cdots & 0 \end{pmatrix}.$$

The resulting trade network is fully deterministic and shaped by countries' fundamentals: market size ($\tilde{Q}^k$, $\tilde{P}^k$ and $\tilde{N}^k$), trade frictions (such as iceberg costs, τ^{jk}, and upfront entry costs, F^{jk}), and financial conditions - at the firm level, a_i, and at the country level s_j. It displays well-known properties summarized in the gravity equation: exports increase in the aggregate demand of the importing countries and decrease in geographical distance and trade frictions (Head and Mayer, 2014), through their effects on the participation threshold. Financially sound countries (i.e., those with lower sovereign spreads) trade more, as firms benefit from easier access to credit and lower entry thresholds.

The matrix G is thus directed and asymmetric, consistent with empirical observations (Fagiolo et al., 2010): countries exhibit unbalanced and zero bilateral flows, reflecting heterogeneous fundamentals. In contrast to symmetric trade in homogeneous models, here trade asymmetries emerge endogenously from the interaction between firm heterogeneity and country characteristics.

To further characterize the structure of the network, we compute two simple statistics. The *density* of the network is the share of strictly positive trade links:

$$\text{Density} = \frac{1}{N_c(N_c-1)} \sum_{j \neq k} \mathbb{1}(X^{jk} > 0). \tag{3.21}$$

The *average out-degree* measures the number of destination markets a country exports to:

$$\text{Out-degree} = \frac{1}{N_c} \sum_{j=1}^{N_c} \sum_{k \neq j} \mathbb{1}(X^{jk} > 0). \tag{3.22}$$

Both statistics are endogenous outcomes of the model, determined by the productivity threshold and, ultimately, by the distribution of country-specific fundamentals and firm characteristics.

3.4 Results

The model's emergent properties are explored through simulation. Some parameters are drawn from existing literature, while the remaining ones are calibrated to match key empirical regularities, as discussed in the next section.

Based on this calibration, we first show that the model successfully replicates several well-established stylized facts about international trade and production networks. We then perform counterfactual experiments to investigate how network-based spillovers shape the propagation of financial shocks. Specifically, we simulate a sovereign spread hike to mimic a financial crisis originating in a particular country. To highlight the role of heterogeneity in the international landscape, we first consider a shock affecting the most central country in the network. We then compare this scenario with an alternative in which the shock randomly hits a peripheral node. Due to the scale-free nature of the trade network, these two experiments yield markedly different outcomes. This highlights the importance of countries' positions within the network in determining their vulnerability to and influence over global financial disturbances.

3.4.1 Calibration

The baseline version of the model is run for 30 countries[6], each of them populated by 1000 firms. The baseline model is run under two alternative scenarios:

- Symmetric and homogeneous countries (**1st scenario**). They are characterized by the same set of firms, in terms of productivity and net worth distribution and they are identical in their fundamental characteristics, i.e. bilateral distance and financial soundness.

- Heterogeneous countries (**2nd scenario**). Countries have symmetric firms' distribution but they are heterogeneous both in terms of geographical distances (τ_{jk}) and financial soundness, proxied by the level of sovereign spread.

The parameters employed in the simulations are summarized in Table 4.1. Some of them have been taken from the relevant literature. Several model parameters are drawn from the literature. The elasticity of substitution across varieties is set to $\sigma = 3.8$, following plant-level estimates by Bernard et al. (2003). Based on this value, Balistreri et al. (2011) calibrate firm productivity as Pareto-distributed with shape parameter $a = 4.5$ and minimum $b = 0.2$. Firm net worth is also assumed to follow a Pareto distribution, with a shape parameter close to 1, consistent with the Zipf law observed in U.S. firm size distributions (Axtell, 2001).

In the second scenario, we introduce country-level heterogeneity. Trade costs τ^{jk} are allowed to vary bilaterally, with domestic sales assumed frictionless. The matrix of iceberg trade costs is symmetric and calibrated using the *ESCAP-World Bank Trade Cost Database*. Estimated trade costs in manufacturing follow a lognormal distribution: $\tau \sim \text{Lognorm}(5.66, , 0.51^2)$. In each Monte Carlo simulation, a random matrix of bilateral trade costs is drawn from this distribution.

We also incorporate financial heterogeneity by assigning each country a sovereign spread over the risk-free rate. Based on the findings of Gilchrist et al. (2022), we calibrate spreads using a lognormal distribution: $s^j \sim \text{Lognorm}(-4.10, , 0.82^2)$, consistent with an average spread of 231 basis points and a standard deviation of 225.

Results from this heterogeneous-country setting are compared to a benchmark featuring only firm-level heterogeneity (1st scenario). In this baseline case, trade costs and sovereign spreads are fixed at the medians of the corresponding empirical distributions used in the second scenario.

[6] The thirty biggest countries in 2019 were responsible for 80% of total exports, with a considerable heterogeneity in their international participation (top 10% of exporters are responsible for almost half of the flows). For this reason - and to avoid excessive computational burden - we believe that it is sufficient to consider 30 countries. Nonetheless, robustness checks have been computed on the number of countries and results are summarized in the Appendix B.

Table 3.1: Numerical values of the parameters in the alternative scenarios.
Note: 1st scenario entails homogeneous countries. In the 2nd scenario heterogeneity among countries, in terms of geographical position and financial soundness, is introduced.

Parameter	Description	1st scenario	2nd scenario
N_f	Number of firms per country	1.000	1.000
N_c	Number of countries	30	30
σ	Elasticity of substitution	3.8	3.8
w	Nominal wage	1	1
i^j	Risk free interest rate	0.02	0.02
s^j	Sovereign spread	0.016	$Lnorm(-4.10, 0.82^2)$
τ^{jj}	Iceberg costs domestic production	1	1
τ^{jk}	Iceberg costs of exporting	3.36	$Lnorm(5.82, 0.47^2)$
F^{jj}	Fixed costs of domestic production	5	5
F^{jk}	Fixed costs of exporting	$F^{jj} + f(\tau^{jk})$	$F^{jj} + f(\tau^{jk})$

The remaining few parameters are calibrated to meet stylized facts in the international trade literature, presented in the next section.

3.4.2 Simulations meet Stylized Facts

Increasing availability of firm-level data has allowed to identify some stylized facts on firm's international activity (Eaton et al., 2004). Results of the simulations - in each scenarios, with and without financial frictions[7] - are compared with a number of them, both at the micro and at the macro level, to calibrate the model. Results are summarized in Table 3.2.

Firstly, it has been possible to identify the characteristics that drive export market participation. Bernard et al. (2007) show that exporters are larger and more productive (**SF1**) than domestic firms, suggesting the existence of an *export productivity premium* (Bernard et al., 1995). Simulations show that exporters have, indeed, an *a priori* advantage that leads to self-selection into international trade activity: exporters are more productive because only the most efficient firms are able to overcome the costs related to global market participation. They are characterized by a stricter participation threshold and, in turn, higher average productivity. Notwithstanding the self-selection mechanism, empirical evidence still document the coexistence of highly productive non-exporters and low productive exporters (see, for instance, Bernard et al., 2003 and Melitz and Trefler, 2012); namely, data show an overlapping distribution of the productivity of exporting and non-exporting firms (**SF2**). By embedding a second layer of firms' heterogeneity, i.e. differences in net worth, the theoretical model discussed above is able to reproduce this empirical regularity in both scenarios, even though the effect of financial heterogeneity is more pronounced when it coexists with differences in interest rate spreads. Figure 3.2 depicts the kernel density of domestic and exporting firms productivity in the first (Figure

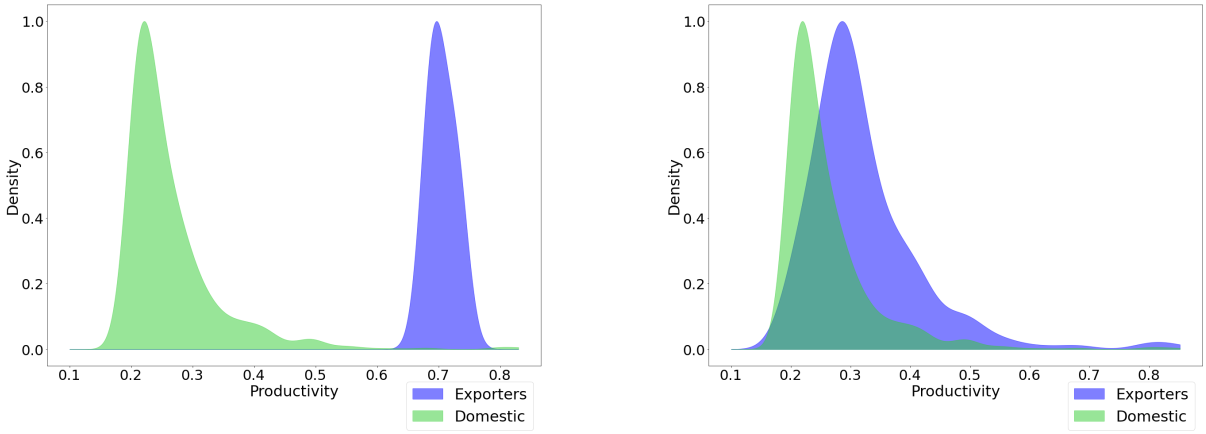
[7]We derived an optimal interest rate in a symmetric information setting. The model without financial frictions is outlined in the Appendix.

Table 3.2: Stylized facts with and without financial frictions.
Note: Data are computed as Monte Carlo averages of country-level means. Standard deviations across countries are reported in brackets when applicable.

		No financial frictions		Financial frictions	
SF	**Stylized Fact**	**1st**	**2nd**	**1st**	**2nd**
SF1	Domestic productivity threshold	0.2000	0.2000	0.2001	0.2005
		(0)	(0.0000)	(0)	(0.0004)
SF1	Exporters productivity threshold	0.4760	0.2082	0.5044	0.2357
		(0)	(0.0026	(0)	(0.0054)
SF1	Average domestic productivity	0.2573	0.2576	0.2631	0.3006
		(0)	(0.0000)	(0)	(0.0016)
SF1	Average exporters productivity	0.5914	0.2707	0.6687	0.4013
		(0)	(0.0038)	(0)	(0.0097)
SF2	Overlapping productivity distribution				
SF3	Share of exporting firms	2.72%	45.46%	0.06 %	22.67%
		(0)	(0.0126)	(0)	(0.0186)
SF4	Exported output share per firm	31.05%	41.14%	48.90%	34.61%
		(0)	(0.0243)	(0)	(0.1548)
SF5	Average export destinations	2.31%	2.40%	0.50%	1.21%
		(0)	(0.1848)	(0)	(0.0285)
SF6	Export share of top 10% exporters	40.17%	54.98%	50.4%	54.70%
		(0)	(0.0494)	(0)	(0.0685)
SF7	Countries' export share	3.33%	3.33%	3.33%	3.33%
		(0)	(0.0166)	(0)	(0.0029)
SF8	Export to GDP	20.15%	55.48%	8.48%	37.91%
		(0)	(0.0032)	(0)	(0.0029)
SF9	Network Density	1	0.9155	1	0.6881
SF10	Disassortativity	-	-0.068	-	-0.0531
SF11	Average Betweenness	0.0667	0.1244	0.0667	0.1164
		(0)	(0.0010)	(0)	(0.0054)

3.2a) and second (Figure 3.2b) scenario. Twofold heterogeneity at the firm-level generates a distributional overlap, consistent with the empirical findings. This arises because the productivity threshold for export market participation (Equation **??**) is decreasing in firm's financial soundness. Consequently, firms with relatively lower productivity can still enter export markets if they have strong internal financial resources. Despite facing higher marginal production costs, these firms benefit from lower interest rates on loans, reducing their overall financial costs, which improves their price competitiveness.

The simulated model shows that exporting is a relatively rare activity and only a small fraction of firms enter the international market. The empirical counterpart of this results is provided, for instance, by Eaton et al. (2004), which establish key features of exporters behavior by exploiting granular data on French firms. According to their em-



(a) Homogeneous countries (1st scenario) (b) Heterogeneous countries (2nd scenario)

Figure 3.2: Productivity distribution of domestic firms and exporters in one representative simulation.
Note: For both scenarios - homogeneous countries (left panel) and heterogeneous countries (right panel) - we depict the productivity distribution of domestic (green) and exporting (blue) firms in one representative simulation.

pirical analysis, in 1986, only 17.4% of French firms were exporters (**SF3**) [8]. Furthermore, most firms export little (**SF4**) and to few markets (**SF5**). They show that the modal French exporter ships to only one foreign destination and just 19.7% of manufacturing firms served more than 10 markets. In a subsequent work, Chaney (2014) finds that French firms export, on average, to between 3.50 (in 1992) and 3.62 (in 1986) different foreign countries. The intensive margin of trade is, as well, weak with respect to domestic sales. In 1986, France exported 21.6% of total manufacturing product (Eaton et al., 2004) while the share shrinks to 10.3% for USA (Bernard et al., 1995).

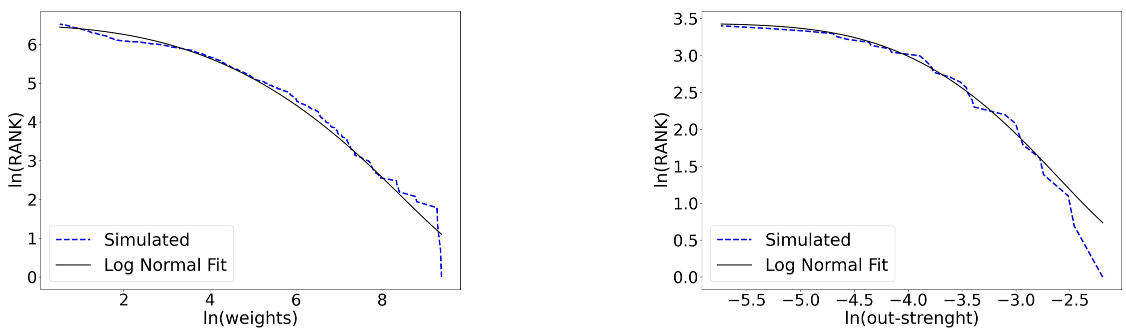
While most firms engage in limited exporting activity, a subset of exporters emerges as superstars in international trade, the so-called 'happy few' (Mayer and Ottaviano, 2008). Namely, the largest exporters account for a disproportionate share of total trade volumes (**SF6**). For instance, in 2020, large U.S. exporters were responsible for over two-thirds of total export value[10].

All the above-mentioned empirical findings led the way to the emergence and the establishment of the *New-new Trade Theory* (see Melitz and Redding, 2014 and Redding, 2022 for an encompassing review of the literature). Nevertheless, new empirical regularities on international trade, coming from the adoption of complex network theory, point toward the need of a new perspective in international economics. Applying network analysis to trade flows yields, indeed, new insights and stylized facts concerning countries' exposure to the global economy (see, among others, Serrano and Boguná, 2003, Garlaschelli and Loffredo, 2004, Kali and Reyes, 2007, Fagiolo et al., 2008). These findings highlight

[8]While the share of exporting firms may vary depending on industries and countries, the percentage generally fluctuates around this value. For instance, in 2002, 18% of American manufacturing firms exported[9] while the share of exporting Italian firms was 14.6% in 2003 (Bottazzi et al., 2014).

[10]U.S. Census Bureau, 'A Profile of U.S. Importing and Exporting Companies, 2019-2020'

a great heterogeneity among countries (**SF7**), which can not be explained by the traditional assumptions of the "Old", "New" and "New-new" trade theory (De Benedictis and Tajoli, 2011). For this reason, Schweitzer et al. (2009) advocate for new approaches able to capture the systemic complexity of economic networks, that can serve as a way to enrich established paradigms in economic theory. Furthermore, international flows recreate a complex network, characterized by the scale-free[11] (SF8) and small-world properties[12] (SF9). The simulated network displays the above-mentioned characteristics, with the link weight and node strength distributions being well proxied by log-normal densities (see Figure 3.3). This means that the majority of trade linkages are relatively weak and coexist with few high-intensity trade partnerships. Notice that this characteristic of the network topology has important consequences on the effects of shocks, as we will show in the next section.



(a) Distribution of nodes weights. (b) Distribution of out-strength.

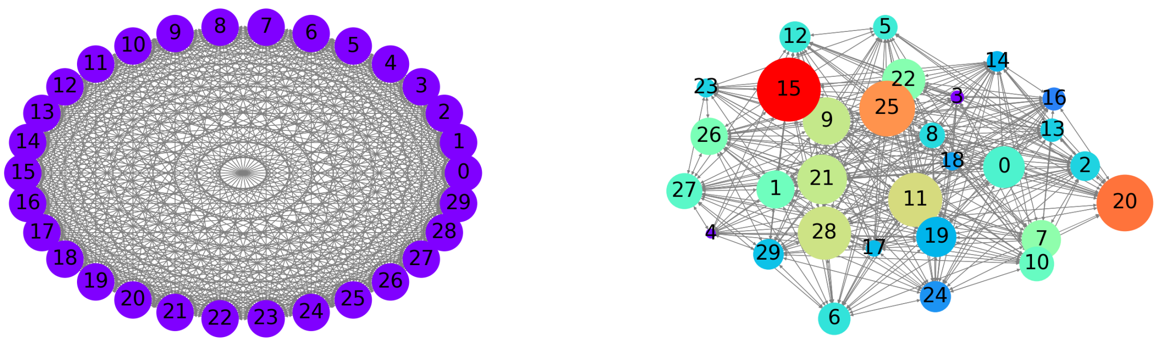
Figure 3.3: Distribution of links and nodes' out-strength.
Note: Size-rank plots for links and nodes' out-strength, i.e. weighted out degree.

De Benedictis and Tajoli (2011) use data on aggregate bilateral imports to study the evolution of the global trade network over the second half of the twentieth century. They show that trade tends to be concentrated among a subgroup of countries and a small percentage of the total number of exchanges account for a disproportionate share of the overall trade. Larger countries play a key role in the international context, being characterized by a greater number of partners. Furthermore, they show that the world trade network is not regular nor complete. In line with their paper, we employ the *BACI Database (CEPII)* for the 2019[13], to reconstruct and analyze the evolution of the world trade network. The empirical regularities detected in real data are further employed to validate the accuracy of the proposed theoretical framework. Notably, the world trade

[11] power law distribution of nodes degree
[12] high clustering coefficient and small path lenght
[13] The year 2019 was selected as the reference point for this study due to the significant temporal distance from the Great Trade Collapse and economic distress of 2008-2009. Additionally, the results were not influenced by the aftermath of the global pandemic of 2020 and the subsequent period of geopolitical instability.

network in 2019 was characterized by a density[14] of 0.64 (**SF9**), a disassortative nature (**SF10**) and a betwenness centralization of 0.025 (**SF11**).

Network statistics have been computed for the simulated model under both scenarios and findings suggest the urge of accounting for both within and between heterogeneity to properly capture real world properties. The first scenario encompasses symmetric and homogeneous countries, populated by heterogeneous firms. This is the economy depicted by Melitz (2003), in which firms trade and aggregate flows among countries depend on micro-level decisions. Results at the firm-level are consistent with the main findings in the New-new Trade Theory. However, countries' symmetry leads to the same exporting share. This result is not consistent with empirical evidences on heterogeneous participation to international trade. Notably, if countries are homogeneous and characterized by the same distribution of agents, aggregate variables at the national level are the same for all countries in equilibrium. The ex-post network is regular and fully connected (see Figure 3.4).



(a) Homogeneous countries (1st scenario) (b) Heterogeneous countries (2nd scenario)

Figure 3.4: Simulated international trade network in one representative simulation.
Note: Each node is a country and links are trade flows among country-pairs. Different colors are associated with different level of GDP while the size of each node reflects export participation.

Financial frictions play a critical role in shaping trade dynamics. Under the assumption of perfect information in the loan market (Table 3.2, first panel), all firms can access credit at the national risk-free rate, defined as the monetary policy rate adjusted for the government spread. In this scenario, the simulated network is fully connected, indicating that financial frictions influence the extensive margin of trade. Introducing asymmetric information in the loan market significantly reduces the share of exporting firms. Firms in weaker financial positions face prohibitively high interest rates, restricting their access to external finance and effectively excluding them from international markets. As a result, the productivity threshold for exporting firms rises.

Financial frictions affect the intensive margin of trade, as well, in both scenarios. Notably, the share of output exported per firm (**SF4**) and the average number of desti-

[14] Network density is the ratio of actual connections to the maximum possible connections in a network, indicating the level of interconnectedness among nodes.

nation markets served (**SF5**) decline in the presence of financial frictions. Limited access to funds under asymmetric information constrains all firms, hindering their ability to expand into new markets or scale up existing operations. Consequently, financial frictions act as a barrier to trade and economic activity. Figure 3.5 illustrates the percentage deviations in aggregate variables resulting from the introduction of financial frictions in the loan market.

By considering multiple layers of heterogeneity - both within and between countries - coupled with financial frictions, the theoretical model proposed is able to replicate all the above mentioned stylized facts.

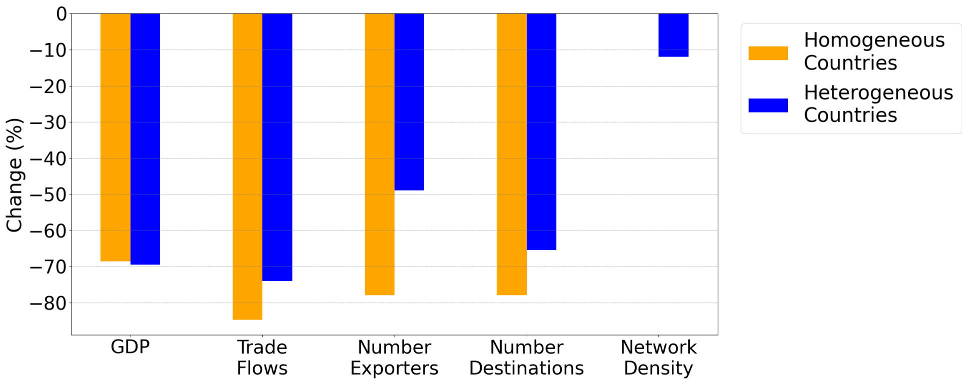


Figure 3.5: Effects of financial frictions.
Note: The figure represents the percentage change in main aggregate variables (computed as the average of the Monte Carlo simulations) with respect to the frictionless case, for both the first scenario, comprising homogeneous countries (in orange), and the second scenario, with heterogeneous countries (in blue).

3.4.3 Financial distress

Once calibrated to meet stylized facts both at the micro and at the macro level, the model has been employed to evaluate the effects of financial shocks on the networked economy. We simulate a deterioration in financial conditions, represented by an increase in the sovereign spread, in the most central country in the network, and compare its effects to those of a randomly targeted shock. In order to identify the main players, alternative centrality measures have been tested[15]. Since most of them lead to the identification of the same hubs - except for betweenness centrality - we will focus the discussion on *out-degree*[16]; definitions and results of alternative centrality measures are presented in the Appendix.

Consistently with the empirical literature on the effects of the *GFC* on exporters, we find that financially fragile firms are the most exposed to the financial distress. Figure 3.6 depicts the estimated kernel density of losses - measured in terms of quantity reductions

[15] Alternative centrality measures may lead to the identification of different nodes as hubs in certain networks, even if a correlation among them is observed (Krackhardt, 1990).

[16] Out-degree measures the centrality of a node considering the number of out-going links. In our case, it accounts for flows originated from country i towards its trade partners.

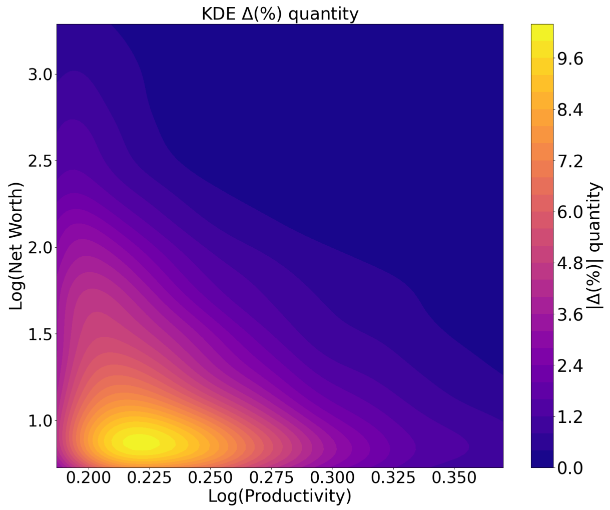


Figure 3.6: Estimated Kernell Density of the losses.
Note: We collect the percentage change in the quantity exported by each firm and compile a dataset across all Monte Carlo simulations. Based on this, we estimate the kernel density of firms' losses, mapped according to their productivity and net worth. Since we consider the absolute value of losses, brighter colors indicate higher losses.

- across the firm population, mapped according to productivity and net worth. An sovereign spread hike raises the cost of external finance for both firms and households, constraining domestic production. Firms with lower net worth, which crucially rely on external funds to sustain operations, face higher borrowing costs. This exacerbates their financial constraint and, in some cases, forces firms out of the market.

A shock to the most central country (left panel of Table 3.3) reduces overall trade flows (FoT), even when the affected node is excluded from the analysis. Financial distress in a major economy amplifies negative foreign demand shocks, leading to a contraction in export activity. The shock propagates through both the intensive margin - reducing the average export share per firm - and the extensive margin - decreasing the number of exporters and destination markets per firm.

Despite the negative impact on trade, the rest of the world benefits from reduced foreign competition in domestic markets. Simulations indicate an increase in the average number of domestic producers and GDP. However, weaker competitive pressure facilitates the entry of less efficient firms, raising the price index for both domestic production and exports. Aggregating the effects of the shock, we find that export prices rise more than domestic prices, mirroring patterns observed during the Great Financial Crisis.

The withdrawal of a key player reshapes the network structure, altering the relative importance of the remaining countries and increasing network density. At a first glance, this result may seem counterintuitive: removing the most central node should, in principle, reduce density by erasing numerous connections and weakening overall trade integration.[17] On the contrary, the observed upsurge in density is the result of the restruc-

[17] This remains true when considering the most central node in terms of betweenness centrality (Table 3.5).

turing of trade links in favor of unaffected nodes. Empirical network analysis confirms this pattern: during the Great Trade Collapse, network density did not decline.

The macroeconomic impact of the shock is less severe when it hits a random country. In this case, economic activity undergoes only a marginal slowdown, characterized by modest declines in aggregate GDP and trade flows. This result is due to the topological property of the trade network, characterized by scale-free characteristics, whereby a small number of highly connected nodes coexist with a majority of nodes having few connections. This structural heterogeneity has important implications for the propagation and impact of shocks. Notably, scale-free networks are robust to random node attacks: when shocks hit nodes at random, the probability of affecting a highly connected hub is low, resulting in limited disruption to the network's overall connectivity and functionality. Conversely, these networks are vulnerable to targeted shocks on hubs, which can trigger rapid fragmentation and systemic breakdown. Theoretical and empirical studies (e.g., Pósfai and Barabási, 2016, Lenzu and Tedeschi, 2012) highlight that random shocks predominantly affect peripheral nodes with limited systemic relevance, thereby preserving the integrity of the giant connected component and maintaining the efficiency of trade and production flows. This dual nature of robustness and fragility is critical for understanding how asymmetric shock may differently propagate across global value chains and influence trade patterns.

Overall, countries that are strongly dependent on trade relationships with the shocked country are the most affected. By considering the distribution of the shocks, in Figure 3.7 we show the correlation between trade intensities and GDP variations when the shocked country is a central hub (Figure 3.7a) or a peripheral node (Figure 3.7b). In the former, a strong negative correlation (-0.88) is evident between the intensity of the trade relationship and the loss recorded by foreign actors. This indicates that countries trading more with the affected country experience greater losses, both in terms of GDP and their position within the network. The correlation is far less evident (-0.08) when considering the impact of a shock to a random node of the network. In this latter case, countries are only marginally affected, and it is not possible to discern a clear pattern.

It is important to note that the heterogeneity in outcomes observed following the shock would have been entirely overlooked in a framework with symmetric countries. To illustrate this point, the same experiments were conducted for the first scenario, which features heterogeneous firms but assumes symmetric and homogeneous countries. The results, presented in Table 3.4, reveal starkly different aggregate outcomes. Notice that when countries are homogeneous, all countries have the same centrality score; thus, it does not make sense to distinguish between the most central hub and the periphery of the network. In this scenario, the shock has only minimal effects on average GDP and the price index.

Table 3.3: Aggregate effects of an increase in the sovereign spread of the most (left panel) central country in terms of out-degree compared with a shock to a random country and (right panel).

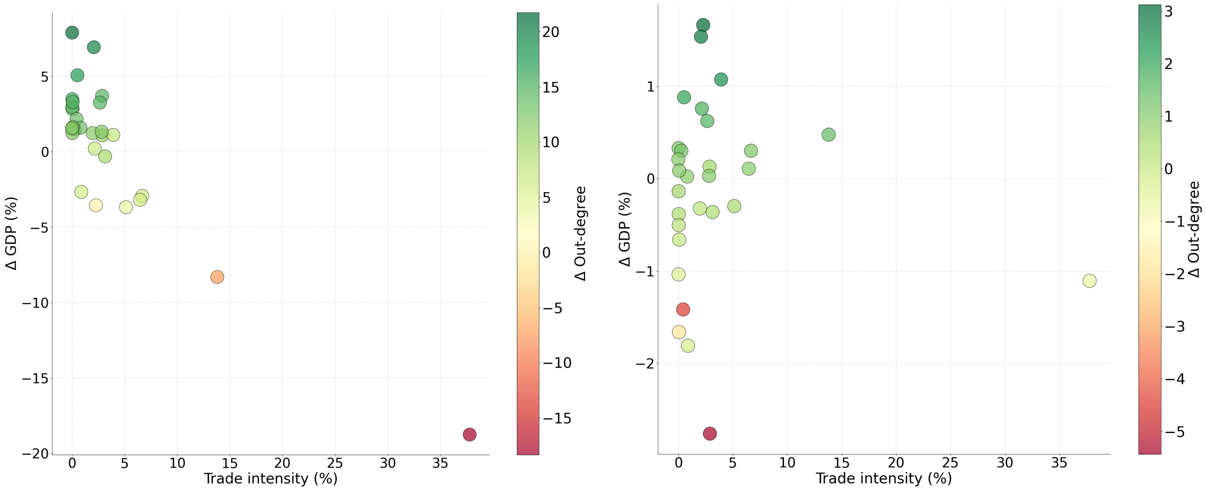
Note: We run 50 Monte Carlo simulation and, for each of them, we compute the average percentage change of main macroeconomic variables. These are calculated for the entire economy (denoted as *All*) and for all countries except for the one that has been subjected to a shock (denoted as *ROW*). Afterwards, we compute the averages across the Monte Carlo simulations and their standard deviations (in brackets)

	Shock to the most central		Random shock	
	All	ROW	All	ROW
Δ GDP	-2.99%	1.48%	-1.94%	0.06%
	(3.17)	(3.71)	(0.99)	(0.20)
Δ P Domestic	0.75%	1.09%	0.18%	0.10%
	(0.97)	(0.99)	(0.13)	(0.13)
Δ P Export	1.11%	0.86%	0.33%	0.01%
	(1.27)	(1.27)	(0.33)	(0.26)
Δ FoT	-9.12%	-3.37%	-2.02%	-0.82%
	(3.55)	(3.23)	(2.51)	(1.14)
Δ Export to GDP	-1.26%	-2.93%	1.05%	-0.69%
	(0.92)	(0.85)	(0.95)	(0.76)
Δ Domestics	2.30%	5.09%	-1.37%	0.41%
	(4.55)	(4.69)	(0.45)	(0.38)
Δ Exporters	-10.32%	-4.07%	2.10%	0.53%
	(5.30)	(4.92)	(0.49)	(0.49)
Δ Export share per firm	10.57%	-4.50%	1.60%	-0.59%
	(5.90)	(2.29)	(5.56)	(0.26)
Δ Average destinations	-4.47%	0.29%	-1.38%	0.34%
	(4.45)	(4.9)	(0.37)	(0.24)
Δ Density	0.82%	0.82%	-0.001%	-0.001%
	(2.56)	(2.56)	(1.27)	(1.27)

3.5 Conclusions

This paper develops a micro-founded framework in which firms endogenously form an international trade network based on their intrinsic characteristics and the surrounding environment. The model bridges microeconomic foundations with macroeconomic outcomes, allowing us to study aggregate trade flows and the propagation of localized shocks. A central result is that productivity differences alone are insufficient to account for the substantial heterogeneity observed in firms' and countries' exposure to international markets. By incorporating financial frictions and heterogeneity, our framework extends the original Melitz setting beyond productivity-based selection. This extension provides a channel through which credit conditions shape trade participation and the resulting network structure of international flows, thereby offering a novel explanation for several puzzles in the trade literature.

In this framework, financial soundness at both the firm and country level, geographic



(a) Shock to the most central country (b) Shock to a random country

Figure 3.7: Correlation between trade intensity and GDP variations
Note: For each experiment, the figure depicts the percentage change in GDP of each country after the shock to the most central one or to a random country, in relation with the trade intensity with the shocked country. Trade intensity is defined as the relative value of exports toward the shocked country with respect to total exports.

Table 3.4: Aggregate effects of an increase in the sovereign spread of the most (and least) central country in terms of out-degree when countries are homogeneous.
Note: We run 50 Monte Carlo simulation and, for each of them, we compute the average percentage change of main macroeconomic variables. These are calculated for the entire economy (denoted as *All*) and for all countries except for the one that has been subjected to a shock (denoted as *ROW*). Afterwards, we compute the average across the Monte Carlo simulations and their standard deviations (in brackets)

	All	ROW
Δ GDP	-2.18%	0.01%
	(1.34)	(1.18)
Δ P Domestic	0.31%	0.036%
	(0.97)	(0.99)
Δ P Export	1.54%	1.16%
	(1.27)	(1.27)
Δ FoT	4.53%	2.18%
	(3.55)	(3.23)
Δ Export to GDP	13.26%	2.93%
	(0.92)	(0.85)
Δ Domestics	2.30%	5.09%
	(4.55)	(4.69)
Δ Exporters	10.32%	4.07%
	(5.30)	(4.92)
Δ Export share per firm	-31.59%	-39.93%
	(5.90)	(2.29)
Δ Average destinations	4.47%	2.59%
	(4.45)	(4.9)
Δ Density	0	0
	(2.56)	(2.56)

characteristics, and asymmetric information emerge as key determinants of the international trade network. Accounting for these factors enables the model to replicate established stylized facts and to generate new insights into the global trade structure. In particular, the resulting network displays scale-free properties that closely resemble empirical trade data.

The network representation also permits an analysis of how shocks propagate across the system. Our results show that the transmission of shocks depends critically on the structure of the network and the centrality of the affected country. Shocks originating in central hubs trigger significant aggregate disruptions, strongly affecting direct partners and cascading throughout the system. By contrast, shocks to peripheral nodes have only limited aggregate effects, underscoring the asymmetric role of countries within the global economy.

Overall, the framework provides a tractable yet flexible extension of the Melitz model that integrates financial frictions and network interactions. We view this as a promising starting point for future research. A natural next step is the empirical validation of the model, aimed at quantifying the relevance of the credit channel and network effects in shaping trade outcomes. Furthermore, some simplifying assumptions, such as the fixed markup inherited from the original Melitz formulation, could be relaxed in light of recent theoretical advances (e.g., Melitz and Ottaviano, 2008). While we retained the original structure here to maintain focus and tractability, relaxing such assumptions would enrich the analysis and broaden the model's applicability.

Appendix

Model without financial frictions

When the assumption of asymmetric information in the market for loans is removed, the firm set the optimal price by maximizing her profits. Given the optimal price, the demand for loans is:

$$M_i^k = \frac{QP^\sigma}{N}\left[\frac{\sigma}{\sigma-1}\frac{\tau^{jk}}{\varphi_i}(1+r_i)\right]^{-\sigma}\frac{\tau^{jk}}{\varphi_i} + F^{jk} - a_i \tag{3.23}$$

Given the demand for loans of the borrower, the bank charges an interest rate that maximize profits, as follows:

$$\max_{r_i^k} \quad \sum_i^{N_j}\sum_k^{N_c}\Big(r_i^k M^k(\varphi_i) - i^j\tau^{jk}M^k(\varphi_i)\Big), \tag{3.24a}$$

$$\text{s.t.} \quad M_i^k = \frac{\tilde{Q}^k\tilde{P}^\sigma}{\tilde{N}^k}\left[\frac{\sigma}{\sigma-1}\frac{\tau^{jk}}{\varphi_i}(1+r_i^k)\right]^{-\sigma}\frac{\tau^{jk}}{\varphi_i} + F^{jk} - a_i^k \tag{3.24b}$$

By solving the maximization problem, we derive the optimal interest rate charged to firm i serving market k as:

$$r_i = \frac{1+\sigma i\tau^{jk}}{\sigma-1}. \tag{3.25}$$

The interest rate is just a mark-up over the risk-free rate, as standard in models characterized by monopolistic competition in the banking sector.

Testing alternative centrality measures

Experiments have been performed considering alternative specifications of network centrality. Namely, we identified the most (and least) central countries in terms of *betweenness centrality*[18], *eigenvector centrality*[19], *PageRank*[20], *In and Out Degree.* Under all these alternative definitions of centrality, the same country has been identified as being

[18] The betweenness centrality of a vertex i is the number of geodesic (shortest) paths between other vertices that run through i. Betweenness centrality captures the importance of a country in terms of connecting others, i.e. being a bridge between other nodes. The country with highest betweenness centrality is crucial intermediary in the network but this information seems to be not much relevant in our framework, since we are considering just flows of trade in final goods; it would become relevant if we study supply chains. This is pointed out also by De Benedictis and Tajoli (2011)

[19] Eigenvector centrality is a global centrality measure stressing the importance of partners in order to determine the centrality of a node. Then, the eigenvector centrality of country i is computed as the sum of the eigenvector centralities of its neighbors. In general, countries with a high value of eigenvector centrality are the ones which are connected to many other well-connected countries.

[20] PageRank is a score assigned to each node aimed at capturing its importance, defined in terms of how many in-links from important partners the node has. For this reason, considering PageRank and Eigenvector Centrality brings the same results

the most (least) central in the network, except when considering betweenness centrality. Aggregate outcomes of the experiments are summarized in Table 3.5 for the most central and Table 3.6 for the least one.

Table 3.5: Aggregate effects of a shock to the most central country.
Note: We run 50 Monte Carlo simulation and, for each of them, we compute the average percentage change of main macroeconomic variables. These are calculated for the entire economy (denoted as *All*) and for all countries except for the one that has been subjected to a shock (denoted as *ROW*). Afterwards, we compute the average percentage change across the Monte Carlo simulations and their standard deviations (in brackets)

	Betweenness		Eigenvector		Pagerank		In-degree	
	All	ROW	All	ROW	All	ROW	All	ROW
Δ GDP	-2.55 %	0,22%	-2.99%	1.48%	-2.99%	1.48%	-2.99%	1.48%
	(4.28)	(5.10)	(3.17)	(3.71)	(3.17)	(3.71)	(3.17)	(3.71)
Δ P Domestic	0.14%	0.24%	0.75%	1.09%	0.75%	1.09%	0.75%	1.09%
	(0.76)	(0.80)	(0.97)	(0.99)	(0.97)	(0.99)	(0.97)	(0.99)
Δ P Export	0.15%	-0.08 %	1.11%	0.86%	1.11%	0.86%	1.11%	0.86%
	(1.10)	(1.15)	(1.27)	(1.27)	(1.27)	(1.27)	(1.27)	(1.27)
Δ FoT	3.48%	-1.5%	-9.12%	-3.37%	-9.12%	-3.37%	-9.12%	-3.37%
	(1.52)	(1.45)	(3.55)	(3.23)	(3.55)	(3.23)	(3.55)	(3.23)
Δ Export to GDP	-0.53%	-2.11 %	-1.26%	-2.93%	-1.26%	-2.93%	-1.26%	-2.93%
	(0.87)	(0.83)	(0.92)	(0.85)	(0.92)	(0.85)	(0.92)	(0.85)
Δ Domestics	-1.54%	0.83%	2.30%	5.09%	2.30%	5.09%	2.30%	5.09%
	(5.12)	(4.48)	(4.55)	(4.69)	(4.55)	(4.69)	(4.55)	(4.69)
Δ Exporters	-3.83%	-1.22%	-10.32%	-4.07%	-10.32%	-4.07%	-10.32%	-4.07%
	(5.60)	(5.27)	(5.30)	(4.92)	(5.30)	(4.92)	(5.30)	(4.92)
Δ Export share per firm	-0.38%	-2.27%	10.57%	-4.50%	10.57%	-4.50%	10.57%	-4.50%
	(6.30)	(3.79)	(5.90)	(2.29)	(5.90)	(2.29)	(5.90)	(2.29)
Δ Average destinations	-2.47%	-0.89%	-4.47%	0.29%	-4.47%	0.29%	-4.47%	0.29%
	(5.34)	(5.67)	(4.45)	(4.9)	(4.45)	(4.9)	(4.45)	(4.9)
Δ Density	-0.43%	-0.43%	0.82%	0.82%	0.82%	0.82%	0.82%	0.82%
	(4.47)	(4.47)	(2.56)	(2.56)	(2.56)	(2.56)	(2.56)	(2.56)

Table 3.6: Aggregate effects of a shock in the least central country

	Betweenness		Eigenvector		Pagerank		In-degree	
	All	ROW	All	ROW	All	ROW	All	ROW
Δ GDP	-2.14 %	-0.01 %	-1.32%	0,04%	-1.32%	0,04%	-1.32%	0,04%
	(0.21)	(0.12)	(0.37)	(0.16)	(0.37)	(0.16)	(0.37)	(0.16)
Δ P Domestic	0.11%	0.25%	0,09%	0,04%	0,09%	0,04%	0,09%	0,04%
	(0.56)	(0.15)	(0.46)	(0.08)	(0.46)	(0.08)	(0.46)	(0.08)
Δ P Export	-0.12%	-0.22%	0,12%	0,06%	0,12%	0,06%	0,12%	0,06%
	(0.14)	(0.22)	(0.21)	(0.49)	(0.21)	(0.49)	(0.21)	(0.49)
Δ FoT	-1.99%	-0.65 %	-0.23%	-0.07%	-0.23%	-0.07%	-0.23%	-0.07%
	(0.58)	(0.34)	(0.46)	(0.21)	(0.46)	(0.21)	(0.46)	(0.21)
Δ Export to GDP	0.76%	-1.02%	1.61%	-0,10%	1.61%	-0,10%	1.61%	-0,10%
	(0.74)	0.30)	(0.65)	(0.26)	(0.65)	(0.26)	(0.65)	(0.26)
Δ Domestics	-2.04%	0,01 %	-1.82%	0,20%	-1.82%	0,20%	-1.82%	0,20%
	(0.48)	(0.33)	(0.45)	(0.38)	(0.45)	(0.38)	(0.45)	(0.38)
Δ Exporters	-1.99 %	-0.83 %	0.09%	0,13%	0.09%	0,13%	0.09%	0,13%
	(0.53)	(0.46)	(0.49)	(0.49)	(0.49)	(0.49)	(0.49)	(0.49)
Δ Export share per firm	1.67%	-0.47%	1.39%	-0.05%	1.39%	-0.05%	1.39%	-0.05%
	(4.32)	(1.23)	(5.56)	(0.26)	(5.56)	(0.26)	(5.56)	(0.26)
Δ Average destinations	-1.64%	-0.53%	0.03%	0.07%	0.03%	0.07%	0.03%	0.07%
	(0.32)	(0.19)	(0.37)	(0.24)	(0.37)	(0.24)	(0.37)	(0.24)
Δ Density	0.2%	0.2%	-0.10%	-0.10%	-0.10%	-0.10%	-0.10%	-0.10%
	(2.34)	(2.34)	(1.27)	(1.27)	(1.27)	(1.27)	(1.27)	(1.27)

Chapter 4

Carbon leakage in production networks under asymmetric climate policies

4.1 Introduction

Climate change poses global challenges that require coordinated efforts for effective mitigation. Although the Paris Agreement signifies an endeavor to achieve global emissions abatement, climate policies continue to be designed at a sub-global level, resulting in considerable heterogeneity in national contributions. The existence of differences between countries in emissions reduction commitments prevents governments from taking stricter actions to fight climate change. Uneven environmental policies, affecting production costs, may, indeed, alter comparative advantages that underpin trade patterns. This results in a reorganization of the global production network through the relocation of economic activities away from countries with more stringent climate policies, in turn causing *carbon leakage*. When this happens, the outsourcing of dirty production will not allow to substantially reduce global emissions. This ultimately leads to an inefficient outcome, whereby abating countries bear the economic costs of their actions without achieving a significant reduction in emissions. Thus, leakage hampers the effectiveness of climate policies, prompting skepticism about sub-global commitments, from both economic and environmental perspectives (Böhringer et al., 2022).

It has been shown that carbon leakage is likely in the wake of non-harmonized climate policies both in the case of the *Kyoto Protocol*[2] (see, for instance, Paltsev, 2001 and Burniaux and Oliveira Martins, 2012) and of the *Paris Agreement*[3] (see King and van den

[*]This paper, currently revised and resubmitted to the *Journal of Economic Dynamics and Control*, has been developed at the Universitat Autònoma de Barcelona (UAB), under the supervision of *Prof. Ivan Savin* and *Prof. Jeroen van den Bergh*.

[2]The potential of carbon leakage in the Kyoto Protocol was clear, since it divided countries in abating and non-abating ones, making emission transfers between countries highly likely.

[3]The Paris Agreement takes a bottom-up approach, envisaging voluntary commitments (the so called Nationally Determined Contributions, NDCs); it does not distinguish between developed and developing countries but it relies on the principle of "common but differentiated responsibilities and respective capabilities". Nevertheless four types of pledges - as derived by King and van den Bergh (2019) -

Bergh, 2021). However, ex-post empirical evidence on the effects of asymmetric climate policies, such as the introduction of the European Emissions Trading Scheme (EU ETS), remains mixed. While **?** find no significant impact of the EU ETS on the relocation of manufacturing activities, **?** document an increase in the carbon content of European imports, implying a partial shift of polluting production abroad. Similarly, Coster et al. (2024) show that the EU ETS induced carbon leakage through supply chain relocation, as French firms increased imports of carbon-intensive intermediates from non-EU suppliers. As discussed by Fontagné and Schubert (2023), the mixed empirical evidence largely reflects the limited stringency of the EU ETS in the past - and of environmental policies more broadly - characterized by relatively low carbon prices and the widespread free allocation of allowances (grandfathering), particularly for emission-intensive and trade-exposed sectors. These design features have weakened potential competitiveness losses.

This paper proposes a model that encompasses uncoordinated climate policies with a twofold purpose: detect the effects of asymmetric environmental policies on supply chains and study the interaction between environmental and trade policies that can help mitigate international carbon leakage. Notably, we evaluate the effectiveness of a border carbon adjustment mechanism, an instrument designed to prevent the outsourcing of emissions-intensive production by putting a price on the carbon-content of imported goods. This is precisely the path endeavored by the European Commission, which proposed the EU Carbon Border Adjustment Mechanism (CBAM) as part of the European Green Deal to meet the "net zero" emissions commitment without hindering its economic and climate objectives. Furthermore, the model is employed to analyze how the properties of the supply chain interact with asymmetric climate regulations, assessing the extent to which these policies distort trade patterns.

To this end, we develop a heterogeneous-firms model with imperfect competition among agents characterized by diverse costs structures. The model connects to the "New-new Trade Theory" (originated by Melitz, 2003), which reflects the empirical evidence on the heterogeneous nature of exporting firms within an industry and it has been shown to be better suited to study carbon leakage (Balistreri and Rutherford, 2012). We embed this backbone of heterogeneous firms and monopolistic competition in international trade into a dynamic model in which firms' outsourcing[4] decisions underpin the emergence of the endogenous production network.

This approach to tackle carbon leakage represents a novelty as most studies currently focus on static computable general equilibrium models (CGEs), while leakage is likely to

emerge, with a distinction between rich countries, low- and middle-income, China and India, and oil suppliers.

[4]Following Antras and Helpman (2004), the term *outsourcing* is employed to denote a firm's decision to purchase an intermediate input rather than produce it internally. If the input is purchased domestically, it is referred to as *domestic outsourcing*; if purchased abroad, it corresponds to *foreign outsourcing*, or arm's-length trade.

be a dynamic phenomenon, which affects the production structure from the bottom-up, altering firms' links in the production network. As pointed out by Pichler et al. (2023), managing the challenges posed by climate change requires a detailed understanding of these micro-level interactions along the supply chain as policy actions will determine a rewiring of production networks with heterogeneous impacts on the agents involved. Furthermore, CGEs are built on the assumption of fully rational agents while bounded rationality, as we will show, plays an important role in understanding the outcomes of asymmetric policies.

Instead, we rely on the Agent Based Modeling (ABM) approach, which offers a flexible tool to study the evolution of out-of-equilibrium systems characterized by boundedly rational agents. Since they allow for a more realistic description of micro behavior, by explicitly modeling agent interactions and coordination, they are increasingly applied to tackle climate change (see Castro et al., 2020 for a review). Moreover, ABMs enable the assessment of various policy scenarios and their differentiated impacts on agents (as argued by Savin et al., 2023). Notably, we model two aggregates - the Global North and the Global South - characterized by different industrial structures that give rise to heterogeneity in income and exposure to trade. The global economy is, indeed, characterized by considerable differences among developed (the Global North) and developing countries (the Global South), in terms of income distribution, industrial structure and emissions intensity of energy and production (Copeland and Taylor, 2004). These differences lie behind the emergence of comparative advantages that shape trade patterns and translate into today's *unbundling of production* (del Río-Chanona et al., 2017). Moreover, they result in asymmetric efforts in fighting climate change, which can undermine the effectiveness of environmental policies, notably through carbon leakage.

The rest of the paper is organized as follows. Section 4.2 provides a brief overview of the literature to which this study connects. Section 4.3 presents the theoretical model. Results of the simulations are discussed in Section 4.4. Section 4.5 concludes the paper and provides suggestions for future research.

4.2 Related literature

This study connects to several strands of literature. As we build a heterogeneous-firms model with international fragmentation of production, a relevant context is provided by the literature on Global Value Chains (GVCs). Here, it is common for models to describe production as consisting of sequential stages, shedding light on the mechanisms underlying firm's boundaries (Antras and Helpman, 2004), the allocation of tasks (Chor et al., 2019) and the geographical location of operations (Antràs and Chor, 2022).

Our model builds on the seminal work by Antras and Helpman (2004), where firms' outsourcing decisions are shaped by heterogeneity in productivity and country factor endowments. We extend this static framework by proposing a dynamic model of firm-to-firm linkages, considering bounded rationality in decision-making. While the leading literature on the relationship between macroeconomics and networks usually assumes an *exogenous* input-output structure at an aggregate industry level (the seminal reference being Acemoglu et al., 2012), we explicitly account for intra-firms trade, contributing to a better understanding of the aggregate effects of policies and shocks that may be dampened or amplified by heterogeneous repercussions on firms and countries. In this regard, Henriet et al. (2012) propose a theoretical framework which disaggregates sector-scale input–output tables to investigate economic robustness to shocks, such as natural disasters. They prove the importance of disaggregated approaches to evaluate amplifications of shocks due to heterogeneity of losses and business interactions within the production network, under various exogenous network structures. The importance of micro-level interactions along supply chains is underscored by Diem et al. (2024), who show that relying on aggregated input–output relationships can substantially underestimate economic losses triggered by the COVID-19 pandemic. This points to a key limitation of industry-level input-output models, namely that they neglect firm-to-firm linkages. In the context of natural disasters, **?** and Inoue and Todo (2019a) highlight how disruptions can propagate through supply chain cascades, generating indirect effects that outweigh the initial idiosyncratic shock. Similar dynamics are documented by Boehm et al. (2019) and Carvalho et al. (2021), who analyze the transmission of earthquake-induced shocks via buyer–supplier networks. Moreover, heterogeneity in supply relationships has been shown to shape business cycle volatility, as argued by Magerman et al. (2016). For an overview of the theoretical foundations and empirical evidence on firm-level production networks, see Carvalho and Tahbaz-Salehi (2019). We move further into the pointed direction, allowing for the endogenous establishment of firm-to-firm relationship.

Regarding the endogenous formation of production networks[5], existing research has examined the factors underpinning the formation and transformation of such networks, by considering technological evolution (Gualdi and Mandel, 2019), endogenous supplier choices (Acemoglu and Azar, 2020), or fixed costs (Dhyne et al., 2023). Some contributions further focus on the existence of switching frictions; for instance, Lim et al. (2017) builds a theoretical framework in which the production network is sticky due to the existence of Calvo (1983)'s price reset shocks, according to which there is randomness in the possibility of changing supplier and fully-rational firms evaluate all the possible links when the so-called "Calvo Fairy" arrives. Along the same line, Chaney (2014) develops a dynamic model with the main assumption that existing connections lower the cost of finding a new partner in the same country. Monarch (2022) proposes and structurally estimates a dynamic discrete choice model where the stickiness of the supply chain arises due to switching frictions. We follow this approach by embedding switching costs into

[5]See Bernard and Moxnes (2018) for a detailed review on the recent literature on networks and trade.

an agent-based model, in which myopic agents seek to maximize their per-period profits, giving rise to the production network. Differently from the above-mentioned papers, we rely on the ABM methodology to depict a more realistic interaction between boundedly rational agents.

In the ABM literature, we detect some contributions to the GVC literature. For instance, Cantner et al. (2019) assess the importance of fit in the value chain integration for firms' competitiveness and market shares. Closely related to our approach, Battiston et al. (2007) propose a value chain model in which the economy is described as a network of interactions between production units. **?**, adopting a broadly related framework, prove that the endogenous reorganization of production linkages may smooth the aggregate effects of localized shocks. While they depict a stylized global value chain, we explicitly investigate the effects of frictions in supply linkages, which have been shown to play a central role in real-world value chains (Monarch, 2022).

Furthermore, our study aims at analyzing climate policy-induced change in international flows of trade, with carbon leakage and the pollution havens as potential outcomes[6]. The majority of studies on the pollution haven hypothesis focuses on the relationship between environmental policies and trade in *final goods*, explicitly modeling trade patterns and exporting decisions. For instance, Kreickemeier and Richter (2014) present a trade model in which firms are characterized by heterogeneous emissions intensity, which is assumed to be negatively related to the level of productivity. Forslid et al. (2018) builds an extension of the Melitz (2003) with endogenous investments in an abatement technology. This paper proposes a detailed mechanism for why exporting firms, subject to an environmental tax, may have a lower emissions intensity. While much of the research has focused on trade in final goods and horizontal FDI [7], the growth of trade in intermediate goods and the fragmented nature of production (Mundt et al., 2023) prompt an examination of the impact of environmental regulations on the organization of production. Our contribution in this field lies in the fact that we consider endogenous supply chains instead of trade in final goods and horizontal FDI. Global value chains have become a distinctive feature of the world economy in recent decades; according to Johnson and Noguera (2017), trade in intermediate inputs, as a typical symbol of GVC, accounts for approximately two thirds of international trade. Global production fragmentation is reshaping international trade patterns; thus taking into account this *new wave of globalization* (Antràs and Chor, 2022) is essential to tackle climate leakage and the effect of environmental regulations. In this spirit, Coster et al. (2024) present

[6]Closely related to carbon leakage, the *pollution haven hypothesis* posits that countries with lax environmental standards may attract pollution-intensive industries from countries with stricter regulations. This creates "pollution havens", where businesses relocate to take advantage of lower regulatory costs, resulting in increased pollution in those regions.

[7]With a horizontal Foreign Direct Investment (FDI), a company establishes the same type of business operation in a foreign country as it operates in its home country.

a heterogeneous-firm model in which carbon taxation, proxying the EU ETS, alters the composition of firms' supply chains by affecting their choice of green versus dirty suppliers. Our contribution extends this framework by accounting for switching frictions and firm interactions within an agent-based structure, thus providing a bridge between the trade literature and complexity approaches to macroeconomic dynamics.

4.3 The model

The economy is characterized by two regions: the Global North (N), which consists of high-income countries with high labour costs and an advanced production structure, and the Global South (S), which represents labour-abundant low-income countries. Lower costs of inputs give rise to a comparative advantage for the South in the manufacturing sector[8]. These cross-country differences in factors of production constitute the fundamental basis of global economic integration. There are two types of firms, down- and upstream. Downstream firms (D-firms) are retailers, since they produce a differentiated variety of final goods, sold to households. To carry out production, they employ labour, inelastically supplied by domestic households, and polluting intermediate goods which are produced by Upstream firms (U-firm) in both regions. In each period, D-firms (retailers) set production levels based on expected market demand and send orders to U-firms, which are suppliers in the production network. Suppliers, in turn, determine their output according to the demand coming from their customers (i.e., the retailers). D-firms and their suppliers interact in the intermediate goods market, which is characterized by search and matching. In each round, D-firms look for the most suitable supplier available, giving rise to a national or international production network, which will be discussed momentarily. Figure 4.1 shows a stylized representation of the interaction between firms, i.e. suppliers and customers, and countries.

4.3.1 Downstream firms

In the final goods market, heterogeneous downstream firms sell differentiated goods to households. The existence of product heterogeneity gives rise to firms' market power, which results in a monopolistic competition setting. D-firms are demand-driven and myopic. In every period, each downstream firm (D-firm) forecasts the demand for the i-th variety produced, based on past values and subjected to an idiosyncratic demand shock. This reflects the uncertainty surrounding realized demand, which arises from

[8]We follow a common assumption in the literature that wages are exogenous and fixed at higher rates in the global North (e.g., Antras and Helpman, 2004). This reflects the fact that non-tradable goods are produced in both regions, though more efficiently in the North. Given perfect labour mobility across sectors within a country, wages equalize domestically across sectors. Hence, the North exhibits a higher wage level in both upstream and downstream activities.

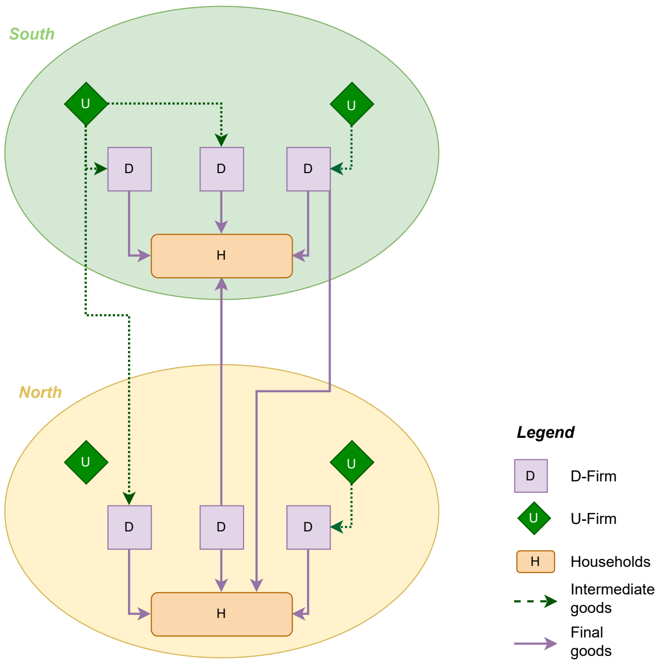


Figure 4.1: Stylized representation of the interactions among firms and countries.
Note: Each country is populated by N_d heterogeneous downstream (D) firms ($N_d^n = N_d^s = 3$ in the figure). D-firms choose a supplier of intermediate inputs among the population of U-firms located in the North ($N_u^n = 2$) or in the South ($N_u^s = 2$). Notice that, some U-firms may remain inactive if they are not selected by any customers and they do not produce.

the sequential nature of economic interactions and the evolving market conditions over time (as discussed in Dawid and Delli Gatti, 2018). Thus, firms form expectations about macroeconomic conditions and set production plans based on anticipated demand. Under monopolistic competition, each firm i, located in country l, faces a downward-sloping demand curve for its differentiated variety. Accordingly, the expected demand faced by firm i for the $k-th$ market (with $k = l$ in case of domestic selling), $q_{i,t}^k$, is given by:

$$q_{i,t}^k = (p_{i,t}^k)^{-\sigma} B_{i,t}^k, \tag{4.1}$$

where $p_{i,t}^k$ is the price set by the firm, $\sigma > 1$ the elasticity of substitution between varieties and $B_{i,t}^k$ the firm's expectation over the aggregate demand level[9]. Firms are boundedly rational and base their expectations on information from the previous period. Notably, aggregate demand, $B_{i,t}^k$, is given by:

$$B_{i,t}^k = \mathbb{E}\left[\frac{Y_t^k}{N_t^k}(P_t^k)^{\sigma-1} u_{i,t}\right] = \frac{Y_{t-1}^k}{N_{t-1}^k}(P_{t-1}^k)^{\sigma-1}\mathbb{E}[u_{i,t}], \tag{4.2}$$

where Y_{t-1}^k denotes nominal aggregate demand observed in the previous period, N_{t-1}^k

[9]This formulation, which captures heterogeneity in firm performance arising from microeconomic uncertainty, aligns, to some extent, with the stochastic demand structure in a monopolistic competition setting introduced by Delli Gatti et al. (2024).

the number of active firms, and P^k_{t-1} the aggregate price index. The idiosyncratic demand component, $u_{i,t}$, represents a stochastic shock with $\mathbb{E}[u_{i,t}] = 1$ and finite variance, reflecting firm-specific market fluctuations. Firms set production to meet the expected demand (Equation 4.1). The realization of the demand shock occurs only after trade links are established and production decisions are made. It follows that the actual market demand for the $i-th$ variety is:

$$q^{k,D}_{i,t} = q^k_{i,t} u_{i,t}. \tag{4.3}$$

Since production must be set in advance and final goods are perishable (firms can not hold inventories from one period to the other), the quantity actually sold by the firm is limited by its production capacity. Hence, the quantity sold is determined by the minimum between the realized, $q^{k,D}_{i,t}$ and the expected, $q^k_{i,t}$, demand:

$$\hat{q}^k_{i,t} = \min\left\{ q^{k,D}_{i,t},\ q^k_{i,t} \right\}. \tag{4.4}$$

It is worth highlighting that firms observe not only the actual quantity sold, but also the potential demand $q^{k,D}_{i,t}$, which serves as a signal of market conditions. Even when supply constraints limit actual sales, potential demand provides valuable information about the firm's market position and guides expectation formation[10]. As such, the nominal aggregate demand in period t is computed as the sum of the individual demand received by all the domestic firms: $Y^k_t = \sum_i y^k_{i,t} = \sum_i p^k_{i,t} q^{k,D}_{i,t}$.

D-firms produce final goods by means of labor (l) and (one type of) intermediate inputs (x), according to a CES production function[11]:

$$q_{i,t} = \varphi_i \left(\alpha l^{\rho^d}_{i,t} + (1-\alpha) x^{\rho^d}_{i,t} \right)^{\frac{1}{\rho^d}}, \tag{4.5}$$

where φ_i if firm's productivity, α represents the labor share in production and $\rho^d = \frac{\sigma^d - 1}{\sigma^d}$ is the elasticity of substitution between factors of production in the downstream sector. The operational costs borne by the generic *i-th* D-firm are:

$$C_{i,t} = (w^l l_{i,t} + \bar{p}^l_{j,t} x_{i,t}) \tau^{lk} + F^{lk} + F^o, \tag{4.6}$$

where w^l and $\bar{p}^l_{j,t}$ are, respectively, the wage rate in the country where production takes place and the price of intermediate goods sourced from supplier j, located in country l. The parameter F^{lk} denotes the fixed organizational costs connected to the sourcing activity, such as supervision, quality control, accounting. We follow Antras and Helpman

[10]This formulation aligns with the agent-based modeling tradition of adjusting production based on unmet demand in the previous period, while keeping the model structure parsimonious.

[11]To ease the notation, we shall henceforth drop the superscript referring to the destination market k, with $k = l$ being the domestic and $k \neq l$ the foreign market (when exporting) Hence, the superscripts shown hereafter refer to the production and sourcing.

(2004) in assuming that these costs are higher when the supplier is located in a foreign country (i.e. $F^{lk} > F^{ll}$). This is due to the fact that the fixed costs of searching, monitoring and communication are significantly greater when the supplier is abroad. Furthermore, if the firm exports to a foreign market, extra fixed (F^o) and variable (τ^{lk}) costs connected to the exporting activity are borne. Notably, the parameter $\tau^l k$ captures shipping costs, that are assumed to be higher in the case of exports: $\tau^{lk} > \tau^{ll} = 1$. The existence of higher fixed and variable costs in case of exporting has been empirically tested in the gravity literature (e.g., Anderson, 2011) and is a common feature of the heterogeneous-firms trade model (e.g. Melitz, 2003).

The optimal demand of labor ($l_{i,t}$) and intermediate goods ($x_{i,t}$) are derived solving firm's costs (Equation 4.6) minimization problem, given the production function (Equation 4.5), as follows:

$$l_{i,t} = \left(\alpha \frac{\tilde{p}_{i,t}}{w^l}\right)^{\sigma^d} \frac{q_{i,t}}{\varphi_i}, \tag{4.7}$$

$$x_{i,t} = \left((1-\alpha)\frac{\tilde{p}_{i,t}}{\bar{p}^l_{j,t}}\right)^{\sigma^d} \frac{q_{i,t}}{\varphi_i}, \tag{4.8}$$

with:

$$\tilde{p}_{i,t} = \left[\alpha^{\sigma^d}(w^l)^{1-\sigma^d} + (1-\alpha)^{\sigma^d}(\bar{p}^l_{j,t})^{1-\sigma^d}\right]^{\frac{1}{1-\sigma^d}}, \tag{4.9}$$

where w^l is the real wage[12] and $\bar{p}^l_{j,t}$ is the price of intermediate goods, purchased from supplier j at time t.

D-firms operating in monopolistic competition maximize their profits given market demand (Equation 4.1). Profits maximization problem results in an optimal price, which entails a constant markup over the marginal costs of production:

$$p_{i,t} = \frac{\sigma}{\sigma-1}\frac{\tilde{p}_{i,t}}{\varphi_i}\tau^{lk} = \frac{\sigma}{\sigma-1}\left(\frac{\alpha^{\sigma^d}(w^l)^{1-\sigma^d} + (1-\alpha)^{\sigma^d}(\bar{p}^l_{j,t})^{1-\sigma^d}}{\varphi_i}\right)\tau^{lk}, \tag{4.10}$$

where $\frac{\sigma}{\sigma-1}$ is the constant mark-up (with σ being the elasticity of substitution among varieties), w^l is the cost of labour (wage) and $\bar{p}^l_{j,t}$ is the price of the intermediate goods supplied by the $j-th$ upstream firm, located in country l, whose functional form will be discussed momentarily.

Revenues of D-firms are stochastic due to the randomness of market demand. Profits will be given by the difference between revenues, $p_{i,t}\hat{q}_{i,t}$, and the costs of production in terms of labour, $w^l l_{i,t}$, intermediate inputs, $\bar{p}^l_{j,t}x_{i,t}$, and the fixed cost of outsourcing, F^{lk}, and exporting, F^o:

$$\pi_{i,t} = p_{i,t}\hat{q}_{i,t} - w^l l_{i,t} - \bar{p}^l_{j,t}x_{i,t} - F^{lk} - F^o. \tag{4.11}$$

[12]We assume that households supply labour inelastically at the fixed wage rate, w^l.

Realized profits are retained to fuel net worth:

$$A_{i,t} = A_{i,t-1} + \pi_{i,t}. \tag{4.12}$$

If the net worth turns negative, the firm will be recapitalized, i.e. it will be endowed with a randomly assigned level of net worth.

4.3.2 Upstream firms

U-firms produce intermediate goods on demand. We denote the set of downstream customers of the j-th supplier with Φ_j. Hence, total demand of intermediate goods faced by the *j-th* U-firm is given by the sum of the intermediate goods demand of all the firms in their subset of customers:

$$x_{j,t} = \sum_{i \in \Phi_j} x_{i,t}. \tag{4.13}$$

U-firms set the production schedule based on collected orders and produce intermediate goods by means of labour (l) and fossil fuels (f), according to a CES production function:

$$x_{j,t} = \varphi_{j,t}\bigg((\alpha l_j)^{\rho^u} + ((1-\alpha) f_j)^{\rho^u}\bigg)^{\frac{1}{\rho^u}}, \tag{4.14}$$

where $\rho^u = \frac{\sigma^u - 1}{\sigma^u}$ is the substitution parameter, with σ^u being the elasticity of substitution between inputs. The parameter $\varphi_{j,t}$ is the productivity of the $j-th$ U-firm, which is heterogeneous among firms. Indeed, we assume that, in each period, U-firms are hit by stochastic technology shocks. As a consequence, firm-level productivity follows a log-normal AR(1) process. Specifically, letting $a_{j,t} = \ln(\varphi_{j,t})$, we can express the dynamics as $a_{j,t} = \rho a_{j,t-1} + \epsilon^{\varphi}_{j,t}$, with $\epsilon^{\varphi}{}_{j,t} \sim$ i.i.d. $N(0, \sigma_\epsilon{}^2)$. Hence, the productivity of firm j is:

$$\varphi_{j,t} = e^{a_{j,t}}. \tag{4.15}$$

Given the production function and orders from customers, the optimal demands for labour and fossil fuels of the $j-th$ supplier are derived solving their cost minimization problem and are, respectively:

$$l_{j,t} = \left(\alpha \frac{\tilde{p}^l_j}{w^l}\right)^{\sigma^u} \frac{x_{j,t}}{\varphi_{j,t}}, \tag{4.16}$$

$$f_{j,t} = \left((1-\alpha)\frac{\tilde{p}^l_j}{p^l_f}\right)^{\sigma^u} \frac{x_{j,t}}{\varphi_j}, \tag{4.17}$$

where $\tilde{p}_j$ is the price index of the input bundle, defined as:

$$\tilde{p}_j^l = \left[\alpha^{\sigma^u} {w^l}^{1-\sigma^u} + (1-\alpha)^{\sigma^u} (p_f^l)^{1-\sigma^u}\right]^{\frac{1}{1-\sigma^u}}. \tag{4.18}$$

In section 4.4.4, a scenario with green energy will be studied. As illustrated in 4.5, this will use a nested CES production function, reflecting that U-Firms can substitute fossil fuels with green energy.

Total operational costs of the *j-th* supplier are:

$$C_{j,t} = \left(w^l l_{j,t} + p_f^l f_{j,t}\right)\tau^{lk}, \tag{4.19}$$

where w^l and p_f^l are, respectively, the wage rate and the price of fossil fuels in the country, l, in which the production is carried out. The parameter τ^{lk} represents iceberg costs, i.e. the costs connected to shipping one unit of good from country l to country k. We assume, as standard in the trade literature, that cross-border shipping, being related to geographical distance, is more expensive than national selling, for which the iceberg cost is normalized to 1: $\tau^{lk} > \tau^{ll} = 1$.

U-firms accommodate all the demand coming from their customers at an optimal price which equalizes marginal costs of production:

$$p_{j,t} = \frac{\tilde{p}_j}{\varphi_{j,t}}\tau^{lk} = \frac{\left[\alpha^{\sigma^u} {w^l}^{1-\sigma^u} + (1-\alpha)^{\sigma^u} (p_f^l)^{1-\sigma^u}\right]^{\frac{1}{1-\sigma^u}}}{\varphi_{j,t}}\tau^{lk}, \tag{4.20}$$

where w^l and p_f^l are respectively the wage rate and the price of fossil fuels in country l.

Upstream firms earn revenues from the business-to-business selling of intermediate goods. Profits of the $j-th$ supplier will be given by the difference between total revenues, $p_{j,t}x_{j,t}$, and total costs of production[13] in terms of labour, $w^l l_{j,t}$ and fossil input, $p_f^l f_{j,t}$:

$$\pi_{j,t} = p_{j,t}x_{j,t} - (w^l l_{j,t} + p_f^l f_{j,t})\tau^{lk}. \tag{4.21}$$

Profits are retained and are funneled into net worth, whose law of motion is:

$$A_{j,t} = A_{j,t-1} + \pi_{j,t}. \tag{4.22}$$

As for D-firms, U-firms go bankrupted if the net worth turns negative. When this happens, the bankrupted agent is recapitalized, i.e. it is endowed with a randomly assigned level of net worth, in order to ensure a fixed number of potential suppliers in every period.

[13]Note that, under the assumption of perfect competition in the intermediate goods market, firms earn zero profits.

4.3.3 Emissions and leakage

Intermediate goods production causes CO_2 emissions. The overall level of emissions produced by the $j-th$ U-firm in country l is a function of the amount of fossil fuels employed in production:

$$E^l_{j,t} = \epsilon^l f_{j,t} = \epsilon^l \left((1-\alpha)\frac{\tilde{p}^l_j}{p^l_f}\right)^{\sigma^u} \frac{x_{j,t}}{\varphi_{j,t}}, \tag{4.23}$$

where $\tilde{p}^l_j$ is the price of the input bundle as defined in Equation 4.18 and ϵ^l represents the level of green technology available in country l. We assume that $\epsilon^n < \epsilon^s$, reflecting the fact that most low CO_2 emitting technologies are implemented in the developed countries[14]. Notice that more productive firms will employ less fossil fuels *per-unit* of output and, in turn, will generate lower *per-unit* emissions: $e^l_{j,t} = \frac{\epsilon^l}{\varphi_{j,t}}\left((1-\alpha)\frac{\tilde{p}^l_j}{p^l_f}\right)^{\sigma^u}$. It has been shown, indeed, that more productive firms are also cleaner (Copeland et al., 2022).

By aggregating the emissions produced by each U-firm active in the country, $E^l_{j,t}$, we get the overall emissions coming from country l at time t:

$$\tilde{E}^l_t = \sum_{j=1}^{N^l_u} E^l_{j,t}, \tag{4.24}$$

where N^l_u is the number of active U-firms in country l.

Both countries can introduce per-unit emission carbon tax (z^l) on domestic production. In this case, U-firms bear an additional cost connected to the climate policy implemented, which alter the cost structure and the conditional input demand derived from firm's cost-minimization problem (details in 4.5):

$$l_{j,t} = \left(\alpha\frac{\tilde{p}^l_j}{w^l}\right)^{\sigma^u} \frac{x_{j,t}}{\varphi_{j,t}}, \tag{4.25}$$

$$f_{j,t} = \left((1-\alpha)\frac{\tilde{p}^l_j}{p^l_f + z^l\epsilon^l}\right)^{\sigma^u} \frac{x_{j,t}}{\varphi_j}, \tag{4.26}$$

with:

$$\tilde{p}^l_j = \left[\alpha^{\sigma^u} {w^l}^{1-\sigma^u} + (1-\alpha)^{\sigma^u}(p^l_f + z^l\epsilon^l)^{1-\sigma^u}\right]^{\frac{1}{1-\sigma^u}}. \tag{4.27}$$

[14]Heterogeneity in emission rates arises from several factors, such as the carbon intensity of energy inputs or the presence of environmental standards and abatement requirements that influence the emissions associated with a given production process. In this paper, we focus exclusively on the latter, i.e. on differences in emissions that stem from regulatory or infrastructural contexts. These differences may reflect the presence of specific standards or non-market-based instruments implemented at the country level, which affect the emissions intensity of the technologies in use.

Hence, the carbon tax affects marginal costs of production and profits accordingly:

$$\pi^l_{j,t} = p^l_{j,t} x^l_{j,t} - (w^l_{j,t} l_{j,t} + p^l_f f_{j,t} + z^l_t e^l f^l_{j,t})\tau^{lk}. \tag{4.28}$$

Profit maximization results in an optimal price of intermediate goods in presence of a carbon tax:

$$p_{j,t} = mc_{j,t} = \frac{\tilde{p_j}}{\varphi_{j,t}} = \frac{\left[\alpha^{\sigma^u} {w^l}^{1-\sigma^u} + (1-\alpha)^{\sigma^u} (p^l_f + z^l \epsilon^l)^{1-\sigma^u}\right]^{\frac{1}{1-\sigma^u}}}{\varphi_{j,t}} \tau^{lk}. \tag{4.29}$$

In the absence of coordination of climate policy among countries, U-firms in different countries bear differentiated costs of fighting climate change, depending on the level of the tax adopted by the local government. In the simulations, we will assume that the Global North is characterized by higher carbon prices, resulting in $z^n > z^s$. This represents an additional cost for upstream firms located in the abating country, which, by charging higher prices, become less competitive. For this reason, environmental policy has a negative effect on competitiveness in affected industries, causing carbon leakage. The *leakage rate*, ζ_t, is defined as the change in foreign emissions relative to domestic emissions reduction as:

$$\zeta_t = -\frac{\Delta^k_{E,t}}{\Delta^l_{E,t}} = \frac{\tilde{E^k_t} - \tilde{E^k_{t-1}}}{\tilde{E^l_t} - \tilde{E^l_{t-1}}}, \tag{4.30}$$

where $\Delta_{E,t}$ is the change in overall country's emissions from the previous period to the current one.

To avoid distortions in international competitiveness, countries can introduce a tariff at the border, which takes the form of a border carbon adjustment (BCA). The abating country can set a tax on the border to levy imported goods produced in countries with laxer carbon prices. In this way, emissions embodied in imported goods from non-regulating countries will be taxed to reach the emission price of the regulating region.

Notice that the actual implementation of a BCA faces several challenges, both in terms of compliance with the WTO rules and in terms of feasibility[15]. Notably, BCA can secure competitiveness neutrality and comply with the WTO rules if the adjustment domestically imposed to imported goods covers only the differences in emissions prices (Cosbey et al., 2019). Ideally, the border adjustment levied on the intermediate goods produced in country k and imported in country l, with a stringent environmental policy, should cover the wedge between the local (z^l) and the foreign carbon tax (z^k):

$$\Delta_{lk} = \mid z^l - z^k \mid. \tag{4.31}$$

[15]Böhringer et al. (2022) provide a comprehensive analysis of the implications and obstacles associated with border carbon adjustment mechanisms, alongside an examination of alternative implementations.

As such, the BCA imposes an extra cost on exporters in country k aiming to equalize prices across domestic and foreign producers within the same industry. Consequently, upstream suppliers located in the non-abating country will face a border tax, which increases the cost borne by exporting firms and, in turn, affects their derived demand for inputs, as determined by the cost minimization problem:

$$l_{j,t} = \left(\alpha \frac{\tilde{p}^l_j}{w^l}\right)^{\sigma^u} \frac{x_{j,t}}{\varphi_{j,t}}, \tag{4.32}$$

$$f_{j,t} = \left((1-\alpha)\frac{\tilde{p}^l_j}{p^l_f + (z^l + \Delta_{lk})\epsilon^l}\right)^{\sigma^u} \frac{x_{j,t}}{\varphi_j}, \tag{4.33}$$

with:

$$\tilde{p}^l_j = \left[\alpha^{\sigma^u} {w^l}^{1-\sigma^u} + (1-\alpha)^{\sigma^u}(p^l_f + (z^l + \Delta_{lk})\epsilon^l)^{1-\sigma^u}\right]^{\frac{1}{1-\sigma^u}}. \tag{4.34}$$

By entering the profit maximization problem, the BCA directly affects the optimal price set by upstream firms:

$$p_{j,t} = \frac{\tilde{p}_j}{\varphi_{j,t}}\tau^{lk} = \frac{\left[\alpha^{\sigma^u} {w^l}^{1-\sigma^u} + (1-\alpha)^{\sigma^u}(p^l_f + (z^l + \Delta_{lk})\epsilon^l)^{1-\sigma^u}\right]^{\frac{1}{1-\sigma^u}}}{\varphi_{j,t}}\tau^{lk}, \tag{4.35}$$

thereby increasing the price of intermediate goods that are imported from downstream firms in the abating country. As a consequence, the combination of asymmetric climate policies and the BCA determines a general price increase in the abating country.

Notice that this specification implies differentiated BCA depending on the difference between the degree of strictness of domestic and foreign climate policies. Nevertheless, there is no guarantee that the information provided concerning the actual level of emissions by firms and countries is entirely transparent. An alternative for the implementation of a BCA in case of asymmetric information on emissions accounting is to set a general benchmark. As highlighted in the academic and policy debate, a uniform domestic benchmark is more convenient in terms of data collection and discrimination, but it would disincentivize foreign producers from reducing their emissions (Zhong and Pei, 2022). The benchmark could be set by considering the average level of emissions intensity of the country, i.e. the ratio between overall emissions and total output:

$$\tilde{e}^l_{t-1} = \frac{\tilde{E}_{t-1}}{X^l_{t-1}} = \frac{\sum_{j=1}^{N^l_u} E^l_{j,t-1}}{\sum_{j=1}^{N^l_u} x_{j,t-1}}, \tag{4.36}$$

where X^l_{t-1} is the total output of the intermediate sector in the previous period, computed as the sum of the quantity, $x_{j,t-1}$, produced by active firms, N^l_u. In this case, firms exporting to the domestic market will pay an extra cost per unit of output, related to the carbon tariff and the emission benchmark: $\tilde{e}^l_{t-1}\Delta_{lk}$. This cost enters the marginal cost function as a uniform per-unit component, affecting all firms regardless of their productivity level. Hence, the price of intermediate goods is:

$$p_{j,t} = \left(\frac{\tilde{p_j}}{\varphi_{j,t}}\right)\tau^{lk} = \left(\frac{\left[\alpha^{\sigma^u} {w^l}^{1-\sigma^u} + (1-\alpha)^{\sigma^u}(p^l_f + z^l\epsilon^l)^{1-\sigma^u}\right]^{\frac{1}{1-\sigma^u}}}{\varphi_{j,t}} + \Delta_{lk}\tilde{e}^l_{t-1}\right)\tau^{lk}. \tag{4.37}$$

It is worth highlighting that, when the BCA targets a uniform emissions benchmark, more efficient (and cleaner) producers pay the same additional cost as more polluting firms. This disproportionately affects them, weakening the market selection and potentially hindering sectoral reallocation toward greener suppliers.

4.3.4 Endogenous production network

We propose a dynamic discrete choice model within an ABM of international trade, where, in every period, the importing firm decides which supplier to use by comparing partner-specific profits across all available suppliers, including its current match. The boundaries of firms in the world economy result, indeed, from firms attempting to organize production in the most profitable way (Antràs, 2015). D-firms are characterized by bounded rationality, thus they can visit just a limited subset of suppliers, W, which is randomly determined in every period by sampling among all possible U-firms in both countries. Given their limited information on the possible matches, D-firms compute the profits under all the available alternatives and choose the supplier with whom profits are higher.

On modeling the supply chain, we follow the approach proposed and empirically tested by Monarch (2022). According to this, there are frictions involved in finding a different supplier, modeled as a multiplicative component of the per unit price paid. These costs can be related to bargaining, contract design, technologies to evaluate the quality of the product or the actual searching. Hence, switching suppliers involves the payment of a set of per unit costs, including an overall switching cost, ξ_j, and an additional cost to be paid if an importer finds a new partner in a different country, ξ_l. Therefore, the expected per unit cost of purchasing intermediate goods for D-firm i will be:

$$\bar{p}^l_{j,t} = p^l_{j,t} e^{\xi_x \mathbf{1}\{j_t \neq j_{t-1}\} + \xi_c \mathbf{1}\{j^l_t \neq j^l_{t-1}\}}, \tag{4.38}$$

where $p^l_{j,t}$ is the fundamental price of the intermediate good charged by supplier j, described in Equation 4.20, $\mathbf{1}\{j_t \neq j_{t-1}\}$ is an indicator taking value equal to 1 if the firm is switching to a different supplier and $\mathbf{1}\{j^l_t \neq j^l_{t-1}\}$ takes value equal to 1 if the new supplier is located in a different country with respect to the previous one. The overall switching cost for a firm changing the supplier is $\beta = \xi_x$ or $\beta = \xi_x + \xi_c$ if the new supplier is located in a different country. The parameter β represents the enforceability of contracts, i.e. how easily a part can break the supply relationship. It can be seen as the stickiness of the supply chain (similar to Cantner et al., 2019), and we will test the results under different value of these parameters. When switching suppliers is costly, supply chains become rigid and, as we will show, less responsive to changes in relative costs, mitigating the carbon leakage that follows the introduction of a unilateral carbon tax.

Thus, when choosing the outsourcing strategy, the $i-th$ D-firm will evaluate expected profits under different suppliers:

$$E[\pi_i] = E[p_{i,t}q_{i,t}] - w^n l_{i,t} - \bar{p}^l_{j,t}x_{i,t} - F^{lk} - F^o, \tag{4.39}$$

where $E[p_{i,t}q_{i,t}]$ are expected revenues, $w^l l_{i,t}$ is the cost of labour, $\bar{p}^l_{j,t}x_{i,t}$ is the cost of acquiring intermediate goods, F^{lk} is the fixed cost connected to the sourcing strategy and F^o is the fixed exporting cost. Notice that, if profits result to be negative in all the alternatives, the firm will not enter the market and remain inactive.

4.3.5 Timeline

At each time step, t, the model processes the following sequence of events:

1. D-firms form expectations about the level of final demand (Equation 4.1).

2. U-firms are affected by idiosyncratic productivity shocks. Given their realized productivity (Equation 4.15) and the cost of inputs (labor and fossil fuels), they set prices by equating marginal costs and post them on the upstream market (Equation 4.20 in the baseline scenario, Equation 4.29 when the carbon tax is implemented, Equations 4.35 in case of firm-specific BCA or 4.37 for average BCA).

3. D-firms visit a subset of potential upstream suppliers and select the one that maximizes expected profits. In doing so, the firm evaluates the profits under all the possible alternatives, knowing that changing supplier is costly, as described in Equation 4.38. In this step, firms decide whether to enter the market or not. Entry into the market is, indeed, endogenously determined based on expected profitability. We will refer to a firm which enters the market as an *active* firm.

4. Once the supplier has been selected, D-firm set the optimal demand of intermediate goods (Equation 4.8) and hire workers (Equation 4.7) to start production.

5. At the same time, each U-firm collects orders from their downstream clients (Equation 4.13); the firm acquires fossil fuels (Equation 4.17) and hires workers (Equation 4.16) to start production.

6. Final demand is realized (Equation 4.3), and transactions take place. Intermediate goods are assumed to be non-storable; hence, any excess production is discarded, while unmet demand results in a backlog of unsatisfied customers. This generates a temporary disequilibrium between supply and demand.

7. Since production decisions are made under uncertainty and input costs are paid up-front, some firms may incur losses and eventually default if their net worth becomes negative.

8. Defaulted firms are recapitalized.

The sequence of events is depicted in Figure 4.2.

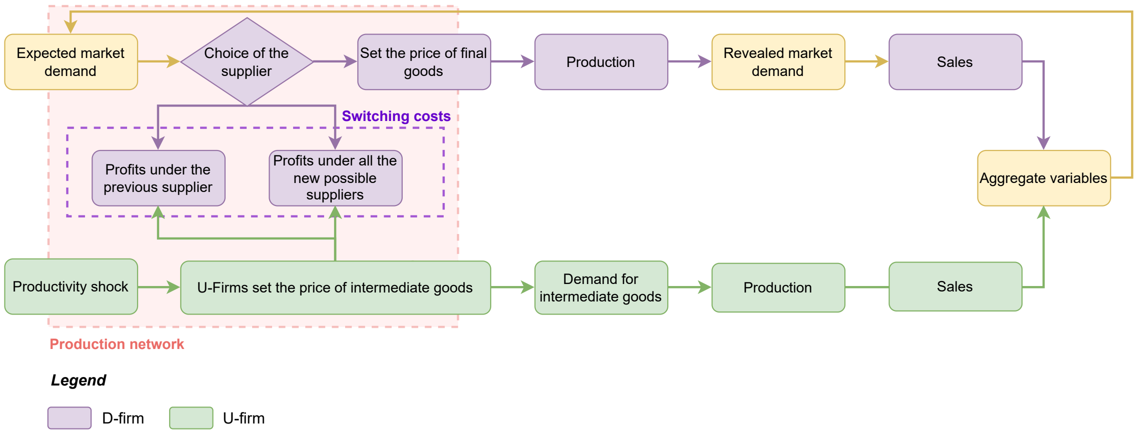


Figure 4.2: Flow chart.
Note: Purple blocks depict D-firms actions, green blocks represent U-firms and yellow blocks are aggregate variables. The choice of the intermediate goods supplier by D-firms gives rise to the endogenous supply chain.

4.4 Results

4.4.1 Calibration

The economy consists of $Nc = 2$ countries, the North and the South, each of them populated by $N_u^l = 200$ heterogeneous upstream firms and $N_d^l = 300$ downstream firms producing final goods. We assume that bankrupted agents are recapitalized, so to ensure a time-invariant size of each group[16]. The baseline version of the model is run for 100 Monte Carlo simulations[17], over a time span of T=500.

[16] This assumption is in line with the tradition of macroeconomic agent-based models (MABMs). According to Dawid and Delli Gatti (2018), most of the MABMs adopt a replacement mechanism for bankrupted firms, so that firm population remains constant over time.

[17] All Monte Carlo simulations are initialized using the same random seed across scenarios, ensuring that the baseline and policy-counterfactual runs are comparable and based on identical initial conditions (while the seed changes across different simulations). This allows us to isolate the effects of the policy interventions from stochastic fluctuations due to random initialization. Each simulation takes

Agents are initially endowed with a level of net worth, which is randomly drawn from a uniform distribution over the support [0,20]. Downstream firms are characterized by heterogeneous productivity, φ, randomly drawn from a uniform distribution: $\varphi^n \sim \mathcal{U}[0.5, 1.5]$ and $\varphi^s \sim \mathcal{U}[0.2, 1.2]$. Upstream firms are heterogeneous as well but they are subjected to a technological shock in each period, whose evolution follows the AR(1) process described in Equation 4.15, where the random component is normally distributed: $\epsilon^{\varphi}_{j,t} \sim i.i.d.\ N(0, 0.1)$.

Table 4.1: **Numerical values of the parameters**
While some parameters are borrowed from the relevant literature, some others are set according to the typical assumptions of trade models and the remaining are arbitrary chosen to meet stylized facts.

Parameter	Description	Value	Reference
N_d	Number of D-firms in the economy	600	
N_u	Number of U-firms in the economy	400	
σ	Elasticity of substitution consumption varieties	3.8	Bernard et al. (2003)
σ^d	Elasticity of substitution labor-inputs	0.7	Burniaux et al. (1992)
σ^u	Elasticity of substitution labor-fossil fuel	0.5	Bosetti et al. (2006)
α	Labor share of the production function D-firms	0.33	
β	Labor share of the production function U-firms	0.5	
w^n	Real wage in the North	2	
w^s	Real wage in the South	1.7	
p_f^n	Price of fossil fuels in the North	1	
p_f^s	Price of fossil fuels in the South	0.85	
τ^{ns}	Iceberg cost of exporting	1.24	Obstfeld and Rogoff (2000)
F^n	Fixed cost of domestic outsourcing	1	
F^s	Fixed cost of foreign outsourcing	3	
u_i	Stochastic demand component	$\mathcal{U}(0.9, 1.1)$	
ξ_x	Cost of switching supplier	0.25	Monarch (2022)
ξ_c	Additional cost of switching country's supplier	0.1316	Monarch (2022)
W	Subset of suppliers visited	20	
ϵ^n	Per-unit emission technology in the North	1	
ϵ^s	Per-unit emission technology in the South	2.5	
ρ	Memory parameter of the technology process	0.9	
ϵ^{φ}	Random component of the technology process	$N(0, 0.1)$	

The numerical values of the parameters employed in the simulations are shown in Table 4.1. Some parameters employed in the simulations are taken from the international economics literature. For instance, the elasticity of substitution among final goods varieties is set to $\sigma = 3.8$ as estimated by Bernard et al. (2003). We set the iceberg trade cost to 24% ($\tau = 1.24$), in line with standard values in the literature, which typically range between 10% and 30% (Obstfeld and Rogoff, 2000).

On the production side, the elasticity of substitution between labor and intermediate inputs in the downstream sector is set to $\sigma_d = 0.7$, aligning with the empirical estimates of capital–labor substitution (see Burniaux et al., 1992). In the upstream sector, the elasticity of substitution between labor and fossil fuels is assumed to be lower, set at $\sigma_u = 0.5$, following the WITCH model (Bosetti et al., 2006), which adopts this value for

approximately 2 minutes of CPU time (Intel Core Ultra 9 185H - E-core up to 3,8 GHz P-core up to 5,1 GHz).

the substitution between a capital–labor aggregate and energy services within a nested CES.

The remaining free parameters are chosen to ensure that the model reproduces key empirical regularities related to the geography of production and emissions in global value chains while maintaining consistency with the trade literature. For example, fixed costs of outsourcing are assumed to be higher for foreign sourcing, in line with Antras and Helpman (2004) and related works. However, their reciprocal magnitude is chosen to ensure a roughly balanced distribution of production across countries, as detected in real world data (*International Yearbook of Industrial Statistics 2024, UNIDO*). Likewise, labor is assumed to be relatively abundant in the South, leading to lower wage rates and reflecting the well-established divide between developed and developing economies. The value of the parameters ϵ^n and ϵ^s are set to have two thirds of total emissions coming from the Global South, as as indicated by various studies (Global Carbon Budget, 2023 – with major processing by *Our World in Data*).

The costs of switching suppliers are multiplicative factors of the expected price, as modeled in Equation 4.38; they are set in accordance with the structural estimation of Monarch (2022), who found that it is 48.6% more expensive to switch to a supplier in a different country. Moreover, asymmetric information in the intermediate goods market limits the subset of possible suppliers, W, which are visited by D-firms in each round; this parameter is set such that each final good producers visit 20 U-firms (5% of the population of suppliers) per period, randomly selected from the northern and southern firms population. As a result, in the baseline scenario, 9.23% of D-firms, on average, switch suppliers in each period.

4.4.2 Baseline scenario

Figure 4.3 depicts the average time series of the Monte Carlo simulations, concerning intermediate quantities and overall emissions. The North is responsible, on average, for 47.26% of total intermediate goods production value added and 26.5% of the overall emissions[18]. As evidenced by real-world statistics (see Miroudot et al., 2009), the Global South is a net exporter of intermediate goods, supplying an average of 25% of the intermediate goods requirement of the Global North[19]. In line with the results of Helpman et al. (2004), only more productive D-firms outsource intermediate goods production to foreign suppliers. Firms outsourcing decisions determine international flows of intermediate goods. This results in the establishment of the global production network, which

[18]According to the “International Yearbook of Industrial Statistics” (2024) provided by UNIDO, high-income industrial economies, predominantly located in Europe and North America, were responsible for 47% of the global manufacturing value added in 2023 and 23.5% of CO_2 emissions in 2021.

[19]According to the “Information Note on trade in intermediate goods: second quarter of 2023”, provided by WTO Economic Research and Statistics Divisions, Europe and North America import 25% of their intermediate goods from low-income countries.

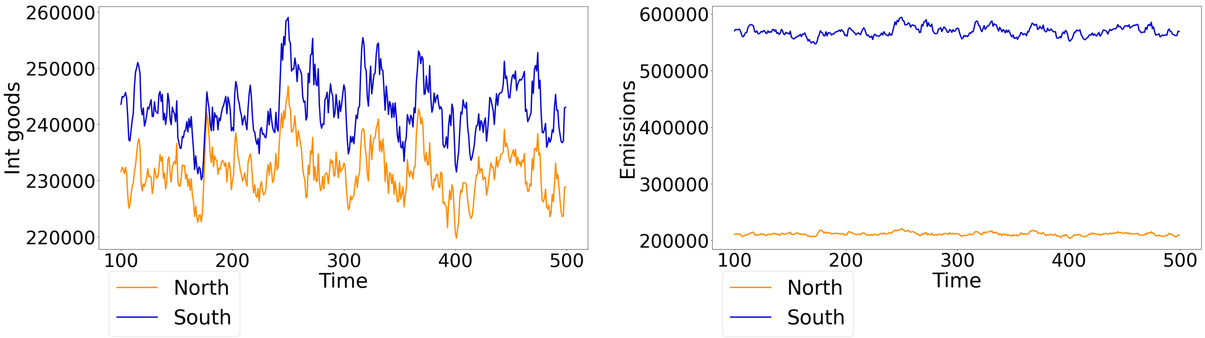


Figure 4.3: Aggregate intermediates and emissions in the baseline scenario.
Note: Time series are computed as the average of 100 MC simulations, net of the initialization phase (first 100 rounds).

evolves according to firms' and countries characteristics. Similar to Gualdi and Mandel (2016), competition among firms in the intermediate goods market leads to the emergence of a complex network in which numerous small-degree nodes coexist with few highly connected hubs. The out-degree and out-strength distribution of upstream nodes displays heavy-tailed behavior (Figure 4.4, left panel), with a power-law exponent ranging from $\alpha = 1.68$ to $\alpha = 2.40$, broadly in line with empirical evidence from real-world production networks reporting exponents below 2 for both out-strength (tail exponent closer to 1) and out-degree (see Lafond et al., 2023 for a detailed analysis of real-world production networks). However, statistical comparison using the Kolmogorov–Smirnov test indicates that a log-normal distribution provides a better fit[20]. The kernel density estimate of link weights (Figure 4.4, right panel) confirms a right-skewed distribution - as recorded in the literature (see, for instance, Bernard et al., 2022) - pointing to a predominance of low-weight connections and the presence of a limited number of strong ties. This suggests the presence of heterogeneity in the strength of firm-to-firm links, possibly reflecting the emergence of key trading relationships and dominant suppliers.

4.4.3 Asymmetric climate policy

The two groups of countries are characterized by different available emitting technologies. The rationale behind this assumption is the empirically observed phenomenon of substantial cross-country differences in pollution emission rates (Copeland et al., 2022). Therefore, we assume that the North can access a greener technology which entails lower per-unit emissions: $\epsilon^n < \epsilon^s$. In the absence of climate policies, the level of technology determines total emissions without affecting relative costs and altering the international fragmentation of production.

The introduction of a carbon tax in the Global North is now assessed. As a result of the asymmetric climate policy introduced in $t = 200$, U-firms located in the North face

[20]Notice that a log-normal distribution of node strengths were detected by Fagiolo et al. (2010) for the country-level trade network.

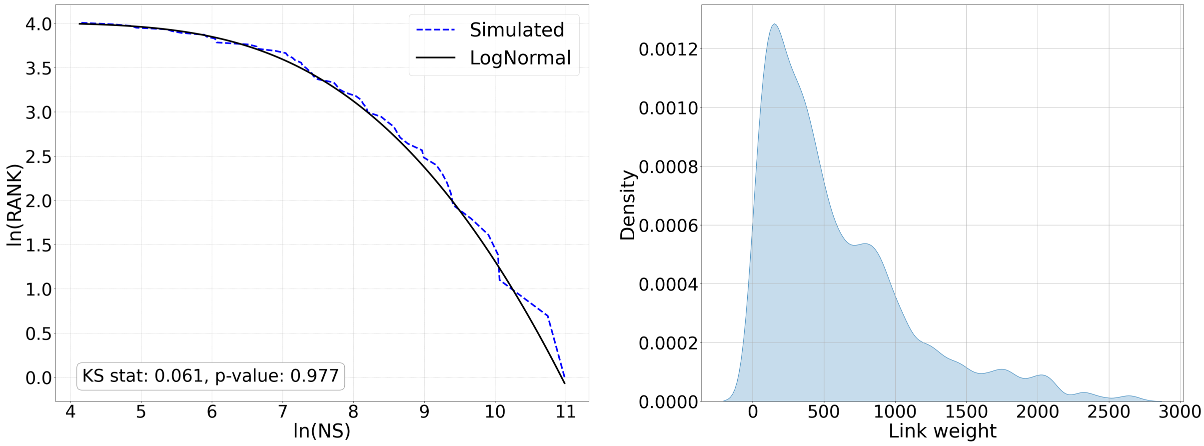


Figure 4.4: Supply network characteristics.
Note: Node strength (NS) (left panel) and link weights distribution (right panel) of the supplier-buyer network for one representative simulation.

an additional cost tied to the emissions generated in the production process, such that $z^n = 0.3 > z^s = 0$, as described in Equation 4.28.

In the wake of the asymmetric climate policy (Figure 4.5), intermediate goods production in the North declines, along with the share of active upstream firms. However, not all final goods producers change suppliers. Although D-firms would attempt to relocate production in the South, their choice of supplier is constrained by the limited subset of upstream firms visited in each round. Additionally, switching suppliers entails costs, and the tax may not be high enough to outweigh the costs of establishing new supply relationships and the productivity differentials. The presence of switching costs and bounded rationality in the matching process hinder the identification of the most efficient producers, resulting in a sub-optimal reorganization of the production network and contributing to a further output contraction.

Some highly productive suppliers in the abating country remain active, since differences in productivity among upstream firms - and hence prices of intermediate goods - partially offset the tax burden. The productivity threshold for market entry rises after the introduction of the tax, leading to a restructuring of the sector: only the most productive (and least polluting) firms in the abating country survive. The redistribution of market shares from brown (less productive, and thus more polluting) firms to more productive and greener firms is a key factor in the improvement of the aggregate emission intensity of the northern upstream sector. This *selection effect* reduces emissions intensity in the North (-8.06%). Conversely, narrowed competition from foreign suppliers lowers the productivity threshold in the South, allowing less productive firms to enter the market. This *"negative" selection effect* in the South mitigates the reduction in emissions intensity in the North and worsens the overall environmental impact of the policy, with the emission intensity of global production increasing by 31.41%. Thus, the reallocation of market shares toward less efficient upstream producers in the South, combined with higher production costs in the North due to the carbon tax, leads to an increase in intermediate goods prices in both regions. This contributes to higher overall inflation, which in turn exacerbates the economic downturn. Cost-pushed inflation triggers a recession, leading to a decline in labor demand as a result of reduced production capacity. This finding is consistent with the results of Fierro et al. (2024), who show that, in the absence of tax revenue redistribution, stringent carbon taxation has regressive effects, raising unemployment and reducing the labor share of income.

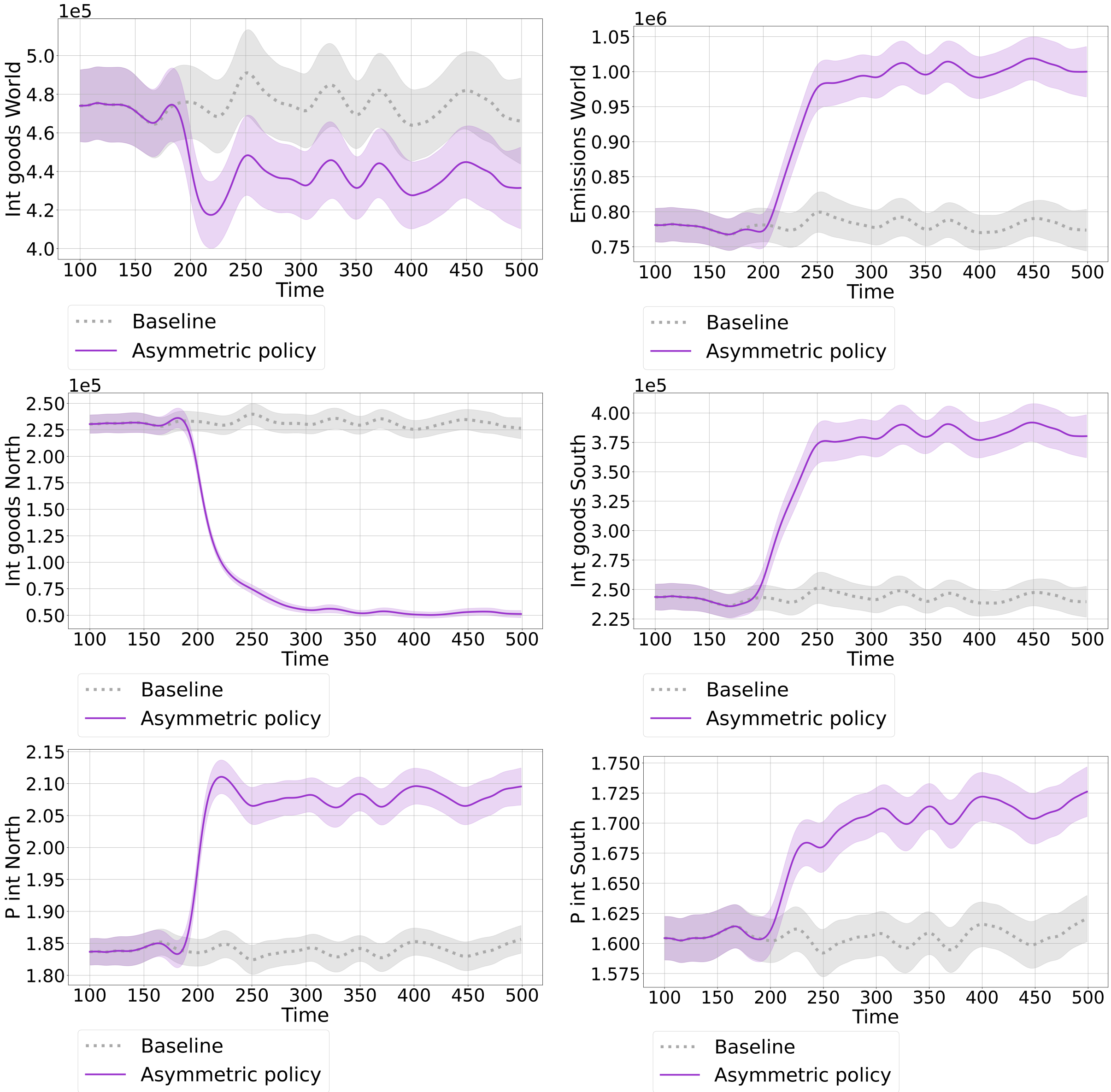


Figure 4.5: HP-filtered time series with and without asymmetric climate policy.
Note: We run 100 Monte Carlo simulations and compute the average time series. The resulting time series (with 95% confidence bands) have been filtered through the HP filter, to isolate the trend component. Afterwards, policy outcomes (solid line) have been compared with the baseline scenario (dashed line). Global intermediate goods production (Int goods world) decreases by 8.96%; Overall emissions increase by 25.19%. Intermediate goods production decreases by 72.88% in the North and increases in the South (+52.96%). The average price of intermediate goods increases both in the North (+13.13%) and in the South (5.96%). Any discrepancy between the two lines prior to $t = 200$ (when the policy is introduced) is due to the filtering procedure.

All in all, the implementation of a unilateral carbon tax results in an inefficient outcome: the acting country bears the economic cost of the policy, while environmental quality deteriorates at the global level. In fact, total emissions increase. Although less efficient and more polluting suppliers are excluded from the abating country, higher production costs in the North lead to the outsourcing of intermediate goods production to regions with more lenient environmental regulations. This results in carbon leakage, as the abating country increases imports of emission-intensive goods from the non-abating region.

The potential for environmental degradation is contingent upon the flexibility of the supply chain. Figure 4.6 illustrates the leakage rate (as defined in Equation 4.30) associated to different levels of switching costs and carbon taxes. Consistent with the literature (see, e.g., Fontagné and Schubert, 2023), low level of carbon pricing results in limited leakage for all level of flexibility of the supply chain. As taxation rises, downstream firms are more likely to outsource polluting activities to suppliers in the South. This, in turn, results in a significant increase in overall emissions and more severe economic downturn. At the same time, the impact of switching costs on carbon leakage becomes evident: for any given tax level, leakage decreases as the production network becomes more rigid. Interestingly, however, it does not decrease monotonically with switching costs but it is higher at intermediate levels of supply chain flexibility.

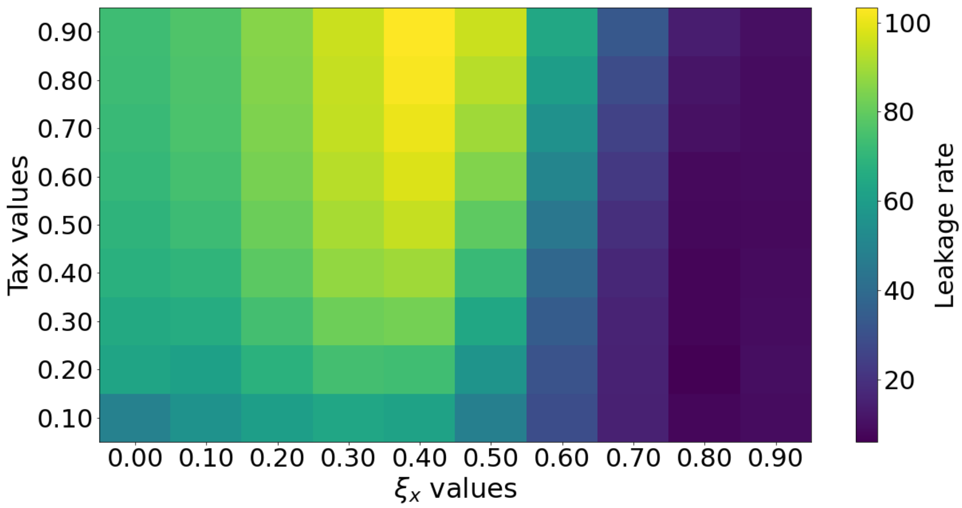


Figure 4.6: Interplay between supply chain stickiness and asymmetric carbon taxes.
Note: We simulate the model under various degree of flexibility of the supply chain, i.e. level of switching costs (ξ_x), and different asymmetric policies, i.e. value of the carbon tax, z. For each combination in the ξ_x - z plan, we take the average of 100 MC simulations, isolate the trend through the HP filter and compute carbon leakage as the change in emissions in the South with respect to the change in emissions in the North, after the introduction of the policy.

In order to more accurately assess the interaction between supply chain rigidity and carbon taxes, it is necessary to undertake a more detailed investigation of the cases in which the tax leads to a non-linear relationship with switching costs. Figure 4.7a depicts the percentage rate of change of main aggregate variables in different scenarios connected to various degree of flexibility of the supply chain, given a level of the tax $z = 0.6$. In the absence of switching costs ($\xi_x = \xi_c = 0$), D-firms transfer the demand for intermediate goods to suppliers located in countries with less stringent environmental regulations - the South - without facing the penalties associated with the withdrawal from current supply contracts. Consequently, overall production is less affected than it would be in a situation in which supply chains are rigid (higher values of ξ_x and ξ_c). In the latter case, firms are required to either bear the costs of switching or pay the increased costs associated with climate policy implementation. As a result, in both instances, firms face higher production costs and aggregate economic activity declines. Supply chain stickiness has, indeed, the potential of reducing the environmental impact of carbon leakage, but it also carries the risk of exacerbating economic downturns at the global level. On the contrary, for the abating country, a sticky production network is delivering the best outcome, with limited economic losses.

Despite the mitigating effect on total output, when production networks easily adapt to shocks, uncoordinated climate policies have a detrimental effect on the environment, through leakage. In this scenario, we detect, indeed, an increase in overall emissions, with the reduction of pollution generated in the North being completely offset by an increase in polluting activity in the South. This leads to an increase of the overall emissions intensity of the system. As long as the supply chain is flexible enough to allow a rewriting of supply contracts in favor of firms in non-abating countries, carbon leakage determines the worsening of the environmental outcome. Conversely, when supply chains are rigid and it becomes prohibitively expensive to switch suppliers, D-firms remain with their domestic partners, absorbing the costs of the tax. This results in a reduction in GDP, which, in turn, contributes to a decrease in overall emissions. Even if the contraction in economic activity drives a reduction in overall emissions in the most rigid cases ($\xi_x = 0.8, 1$), the emissions intensity of the system is still higher than in the baseline scenario. In this case, the tax affects the *intensive margin* of trade rather than the number of active suppliers in both countries (*extensive margin*), and downstream firms with suppliers located in the abating country suffer from it, reducing their output and, in turn, the demand of intermediate goods, in favor of firms with suppliers located in non-abating countries. In intermediate cases, supply chain rewiring occurs only when it leads to a productivity gain; hence, D-firms will incur the cost of switching suppliers only if the new supplier visited is more efficient. On the one hand, this leads to a restructuring of the sector in favor of more productive suppliers. On the other hand, some firms remain locked into existing supply relationships with U-firms located in abating countries. The combination of these two effects results in a smaller reduction in emissions from the North, thereby increasing the leakage rate (the numerator of Equation 4.30 shrinks).

Asymmetric information in the search and matching process contributes to a complex relationship between the flexibility and the economic and environmental outcomes of the policy. When switching costs are low, firms reallocate demand sub-optimally to avoid the tax, even if new suppliers are less efficient. This results in both lower output and higher

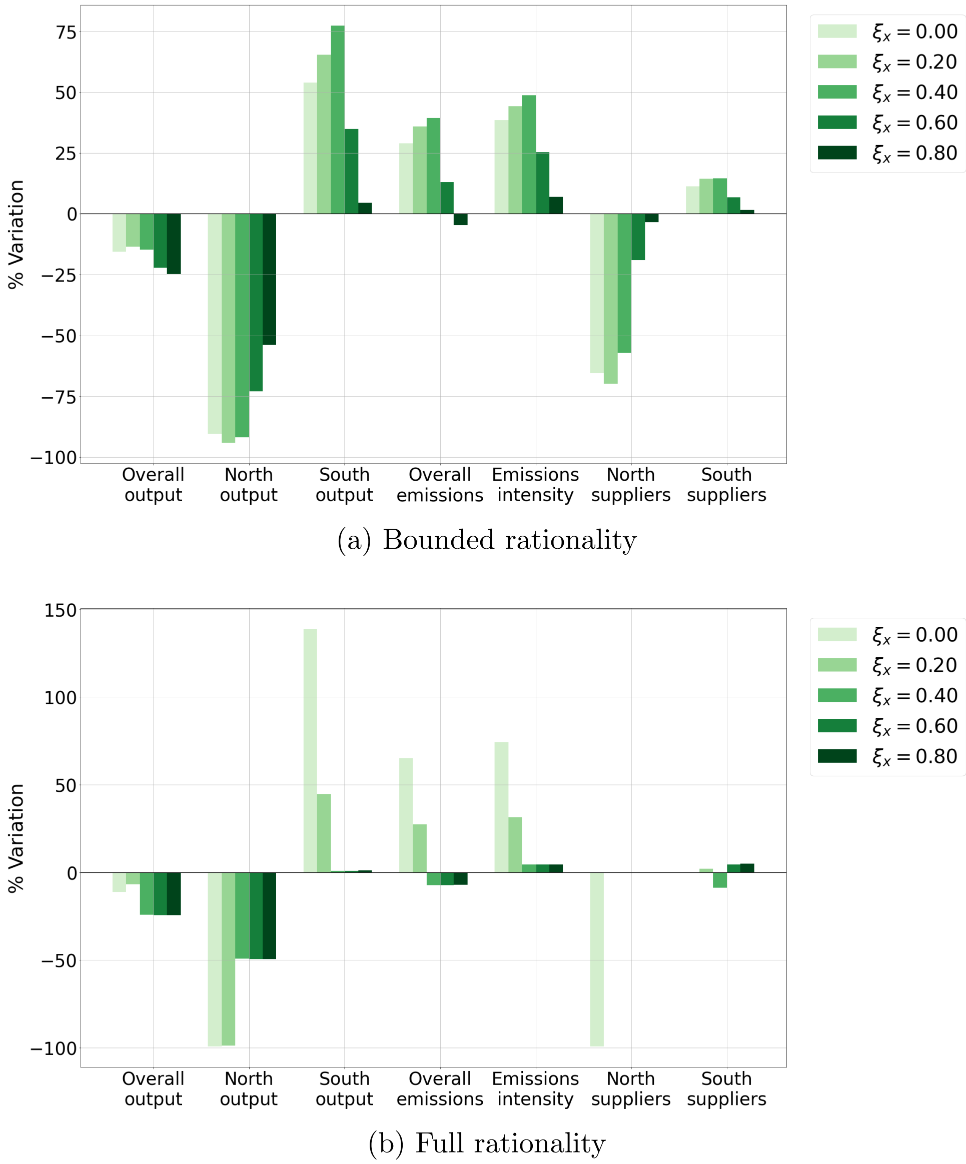


Figure 4.7: Interplay between supply chain stickiness and asymmetric climate policies.
Note: We simulate the model under various degree of flexibility of the supply chain, i.e. level of switching costs (ξ_x). In each scenario, we take the average of 100 MC simulations, isolate the trend through the HP filter and evaluate the effects of the same tax ($z = 0.6$) introduced at $t = 200$, by computing the percentage deviation from the baseline scenario.

emissions intensity. As switching costs increase, reallocation becomes more selective, occurring only when efficiency gains outweigh the costs of switching. However, when the network becomes too rigid, firms lose this adaptability and the full tax burden translates into deeper economic losses. In order to appreciate the role of bounded rationality, in Figure 4.7b, we replicate the same experiment, under the assumption that D-firms visit all the possible suppliers in each round. In this case, in the absence of switching costs, the intermediate goods market collapses to a monopoly, in which just one supplier in each country serves the whole economy. When the tax is introduced and supply chains are utterly flexible, all D-firms outsource the intermediate goods production to the South, so that the reduction in emissions in the abating country is completely compensated by a corresponding increase in emissions abroad. Since there are no costs involved and firms are able to select the most efficient supplier, output is not affected by the tax while the environmental outcome is detrimental. Then, when supply chains are rigid but firms are fully rational, they can directly choose the best supplier, without wasting resources on sub-optimal options or settling for locally optimal matches during the restructuring of the production network. In this case, the economy exhibits a limited economic loss which is either due to the costs paid to rewrite supply contracts or the tax burden.

These findings highlight how our modeling approach departs significantly from standard CGE frameworks. In particular, two key features, such as heterogeneity and bounded rationality, play a crucial role in shaping the relationship between supply chain rigidity and environmental policy outcomes. First, firm heterogeneity amplifies the competitiveness channel of carbon leakage. As shown by Balistreri and Rutherford (2012), a heterogeneous-firms model à la Melitz can lead to substantially higher estimates of carbon leakage in CGE models. Second, bounded rationality plays a pivotal role in our framework, as downstream firms are not assumed to operate under full information when searching for alternative suppliers, i.e. they visit only a subset of the population. This introduces matching frictions in the supply chain that, together with switching costs, influence the relocation of polluting activities. Certain combinations of carbon prices and switching costs allow for dynamic and time-lagged rewiring of production links, which is inherently excluded from standard CGE models. This endogenous adjustment mechanism enables firms to adapt to the policy shock in a non-linear way, sometimes mitigating the adverse effects of the tax through reallocation - although often at the cost of increased emissions abroad.

In conclusion, our analysis shows that carbon leakage consistently undermines the effectiveness of asymmetric climate policies, as it results in a reduction of output for the abating country alongside an increase in the emissions intensity of the economy.

While empirical evidence on carbon leakage remains mixed, our simulated model delivers results that are qualitatively consistent with ex-ante predictions. Namely, estimates of carbon leakage rates ranges between 5% and 30%, depending on modelling assumptions and the sector considered (see, among others, Branger and Quirion, 2014, King and van den Bergh, 2021, Fontagné and Schubert, 2023). In our model, estimated leakage rates are higher, due to bounded rationality, supply frictions, and the absence of a green energy substitute. This is in line with findings from highly fossil-intensive sectors. For example, in the cement industry - characterized by high CO_2 emissions and limited substitution possibilities - carbon pricing has been estimated to induce an increase of the emissions intensity of non-abating countries up to 20% (Demailly and Quirion, 2008) or even 70% when regional heterogeneity and complex production systems are taken into account (Ponssard and Walker, 2008). In sum, the unilateral carbon tax induces a reallocation of intermediate production toward the non-abating country. The direction of change aligns with standard leakage theory, but the magnitude and non-linear pattern depend crucially on network frictions and bounded rationality, which generate realistic inertia and selection effects absent in aggregate models.

4.4.4 Green alternative

Here we examine how the results change if we account also for a green, low-carbon energy alternative, such as renewable energy, being available. This will make the model more realistic and possibly avoid extreme outcomes, in terms of outsourcing and carbon leakage. We therefore consider a scenario in which U-firms can substitute fossil fuels with green energy. We assume that energy sources are exogenously supplied, and firms combine them with labor in a nested CES production function, where energy options are introduced at the lowest level (detailed in Appendix 4.5). In the short run, and absent endogenous learning dynamics, renewable energy is assumed to be more expensive than fossil fuels, due to higher fixed costs and the lack of mature infrastructure, as discussed in Emmerling et al. (2016). In particular, green energy is assumed to be 2% more expensive in the North and 7% in the South. The assumption that green energy remains relatively more costly is also consistent with empirical evidence from Köveker et al. (2023), who document that green inputs still carry a persistent "green premium" compared to carbon-intensive alternatives. This setup allows us to assess to what extent a carbon tax can induce a shift toward greener inputs, even in the absence of a fully modeled green transition.

To capture sectoral differences in energy substitutability, we consider two scenarios: one featuring a high elasticity of substitution (elasticity ¿ 1) between fossil and green energy source and another one with limited substitutability (elasticity ¡ 1). Aggregate outcomes for both configurations are presented in Figure 4.8.

In the high substitutability case, the carbon tax reduces demand for fossil fuels, thereby lowering emissions in the abating country and increasing the relative use of clean energy. Crucially, this reallocation occurs via input substitution within existing production structures, rather than through firm exit or entry. The availability of a green energy alternative also mitigates the recessionary impact of the carbon tax in the abating country and reduces the extent of carbon leakage. These mitigating effects would likely be even stronger in a dynamic framework where green technologies evolve endogenously and support the expansion of green industries, as argued by Bücker et al. (2025).

However, even when allowing for a green substitute, global emissions increase relative to the baseline, though less so than in the case without low-carbon energy options (Section 4.4.3). This occurs because upstream firms still rely on fossil fuels, though to a lesser extent, making production more costly in the North and inducing downstream firms to shift activities to non-abating regions.

We then contrast these findings with a scenario characterized by low substitutability across energy sources (elasticity ¡ 1), which captures sectors that remain highly dependent on fossil fuels and exhibit limited potential for input substitution. Consistent with expectations, when northern firms face stronger technological constraints and cannot readily adjust their production structures in response to the carbon tax, the adverse economic effects intensify, resulting in greater outsourcing of carbon-intensive activities and an overall increase in the emission intensity of the system.

Notice that, similar results hold even when considering a declining relative price of renewables - a trend anticipated by Way et al. (2022). A scenario with a similar cost of green and brown energy sources is presented in 4.5. In this case, the economic effects of the asymmetric carbon price are milder, yet some production relocation still occurs, as the energy mix continues to depend partly on fossil fuels.

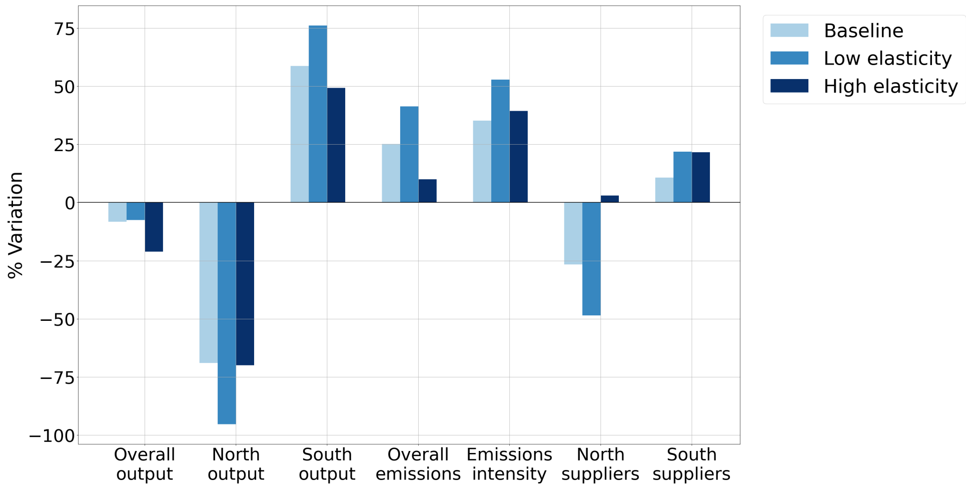


Figure 4.8: Aggregate outcome with a green input alternative.
Note: We simulate the model with different values of the elasticity of substitution between fossil fuels and renewable energy: no substitution (baseline model presented in section 4.4.3), low elasticity ($\sigma_{ue} = 0.5$), and high elasticity ($\sigma_{ue} = 2$). For each scenario, we run 100 Monte Carlo simulations, compute the average time series, and apply the HP filter to extract the trend component. We then report the percentage deviations of the filtered series from the baseline scenario following the introduction of the climate policy ($z = 0.3$).

4.4.5 Border carbon adjustment mechanism

We now assess how the border carbon adjustment (BCA) mechanism interacts with asymmetric climate policies. Hence, we assume that the abating country - the North - adopts a border tax on the carbon content of imported goods, with the objective of safeguarding domestic production. This measure is designed to achieve a level playing field for competition by aligning the carbon price paid by importers with the price paid by domestic firms. The BCA is adopted after 100 rounds [21] following the implementation of the national carbon tax, at $t = 300$.

Thus, U-firms in the Global South will pay an extra fee when the BCA is implemented by the abating country. The amount of the carbon tax paid by U-firms will be

[21] This modeling choice is motivated by the need of appreciating the effectiveness of the BCA in mitigating the loss of competitiveness of the abating country; otherwise, we could have also implemented the climate policy coupled with the BCA and evaluate their joint effect.

different depending on the actual implementation of the BCA. If the border adjustment is firm-specific (*first scenario*), each firm will be levied by an amount which is directly proportional to their actual level of emissions. As opposed, in case of a BCA targeting a benchmark level of emissions (*second scenario*), every U-firm will pay the same amount, notwithstanding their level of efficiency.

If countries can collect information regarding the carbon content of imported goods (*first scenario*), the BCA is implemented as described in Equation 4.35 and main aggregate results are summarized in Figure 4.9. The border carbon tax succeeds in restoring abating country's competitiveness, whose activity goes back to almost the baseline scenario, to the detriment of aggregate output in the South. All in all, the system records a severe economic downturn, with a contraction of real output due to higher intermediate goods prices in all the regions (Figure 4.9). Higher import costs trigger a reorganization of the production network, which adjusts to the increase in global prices. In the South, the productivity threshold for market entry rises, as only the most productive and greener suppliers remain competitive. This selection effect translates into a decline in the fundamental price index, i.e., the price level prior to the carbon tax. Conversely, the aggregate productivity of Northern suppliers declines, resulting in a higher average price index and in increased prices for outsourced inputs from the non-abating country. Consistent with the findings of Coster et al. (2024), the BCA induces northern D-firms to reshore carbon-intensive production, thereby reducing their international competitiveness and ultimately raising the prices faced by domestic households. The recession drives down overall emissions. However, pollution decreases more than output, with the overall emissions intensity of the system also declining with respect to the baseline scenario for all levels of flexibility of the supply chain (Figure 4.10). This is due to the fact that most of the U-firms in the South, which are, by assumption, more polluting-intensive than their counterparts in the North, are excluded from the market. The enhanced competitiveness of the North, and the resulting improvement in environmental outcomes, have been made possible by significant costs borne primarily by the South. According to Beaufils et al. (2023), low and middle income countries - the Global South - are disproportionately affected by the BCA, as they mostly rely on exports to developed countries - the Global North.

As discussed in Section 4.3.3, the carbon border tax faces several challenges. In terms of actual implementation, a firm-specific BCA would require full disclosure on the emissions technologies adopted in foreign countries and on the energy efficiency of each firm. This information may not be available for some agents which can - either purposely or due to its cost and complexity - decide not to report the emissions generated in their production process. In this case, abating countries may opt for a border tax aimed at covering the average emissions intensity of specific goods. Although this alternative may appear easier to implement, the challenge lies in identifying an appropriate benchmark.

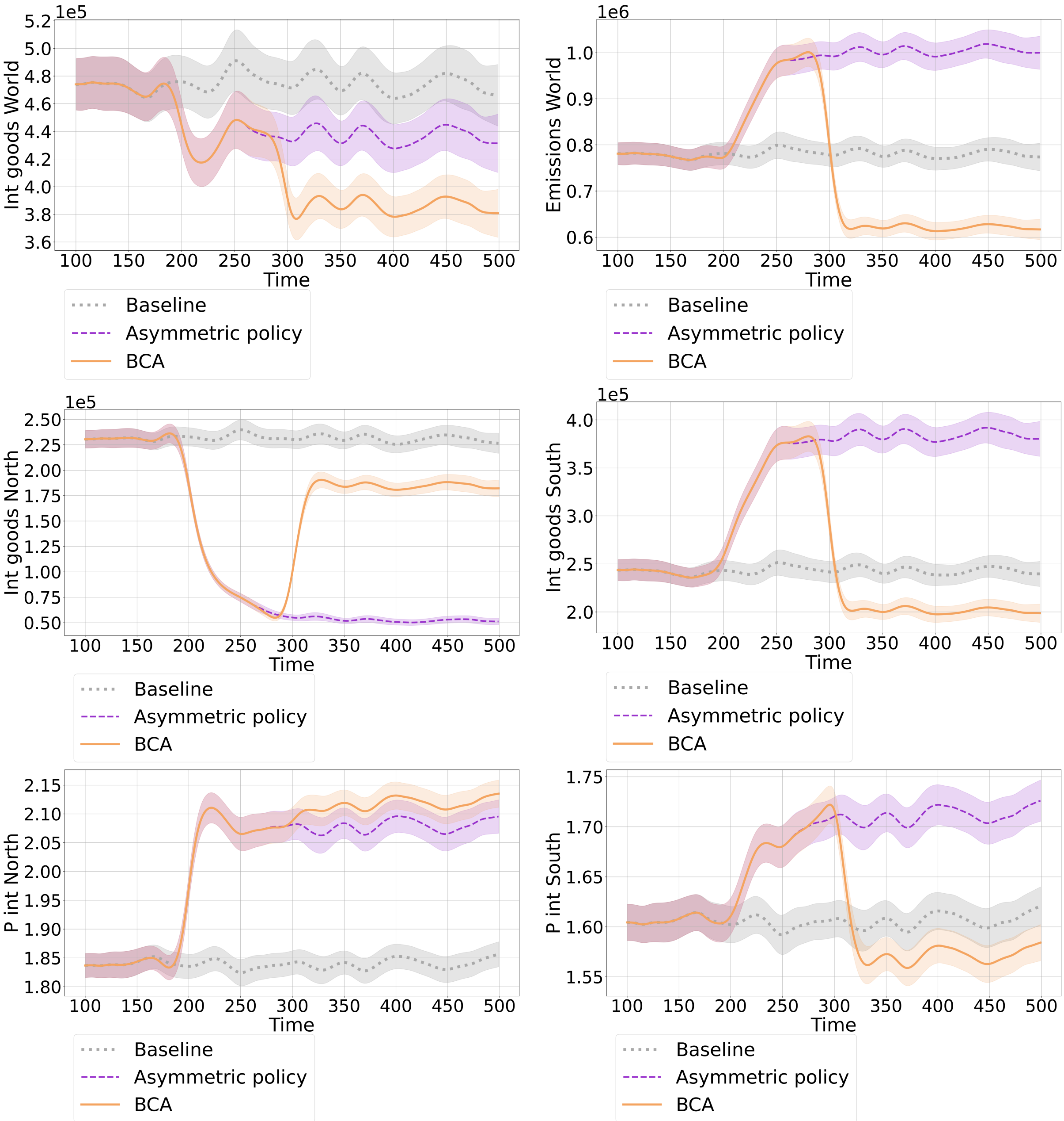


Figure 4.9: HP-filtered time series with and without BCA.
Note: We run 100 Monte Carlo simulations and compute the average time series. The resulting time series (with 95% confidence bands) have been filtered through the HP filter, to isolate the trend component. Afterwards, BCA outcomes (orange solid line) have been compared with the asymmetric policy (dashed purple line) and baseline scenario (dotted gray line). Global intermediate goods production (Int goods world) decrease by 18.56% with respect to the baseline scenario, when BCA is implemented following the asymmetric carbon tax; overall emissions decrease by 19.75%. Intermediate goods production decreases by 21.35% in the North and 15.95% in the South. The average fundamental price of intermediate goods increases in the North (+15.03%) and decreases in the South (-1.66%). Any discrepancy between the lines prior to the introduction of the policies is due to the filtering procedure.

One can opt for the average emissions intensity of all intermediate goods producers in the whole economy or in a specific country. In both cases, simulations do not display significant differences with respect to the firm-specific scenario in terms of effectiveness of the policy and its aggregate outcomes. Suppliers from the South are excluded from the market since the cost borne for the pollution generated by their available technology is prohibitively high, rendering them unable to compete with firms in the North.

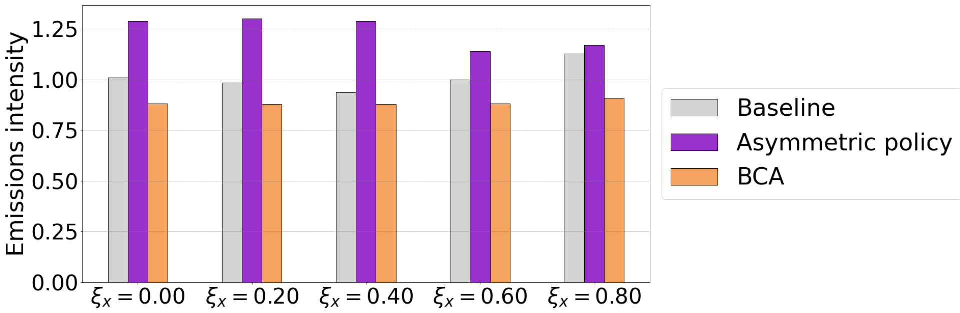


Figure 4.10: Emissions intensity in the three scenarios.
Note: We simulate the model under various degrees of flexibility of the supply chain, i.e. level of switching costs (ξ_x), in the three scenarios (baseline, asymmetric policy, BCA). For each of them, we compute the time series as the average of 100 MC simulations, isolate the trend through the HP filter and quantify the emissions intensity of the system as total emissions over output. Colors are associated with different scenarios: baseline (gray), asymmetric policy (purple) and BCA (orange).

Interestingly, when the benchmark is set to the emissions intensity of the abating country - which is also, by assumption, endowed with the cleanest technology - the BCA appears to be less inequitable for the South (Figure 4.11). While aggregate outcomes, in terms of GDP and overall emissions, remain largely unchanged - with a slight worsening of the economic condition of the North - some highly productive suppliers continue to operate in the South, as the costs associated with this benchmark are lower than those incurred in the firm-specific case. Consequently, the emissions intensity is higher than in the firm-specific BCA scenario but remains below the baseline. This is in line with the prediction of Bellora and Fontagné (2023). A conservative scenario, in which the basis for the BCA is the average emission intensity of the acting country, has limited impact on overall emissions with respect to a country-specific scenario[22].

These results are important in light of the intrinsically protectionist nature of the BCA; quantifying its competitiveness impacts under different policy designs is, indeed, central to identify which strategy leads to the most desirable outcome.

4.5 Conclusion

Climate change is a global challenge that requires coordinated action for effective mitigation. However, the geopolitical landscape remains highly diverse, with nations adopting heterogeneous levels of commitment in their fight against climate change. Our analysis shows that uncoordinated climate policies not only fall short to effectively address the problem but can also lead to counterproductive outcomes.

In particular, this paper evaluates the effects of asymmetric climate policies on the international fragmentation of production and the role of trade measures, such as the Border Carbon Adjustment (BCA) mechanism, in handling the competitiveness losses

[22] Notice that Bellora and Fontagné (2023) considers average emission intensity of the sector instead of a firm-country specific BCA as we did.

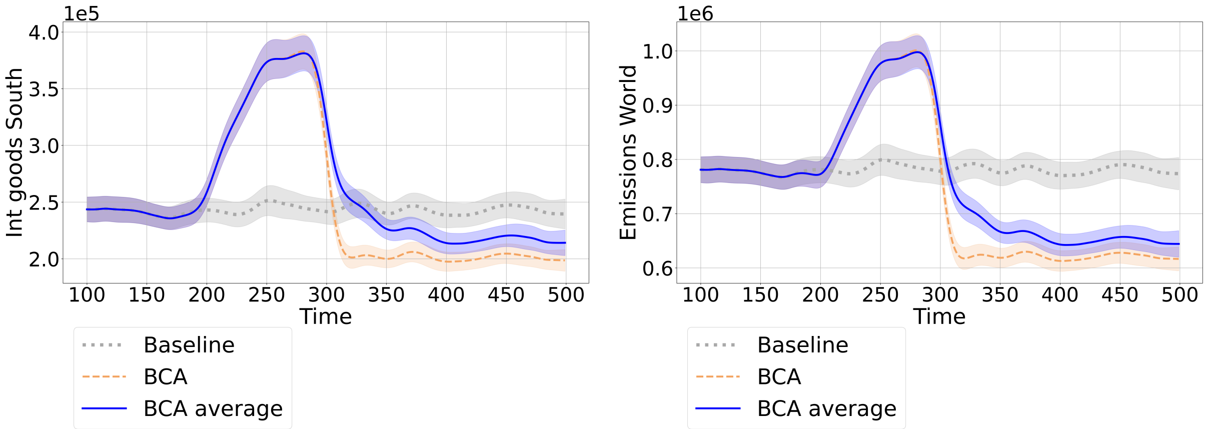


Figure 4.11: HP-filtered time series when the BCA is implemented targeting a benchmark. *Note*: We run 100 Monte Carlo simulations and compute the average time series when the abating country introduces an average BCA, i.e. targeting the average emissions intensity, at t=300. The resulting time series (with 95% confidence bands) have been filtered through the HP filter, to isolate the trend component and results of the experiments (blue solid line) are compared to the firm-specific BCA (orange dashed line) and the baseline (gray dotted line). With respect to the baseline scenario, intermediate goods production in the South decreases by 6.33%. Overall emissions are lower than in the baseline (-14.17%).

these policies can cause. To this end, we propose an agent-based model on the establishment of the global production network, focusing on firm-to-firm links. Although the stylized supply chain reproduced by our model captures some properties observed in real-world production networks, characterized by a fat-tail distribution of nodes degree and links, it does not account for other structural features such as core-periphery organization, community structure or the existence of a giant weakly connected component (see, e.g., **?**), with important implications for indirect propagation of losses. Nonetheless, the main contribution of the paper is to offer a granular view on micro-level decisions that underpin the emergence of aggregate outcomes. A bottom-up approach to understand the functioning of supply chains is, indeed, pivotal to navigating the transition towards a carbon-neutral economy, which will inevitably affect relationships among firms.

Our simulations reveal that non-harmonized carbon pricing results in a reorganization of production networks that leads to inefficient outcomes. The abating country faces an economic downturn due to reduced international competitiveness, while carbon leakage, through the relocation of polluting activities to foreign countries, undermines the environmental goals of the policy. Even though the extent of leakage is contingent upon the characteristics of the supply chain and the policy, emissions intensity of the economy is always deteriorating.

Border carbon adjustment mechanisms are a necessary component of asymmetric climate policy in order to ensure their competitiveness and efficacy; nonetheless our results suggest that they come at economic (and social) costs that should not be underestimated. Carbon taxes influence, indeed, production costs and consumers prices, in turn affecting firm profits and income. At this point, it is worth highlighting that inflationary pressures may arise not only from supply-side disruptions caused by extreme weather events, but also from the policy tools designed to mitigate them. The paper shows, indeed, that non-harmonized climate policies and the mechanisms implemented to cope with them (namely the BCA) are likely to increase production costs, which, in turn, cause an inflationary pressure that stifles economic activity. This emphasizes the need for monetary policy objectives to be reassessed in light of the challenges posed by climate change.

We acknowledge the limitations of our model, which offers a simplified representation of the production network without incorporating a full input-output structure. Featuring a dyadic supply chain, the model is limited in mimicking the cascade effects that have been shown to be a salient characteristic of modern intertwined economies and a crucial amplification mechanism of shocks. We instead focus on the direct effects of asymmetric climate policies, leaving more in-dept analysis of the indirect consequences of such shocks to future research. However, by focusing on disaggregated firm-level behavior, we capture important insights into how non-harmonized climate policies affect firms in a context characterized by bounded rationality.

In addition, the model abstracts from the possibility of an endogenous green transition, in which firms progressively shift toward cleaner production processes. Although we include a scenario with a low-carbon alternative to fossil fuels, energy sources are treated as exogenous. As a result, the model does not capture potential feedback mechanisms in the energy market, and the aggregate effects of asymmetric climate policies may appear more persistent than they would under a setting with endogenous technological adaptation. This limitation may therefore overstate the long-term costs of climate policies, particularly in scenarios where the costs of adopting clean technologies continue to decline rapidly.

A related limitation concerns the treatment of carbon tax revenues, which are not explicitly reinvested in the model. Channeling these revenues toward the diffusion of low-carbon technologies could substantially alter the results, mitigating carbon leakage and reducing global environmental pressures through cleaner production worldwide. Moreover, as discussed, among others, by Konc et al. (2022), Fierro et al. (2024), and Lamperti et al. (2024), carbon tax revenues can also ease the macroeconomic and distributional burden of climate policies.

Acknowledgments

The authors are grateful to two anonymous referees for their useful comments and suggestions. They thank all the participants of the *27th Annual Workshop on Economics with Heterogeneous Interacting Agents (WEHIA)* and the *EPOC International Conference* for their valuable comments.

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Appendix

Conditional demand of inputs with carbon tax

This section provides the analytical derivation of the conditional demand of inputs under asymmetric climate policies (Equations 4.25 and 4.26).

Consider an upstream firm j in country l that produces intermediate output $x_{j,t}$ employing labour $l_{j,t}$ and fossil fuel $f_{j,t}$ through a CES production function, as described in Equation 4.14. The firm faces input unit costs, w^l and p_f^l, and (domestic) per-unit carbon tax z^l on emissions, that are proportional to fossil fuel use, as in Equation 4.23. Thus, the per-unit price of fossil fuel is: $p_{lf} + z_l\varepsilon_l$. The firm's (operational) costs are:

$$C_{j,t} = \left(w^l\, l_{j,t} + \left(p^l f + z^l \varepsilon^l\right) f_{j,t}\right) \tau^{lk}.$$

The firm solves a cost minimization problem (as described in **?**) for a given output $x_{j,t}$:

$$\min_{l_{j,t},\, f_{j,t}} \quad \left(w^l\, l_{j,t} + \left(p_f^l + z^l \varepsilon_l\right) f_{j,t}\right)\tau^{lk} \quad \text{s.t.} \quad x_{j,t} \;=\; \varphi_{j,t}\left(\alpha\, l_{j,t}^{\rho_u} + (1-\alpha)\, f_{j,t}^{\rho_u}\right)^{1/\rho_u}. \tag{4.40}$$

The Lagrangian for the constrained minimization is:

$$\mathcal{L} \;=\; \left(w^l\, l_{j,t} + \left(p_f^l + z^l \varepsilon^l\right) f_{j,t}\right)\tau^{lk} \;+\; \lambda\left[x_{j,t} - \varphi_{j,t}\left(\alpha l_{j,t}^{\rho_u} + (1-\alpha) f_{j,t}^{\rho_u}\right)^{1/\rho_u}\right]. \tag{4.41}$$

By differentiating[23] $\mathcal{L}$ w.r.t. l, f and λ, we get the FOCs. From here, it is possible to write the marginal rate of technical substitution $MRTS_{l,f} = \frac{\partial x/\partial l}{\partial x/\partial f}$, equal to the input price ratio:

$$\frac{w_l}{p_{lf} + z_l \varepsilon_l} \;=\; \frac{\alpha}{1-\alpha}\,\frac{l^{\rho_u - 1}}{f^{\rho_u - 1}} \quad \Longrightarrow \quad \left(\frac{l}{f}\right)^{\rho_u - 1} \;=\; \frac{1-\alpha}{\alpha}\,\frac{w^l}{p_f^l + z^l \varepsilon_l}.$$

Combining the expression for the MRTS with the production constraint (third FOC) yields the conditional input demands.

Recalling that $\rho_u = \frac{\sigma_u - 1}{\sigma_u}$ and defining the input-bundle price index $\tilde{p}_j^l$ (the unit cost of producing one unit of the composite input) as:

$$\tilde{p}_j^l \;=\; \left(\alpha\,(w^l)^{1-\sigma_u} + (1-\alpha)\left(p_f^l + z^l \varepsilon^l\right)^{1-\sigma_u}\right)^{\frac{1}{1-\sigma_u}},$$

the conditional demands that minimize cost for producing $x_{j,t}$ are:

$$l_{j,t} = \left(\alpha \frac{\tilde{p}_j^l}{w}\right)^{\sigma_u} \frac{x_{j,t}}{\varphi_{j,t}}, \tag{4.42}$$

[23] For notational simplicity, we suppress subscripts j, t during the derivation and use l, f, φ, x instead.

$$f_{j,t} = \left((1-\alpha)\frac{\tilde{p}_j^l}{p_f^l + z^l\varepsilon^l}\right)^{\sigma_u} \frac{x_{j,t}}{\varphi_{j,t}} \tag{4.43}$$

where $\sigma_u > 0$ is the elasticity of substitution.
Notice that when $z^l = 0$, we get Equations 4.16 and 4.17.
The same procedure is applied to derive the conditional demand for inputs under the Border Carbon Adjustment (BCA). Consider the case of an upstream firm j in country l exporting to country k, where the carbon tax is higher ($z^k > z^l$). When the BCA is implemented, the firm faces an additional cost equal to the difference in carbon taxes, $\Delta_{lk} = |z^l - z^k|$, on the carbon content of exported goods, i.e. $\Delta_{lk}\varepsilon f_{j,t}\tau^{lk}$. Accordingly, the cost function becomes:

$$C_{j,t} = \left(w^l\, l_{j,t} + \left(p_f^l + (z^l + \Delta_{lk})\,\varepsilon^l\right) f_{j,t}\right) \tau^{lk}.$$

Solving the cost minimization problem as described above yields the conditional input demands reported in Equations 4.32 and 4.33. Notice that, the only difference relative to the scenario derived above, lies in the effective fossil-fuel price, which now includes the BCA adjustment $\Delta_{l,k}$.

Green energy and inputs substitution

In Section 4.4.4, we extend the baseline framework to account for substitution between energy inputs and assess how this modification alters the effects of the carbon tax. To this end, we model a nested CES production function, according to which U-firms employ labor and energy, which can come from brown (f) or green (g) sources. Accordingly, the production function of the j-th supplier reads as follows:

$$x_{j,t}^l = \varphi_{j,t}\left[\alpha(l_{j,t})^{\rho^u} + (1-\alpha)\left(\beta f_{j,t}{}^{\rho_e} + (1-\beta) g_{j,t}{}^{\rho_e}\right)^{\frac{\rho^u}{\rho^e}}\right]^{\frac{1}{\rho^u}} \tag{4.44}$$

Given the firm's cost-minimization problem, the firm chooses input quantities that minimize production costs subject to the production function. The corresponding conditional input demands are therefore derived as follows:

$$l_{j,t} = \left(\alpha\frac{\tilde{p}_{j,t}}{w^l}\right)^{\sigma^u} \frac{x_{j,t}}{\varphi_{j,t}}, \tag{4.45}$$

$$f_{j,t} = \left(\beta\frac{p_{j,t}^e}{p^f}\right)^{\sigma^e} \left((1-\alpha)\frac{\tilde{p}_{j,t}}{p_{j,t}^e}\right)^{\sigma^u} \frac{x_{j,t}}{\varphi_{j,t}}, \tag{4.46}$$

$$g_{j,t} = \left((1-\beta)\frac{p_{j,t}^e}{p^g}\right)^{\sigma^e} \left((1-\alpha)\frac{\tilde{p}_{j,t}}{p_{j,t}^e}\right)^{\sigma^u} \frac{x_{j,t}}{\varphi_{j,t}}, \tag{4.47}$$

where are the average prices of the input bundles are:

$$p^e_{j,t} = \left[\beta^{\sigma_e} \cdot (p^f)^{1-\sigma_e} + (1-\beta)^{\sigma_e} \cdot (p^g)^{1-\sigma_e}\right]^{\frac{1}{1-\sigma_e}}, \tag{4.48}$$

$$\tilde{p}_{j,t} = \left[\alpha^{\sigma_u} \cdot (w^l)^{1-\sigma_u} + (1-\alpha)^{\sigma_u} \cdot (p^e_{j,t})^{1-\sigma_u}\right]^{\frac{1}{1-\sigma_u}} \tag{4.49}$$

Parameters are calibrated to ensure consistency with the baseline model, such that, before the policy implementation, the cost of the energy bundle equals that in the original specification. The degree of substitution between fossil fuel and green energy has been chosen consistently with the assumption of Bosetti et al. (2006) and two different scenarios are tested.

Cost parity between energy sources

Empirical evidence shows that the prices of renewable technologies - such as solar, wind, and battery storage - have consistently declined over time and are expected to become increasingly competitive in the future (Way et al., 2022). To capture this trend, we rerun the model presented in Section 4.4.4, assuming cost parity between green and brown energy sources. The corresponding results are reported in Figure 4.12.

The qualitative patterns remain consistent with the baseline results. A lower price of green substitutes alleviates both the economic costs of the transition and the environmental consequences of carbon leakage. Although some production relocation persists, as the energy mix still partly relies on fossil fuels, the overall economic impact is milder, and environmental outcomes improve relative to the baseline scenario without energy substitution. Despite the reduced costs, asymmetry in carbon pricing continues to undermine both domestic competitiveness and global emission performance.

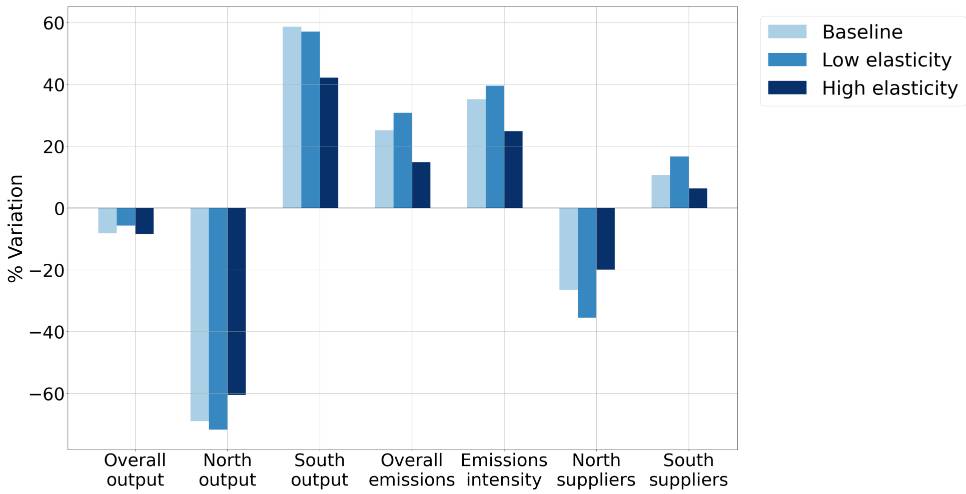

Figure 4.12: Aggregate outcome with a green input alternative and same price of energy sources.

Note: We simulate the model with different values of the elasticity of substitution between fossil fuels and renewable energy: baseline model (no energy substitution, section 4.4.3), low elasticity ($\sigma_{ue} = 0.5$), and high elasticity ($\sigma_{ue} = 2$). For each scenario, we run 100 Monte Carlo simulations, compute the average time series, and apply the HP filter to extract the trend component. We then report the percentage deviations of the filtered series from the baseline scenario following the introduction of the climate policy ($z = 0.3$).

Chapter 5

A network perspective on the environmental policy - trade nexus

5.1 Introduction

How do environmental policy asymmetries influence international trade patterns? This question lies at the core of the longstanding and contentious debate on the relationship between trade and the environment. In this dispute, two opposing views have emerged. According to the *Pollution Haven Hypothesis* (PHH, Copeland and Taylor, 2004), stringent environmental regulations raise production costs and lead firms to relocate pollution-intensive activities to countries with more lenient regulations. In contrast, the *Porter Hypothesis* (PoH, Porter and Linde, 1995) posits that well-designed environmental policies can stimulate innovation and productivity, thereby enhancing competitiveness in the long run and delivering beneficial effects from the interaction of trade and environmental policy measures. Which of the two hypotheses prevails has clear and important implications for climate policy design and the public support for more ambitious actions to protect the environment.

Empirical findings remain mixed (see Copeland et al., 2022 for a review). Some studies detect trade diversion consistent with carbon leakage postulated by the PHH, while others find no significant impact or even positive effects of environmental regulations on trade. One possible reason is that ambitious climate policies have only recently begun to be implemented, narrowing the availability of data on their long-term effects (Fontagné and Schubert, 2023). Another reason lies in the inherent limitations of traditional bilateral approaches, which tend to evaluate the effects of policies by looking only at direct country-pair relationships. In a highly interconnected global economy, however, these methods may fail to capture important systemic mechanisms, i.e. the indirect, economy-wide repercussions that policies in one country can generate through the structure of

[*]This chapter presents a research project that is complementary to Chapter 4, but still at an early stage of development. It has been developed at the Universitat Autònoma de Barcelona (UAB), under the supervision of *Prof. Ivan Savin* and *Prof. Jeroen van den Bergh*.

global trade linkages. Bilateral trade relationships are embedded within a complex network of interdependencies, where a change in one country's policy or economic conditions can propagate not only to its direct trading partners, but also to partners of partners, and further throughout the network. These are referred to as higher-order spillovers: indirect effects that occur beyond the immediate bilateral level, and which can significantly alter aggregate trade flows and the distributional impact of shocks. To address this limitation, this study revisits the trade–environment nexus through the lens of network analysis. We adopt a network-based approach that allows for a more structural assessment of how environmental policy stringency relates to international trade. As shown by Fagiolo (2010), network analysis provides a useful framework to analyze the higher-order architecture of trade flows, capturing indirect effects and systemic properties often neglected in standard models. Similarly, Reyes et al. (2008) and Aller and Ductor (2015) argue for the importance of network metrics to enrich our understanding of trade integration, going beyond what is observable through bilateral statistics. For instance, Reyes et al. (2008) show that structural network properties help explain the divergence in growth trajectories between High Performing Asian Economies (HPAE) and Latin American (LATAM) countries, an insight unattainable through standard trade indicators[2]. Moreover, recent theoretical advances, such as Chaney (2014), stress how shocks propagate through the trade network rather than solely affecting bilateral channels. This implies that a change in environmental policy in one country could alter trade patterns far beyond its direct trading partners. Network analysis thus provides two distinct advantages for addressing the trade-environmental policy debate: it enables to (i) detect structural shifts in countries' positions within the trade network, and (ii) capture spillover effects associated with policy asymmetries.

This study offers a preliminary attempt to investigate the relationship between trade and the environment through the lens of network analysis. The paper proposes an empirical exploration of how countries' position within the global trade network correlates with environmental policy stringency. Firstly, we construct the international trade network and trace its evolution over the last decades. The trade network is further disaggregated into two separate networks: one representing green flows, capturing trade between industries considered environmentally friendly according to the *U.S. Bureau of Labor Statistics*

[2]Notably, Reyes et al. (2008) show that greater openness to trade does not necessarily imply deeper integration into the global trade network, which is the key strategic feature of successful countries. In their analysis, HPAEs exhibited a more central and cohesive position in the trade network compared to Latin American (LATAM) countries, which helps explain their divergent growth trajectories. Beyond this specific example, the broader takeaway is that trade volumes in isolation (exports or imports) can not capture country's strategic importance within the global economy, which is the determinant of its economic performance. Growth opportunities are, indeed, shaped not only by how much a country trades, but also by how it is positioned within the network. Central countries enjoy preferential access to key markets, faster diffusion of innovation, and stronger integration into global value chains. These network-based advantages translate into greater resilience, faster technological upgrading, and ultimately higher growth potential.

(BLS) (definition of green jobs), and one encompassing brown flows, which include all other sectors. We then test whether the degree of environmental policy stringency exerts different effects on countries' centrality[3] and trade integration.

To benchmark our findings, we estimate a standard gravity model - the workhorse framework for analyzing international trade - which explains trade flows between country pairs based on their relative characteristics, such as economic size and bilateral frictions (see, among others, Anderson, 2011). We augment the model by including differences in environmental policy stringency between trading partners, in addition to the conventional macroeconomic variables, as determinants of trade flows. In particular, differently from the relevant literature, we account for directional asymmetry variables to assess whether the observed patterns are more consistent with the predictions of the *Pollution Haven Hypothesis* or the *Porter Hypothesis*.

This paper adopts an exploratory perspective, with the primary objective of establishing a network-based analytical framework to revisit longstanding questions in international economics, particularly the interaction between environmental regulation and trade flows. The proposed approach is designed to uncover indirect effects of climate policies, thereby providing a more comprehensive view of their implications for trade. The empirical specification controls for unobserved country characteristics and exploits the panel dimension of the data to mitigate concerns about time-invariant heterogeneity. Nevertheless, the analysis should be interpreted as correlational rather than causal. Endogeneity concerns remain, most notably the possibility of reverse causality between environmental policy stringency and a country's position in the trade network. For example, countries more integrated into global markets may face stronger pressures to adopt stricter environmental standards, while more stringent regulation may in turn reshape their trade integration. Ignoring this bidirectional relationship may bias estimates of the effects of environmental regulation on economic performance. Addressing such simultaneity and omitted-variable biases would require more advanced econometric strategies - such as instrumental variable approaches or regression discontinuity designs - which lie beyond the scope of this paper but represent a natural direction for future research.

The rest of the chapter is organized as follows. Section 5.2 reviews the related literature. Section 5.3 describes the database employed in the analysis. Section 5.4 presents the trade network and its evolution over time. Then we move to the core of the analysis, with Section 5.5 analyzing the correlation between environmental policy stringency and network position and Section 5.6 estimating a gravity model with environmental asymmetries. Section 5.7 concludes.

[3]Centrality is defined according to standard network metrics such as out-degree, betweenness, closeness, eigenvector centrality, which captures both direct and indirect connectivity by accounting for the importance of a country's trade partners. A definition of these measures is summarized in Table 5.8

5.2 Relevant literature

The relationship between environmental policy stringency (EPS) and international trade has been widely explored in the literature, yet findings remain mixed. Table 5.1 provides an overview of key contributions in this field, highlighting differences in data studied, coverage and proxies of environmental policy employed. A substantial number of studies rely on gravity models to assess how EPS shapes bilateral trade flows. Some works provide empirical support for the pollution haven hypothesis, suggesting that stricter regulations may push production toward countries with looser standards (e.g., van Beers and van den Bergh, 1997), while others report no statistically significant effect of environmental regulatory gaps on trade (e.g., Combes et al., 2014).

Few studies have extended the gravity framework to explicitly address endogeneity, often relying on structural models or instrumental variable approaches. For example, Jug and Mirza (2005) interpret stringent environmental policies as cost shocks and show that they tend to reduce export performance. Carrión-Flores and Innes (2010) estimate a simultaneous panel model to capture the bi-directional relationship between emission reduction and innovation, finding that innovation is a key driver of reductions in U.S. toxic emissions, while tighter pollution targets induce environmental innovation. Similarly, Rubashkina et al. (2015) adopt an instrumental variable strategy and report a positive effect of environmental regulation on innovative activity, in line with the "weak" Porter Hypothesis.[4] In parallel, research on trade in environmental goods (e.g., Cantore and Cheng, 2018) emphasizes how well-designed policy stringency can promote trade in clean technologies, particularly in sectors aligned with green innovation, thereby providing further support for the Porter Hypothesis.

A related body of work examines how energy price differentials, often influenced by environmental regulation, affect trade patterns. These studies find that energy-intensive sectors in high-cost countries tend to experience a shift toward increased imports, reflecting reduced competitiveness (e.g., Sato and Dechezleprêtre, 2015; Aldy and Pizer, 2015).

In addition to trade, environmental policies also influence foreign direct investment (FDI). The impact appears to differ across investment types: while greenfield investment in pollution-intensive sectors is negatively affected by stringent environmental regulation (e.g., Bialek and Weichenrieder, 2021), the effect on mergers and acquisitions is generally weaker. Moreover, empirical assessments of carbon pricing mechanisms such as the EU Emissions Trading System (EU ETS) show limited evidence of firm relocation (Koch and Mama, 2019), suggesting that carbon leakage may be less pervasive than often presumed.

Overall, the literature underscores the nuanced and complex nature of the trade-

[4]The "weak" Porter Hypothesis concerns the link between environmental policies and innovation, while the "strong" version focuses on the effects of regulation on competitiveness.

environment nexus. The impact of environmental regulation on trade and investment varies across sectors, policy instruments, and country-specific economic conditions. In this paper, we address these complexities by combining a standard gravity estimation approach with network analysis, allowing us to capture both direct and indirect effects of environmental policy stringency across global trade relationships.

Table 5.1: Literature review on the relation between trade and environmental policy stringency (EPS)

Paper	Summary	Data	Coverage	EPS indicator
	Environmental policy and gravity			
van Beers and van den Bergh (1997)	Gravity equation to test the impact of environmental stringency on bilateral export. → They find partial support for the pollution haven hypothesis.	21 OECD countries	1990	Energy intensity and recycling rates.
Tobey (2001)	Regress cross-country data on exports of five dirty commodity groups on country-specific measures of factor endowments and environmental stringency → Environmental stringency variable is an insignificant determinant of net export flows.	23 countries	1960-1970	EPS from UNCTAD 1976
Jug and Mirza (2005)	Derive a structural gravity relation based on monopolistic competition and account for endogeneity by running Instrumental Variables (IV) and Generalised Method of Moments (GMM). → More stringent environmental regulations, when depicting a pure cost effect, are reducing exports.	12 importing countries from the EU15 and 19 exporting countries from the EU15 and Central and Eastern Europe.	1996 - 1999	Environmental expenditure by EUROSTAT: Total current expenditure as a measure of abatement costs.
Combes et al. (2014)	Effect of a gap in revealed environmental policies between trading partners on bilateral trade → No significant effect of regulatory gap	72 exporters and 128 importers countries.	1980-2010	Difference between observed pollution and structural pollution
Larch and Wanner (2017)	Multi-sector, multi-factor structural gravity model to analyze the effects of carbon tariffs on trade and welfare mostly trough counterfactual scenarios → Carbon tariffs are able to reduce world emissions, altering the production composition within and across countries	GTAP 8 database to estimate the model	-	Country-specific emission reduction pledges specified (Copenhagen Accord).
Cantore and Cheng (2018)	Effects of policy stringency on environmental goods, i.e. goods that reduce air and water pollution → Opportune environmental policies prompt trade in environmental goods.	38 developed countries and 33 developing.	2000-2014	Environment-related tax revenue

Paper	Summary	Data	Coverage	EPS indicator
Kang and Lee (2021)	Impact of environmental policies on bilateral green exports with a fixed-effects gravity estimation using Poisson pseudo-maximum likelihood → Environmental tax increases green exports among high-income countries	Green industries in high and low-middle income countries	1990 - 2019	Environment-related tax (environmental tax revenue to GDP) and energy intensity.
	Environmental policy and trade flows			
Levinson and Taylor (2008)	Multi-sector, partial equilibrium model + empirical estimation through Fixed Effects and 2SLS. → Positive correlation between industry PAC (pollution abatement costs) and net imports.	US imports from Mexico and Canada at the industry level	1977 - 1986	Pollution abatement costs
Sato and Dechezleprêtre (2015)	They study the effect of energy price differences on trade flows → They find a small but significant effect of energy price differences on imports in energy-intensive sectors (higher prices imply higher imports).	42 trading partners with data at the sector level	1996-2011	Industrial level energy prices
Aldy and Pizer (2015)	Study how production and net imports change in response to energy prices → Energy-intensive manufacturing industries are more likely to experience decreases in production and increases in net imports	45 US manufacturing industries	1974-2009	Energy intensity
	Environment and trade network			
Aller and Ductor (2015)	Estimate the direct and indirect effects of trade on environmental quality → Networks' effects harm the environmental quality of developed countries but indirect effects are beneficial for developing countries.	177 countries from COMTRADE	1996 -2010	per capita carbon dioxide emissions as a proxy variable of environmental quality.

Paper	Summary	Data	Coverage	EPS indicator
	Environmental policy and FDI			
Kahouli et al. (2014)	Two-way linkages between trade and FDI using to examine the impact of (i) FDI, environmental regulations and others variables on international trade; and (ii) international trade, environmental regulations and other variables on FDI. They use simultaneous gravity equations estimated by GMM. → Positive and significant effect of environmental regulations on trade but insignificant in the dynamic estimation. The effect is as well insignificant for FDI, in both estimations.	39 host countries for 6 RTAs	1990 -2011	Difference of carbon intensity of partners
Koch and Mama (2019)	The study exploit incomplete participation to the EU ETS of German firms to evaluate its effects on outflows of foreign direct investments with dif-in-dif and biased corrected matching to account for endogeneity and countries- firms heterogeneity. → Small number of firms have shifted part of their production to non-EU ETS countries	Unique database on firm-level FDI by Bundesbank (MiDi database)	1999 - 2013	Participation to the EU ETS
Kox and Rojas-Romagosa (2020)	Structural gravity approach to analyse the impact of preferential trade agreements (PTAs), bilateral investment treaties (BITs) and other policies on bilateral foreign direct investment (FDI). → Signing a PTA increases bilateral FDI stocks by around 30% but the effect is similar in case of‘deeper’ or comprehensive PTAs .	203 countries from UNCTAD's Bilateral FDI dataset	2001-2011	No environmental policy considered
Bialek and Weichenrieder (2021)	Assessing if and to what extent German investments location decisions are sensitive towards the spacial variation of policy stringency. They use a mixed logit considering: the environmental policy stringency of the hosting country, the mode of investment (greenfield or brownfield), the industry and other control variables. → Stricter regulation reduces new Greenfield projects in polluting industries, but has a much smaller impact on the number of M&As	Unique database on firm-level FDI by Bundesbank (MiDi database)	2005 - 2009	Redefined index: policy stringency multiplied by the Environmental Policy Enforcement Index to account for the stringency of the policy and the intensity of the enforcement.

5.3 Data

Trade data. We draw bilateral trade data from the *BACI-CEPII* database, which reports trade flows between more than 200 countries. For the purposes of this study, we restrict the sample to 173 countries that reported at least one positive trade flow during the period 2000–2019.[5]. Our main analysis focuses on aggregate - either country or sectorial - bilateral trade flows, though the underlying data allow for a more granular approaches thanks to product-level information at the HS 6-digit classification. We further complement the trade dataset with variables from the *CEPII Gravity* dataset (see Conte et al., 2022), which provides bilateral economic and socio-cultural indicators, including, among others, common language, shared legal origins, colonial ties.

Classification of industries. To distinguish between green and brown trade flows, we match product-level trade data (HS-6) with the green industry classification developed by the *U.S. Bureau of Labor Statistics (BLS).* The BLS identifies 325 NAICS codes associated to green industries, focusing on activities related to pollution mitigation, greenhouse gas (GHG) emission reduction, and recycling or reuse.[6] This classification has been integrated into our dataset to allow differentiation between environmentally sustainable and conventional sectors.

Environmental Policy Stringency (EPS). The analysis focuses on the *Environmental Policy Stringency* (EPS) index developed by the OECD, which quantifies the relative stringency of environmental policies across countries (see Kruse et al., 2022 for a detailed description of the database)[7]. The index is available for all OECD member states as well as for a set of emerging economies (BRIICS+). Figure 5.1 illustrates the country-level EPS scores in 2019. The empirical analysis is restricted to the subset of countries for which the EPS index is available. In what follows, we explore how changes in environmental policy stringency affect both the trade position of countries within the global network and their export performance.

The OECD EPS dataset distinguishes among three main types of policy instruments: *Market-based instruments* (MKT), *Non-market-based instruments* (NMKT), and *Technology support measures* (TECHSUP). Table 5.2 summarizes the classification, listing representative instruments under each category. Figure 5.2 provides a comparative view of the policy mix adopted by OECD and BRIICS+ countries. While non-market-based instruments dominate in both groups, OECD countries implement more stringent

[5]Country definitions follow the legal classifications in force during the observation period. As a result we account for 178 entities. We exclude ISO codes such as "ANT", "YUG", "ZAR", "BLX", and "TWN", due to inconsistencies or changes over the time span.

[6]The full list is publicly available at *www.bls.gov/green/*.

[7]The database can be downloaded from the OECD Data explorer website.

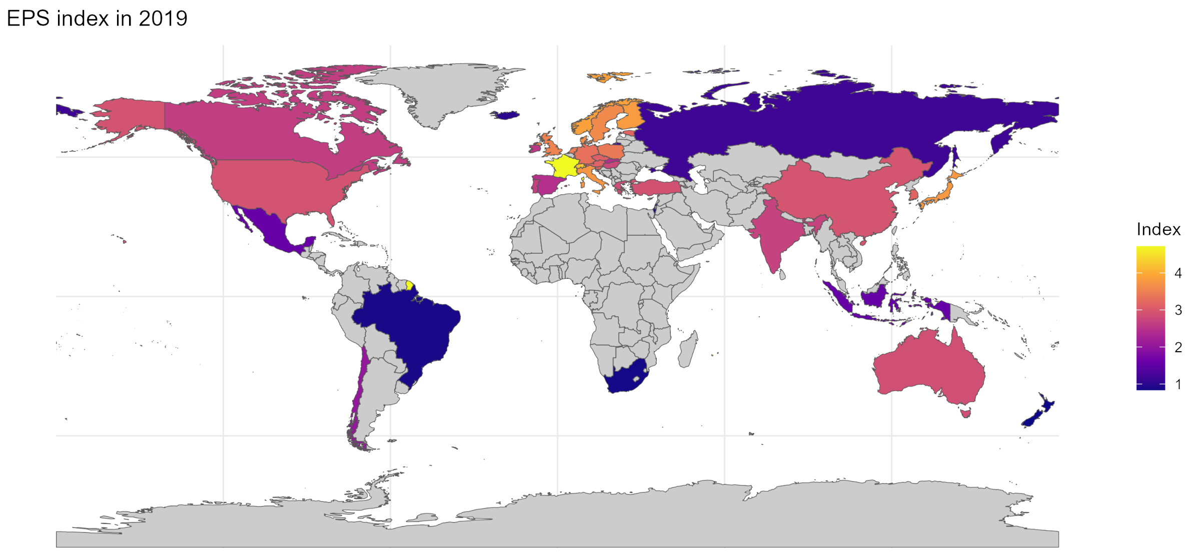

Figure 5.1: World map of the EPS index in 2019.
Note: The figure reports the aggregate Environmental Policy Stringency (EPS) index for each country in the sample.

policies across all categories. Notably, the gap between groups narrows in the case of technology support measures, whereas CO_2 taxation remains largely confined to OECD economies. Notably, BRIICS+ countries invest more in technology support measure rather than implementing market-based instruments, as tax or schemes.

Table 5.2: OECD classification of environmental policy instruments.

Market-based instruments	**Non-market-based instruments**	**Technology support**
CO_2 trading schemes (TRADESCH_CO2)	Emission limits for NOx (ELV_NOX)	Public R&D expenditure (RD_SUB)
Renewable energy schemes (TRADESC_RENEW)	Emission limits for SOx (ELV_SOX)	Solar energy support (FIT_solar)
CO_2 taxes (TAXCO2)	Particulate matter limits (ELV_PM)	Wind energy support (FIT_wind)
NOx taxes (TAXNOX)	Sulphur limits for diesel (ELV_DIESELSO)	
SOx taxes (TAXSOX)		
Fuel taxes (TAXDIESEL)		

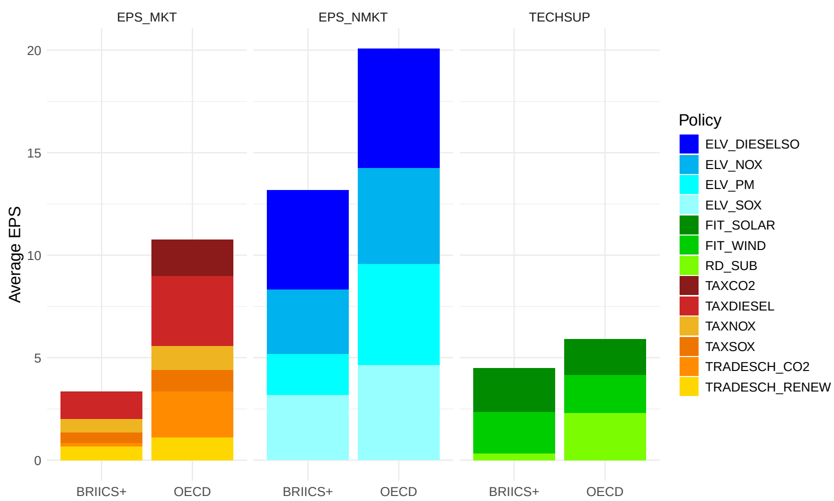

Figure 5.2: Policy mix in OECD and BRIICS+ countries.
Note: Each bar shows the average score for the policy instruments grouped under market-based (EPS_MKT), non-market-based (EPS_NMKT), and technology support (TECHSUP) measures. See Table 5.2 for details on the classification.

5.4 Analysis of the trade network

5.4.1 Global trade network

Adopting network analysis provides a comprehensive approach to examining international trade. Traditional frameworks, including gravity models, often treat countries in isolation (Chaney, 2014). In contrast, a network-based approach accounts for both direct and indirect interactions among countries, capturing spillover effects stemming from changes in trade relations between third-country pairs and their impact on the global structure.

Based on the database described in section 5.3, we reconstruct a *directed* and *weighted* trade network for each year, capturing the intensity of trade relations between countries. Specifically, each country pair is connected to the rest through a link weighted by the value of exports from country i (exporter) to country j (importer), computed as the total annual export flows from i to j. This methodology follows the approach adopted in the literature (see, e.g., Bhattacharya et al., 2008; Fagiolo et al., 2009). Weighted network analysis provides, indeed, a richer and more accurate depiction of international trade patterns than binary representations. For instance, Fagiolo et al. (2009) show that the statistical properties of the international trade network differ markedly when weights are taken into account. In line with this, we compute a time series of weighted network statistics to describe the structure and evolution of global trade. The main centrality measures used are defined in Table 5.8 in the Appendix.

We analyze the evolution of the network's topological features from 2000 to 2019.[8] Over this time span, trade interconnections among the fixed set of countries intensified, as evidenced by an increase in network density from 0.64 in 2000 to 0.79 in 2019.

The out-degree distribution remained relatively stable throughout the period (Figure 5.3), and its log-normal fit (Figure 5.4) confirms the coexistence of many weakly connected countries with a few highly connected hubs. These hubs tend to trade with less connected nodes, reflecting the disassortative nature of the trade network, with a disassortativity coefficient of -0.1235. This findings are in line with the scale-free properties of the trade network, extensively discussed in the literature (De Benedictis and Tajoli, 2011); a feature delivering important consequences for the international spillover of shocks and policies. The stability in the distribution's first moments suggests that the overall structure of global trade has not undergone radical shifts despite increasing globalization.

[8]Our results have been compared to previous findings for earlier periods (Fagiolo et al., 2008, Fagiolo et al., 2009, De Benedictis and Tajoli, 2011, De Benedictis et al., 2014) to ensure the robustness of our conclusions.

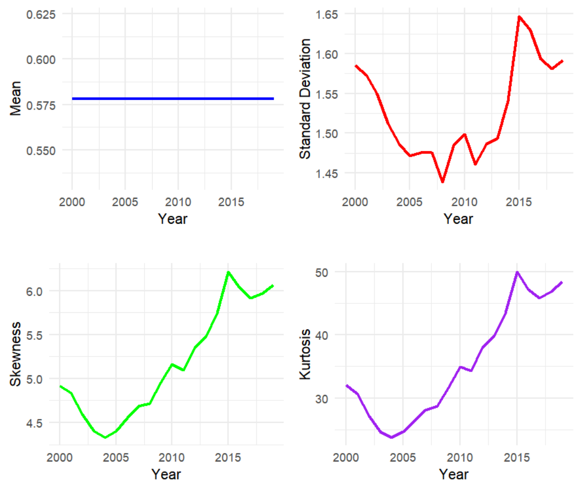

Figure 5.3: First four moments of the out-degree distribution over time.

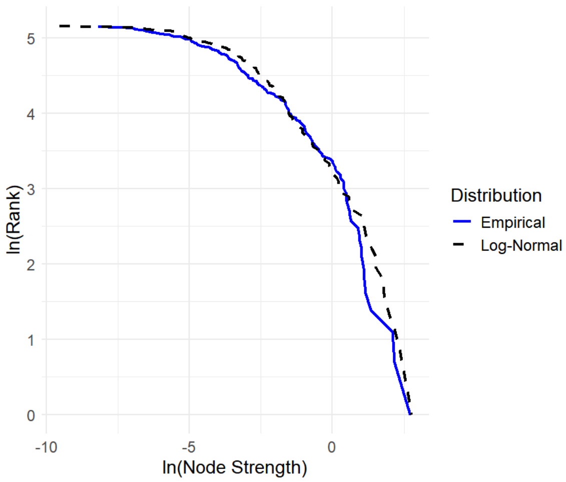

Figure 5.4: Size-rank (log-log) plot of out-degree distribution in 2019.

To illustrate changes in global trade leadership, we rank countries based on weighted out-degree centrality (as in Fagiolo et al., 2009) for the year 2000 and trace their ranking from the beginning of the century until today. Figure 5.5 shows the evolution of major players: the United States lost their leadership in terms of export intensity to China, which rose to the top position by 2019. European countries lost influence in the last two decades, with Germany being the fist one in terms of out-degree. Notice that, despite shifts in ranking, the top 10 exporters still accounted for about 67% of total global trade in 2019, similarly to their share in 2000 (71%). This confirms the persistence of a skewed and stable distribution of trade flows.

In terms of Random Walk Betweenness Centrality (RWBC)[9], the U.S. retained a central role, although China's importance as a strategic intermediary grew considerably. It is worth highlighting that both measures identify the same top three global players, highlighting a consistent dominance at the core of the network. However, the composition of the remaining countries differs depending on whether one considers export volumes or strategic centrality. While the export-based ranking reflects sheer trade flows, the hub-based measure captures the structural role countries play in the network—revealing that some economies, although not among the largest exporters, occupy key positions in terms of connectivity and intermediation.

[9]RWBC, introduced by Reyes et al. (2008), measures the expected number of times a random walker passes through a node when traveling between all possible source-target pairs. It reflects the country's role as an intermediary in global trade.

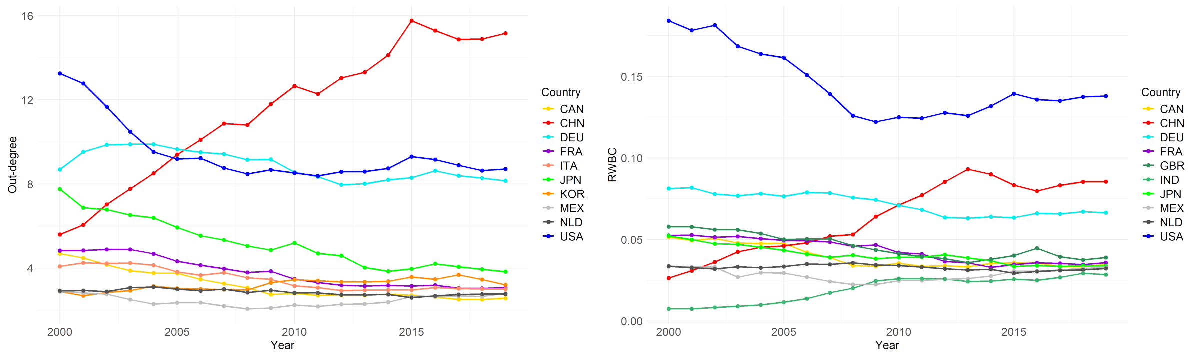

Figure 5.5: Evolution of the out-degree share (left) and RWBC (right) for the 10 highest-ranked countries in 2019.

Next, we explore how macroeconomic fundamentals shape a country's role within the trade network. While Fagiolo et al. (2009) found strong and stable correlations between GDP per capita and node strength between 1980 and 2000, we observe a declining trend over the 2000–2019 period (Figure 5.6). This likely reflects the emergence of China and other BRICS+ economies as major exporters, which diluted the strong historical link between income levels and trade centrality. More broadly, the reallocation of trade flows from advanced (OECD) economies toward the Global South has reshaped this association.

We also correlate trade network centralities with countries' environmental policy stringency (EPS), as defined by the OECD. While a positive relationship exists between EPS and trade centrality, the correlation remains relatively low and does not exhibit a strong upward trend (Figure 5.7).

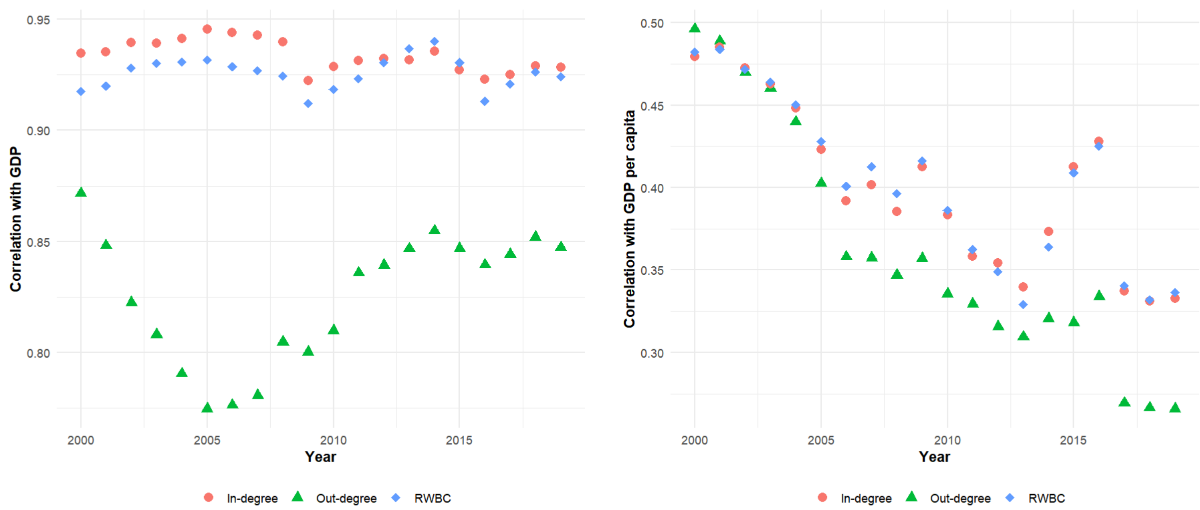

Figure 5.6: Correlation between centrality measures and GDP (left) and GDP per capita (right).
Each year, the Pearson correlation between country i's centrality measure $N_{i,t}$ (in-degree, out-degree, RWBC) and the economic indicator $X_{i,t}$ (GDP or GDP per capita) is computed.

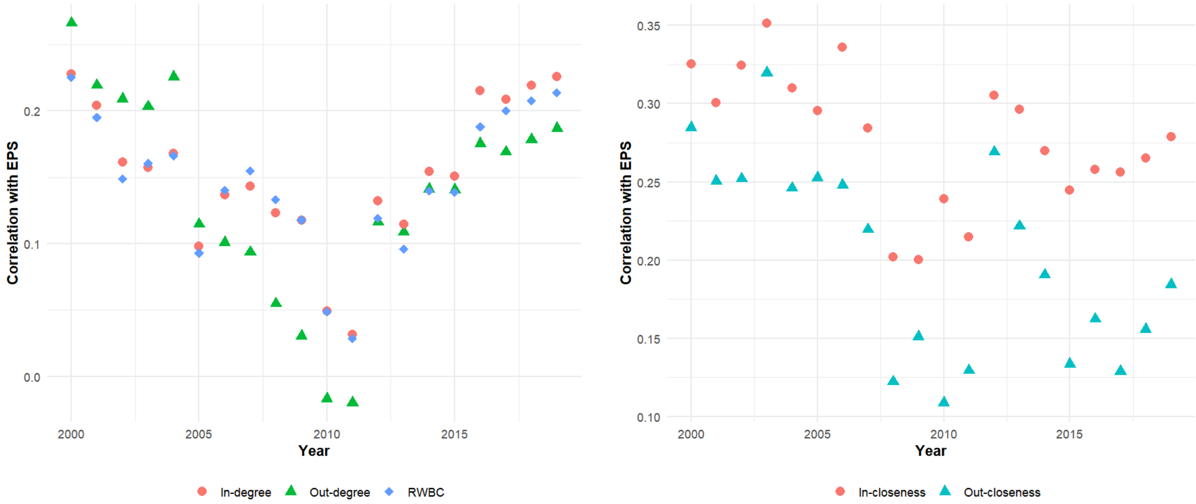

Figure 5.7: Correlation between centrality measures and EPS.
Each year, the Pearson correlation between country i's centrality $N_{i,t}$ (in-degree, out-degree, RWBC, in-closeness, out-closeness) and environmental stringency $EPS_{i,t}$ is computed.

5.4.2 The networks of green and brown industries

To further investigate the relationship between environmental policy stringency and network position, we disaggregate the country-level data to account for sector-specific characteristics. Even when considering green industries, China's prominence remains evident (see Figure 5.8). A similar trajectory has been observed in all other countries over the past two decades. Similar patterns are detected for correlations between centrality mea-

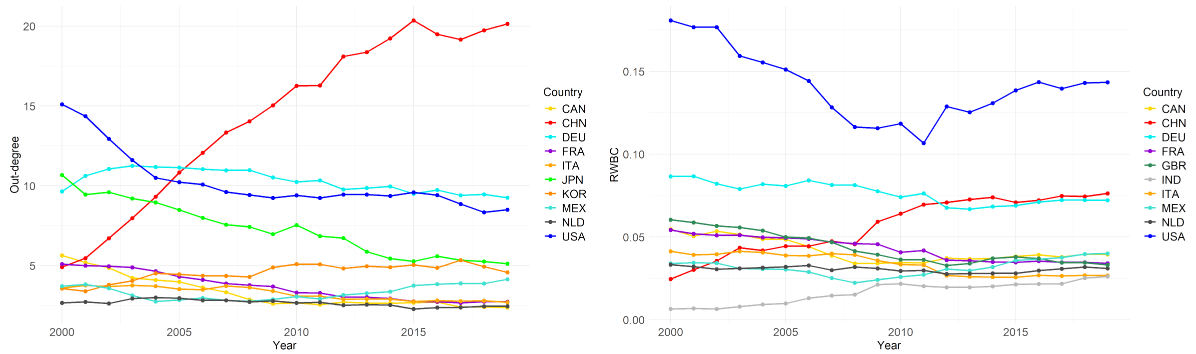

Figure 5.8: Evolution of the out-degree (%) and RWBC of the 10 highest-ranked countries in 2019 for green industries.

sures and macroeconomic variables (Figure 5.9). Countries position in the green network displays a slightly stronger correlation with EPS.

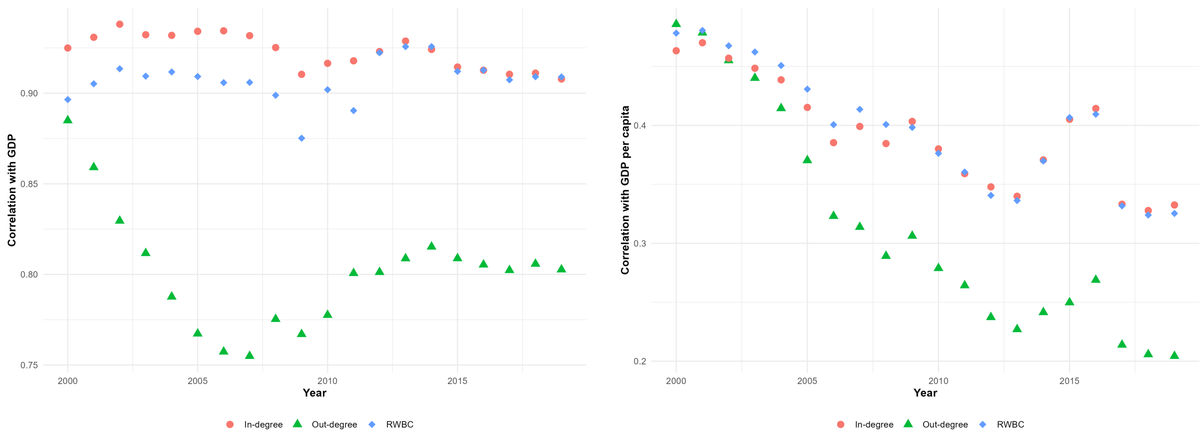

Figure 5.9: Correlation between centrality measures and GDP (left) and GDP per capita (right) for green industries.
Each year, the Pearson correlation between country i's centrality measure $N_{i,t}$ (in-degree, out-degree, RWBC) and the economic indicator $X_{i,t}$ (GDP or GDP per capita) is computed.

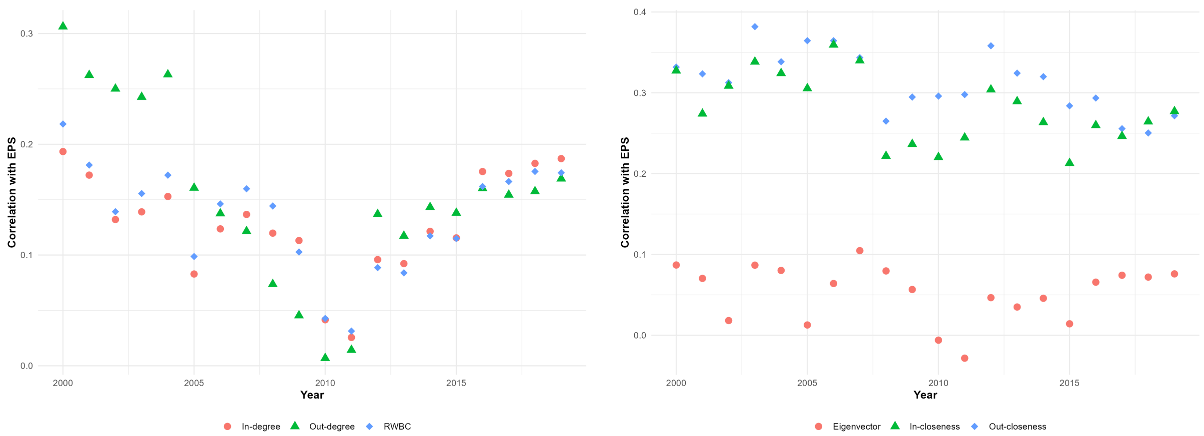

Figure 5.10: Correlation between centrality measures and EPS for green industries.
Each year, the Pearson correlation between country i's centrality $N_{i,t}$ (in-degree, out-degree, RWBC, in-closeness, out-closeness) and environmental stringency $EPS_{i,t}$ is computed.

5.5 Network centrality and environmental policy stringency

5.5.1 Global trade network

To investigate the relationship between network statistics and environmental policy stringency (EPS), we conduct a regression analysis that incorporates both conventional explanatory variables commonly used in the trade-gravity literature and our variable of interest. In this preliminary analysis, we employ a year and country fixed-effects regression model, specified as follows:

Table 5.3: Results of the fixed effects regression on network statistics

	$Out - degree_i$				$In - degree_i$				$RWBC_i$				$Out - eigenvector_i$			
log_gdp_o	0.020***	0.019***	0.018***	0.017***	0.017***	0.017***	0.016***	0.016***	0.018***	0.018***	0.018***	0.017***	0.057***	0.057***	0.053***	0.049***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)
log_dist	−0.564***	−0.433***	−0.243*	−0.182	−0.757***	−0.624***	−0.459***	−0.370***	−0.764***	−0.640***	−0.496***	−0.384***	−2.491***	−1.955***	−1.072**	−0.867*
	(0.131)	(0.125)	(0.119)	(0.117)	(0.111)	(0.109)	(0.108)	(0.107)	(0.114)	(0.113)	(0.114)	(0.114)	(0.461)	(0.438)	(0.413)	(0.401)
log(1 + EPS)	0.007***				0.003*				0.003**				0.010*			
	(0.001)				(0.001)				(0.001)				(0.005)			
log(1 + EPS_lag1)		0.006***				0.002*				0.003**				0.008		
		(0.001)				(0.001)				(0.001)				(0.004)		
log(1 + EPS_lag2)			0.006***				0.002*				0.003*				0.007	
			(0.001)				(0.001)				(0.001)				(0.004)	
log(1 + EPS_lag3)				0.006***				0.002*				0.001				0.004
				(0.001)				(0.001)				(0.001)				(0.004)
Num.Obs.	760	722	684	646	760	722	684	646	760	722	684	646	760	722	684	646
R2	0.454	0.458	0.462	0.455	0.459	0.453	0.436	0.430	0.473	0.466	0.448	0.436	0.370	0.361	0.358	0.349
R2 Adj.	0.407	0.409	0.412	0.402	0.413	0.404	0.384	0.374	0.428	0.418	0.396	0.382	0.316	0.304	0.298	0.286

$$\log(N_{i,t}) = \beta_1 \log(EPS_{i,t-n}) + \beta_2 \log(GDP_{i,t}) + \beta_3 \log(dist_i) + \mu_i + \tau_t + \epsilon_{i,t} \tag{5.1}$$

where the dependent variable, $N_{i,t}$ is the network statistics computed for country i at time t, which can be either *out-degree*, *in-degree*, *out-closeness*, *in-closeness out-eigenvector*, *in-eigenvector* and *random walk betweenness centrality (RWBC)*. The distribution of the dependent variables (Figure 5.16 in the Appendix) exhibits a pronounced right skew. The Kolmogorov-Smirnov test confirms that out-degree, in-degree, RWBC, and eigenvector centralities follow a log-normal distribution. This finding aligns with the results of Fagiolo et al. (2009) for node degrees and node strength. Consequently, we employ a fixed-effects model using the logarithmic transformation of the dependent variable.

The set of predictors includes both current and lagged values of the environmental policy stringency indicator, $EPS_{i,t-n}$ (with $n = 1, 2, 3$). Additionally, we incorporate key country-level covariates commonly used in gravity models, such as GDP ($log(GDP_{i,t})$) and the average distance from trading partners ($log(dist_{i,t})$). The results of the log-linear estimation, controlling for year and country fixed effects, are reported in Table 5.3.

The coefficients for the standard gravity model variables generally exhibit the expected signs and are statistically significant. Trade flows—both imports and exports—increase with the size of the economy, as proxied by GDP, and decrease with geographical distance. Moreover, countries that are, on average, more geographically distant from the rest of the world exhibit lower strategic centrality within the trade network, as captured by Random Walk Betweenness Centrality and eigenvector centrality measures.

The Environmental Policy Stringency (EPS) indicator exhibits a statistically significant effect across all centrality measures. The adoption of more stringent environmental policies is associated with a more central position of a country within the trade network, both in terms of directed trade flows and hub-related metrics. Moreover, the inclusion of lagged values of the EPS index yields positive and significant coefficients for out-degree, in-degree, and random walk betweenness centrality (RWBC). This result suggests that higher policy stringency in previous periods is correlated with increased export flows and a more prominent role of the country in facilitating international trade. While the estimated coefficients point to a positive association between environmental policy stringency and countries' centrality in the trade network, this analysis is conducted at an aggregate level. As such, it does not allow us to disentangle whether this increased integration is driven by changes in trade flows in brown sectors - suggesting, to some extent, the presence of carbon leakage - or in green sectors - providing evidence of the Porter Hypothesis . To better understand the underlying mechanisms behind this aggregate correlation, the next section explores sector-level heterogeneity. In particular, we assess whether more stringent environmental policies are associated with trade reallocation towards greener sectors, or whether the observed increase in centrality stems from a strengthening of traditional trade relationships across both green and brown industries.

Given the highly skewed distribution of the dependent variables, we further explore the effects of environmental policy stringency across the distribution using *quantile regression*. The residuals from the fixed-effects OLS estimation significantly deviate from normality, providing additional motivation for this approach. Figure 5.11 presents the results of the fixed-effects quantile regression, showing that the EPS score has a statistically significant impact only at the tails of the distribution (i.e., at the 10th and 90th percentiles). Interestingly, the direction of the effect differs across these extremes: more stringent environmental policies are associated with an improvement in network positioning for more peripheral countries, while they are linked to a decline in centrality for countries in core positions of the network. This asymmetric effect suggests that the marginal impact of environmental regulation on trade network integration depends on a country's initial position within the network. Peripheral countries may leverage stricter environmental policies as a signal of regulatory quality or long-term sustainability, thus enhancing their attractiveness as trade partners - possibly specializing and entering green value chains. Conversely, for countries that are already central, stricter environmental policies may impose compliance costs or regulatory frictions that temporarily weaken their position, particularly if their existing trade partners are slower to adopt similar standards. Once again, to better appreciate the underling mechanisms, it is essential to disentangle the effects on green and brown flows.

However, these preliminary results underscore the importance of accounting for heterogeneity in network status when assessing the trade implications of climate policy, and motivate a more granular, sectoral-level analysis to disentangle whether this complex relation reflects a reorientation toward greener trade or a general reshuffling of commercial ties.

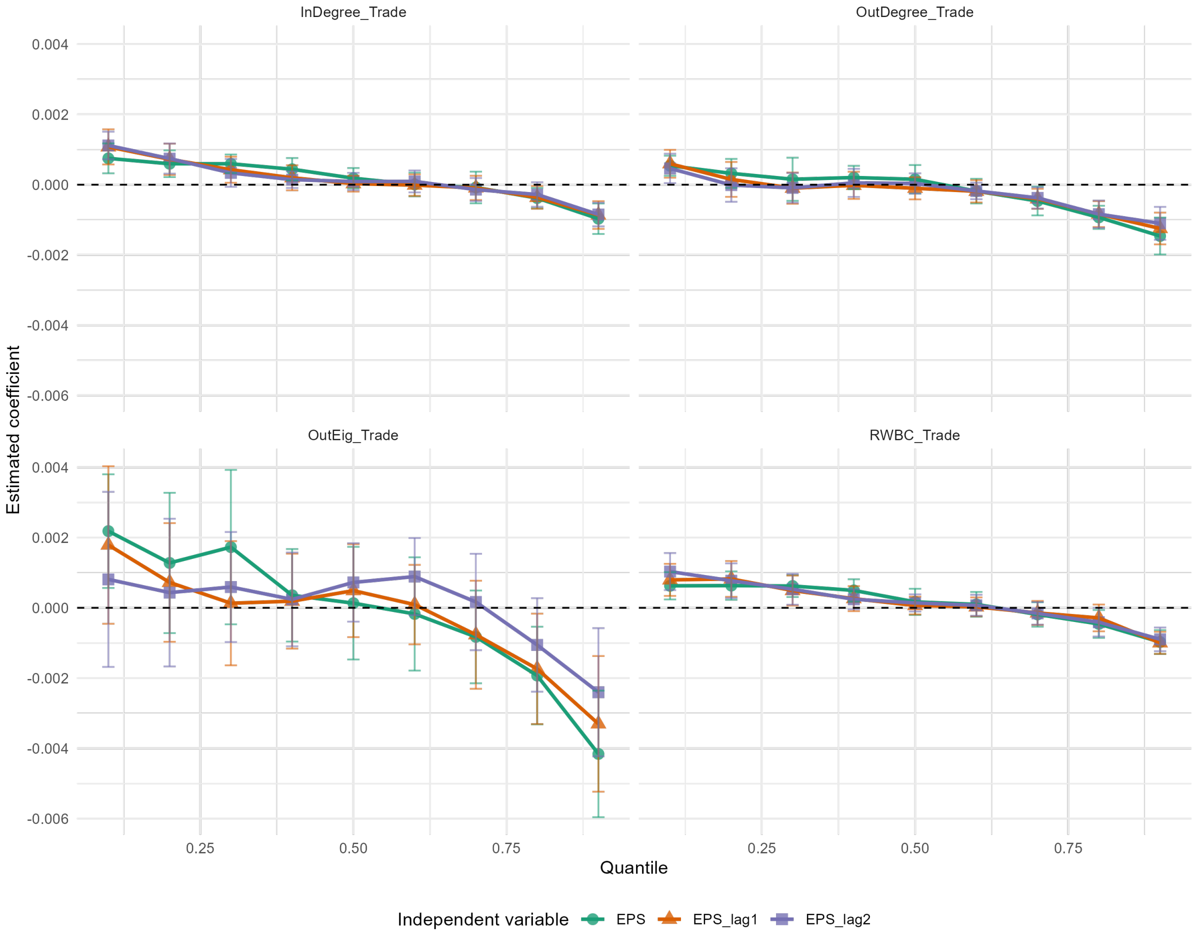

Figure 5.11: Quantile regression EPS estimates.
Note: We compute the quantile regression of the baseline specification for the c(0.10, 0.20, 0.30, 0.40, 0.50, 0.60, 0.7, 0.8, 0.9) quantiles.

5.5.2 The networks of green and brown industries

We run the generalized linear model with year and country fixed effects to analyze which factors influence network centralities in both the green and brown networks. The same specification used in the previous section (Equation 5.1) is now applied to the green and brown industry data separately. Notice that the distribution of centrality statistics remains right-skewed both for both networks.

The regression results reveal distinct patterns across the four dependent variables representing different network metrics (Out-degree, In-degree, RWBC and out-eigenvector). Results for the brown network are summarized in Table 5.4 and Table 5.5 for the network of green industries. Gravity indicators, such as GDP and distance, consistently demonstrate a significant positive relationship with most network measures, confirming their central role in shaping global trade in both green and brown industries. As expected, increasing average distance from trade partners hinder economic integration, as shown by the negative sign of geographic distance in all the specifications.

An increase in environmental policy stringency is associated with a higher out-degree in both brown and green sectors. However, it is positively correlated with in-degree only in the network of brown sectors. This indicates a rise in imports from polluting industries, which may suggest the presence of carbon leakage - though the evidence remains correlational rather than causal. The corresponding increase in in-degree enhances the country's strategic position in the network, as it becomes more central in terms of inbound connections; this is represented by the positive correlation between RWBC and EPS, at all lags, for the brown network. On the contrary, the effect on RWBC is weaker and only occasionally significant in the case of green trade flows. These findings highlight a potential asymmetry in the trade adjustments associated with stricter environmental policies.

We test the relationship between environmental policy stringency and trade in green and brown industries by running *quantile regression*. Results are summarized in Figures 5.12 and 5.13. For both database we identify a similar pattern to the one observed at the aggregate level. The increase in EPS has statistically significant effects only for countries at the tail of the distribution.

Table 5.4: Results of the fixed effects regression for brown flows.

	$Out-degree_i$				$In-degree_i$				$RWBC_i$				$Out-eigenvector_i$			
log_gdp_i	0.014***	0.014***	0.013***	0.012***	0.018***	0.018***	0.018***	0.017***	0.019***	0.019***	0.018***	0.018***	0.052***	0.051***	0.048***	0.046***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)
log_dist	−0.269**	−0.185*	−0.051	−0.013	−0.787***	−0.679***	−0.548***	−0.532***	−0.921***	−0.802***	−0.673***	−0.596***	−0.700	−0.316	0.323	0.235
	(0.089)	(0.087)	(0.085)	(0.086)	(0.121)	(0.121)	(0.124)	(0.125)	(0.134)	(0.136)	(0.141)	(0.147)	(0.400)	(0.401)	(0.404)	(0.421)
$log(1+EPS_{i,t})$	0.002*				0.004***				0.004**				−0.001			
	(0.001)				(0.001)				(0.001)				(0.004)			
$log(1+EPS_{i,t-1})$		0.003**				0.004**				0.004**				0.001		
		(0.001)				(0.001)				(0.001)				(0.004)		
$log(1+EPS_{i,t-2})$			0.003***				0.003***				0.003*				0.003	
			(0.001)				(0.001)				(0.001)				(0.004)	
$log(1+EPS_{i,t-3})$				0.003***				0.003**				0.001				0.003
				(0.001)				(0.001)				(0.001)				(0.004)
Num.Obs.	760	722	684	646	760	722	684	646	760	722	684	646	760	722	684	646
R2	0.462	0.458	0.454	0.436	0.446	0.437	0.413	0.405	0.408	0.392	0.365	0.337	0.366	0.348	0.335	0.309
R2 Adj.	0.415	0.410	0.403	0.381	0.398	0.387	0.359	0.347	0.357	0.338	0.306	0.273	0.312	0.290	0.273	0.242

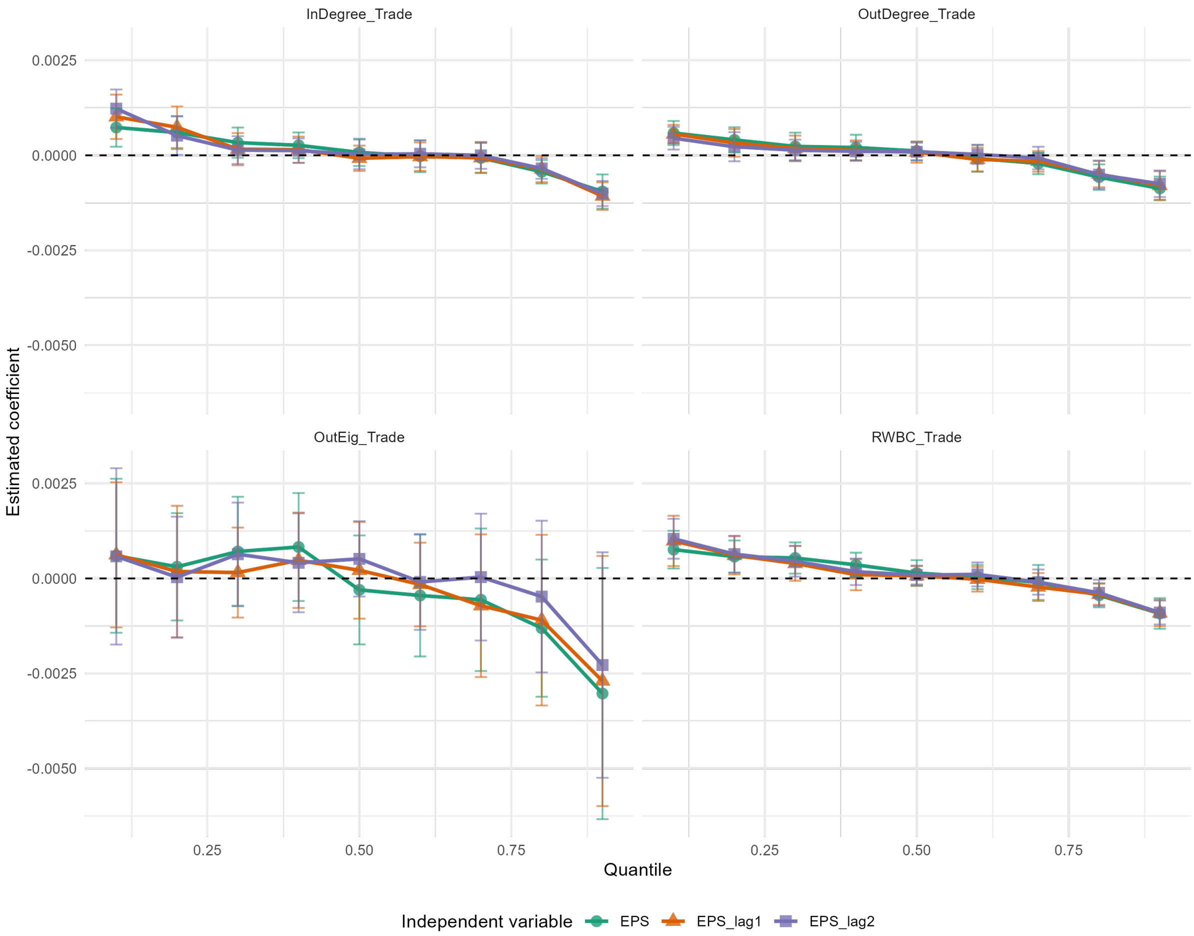

Figure 5.12: Quantile regression EPS estimates for the brown industries database.
Note: We compute the quantile regression of the baseline specification for the c(0.10, 0.20, 0.30, 0.40, 0.50, 0.60, 0.7, 0.8, 0.9) quantiles.

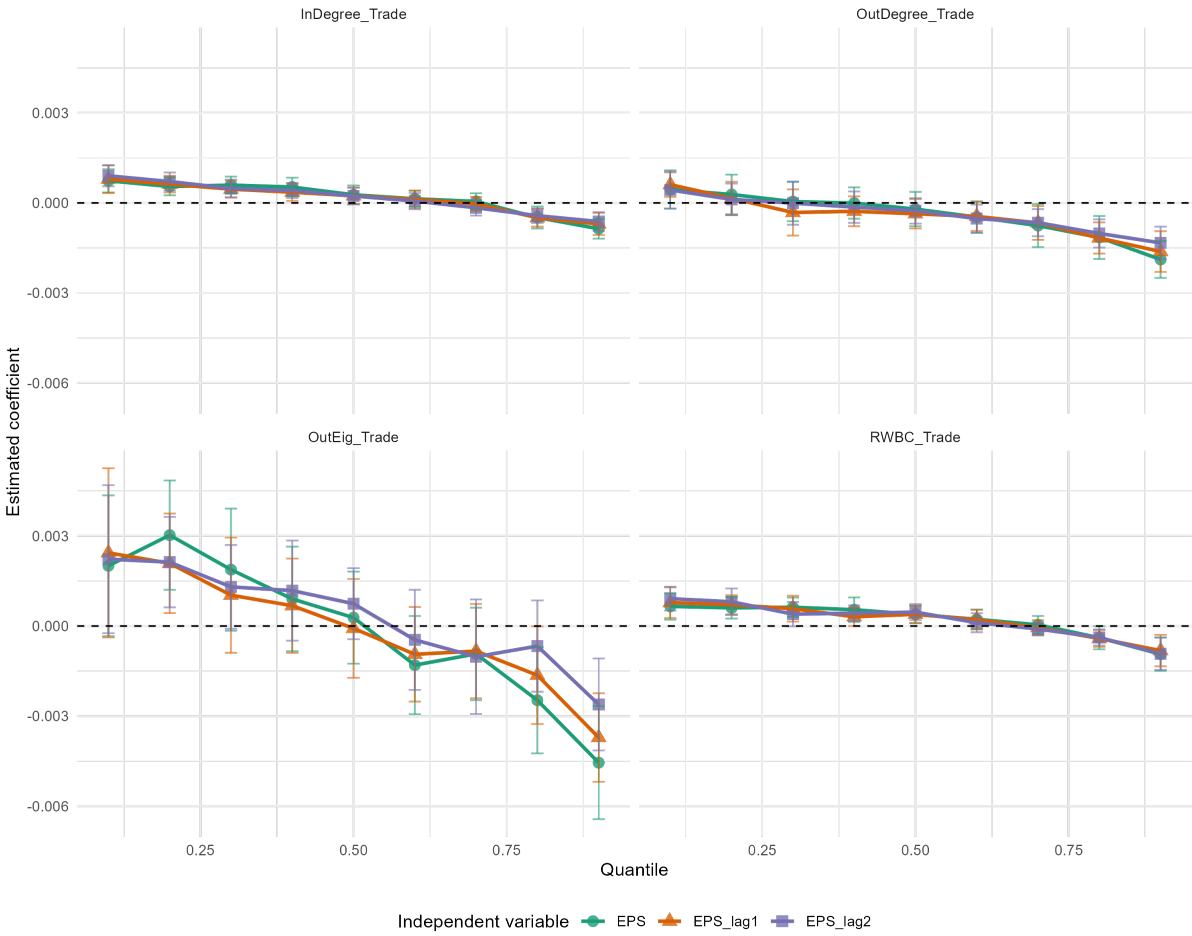

Figure 5.13: Quantile regression EPS estimates for the green industries database.
Note: We compute the quantile regression of the baseline specification for the c(0.10, 0.20, 0.30, 0.40, 0.50, 0.60, 0.7, 0.8, 0.9) quantiles.

Table 5.5: Results of the fixed effects regression for green flows.

	$Out-degree_i$				$In-degree_i$				$RWBC_i$				$Out-eigenvector_i$			
log_gdp_i	0.025***	0.025***	0.024***	0.022***	0.016***	0.016***	0.015***	0.013***	0.017***	0.017***	0.016***	0.015***	0.057***	0.057***	0.052***	0.047***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)	(0.004)	(0.003)
log_dist	−0.839***	−0.646**	−0.380*	−0.305+	−0.656***	−0.505***	−0.306**	−0.140	−0.563***	−0.422***	−0.253*	−0.079	−4.018***	−3.401***	−2.359***	−1.941***
	(0.204)	(0.196)	(0.187)	(0.181)	(0.106)	(0.103)	(0.101)	(0.096)	(0.111)	(0.110)	(0.112)	(0.112)	(0.600)	(0.561)	(0.516)	(0.476)
$log(1+EPS_{i,t})$	0.012***				0.001				0.002*				0.018**			
	(0.002)				(0.001)				(0.001)				(0.006)			
$log(1+EPS_{i,t-1})$		0.011***				0.001				0.002				0.012*		
		(0.002)				(0.001)				(0.001)				(0.006)		
$log(1+EPS_{i,t-2})$			0.010***				0.001				0.001				0.008	
			(0.002)				(0.001)				(0.001)				(0.005)	
$log(1+EPS_{i,t-3})$				0.009***				0.001				0.001				0.003
				(0.002)				(0.001)				(0.001)				(0.004)
Num.Obs.	760	722	684	646	760	722	684	646	760	722	684	646	760	722	684	646
R2	0.384	0.384	0.385	0.382	0.429	0.421	0.404	0.403	0.447	0.431	0.410	0.395	0.277	0.271	0.261	0.258
R2 Adj.	0.331	0.329	0.328	0.322	0.380	0.369	0.348	0.345	0.400	0.381	0.355	0.336	0.215	0.207	0.192	0.186

Disentangling the effects of different policy instruments

We now delve deeper into the effects of environmental policies on flows of trade and network statistics, by disentangling the effects of different categories of instruments. The OECD EPS database gather information on policy stringency, distinguishing between *Market-based instruments* (*MKT* hereafter), *Non-market based instruments* (*NMKT*) and *technological support measures* (*TECHSUP*), as discussed in Section 5.3. We run the country and year fixed effects regression specified in Equation 5.1 considering different type of policies and lags. Since the only regressor changing is $EPS_{i,t-n}$, in Figure 5.15 and 5.14, we report the matrices of estimated coefficients (betas) associated with each policy instrument - time lag combination, for the green and brown sectors respectively.

The composite indicator of Environmental Policy Stringency (EPS) has been found to exert a positive and statistically significant effect on all network statistics, both in green and brown sectors, as previously discussed. A more granular analysis of individual policy instruments confirms this general pattern, showing a significant positive impact on trade outflows for both green and brown products.

In particular, both market-based and non-market-based instruments positively affect trade in green products, increasing their outflows. However, they are also associated with an increase in imports from polluting industries. Notably, both policy types contribute to increased inflows in brown industries, raising concerns about the potential of carbon leakage that can arise in the wake of asymmetric climate policies. Increased inflows also drives deeper economic integration within the brown network of countries engaged in carbon-intensive trade. This means that as environmental actions become tighter, countries tend to resort more to import of polluting-intensive product, as the pollution heaven hypothesis would predict. These instruments are also positively correlated with eigenvector centrality in the brown network, suggesting that as policy stringency increases, the relative importance of major exporters of polluting goods also rises. At the same time, EPS is associated with higher eigenvector centrality in the green network, indicating a growing centrality of destination countries for green exports.

Technological support measures show a consistently positive effect on all network statistics in the green sector. These policies appear to foster trade integration—both upstream and downstream—and strengthen countries' centrality within the green trade network. In contrast, they exhibit no significant effect on brown flows, except for a negative association with out-eigenvector centrality. This implies that, as technological support increases, the relative importance of trading partners in the brown network tends to decline.

Figure 5.14: Beta matrix for the brown sector.
Note: We run the fixed effects model specified in Equation 1 for each combination of network statistics (From the bottom: Out-degree, In-degree, Out-closeness, In-closeness, Out-eigenvector, In-eigenvector, Random Walk Betweenness Centrality) and time-lag of different environmental policy instruments. The matrix summarized the changing in the estimation of $\beta_1 * 100$ of Equation 1, depending on the proxy of environmental policy considered.

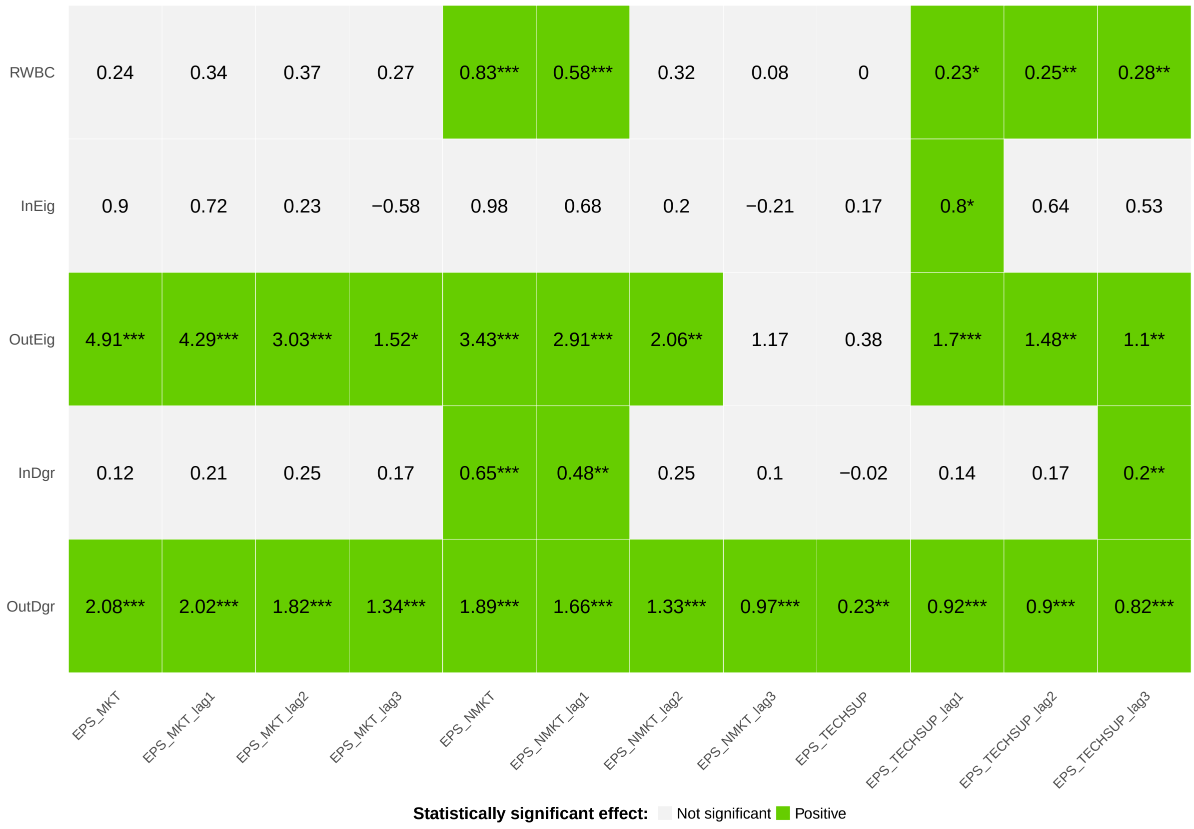

Figure 5.15: Beta matrix for the green sector.
Note: We run the fixed effects model specified in Equation 1 for each combination of network statistics (from the bottom: Out-degree, In-degree, Out-closeness, In-closeness, Out-eigenvector, In-eigenvector, Random Walk Betweenness Centrality) and time-lag of different environmental policy instruments. The matrix summarized the changing in the estimation of $\beta_1 * 100$ of Equation 1, depending on the proxy of environmental policy considered.

5.6 Comparison with the gravity model

We now want to compare our results with the predictions of the gravity model. In this regard, we follow Anderson and Van Wincoop (2003), which were the first to formally derive a gravity model from microeconomic foundations incorporating multilateral resistance terms, capturing the idea that bilateral trade flows are influenced not only by the characteristics of the trading partners, but also by their relative trade frictions with all other countries. This has since become the standard in empirical trade analysis. The general form of the model is the following:

$$X_{ij} = \alpha_0 Y_i^{\alpha_1} Y_j^{\alpha_2} \tau_{ij}^{\alpha_3} A_{ij}^{\alpha_4} e^{\omega_i} e^{\omega_j} \tag{5.2}$$

where the dependent variable, X_{ij}, represents exports from country i (exporter) to country j (importer). Bilateral trade flows are explained by the economic size of the trading partners, measured by their respective GDPs (Y_i and Y_j), and trade costs (τ_{ij}). The latter is a function of both geographical distance and barriers (e.g. waters, mountains) and additional factors that either facilitate or hinder trade, such as socio-cultural similarities and trade agreements. The vector A_{ij} captures other relevant determinants of trade flows. In particular, we hypothesize that environmental policies play a significant role, which we empirically assess by including a proxy for environmental policy divergence. The terms e^{ω_i} and e^{ω_j} account for exporter and importer fixed effects, respectively.

Hence, we propose a structural gravity approach à la Anderson and Van Wincoop (2003) by including exporter-year and importer-year fixed effects, which account for multilateral resistance terms and control for time-varying country-specific factors affecting trade. Among the time-invariant variables influencing trade, we include standard gravity model predictors: (i) *contig*, a dummy variable indicating whether the two countries share a border (it stems for contiguity); (ii) *comcol*, a dummy variable equal to 1 if the two countries share a colonial history; (iii) *comlang*, a dummy variable equal to 1 if they have a common official language; (iv) *wto*, a dummy variable equal to 1 if both countries participate in a trade agreement or organization.

Our specification further introduces a variable capturing the distance in environmental policy stringency between countries. Specifically, we define the environmental policy distance as the absolute value of the difference between the EPS of the exporter, i, and the EPS of the importer, j:

$$\Delta EPS_{ij,t} = |EPS_{i,t} - EPS_{j,t}| \tag{5.3}$$

An increase in $\Delta EPS_{ij,t}$ reflects a widening policy divergence between two trading partners but does not indicate which country is implementing a more stringent environmental policy mix. We argue that this relative position is crucial for explaining export patterns.

In the presence of carbon leakage, countries with stricter environmental policies are expected to import more pollution-intensive goods. This means that, when $EPS_{i,t} < EPS_{j,t}$, a rise in policy distance represents a tightening of the importer's environmental regulations, potentially increasing demand for "brown" imports.

To account for this, we interact the policy distance measure with a dummy variable identifying the country with the higher EPS score. Accordingly, the model includes two variables: $\delta EPS_{i,t}$ which takes value equal to $\Delta EPS_{ij,t}$ if the exporter has the higher EPS and 0 otherwise, and $\delta EPS_{j,t}$ which represents the distance between the two countries, $\Delta EPS_{ij,t}$, only when the importer has the higher stringency, taking a value of 0 otherwise[10].

These policy distance measures have been computed both for the overall EPS index and for each policy dimension separately.

Thus, our empirical specification reads:

[10] We test a different specification with the ratio of EPS scores of the importer and the exporter. Results are consistent with the findings discussed hereafter.

Table 5.6: Gravity estimation results for brown and green sector

	Brown flows				Green flows			
	$Export_{ij}$	$Export_{ij}$	$Export_{ij}$	$Export_{ij}$	$Export_{ij}$	$Export_{ij}$	$Export_{ij}$	$Export_{ij}$
log_gdp_i	0.396***	0.354***	0.358***	0.393***	0.604***	0.565***	0.572***	0.602***
	(0.038)	(0.037)	(0.039)	(0.037)	(0.033)	(0.033)	(0.033)	(0.032)
log_gdp_j	0.611***	0.579***	0.590***	0.611***	0.595***	0.560***	0.581***	0.597***
	(0.035)	(0.035)	(0.036)	(0.034)	(0.037)	(0.037)	(0.037)	(0.037)
log_dist_ij	−0.780***	−0.771***	−0.778***	−0.768***	−0.730***	−0.722***	−0.729***	−0.723***
	(0.012)	(0.013)	(0.012)	(0.013)	(0.012)	(0.012)	(0.012)	(0.012)
contig	0.438***	0.421***	0.428***	0.454***	0.429***	0.418***	0.423***	0.436***
	(0.023)	(0.023)	(0.023)	(0.023)	(0.022)	(0.021)	(0.021)	(0.021)
comcol	0.756***	0.683***	0.712***	0.702***	0.508***	0.445***	0.480***	0.476***
	(0.102)	(0.096)	(0.099)	(0.097)	(0.066)	(0.063)	(0.065)	(0.064)
comlang	0.285***	0.285***	0.273***	0.307***	0.246***	0.251***	0.241***	0.260***
	(0.032)	(0.032)	(0.032)	(0.032)	(0.022)	(0.022)	(0.022)	(0.022)
wto	0.277***	0.266***	0.273***	0.274***	0.502***	0.500***	0.501***	0.501***
	(0.031)	(0.030)	(0.030)	(0.030)	(0.024)	(0.024)	(0.024)	(0.024)
δEPS_i	0.105***				0.070***			
	(0.018)				(0.017)			
δEPS_j	0.101***				0.051***			
	(0.017)				(0.015)			
δEPS_MKT_i		−0.019				−0.033		
		(0.016)				(0.017)		
δEPS_MKT_j		−0.030				−0.062***		
		(0.017)				(0.016)		
δEPS_NMKT_i			0.036**				0.019	
			(0.011)				(0.012)	
δEPS_NMKT_J			0.041***				0.020*	
			(0.010)				(0.010)	
$\delta EPS\_TECHSUP_i$				0.084***				0.057***
				(0.011)				(0.010)
$\delta EPS\_TECHSUP_j$				0.076***				0.044***
				(0.010)				(0.009)
Num.Obs.	28 120	28 120	28 120	28 120	28 120	28 120	28 120	28 120
R2	0.911	0.910	0.910	0.911	0.944	0.944	0.944	0.944
FE: Exporter	yes	yes	yes	yes	yes	yes	yes	yes
FE: Importer	yes	yes	yes	yes	yes	yes	yes	yes
FE: year	yes	yes	yes	yes	yes	yes	yes	yes

$$\begin{aligned} Export_{ij,t} =& \beta_0 + \beta_1 \log(GDP_{i,t}) + \beta_2 \log(GDP_{j,t}) + \beta_3 \log(dist_{ij,t}) + \beta_4 contig + \\ & \beta_5 comcol + \beta_6 comlang + \beta_7 wto + \beta_8 \delta EPS_{i,t} + \beta_9 \delta EPS_{j,t} + \omega_i + \omega_j + \epsilon_{ijt} \end{aligned} \tag{5.4}$$

We follow Silva and Tenreyro (2006) and employ the Poisson Pseudo Maximum Likelihood (PPML) approach to estimate the gravity model, to account for zero trade flows. To address the omitted variable bias that arises from the presence of multilateral resistance, we adopt the approach of Savin et al. (2020), which include both countries and year fixed effects. Including the former has been shown to deliver unbiased and consistent estimates of coefficients of the regressors (Harrigan, 1996). In addition, year fixed effects control for business cycles and common trends. Furthermore, we compute heteroschedasticity-robust standard errors. Results are reported in Table 5.6.

Macro variables usually employed in Gravity models exhibit the expected signs and significance. Environmental policy distance also appears to influence trade flows in both green and brown industries. Namely, a greater policy divergence between trading partners positively impacts exports of both green and brown goods, regardless of the country implementing tighter policies. This finding aligns with the results from the previous section on network statistics, where an increase in EPS at the country level was associated with a higher out-degree for a country in both the brown and green trade networks. Examining the effects of different policy interventions in greater detail, we find that the distance in market-based measures is not statistically significant. An exception arises for green product flows, where the estimated coefficient for $\delta\_EPS_MKT_j$, suggests that exports decline when market-based environmental policies are implemented in the exporter country. This may be explained by lower demand for green goods in trading partners that are less committed to climate action. Conversely, when non-market-based instruments—such as standards and certifications—are introduced in the exporting country, exports increase. This likely reflects the role of such instruments as quality signals that enhance the attractiveness of green products in international markets.

All other policy measures positively impact trade flows, regardless of which country enforces the more stringent regulation. Our findings suggest that what matters is the environmental policy distance itself, rather than the relative stringency of individual countries.

The inclusion of a one-period lag in the environmental policy variables (Table 5.7) substantially alters the estimated effects on trade flows, highlighting the importance of accounting for dynamic responses. Notably, when considering lagged policies, we observe that export volumes decrease with increasing environmental policy distance between trading partners; the effect is statistically significant for the brown network only when the exporter implements more stringent regulations. The lagged specification suggests that the economic and regulatory adjustments induced by environmental policies may take time to materialize in trade patterns, reflecting delayed cost pass-through, adaptation processes, or gradual shifts in comparative advantages. Notably, the effects of non-market-based instruments lose statistical significance under this lag structure, indicating that their impact on trade may be more immediate or transient. These findings underscore the necessity of incorporating temporal dynamics in empirical assessments of environmental policy impacts on international trade.

5.7 Conclusions

This paper offers a preliminary empirical investigation into how environmental policy stringency relates to countries' integration within the global trade network. By combining network analysis with standard gravity estimations, we document a general positive association between stricter environmental regulations and centrality in global trade - particularly for peripheral economies and in green sectors. At the same time, analysis of the effect of EPS on network centrality reveals a positive correlation with in-degree in

Table 5.7: Gravity estimation results for brown and green sector with one lag of the policies.

	Brown flows				Green flows			
	$Export_{ij}$	$Export_{ij}$	$Export_{ij}$	$Export_{ij}$	$Export_{ij}$	$Export_{ij}$	$Export_{ij}$	$Export_{ij}$
log_gdp_o	0.326***	0.331***	0.323***	0.319***	0.475***	0.527***	0.498***	0.499***
	(0.047)	(0.047)	(0.048)	(0.046)	(0.047)	(0.049)	(0.046)	(0.047)
log_gdp_d	0.302***	0.321***	0.301***	0.322***	0.221***	0.242***	0.234***	0.236***
	(0.033)	(0.033)	(0.034)	(0.032)	(0.033)	(0.033)	(0.033)	(0.033)
log_dist_arithm	−0.773***	−0.770***	−0.770***	−0.772***	−0.720***	−0.718***	−0.719***	−0.719***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.012)	(0.012)	(0.012)	(0.012)
contig	0.413***	0.416***	0.419***	0.416***	0.401***	0.404***	0.406***	0.404***
	(0.024)	(0.023)	(0.023)	(0.023)	(0.021)	(0.021)	(0.022)	(0.021)
comcol	0.651***	0.682***	0.677***	0.697***	0.433***	0.467***	0.460***	0.488***
	(0.101)	(0.098)	(0.100)	(0.097)	(0.070)	(0.068)	(0.070)	(0.071)
comlang_off	0.291***	0.290***	0.286***	0.287***	0.267***	0.265***	0.261***	0.266***
	(0.034)	(0.033)	(0.033)	(0.033)	(0.023)	(0.023)	(0.023)	(0.023)
fta_wto	0.287***	0.295***	0.294***	0.293***	0.551***	0.557***	0.552***	0.562***
	(0.033)	(0.033)	(0.033)	(0.033)	(0.026)	(0.026)	(0.026)	(0.025)
$\delta EPS_{i,t-1}$	−0.065***				−0.033*			
	(0.017)				(0.015)			
$\delta EPS_{j,t-1}$	−0.010				−0.074***			
	(0.019)				(0.016)			
$\delta EPS\_MKT_{i,t-1}$		−0.070***				−0.084***		
		(0.018)				(0.016)		
$\delta EPS\_MKT_{j,t-1}$		0.009				−0.025		
		(0.018)				(0.020)		
$\delta EPS\_NMKT_{i,t-1}$			−0.017+				−0.006	
			(0.010)				(0.009)	
$\delta EPS\_NMKT_{j,t-1}$			−0.005				−0.028**	
			(0.011)				(0.009)	
$\delta TECHSUP_{i,t-1}$				−0.022*				−0.016+
				(0.010)				(0.008)
$\delta TECHSUP_{j,t-1}$				0.000				−0.043***
				(0.012)				(0.011)
Num.Obs.	27 360	27 360	27 360	27 360	27 360	27 360	27 360	27 360
R2	0.907	0.907	0.907	0.907	0.940	0.940	0.940	0.940
R2 Adj.	0.907	0.907	0.907	0.907	0.940	0.940	0.940	0.940
R2 Within	0.677	0.676	0.676	0.676	0.757	0.756	0.756	0.756
FE: Exporter	yes	yes	yes	yes	yes	yes	yes	yes
FE: Importer	yes	yes	yes	yes	yes	yes	yes	yes
FE: year	yes	yes	yes	yes	yes	yes	yes	yes

brown sectors, an early warning of potential carbon leakage effects.

This work is still in progress, and we fully acknowledge its current limitations. In the near future, we aim to perform a comprehensive set of robustness checks and explore alternative model specifications, including different measures of environmental policy distance. Importantly, the present analysis does not seek to establish causal relationships between the variables of interest. While we account for unobserved country characteristics and exploit the panel dimension of the data, potential endogeneity concerns - most notably reverse causality between environmental policy stringency and trade network integration - are not addressed in the present study. Tackling these issues with more advanced econometric techniques, such as instrumental variable approaches or regression discontinuity designs, represents a promising avenue for future research.

Second, and more fundamentally, our analysis inherits a structural limitation common to much of the existing literature: namely, the classification of green and brown industries does not align with the actual sectors targeted by environmental policies. While we tested two alternative classifications in addition to the main one used in the analysis - one from Jug and Mirza (2005), and one based on the EU list of sectors at risk of carbon leakage - a clear correspondence is still missing. These classifications are based on production characteristics or emission intensity but do not necessarily align with policy implementation. This undermines our ability to make strong inferences about the sectoral effects of environmental regulations. To overcome this, future research could aim to design a comprehensive database linking policies to targets sectors or, at least, sectorally disaggregated enivronmental policy stringency data. A promising direction would be to use the OECD's *Climate Actions and Policies Measurement Framework (CAPMF)* (see Nachtigall et al., 2022 for a detailed description of the database), which provides policy stringency scores for four broad sectors; however, it still remains at a high level of aggregation, distinguishing only between building, transports, electricity and industry. An alternative is to focus on a single, well-defined policy instrument, such as carbon pricing or emissions trading schemes, to enable a more precise evaluation of the trade–policy nexus. This could be achieved by exploiting cross-country, sectoral variation in the adoption of the policy and the concurrent changes in network centralities.

Appendix

Definition of network centralities

Table 5.8: Centrality measures

Centrality	Definition
Out-degree centrality	The degree is the number of links a given node has. More specifically, out-degree deals with the outbound links, i.e. exports flows.
In-degree centrality	The degree is the number of links a given node has. In-degree centrality deals with inbound links (imports).
Eigenvector centrality	Eigenvector centrality measures the importance of a node in a network by considering the importance of its neighbors. It builds on degree centrality and define a score for each node by considering the degree centrality of nodes linked to it.
Betwenness centrality	It counts how often a node acts as a bridge along the shortest path between two other nodes. It states the importance of a node in connecting other nodes and acting as an intermediary.
Random walk betweenness centrality (RWBC)	Proxy of economic integration used in Reyes et al. (2008). It considers all possible paths and weights them based on how likely they are in a random selection process. It accounts for the fact that real-world flows do not follow just the shortest path.
Out-closeness centrality	It identifies how close a node is to all others. Namely, it is the sum of the geodesic distances (shortest paths, i.e. the number of steps needed for one node to reach the other) of country i, normalized by the maximum number of possible export partners.
In-closeness centrality	It indicates the sum of the geodesic distances of country i, normalized by the maximum number of possible import partners.

Table 5.8: Centrality measures

Centrality	Definition
Katz centrality	It measures influence by taking into account the total number of walks between a pair of nodes. It does not solely focus on the shortest path. Instead, it considers the full network of nodes to which a given node is connected through its neighbors, with the weight of each connection decaying according to the distance between the nodes.
Clustering coefficient	The local clustering coefficient measures the likelihood that two neighbors of a node are also directly connected to each other (clique)

Distribution of network statistics

Figure 5.16 depicts the distribution of network statistics in a representative year (2019). They are all characterized by a non-normal distribution, which, in most of the cases, takes the form of a right-skewed distribution. For this reason, we apply the natural logarithm (Figure 5.17) of the network statistics in the analysis discussed in the paper. Out and in degree and RWBC of the world trade web have been, indeed, shown to follow a log-normal distribution.

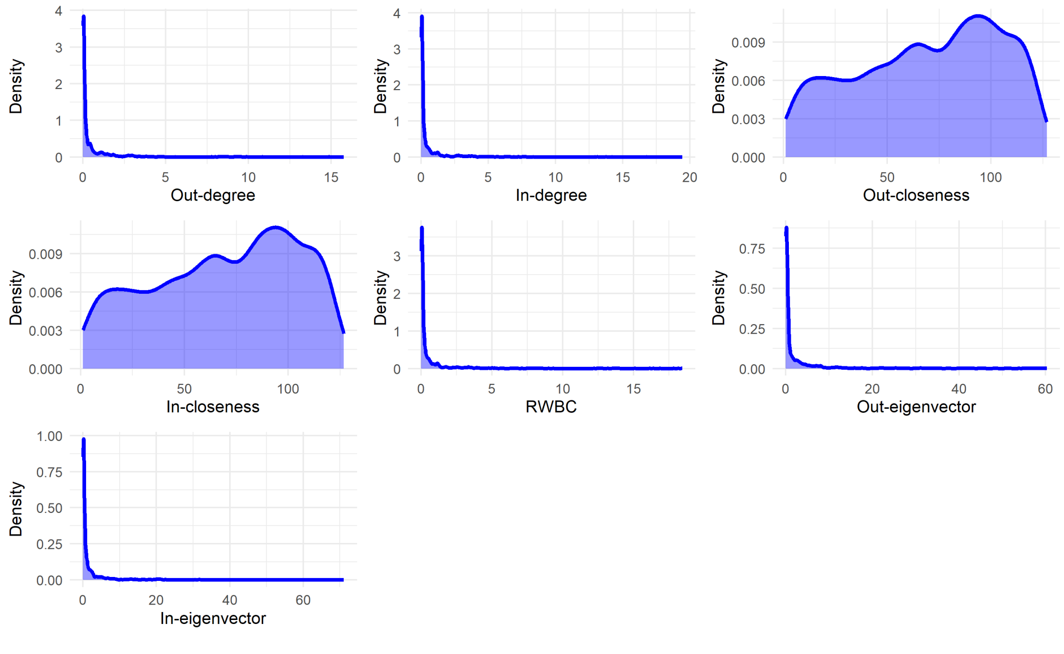

Figure 5.16: Density distribution of the network statistics

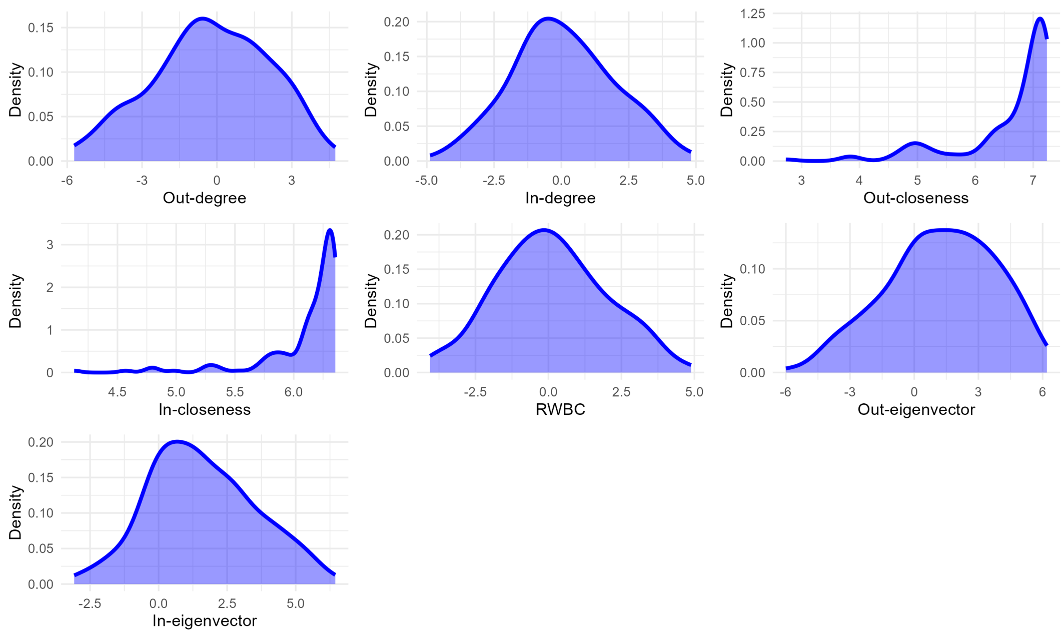

Figure 5.17: Density distribution of the log of network statistics

Chapter 6

Overall conclusions

This thesis has analyzed the macroeconomic consequences of asymmetric shocks and policies in a globalized economy, characterized by complex trade and production networks. A common thread running through the thesis is the emergence and evolution of international networks, driven by decentralized firm-to-firm interactions, and the analysis of how these networks shape - and are shaped by - the cross-border propagation of shocks. To this end, the chapters adopt a bottom-up perspective, integrating models of international trade with agent-based simulations that capture the dynamic, adaptive, and networked nature of the global economy. The four essays covered in the thesis offer complementary insights into different dimensions of global trade and challenges to the network economy.

The first essay investigates the macro-financial consequences of supply chain disruptions within a streamlined agent-based framework that combines a production and a financial network. Motivated by the COVID-19 pandemic, the chapter analyzes two scenarios: a generalized lockdown affecting all upstream firms, and a localized lockdown ('red zone') affecting only a subset. The simulations show that generalized disruptions trigger a deep recession through simultaneous declines in profits, net worth, and a rise in non-performing loans. In contrast, when the shock is localized, downstream firms can reorganize their supply relationships by switching to unaffected upstream firms. The rewiring of the supply chains mitigates the shock. This 'diversification effect' highlights a key trade-off in global value chains between efficiency and resilience: while lean, just-in-time systems perform well in normal times, networks with built-in redundancy are more robust under stress. The findings contribute to the growing literature on the systemic vulnerabilities of production networks and offer policy-relevant insights on how firm-level flexibility and alternative sourcing can enhance macroeconomic stability in the face of global shocks.

The second essay develops a micro-founded model of international trade, in which the global trade network emerges endogenously from the export decisions of heterogeneous firms operating under financial frictions and country-level asymmetries. The resulting network displays real-world characteristics, such as a scale-free structure and a limited and heterogeneous export participation at the firm level. This framework has then been employed to study the propagation of financial distress. Simulation results show that the macroeconomic effects of the shock depend critically on the network position of the affected country. Shocks hitting central hubs generate significant disruptions and widespread contagion, while those originating in peripheral countries have limited effects. The chapter highlights the importance of integrating financial frictions, heterogeneity into trade models of endogenous network formation, offering a unified framework to understand how micro-level constraints aggregate into systemic vulnerabilities. Furthermore, by introducing credit market into trade models, it opens the door to an in-depth understanding of the effect of monetary policy on global trade, a topic still understudied.

The third essay analyzes the macroeconomic and environmental implications of asymmetric climate policies in a global production network. Using an agent-based model in which the trade network emerges from the outsourcing decisions of heterogeneous and boundedly rational firms, the chapter investigates how unilateral carbon pricing affects the unbundling of production, leading to carbon leakage. The paper shows that non-harmonized climate policies distort comparative advantages and trigger a reorganization of global production, with polluting activities shifting toward less regulated countries. This not only undermines the environmental effectiveness of abating countries' efforts, but also imposes economic costs - such as competitiveness losses and inflationary pressures - that further challenge climate policy implementation. To avoid the distorsionary effect of uncoordinated policies, the chapter evaluates the role of a border carbon tariff, such as the EU's CBAM, in mitigating leakage. The results suggest that while these instruments can restore competitiveness and reduce leakage, they also raise production costs and global prices, with repercussions on the international economic activity. By modeling the economy as an evolving network shaped by decentralized firm interactions and bounded rationality, the paper offers a novel bottom-up perspective on the economic impacts of climate policy. It highlights the tension between environmental effectiveness and macroeconomic stability under asymmetric regulation, and calls for a careful rethinking of monetary and trade policy in light of climate-related disruptions.

The fourth essay presents a preliminary empirical investigation into the relationship between environmental policies and international trade. It analyzes how environmental policy stringency affects a country's position within the global trade network, distinguishing between green and brown trade flows based on sectoral classifications. The chapter explores whether stricter environmental regulation correlates with countries' centrality and integration within these networks; the analysis is complemented with the estimation of a gravity model of bilateral trade flows. Results indicate that stronger environmental policies are associated with increased centrality and integration in green trade flows, while their effects on brown sectors are more nuanced, influencing both import and export dynamics. This work opens a promising line of interdisciplinary research at the intersection of trade theory, environmental policy, and network analysis. Although still at an early stage, this direction complements the theoretical core of the thesis and contributes to its broader ambition of connecting trade models with complex systems methods.

Taken together, these essays contribute to the trade and macroeconomic ABM literature by offering a comprehensive analysis of trade in times of disruptions. The thesis bridges general equilibrium trade theory with macroeconomic agent-based modeling, providing new tools to analyze resilience, propagation mechanisms, and the unintended effects of policy interventions in an interconnected economy. The key takeaway of this thesis is that in a deeply interconnected global economy, countries are not isolated entities: each shock affecting a node in the international network can propagate across borders through trade and financial linkages. These systemic effects are not simply the result of aggregate forces, but rather emerge from the decentralized decisions and interactions of heterogeneous agents. As the chapters have shown, micro-level frictions and behavioral adjustments play a crucial role in amplifying or mitigating the transmission of shocks. Understanding the structure and dynamics of global networks, and how they evolve in response to economic and policy disturbances, is therefore essential for designing resilient and effective policy approaches. This bottom-up perspective calls for greater attention to the granular foundations of globalization, where heterogeneity, firm behavior, bounded rationality and network topology shape macroeconomic outcomes.

This thesis offers a step in that direction, placing microeconomic complexity at the core of macroeconomic analysis. Building on trade models with heterogeneous agents and decentralized decision-making, it advances a bottom-up perspective that captures the dynamic and adaptive nature of the global economy. In doing so, it opens the door to a broader research agenda at the intersection of trade, policy, and complex systems. Much remains to be explored about how the structure of global production interacts with economic policy, how firms adjust to systemic disruptions, and how international networks shape - rather than merely transmit - macroeconomic fluctuations. Bridging trade theory with the tools of computational science offers a promising path forward, laying the groundwork for an interdisciplinary research agenda focused on the structural foundations and systemic risks of an interconnected global economy.

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