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SHOCK PROPAGATION AND ECONOMIC POLICIES IN THE ITALIAN PRODUCTION NETWORK

by Fabio Bertolotti*, Andrea Linarello** and Patrick Zoi***

Abstract

We have developed a quantitative framework to study shock propagation in the Italian economy, building on Baqaee and Rubbo (2023) and extending it to include trade openness and endogenous labour supply. The model is calibrated using detailed input-output data for 98 sectors and macroeconomic aggregates. We illustrate the role of network linkages by comparing the effects of sectoral productivity shocks in a full network economy versus a counterfactual `island' economy. In the former, shocks to upstream industries are significantly amplified while those to downstream industries are dampened, relative to the effects of the same shocks in the island economy. We then apply the model to four policy scenarios: an increase in R&D tax credits; a set of entry regulation reforms; a spike in the price of imported oil and gas inputs; and an assessment of the aggregate productivity gains from AI adoption. In all cases, network forces account for a substantial share of aggregate effects. The framework provides a flexible and data-consistent tool for evaluating policies with strong sectoral dimensions.

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1 Introduction[1]

Understanding how sectoral shocks propagate through the economy is crucial for the design and evaluation of industrial and macroeconomic policies. This paper develops a quantitative framework to study shock transmission in the Italian economy, leveraging its rich input-output structure. We build on the network model of Baqaee and Rubbo (2023), extending it to incorporate trade openness and endogenous labor supply—two features that are quantitatively important to capture salient characteristics of Italy's production system.

At the core of our analysis is a production network model in which sectors are interconnected through input-output linkages. Each sector produces output using labor and intermediate goods sourced from other sectors, and sells its output both for final consumption and as inputs to other domestic producers, forming the input-output structure of production. Prices reflect the cost of these inputs and markups, which are modeled as exogenous, sector-specific wedges between price and marginal costs. These interdependencies form a directed network, where shocks to one sector—such as changes in productivity or markups—can propagate through the supply chain, affecting prices and quantities in downstream and upstream industries. The strength and direction of these propagation effects are governed by the structure of the input-output matrix and the Leontief inverse, which captures both direct and indirect exposure of each sector to others. This framework allows us to trace how sectoral shocks translate into aggregate outcomes, to quantify the amplification or dampening effects of network linkages, and to assess the impact of industrial policies.

We calibrate the model to the Italian economy using sectoral input-output tables provided by ISTAT, covering 98 industries. We assume a CES production function for each sector, with a uniform elasticity of substitution across inputs set to 0.15, consistent with the estimates by Atalay (2017). Sectoral wedges are interpreted as markups and inferred from the ratio of nominal output to total input costs, capturing deviations from perfect competition. We also calibrate household preferences for consumption and leisure using standard macroeconomic parameters (King and Rebelo, 1999), including a Frisch elasticity of labor supply of 0.4 (Reichling and Whalen, 2012). In the model, the absence of frictions in reallocating labor across sectors tends to amplify the impact of shocks on output. However, our calibration, which assumes a relatively rigid labor supply, dampens labor movements and therefore leads the model to produce conservative estimates of the output effects of positive shocks.

We explore the sensitivity of our results to alternative values of the elasticity of substitution and introduce sectoral heterogeneity based on the position of each industry in the input-output network. These robustness checks confirm the qualitative validity of our findings across different model specifications. We acknowledge, however, some limitations of our setting. First, in our model markups are constant, so we are unable to capture how changes in markups in response to aggregate shocks affect the dynamics of prices. Second, we always assume balanced trade. As a result, the model cannot capture the effects of shocks that influence both the domestic and foreign economies on domestic competitiveness and

[1] We thank Federico Cingano, Francesco D'Amuri, Roberto Torrini and seminar participants at the Bank of Italy for useful comments. The views expressed are those of the authors and do not necessarily reflect those of the Bank of Italy.

competition from foreign inputs.

To illustrate the properties of the model, we simulate a series of sectoral productivity shocks and compare their aggregate effects in the full network economy versus a counterfactual "island" economy without inter-sectoral linkages. The results show that network effects can amplify the impact of shocks to upstream sectors (central in the network) up to four times, while dampening the effects of downstream ones.[2] Among the most central sectors, we identify electricity generation and distribution, warehousing and transport support, financial services, and road freight transport. These sectors serve as key inputs across a wide range of industries, and their productivity improvements generate substantial spillovers throughout the economy. For example, a +1% TFP shock in electricity raises aggregate GDP by 0.02% in the island economy, but by 0.06% in the network model. A positive technology shock to electricity production lowers its price by 1.9%, reducing marginal costs in several downstream industries using electricity as a key input. As a result, productivity gains propagate in the economy, raising real output.[3] We also decompose the aggregate GDP effect into the contribution of the shocked sector and the spillovers to other sectors, highlighting the importance of indirect effects in upstream industries.

We further show that the model captures important nonlinearities in the propagation of shocks. Comparing the full solution of the model to a first-order approximation based on fixed input shares, we find that the linear approach systematically underestimates the aggregate impact of sectoral shocks—by more than 20% in a signifcant share of sectors. Moreover, when simulating aggregate TFP shocks of varying size, we find that the model dampens the effect of large positive shocks and amplifies the impact of large negative ones relative to a first order linear approximation of the exact solution. These findings underscore the importance of accounting for endogenous changes in the input-output structure when evaluating the macroeconomic consequences of sectoral shocks.

We then apply the model to four sets of policy exercises. The first evaluates the macroeconomic impact of an increase in the R&D tax credit rate from 10% to 20%, targeted at eight R&D-intensive sectors that together account for roughly two-thirds of business R&D expenditures in Italy. Using empirical elasticities from the literature (Parisi and Sembenelli, 2003; Bertolotti et al., 2024), we translate this policy change into sector-specific TFP shocks and simulate their aggregate effects. We find that real GDP increases by 0.11%, with approximately 35% of the gains attributable to network effects – i.e., productivity spillovers to non-targeted sectors. Similarly to the case of productivity shocks analyzed in the quantitative exercises, a positive TFP shock in upstream sectors determines a reduction of input costs in other industries, thus stimulating real output and welfare through lower prices for final consumers.

[2]We define network centrality based on the values of the first eigenvector of the inverse-Leontief input-output matrix, consistent with the network literature. Sectors with higher entries are more "central", meaning that they act as suppliers of inputs to many other industries. Therefore, we alternatively refer to these sectors as "upstream".

[3]In policy analyses in Section 4, we analyze the effect of shocks to the price of imported oil and gas inputs, which disproportionately affect production costs in electricity generation, and study aggregate effects given the centrality of the latter sector.

These results highlight the importance of considering not only the responsiveness of TFP to R&D, but also the network centrality of the targeted sectors. For instance, although the vehicle manufacturing sector displays a higher elasticity of TFP to R&D than machinery production, the latter generates a larger aggregate GDP effect due to its more upstream position in the production network.

The second policy exercise assesses the aggregate consequences of entry regulation reforms implemented in Italy between 2006 and 2019. Drawing on sector-level estimates of markup reductions from Cintolesi et al. (2024), we simulate the impact of these reforms as shocks to sectoral wedges in our model. The results show that aggregate real GDP increases by 0.6%, with only 0.2% of the gains stemming from the sectors directly affected by the reforms. Two thirds of the overall impact are driven by network effects, as lower markups in service sectors—such as professional consulting, property management, and broadcasting—reduce input costs for a wide range of downstream industries. These findings underscore the importance of accounting for sectoral interdependencies when evaluating the aggregate impact of structural reforms.

The third policy exercise illustrates the value of our extension featuring imported foreign inputs. Specifically, we study the aggregate and sectoral effects of the large increase in the price of two key imported inputs—crude oil and natural gas—following European sanctions on Russia. The price of these two inputs increased by 58% and 193%, respectively, between 2021 and 2022. We estimate a decline in aggregate real GDP equal to 0.9%, consistent across calibrations of the elasticity of substitution parameter. Aggregate effects are mostly driven by the adverse effect of the shock on energy production, a key input to most manufacturing sectors of the economy. Energy prices increase by 26% in the model (compared to 35% in the data) and determine a widespread increase in the marginal cost of manufacturing sectors, driving losses in sectoral value added between -1.2% and -0.5%. The network centrality of energy production is of course crucial to correctly infer these aggregate effects.

The fourth policy exercise quantifies the aggregate productivity gains from AI adoption in the Italian economy. Using sector-level TFP shocks derived from Filippucci et al. (2025), we find that annual labor productivity growth could increase by between 0.2 and 1.1 percentage points over a ten-year horizon, depending on the speed of AI diffusion. As in the R&D tax credit exercise, network effects play a significant role: professional services, acting as a hub in the input-output network, generate disproportionately large indirect gains relative to their direct productivity shock.

Beyond the specific applications explored in this paper, our quantitative framework offers a flexible tool for future research on industrial and macroeconomic policy in Italy. For instance, our extension featuring foreign inputs enables the analysis of the effect of tariffs on imported strategic inputs.[4] The model can be extended to incorporate additional features such as sectoral demand shocks and government spending, enabling the analysis of fiscal interventions. Moreover, the framework is well-suited to evaluate the impact of shocks or

[4] Unfortunately, the simplifying assumption that the domestic economy can only exports the final consumption good does not allow us to analyze the effect of tariffs applied by foreign economies on the domestic exports of specific sectoral goods.

reforms in specific sectors – such as defense, energy, or digital services – where network centrality and inter-sectoral spillovers are likely to play a critical role. By providing a structured and data-consistent approach to modeling the Italian production network, our framework lays the groundwork for richer policy simulations and more informed decision-making.

The remainder of the paper is organized as follows. Section 1.1 discusses our contributions to existing literature. Section 2 presents the model environment and its key equilibrium conditions. Section 3 describes the calibration strateg, illustrates the network properties of the model through sectoral shock simulations, and explores the sensitivity of our results to alternative assumptions on input substitutability. Section 4 applies the framework to evaluate two policy scenarios. Section 5 concludes.

1.1 Connection to Existing Literature

Our work contributes to four strands of the literature. First, we connect to the growing body of work on quantitative macroeconomic models of input-output networks calibrated to specific countries. Recent studies have applied network-based frameworks to analyze shock propagation and systemic risk in national contexts such as the United States Baqaee and Farhi (2020), Turkey Bilgin (2023), and several European economies Alatriste Contreras and Fagiolo (2014). These models typically use national input-output tables to estimate sectoral interdependencies and simulate the effects of shocks. To our knowledge, our paper is the first to provide a fully calibrated general equilibrium network model for Italy, incorporating both trade openness and endogenous labor supply. This fills a gap in the literature by offering a country-specific framework that can be used to evaluate sectoral policies and macroeconomic dynamics in the Italian context.

Second, we contribute to the literature on the evaluation of R&D policies in Italy. Several studies have examined the effects of R&D incentives on firm-level innovation and productivity. For example, Parisi and Sembenelli (2003) analyze the link between innovation and productivity using firm-level panel data, while Zuniga and Crespi (2009) study the effectiveness of public support for innovation. Bronzini and Piselli (2016) provide quasi-experimental evidence on the impact of R&D subsidies on firm performance. More recently, Bertolotti et al. (2024) offer a comprehensive review of public support instruments and their effects on innovation outcomes in Italy. Our contribution complements this literature by emphasizing the role of input-output linkages in shaping the aggregate effects of sectoral R&D policies, and by proposing network centrality as an additional criterion for policy targeting.

Third, we connect to the literature on the effects of trade liberalization and structural reforms. The impact of entry regulation on firm dynamics and productivity has been widely studied. Klapper et al. (2006) show that entry regulation negatively affects entrepreneurship and productivity across countries. Scarpetta and Nicoletti (2003), Fiori et al. (2012) and Andrews and Cingano (2014) provide cross-country evidence on the role of competition and regulatory policies in driving productivity growth, employment, and misallocation. Schivardi and Viviano (2010) carry out a similar analysis for the Italian retail trade sector. Alesina et al. (2005) and Mocetti et al. (2019) focus on the impact of regulation on investment and labor, respectively. Furthermore, Barone and Cingano (2011) and Bourles et al. (2013) investigate empirically the cross-industry effects of regulation, in the spirit of our quantitative analysis of input-output network linkages. In the Italian context, Ciapanna et al. (2022) estimates the aggregate effects of structural reforms, which they find to boost GDP between 3.5% and 8% over a decade. Our findings imply slightly larger effects over ten years, taking into account network effects. Cintolesi et al. (2024) builds on this literature by constructing a novel indicator of entry regulation at the 5-digit sector level and exploiting variation from multiple reforms. Our network framework complements these studies by showing that when liberalization targets service sectors that are central in the input-output network, the aggregate GDP effects can be large due to network propagation—even if the sectors themselves are relatively small.

Fourth, we relate to a recent set of papers studying the consequences of 2021-2022 energy crisis. Previous papers have analyzed the aggregate effects of the crisis either simulating a ban on Russian imports in input-output network models calibrated to Germany (Bachmann et al., 2022; Moll et al., 2023) or through macroeconomic (Ruhnau et al., 2023; Alessandri and Gazzani, 2023) and microeconomic (Alpino et al., 2023) empirical analyses. Particularly relevant to our paper is Alessandri and Gazzani (2023), which employs Bayesian VAR models to estimate the effects of a shock to gas price on Italian inflation and industrial production. They find that a 25% increase in gas price at peak reduces industrial production by approximately 0.7%. We focus instead on real GDP and real value added in manufacturing, and find smaller effects (a +193% in the price of imported natural gas reduces real GDP by around 1.6%). These discrepancies are consistent with the fact that gas is a key input in part of the industrial sector and that the index of industrial production tends to over-weight low-value added goods. Moreover, Alessandri and Gazzani (2023) find that oil and gas shocks have markedly different aggregate effects, consistent with the very different relevance of these inputs for the Italian input-output network.

Finally, our fourth policy exercise connects to a growing literature on the macroeconomic effects of AI adoption. The dominant approach models AI as a new wave of automation within a task-based framework (Acemoglu, 2025): AI raises efficiency in a subset of tasks, and the aggregate impact is the product of four factors—the share of tasks exposed to AI, the share of those for which adoption is economically viable, the efficiency gain per task, and the labor share in exposed activities. Starting from different assumptions on these components, Acemoglu (2025) and Aghion and Bunel (2024) arrive at sharply divergent estimates of the annual TFP growth attributable to AI—0.07 and 0.68 percentage points, respectively—with roughly three quarters of the gap driven by differences in assumed task exposure. Filippucci et al. (2025) extend the framework of Acemoglu (2025) to compute sector-level productivity gains for G7 economies and aggregate them using the general equilibrium network model of Baqaee and Rubbo (2023). Our contribution complements this analysis by feeding their sector-level shocks into a distinct general equilibrium framework calibrated to Italy, which incorporates a more disaggregated input-output table and an elastic labor supply, and by highlighting the role of network centrality in determining the sectoral distribution of aggregate AI gains.

2 Environment

In this section, we present the model environment. We first derive the key equilibrium conditions for a closed economy with exogenous labor supply, akin to Baqaee and Rubbo (2023). We then present two model extensions that consider (i) the use of foreign inputs at the sectoral level – and thus openness to international trade – and (ii) an endogenous labor supply. Both extensions allow the model to match salient aspects of the Italian economy.

2.1 Notation and Definitions

We assume there exists a population of consumers with identical homothetic preferences given by a homogeneous-of-degree-one function $C = \mathcal{C}(y_1, y_2, \ldots, y_N)$, where N denotes the total number of goods produced in the domestic economy and y_i for $i = 1, \ldots, N$ their final output quantity. Moreover, we define endowment goods, i.e., goods that are produced with zero returns to scale, as factors. We denote by $\mathcal{N}$ the set of goods in the economy, by $\mathcal{F}$ the set of factors, and by $\mathcal{U} = C \cup \mathcal{N} \cup \mathcal{F}$ the joint set of goods – including the consumption good C – and factors. We initially assume there is a single primary factor, labor, whose supply is exogenous. In Section 2.5 we consider the case of endogenous labor supply and of additional factors being foreign inputs.

Each good $i = 1, \ldots, N$ is produced according to the following constant returns-to-scale production technology

$$x_i = A_i f_i \left(\{x_{ij}\}_{j \in N}, L_i \right). \tag{1}$$

where A_i is a Hicks-neutral productivity shock, x_{ij} is the quantity of good j used as intermediate in the production of good i, and L_i is the quantity of labor employed in the production of i.

Therefore, we require that the following resource constraints holds for every good $i \in \mathcal{N}$:

$$x_i = y_i + \sum_{j \in \mathcal{N}} x_{ji}, \tag{2}$$

which states that total production for good i must equal the quantity consumed y_i plus the quantity used as intermediate input in the production of other goods.

The budget constraint of the consumer in this simple setting is:

$$E = \sum_{i=1}^{N} p_i y_i = wL + \sum_{i=1}^{N} \pi_i \tag{3}$$

where E is household's total expenditure, w the labor wage rate, and π_i represent profits from sector i, which accrue to the consumers because we assume that they own all the firms in the economy.

To introduce the input-output notation, we arrange goods and factors in the set $\mathcal{U}$ such that the sector producing the consumption good through $\mathcal{C}$ comes first and factors come last.

Therefore, the input-output matrix in this economy is:

$$\Omega = \left[\begin{array}{c|ccc|c} 0 & \Omega_{C,1} & \cdots & \Omega_{C,N} & 0 \\ \hline 0 & & & & \Omega_{1,L} \\ 0 & & \Omega^* & & \\ 0 & & & & \Omega_{N,L} \\ \hline 0 & 0 & \cdots & 0 & 0 \end{array}\right] \tag{4}$$

where

$$\Omega^* = \begin{bmatrix} \Omega_{1,1} & \cdots & \Omega_{1,N} \\ & \ddots & \\ \Omega_{N,1} & & \Omega_{N,N} \end{bmatrix}$$

$$\Omega_{i,j} = \frac{x_{i,j}p_j}{x_i p_i}, \qquad \Omega_{i,L} = \frac{wL_i}{x_i p_i}, \qquad \Omega_{C,i} = \frac{y_i p_i}{\sum_j y_j p_j} \tag{5}$$

The first column of Ω is identically zero because the consumption good is not an input to any other goods or factors. Moreover, since the consumption good is produced as a combination of sectoral products without any labor, the first row collects the weight of different goods $i = 1, \ldots, N$ in the total value of consumption and it has a zero in the last column. The last row is also identically zero because labor is a primary factor and its quantity does not depend on other inputs but equals the Hicks neutral factor A_L which controls the (exogenous) labor supply in the economy. Finally, the terms $\Omega_{i,L}$ and $\Omega_{i,j}$ represent the weight of labor costs (wL_i) and of intermediate input j ($p_j x_{ij}$) on the total value of production $p_i x_i$ in sector i, respectively. Sector-specific markups are defined as the ratio between total production value (sales) and total production costs, i.e.:

$$\mu_i = \frac{x_i p_i}{\sum_{j \in \mathcal{N}} x_{i,j} p_j + L_i w} = \left(\sum_{j \in \mathcal{N}} \Omega_{i,j} + \Omega_{i,L} \right)^{-1} \tag{6}$$

Because we do not explicitly model capital, our definition of markups includes also the remuneration to this factor of production.

The inverse Leontief matrix is the solution of the equation

$$\Psi(I - \Omega) = I \tag{7}$$

where I denotes the identity matrix. Therefore, the Leontief inverse matrix Ψ features the following structure:

$$\Psi = \left[\begin{array}{c|ccc|c} 1 & \lambda_1 & \cdots & \lambda_N & \Lambda \\ \hline 0 & & & & \Psi_{1,L} \\ 0 & & \Psi^* & & \\ 0 & & & & \Psi_{N,L} \\ \hline 0 & 0 & \cdots & 0 & 1 \end{array}\right] \tag{8}$$

The elements in the first row represent the Domar weights – i.e., the ratio of gross output to aggregate value added – of the consumption good (1), of the intermediate goods (λ_i), and labor (Λ), respectively. In Appendix A.1 we derive them as:

$$\lambda_i = \frac{x_i p_i}{\sum_{j\in\mathcal{N}} y_j p_j} \qquad \text{and} \qquad \Lambda = \frac{Lw}{\sum_{j\in\mathcal{N}} y_j p_j}.$$

Moreover, $\Psi^* = (\mathbb{1} - \Omega^*)^{-1}$ and the elements of the last column satisfy the equation:

$$\begin{pmatrix} \Psi_{1,L} \\ \vdots \\ \Psi_{N,L} \end{pmatrix} = \Psi^* \begin{pmatrix} \Omega_{1,L} \\ \vdots \\ \Omega_{N,L} \end{pmatrix} \tag{9}$$

Markups allow us to define the cost-based input-output matrix as $\tilde{\Omega}_{i,j} = \mu_i \Omega_{i,j}$. This matrix describes an economy where the expenditure shares on intermediate goods and labor over total costs for each industry are the same but the markups are identically equal to 1. The cost-based inverse Leontief is:

$$\tilde{\Psi} = \left[\begin{array}{c|ccc|c} 1 & \tilde{\lambda}_1 & \cdots & \tilde{\lambda}_N & 1 \\ \hline 0 & & & & 1 \\ 0 & & \tilde{\Psi}^* & & \\ 0 & & & & 1 \\ \hline 0 & 0 & \cdots & 0 & 1 \end{array}\right] \tag{10}$$

where $\tilde{\Psi}^* = \left(1 - \tilde{\Omega}^*\right)^{-1}$ and $\tilde{\lambda}_i$ are the Domar weights in this hypothetical economy. Note that the last element of the first row is equal to 1 beacause in this economy $\pi_i = 0$ for $i = 1, \ldots, N$ and the total consumption is $E = Lw$ (see Appendix A.1 for further details).

2.2 Evolution of Prices : Forward Propagation

We now characterize the dynamics of sectoral prices in response to shocks to productivity, markups, or wages. In response to small shocks, price dynamics represent an accurate approximation of the response of the economy up to first-order effects, i.e., without considering higher-order effects due to changes in the (endogenous) elements of the input-output matrix, which we further derive in the next subsection. The assumptions that firms combine input factors in order to minimize the production costs and that the production functions have constant return to scale, allow to apply the envelope theorem and ignore the changes of the input output matrix elements at the first order. Taking natural logs of equation (6) and differentiating (see Appendix A.2 for details) we obtain:

$$d\log p_i = \sum_{j=1,\ldots,N} \tilde{\Omega}_{i,j} d\log p_j + \tilde{\Omega}_{i,L} d\log w + d\log \mu_i - d\log A_i \tag{11}$$

This equation relates variation in sectoral prices to changes in the price of other sectors and to shocks to productivity and (exogenous) markups. In so doing, it describes the propagation of shocks downstream in the production network (*forward propagation*). Specifically, the first and the second terms represent the response of p_i to input price shocks – either intermediates or labor – which is proportional to the input shares Ω_{ij} and Ω_{iL}, respectively, and to the markup μ_i. The third term captures the contribution due to exogenous changes in the markup for good i. The last represents the *direct* effect of a technology shock on the price in the same sector: A positive productivity shock lowers output price by reducing production marginal cost.

Of course, changes in the price of other sectoral goods are themselves endogenous objects. Therefore, we solve equation (11) for $d\log p_i$ by leveraging the fact that $\sum_{j=1}^{N} \tilde{\Psi}^*_{i,j}\tilde{\Omega}_{j,L} = 1$ and equation (10). We finally obtain an expression linking changes in sectoral prices to exogenous shocks to labor costs and to markups and technology in other sectors.

$$d\log p_i = d\log w + \sum_{j=1}^{N} \tilde{\Psi}^*_{i,j} \left(d\log \mu_j - d\log A_j\right). \tag{12}$$

the effect of shocks to markups and productivity in sector j on the price of a different sector i depend on the weight of j for i according to the cost-based Leontief inverse matrix, which captures the relevance of sector j once considering the sectoral input-output structure.

2.3 Evolution of Sales Shares: Backward Propagation

Next, we characterize the dynamics of the input-output structure of the economy, and thus the dynamics of quantities given the evolution of prices, in response to sectoral shocks. These equations are useful to characterize the response of the economy to sectoral shocks beyond the first order, i.e., considering that shocks may endogenously affect expenditure shares due to firms' cost-minimization.

Starting from the definition of Ω_{ij} in equation (5), in Appendix A.3 we derive the change in the use of input i for the production of good j as:

$$d\log \Omega_{i,j} = -d\log \mu_i + \sum_{k=1}^{N+1} \left[\frac{\partial \log \tilde{\Omega}_{i,k}}{\partial \log p_k} + \left(\theta_{i,j,k} - 1\right)\left(1 - \delta_{j,k}\right)\right] d\log p_k \tag{13}$$

where the first term represents the effect of a markup shock to good i – which reduces expenditures on all inputs – and the second term captures variation in input shares after changes in sectoral prices, which depend on the sensitivity of expenditure shares to the shocked price $\left(\frac{\partial \log \tilde{\Omega}_{i,k}}{\partial \log p_k}\right)$ and on the the elasticity of substitution between goods j and k in the production of i ($\theta_{i,j,k}$).[5] The term $\delta_{j,k}$ simply denotes an indicator function that equals one if j and k coincide. We provide further intuition on this expression in the case of the CES production function below.

[5]The elasticity of substitution is defined by the expression $\theta_{i,j,k} = 1 + \frac{\partial \log(x_{i,j}p_j/x_{i,k}p_k}{\partial \log(p_k/p_j)}$.

Therefore, in equilibrium, equation (12) defines the change in prices due to exogenous shocks given the input-output structure, and equation (13) in turn describes how input-output weights vary due to the changes in prices.

In the special case of a Constant Elasticity of Subsititution (CES) production function with (constant) sector specific elasticity of substitution θ_i and weights $\omega_{i,j}$, i.e.,

$$x_i = A_i \left(\sum_{j=1}^{N+1} \omega_{i,j} x_{i,j}^{\frac{\theta_i - 1}{\theta_i}} \right)^{\frac{\theta_i}{\theta_i - 1}} \quad \text{with} \quad \sum_j \omega_{i,j} = 1,$$

equation (13) simplifies to

$$d \log \Omega_{i,j} = -d \log \mu_i + (1 - \theta_i) \left(d \log p_j - \sum_{k=1}^{N+1} \tilde{\Omega}_{i,k} d \log p_k \right). \tag{14}$$ [6]

Specifically, the first term captures the fact that an increase in sector i's markup reduces expenditures on all inputs, while the second term shows that sector i re-optmizes input sourcing – and thus increases expenditures – towards sector j when the price of j increases by more than the prices of other industries on average (weighted by input-output weights) conditional on j being complements with other inputs ($\theta_i < 1$).

For the calibration and the quantitative exercises of Section 3, we will mostly focus on this functional specification of the sectoral production functions.

2.4 Closing the model: Nominal output and Domar weights

To close the model, we characterize the evolution of the nominal output $E = \sum_{i=1}^{N} y_i p_i$. Since we have assumed for now that labor is inelastically supplied in fixed amount – i.e., $d \log L = 0$ – from the definition of Λ it follows that:

$$d \log \Lambda = d \log w - d \log E.$$

Choosing nominal output as the numeŕaire – i.e., E is identically equal to one and thus $d \log E = 0$ – we can further derive that the changes to the labor share coincide with changes in the wage:

$$d \log \Lambda = d \log w \tag{15}$$

Similarly, we characterize the dynamics of Domar weights, which constitute the elements of the first row of the inverse Leontief matrix and thus represent the direct "weight" of different sectors on aggregate output in terms of the final good. In Appendix A.4 we derive the following equation:

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[6] To see this, consider that the expenditure shares take the form $\tilde{\Omega}_{i,j} = \frac{\omega_{i,j}^{\theta_i} p_j^{1-\theta_i}}{\sum_k \omega_{i,k}^{\theta_i} p_k^{1-\theta_i}}$. Therefore, $\frac{\partial \log \tilde{\Omega}_{i,j}}{\partial \log p_k} = (1 - \theta_i) \left(\delta_{j,k} - \tilde{\Omega}_{i,k} \right)$, which delivers (14) once replaced into (13).

$$d\lambda_i = \sum_{j=0}^{N} \lambda_j \left[(\Psi_{j,i} - \delta_{j,i}) \left(-d\log\mu_j - \sum_{k=1}^{N+1} \frac{\partial \log \tilde{\Omega}_{j,k}}{\partial \log p_k} d\log p_k \right) + \sum_{l=1}^{N+1} \sum_{k=1}^{N+1} \Omega_{j,l} \Psi_{l,i} (\theta_{j,l,k} - 1)(1 - \delta_{k,l})\, d\log p_k \right] \tag{16}$$

where $\Psi_{j,i}$ denotes the elements of the Leontief-inverse matrix, $\delta_{j,i}$ is an indicator function equal to one if sector j coincides with i, $\theta_{j,l,k}$ is the elasticity of substitution between input l and k in the production of good j, and all other terms have been previously defined. We interpret this expression more transparently for the case of a CES production function below.

In the CES case, the two following equations characterize the dynamics of the Domar weights for goods:

$$d\lambda_i = \sum_{j=0}^{N} \lambda_j \left\{ (\Psi_{j,i} - \delta_{j,i}) \left[-d\log\mu_j - (1 - \theta_j) \sum_{k=1}^{N+1} \tilde{\Omega}_{j,k} d\log p_k \right] + \sum_{l=1}^{N+1} \Omega_{j,l} \Psi_{l,i} (1 - \theta_j)\, d\log p_l \right\} \tag{17}$$

and factors ($i = N + 1$)

$$d\Lambda = \sum_{j=0}^{N} \lambda_j \left\{ \Psi_{j,L} \left[-d\log\mu_j - (1 - \theta_j) \sum_{k=1}^{N+1} \tilde{\Omega}_{j,k} d\log p_k \right] + + \sum_{l=1}^{N+1} \Omega_{j,l} \Psi_{l,L} (1 - \theta_j)\, d\log p_l \right\} \tag{18}$$

The intuition for both equations is similar, so we focus on the latter equation, which refers to the labor input. The first part of the expression captures a (negative) level effect on the labor share if the markup of any industry j increases. The size of the effect of this shock in each industry depends on its size λ_j for the economy times the fraction of its revenues that are ultimately paid out to labor $\Psi_{j,L}$ (or input i, in the case of equation 17). The second and the third set of terms describe a composition effect due to expenditure-switching in relation to cross-industry input substitution. The second term describes the change in weights related to sectoral price variations: if the price of other inputs increases, the relative weight of labor decreases unless these other inputs whose price has increased can be easily substituted (θ approaches 1). The last term captures substitution effects with labor: the labor share increases when goods are substitutes and the covariance between price changes $d\log p_l$ and total labor payments $\Psi_{j,L}$ is negative. A similar variaon in Λ occurs when goods are complements and the covariance is positive.

2.5 Extensions

To enhance the ability of the model to provide an accurate quantitative description of the response of the Italian economy to sectoral shocks, we propose two extensions to the baseline framework. First, we introduce trade openness with a foreign country, to account for the fact that a large share of inputs are sourced abroad and a fraction of domestic goods and services are shipped internationally. This extension also allows us to study the effect of shocks to the price of foreign inputs, which are of independent interest. Second, we allow for an endogenous labor supply, which allows producers to absorb the effect of exogenous shocks by adjusting a different input than intermediate products from other sectors. This extension enhances the realism of the model and allows us not to overstate the relevance of input-output linkages in response to shocks.

2.5.1 Open economy

We assume that a subset of goods, denoted by $\mathcal{I}$, is produced abroad and imported in the domestic economy. We require such goods to be used exclusively as intermediate inputs and we treat them as "factors" from the perspective of the domestic economy, i.e., their production does not involve any domestic input of factor.[7] In other words, $\Omega_{C,i} = 0$ for all $i \in \mathcal{I}$, $\Omega_{i,j} = 0$ for all $i \in \mathcal{I}$ and for all $j \in \mathcal{N}$, but $\Omega_{j,i} \geq 0$ for $i \in \mathcal{I}$ and $j \in \mathcal{N}$. Therefore, the total value of goods imported by the domestic economy equals:

$$I = \sum_{j \in \mathcal{N}} \sum_{i = \mathcal{I}} x_{j,i} p_i,$$

where $x_{j,i}$ is the quantity of imported good i used in the production of domestic good j and p_i is its price.

We further assume that a foreign consumer demands S units of the final good, which the domestic economy exports abroad to keep trade balanced, i.e., $S = I$. The resource constraint of the economy requires that nominal exports S (foreign consumption) and nominal domestic consumption C add up to nominal domestic output E, i.e.,

$$E = C + S.$$

As before, nominal expenditures must equal $E = C + S = \sum_{j=1}^{N} p_j y_j$ and domestic nominal consumption equals the sum of labor income wL and profits from domestic firms – which are assumed to be owned by the household.

As a result, the *forward propagation* equation describing price dynamics in response to shocks is similar to the closed economy case, but for the fact that it now reflects the impact of shocks to (exogenous) prices of foreign, imported, inputs:

$$d \log p_i = \sum_{j \in \mathcal{S}} \tilde{\Psi}^*_{i,j} \left(d \log \mu_j - d \log A_j + \tilde{\Omega}_{j,L} d \log w + \sum_{k \in \mathcal{I}} \tilde{\Omega}_{j,k} d \log p_k \right) \quad (19)$$

[7] In reality, the Italian economy also imports final goods. For tractability, we only focus on the import of intermediates and calibrate our model consistently.

which are reflected by the last summation $\sum_{k\in\mathcal{I}} \tilde{\Omega}_{j,k} d\log p_k$ in brackets, which weighs changes in foreign input prices by their expenditures shares in the production of good i. Specifically, equation (19) features the elements of the matrices Ω^*, Ψ^*, $\tilde{\Omega}^*$, and $\tilde{\Psi}^*$, which are equivalently defined as in the closed-economy case.

The evolution of the elements of the input-output matrix is still governed by equation (13).

We finally specify the wage dynamics to close the model. Differently from the closed economy setting, we set nominal domestic consumption C rather than nominal expenditures E to be numéraire. We denote by Λ_L the total labor share and by Λ_I the total import share of nominal income, which we formally define by:

$$\Lambda_L = \frac{wL}{C+I} \qquad \Lambda_I = \frac{I}{C+I}.$$

Therefore, using the definition of Λ_L and the fact that we set nominal consumption as the numéraire, we obtain:

$$d\log \Lambda_L = d\log w + d\log L - \Lambda_I d\log I \tag{20}$$

Moreover, using the balanced-trade condition, which implies:

$$d\log \Lambda_I = (1-\Lambda_I)\, d\log I \tag{21}$$

and assuming a fixed labor supply, we finally express the wage equation as:

$$d\log w = d\log \Lambda_L + \frac{\Lambda_I}{1-\Lambda_I} d\log \Lambda_I, \tag{22}$$

which expresses wage variation as a function of changes in labor use in production and of the share of imported goods in the economy.

2.5.2 Endogenous Labor Supply

In this subsection, we introduce an endogenous labor supply in the model. We consider that the representative domestic consumer has utility function $U(Q_C, L)$, increasing in real consumption $Q_C = C/p_C$, where p_C represents the nominal price of domestic consumption, and decreasing in hours worked L. We further assume that the consumer has homothetic preferences, which implies that her expenditure shares depend only on the relative prices and are given by the coefficients $\Omega_{C,j}$ in the first row of the input-output matrix. As a result, the nominal price of consumption equals $p_C = \sum_{i=1}^{N} \Omega_{C,i} p_i$.

For a generic utility function, the maximization problem of the consumer yields the following optimality condition, which determines the labor supply:

$$\frac{dU}{dL} = \frac{\partial U}{\partial Q_C}\frac{w}{p_C} + \frac{\partial U}{\partial L} = 0$$

Furthermore, specializing the utility function to the following functional form:

$$U(Q_C, L) = \frac{Q_C^{1-\gamma}}{1-\gamma} - \frac{L^{1+\alpha}}{1+\alpha} \text{ with } \gamma > 0 \text{ and } \alpha > 0$$

we obtain $L^{\alpha} = Q_C^{-\gamma} w/p_C$, which implies

$$\alpha \, d\log L = -\gamma d\log Q_C + d\log w - d\log p_C$$

. Again, taking the nominal domestic consumption C as the numéraire we finally derive:

$$d\log L = -\frac{1-\gamma}{\alpha} d\log p_C + \frac{1}{\alpha} d\log w \tag{23}$$

2.6 Full Model

In this subsection, we briefly describe how to combine the two model extensions presented in the previous subsections. Specifically, because the introduction of an endogenous labor supply does not interact with input-output structure of the model, the price equation (19) derived for the open economy still described the dynamics of prices in response to shocks. Similarly, equation (13) determines the evolution of the elements of the input-output matrix and, therefore, of real quantities.

The two model extensions interact when it comes to the labor factor. Specifically, substituting equation (23) into equations (20) and (21) derived in the open-economy model and describing factor-share dynamics, we obtain:

$$d\log w = \frac{1}{\alpha+1}\left[\alpha d\log \Lambda_L + \alpha \frac{\Lambda_I}{1-\Lambda_I} d\log \Lambda_I + (1-\gamma) d\log p_C\right] \tag{24}$$

Therefore, equations (13), (19), and (24) fully characterize the dynamics of prices and quantities in the economy.

2.7 Key Aggregates

In this subsection, we define key aggregates in the model, which we use to quantitatively assess the impact of shocks in the model.

Sectoral Value Added The nominal value added in each sector i is defined by:

$$VA_i = x_i p_i - \sum_{j \in \mathcal{N} \cup \mathcal{I}} x_{i,j} p_j .$$

In contrast, *real* value added after a shock s occurs is obtained as the difference between output and intermediates evaluated at the pre-shock prices, i.e.:

$$\begin{aligned} RVA_i &= x_i^{(s)} p_i^{(0)} - \sum_{j \in \mathcal{N} \cup \mathcal{I}} x_{i,j}^{(s)} p_j^{(0)} \\ &= x_i^{(s)} p_i^{(s)} \left(\frac{p_i^{(0)}}{p_i^{(s)}} - \sum_{j \in \mathcal{N} \cup \mathcal{I}} \Omega_{i,j}^{(s)} \frac{p_j^{(0)}}{p_j^{(s)}} \right) \end{aligned} \tag{25}$$

where upperscripts (0) and (s) denote the value of variables before and after the shock, respectively. Nominal output $x_i^{(s)} p_i^{(s)}$ after the shock is determined by equation (A6) in Appendix A.5.

Real GDP. Real GDP equals the sum of real value added across sectors of the domestic economy, which we derive in Appendix A.5 to be:

$$RGDP = \underbrace{\sum_{i\in\mathcal{N}} y_i^{(s)} p_i^{(0)}}_{C+F=\text{Cons. + Export}} - \underbrace{\sum_{i\in\mathcal{I}} x_i^{(s)} p_i^{(0)}}_{I=\text{Import}}$$

Using the trade-balance condition and differentiating previous expression for small shocks, in Appendix A.5 we derive the following characterization of real GDP changes in response to exogenous shocks in the model:

$$\begin{aligned} d\log RGDP = & \underbrace{\frac{\Lambda_S}{1-\Lambda_S} d\log\Lambda_S - \frac{\Lambda_I}{1-\Lambda_I} d\log\Lambda_I}_{\text{trade imbalance}} \\ & \frac{1}{1-\Lambda_I}\Bigg[\underbrace{\sum_{j\in\mathcal{N}} \tilde{\lambda}_j d\log A_j + \tilde{\Lambda}_L\, d\log L}_{\text{technology}} \\ & \underbrace{-\sum_{j\in\mathcal{N}} \tilde{\lambda}_j d\log\mu_j - \tilde{\Lambda}_L \left(d\log\Lambda_L + \frac{\Lambda_S}{1-\Lambda_S} d\log\Lambda_S\right)}_{\text{allocation}} \\ & \underbrace{+\sum_{k\in\mathcal{I}} \left(\lambda_k - \tilde{\lambda}_k\right) d\log p_k}_{\text{price of imported goods}}\Bigg]. \end{aligned} \tag{26}$$

The first term of the expression reflects the impact of exogenous shocks to trade balance on real GDP. The second term reflects the impact of technology shocks, similarly to the closed-economy case. The third term captures allocation effects due to markup shocks or trade. The fourth term reflects the impact of shocks to the exogenous prices of imported inputs through the network.

In undistorted economies, i.e., if $\tilde{\lambda}_k = \lambda_k$, the last term related to import price shocks disappears: the first order effect of a change in the price of imported goods has no effect on the real GDP, consistent with Hulten's theorem. However, in our benchmark setting considering markup distortions λ_k is generally smaller than $\tilde{\lambda}_k$, Therefore, an increase in the price of foreign inputs reduces real GDP in the domestic economy.

3 Quantitative Analysis

In this section, we describe the calibration of the model and perform preliminary quantitative exercises to illustrate the properties of the model.

3.1 Calibration

We now describe our choices of functional forms and parameter values.

We assume that firms operate a Constant Elasticity of Substitution (CES) production function at the sectoral level, i.e., the aggregate production function for sector i equals:

$$x_i = A_i \left(\sum_{j \in \mathcal{N} \cup \mathcal{I}} \omega_{i,j} x_{i,j}^{\frac{\theta_i - 1}{\theta_i}} \right)^{\frac{\theta_i}{\theta_i - 1}} \text{ with } \sum_j \omega_{i,j} = 1,$$

where A_i is sector-specific TFP parameter, $\omega_{i,j}$ represent the weight of sector j's inputs in the production of i, and θ_i is the (constant) elasticity of substitution among different inputs in the production function. Given this functional form assumption, equations (13) and (16) governing the dynamics of input-output shares and Domar weights specialize to equations (14) and (17), respectively.

Therefore, the "deep" parameters of the production function ultimately inform the elements of the input-output matrix $\Omega^*_{i,j}$ and the substitution parameters θ_i, which we ultimately need to calibrate to solve the model. To this end, we leverage the input-output matrices as of 2021, for $i = 1, ..., 97$ sectors provided by the Italian institute of national statistics (ISTAT) and compute final output from these tables as $p_i y_i = x_i p_i - \sum_j x_{j,i} p_j$. Table C1 reports the full list of sectors included in the analysis.

We then set the elasticity of substitution parameter θ_i equal to 0.15 for all sectors, consistent with estimates by Atalay (2017) for the U.S. economy. This parameter value implies a moderate degree of substitutability among inputs. Unfortunately, empirical estimates of this parameter at the sectoral level or for the Italian economy only are unavailable. Therefore, in Section 3.4 we experiment with alternative values of this parameter and experiment with sectoral heterogeneity based on the posititie of the industry in the input-output network.

The price-dynamics described by equation (19) involve the elements of the cost-based inverse-Leontief matrix $\tilde{\Psi}^*_{i,j}$, which require the computation of sectoral distortions μ_i. Given the definition provided by equation (6), we calibrate the levels of μ_i based on input-output tables as the ratio between nominal output divided by intermediate plus labor costs. Therefore, deviations of this empirical proxy from one represent a departure from the perfect competition benchmark due to market power or other frictions.

We finally calibrate the parameters of the domestic household's utility function. We set $\gamma = 1$, a standard assumption in the quantitative macroeconomic literature (King and Rebelo, 1999), and calibrate $\alpha = 1/0.4$ to match a Frisch elasticity of substitution equal to 0.4, consistent with a review of estimates in the economic literature by the Congressional Budget Office (Reichling and Whalen, 2012).

3.2 The Role of Input-Output Linkages: Sectoral Productivity Shocks

To illustrate the properties of the model and to quantitatively assess the importance of input-output linkages for the Italian economy, we simulate a 1% increase in sectoral TFP in each of the 98 sectors included in the model. Appendix B describes the solution algorithm.

For each shock, we compute the aggregate effect of the sectoral TFP change on real GDP, based on equation (26), and perform two comparisons.

In a first exercise, we compute the impact of the same shock in a counterfactual economy where we shut down all inter-sectoral linkages—i.e., we impose a diagonal input-output matrix Ω^*—which we define as an "island" economy. The comparison between the baseline economy with sectoral links and the "island" economy highlights the amplification (or dampening) role of the network for specific sectors and the overall importance of these linkages to correctly infer the aggregate impact of shocks.

Figure 1 provides a graphical representation of the comparison between the aggregate effect of these sectoral shocks in the network economy (y-axis) and in the island economy (x-axis). Each dot represents a shock to a different sector. Dots above (below) the 45 degree line indicate that the input-output linkages of the economy amplify (dampen) the impact of a specific sectoral shock relative to the case in which network effects are disregarded. Table C2 reports detailed figures for all sectors.

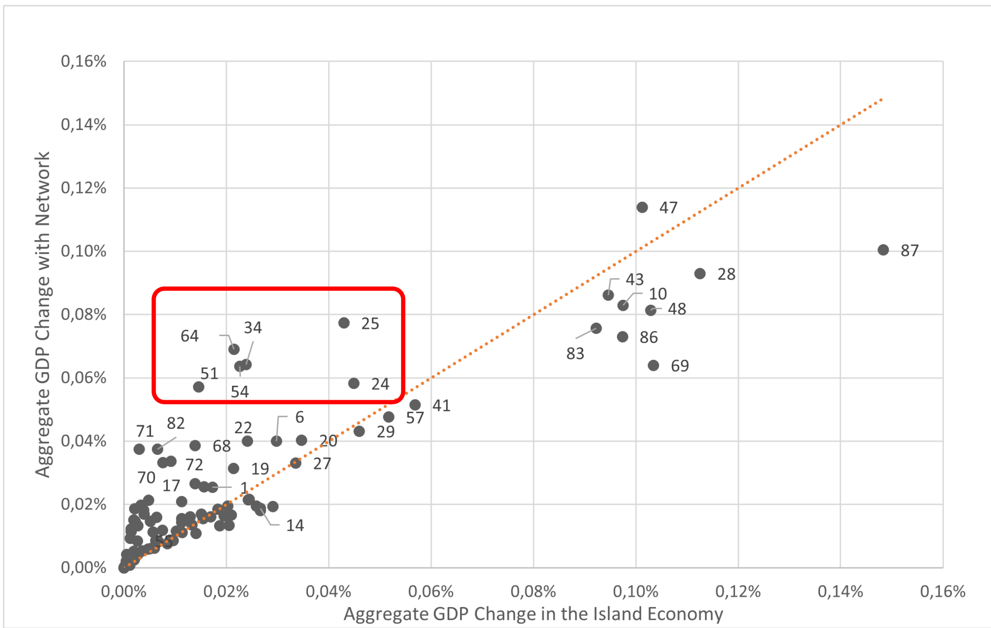
The figure shows that there exists significant dispersion around the 45 degree line (dotted line), meaning that network effects are quantitatively substantial. Specifically, the red rectangle highlights that for some industries the network structure can amplify the impact of sectoral shocks up to four times. These sectors are those positioned relatively "upstream" in the input-output structure, i.e., those that directly or indirectly serve as crucial inputs in other industries. In contrast, dots below the 45 degree line identify sectors that are relatively downstream.

Table 1 further investigates which are the most relevant upstream and downstream sectors based on the comparison of the network and island economies. *Panel A* of the table list four sectors whose impact would be large in the island economy—due to their overall size—but even larger once accounting for input-output linkages, as they are central in the network. For instance, a positive 1% TFP shock to production and storage of electricity, a key input in most manufacturing and services industries, would raise aggregate real GDP by 0.02% in the island economy, but this effect nearly triples once considering the importance of this input in the production function of other industries. Similar considerations hold for other sectors such as logistics, financial services, and transportation.

Panel B of Table 1 lists sectors displaying the largest amplification of sectoral shocks to due network effects, despite their limited overall size in the economy, as reflected by the small change in aggregate GDP in the island economy. In line with intuition, these sectors provide services that do not capture a large share of input costs across industries, but do enter the production function of most goods and services. As a result, the reduction in the price of these inputs due to a positive TFP shock trickles down to other sectors in a pervasive manner, and widespread cost advantages result in larger production and aggregate GDP gains.

Lastly, *Panel C* of the table shows two examples of large downstream sectors that (i) are close to final consumers and thus peripheral in the input-output network and (ii) generate smaller GDP effects in the network than in the island economy, for a TFP shock of given size. This ranking originates from the fact that a price reduction in these large downstream sectors

Figure 1: Impact of Sectoral Shock in the Network vs. Island Economy



Notes: The figure illustrates the effect of a +1% shock to sectoral TFP on aggregate real GDP in the full network model (y-axis) and in the counterfactual island economy without input-output sectoral linkages (x-axis). Each dot represents a sector and label indicates sector codes. Table C1 maps sector codes to a brief description thereof. The effects refer to one distinct shock for each sector, while holding TFP constant in all other industries. The dotted line represents the 45 degree line. The red rectangle highlights sectors in which the network amplifies the aggregate impact of sectoral shocks relative to the island economy.

Table 1: Sectoral TFP Shocks: Island vs. Network Economy, Selected Industries

Code	Sector	Island Economy	Network Economy
Panel A: Large Upstream			
34	Electricity generation and distribution	0.02%	0.06%
54	Warehousing and transport support	0.02%	0.06%
64	Financial services (excl. insurance)	0.02%	0.07%
51	Road freight and pipeline transport	0.01%	0.06%
Panel B: Small Upstream			
70	Legal and accounting activities	0.01%	0.03%
72	Architecture and engineering	0.01%	0.03%
82	Business support services	0.01%	0.04%
Panel C: Large Downstream			
87	Healthcare services	0.15%	0.10%
48	Retail trade (excl. vehicles)	0.10%	0.08%

Notes: The table reports the change in aggregated real GDP due to a +1% shock to sectoral TFP for selected industries, based on a counterfactual economy where we neutralize all input-output network linkages ("Island Economy" column) and in the full network model ("Network Economy" column). The first and second column report the code and a brief description of the shocked sectors.

might increase rather than reduce input costs in other industries. A larger demand—and thus production—in these downstream sectors requires more inputs, commanding a negative price externalities on other industries. Therefore, while the TFP shock would benefit consumers, it would not reduce production costs in other sectors, a key driver of network amplification of shocks in upstream industries.

As a second exercise, we propose an alternative illustration of the network properties of the model by performing a decomposition of aggregate GDP effects of sectoral shock for the same subset of industries analyzed in Table 1. Specifically, in Table 2 we leverage the fact that aggregate GDP is the sum of real value added across sectors and thus decompose the aggregate GDP effect (reported in first column) into a component related to the change in real value added in the shocked sector (second column), and a component due to variation in real value added in other industries (third column). The relative importance of the two terms, captured by the ratio in the fourth column, reflects the amplification forces of the network. As shown by the table, for most upstream activities the contribution of other sectors to aggregate effects is significantly larger than their own contribution, while the two items are roughly equivalent in the case of downstream sectors. The case of electricity generation and distribution and warehousing and transport deserves additional comment. While the activity in these sectors is a key input to several downstream industries, a significant fraction of output is also very close to the final consumer. Therefore, while being predominantly upstream, the relative importance of own and network effects terms is more even.

Of course, these quantitative conclusions depend on the elasticity of substitution of inputs across sectors. Therefore, in Section 3.4 we experiment with these parameters and show that results are qualitatively consistent when assuming more or less substitutability of in-

Table 2: Sectoral TFP Shocks: Own Contribution and Newtork Effects, Selected Industries

Code	Sector	Aggregate Effect	Own Contrib.	Network Effects	Ratio
Panel A: Large Upstream					
34	Electricity generation and distribution	0.06%	0.04%	0.03%	0.79
54	Warehousing and transport support	0.06%	0.03%	0.03%	1.13
64	Financial services (excl. insurance)	0.07%	0.02%	0.05%	2.56
51	Road freight and pipeline transport	0.06%	0.03%	0.03%	1.25
Panel B: Small Upstream					
70	Legal and accounting activities	0.03%	0.01%	0.04%	1.93
72	Architecture and engineering	0.03%	0.01%	0.02%	1.68
82	Business support services	0.04%	0.02%	0.02%	1.34
Panel C: Large Downstream					
87	Healthcare services	0.10%	0.05%	0.05%	1.17
48	Retail trade (excl. vehicles)	0.08%	0.04%	0.04%	0.91

Notes: The table reports the GDP effect of a +1% shock to sectoral TFP for selected industries, based on the full network model. The first and second column report the code and a brief description of the shocked sectors. The "Aggregate Effect" column reports the percent change in aggregate real GDP; the "Own Contribution" column reports the contribution of the shocked industry's real value added to the aggregate GDP change; the "Network Effects" column reports the contribution of all other non-shocked industries; the "Ratio" column reports the ration of Network Effects to Own Contribution.

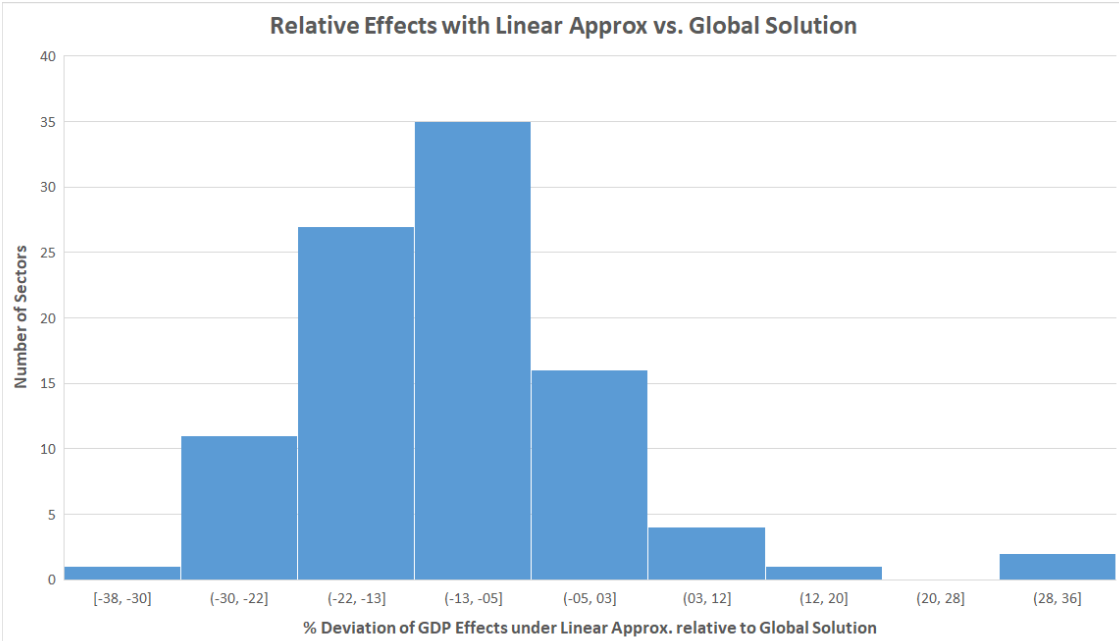
puts.

3.3 The Role of Nonlinearities: Aggregate Shocks of Varying Size

Next, we illustrate the role of nonlinearities in the network economy by comparing a first order approximation of the effect of sectoral and aggregate shocks in the model—i.e., a solution just based on price effects described by the *forward propagation* equation (19), keeping constant input-output shares—to the global solution of the model considering endogenous variation in the input-output structure. A larger discrepancy between the two solutions highlights the relevance of conducting inference on the impact of sectoral shocks using the proposed model compared to a simpler approach taking input-output shares as given.

Specifically, we perform two complementary analyses. The first one shocks the model with +1% TFP variations one sector at a time, similarly to the analysis of previous subsection. For each shock, we compare aggregate effects on real GDP when using the global solution and when considering a first order approximation based on price variation only. In the latter case, we only use price equation for forward proapgation of the shocks while keeping input-output shares fixed. Figure 2 depicts the distribution of the percent deviation of the effects under the approximated solution from those obtained with the global solution. On average, the first order approximation tends to under-predict the correct effect of sectoral shocks. Specifically, in most cases the error hovers between -20% and -5%, which is quantitatively significant. Moreover, for approximately 15% of sectoral shocks, the under-prediction is

Figure 2: Real GDP Effects to Sectoral TFP shock: First Order Approximation vs. Global Solution



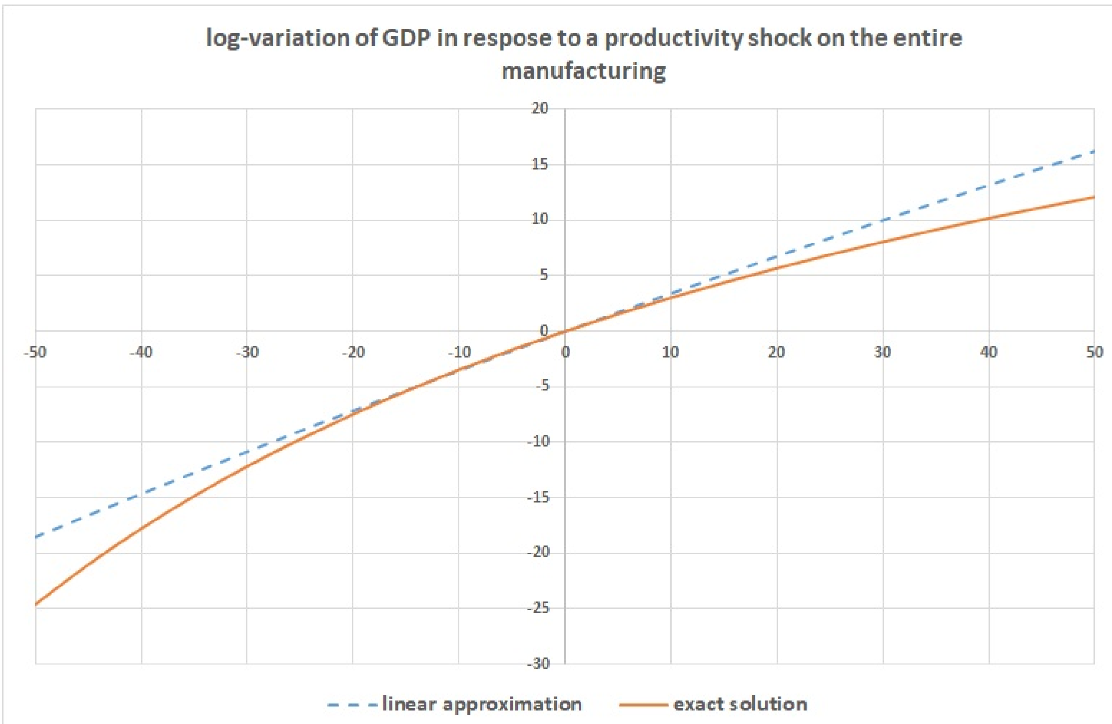
Notes: The figure illustrates the percent deviation of real GDP changes in response to sectoral +1% TFP shocks under a first-order approximation of the model solution compared to the exact global solution. The y-axis reports the fraction of sectoral shocks that fall into each bin of percent deviation between the two solution methods (x-axis).

even more severe and larger than -20%. This evidence further supports the importance of the present work for the correct assessment of the effect of industry-specific shocks on the Italian economy.

In the second exercise, we shock the model with "aggregate" TFP shocks of varying size, which we implement through symmetric and simultaneous TFP shocks to all sectors. Crucially, this experiment aims at testing model nonlinearities in the size of shocks, which interact but are distinct from nonlinearities related to the network structure of the economy. As we expect the difference between the first order approximation and the global solution to widen as the size of the shock increases, we experiment with aggregate shocks ranging between -50% and +50%. We then represent in Figure 3 the aggregate real GDP change (y-axis) according to the global exact solution (orange solid line) and to the linear approximation (blue dashed line).

For shocks of reasonable size—i.e., smaller than 5%—the two solutions are close. However, as expected, the linear approximation becomes more imprecise as the shock size widens. The model dampens the effect of very large positive shocks relative to the linear benchmark, while it amplifies the consequences of large negative shocks. Interestingly, this implies that "disruptions" of production are exceedingly costly with the severity of the adverse shock, while the marginal benefit of positive technology shocks decreases with their size. While we further stress that nonlinearities in the size of the shock become evident for extremely

Figure 3: Aggregate TFP Shocks of Varying Size: First Order Approximation vs. Global Solution



Notes: The figure illustrates the change real aggregate GDP (y-axis) in response to aggregate TFP shocks of varying size (x-axis) under a linear approximation of the solution (blue dashed line) and under the exact global solution (orange solid line).

large shocks, unlikely to be observed in reality, we also iterate that nonlinearities related to network dynamics are very important, as we show in Figure 2 above.

3.4 Sensitivity Analyses

In this section, we investigate the sensitivity of our quantitative results to alternative assumptions about the value of the elasticity of substitution across inputs in the sectoral production functions. In the first analysis, we consider smaller (0.05) and larger (0.5) values of θ_i—corresponding to less or more substitutable inputs—but we still keep this parameter homogeneous across sectors. We refer to these two alternative set of assumptions as Sensitivity Analysis 1 and 2, respectively.

In the second analysis, we introduce heterogeneity in the θ_i parameter. We experiment with more (less) complementarity in industries that are more upstream (downstream) in the input-output network. We perform this classification based on the standard measure of upstreamness of Antràs–Chor:

$$u_j = \sum_i \Psi_{i,j}$$

which counts the average distance from the final consumption. We report the 20 most and least upstream industries in Appendix Table C3. In practice, in a first scenario we assign a value of $\theta_i = 0.05$ to the 20 most central industries and a value equal to 0.5 to the 20 most peripheral ones, holding $\theta_i = 0.15$ for all the others (Sensitivity Analysis 3). This implies that inputs become more substitutable in downstream sectors. In a second scenario, we consider the symmetric case, i.e., we assign $\theta_i = 0.5$—i.e., higher input substitutability—to the most central industries and $\theta_i = 0.15$ to the least central ones (Sensitivity Analysis 4).

In Appendix C, Tables C4, C5, C6, and C7 replicate the results of Table 2—i.e., the aggregate GDP effects of 1% sectoral TFP shocks, distinguishing between own and network contribution—for Sensitivity Analyses 1,2,3, and 4, respectively. The tables highlight that our baseline findings on the role of upstream and downstream industries are remarkably stable across the four analyses.

The largest difference with our baseline results is observed when we uniformly raise the elasticity of substitution across inputs. In this scenario, the aggregate effects of sectoral TFP shocks to upstream industries become larger, mainly due to an increase in the percent change in value added in the shocked sector. As inputs are more substitutable, there is a larger scope for using as intermediates the goods of the sector that has become more efficient. As a result, production in this sector increases by more, driving a larger increase in aggregate real GDP.[8] This robustness analysis also helps highlight that, by considering a moderate degree of substitutability across inputs in our baseline calibration, our result represent conservative estimates of aggregate GDP effects of TFP shocks.

[8] A caveat with the interpretation of this result concerns the role of markups. While fixed in our setting, in practice they may increase in response to a TFP gain. This would partially offset the scope for reallocation, dampening output effects.

4 Policy Analysis

In this section, we use our calibrated model to quantify the impact of two policy interventions, a real-world shock to imported inputs and the potential impact of AI adoption on productivity in the Italian economy. We first consider the case of an R&D tax credit increasing TFP in several industries. For this policy exercise, we complement our model with empirical estimates from prior literature on the elasticity of R&D investment to R&D tax credits and on the elasticity of TFP to R&D investment, in order to map the policy change of interest to exogenous shocks in our model. In a second analysis, we investigate the aggregate effects of liberalization reforms which increased competition in several services sectors in Italy. In this case, we leverage estimates of markup reductions due to the policy change by Cintolesi et al. (2024) and interpret them as shocks to sectoral wedges in our theoretical framework. In the third exercise, we simulate an increase in the price of imported oil and natural gas, consistent with the spike in the price of these commodities observed between 2021 and 2022. The fact that most oil refinement and energy production in the Italian economy uses imported natural resources as well as the centrality of energy production in the input-output network motivate the relevance of this exercise, which also allows us to illustrate the value in our open-economy extension of the model. Finally, we use our model to assess the potential impact of AI adoption on aggregate productivity. In particular, we combine the sector-specific estimates of AI adoption and its productivity effects from Filippucci et al. (2025) to quantify their aggregate impact on the Italian economy.

4.1 R&D Tax Credit

We now analyze the aggregate effect of an increase in the R&D tax credit rate on eight R&D-intensive sectors—listed in Table 3—that account for approximately two thirds of aggregate R&D expenditures in Italy.[9] These industries are mainly in manufacturing, including vehicles and equipment production, information and communication technologies, and pharmaceutical products. Moreover, we include research and development professional services and software production. Specifically, we study an increase in the R&D tax credit rate from 10%—the statutory rate in Italy as-of 2024—to 20%.

Because we do not explicitly model productivity growth through R&D activity and innovation in our framework, we perform back-of-the-envelope calculations to infer the size of sectoral TFP variation—the exogenous shock of interest in our model—corresponding to the change in the R&D tax credit described above. First, we determine the percent variation in R&D expenditures corresponding to the implied variation in the statutory rate. We use an elasticity of R&D to its own price equal to -2 for all sectors. This value lies in the mid-range of the empirical estimates by the innovation literature (Becker, 2015; Dechezleprêtre et al., 2023; Agrawal et al., 2020) and is close to the estimate of -1.8 by Parisi and Sembenelli (2003) for Italy. Second, we translate the implied variation in R&D into TFP changes using sector-specific estimates of the elasticity of productivity to R&D from Bertolotti et al. (2024), reported in the second column of Table 3. As a result, we obtain the sectoral TFP shocks

[9] We obtain data on Business Expenditures on R&D (BERD) by industry from Eurostat (BERD by NACE Rev. 2 activity) and compute the share of R&D by industry using data for year 2021.

Table 3: Sectoral TFP Shocks implied by an R&D Tax Credit Increase

Code	Sector	R&D Share (% of total)	Elasticity (TFP to R&D)	TFP Shock (%)
29	Manufacture of motor vehicles	13.3%	0.021%	0.5%
28	Manufacture of machinery and equip.	12.3%	0.018%	0.4%
30	Manufacture of other transport	10.1%	0.015%	0.3%
26	Manufacture of computers	7.9%	0.020%	0.5%
21	Manufacture of pharmaceuticals	5.1%	0.020%	0.4%
27	Manufacture of electrical equipment	4.3%	0.016%	0.4%
72	Scientific research and development	6.9%	0.016%	0.4%
62	Software production, IT consultancy	6.4%	0.016%	0.4%

Notes: The table reports the size of the simulated TFP shocks in response to an increase in the R&D tax credit rate from 10% to 20% in eight selected industries with the highest R&D business expenditures. The first and second columns report industry codes and descriptions. The third column reports the share of total business R&D accounted for by the specific industry in Italy in 2021. The fourth column reports industry-specific estimates of the elasticity of TFP to R&D from Bertolotti et al. (2024) used to compute the change in TFP implied by the increase in the R&D tax credit rate. The last column reports the implied percent change in sectoral TFP used as shock in the model. The latter figures are obtained as follows. We first compute the percent change in the unit cost of R&D given by an increase in the R&D tax credit from 10% to 20%, i.e., approximately 11% (0.8/0.9-1). Second, we use the elasticity of R&D to its own price, which we assume equals 2 for all industries considered, to convert the percent variation in R&D price into a change in R&D. Lastly, we use the elasticity estimates reported in the fourth column of the Table to obtain the implied TFP change. Industries not reported in the table are not shocked.

reported in the last column of Table 3, which we simulaneously feed into the model.

We find that real aggregate GDP increases by 0.11%, in light of a fiscal cost equal to 0.03% of yearly GDP. Therefore, consistent with the findings on the long run benefits of R&D support policies and the under-supply of R&D due to positive knowledge externalities, this intervention would involve significant output and welfare gains.

Furthermore, approximately 35% of implied output gains would be determined by network effects, i.e., relates to value added gains in other sectors different from the ones targeted by the policy. This effect is partly due to the fact that the target sectors are mainly producers of intermediate inputs for other sectors. Being relatively upstream in the input-output network, the price reductions obtained through the simulated productivity gains trickle down in the economy.

These findings on the quantitative relevance of network effects also highlight an interesting policy consideration. While the economic literature has traditionally focused on targeting innovation policies to areas of economic activity where the resulting increase in R&D could be more beneficial on TFP and output, the network centrality of a specific industry has rarely being considered as a driver of these effects. Specifically, previous studies have mostly focused on understanding the elasticity of sectoral TFP to R&D in isolation.[10] However,

[10] Liu and Ma (2021) is a notable exception. They study optimal sectoral R&D allocations considering the network of knowledge creation at the technology level. We abstract from the latter, but cosider input-output

as our results show, this is just one part of the story, because how sectoral TFP gains transmit to the aggregate economy also depends on their position in the network. If the latter effects are quantitatively significant, targeting sectors where TFP is most responsive to R&D may involve a trade-off, as it is not guaranteed that they would drive the largest aggregate gains.

We further illustrate this point with an example based on two industries: manufacturing of vehicles and parts (NACE 29) and manufacturing of machinery and equipment (NACE 28). The former displays a larger elasticity of TFP to R&D (0.021%) than the latter (0.018%). However, vehicles manufacturing is also a more downstream sector than equipment manufacturing, as a larger fraction of output accrues to final consumers rather than being used as an intermediate in other sectors. Therefore, the aggregate effect of a same-sized TFP shock on real GDP is more than double in equipment manufacturing compared to vehicles.[11] An equivalent policy intervention increasing the R&D tax credit from 10% to 20% in the two sectors would induce a larger TFP gain in vehicles than equipment, but due to larger network effects in the equipment the aggregate GDP impact would be larger in the latter (0.039% as opposed to 0.022%).

4.2 Entry Regulation Reforms

The second policy experiment aims to assess the aggregate impact of entry regulation reforms that occurred in Italy between 2006 and 2019. To this end, we rely on estimates by Cintolesi et al. (2024), who build a novel indicator of entry regulation at a granular sector level and exploit different reforms that heterogeneously affects entry costs across industries. Their paper estimates the effect of such reforms on changes in sectoral markups, reported in Table 4, which we can directly map to structural shock to sectoral wedges μ_i in our model.

Consistent with the fact that most of entry regulations—such as professional requirements and red tape—are more prevalent in services sectors, Table 4 shows that the largest reduction in sectoral wedges due to the reforms were observed in professional services (-8%), property management and leasing (-7%), programming (-6%), consulting (-5%), wholesale trade (-5%) and social assistance (-5%).

To analyze the aggregate effects of the reforms, we thus simulate in the model the joint effect of these sectoral changes to wedges. We find that aggregate real GDP increases by 0.6%, of which only 0.2% are due to real value added variation in the sectors targeted by the liberalization policies. Therefore, consistent with the fact that these sectors are relatively small but used as intermediate inputs to several other industries, a reduction in their prices due to a reduction in wedges determines large output gains due to significant trickle down price effects.

Quantitatively, when we cumulate the estimated effects over a decade, the resulting GDP changes align with the findings of Ciapanna et al. (2022). In particular, the cumulative impact excluding network multipliers is just below their lower-bound estimate of +3.5%,

linkages.

[11] A +1% TFP shock in vehicles manufacturing determines a +0.04% increase in real GDP, while the same shock yields a +0.09% real GDP increase when considering manufacturing of machinery and equipment.

Table 4: Sectoral Shocks to Wedges

Code	Sector	Wedge Reduction
45	Maintenance and repair of motor vehicles	-4%
47	Wholesale trade	-5%
58	Publishing activities	-3%
60	Programming and broadcasting activities	-6%
63	Information services and other IT services	-2%
69	Rental and leasing of owned real estate	-7%
71	Management consultancy activities	-5%
74	Advertising and market research	-1%
75	Other professional, scientific and technical activities	-8%
86	Education	-3%
87	Healthcare services	-3%
88	Residential social assistance services	-5%

Notes: The table reports the size of the simulated shocks to wedges based on empirical estimates by Cintolesi et al. (2024) on the effect of entry regulation reforms in Italy between 2005 ans 2019. Industries not reported in the table are not shocked.

while incorporating the network structure yields effects in the mid-range of their estimates, considering their upper bound equal to 8.5%. This comparison highlights how accounting for production linkages substantially amplifies aggregate outcomes. Moreover, our model provides a framework to disentangle the underlying drivers of these similar aggregate impacts, offering insights into the relative contribution of direct and network-mediated channels.

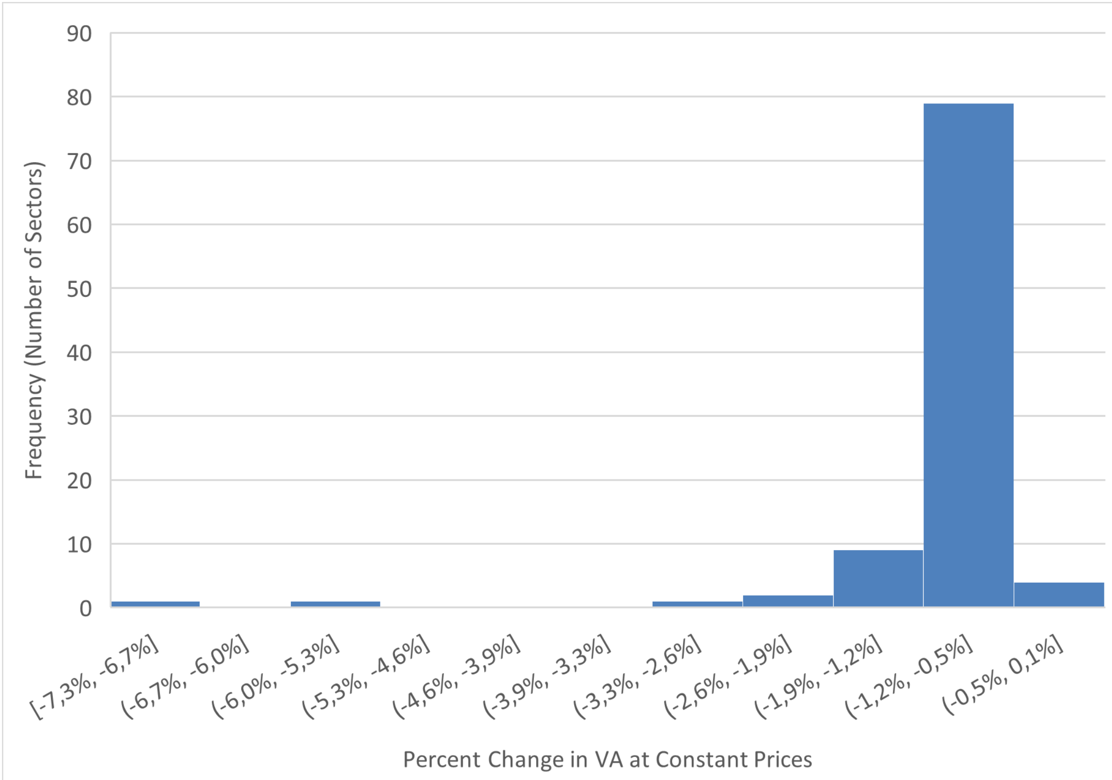
4.3 Oil and Gas Import Shock

The third policy exercise simulates an exogenous increase in the price of two imported inputs—crude oil and natural gas—as observed in Italy between 2021 and 2022. Specifically, during the turmoil following the EU sanctions on Russia, which was one of the main supplier of natural gas to Italy, the import price of this commodity almost tripled (+193%) in 2022 relative to 2021. For similar reasons, the price of imported oil jumped by almost 58%. In our industry classification, the extraction of such natural resources falls into sector 6, whose price of imported goods we shock to examine the aggregate and sectoral impact of these price changes.[12]

We start by analyzing the aggregate effects of this shock to imported inputs in our baseline calibration of the elasticity of substitution. We find that aggregate real GDP declines by 0.9% in response to the shock, driven by a 1.0% decline in the real value added of manufacturing industry. Compared to the change in total value added, the shock generates a larger decline in total output (1.2%). Two endogenous forces of our model explain this discrepancy: the

[12] To account for the different size of the observed price changes for oil and natural gas, for this exercise only we adjust our calibration and breakdown sector 6 into two distinct activities related to the extraction of the two commodities. We then feed shocks equal to the observed price changes to the corresponding sub-industry.

Figure 4: Oil and Gas Import Shock: Sectoral Real Value Added Changes



Notes: The figure illustrates the distribution of percent changes in sectoral real value added (x-axis) in response to an exogenous increase in the price of imported crude oil (+50%) and imported natural gas (+193%). The y-axis reports the number of sectors in each bin.

change in the relative sectoral prices induced by the shock determines the substitution of inputs that have become relatively more expensive with those less exposed to the exogenous price increase (+0.1% in value added relative to gross output), as well as a re-composition of the final consumption bundle toward goods whose price has increase relatively less (another +0.1%).[13]

We then focus on heterogeneous effects across sectors. Figure 4 represents the distribution of the percent change in real value added due to the shock. At the extreme left of the histogram, oil refinement and electricity production display the largest drop in real value added (-7.3% and -5.6%, respectively), because natural gas and crude oil are particularly relevant inputs to their activities. As a validation of our exercise, we note the change in the output prices induced by the shock in our model to the sector "electricity, gas, steam and air conditioning supply" is about 26%, comparable with the increase implied by the sector-specific output deflator of the annual national accounts (35%).

Given the centrality of energy production in the input-output network and the size of the

[13]Section 3.4 describes how these baseline effects change as we vary out assumptions about the elasticity of substitution.

shock, it is unsurprising to observe substantial losses in value added (between -1.2% and -0.5%) in most industries. This widespread reduction in value added drives the significant aggregate GDP loss.

This exercise illustrates the relevance of our extension of the model to foreign intermediate inputs. Without imported intermediates, we would not be able to correctly represent the shock. Furthermore, the input-output structure of our model captures the propagation of the price changes to sectors of the economy not directly related to crude oil or natural gas resources, with endogenous the adjustment of consumption and input sourcing decisions dampening the adverse effects on total value added.

4.4 AI adoption and productivity

The fourth exercise quantifies the aggregate productivity gains from the adoption of artificial intelligence (AI) in the Italian economy. To this end, we use sectoral TFP shocks derived from Filippucci et al. (2025), who extend the framework of Acemoglu (2025) to compute sector-level productivity gains from AI adoption across G7 economies. Their approach accounts for differences in sectoral AI exposure and can be mapped directly to exogenous shocks to sectoral TFP in our model.

Specifically, Filippucci et al. (2025) consider three adoption scenarios that differ along two dimensions: the speed of AI diffusion and the degree of sectoral exposure to AI. On the adoption side, a *slow* scenario is calibrated on the historical diffusion of electricity, a *medium* scenario on personal computers, and a *fast* scenario on mobile phones. On the exposure side, the slow scenario assumes *baseline* exposure—defined as the share of tasks that can be completed substantially faster using current LLMs—while the medium and fast scenarios assume *expanded* exposure, which additionally includes tasks that become feasible with complementary software built on top of LLMs.[14]

We use these sector-level TFP estimates as inputs to our model to quantify the aggregate productivity effects of AI adoption for the Italian economy.[15] Our model departs from that of Filippucci et al. (2025) along two dimensions. First, we use an updated and more disaggregated symmetric input-output table for Italy (year 2021), which captures finer inter-industry relationships than the tables available to the OECD analysis. Second, our framework incorporates an elastic labor supply, adding a macroeconomic amplification channel that is absent in the Filippucci et al. (2025) specification: positive TFP shocks raise real wages, inducing an endogenous increase in labor input that may further amplify output gains. However, this amplification channel is quantitatively limited by the calibration of a relatively inelastic labor supply with respect to real wages.

[14]Sector-level TFP shocks are constructed as the product of three components: a micro-level productivity gain, the sectoral exposure to AI, and the projected increase in adoption rate over a ten-year horizon. The micro-level gain is set at 30% for all scenarios, consistent with the average across several experimental studies; estimates in the underlying literature range from 14% in customer service tasks to 56% in coding (see Filippucci et al. 2025 for a review). Sector-level shocks under the slow and fast scenarios are proportionally rescaled versions of the medium scenario shocks, preserving the relative exposure pattern across industries.

[15]Filippucci et al. (2025) also report aggregate productivity estimates for Italy. Our results differ because we feed their sector-level shocks into a distinct general equilibrium framework.

Table 5: Aggregate Effects of AI Adoption
Annual Change over a Ten-Year Horizon, Percentage Points

	Adoption Scenario		
	Slow	Medium	Fast
Labor Productivity	0.2	0.7	1.1

Notes: The table reports simulated annual changes in labor productivity over a ten-year horizon under three AI adoption scenarios (slow, medium, and fast). Shocks are derived from Filippucci et al. (2025) and fed into our model. The slow scenario is calibrated on the historical diffusion of electricity; the medium scenario on the diffusion of personal computers; the fast scenario on the diffusion of mobile phones.

Table 5 reports the implied annual changes in labor productivity over a ten-year horizon under the three adoption scenarios. Under the slow scenario, annual labor productivity growth increases by 0.2 percentage points; under the fast scenario, the gain reaches 1.1 percentage points; it is also estimated that there is a slight positive effect on employment (of approximately one-tenth of a percentage point in all three scenarios). These estimates are modestly above those reported by Filippucci et al. (2025) for Italy under the medium and fast scenarios, consistent with the amplification generated by elastic labor supply. Overall, the results confirm that rapid AI diffusion could generate substantial long-run productivity effects.

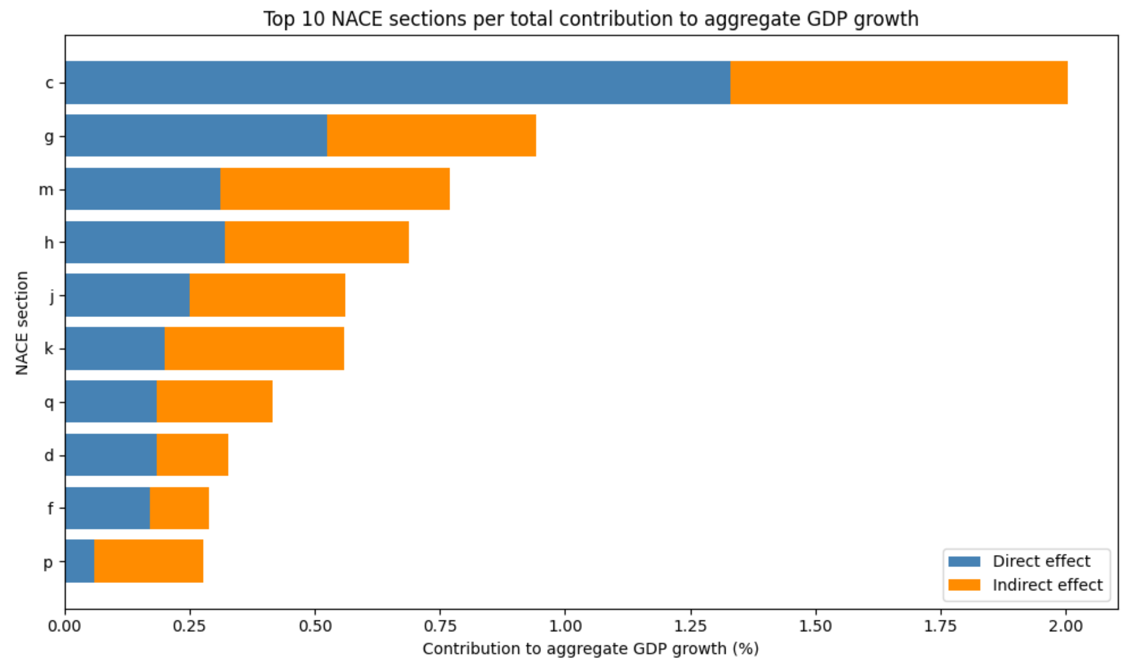
Estimates are subject to wide margins of uncertainty. On the one hand, the impact could prove even larger: more than past innovations, artificial intelligence can directly affect research and development activities, including those aimed at advancing AI itself, potentially accelerating innovation and therefore productivity growth.[16] On the other hand, several factors call for caution. Because AI affects sectors differentially, the productivity gains in the model implicitly assume a significant capacity for sectoral labor reallocation, which may in practice be limited in the Italian context. Moreover, while the model allows for the import of intermediate inputs, it does not fully capture potential productivity improvements in foreign sectors more exposed to AI, potentially leading to an overestimation of domestic productivity growth.

We further decompose the sectoral contributions to GDP growth under the fast adoption scenario, distinguishing between direct effects—reflecting the productivity gain in each sector—and indirect effects—arising from input-output linkages. Figure 5 reports these decompositions for the ten sectors with the largest contributions.

Manufacturing (NACE C) provides the largest contribution to GDP growth, approximately 2 percentage points over the decade, followed by wholesale and retail trade (NACE G, about 1 percentage point) and professional services (NACE M, about 0.8 percentage points). The size of each sector's contribution reflects the interplay of three factors: its weight in total value added, its direct exposure to AI, and its centrality in the production network. In

[16]For a more detailed discussion of AI effects see Bellomarini et al. (2026), in particular in the context of the Italian economy.

Figure 5: AI Adoption: Sectoral Contributions to GDP Growth, Ten-Year Horizon



Notes: The figure reports sectoral contributions to annual real GDP growth (percentage points) under the fast AI adoption scenario over a ten-year horizon. Each bar is decomposed into a direct component (own-sector productivity gain) and an indirect component (network spillovers through input-output linkages). Sector codes follow NACE Rev. 2 classification: C = Manufacturing; G = Wholesale and retail trade; M = Professional, scientific and technical activities; H = Transportation and storage; J = Information and communication; K = Financial and insurance activities; Q = Human health and social work; D = Electricity, gas and steam supply; F = Construction; P = Education.

particular, professional services stand out because most of their contribution is indirect: the sector acts as a hub in the input-output network, supplying intermediate inputs to many downstream industries, so that its own productivity gains propagate broadly throughout the economy. This pattern echoes the finding for the R&D tax credit exercise: network centrality can be as important as the size of the direct productivity shock in determining aggregate output effects.

5 Conclusions

This paper develops a quantitative framework to study shock propagation in the Italian economy, grounded in its detailed input-output structure. By extending existing models to include trade openness and endogenous labor supply, we offer a tool tailored to Italy's production system.

Our framework offers a powerful and flexible tool for policy evaluation. First, it helps identify sectors that are particularly central to the Italian production network—such as electricity, logistics, and professional services—whose position makes them critical for the transmission of shocks and the amplification of policy effects. This insight is especially valuable for designing targeted interventions, as it allows policymakers to prioritize sectors not only based on their size or productivity potential, but also on their network centrality and spillover capacity.

Second, the model provides a structured, data-consistent approach to quantify the aggregate impact of policies and economic shocks with strong sectoral dimensions. Our applications to R&D tax credits and entry regulation reforms show that network effects can account for a substantial share of the total gains—up to 40% in the case of R&D support and over 75% for regulatory reforms. In a separate experiment, we document strong sectoral heterogeneity in the effect of a shock to the price of imported crude oil and natural gas, illustrating the value of our open-economy extension in capturing how foreign input price changes propagate through the domestic production network. Finally, our analysis of AI adoption shows that rapid AI diffusion could generate annual labor productivity gains of up to 1.1 percentage points over a decade for Italy, with network spillovers playing a particularly prominent role for upstream sectors such as professional services.

These findings suggest that ignoring sectoral interdependencies may lead to significant underestimation of both policy effects and technological shocks. By capturing both direct and indirect channels of transmission, the framework enables more accurate and comprehensive assessments of industrial and macroeconomic policies, and can be readily extended to evaluate future reforms in areas such as energy, digital services, or defense

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Online Appendix

A Additional Model Derivations

A.1 Derivation of the Domar Weights

To derive the Domar weights λ_i and Δ note, we first note that equation (7) for the first row gives:

$$\Psi_{C,C} = 1; \quad \Psi_{C,i} - \Omega_{C,i} - \sum_{j\in\mathcal{N}} \Psi_{C,j}\Omega_{j,i} = 0 \ \forall i \in \mathcal{N}; \quad \Psi_{C,L} - \sum_{j\in\mathcal{N}} \Psi_{C,j}\Omega_{j,L} = 0.$$

The Domar weight of the consumption good is $1 = \Psi_{C,C}$ and the remaining conditions are satisfied if $\Psi_{C,i} = \lambda_i$ and $\Psi_{C,L} = \Lambda$:

$$\Omega_{C,i} + \sum_{j=1}^{N} \lambda_j \Omega_{j,i} = \frac{y_i p_i}{\sum_{k=1}^{N} y_k p_k} + \sum_{j=1}^{N} \frac{x_j p_j}{\sum_{k=1}^{N} y_k p_k} \frac{x_{j,i} p_i}{x_j p_j} = \lambda_i$$

To see why in expression (10) $\tilde{\Psi}_{i,L} = 1$ for $i = 1, \ldots, N$ note that equations (9) can be written as

$$\tilde{\Psi}_{i,L} - \sum_{j=1}^{N} \tilde{\Omega}_{i,j} \tilde{\Psi}_{j,L} = \tilde{\Omega}_{i,L}$$

for the cost-based input/output matrix we have:

$$\sum_{j=1}^{N} \tilde{\Omega}_{i,j} + \tilde{\Omega}_{i,L} = 1$$

thus equations (9) are satisfied for $\tilde{\Psi}_{i,L} = 1$.

A.2 Derivation of the forward propagation equation

To derive the forward propagation equation we take the natural logs in equation (6) and differentiate with respect to the log of μ_i, A_i,$\{p_j\}_{j=1,\ldots,N}$ and w:

$$d\log \mu_i = d\log p_i + d\log A_i + \sum_{k,j=1}^{N} \frac{d\log(f_i/c_i)}{d\log p_j} d\log p_j + \frac{d\log(f_i/c_i)}{d\log w} d\log w \qquad \text{(A1)}$$

where $c_i = \sum_{j=1}^{N} x^*_{i,j} p_j + L^* w$ are the total costs in the sector i. Note that the input factors (intermediates $x^*_{i,j}$ and labor L^*) depend on the input prices $\{p_j\}_j = 1 \ldots, N$, w because firms face the following optimization problem:

$$\max_{x_{i,j},L} f_i\left(\{x_{i,j}\}_j, L\right) \text{ s.t. } \sum_{j=1,\ldots,N} x_{i,j} p_j + L_i w = c_i.$$

Taking the log and applying the first order conditions we obtain:

$$\frac{d\log f_i}{d\log x_{i,j}} = \xi_i \frac{x_{i,j}p_k}{c_i} \qquad\qquad \frac{d\log x_i}{d\log L} = \xi_i \frac{Lw}{c_i}$$

where ξ_i is the Lagrange multiplier. Taking the sum over all input factors we obtain:

$$\sum_{k=1,\ldots,N} \frac{d\log f_i}{d\log x_{i,k}} + \frac{d\log f_i}{d\log L} = \xi_i$$

but the constant return to scale implies $\lambda = 1$. Thus $\log(f_i/c_i)$ is the Lagrangian of the optimization problem and the and from the envelop theorem we have:

$$\frac{d\log f_i}{d\log p_j} = \frac{\partial \log c_i}{\partial \log p_j} = \frac{x_{i,j}p_j}{c_i} = \tilde{\Omega}_{i,j} \qquad\qquad \frac{d\log f_i}{d\log w} = \frac{L_i w}{c_i} = \tilde{\Omega}_{i,L}$$

substituting this expression into expression (A1) we obtain the equations (11).

A.3 Input/Output Matrix Dynamics

We start from the definition (5) of Ω_{ij}. Taking the natural logarithm and differentiating, we obtain:

$$\begin{aligned} d\log \Omega_{i,j} &= \frac{\partial \log \Omega_{i,j}}{\partial \log \mu_i} d\log \mu_i + \frac{\partial \log \Omega_{i,j}}{\partial \log \tilde{\Omega}_{i,j}} \sum_{k=0}^{N+1} \frac{\partial \log \tilde{\Omega}_{i,j}}{\partial \log p_k} d\log p_k \\ &= \underbrace{-d\log \mu_i}_{\text{change in the markup}} + \underbrace{\sum_{k=1}^{N+1} \frac{\partial \log \tilde{\Omega}_{i,j}}{\partial \log p_k} d\log p_k}_{\text{change in the input shares}} \end{aligned} \tag{A2}$$

where $i = 0, 1, \ldots, N$ and $j = 1, \ldots, N+1$, where $i = 0$ is the index for the consumption good and $i = N+1$ corresponds to the labor input. The summation starts from $i = 1$ because the consumption good is never used as an input. Moreover, for $j \neq k$ it holds:

$$\frac{\partial \log \tilde{\Omega}_{i,j}}{\partial \log p_k} - \frac{\partial \log \tilde{\Omega}_{i,k}}{\partial \log p_k} = \frac{\partial \log(x_{i,j}p_j/x_{i,k}p_k)}{\partial \log(p_k/p_j)} = \theta_{i,j,k} - 1$$

where $\theta_{i,j,k}$ represents the elasticity of substitution between j and k in the production of i. Therefore, we can finally derive:

$$d\log \Omega_{i,j} = -d\log \mu_i + \sum_{k=1}^{N+1} \left[\frac{\partial \log \tilde{\Omega}_{i,k}}{\partial \log p_k} + (\theta_{i,j,k} - 1)(1 - \delta_{j,k}) \right] d\log p_k \tag{A3}$$

A.4 Dynamics of the Domar Weights

The Domar weights constitute the first row of the inverse Leontief matrix. Therefore:

$$\boldsymbol{\lambda} = \Psi_{0,:} = (1, \lambda_1, \ldots, \lambda_N, \Lambda_L)'$$

thus the vector $\boldsymbol{\lambda}$ solves the equation

$$\boldsymbol{\lambda}' - \boldsymbol{\lambda}'\Omega = (1, 0, \ldots, 0)'$$

which implies that it satisfies the following differential equation:

$$d\boldsymbol{\lambda}' = d\boldsymbol{\lambda}'\Omega + \boldsymbol{\lambda}' d\Omega = \boldsymbol{\lambda}' d\Omega\Psi. \tag{A4}$$

that can be written as

$$d\lambda_i = \sum_{j=0}^{N} \lambda_j \sum_{l=1}^{N+1} \Omega_{j,l} d\log\Omega_{j,l} \Psi_{l,i}$$

where $i = 0, 1, \ldots, N+1$, the summation on j stops at N since $\Omega_{N+1,l} = 0$ and l starts from 1 because $\Omega_{j,0} = 0$. The backward propagation equation therefore is

$$d\lambda_i = \sum_{j=0}^{N} \lambda_j \sum_{l=1}^{N+1} \Omega_{j,l}\Psi_{l,i} \Bigg\{ -d\log\mu_j + \sum_{k=1}^{N+1} \left[\frac{\partial \log \tilde{\Omega}_{j,k}}{\partial \log p_k} + (\theta_{j,l,k} - 1)(1 - \delta_{l,k}) \right] d\log p_k \Bigg\}$$

Note that

$$\sum_{l=1}^{N+1} \Omega_{j,l}\Psi_{l,i} = \sum_{l=0}^{N+1} \Omega_{j,l}\Psi_{l,i} = \Psi_{j,i} - \delta_{j,i}$$

$$d\lambda_i = \sum_{j=0}^{N} \lambda_j \left[(\Psi_{j,i} - \delta_{j,i}) \left(-d\log\mu_j - \sum_{k=1}^{N+1} \frac{\partial \log \tilde{\Omega}_{j,k}}{\partial \log p_k} d\log p_k \right) + \sum_{k,l=1}^{N+1} \Omega_{j,l}\Psi_{l,i} (\theta_{j,l,k} - 1)(1 - \delta_{k,l}) \, d\log p_k \right] \tag{A5}$$

A.5 Key Aggregates

Input-Output Matrix The numerical integration of equations (19), (13). and (24) determines the normalized input-output matrix after the shock. To obtain the standard input-output matrix, we first compute sectoral outputs exploiting the following relationships:

$$\begin{aligned} x_i p_i &= (C+S)\lambda_i \text{ for } i \in \mathcal{N} \\ C + S &= \frac{C}{1 - \Lambda_I} \end{aligned}$$

Therefore, we obtain:

$$x_i^{(s)} p_i^{(s)} = \frac{C}{1 - \Lambda_I} \lambda_i^{(s)} \tag{A6}$$

where upperscripts (0) and (s) denote variables before and after the shock, respectively. Being nominal domestic consumption the numéraire, $C^{(s)} = C^{(0)}$.

Real GDP. Real GDP equals the sum of sectoral real value added. Therefore, we derive it as:

$$\begin{aligned}
RGDP &= \sum_{i\in\mathcal{N}} RVA_i \\
&= \sum_{i\in\mathcal{N}} \left(x_i^{(s)} p_i^{(0)} - \sum_{j\in\mathcal{N}\cup\mathcal{I}} x_{i,j}^{(s)} p_j^{(0)} \right) \\
&= \sum_{i\in\mathcal{N}} \left(x_i^{(s)} p_i^{(0)} - \sum_{j\in\mathcal{N}} x_{i,j}^{(s)} p_j^{(0)} - \sum_{j\in\mathcal{I}} x_{i,j}^{(s)} p_j^{(0)} \right) \\
&= \sum_{i\in\mathcal{N}} \left(x_i^{(s)} - \sum_{j\in\mathcal{N}\cup\mathcal{I}}^{N} x_{j,i}^{(s)} \right) p_i^{(0)} - \sum_{i\in\mathcal{N}} \sum_{j\in\mathcal{I}} x_{i,j}^{(s)} p_j^{(0)} \\
&= \underbrace{\sum_{i\in\mathcal{N}} y_i^{(s)} p_i^{(0)}}_{C+S=\text{Cons. + Export}} \quad \underbrace{-\sum_{i\in\mathcal{I}} x_i^{(s)} p_i^{(0)}}_{I=\text{Import}}
\end{aligned}$$

Based on this expression, we then derive equation (26) in several steps. First, we note that, while the contribution of net export to nominal GDP is null due to the assumption of balanced trade, this is no longer true in the case of the real GDP. Specifically, we derive that:

$$\sum_{i\in\mathcal{N}} y_i^{(s)} p_i^{(0)} = \frac{C}{1-\Lambda_S^{(s)}} \sum_{i\in\mathcal{N}} \Omega_{0,i}^{(s)} \frac{p_i^{(0)}}{p_i^{(s)}}$$

from which we obtain the following ew-writing of post-shock real GDP:

$$RGDP^{(s)} = \frac{C}{1-\Lambda_S^{(s)}} \left(\sum_{i\in\mathcal{N}} \Omega_{0,i}^{(s)} \frac{p_i^{(0)}}{p_i^{(s)}} - \sum_{k\in\mathcal{I}} \lambda_j^{(s)} \frac{p_j^{(0)}}{p_j^{(s)}} \right). \tag{A7}$$

For small shocks, equation (A7) can be expressed as follows:

$$\begin{aligned}
d\log RGDP = &\frac{\Lambda_S}{1-\Lambda_S} d\log\Lambda_S - \frac{\Lambda_I}{1-\Lambda_I} d\log\Lambda_I + \frac{1}{1-\Lambda_I} \times \\
&\times \underbrace{\left(-\sum_{i\in\mathcal{N}} \Omega_{0,i} d\log p_i + \sum_{j\in\mathcal{I}} \lambda_j d\log p_j + \Lambda_S \Lambda_L d\log\Lambda_S \right)}_{\equiv\Gamma}
\end{aligned}$$

where we use the relations:

$$d\log(1-\Lambda_S) = \frac{\Lambda_S}{1-\Lambda_S} d\log\Lambda_S \text{ and } \sum_{i\in\mathcal{N}} \Omega_{0,i} - \sum_{k\in\mathcal{I}} \lambda_j = 1 - \Lambda_I = \Lambda_L$$

and from equation (19) we obtain:

$$\Gamma = \sum_{i,j\in\mathcal{N}} \Omega_{0,i} \tilde{\Psi}_{i,j}^{*} \left(d\log A_j - d\log\mu_j - \sum_{k\in\mathcal{I}} \tilde{\Omega}_{j,k} d\log p_k - \tilde{\Omega}_{j,L} d\log w \right) + \sum_{k\in\mathcal{I}} \lambda_k d\log p_k$$

We further note that for $j \in \mathcal{N}$

$$\sum_{i \in \mathcal{N}} \Omega_{C,i} \tilde{\Psi}^*_{i,j} = \sum_{i \in \mathcal{N}} \tilde{\Omega}^*_{C,i} \tilde{\Psi}^*_{i,j} = \tilde{\lambda}_j$$

and the following relations hold

$$\sum_{j \in \mathcal{N}} \tilde{\lambda}_j \tilde{\Omega}^*_{j,k} = \tilde{\lambda}_k; \qquad \sum_{j \in \mathcal{N}} \tilde{\lambda}_j \tilde{\Omega}^*_{j,L} = \tilde{\Lambda}_L.$$

Therefore, we can re-express:

$$\Gamma = \sum_{j \in \mathcal{N}} \tilde{\lambda}_j \left(d \log A_j - d \log \mu_j \right) + \sum_{k \in \mathcal{I}} \left(\lambda_k - \tilde{\lambda}_k \right) d \log p_k - \tilde{\Lambda}_L d \log w$$

Moreover, as

$$d \log w = d \log \Lambda_L - d \log L + \Lambda_S d \log S,$$

we finally obtain:

$$\begin{aligned} d \log RGDP = & \underbrace{\frac{\Lambda_S}{1 - \Lambda_S} d \log \Lambda_S - \frac{\Lambda_I}{1 - \Lambda_I} d \log \Lambda_I}_{\text{trade imbalance}} \\ & \frac{1}{1 - \Lambda_I} \Bigg[\underbrace{\sum_{j \in \mathcal{N}} \tilde{\lambda}_j d \log A_j + \tilde{\Lambda}_L \, d \log L}_{\text{technology}} \\ & \quad \underbrace{- \sum_{j \in \mathcal{N}} \tilde{\lambda}_j d \log \mu_j - \tilde{\Lambda}_L \left(d \log \Lambda_L + \frac{\Lambda_S}{1 - \Lambda_S} d \log \Lambda_S \right)}_{\text{allocation}} \\ & \quad \underbrace{+ \sum_{k \in \mathcal{I}} \left(\lambda_k - \tilde{\lambda}_k \right) d \log p_k}_{\text{price of imported goods}} \Bigg]. \end{aligned} \tag{A8}$$

B Solving for Propagation of Shocks: Pseudo-Code

The algorithm performs a numerical integration of the differential equations described in the main text, allowing the full computation of prices and quantities after the shocks. We fix a small step h (for instance $h = 10^{-4}$) and then we repeat the iteration below m times where $m = \max(\{d \log \mu_i\}_i, \{d \log A_i\}_i)$. At each step $k = 1, \dots, m$ the algorithm works as follows:

1. Pose $\Delta \log \mu_i = \mathbf{1}_{(kh < d \log \mu_i)} h$, $\Delta \log A_i = \mathbf{1}_{(kh < d \log A_i)} h$ for $i = 1, \dots, N$ and if $k = 1$ pose also $\Delta \log w = 0$.
2. Use equation 12 to compute the change in log- prices $\Delta \log p_i$.
3. Compute the new input-output matrix as $\Omega_{i,j}^{(k+1)} = \Omega_{i,j}^{(k)} \exp(\Delta \log \Omega_{i,j})$ where $\Delta \log \Omega_{i,j}$ is given by equation 14 for CES production functions (or by equation A2 in more general cases).
4. Compute the inverse Leontief $\Psi^{(k)} = \left(\mathbb{1} - \Omega^{(k)}\right)^{-1}$
5. Pose $\Delta \log w = \Lambda$ if the total output are chosen to be the numeraire.

C Additional Quantitative Results

Table C1: Sector Description

Code	Label	Code	Label	Code	Label
1	Crop cultivation	33	Repair, maint. of machinery	65	Insurance, reinsurance...
2	Animal prod., hunting...	34	Electricity generation...	66	Auxiliary financial services
3	Forestry and forest use	35	Gas production and distrib.	67	Real estate services
4	Fishing and aquaculture	36	Water supply	68	Property rental and mgmt.
5	Coal mining	37	Sewerage mgmt.	69	Imputed rents
6	Oil and gas extraction	38	Waste treatment	70	Legal and accounting
7	Metal ore mining	39	Material recovery	71	Business consultancy
8	Other mining activities	40	Waste mgmt. services	72	Architecture and engineering
9	Mining support services	41	Building construction	73	Scientific research
10	Food industries	42	Civil engineering	74	Advertising and research
11	Beverage industry	43	Specialized construction	75	Other prof. activities
12	Tobacco industry	44	Vehicle trade	76	Veterinary services
13	Textile industries	45	Vehicle repair	77	Leasing activities
14	Clothing and leather...	46	Trade intermediaries	78	Personnel services
15	Leather goods	47	Wholesale trade	79	Travel and reservation
16	Wood and cork industry	48	Retail trade	80	Security services
17	Paper products	49	Rail transport	81	Building and landscape
18	Printing and media	50	Land passenger transport	82	Office support services
19	Coke and petroleum	51	Road freight and pipeline	83	Public admin. and safety
20	Chemical products	52	Maritime transport	84	National defense
21	Pharma products	53	Air transport	85	Justice and security
22	Rubber and plastics	54	Warehousing	86	Education
23	Non-metallic minerals	55	Postal and courier	87	Healthcare
24	Metallurgy	56	Accommodation	88	Residential social care
25	Metal products	57	Food services	89	Non-residential social care
26	Computers and optics	58	Publishing	90	Creative activities
27	Electrical appliances	59	Film and music prod.	91	Libraries and museums
28	Machinery n.e.c.	60	Broadcasting	92	Gambling activities
29	Motor vehicles	61	Telecom	93	Sports and entertainment
30	Other transport equip.	62	Software and IT consult.	94	Membership orgs.
31	Furniture	63	Info and IT services	95	Computer and goods repair
32	Other manufacturing	64	Financial services	96	Other personal services
				97	Households as employers

Notes: The table associates sectoral codes to a brief description of the industries considered in the analysis.

Table C2: Sectoral TFP Shocks: Island vs. Network Economy, All Industries

Code	Island	Network	Code	Island	Network	Code	Island	Network
1	0.02%	0.03%	2	0.00%	0.01%	3	0.00%	0.00%
4	0.00%	0.00%	5	0.00%	0.00%	6	0.00%	0.00%
7	0.00%	0.00%	8	0.00%	0.00%	9	0.00%	0.00%
10	0.10%	0.08%	11	0.02%	0.02%	12	0.00%	0.00%
13	0.01%	0.01%	14	0.03%	0.02%	15	0.03%	0.02%
16	0.01%	0.01%	17	0.01%	0.02%	18	0.00%	0.01%
19	0.02%	0.03%	20	0.03%	0.04%	21	0.02%	0.02%
22	0.02%	0.04%	23	0.01%	0.03%	24	0.04%	0.06%
25	0.04%	0.08%	26	0.02%	0.02%	27	0.03%	0.03%
28	0.11%	0.09%	29	0.05%	0.04%	30	0.02%	0.02%
31	0.02%	0.02%	32	0.02%	0.02%	33	0.01%	0.02%
34	0.02%	0.06%	35	0.00%	0.02%	36	0.00%	0.00%
37	0.00%	0.00%	38	0.01%	0.01%	39	0.00%	0.01%
40	0.00%	0.00%	41	0.06%	0.05%	42	0.02%	0.02%
43	0.09%	0.09%	44	0.01%	0.02%	45	0.01%	0.01%
46	0.00%	0.02%	47	0.10%	0.11%	48	0.10%	0.08%
49	0.00%	0.00%	50	0.01%	0.01%	51	0.01%	0.06%
52	0.00%	0.00%	53	0.00%	0.00%	54	0.02%	0.06%
55	0.00%	0.01%	56	0.02%	0.02%	57	0.05%	0.05%
58	0.00%	0.00%	59	0.00%	0.00%	60	0.00%	0.00%
61	0.02%	0.03%	62	0.03%	0.04%	63	0.00%	0.01%
64	0.02%	0.07%	65	0.02%	0.02%	66	0.00%	0.02%
67	0.00%	0.00%	68	0.01%	0.04%	69	0.10%	0.06%
70	0.00%	0.03%	71	0.00%	0.04%	72	0.00%	0.03%
73	0.01%	0.01%	74	0.00%	0.02%	75	0.00%	0.02%
76	0.00%	0.00%	77	0.00%	0.01%	78	0.00%	0.02%
79	0.00%	0.00%	80	0.00%	0.00%	81	0.00%	0.02%
82	0.00%	0.04%	83	0.09%	0.08%	84	0.02%	0.01%
85	0.03%	0.02%	86	0.10%	0.07%	87	0.15%	0.10%
88	0.01%	0.01%	89	0.01%	0.01%	90	0.00%	0.00%
91	0.00%	0.00%	92	0.01%	0.01%	93	0.01%	0.01%
94	0.00%	0.00%	95	0.00%	0.00%	96	0.02%	0.01%
97	0.03%	0.02%						

Notes: The table reports the change in aggregated real GDP due to a +1% shock to sectoral TFP for all industries, based on a counterfactual economy where we neutralize all input-output network linkages ("Island" columns) and in the full network model ("Network" columns). The first and second column report the code and a brief description of the shocked sectors.

Table C3: List of Upstream and Downstream Industries

Sector Code	Description	Classification
Upstream		
10	Food industries	Upstream
19	Coke and petroleum products	Upstream
22	Rubber and plastic products	Upstream
24	Metallurgy	Upstream
25	Metal products (excl. machinery)	Upstream
28	Machinery and equipment n.e.c.	Upstream
34	Electricity generation and supply	Upstream
43	Specialized construction	Upstream
47	Wholesale trade	Upstream
51	Road freight and pipelines	Upstream
54	Warehousing and transport support	Upstream
61	Telecommunications	Upstream
62	Software and IT consulting	Upstream
64	Financial services (non-insurance)	Upstream
68	Property rental and management	Upstream
70	Legal and accounting	Upstream
71	Business consultancy	Upstream
72	Architecture and engineering	Upstream
82	Office and business support	Upstream
83	Public admin. and safety	Upstream
Downstream		
3	Forestry and forest land use	Downstream
4	Fishing and aquaculture	Downstream
5	Coal mining (excl. peat)	Downstream
7	Metal ore mining	Downstream
8	Other mining activities	Downstream
9	Mining support services	Downstream
12	Tobacco industry	Downstream
21	Pharmaceutical products	Downstream
37	Sewerage management	Downstream
52	Road freight and pipeline	Downstream
53	Air transport	Downstream
60	Broadcasting activities	Downstream
69	Imputed rents (housing)	Downstream
76	Veterinary services	Downstream
84	National defense	Downstream
85	Justice and public order	Downstream
91	Libraries and museums	Downstream
95	Computer and goods repair	Downstream
96	Other personal services	Downstream
97	Households as employers	Downstream

Notes: The table reports a list of sectors classified as either upstream or downstream based on the entries of the first eigenvector of the inverse-Leontief matrix. The twenty sectors with the largest entry are classified as upstream (or central). The twenty sectors with the smallest one are classified as downstream.

Table C4: Sectoral TFP Shocks: Uniformly Lower Elasticity of Substitution $\theta_i = 0.05$

Code	Sector	Aggregate Effect	Own Contrib.	Network Effects	Ratio
Panel A: Large Upstream					
34	Electricity generation and distribution	0.06%	0.03%	0.03%	0.83
54	Warehousing and transport support	0.06%	0.03%	0.03%	1.24
64	Financial services (excl. insurance)	0.07%	0.02%	0.05%	3.17
51	Road freight and pipeline transport	0.05%	0.02%	0.03%	1.39
Panel B: Small Upstream					
70	Legal and accounting activities	0.03%	0.01%	0.02%	2.29
72	Architecture and engineering	0.03%	0.01%	0.03%	1.84
82	Business support services	0.04%	0.02%	0.02%	1.40
Panel C: Large Downstream					
87	Healthcare services	0.10%	0.04%	0.06%	1.48
48	Retail trade (excl. vehicles)	0.08%	0.04%	0.04%	1.11

Notes: The table reports the GDP effect of a +10% shock to sectoral TFP for selected industries, based on the full network model, with elasticity of substitution across inputs set to $\theta_i = 0.05$ for all industries. The first and second column report the code and a brief description of the shocked sectors. The "Aggregate Effect" column reports the percent change in aggregate real GDP; the "Own Contribution" column reports the contribution of the shocked industry's real value added to the aggregate GDP change; the "Network Effects" column reports the contribution of all other non-shocked industries; the "Ratio" column reports the ration of Network Effects to Own Contribution.

Table C5: Sectoral TFP Shocks: Uniformly Higher Elasticity of Substitution $\theta_i = 0.5$

Code	Sector	Aggregate Effect	Own Contrib.	Network Effects	Ratio
Panel A: Large Upstream					
34	Electricity generation and distribution	0.08%	0.05%	0.03%	0.68
54	Warehousing and transport support	0.07%	0.04%	0.03%	0.84
64	Financial services (excl. insurance)	0.08%	0.03%	0.05%	1.48
51	Road freight and pipeline transport	0.07%	0.03%	0.03%	0.93
Panel B: Small Upstream					
70	Legal and accounting activities	0.04%	0.02%	0.02%	1.28
72	Architecture and engineering	0.04%	0.02%	0.02%	1.27
82	Business support services	0.04%	0.02%	0.02%	1.14
Panel C: Large Downstream					
87	Healthcare services	0.10%	0.07%	0.03%	0.50
48	Retail trade (excl. vehicles)	0.09%	0.06%	0.03%	0.46

Notes: The table reports the GDP effect of a +10% shock to sectoral TFP for selected industries, based on the full network model, with elasticity of substitution across inputs set to $\theta_i = 0.5$ for all industries. The first and second column report the code and a brief description of the shocked sectors. The "Aggregate Effect" column reports the percent change in aggregate real GDP; the "Own Contribution" column reports the contribution of the shocked industry's real value added to the aggregate GDP change; the "Network Effects" column reports the contribution of all other non-shocked industries; the "Ratio" column reports the ration of Network Effects to Own Contribution.

Table C6: Sectoral TFP Shocks: Heterogeneous Elasticities, $\theta_i = 0.5$ Downstream and $\theta_i = 0.05$ Upstream

Code	Sector	Aggregate Effect	Own Contrib.	Network Effects	Ratio
Panel A: Large Upstream					
34	Electricity generation and distribution	0.07%	0.04%	0.03%	0.71
54	Warehousing and transport support	0.07%	0.03%	0.03%	0.94
64	Financial services (excl. insurance)	0.07%	0.03%	0.05%	1.70
51	Road freight and pipeline transport	0.06%	0.03%	0.03%	1.05
Panel B: Small Upstream					
70	Legal and accounting activities	0.04%	0.01%	0.02%	1.52
72	Architecture and engineering	0.04%	0.01%	0.02%	1.41
82	Business support services	0.04%	0.02%	0.03%	1.22
Panel C: Large Downstream					
87	Healthcare services	0.10%	0.07%	0.03%	0.50
48	Retail trade (excl. vehicles)	0.08%	0.06%	0.03%	0.48

Notes: The table reports the GDP effect of a +10% shock to sectoral TFP for selected industries, based on the full network model, with elasticity of substitution across inputs set to $\theta_i = 0.05$ ($\theta_i = 0.5$) for the 20 most (least) central industries. The first and second column report the code and a brief description of the shocked sectors. The "Aggregate Effect" column reports the percent change in aggregate real GDP; the "Own Contribution" column reports the contribution of the shocked industry's real value added to the aggregate GDP change; the "Network Effects" column reports the contribution of all other non-shocked industries; the "Ratio" column reports the ration of Network Effects to Own Contribution.

Table C7: Sectoral TFP Shocks: Heterogeneous Elasticities, $\theta_i = 0.05$ Downstream and $\theta_i = 0.5$ Upstream

Code	Sector	Aggregate Effect	Own Contrib.	Network Effects	Ratio
Panel A: Large Upstream					
34	Electricity generation and distribution	0.08%	0.05%	0.03%	0.68
54	Warehousing and transport support	0.07%	0.04%	0.03%	0.84
64	Financial services (excl. insurance)	0.08%	0.03%	0.05%	1.54
51	Road freight and pipeline transport	0.06%	0.03%	0.03%	0.92
Panel B: Small Upstream					
70	Legal and accounting activities	0.04%	0.02%	0.02%	1.29
72	Architecture and engineering	0.04%	0.02%	0.02%	1.27
82	Business support services	0.04%	0.02%	0.02%	1.14
Panel C: Large Downstream					
87	Healthcare services	0.10%	0.07%	0.03%	0.50
48	Retail trade (excl. vehicles)	0.09%	0.06%	0.03%	0.46

Notes: The table reports the GDP effect of a +10% shock to sectoral TFP for selected industries, based on the full network model, with elasticity of substitution across inputs set to $\theta_i = 0.5$ ($\theta_i = 0.05$) for the 20 most (least) central industries. The first and second column report the code and a brief description of the shocked sectors. The "Aggregate Effect" column reports the percent change in aggregate real GDP; the "Own Contribution" column reports the contribution of the shocked industry's real value added to the aggregate GDP change; the "Network Effects" column reports the contribution of all other non-shocked industries; the "Ratio" column reports the ration of Network Effects to Own Contribution.