Growth Through Industrial Linkages

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Abstract

In this paper, we estimate how changes in the structure of global input-output networks have influenced growth. Using an open economy production network model, we identify sufficient statistics that characterize how productivity shocks across domestic and foreign firms influence country-level TFP. We estimate these sufficient statistics using data on input-output networks and sectoral productivity shocks. Structural changes in global input-output networks between 1965 and 2000 were advantageous for developing countries and unfavorable for advanced economies. Holding the global input-output network fixed, TFP growth in China and India would have been 26.6% and 9.7% lower between 1965 and 2000. Whereas for the US and Australia, TFP growth would have been 4.0% and 16.8% higher. Finally, we show that the dynamics of the domestic intermediate input cost share capture the importance that the structure of the global input-output network has on the amplification of shocks on TFP. Our analysis illustrates the importance of industrial linkages and robust domestic intermediate input markets for economic growth.

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1 Introduction

This paper explores how the transformation of the global production network has influenced technologically driven growth across multiple countries. The global production network refers to the intricate web connecting households and firms via markets for final goods, intermediate inputs, and primary factors. We show that changes in the global production network's structure have been favorable for emerging economies and unfavorable for developed countries. Developing economies primarily benefited from shifts in the global intermediate input market, with secondary gains from variations in consumption expenditure. The primary adverse effects for developed countries come from household consumption expenditure variations, with the global intermediate input market shifts having minimal influence. We show that difference on how intermediate input markets influence emerging and developed countries are correlated to the country-level ratio of intermediate input costs to total costs. During the second half of the twentieth century, this ratio rose in emerging economy, while it either remained stable or declined for developed countries. The domestic share of intermediate input costs is monotonically linked to the multiplier effect of intermediate input markets on productivity shocks. We find that the rise of these ratios positively correlates with productivity shocks in manufacturing and upstream industries and negatively correlates with productivity shocks in services and downstream sectors.

We use the results from Rojas-Bernal (2023b) that characterize the first-order variation for country-level TFP in a general distorted production network open economy that accounts for the possibility that factors of production and dividends cross national boundaries. This project studies these effects in an environment with perfect competition, country-specific factor markets, and complete equity home bias. These assumptions allow us to use a country-level decomposition of TFP that is analogous to Hulten's (1978) theorem. This result shows that country-level TFP growth is proportional to the sales-weighted variation of domestic productivity shocks. The two implications of this result on how productivity shocks aggregate into country-level TFP are that there are no cross-country spillovers and that the domestic sales distribution is a sufficient statistic.

The domestic sales distribution estimated from the model equilibrium depends on the structure of the global production network. To be more precise, it relies on the worldwide distribution of expenditure from households and firms in goods and services. We take the variations in the global production network structure as given and evaluate how these transformations influence the domestic sales distribution.

The Long-run World Input-Output Database allows us to implement the country-level TFP decomposition. This dataset provides a detailed input-output matrix for 23 sectors in 25 countries that we use to parameterize the model from 1965 to 2000. From this specification, we estimate country-sector-specific Solow residuals that we use to measure productivity shocks. We show that the simple sales-weighted variation of domestic productivity shocks captures a good empirical representation of the observed variation in country-level TFP.

We use the productivity shocks and the model to estimate alternative counterfactual trajectories for country-level TFP. The first counterfactual exercise leaves the global consumption or intermediate input structure fixed at its 1965 level. From here, we evaluate the difference in the amplification of the same productivity shocks under alternative histories of domestic sales distributions. We aim to identify how the global network structure by itself affected TFP growth. From here, we learn that changes between 1965 and 2000 in the global consumption and intermediate input expenditure structure have benefited emerging economies. Furthermore, global consumption expenditure variations dampened the amplification of productivity shocks in developed countries. For example, without changes in the global production structure, the TFPs from Australia, Austria, Ireland, France, Portugal, Spain, and Italy would have been 16.8%, 11.9%, 10.5%, 8.3%, 8.0%, 7.9%, and 5.0% higher in the year 2000. In contrast, the TFPs from China, Hong Kong, Korea, India, Brazil, and Mexico would have been 26.6%, 12.9%, 10.3%, 9.7%, 7.2%, and 5.8% lower in the year 2000.

The second counterfactual exercise takes the global intermediate input market structure from each year between 1965 and 2000, and keeps it fixed for the whole time window. We find that the share of domestic intermediate input costs highly correlates with the importance of the global intermediate input market structure on country-level TFP growth. This share increased substantially for developing countries, while it stayed constant or fell slightly for developed economies. This share of intermediate input costs is a monotonic transformation of the domestic network multiplier. Hence, the explanation for why the structural change of the global intermediate input markets has been favorable for emerging economies is that it has increased their domestic network multiplier. In comparison, the domestic network multipliers for developed economies have barely changed.

Finally, motivated by the results of the second counterfactual, we investigate which country-sector productivity shocks may have influenced the domestic intermediate input cost share. We analyze this using the local projection method from Jordà (2005) with a panel of country intermediate input cost shares and productivity shocks. We find that productivity shocks in a couple of upstream manufacturing sectors correlate negatively with the domestic intermediate input cost share. In contrast, productivity shocks in several downstream manufacturing sectors and one service sector correlate positively with the domestic intermediate input cost share. The impulse responses are especially large for the two sectors: i) electrical and optical equipment and ii) real estate, renting, and business services. These sectors include activities like the production, manufacturing, and renting of machinery and equipment.

Our paper contributes to the literature on production networks and structural transformation. First, the research on shock propagation in production networks builds on the canonical multisector models from Hulten (1978) and Long & Plosser (1983). These models have been used to study the propagation of sectoral productivity shocks (Foerster et al., 2011; Horvath, 1998, 2000; Dupor, 1999; Acemoglu et al., 2012, 2016; Carvalho et al., 2021) and distortions (Basu, 1995; Ciccone, 2002; Yi, 2003; Jones, 2011, 2013; Asker et al., 2014; Baqaee, 2018; Liu, 2019; Baqaee & Farhi, 2020; Bigio & La'O, 2020; Rojas-Bernal, 2023a). Huo et al. (2021), Baqaee & Farhi (2023), Rojas-Bernal (2023b) implement these models in an open economy setting to study the propagation of shocks through global supply chains.

The second strand of literautre our paper contributes to is the literature on input-output linkages and economic evelopment. Bartelme & Gorodnichenko (2015) first document a strong and robust positive correlation between the strength of industry linkages and aggregate productivity. Then they find that distortions in intermediate input choices at the industry level result in significant aggregate welfare losses, especially for poor and middle income countries. Our paper exploiting an open economy framework finds that the global input-output structure between 1965 and 2000 has evolved in such way that it has been favorable for emerging countries like China, Korea and India, while unfavorable for advanced economies.

Outline

The structure of the paper is as follows. Section 2 introduces the open economy multisector input-output model with country-level representative households. Section 3 characterizes the equilibrium, the network centrality measures, and the open economy Hulten's theorem. Section 4 presents data, the parameterization, and the sectoral Solow residual and country-level TFP decomposition estimates. Section 5 evaluates the counterfactual exercise that keeps the global production network structure fixed at 1965. Section 6 introduces the domestic intermediate input market share and estimates its correlation with the counterfactual results from using global intermediate input market structures from multiple years. Section 7 study how productivity shocks in different sectors influence the domestic intermediate input share. Section 8 concludes.

2 The Environment

This section sets up a static nonparametric general equilibrium model with constant-returns-to-scale (CRS) for economies with N firms and R countries. Firm $i \in \mathcal{N} = \{1, \cdots, N\}$ is a perfectly competitive producer that uses labor and intermediate inputs. Firms have different technologies, and a subset of firms $\mathscr{N}_r \subseteq \mathscr{N}$ produce in the country r. Country $r \in \mathscr{R} = \{1, \cdots, R\}$ has a representative household that consumes goods using their labor income. The country-level representative households have different preferences and can only work for domestic firms. Global financial markets are incomplete, and households cannot cross-insure their idiosyncratic income shocks. This moel follows the open economy environment with production networks from Rojas-Bernal (2023b).

2.1 Production

The production for firm $i \in \mathscr{N}_r$ follows

$$y_i = A_i \, Q_i \left(\ell_{ir}, \{x_{ij}\}_{j \in \mathscr{N}} \right), \tag{1}$$

where y_i stands for output, A_i is the firm-specific Hicks-neutral productivity term. ℓ_{ir} is labor hired from household r. x_{ij} is the amount of intermediate input goods purchased from firm j. The technology $Q_i : \mathbb{R}^2_+ \to \mathbb{R}_+$ is neoclassical and satisfy the following regularity conditions: they are positive, finite, and when there is effective demand for labor or intermediate inputs, they are monotonically increasing, twice continuously differentiable, strictly concave, and the Inada conditions hold.

The profits for firms i are given by

$$\pi_i = p_i y_i - w_r \, \ell_{z_i r} - \underbrace{\sum_{j \in \mathscr{N}} p_j \, x_{z_i j},}_{= p^x_{z_i} X_{z_i}} \tag{2}$$

where p_i is the price of its output, p^x_i is the price for the intermediate input composite, w_r is the wage received by households of type r, and p_j is the market price for the good produced by firm j.

2.2 Households

In each country there is a unit mass of homogenous households that take prices and wages as given. Consequently, for any two households within the same country, their choices are equivalent, and the model is simplified by assuming a country-specific representative household.

The representative household from country r has the utility function $U_r(C_r, L_r)$, where C_r stands for real consumption, and L_r for the labor supply. The utility $U_h : \mathbb{R}^2_+ \to \mathbb{R}_+$ satisfies the usual regularity conditions: $U_{C_h} > 0$, $U_{L_h} < 0$, twice continuously differentiable, strictly concave, and the Inada conditions hold. Their composite real consumption $C_r = Q^c_r \left(\{C_{ri}\}_{i \in \mathscr{N}} \right)$

depends on the consumption C_{ri} of goods from firm i. The consumption aggregation technology $Q_r^c : \mathbb{R}_+^N \to \mathbb{R}_+$ is neoclassical: positive, finite, homogeneous of degree one, and for the set of goods for which there is effective final demand, it is monotonically increasing, twice continuously differentiable, strictly concave, and the Inada conditions hold. Household r's budget constraint is given by

$$GNI_r = p_r^c\, C_r = \sum_{i \in \mathscr{N}} p_i\, C_{ri} \leq J_r + \Pi_r, \qquad \text{and} \qquad \Pi_r = \sum_{i \in \mathscr{N}} \kappa_{ir}\, \pi_r. \tag{3}$$

Gross national income GNI_r must not be greater than income; the latter includes labor income $J_r = w_r L_r$, and dividend income Π_r. Households from country r own a fraction κ_{ir} of the firms in sector i. p_r^c represents country r's consumer price index.

2.3 Market Clearing

For this economy, the technologies, productivities, and ownership distributions are primitives. The economy operates under perfect competition. Goods and labor market clearing conditions are given by

$$\begin{aligned} y_i &= \sum_{r \in \mathscr{R}} C_{ri} + \sum_{j \in \mathscr{N}} x_{ji} \quad \forall i \in \mathscr{N}, \\ L_r &= \sum_{i \in \mathscr{N}_r} \ell_{ir} \quad \forall r \in \mathscr{R}. \end{aligned} \tag{4}$$

3 Equilibrium, Centralities, and Open Economy Hulten's Theorem

In this section, first, we characterize the equilibrium for this economy. Second, we introduce measures of bilateral centrality that capture the connections between firms and households, and measures of aggregate centrality that portray each firm or household's role in the economy.

3.1 Equilibrium Characterization

Let $e \equiv (A, \kappa)$ represent the aggregate state, and $\mathscr{E}$ denote the measurable collection of all possible realizations for this state. The vector $a \equiv (A_1, \ldots, A_N)$ collects all productivities measures. The equity matrix $\kappa \equiv (\kappa_1, \cdots, \kappa_N)'$ of size $N \times H$ contains the ownership distribution of firms in sector i represented by the vector $\kappa_i \equiv (\kappa_{i1}, \cdots, \kappa_{iH})'$, with $\kappa_i' \mathbb{1}_H = 1$, and where $\mathbb{1}_H$ is an H sized vector of ones. For this economy, a mapping of the realization of the aggregate state to an allocation $\vartheta = (\vartheta(e))_{e\in\mathscr{E}}$ and the price system $\rho = (\rho(e))_{e\in\mathscr{E}}$ is represented by the set of functions

$$\vartheta(e) \equiv \left\{\left\{y_i(e), \ell_{ir}(e), \{x_{ij}(e)\}_{j\in\mathscr{N}}, \{C_{bi}(e)\}_{b\in\mathscr{R}}\right\}_{i\in\mathscr{N}_r}, C_r(e), L_r(e)\right\}_{r\in\mathscr{R}},$$

$$\rho(e) \equiv \left\{\{p_i(e), p_i^x(e)\}_{i\in\mathscr{N}}, \{w_r(e), p_r^c(e)\}_{r\in\mathscr{R}}\right\}.$$

For simplicity, allocation, prices, and parameters are conditional on a specific aggregate state $e \in \mathscr{E}$. So from now on, we drop e.

Definition 1. For any realization of the aggregate state e in the state space $\mathscr{E}$, an equilibrium is the combination of an allocation and a price system (ϑ, ρ) such that:

(i) given wages $\{w_r\}_{r\in\mathscr{R}}$ and prices $\{p_j\}_{j\in\mathscr{N}}$, firms i's in country r labor ℓ_{ir} and intermediate input demand $\{x_{ij}\}_{j\in\mathscr{N}}$, and output y_i maximize their profits;

(ii) given prices $\{p_i\}_{i\in\mathscr{N}}$ and wages $\{w_r\}_{r\in\mathscr{R}}$, households' consumption bundles $\{C_{ri}\}_{i\in\mathscr{N}}$ and labor supply L_r maximize utility while satisfying their budget constraint;

(iii) goods and labor markets clear.

Proposition 1. The set of functions (ϑ, ρ) are an equilibrium if and only if the following set of conditions are jointly satisfied $\forall e \in \mathscr{E}$

$$\frac{\partial C_r/\partial C_{rj}}{\partial C_r/\partial C_{ri}} = \frac{\partial y_i}{\partial x_{ij}} \quad \forall i, j \in \mathscr{N}, \text{ and } \forall r \in \mathscr{R} \text{ such that } C_{ri} > 0,\ C_{rj} > 0, \text{ and } x_{ij} > 0, \tag{5}$$

$$-\frac{w_b}{w_r}\frac{U_{L_r}}{U_{C_{ri}}} = \frac{\partial y_i}{\partial \ell_{ib}} \quad \forall i \in \mathscr{N}, \text{ and } \forall h, b \in \mathscr{H} \text{ such that } C_{ri} > 0, \text{ and } \ell_{ib} > 0, \tag{6}$$

and resource constraints

$$\begin{aligned} y_i &= \sum_{r\in\mathscr{R}} C_{ri} + \sum_{j\in\mathscr{N}} x_{ji} \quad \forall i \in \mathscr{N}, \\ \text{and} \qquad L_r &= \sum_{i\in\mathscr{N}_r} \ell_{ir} \quad \forall r \in \mathscr{R}. \end{aligned} \tag{7}$$

Proposition 1 identifies the set of equilibrium allocations. The intuition for equation (5) is that for firm i, the marginal productivity of using the good from sector j as an intermediate input has to equate the marginal rate of substitution between goods i and j for every household. In equation (6), for firm i, the marginal productivity from using the labor supplied by households of type b, has the equate for every household a wage-adjusted marginal rate of substitution between the consumption of the good from sector i and their labor supply. This equilibrium is a specific case of the economies in Rojas-Bernal (2023a) and Rojas-Bernal (2023b) with no distortions, and national boundary restrictions on how firms can hire workers.

3.2 Direct Centralities

The $N \times R$ matrix Ω_ℓ depicts direct labor cost centralities. For firm $i \in \mathscr{N}_r$, the element $\Omega^\ell_{ib} \equiv \frac{\partial \log c_i(\vartheta,\rho)}{\partial \log w_b} = \mathbb{1}\{r=b\} \frac{w_b\, \ell_{ib}}{c_i(\vartheta,\rho)}$ captures the cost elasticity to w_r. This means that row i of matrix Ω_ℓ is a vector of zeros that contains Ω^ℓ_{ir} in its r position. $\Omega^\ell_{ir} > 0$ when the firm uses labor.

The $N \times N$ matrix Ω_x depict direct intermediate input cost centralities. Its element $\Omega^x_{ij} \equiv \frac{\partial \log c_i(\vartheta,\rho)}{\partial \log p_j} = \frac{p_j\, x_{ij}}{c_i(\vartheta,\rho)}$ capture firm i's cost elasticities to p_j, and in equilibrium they equal the cost share of the good from firm j. The fact that for firm $i \in \mathscr{N}_r$ the condition $\Omega^\ell_{ir} + \sum_{j\in\mathscr{N}} \Omega^x_{ij} = 1$ is satisfied indicates that all costs come from labor or intermediate inputs.

Finally, for households, the $R \times N$ consumption network $\beta = (\beta_1, \cdots, \beta_R)'$ contains the vectors $\beta_r \equiv (\beta_{r1}, \cdots, \beta_{rN})'$. Its element $\beta_{ri} \equiv \frac{\partial \log GNI_r}{\partial \log p_i} = \frac{p_i\, C_{hi}}{GNI_r}$ captures the expenditure elasticity for the representative household from country r to p_i, and in equilibrium they equal the expenditure share on the good supplied by firm i. For this reason $\sum_{i\in\mathscr{N}} \beta_{ri} = 1$.

Table 1: Direct Centralities for $i \in \mathscr{N}_r$ and $h \in \mathscr{H}_r$

Matrix	***Definition***	***In Equilibrium***	***Properties***
Ω_ℓ	$\Omega^\ell_{ib} \equiv \mathbb{1}\{r=b\} \frac{\partial \log c_i(\vartheta,\rho)}{\partial \log w_b}$	Cost share of ℓ_{ib}	$\sum_{b\in\mathscr{R}} \Omega^\ell_{ib} + \sum_{j\in\mathscr{N}} \Omega^x_{ij} = 1$
Ω_x	$\Omega^x_{ij} \equiv \frac{\partial \log c_i(\vartheta,\rho)}{\partial \log p_j}$	Cost share of x_{ij}	
β	$\beta_{ri} \equiv \frac{\partial \log GNI_r}{\partial \log p_i}$	Cost share of C_{ri}	$\sum_{i\in\mathscr{N}} \beta_{ri} = 1$

3.2.1 Network Adjusted Centralities

The firm-to-firm centrality matrix or Leontief inverse matrix is given by $\Psi_x \equiv (I - \Omega_x)^{-1} \equiv \sum_{q=0}^{\infty} \Omega_x^q$. Its element ψ^x_{ij} captures the centrality of intermediate inputs supplied by firm j on the costs of firm i. The firm-to-consumer downstream centrality matrix is given by the $\mathscr{B} \equiv \beta\, \Psi_x$. Its element $\mathscr{B}_{ri} = \sum_{j\in\mathscr{N}} \beta_{rj}\, \psi^x_{ji}$ captures all direct or indirect paths through which the costs of firm i can reach the expenditure from the representative household of country r. The sales Domar weight $\lambda_i = \sum_{r\in} \chi_r\, \mathscr{B}_{ri} = S_i/GDP$ stands for the average firm-to-consumer centrality from sector i, where $\chi_r = GNI_r/GDP$ represents the expenditure from country r in global GDP. In equilibrium, λ_i coincides with the ratio of sales to global GDP. Country r's network multiplier ξ_r is given by the summation of the domestic sectoral ratios of sales to GDP, i.e., $\xi_r = \sum_{i\in\mathscr{N}_r} \lambda_i/\chi_r$.

The worker-to-firm centrality matrix is given by $\Psi_\ell \equiv \Psi_x\, \Omega_\ell$. Given that $\sum_{r\in\mathscr{R}} \psi^\ell_{ir} = 1$, all costs for a firm can be traced back through the production network to direct or indirect labor cost. As a consequence, ψ^{ℓ}_{ib} is the value-added share by workers from country b on firm i's production. The worker-to-consumer centrality matrix is given by $\mathscr{C} \equiv \beta\, \Psi_{\ell}$. Given that $\sum_{b\in\mathscr{R}} \mathscr{C}_{rb} = 1$, its element $\mathscr{C}_{hb}$ represents the value-added share for the consumption from the representative household of country r attributed to the workers from country b. The factor Domar weight $\Lambda_r = \sum_{b\in\mathscr{R}} \chi_b \mathscr{C}_{br} = J_r/GDP$ stands for the average worker-to-consumer centrality from workers of country r. Consequently, Λ_r is the global share of value-added by their labor, and it coincides in equilibrium with the ratio of labor income to global GDP. All costs in the global economy originate in labor costs, and for this reason, $\sum_{r\in\mathscr{R}} \Lambda_r = 1$. Finally, in equilibrium GNI depends only on labor income and $\chi_r = \Lambda_r$.

Table 2: Network Adjusted Centralities for $i \in \mathscr{N}_r$ and $h \in \mathscr{H}_r$

Matrix	***Definition in Equilibrium***	***Properties***
$\Lambda_x = (I - \Omega_x)^{-1}$	ψ^x_{ij} *firm-to-firm* Centrality of j in the costs of i	
$\mathscr{B} = \beta\, \Psi_x$	$\mathscr{B}_{ri}$ *firm-to-consumer* Centrality of i in the costs of r	
$\Psi_{\ell} = \Psi_x\, \Omega_{\ell}$	ψ^{ℓ}_{ib} *worker-to-firm* Value-added share by b in the production of i	$\sum_{b\in\mathscr{R}} \psi^{\ell}_{ib} = 1$
$\mathscr{C} = \beta\, \Psi_{\ell}$	$\mathscr{C}_{rb}$ *worker-to-consumer* Value-added share by b in the consumption of r	$\sum_{b\in\mathscr{R}} \mathscr{C}_{rb} = 1$
$\lambda = \mathscr{B}'\, \chi$	λ_i *cost-based Domar weight* Share of global value-added that passes through i	$\sum_{r\in\mathscr{R}} \sum_{i\in\mathscr{N}_r} \Omega^{\ell}_{ir}\, \lambda_i = 1$
$\Lambda = \mathscr{C}'\, \chi$	Λ_r *cost-based labor share* Share of global value-added generated by r	$\sum_{r\in\mathscr{R}} \Lambda_r = 1$
$\chi = \Lambda$	χ_r *expenditure share* Share of global expenditure from r	$\sum_{r\in\mathscr{R}} \chi_r = 1$
ξ	ξ_r *network multiplier* Share of domestic sales to value-added in r	$\xi_r = \sum_{i\in\mathscr{N}_r} \frac{\lambda_i}{\chi_r} \geq 1$

3.2.2 Gross Domestic Product and Gross National Income

Nominal GDP for country $r \in \mathscr{R}$ equals the revenue from domestic firms minus their intermediate input costs

$$GDP_r = \sum_{i\in\mathscr{N}_r} \left(1 - \sum_{j\in\mathscr{N}} \Omega^x_{ij}\right) S_i = \sum_{i\in\mathscr{N}_r} \Omega^{\ell}_{ir}\, S_i. \tag{8}$$

This definition coincides with the total value-added extracted from labor by domestic firms, i.e., total labor income

$$GDP_r = w_h \sum_{i \in \mathcal{N}_r} \ell_{ir} = w_r L_r.$$

Gross National Income (GNI) is equal to the consumption expenditure from domestic households

$$GNI_r \equiv p_r^c \, C_r.$$

Consequently, GDP and GNI coincide in equilibrium

$$GNI_r = GDP_r,$$

and χ_r captures the share of country r's in global GDP.

3.3 Open Economy Hulten's Theorem

Rojas-Bernal (2023b) finds that for an open production network economy with national segmentation of labor markets, the first-order local variation around the efficient equilibrium for country-level TFP is given by Theorem 1.

Theorem 1. $d\,log\,TFP_r$ around the efficient equilibrium.

In the absence of distortions and with country-specific labor markets

$$d\,log\,TFP_r \approx \overbrace{\sum_{i \in \mathcal{N}_r} \frac{\lambda_i}{\chi_r} d\,log\,A_i}^{Technology_r} + \overbrace{\sum_{i \in \mathcal{N}_r} \frac{\lambda_i}{\chi_r} d\,log\,\mu_i - \sum_{i \in \mathcal{N}} \frac{\lambda_i}{\chi_r}\,\kappa_{ir}\,d\,log\,\mu_i}^{Competitiveness_r},$$

where μ_i stands for the markdown between prices and marginal costs, i.e., $\mu_i\,p_i = \frac{\partial\,c_i(\vartheta,\rho)}{\partial\,y_i}$.

Theorem 1 characterizes the local variation for country-level TFP around the undistorted global allocation, i.e., $\mu = \mathbb{1}_N$. First, domestic firms' productivity shocks directly influence country-level TFP. Second, markdown shocks in domestic and foreign firms can directly affect the country-level efficiency wedge. For instance, assume $d\,log\,A_i = 1\%$ for $i \in \mathcal{N}_r$. The elasticity of TFP_r in response to this shock will equal λ_i/χ_r. Now, for *competitiveness*$_r$, assume a markdown reduction $d\,log\,\mu_i = -1\%$ for $i \in \mathcal{N}_r$. The elasticity of TFP_r in response to this shock equals $-\frac{\lambda_i}{\chi_r}(1-\kappa_{ir})$. On the one hand, lower input demand from domestic firms reduces TFP and allows firms to create a profit margin. On the other hand, a fraction κ_{ir} of the additional profits are distributed to domestic households, increasing GNI_r. If instead, a similar markown would have taken place in a foreig firm $i \notin \mathscr{N}_r$, then the TFP_r would equal $\frac{\lambda_i}{\chi_r}\kappa_{ir}$. This positive effect captures the GNI_r increase from additional profits distributed to domestic households.

Corollary 1. Open economy Hulten's theorem. In the absence of distortions, with country-specific labor markets, and with full equity home bias

$$d\,log\,TFP_r \approx \sum_{i\in\mathscr{N}_r} \frac{\lambda_i}{\chi_r} d\,log\,A_i.$$

Corollary 1 characterizes the local variation for country-level TFP around the undistorted global allocation when factor markets are domestic and there is full equity home bias. This is a Hulten (1978) theorem type of result for an open economy that characterizes the country-specific envelope condition for the efficiency wedge. A symmetric domestic productivity shock of 1% has an effect on country r's TFP equal to the network multiplier ξ_r

$$d\,log\,TFP_r \approx \xi_r = \frac{\sum_{i\in\mathscr{N}_r}\lambda_i}{\sum_{i\in\mathscr{N}_r}\Omega^{\ell}_{ir}\,\lambda_i} \geq 1.$$

3.4 Structural Transformation

Domar weights λ and shares in global GDP χ for period t are given by the following system of equations

$$\lambda_{i,t} = \sum_{r\in\mathscr{R}} \mathscr{B}_{ri,t}\,\chi_{r,t} \qquad \forall i \in \mathscr{N} \qquad \text{and} \qquad \chi_{r,t} = \sum_{i\in\mathscr{N}_r} \Omega^{\ell}_{ir,t}\,\lambda_{i,t} \qquad \forall r \in \mathscr{R}. \tag{9}$$

with $\mathscr{B}_t = \beta_t\ (I - \Omega_{x,t})^{-1}$. The system of equations 9 show that changes in the structure of β_t and $\Omega_{x,t}$ are sufficient to capture the global structural transformation effects from variations in consumption patterns, labor intensity, and firm connectivity. By global structural transformation we mean both the composition of λ and χ, and the magnitude for the aggregate input-output multiplier $\xi = \sum_{i\in\mathscr{N}}\lambda_i$. To be clear, in this project we are taking β and Ω_x as given. We are not trying to explain the underlying sources of structural transformation that generate endogenous variations for β and Ω_x in response to shocks. For this, we would require a parametric model as the one used by Rojas-Bernal (2023a), which goes beyond the objectives of this paper.

4 Total Factor Productivity

In this section, we use the decomposition from Corollary 1 to estimate a model-based variation for country-level TFP. The model from Section 2 requires measures for three types of money flows: (1) firm-to-firm in the supply of intermediate inputs, (2) firm-to-workers in the supply of labor, and (3) consumer-to-firm in the supply of final goods. We calibrate the model to the long-run world input-output database (Woltjer et al., 2021) and the Penn World tables (Feenstra et al., 2015). In this section we are going to evaluate the performance from Corollary 1 as a measure for country-level TFP dynamics.

4.1 Data and Calibration

The long-run world input-output database covers the period 1965 to 2000. It provides a detailed input-output matrix for 23 sectors in 25 countries and the rest of the world. On the production side, it captures two dimensions of heterogeneity: (i) sectoral heterogeneity in the demand for intermediate inputs across all sectors in the global economy and (ii) sectoral heterogeneity in the demand for labor. Additionally, for each country, there are measures of the final expenditure intensity across sectors. Hence, under the assumptions of a country-level representative household, a single country-specific factor (labor), and complete equity home bias, household heterogeneity has three dimensions: (i) heterogeneity in the sources of factoral income, (ii) heterogeneity in the sources of rebated profits, and (iii) heterogeneity in their consumption expenditure intensity.

One feature of the long-run world input-output database is that there is no decomposition of the value-added extracted by a sector. Hence, by imposing the assumption of no distortions, extracted value added corresponds to labor costs, and there are no profits on equilibrium. These assumptions allow us to calibrate for all years t from 1965 to 2000 the following parameters for all countries $r \in \mathscr{R}$ and for all sectors $i \in \mathscr{N}_r$.

$$\Omega^{\ell}_{ir,t} = \frac{\text{Value Added}_{i,t}}{\text{Total Costs}_{i,t}}, \qquad \Omega^{x}_{ij,t} = \frac{\text{Sales from } j \text{ to } i_t}{\text{Intermediate Cost}_{i,t}},$$

$$\text{Total Cost}_{i,t} = \text{Value Added}_{i,t} + \text{Intermediate Cost}_{i,t}, \qquad \text{Value Added}_{i} = \text{Labor Costs}_{i,t},$$

$$\text{Sales}_{i,t} = \text{Total Cost}_{i,t}, \qquad \beta_{ri,t} = \frac{\text{Sales from } j \text{ to } i_t}{\text{GDP}_{r,t}}, \qquad \text{GDP}_{r,t} = \sum_{i \in \mathscr{N}_r} \text{Value Added}_{i,t}.$$

The world input-output database also provides a price index $p_{i,t}$ for the goods from each sector. Using this index and nominal flows, one can estimate real quantities. We obtain a country-level yearly estimate of labor force participation $L_{r,t}$ from the Penn World tables. This measure allows us to estimate a country-level yearly wage $w_{r,t} = GDP_{r,t}/L_{r,t}$.

Figure 1 shows the heatmap for the global intermediate input-output matrix in 1965 and 2000. Figure 2 shows the heatmap for the global final consumption matrix in 1965 and 2000. For both matrices, there are two features that stayed constant over time. First, the red block diagonal indicate that intermediate input markets and final consumption are biased towards domestic goods. Second, developed economies had a more significant role as exportes of intermediate inputs and final goods. For example, look at the columns for Germany, France, Great Britain, Netherlands and the United States. The off-diagonal blocks for these columns are more dense than for other countries. Additionally, there are two features that changed in these markets between 1965 and 2000. First, their interconnectivity increased and the input-output matrix became less sparse. Second, emerging economies such as China, India, Korea, Mexico, and Taiwan became more interconnected as exporters and importers of intermediate inputs and final goods.

4.2 Sectoral Solow Residuals

The assumption of no distortions allows us to use the sectoral Solow (1957) residual decomposition for an input-output economy introduced by Caves et al. (1982) and Jorgenson et al. (1987). This decomposition has been more recently implemented by Fadinger et al. (2022), McNerney et al. (2022), and Rojas-Bernal (2023b). This decomposition assumes that the global economy is at an efficient equilibrium and markdown variations are null. Productivity shocks for sector $i \in \mathcal{N}$ are given by

$$d\,log\,\mathcal{A}_{i,t} = -\,\omega^{\ell}_{i,t-1}\,d\,log\,\frac{\ell_{ir,t}}{y_{i,t}} - \omega^{x}_{i,t-1}\sum_{j\in\mathcal{N}}\omega^{x}_{ij,t-1}\,d\,log\,\frac{x_{ij,t}}{y_{i,t}},$$

with $d\,log\,\frac{\ell_{ir,t}}{y_{i,t}} = d\,log\,\omega^{\ell}_{i,t} - d\,log\,\frac{w_{r,t}}{p_{i,t}}$ and $d\,log\,\frac{x_{ij,t}}{y_{i,t}} = d\,log\,\Omega^{x}_{ij,t} - d\,log\,\frac{p_{j,t}}{p_{i,t}}$.

Figure 3 shows the productivity levels for the 23 sectors in China and the United States. We normalize the 1965 levels of productivity at 100. There has been plenty of heterogeneity in sectoral productivity shocks for both countries. On the one hand, China's technology was mainly driven by productivity shocks in the manufacturing, and electrical and optical equipment sectors. On the other hand, the US's technology was primarily driven by shocks in the electrical and optical equipment and secondarily by productivity shocks in the telecommunication and retail sectors.

Corollary 1 allows us to estimate

$$d\,log\,TFP_{r,t} = \sum_{i\in\mathcal{N}_r}\frac{\lambda_{i,t-1}}{\chi_{r,t-1}}\,d\,log\,A_{i,t}.$$

From the Penn World tables we obtain a rough measure for country-level TFP variation given by the difference between the growth in real GDP and the labor force participation, i.e.,

$$d\,log\,TFP^*_{r,t} = d\,log\,\frac{Y_{r,t}}{L_{r,t}}.$$

Using the same data, Rojas-Bernal (2023b) shows that $d\,log\,TFP_{r,t}$ and $d\,log\,TFP^*_{r,t}$ are highly correlated. Table 3 shows the Pearson correlation coefficients estimated in Rojas-Bernal (2023b). The average Pearson correlation coefficient across countries is 0.69. Hence, Corollary 1 captures a good empirical representation for the empirical variation of country-level TFP.

Table 3: Pearson Correlation Coefficients between $d\,log\,TFP_r$ and $d\,log\,TFP^*_r$

Country	Correlation	Country	Correlation
Australia	0.79	India	0.73
Austria	0.67	Ireland	0.55
Belgium	0.35	Italy	0.71
Brazil	0.55	Japan	0.95
Canada	0.63	Korea	0.73
China	0.82	Mexico	0.50
Denmark	0.56	Netherlands	0.65
Finland	0.69	Portugal	0.81
France	0.82	Spain	0.81
Germany	0.79	Sweden	0.61
Great Britain	0.65	Taiwan	0.21
Greece	0.88	United States	0.93
Hong Kong	0.74		

Note: Pearson correlation coefficient for each country between $d\,log\,TFP_{r,t}$ and $d\,log\,TFP^*_{r,t}$ between 1966 and 2000.

4.3 Adjusted TFP

The objective from this project goes beyond capturing the empirical variation for TFP. For the counterfactual exercises that we estimate in Section 5, we need the model TFP estimates to be good predictor for the actual TFP level in the long-run. We recognize that Corollary 1 imposes stringent conditions in the identification of TFP. For this reason, we proceed to correct its estimation using a country fixed effect ϕ_r

$$d\,log\,\widehat{TFP}_{r,t} = \phi_r + d\,log\,TFP_{r,t}.$$

where ϕ_r is coming from an OLS regression of $d\,log\,TFP^*_{r,t} - d\,log\,TFP_{r,t}$ on a constant. The adjusted TFP variation $d\,log\,\widehat{TFP}_{r,t}$ satisfies the within sample property that the average of the difference $d\,log\,TFP^*_{r,t} - d\,log\,\widehat{TFP}_{r,t}$ equals zero. The fixed effect ϕ_r capture two things. First, a measurement error for the effect from productivities on r. For example, when there are distortions, as shown by Rojas-Bernal (2023b), the multiplier for productivity shocks is not given by the Domar weight from domestic sectors, but by larger statistics that reflect how a country is able to capture foreign value-added by using foreign intermediate inputs to produce domestic goods that generate surplus. Consequently, ignoring distortions will most likely introduce a positive measurement error on the country-level effect from distortions. Second, ϕ_r captures how the variations in the global allocation of resources had an effect on country r's efficiency wedge. Under the assumptions from Corollary 1, these reallocation effects are neutral on country-level TFP.

Figure 4 reports the estimates for ϕ_r. Our preffered interpretation is that the higher the value of ϕ_r, the more favorable was the global reallocation of resources for country r between 1965 and 2000. First, for most countries, ϕ_r is small. Only Portugal, Greece, Taiwan, and China have estimates larger than 1% in absolute value. Brazil, Netherlands, Japan, and Italy have values between 0.5% and 1%. All other countries have estimates for ϕ_r smaller than 0.5% in absolute value. Second, the global reallocation of resources between 1965 and 2000 was favorable for Portugal, Greece, Brazil, and the Netherlands, and it was unfavorable for China, Taiwan, and France.

Figure 5 shows the effect of ϕ_r on the TFP growth estimate for China and the United States. From Table 3, we already know that the correlation between $d\,log\,TFP_{r,t}$ and $d\,log\,TFP^*_{r,t}$ for China is 0.82 and for the United States is 0.93. By itself we find this surprising, as it is telling us that removing the stringent assumptions from Corollary 1 might have very little to add to these variation estimates. Figure 6 shows the sectoral productivity shock estimates for the United States. One can see from this graph that there is a lot of heterogeneity on sectoral productivity shocks. Nevertheless, Corollary 1 succesfully aggregates this heterogeneity into a country-level efficiency wedge.

Adding up the fixed effect ϕ_r will improve the model-based level estimates for TFP. The level estimates for TFP are given by

$$\widehat{TFP}_{r,t} = TFP_{r,0} \prod_{s=1}^{t} \left(1 + d\,log\,\widehat{TFP}_{r,s}\right),$$

where $TFP_{r,0}$ captures the initial observed level of TFP and $\widehat{TFP}_{r,t}$ shows the model-based estimate for the level of TFP.

5 The Global Production Network and TFP

In this section we are going to compare the model estimate for country-level TFP growth between the years 1965 and 2000 with equivalent estimates for the following four counterfactual scenarios. All of these counterfactuals use the same sequences of sectoral Solow residuals estimated in Section 4.2.

Base Scenario
Consumption matrix and input-output network changing, i.e., β_t and $\Omega_{x,t}$
Counterfactual Scenario 1
Consumption matrix and input-output network from 1965, i.e., β_{1965} and $\Omega_{x,1965}$
Counterfactual Scenario 2
Consumption matrix from 1965 and input-output network changing, i.e., β_{1965} and $\Omega_{x,t}$
Counterfactual Scenario 3
Consumption matrix changing and input-output network from 1965, i.e., β_t and $\Omega_{x,1965}$
Counterfactual Scenario 4
No intermediate inputs and consumption network changing, i.e., β_t and $\Omega^{\ell}_{ir} = 1 \; \forall i \in \mathcal{N}_r$

Table 4 captures the difference in $\widehat{TFP}_{r,2000}$ between the base estimation and each of the counterfactual scenarios, i.e.,

$$\frac{\widehat{TFP}^{Counterfactual}_{r,2000} - \widehat{TFP}^{Base}_{r,2000}}{\widehat{TFP}^{Base}_{r,2000}}.$$

Figures 9 to 21 show the dynamics for $\widehat{TFP}_{r,t}$ for the 25 countries and each of the scenarios.

The difference from these estimates comes exclusively from the implication of chaging β_t and $\Omega_{x,t}$ on the weights λ_t and χ_t that are used to estimate Corollary 1. To be more precise, different assumptions on β_t and $\Omega_{x,t}$ will alter the structural transformation patterns in the global economy, which will modify the amplification effect that the multipliers λ_i/χ_r have on the estimation of $d\,log\,TFP_{r,t}$. In other words, what this counterfactual scenarios are measuring is the difference in the amplification of the same productivity shocks under alternatives histories for the global patterns of structural transformation.

To illustrate this more clearly, Figure 7 estimates $d\,log\,\widehat{TFP}_{r,t}$ for China using the counterfactual scenarios 1 and 4. The mean squared error is the lowest for the base scenario, it increases when only the 1965 weights are considered, and it more than doubles when no intermediate input markets are assumed. Figure 8 portrays the equilibrium λ_i/χ_r ratios for China in 1965 and 2000. The variation in weights are capturing a process of structural transformation from the agricultural to the manufacturing and service sector.

One could argue that using the same productivity shocks while changing the global production network ignores the role that the network structure has on the sectoral productivities. While we acknowledge the validity from this argument, we want to emphasize that our empirical exercise

Table 4: Counterfactual Growth in TFP relative to data using β and Ω_x from 1965

Country	Ω_x & β fixed	β fixed	Ω_x fixed	No Ω_x
	(1)	(2)	(3)	(4)
Australia	16.8%	7.2%	7.4%	-31.3%
Austria	11.9%	8.8%	2.3%	-42.8%
Belgium	2.8%	2.5%	-0.7%	-36.2%
Brazil	-7.2%	-2.3%	-3.5%	-11.5%
Canada	2.5%	3.3%	-0.6%	-19.2%
China	-26.6%	-11.15%	-19.7%	-64.3%
Denmark	3.2%	4.2%	-0.6%	-31.1%
Finland	3.0%	-6.0%	-4.5%	-44.0%
France	8.3%	4.3%	2.9%	-42.8%
Germany	-1.2%	0.3%	-1.6%	-33.6%
Great Britain	2.7%	1.0%	0.9%	-38.4%
Greece	2.9%	3.5%	-0.3%	-26.6%
Hong Kong	-12.9%	-2.3%	-9.5%	-51.2%
India	-9.7%	-4.1%	-7.3%	-32.8%
Ireland	10.5%	6.3%	4.5%	-55.4%
Italy	5.0%	5.3%	-1.3%	-35.2%
Japan	4.9%	3.4%	0.9%	-44.7%
Korea	-10.3%	1.2%	-6.8%	-71.1%
Mexico	-5.8%	1.0%	-6.8%	-9.0%
Netherlands	4.7%	4.9%	-0.4%	-22.0%
Portugal	8.0%	9.0%	0.5%	-24.2%
Spain	7.9%	6.1%	1.2%	-45.0%
Sweden	3.5%	2.9%	0.4%	-32.3%
Taiwan	-3.8%	0.8%	-4.3%	-72.8%
USA	4.0%	3.5%	0.2%	-20.1%

Note: Values in each column correspond to $\frac{\widehat{TFP}^{Counterfactual}_{r,2000} - \widehat{TFP}^{Base}_{r,2000}}{\widehat{TFP}^{Base}_{r,2000}}$ for each one of the counterfactual scenarios. Column n corresponds to counterfactual scenario n.

aims to identify the effect that the structure of the global network has by itself on TFP growth. For this reason, we use the same productivity estimates across all scenarios.

The first column in Table 4 tells us that the variations in both patterns of global consumption and intermediate input usage have been unfavorable for developed economies and favorable to emerging markets. On the one hand, with the β and Ω_x from 1965, the TFPs from Australia, Austria, Ireland, France, Portugal, Spain, Italy, Japan, Netherlands, USA, Sweden, Denmark, Finland, Greece, Belgium, Great Britain, and Canada would have been higher by 16.8%, 11.9%, 10.5%, 8.3%, 8.0%, 7.9%, 5.0%, 4.9%, 4.7%, 4.0%, 3.5%, 3.2%, 3.0%, 2.9%, 2.8%, 2.7%, and 2.5%, respectively. On the other hand, with the β and Ω_x from 1965, the TFPs from China, Hong Kong, Korea, India, Brazil, Mexico, Taiwan, and Germany would have been lower by 26.6%, 12.9%, 10.3%, 9.7%, 7.2%, 5.8%, 3.8%, and 1.2%, respectively.

The second column in Table 4 show us that the variations in the patterns of global consumption have been mostly unfavorable for developed economies and favorable to emerging markets. With the β from 1965, the TFPs from Portugal, Austria, Australia, Ireland, Spain, and Italy would have been 9.0%, 8.8%, 7.2%, 6.3%, 6.1%, and 5.3% higher, respectively. For developing economies, the TFPs from China, Finland, India, and Hong Kong would have 11.15%, 6.0%, 4.1%, and 2.3% lower, respectively.

The third column in Table 4 portray that the variations in the patterns of intermediate input trade have been mostly favorable for emerging markets. With the Ω_x from 1965, the TFPs from China, Hong Kong, India, Korea, Mexico, Taiwan, and Brazil would have been 19.7%, 9.5%, 7.3%, 6.8%, 6.8%, 4.3%, and 3.5% lower, respectively. For developed economies, the TFPs from Australia, France, and Austria would have been 7.4%, 2.9%, and 2.3% higher, respectively.

The first three columns show us that the global structural transformation variations have been favorable for emerging economies. This effect has taken place mainly due to more interconnected global intermediate input markets. The higher connectivity accentuated the amplification effect from productivity shocks through networks on the TFP from developing economies. On the other hand, global structural transformation has reduced the amplification effect from productivity shocks on the TFP from developed countries, and this effect is mainly explain by unfavorable variations in global consumption patterns.

For instance, China and Australia are opposite examples. On the one hand, global structural transformation in both consumption and intermediate input markets, but mainly in intermediate input markets, have increased the amplification effect from productivity shocks on China's TFP. On the other hand, global structural transformation has reduced the amplification effect from productivity shocks on Australia's TFP.

The fourth column in Table 4 illustrates the role that the amplification effect from production networks had on TFP growth. Without intermediate input markets, the TFP grow would have been lower for all economies, but mainly for emerging economies. TFP growth in Taiwan, Korea, China, Ireland, and India would have been 72.8%, 71.1%, 64.3%, 55.4%, and 51.2% lower in the absence of intermediate input networks.

The conclusion that we want the reader to extract from this section is that global structural transformation in intermediate input markets was of first order importance for explaining growth in emerging economies over the last 35 years of the twentieth century.

6 Growth and the Intermediate Input Share

In this section we show that the domestic intermediate input share (IIS) is highly correlated with the role that the global economic structure has on country-level TFP. We start by defining the IIS and describing its variation across developed an emerging economies. We find that the IIS has increased susbtantially for developing countries, while it has stayed constant or fallen for developed economies. We proceed to estimate some counterfactual exercises that allow us to evaluate how the global intermediate input market structure at a particular time could affect the growth from a country. We uncover that the role from the global intermediate input market on a country's growth highly correlates with their domestic intermediate input market share. Finally, we provide an statistical explanation for this finding.

6.1 The Intermediate Input Share

The domestic IIS is the ratio of domestic intermediate inputs to total cost, i.e.,

$$IIS_{r,t} = \frac{\text{Intermediate Costs}_{r,t}}{\text{Total Costs}_{r,t}}.$$

There is positive monotonic relationship between a country's IIS and its network multiplier. To be more precise

$$IIS_{r,t} = \frac{\text{Total Costs}_{r,t} - \text{Labor Costs}_{r,t}}{\text{Total Costs}_{r,t}} = 1 - \frac{\text{Labor Costs}_{r,t}}{\text{Total Costs}_{r,t}} = 1 - \frac{\text{GDP}_{r,t}}{\text{Sales}_{r,t}} = 1 - \frac{1}{\xi_{r,t}}.$$

Hence, the network multiplier has a positive and diminishing effect on the IIS. To be more precise $\frac{dIIS_{r,t}}{d\xi_{r,t}} = \frac{1}{\xi_{r,t}^2}$.

Chenery et al. (1986) show that during industrialization, ISS for manufacuturing and the input-output marix density increase. Ghassibe (2021) studies the long-run stability and short-run procyclicality for the IIS in the USA.

Figure 22 shows the IIS for the US and Canada. The IIS for the US is stable in the long-run and procyclical. The same long-run stability is not observed in Canada, were there was a marginal increase of 4 percentage points in the 90s. Figure 23 portrays the ISS for China and India. On the one hand, the IIS increased in China between 1985 and 1993, and between 2001 and 2008.

On the other hand, the ISS increase in India took place primarily over the 70s. Figure 24 shows that the growth of the IIS has been a process exclusive to some emerging economies like China, India, Mexico, and what the WIOD classifies as the rest of the world.

6.2 Intermediate Input Intensity and Domestic Growth

In this section we evaluate the effect of the global intermediate input market structure from each year between 1965 and 2000 in country-level growth. We find that the effect of the global network correlates with the domestic IIS.

For each year between 1965 and 2000 we fixed the structure of the global intermediate input market for the whole time window. For example, for year s, we take $\Omega_{x,s}$, and we estimate the model equilibrium $\lambda_{t|s}$ and $\chi_{t|s}$ using the observed β_t. This provides us with the following set of weights

$$\left\{ \left\{ \lambda_{i,t|s} \right\}_{i \in \mathscr{N}} , \ \left\{ \chi_{r,t|s} \right\}_{r \in \mathscr{R}} | \beta_t, \Omega_{x,s} \right\}_{t,s \in \{1965,\ldots,2000\}} .$$

We use these weights to predict country-level TFP growth

$$d\,log\,\widehat{TFP}_{r,t|s} = \phi_r + \sum_{i \in \mathscr{N}_r} \frac{\lambda_{i,t-1|s}}{\chi_{r,t-1|s}}\, d\,log\,A_{ri,t}$$

This provides us with a prediction of country-level growth conditional on the global input-output network from year s

$$\widehat{TFP}_{r,t|s} = TFP_{r,0} \prod_{q=1}^{t} \left(1 + d\,log\,\widehat{TFP}_{r,q|s} \right) .$$

Figures 25 to 37 show the dynamics for $\widehat{TFP}_{r,2000|s}$ and $IIS_{r,s}$ for the 25 countries. Table 5 captures the correlation between the 2000 growth difference in the counterfactual and the base scenario

$$\frac{\widehat{TFP}_{r,2000|s} - \widehat{TFP}^{Base}_{r,2000}}{\widehat{TFP}^{Base}_{r,2000}}.$$

with the $IIS_{r,s}$.

The figures and correlations show that the share of domestic intermediate input costs highly correlates with the importance of the global intermediate input market structure on country-level TFP growth.

Table 5: Pearson Correlation Coefficients between counterfatual difference in growth and the IIS

Country	Correlation	Country	Correlation
Australia	0.92	India	0.96
Austria	0.86	Ireland	0.94
Belgium	0.80	Italy	0.89
Brazil	-0.43	Japan	0.84
Canada	0.63	Korea	0.94
China	0.99	Mexico	-0.22
Denmark	0.72	Netherlands	0.36
Finland	0.86	Portugal	-0.28
France	0.89	Spain	0.93
Germany	0.12	Sweden	0.68
Great Britain	0.95	Taiwan	0.78
Greece	0.84	United States	0.03
Hong Kong	-0.32		

7 Impulse Responses to Productivity Shocks

In the previous section, we showed that for most countries in our sample, the domestic intermediate inputs cost share summarizes well the importance of the global input-output structure for country-level TFP growth. In this section, we take a step further and investigate if the changes in the domestic IIS correlate with country-sector productivity shocks, and if so, which industries' productivity shocks matter more.

To do this, we use the method of local projection proposed by Jordà (2005) and estimate the following equation:

$$\log \mathrm{IIS}_{r,t+h} = \alpha_r + \alpha_t + \sum_{i \in \mathcal{N}_r} \delta^h_{ri} \, \mathrm{d} \log A_{ri,t} + \epsilon_{r,t+h} \tag{10}$$

In this specification, α_r is the country fixed effect, α_t is the time fixed effect, $\mathrm{IIS}_{r,t+h}$ is the share of intermediate input expenditure over total expenditure in sector r at time $t+h$ (h periods after the productivity shocks occur). $A_{ri,t}$ is the productivity shock in sector i in country r at time t. δ^h_{ri} is the coefficient of interest, which measures the impulse response of the domestic IIS at time $t+h$ of country r to a productivity shock in sector i and country r at time t.

The country-sector productivity shocks vary across 25 countries, 23 sectors, and 36 years, whereas the domestic intermediate input cost share only varies across countries and years. The final dataset used is thus a balanced panel of 25 countries and 36 years. Using a panel dataset offers opportunities for us to take advantage of the cross-sectional and time-series dimensions to adjust standard errors for serial correlation and potential heteroscedasticity. This is especially useful since our sample is small in n relative to T. The standard errors are clustered by time, which utilizes the time dimension to construct residual-variance estimates that vary by country, hence correcting non-parametrically for heteroscedasticity.

Figures 38 - 40 present the impulse responses. We only include the plots of the seven sectors where their productivity shocks lead to statistically significant impulse responses of $\log(\mathrm{IIS}_{r,t+h})$. Graphs of the rest of the sectors are included in the Appendix Section A. Among the seven sectors from which the productivity shocks have significant impacts on $\log(\mathrm{IIS}_{r,t+h})$, five of them result in positive impulse responses. These sectors are Chemicals and Chemical Products, Other Non-Metallic Mineral, Electrical and Optical Equipment, Manufacturing, nec and Real Estate, Renting and Business Activities. These are relatively downstream manufacturing sectors, for which a positive productivity shock from those sectors is correlated with a higher domestic intermediate input cost share afterward. The only exception is Real Estate, Renting, and Business Activities, which is usually classified as service sector. However, after taking a closer look at the ISIC Rev 3 classifications of the industries, we find that a significant portion of the business activities included in this sector are the renting of machinery and equipment that are used by manufacturing sectors.

Productivity shocks from the other two sectors result in negative impulse responses of the country's domestic intermediate input cost share. These sectors are Basic Metals and Fabricated Metal and Electricity, Gas and Water Supply. These are relatively upstream manufacturing sectors, for which a positive productivity shock from those sectors is correlated with a lower domestic intermediate input cost share.

8 Conclusion

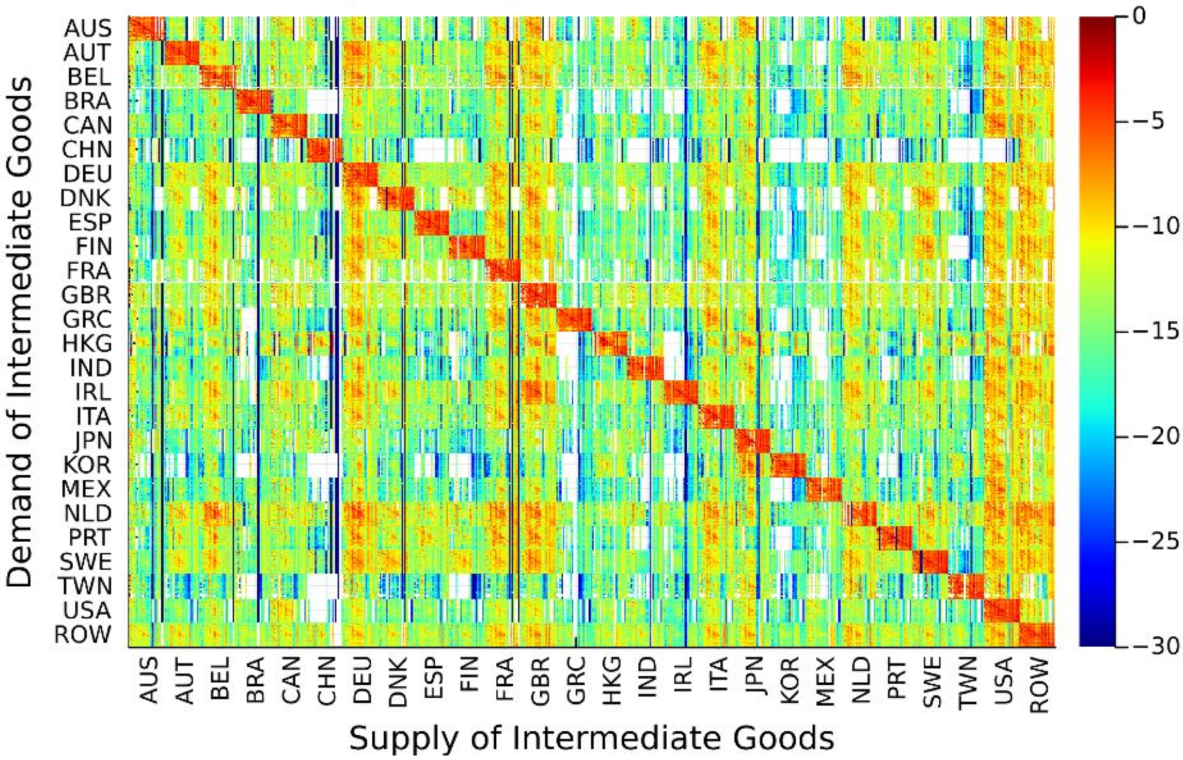
Recent theoretical and empirical research revealed that input-output relationships matter for aggregate TFP. In our paper, we take seriously the input-output relationships between firms and sectors within and across countries and household consumption preferences to study the importance of those linkages in country-level aggregate TFP growth in the second half of the XXth century. We find structural changes in the global network structure have been favorable for emerging economies such as China, Korea, and India and unfavorable for advanced economies. Moreover, we find that a simple measure of a country's domestic intermediate input cost share (over total costs) correlates surprisingly well with the effects on that country's TFP growth from changes in the global network structure. The intuition for this comes from the model, where we show that country-level domestic intermediate input cost share is a monotonic transformation of the domestic input-output multiplier. Therefore, a higher share is associated with a more substantial impact of the sectoral productivity shocks on the country's TFP growth. This is consistent with what we observe in the data: domestic intermediate input cost shares have increased substantially for developing countries, while they have stayed constant or fallen for developed economies.

Finally, we investigate which country-sector productivity shocks may matter more for the observed changes in the domestic intermediate input cost share. We find that productivity shocks from downstream manufacturing sectors (in particular, electrical and optical equipment) tend to have a positive impact on the domestic intermediate input cost share. In contrast, productivity shocks from upstream manufacturing sectors tend to have a negative impact on the domestic intermediate input cost share. Conceptually, if a developing country is shifting towards downward manufacturing sectors, which experienced positive productivity shocks and use production technologies that require more intermediate inputs from other sectors. Moreover, if the global network structure was evolving so that there was a higher demand for the final products of those downstream manufacturing sectors, or the intermediate inputs used by those downstream manufacturing sectors were more available / cheaper in the global market. These altogether could lead to a higher aggregate TFP growth for the developing country. However, testing this hypothesis is beyond the scope of our paper and will be left for future research.

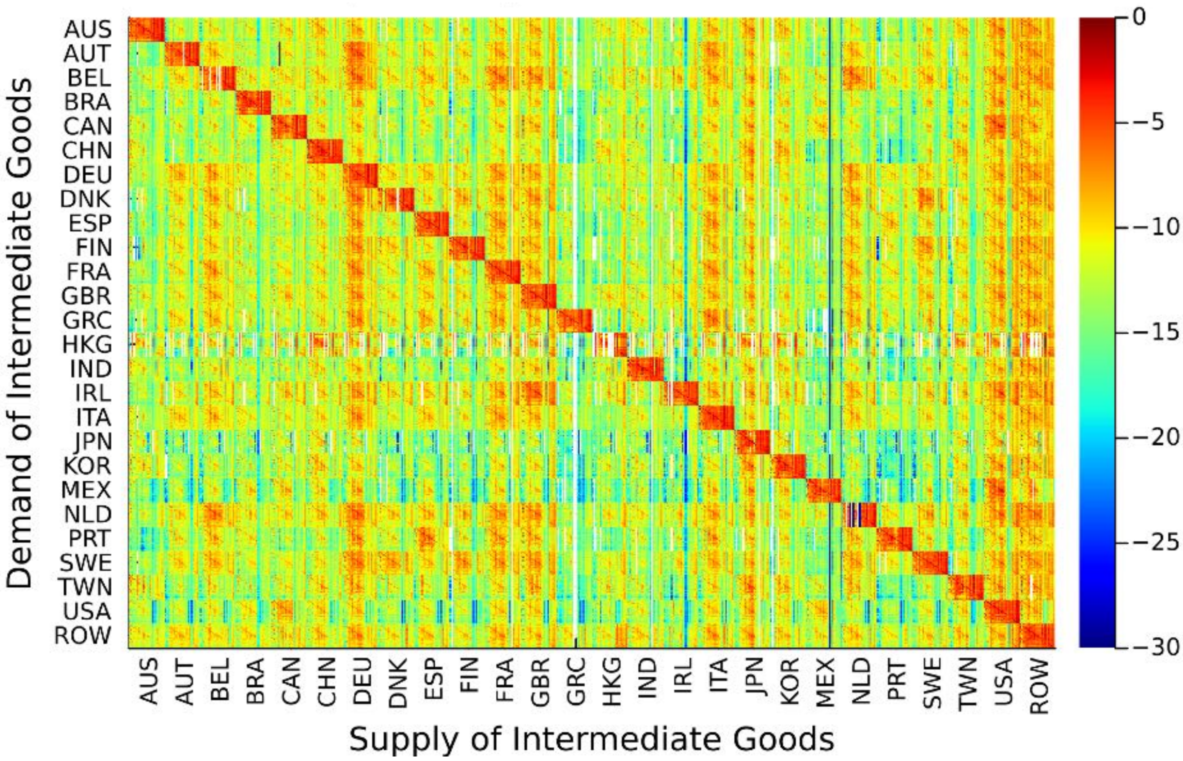
Figures and Tables

Figure 1: Global Input-Output Network Heatmap in 1965 and 2000

A. Global Intermediate Input-Output Network in 1965



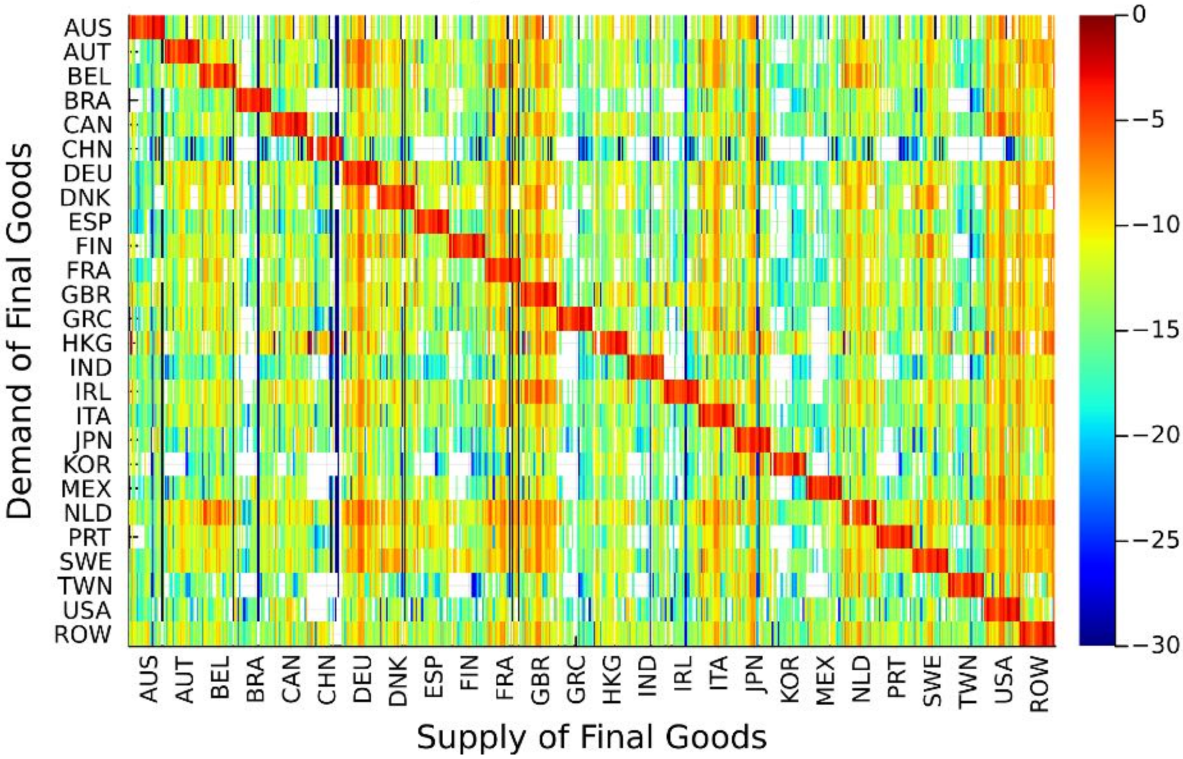
B. Global Intermediate Input-Output Network in 2000



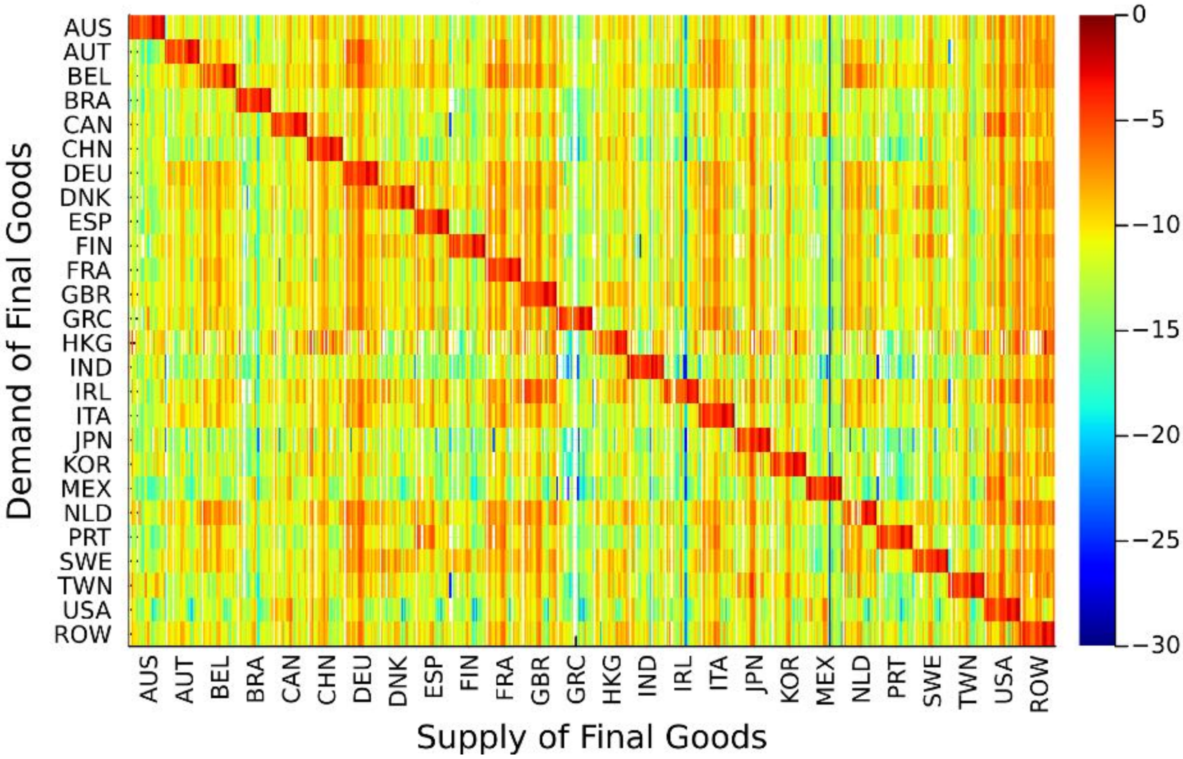
Note: Position (i, j) shows the logarithm of Ω^x_{ij}.

Figure 2: Global Consumption Matrix Heatmap in 1965 and 2000

A. Global Consumption Matrix in 1965



B. Global Consumption Matrix in 2000



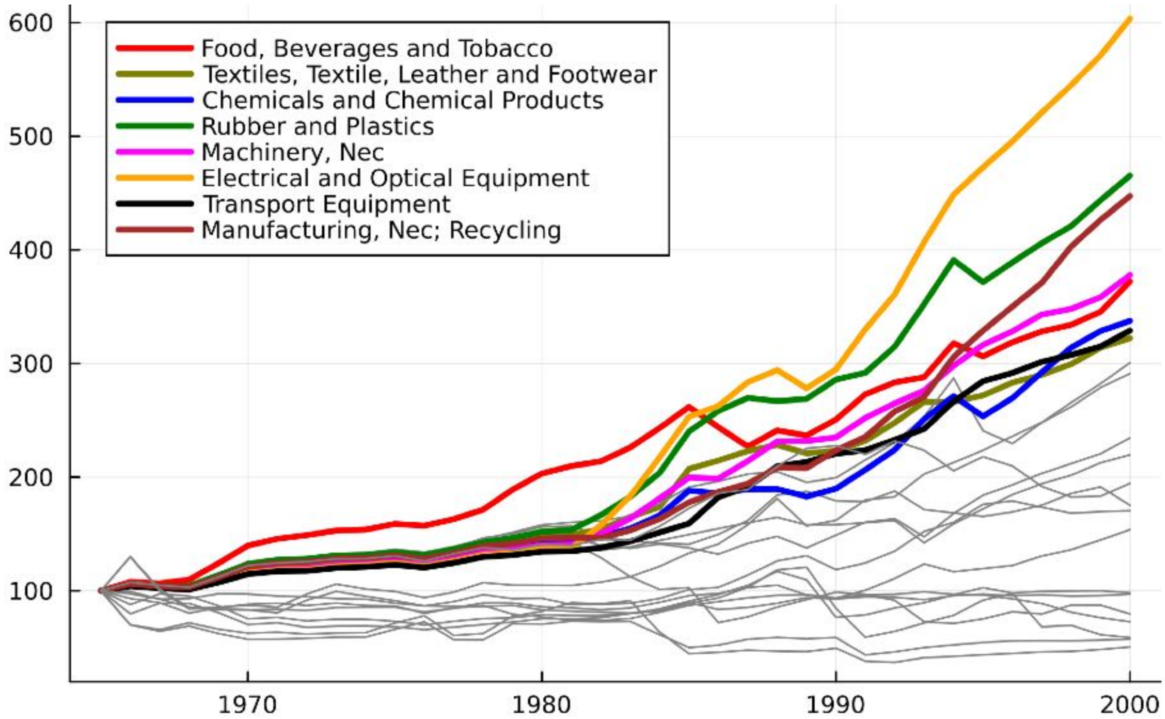
Note: Position (r, i) shows the logarithm of β_{ri}.

Appendix

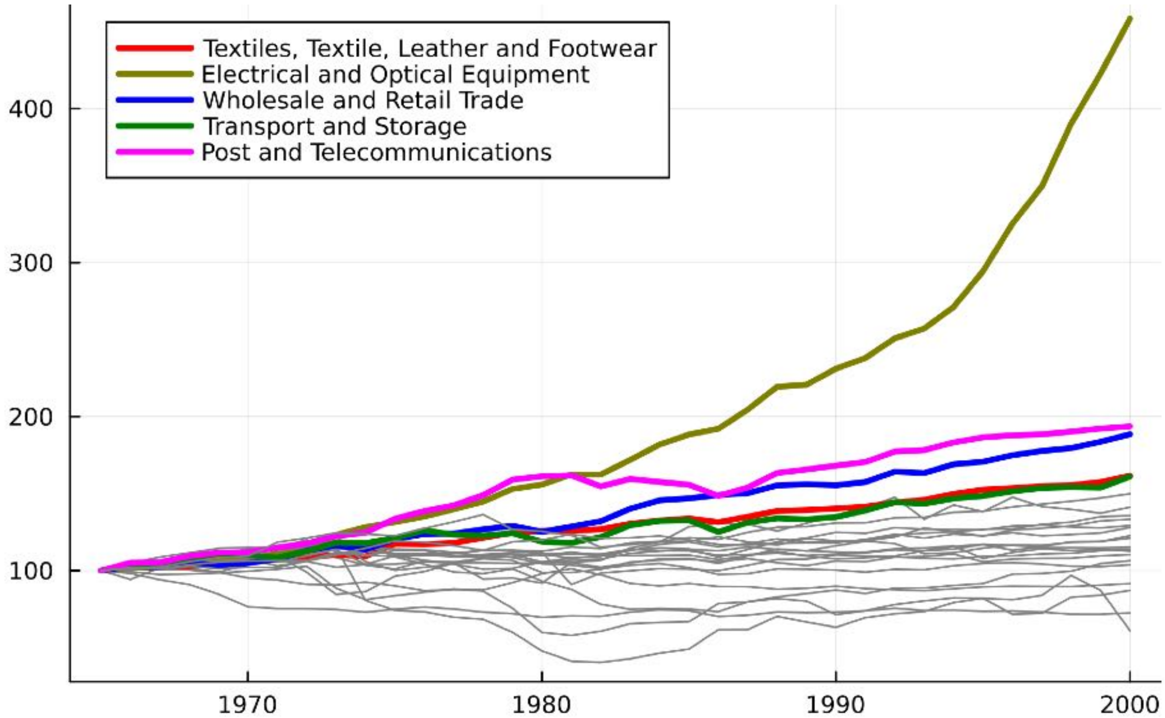
A Impulse Responses

Figure 3: Sectoral Solow Residuals

A. Productivity Shocks in China

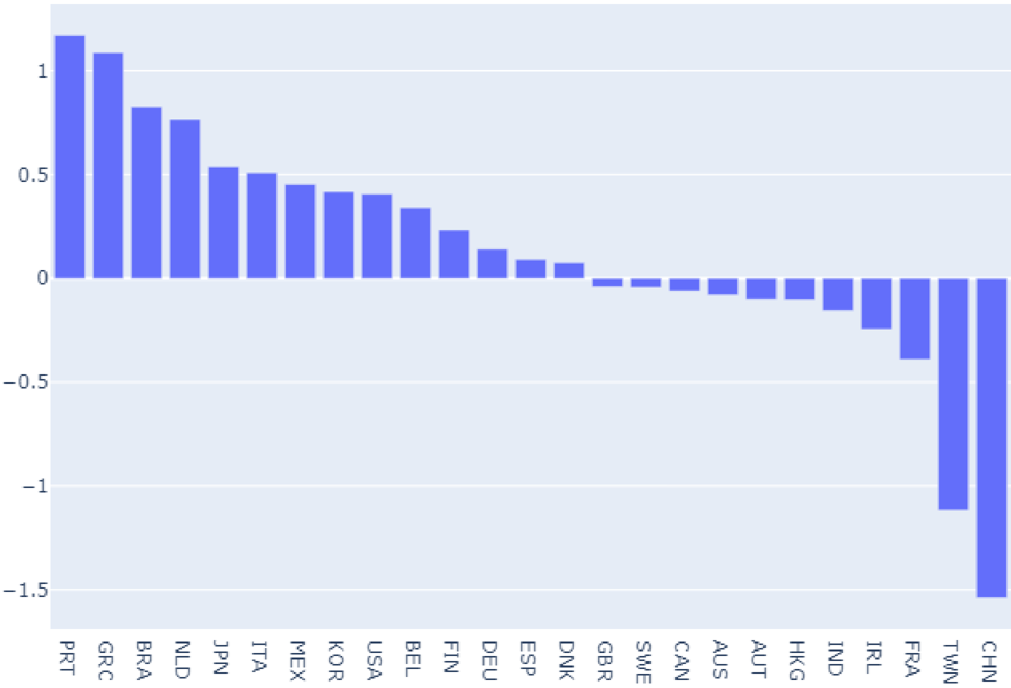


B. Productivity Shocks in the United States



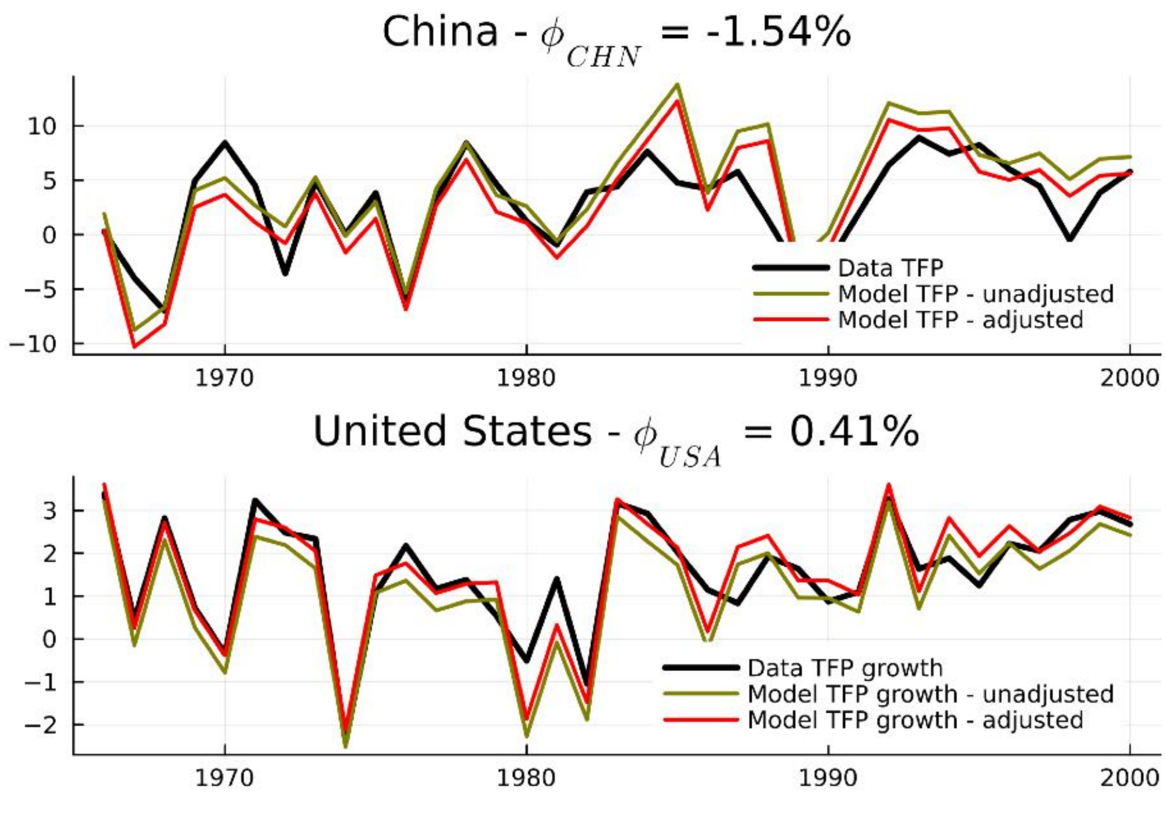
Note: Sectoral productivity levels for 1965 are normalized at 100.

Figure 4: Country Fixed Effect ϕ



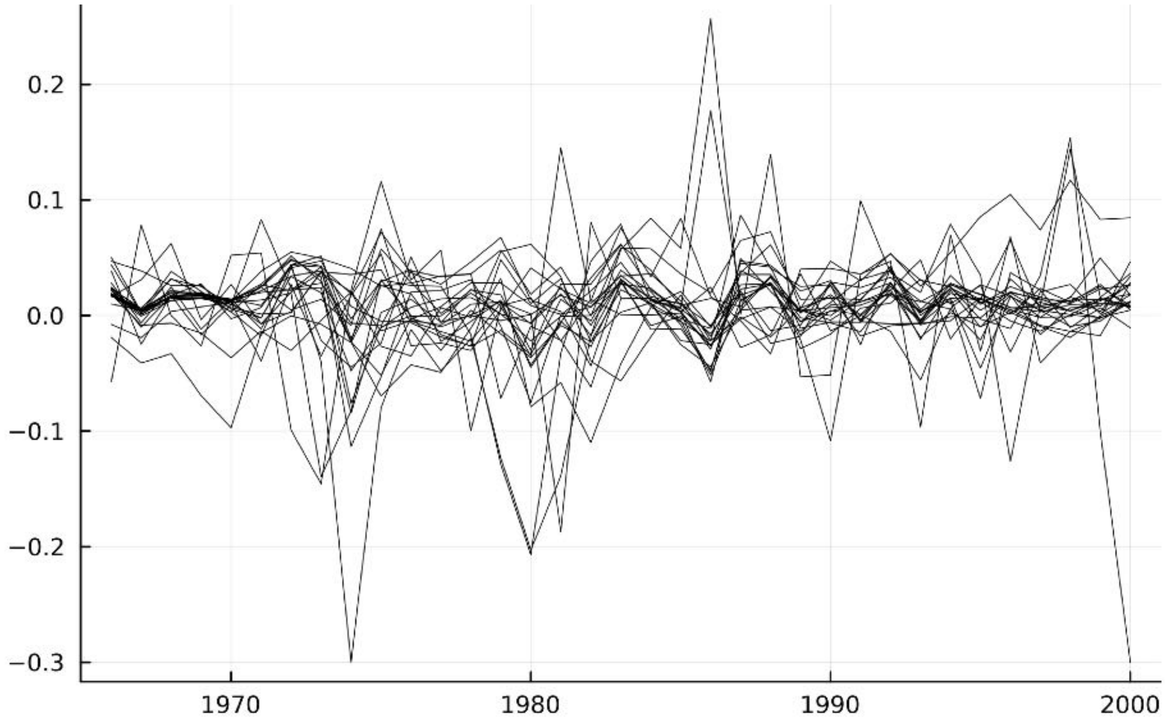
Note: ϕ_r is given by the regression $d\,log\,TFP^*_{r,t} - d\,log\,TFP_{r,t} = \phi_r + \epsilon_{r,t}$.

Figure 5: Effect of ϕ in China and the US



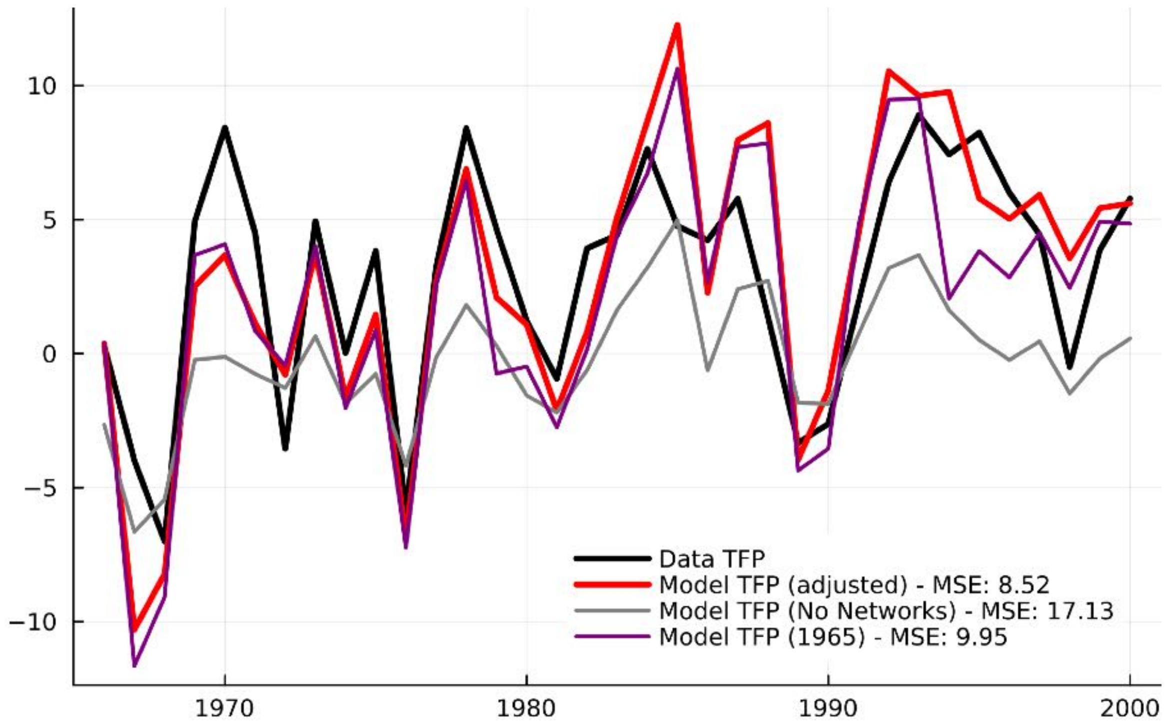
Note: Data TFP corresponds to $d\,log\,TFP^*_{r,t}$. Model TFP (unadjusted) corresponds to $d\,log\,TFP_{r,t}$. Model TFP (adjusted) corresponds to $d\,log\,\widehat{TFP}_{r,t}$.

Figure 6: $d\,log\,A_{i,t}$ for US Sectors



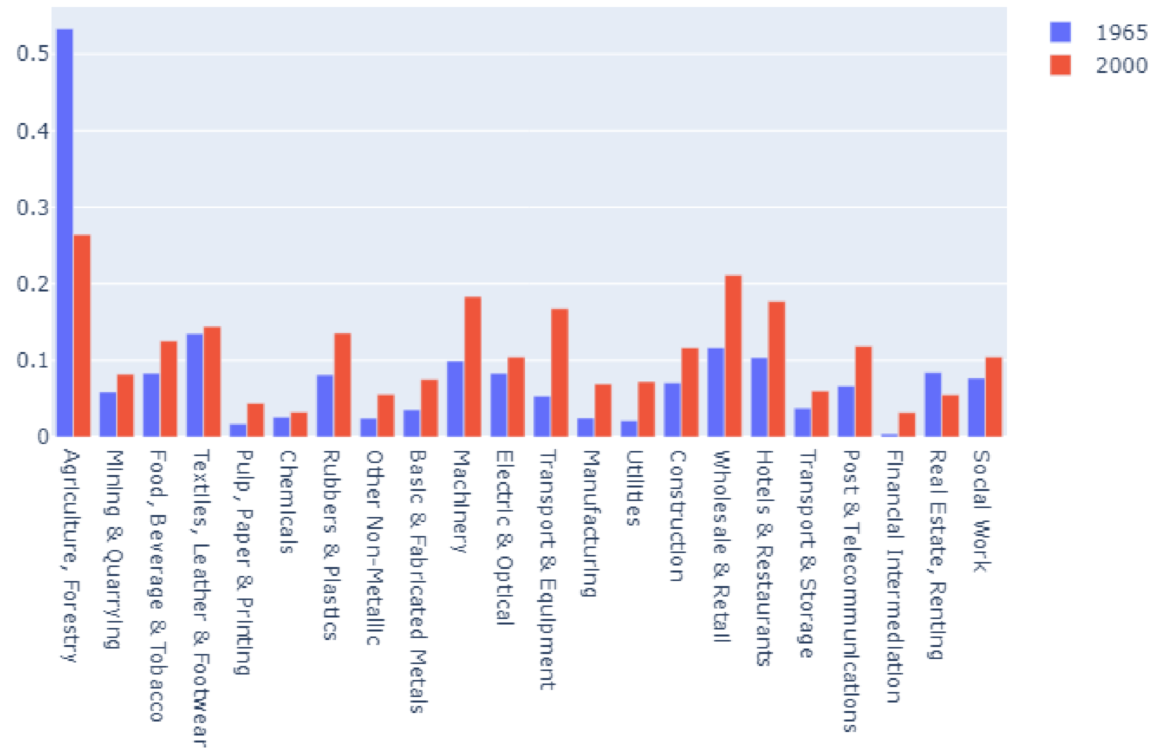
Note: $d\,log\,A_{i,t}$ for the 23 US sectors.

Figure 7: Weight Effects in China



Note: Data TFP corresponds to $d\,log\,TFP^{*}_{r,t}$. Model TFP (unadjusted) corresponds to $d\,log\,TFP_{r,t}$. Model TFP (No Networks) estimates Corollary 1 using weights for an equivalent counterfactual economy without intermediate input markets, i.e., $\lambda_{i,t}/\chi_{r,t}$ corresponde to the solution of the model from Section 2 assuming $\Omega^{x}_{ij} = 0$ for all $i, j \in \mathcal{N}$. Model TFP (1965) estimates Corollary 1 using the 1965 weights, i.e., $\lambda_{i,1965}/\chi_{r,1965}$. The mean squared error caputes the average of the squares of the difference between the corresponding graph and data TFP.

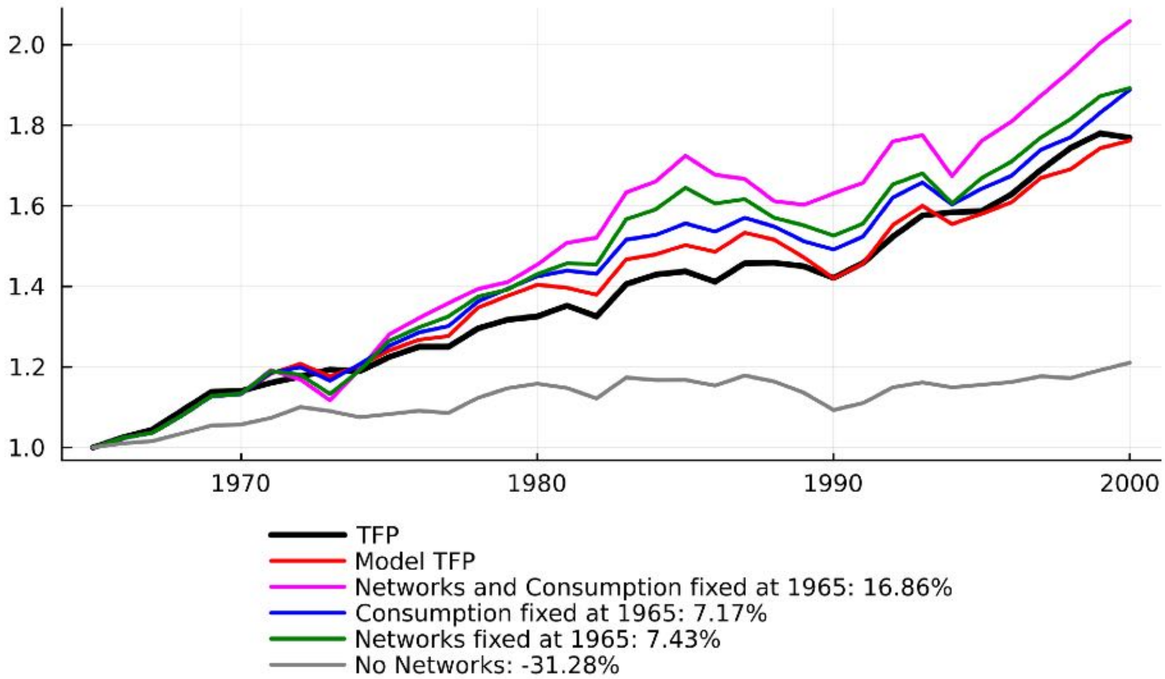
Figure 8: Sectoral Weights in China for 1965 and 2000



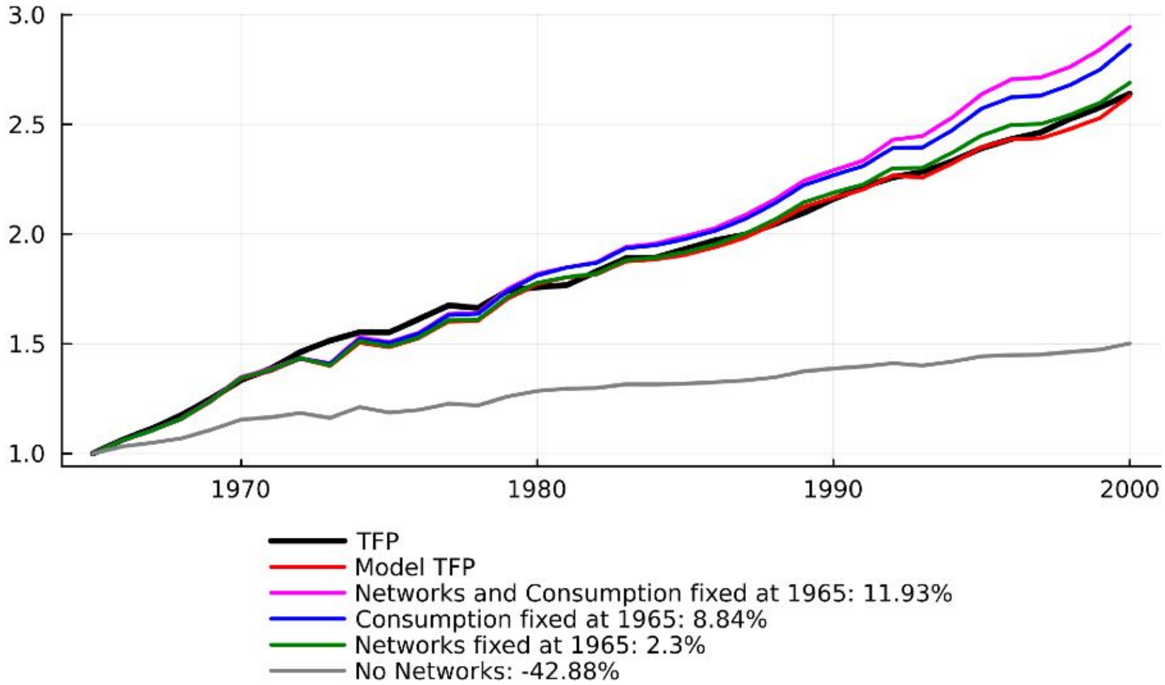
Note: 1965 and 200 show respectively the ratios $\lambda_{i,1965}/\chi_{China,1965}$ and $\lambda_{i,2000}/\chi_{China,2000}$ for the 23 sectors in China.

Figure 9: Conterfactuals with 1965 Global Network

A. Australia



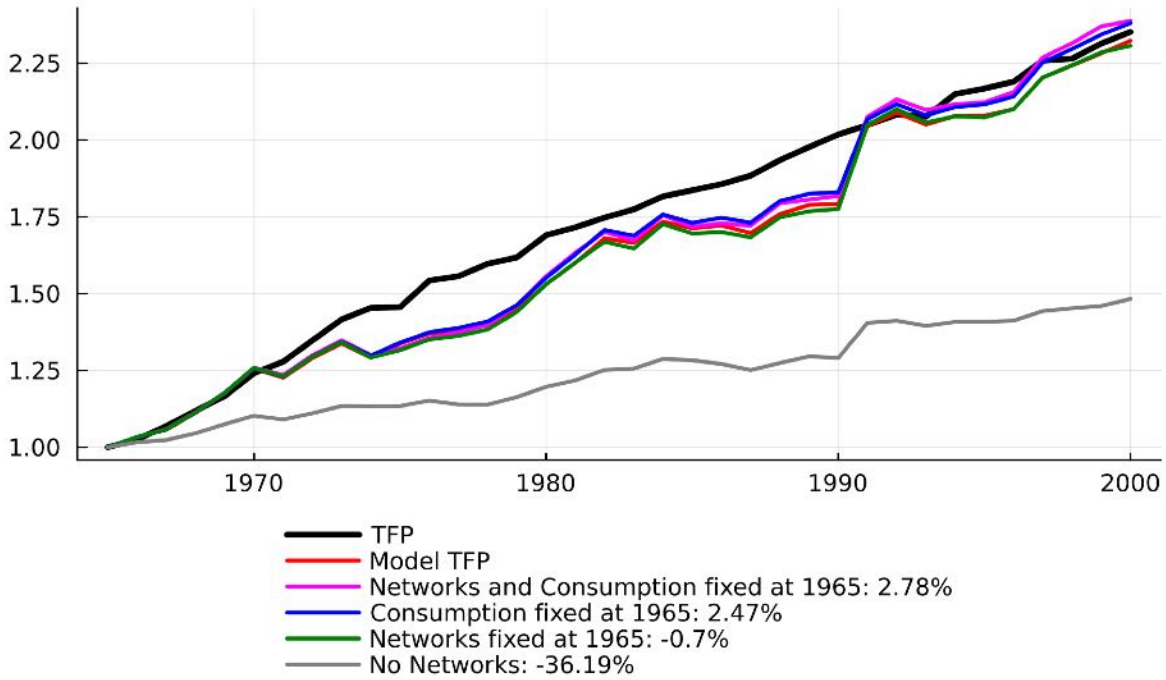
B. Austria



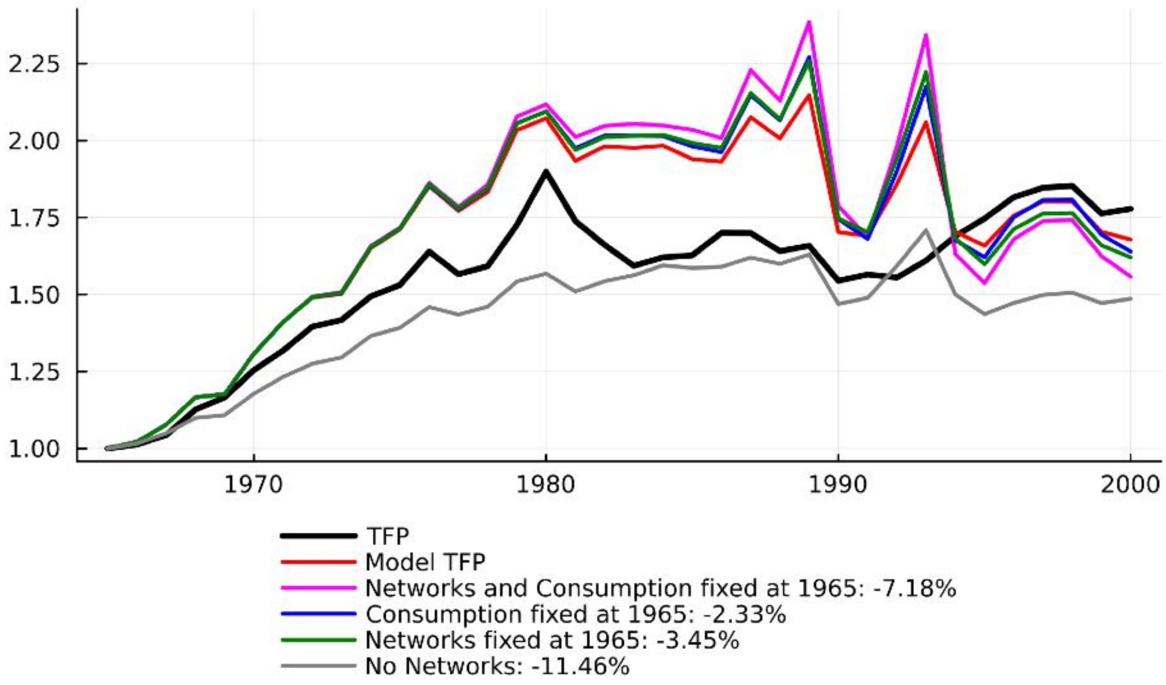
Note: $TFP_{r,1965}$ is normalized at 1 $\forall r \in \mathscr{R}$. Each line estimates $TFP_{r,t}$ introducing a a different sequence for $\{d\,log\,TFP_{r,t}\}_{t=1966}^{2000}$ in the equation $TFP_{r,t} = \prod_{s=1966}^{t}(1 + d\,log\,TFP_{r,s})$. All estimates utilize the same sectoral productivity sequences. The black line TFP uses the data estimate from the Penn World Tables for $d\,log\,TFP^{*}_{r,t}$. The red line uses the adjusted model-based TFP with varying weights $\phi_{r,t} + d\,log\,TFP_{r,t}$. The purple line fixes both the matrices Ω_x an β at their 1965 levels and uses them to estimate a set of weights λ and χ that are used to estimate $d\,log\,TFP_{r,t}$. The blue line fixes the matrices β at their 1965 level, allows Ω_x to follow the observed variation, and uses them to estimate a set of weights λ and χ that are used to estimate $d\,log\,TFP_{r,t}$. The blue line fixes the matrices Ω_x at their 1965 level, allows β to follow the observed variation, and uses them to estimate a set of weights λ and χ that are used to estimate $d\,log\,TFP_{r,t}$.

Figure 10: Conterfactuals with 1965 Global Network

A. Belgium



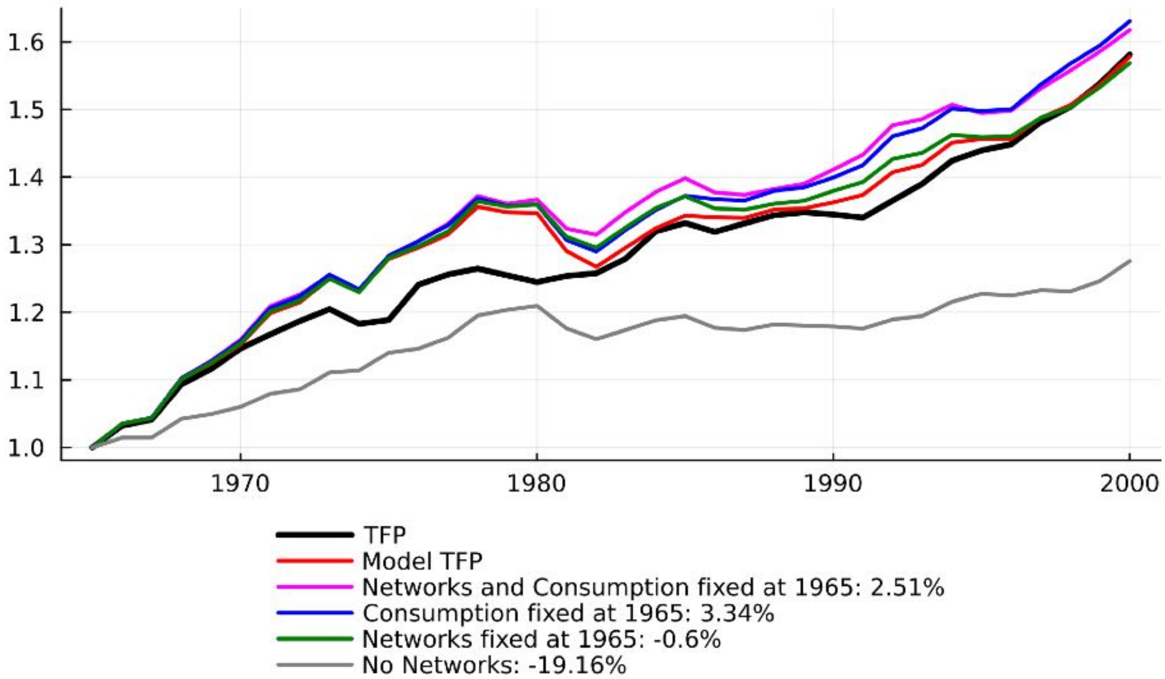
B. Brazil



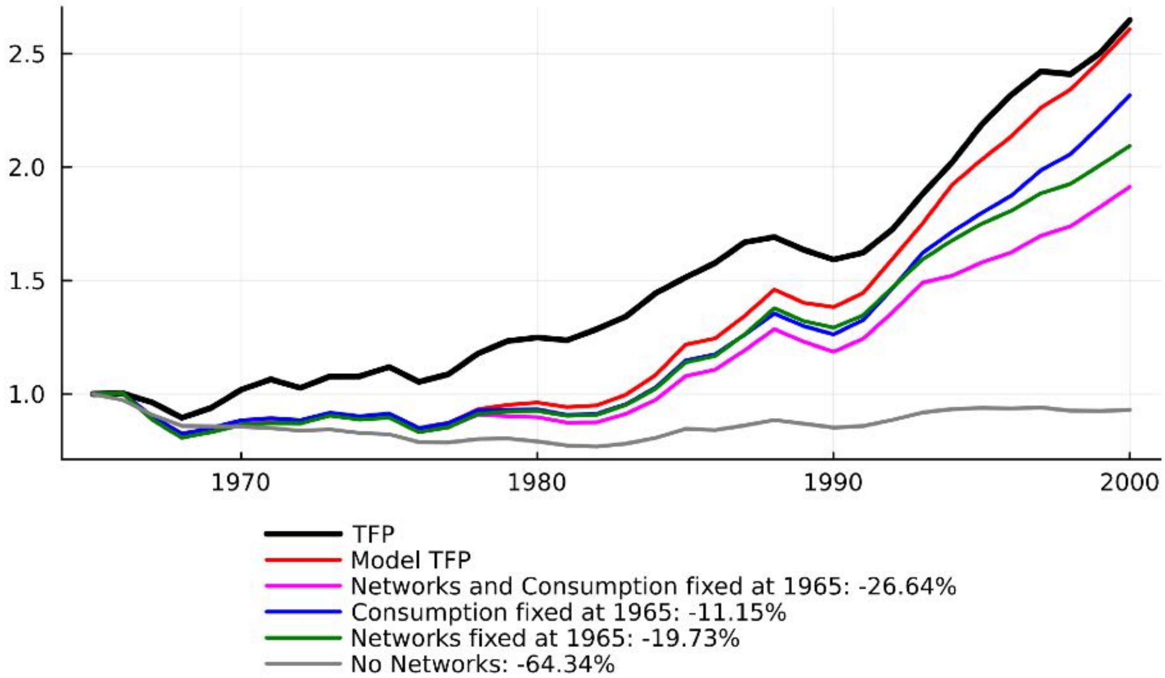
Note: $TFP_{r,1965}$ is normalized at 1 $\forall r \in \mathscr{R}$. Each line estimates $TFP_{r,t}$ introducing a a different sequence for $\{d\,log\,TFP_{r,t}\}_{t=1966}^{2000}$ in the equation $TFP_{r,t} = \prod_{s=1966}^{t}(1 + d\,log\,TFP_{r,s})$. All estimates utilize the same sectoral productivity sequences. The black line TFP uses the data estimate from the Penn World Tables for $d\,log\,TFP^{*}_{r,t}$. The red line uses the adjusted model-based TFP with varying weights $\phi_{r,t} + d\,log\,TFP_{r,t}$. The purple line fixes both the matrices Ω_x an β at their 1965 levels and uses them to estimate a set of weights λ and χ that are used to estimate $d\,log\,TFP_{r,t}$. The blue line fixes the matrices β at their 1965 level, allows Ω_x to follow the observed variation, and uses them to estimate a set of weights λ and χ that are used to estimate $d\,log\,TFP_{r,t}$. The blue line fixes the matrices Ω_x at their 1965 level, allows β to follow the observed variation, and uses them to estimate a set of weights λ and χ that are used to estimate $d\,log\,TFP_{r,t}$.

Figure 11: Conterfactuals with 1965 Global Network

A. Canada



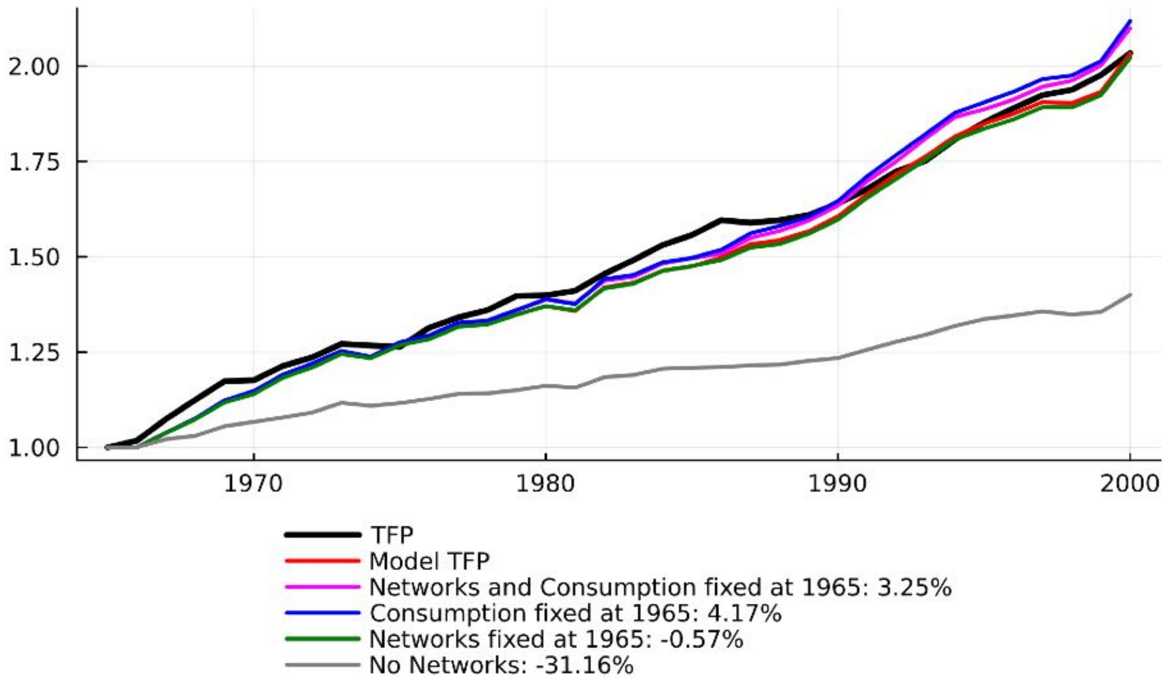
B. China



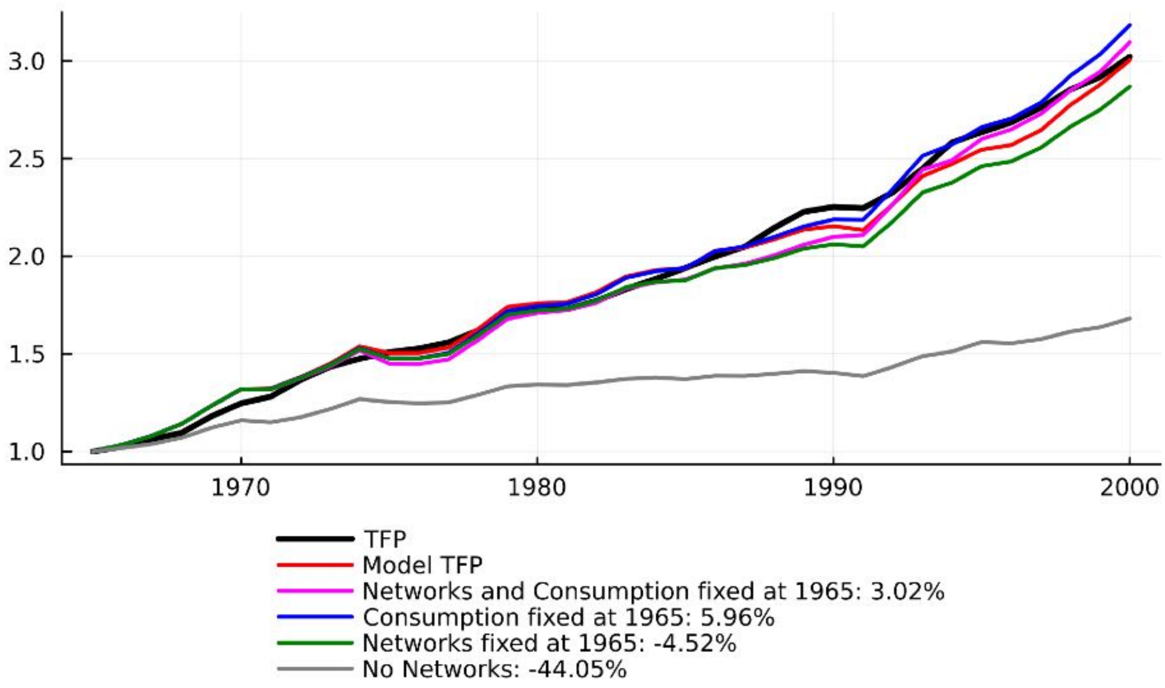
Note: $TFP_{r,1965}$ is normalized at 1 $\forall r \in \mathscr{R}$. Each line estimates $TFP_{r,t}$ introducing a a different sequence for $\{d\,log\,TFP_{r,t}\}_{t=1966}^{2000}$ in the equation $TFP_{r,t} = \prod_{s=1966}^{t}(1 + d\,log\,TFP_{r,s})$. All estimates utilize the same sectoral productivity sequences. The black line TFP uses the data estimate from the Penn World Tables for $d\,log\,TFP_{r,t}^{*}$. The red line uses the adjusted model-based TFP with varying weights $\phi_{r,t} + d\,log\,TFP_{r,t}$. The purple line fixes both the matrices Ω_x an β at their 1965 levels and uses them to estimate a set of weights λ and χ that are used to estimate $d\,log\,TFP_{r,t}$. The blue line fixes the matrices β at their 1965 level, allows Ω_x to follow the observed variation, and uses them to estimate a set of weights λ and χ that are used to estimate $d\,log\,TFP_{r,t}$. The blue line fixes the matrices Ω_x at their 1965 level, allows β to follow the observed variation, and uses them to estimate a set of weights λ and χ that are used to estimate $d\,log\,TFP_{r,t}$.

Figure 12: Conterfactuals with 1965 Global Network

A. Denmark



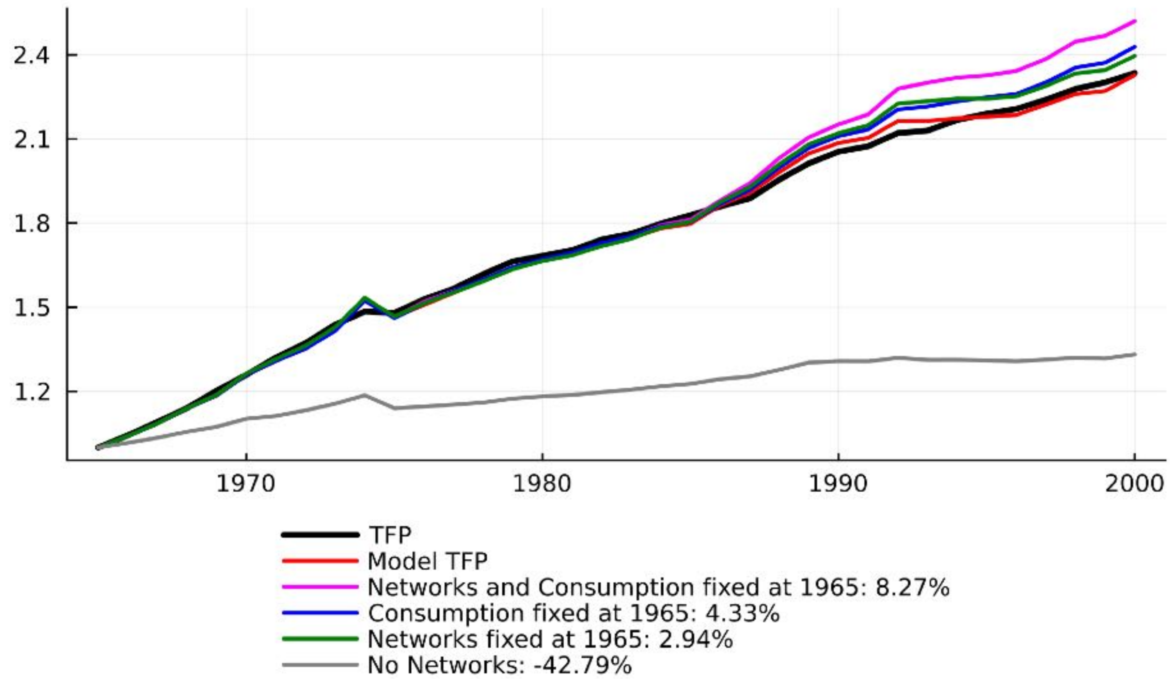
B. Finland



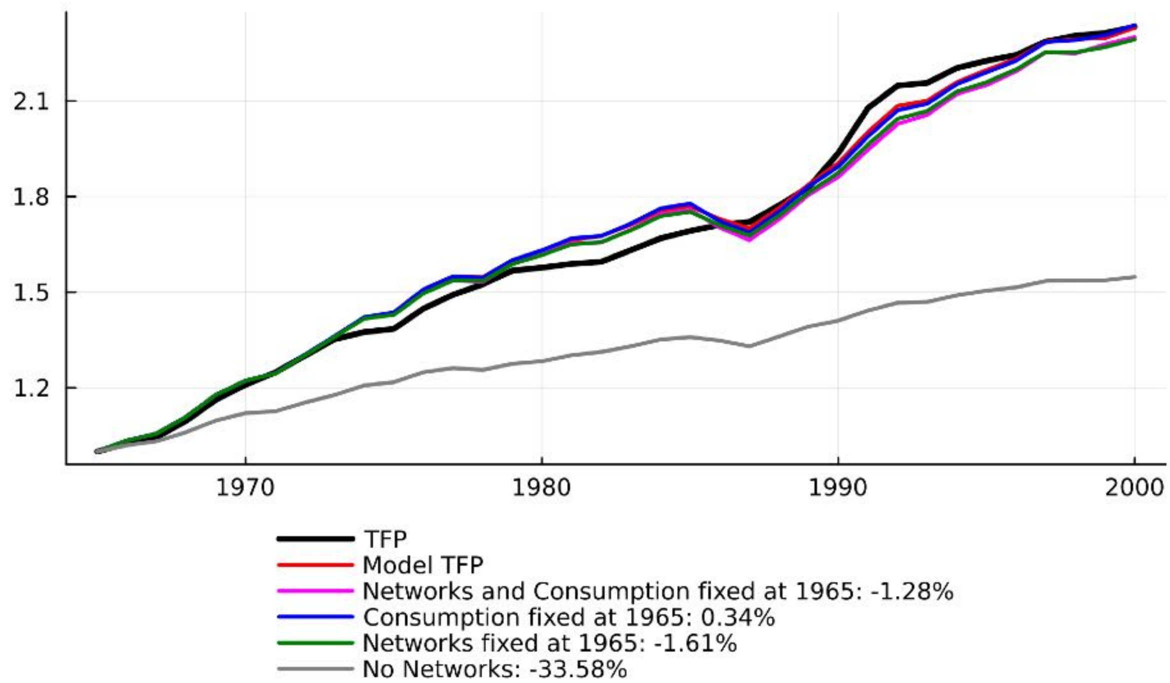
Note: $TFP_{r,1965}$ is normalized at 1 $\forall r \in \mathscr{R}$. Each line estimates $TFP_{r,t}$ introducing a a different sequence for $\{d\,log\,TFP_{r,t}\}_{t=1966}^{2000}$ in the equation $TFP_{r,t} = \prod_{s=1966}^{t}(1 + d\,log\,TFP_{r,s})$. All estimates utilize the same sectoral productivity sequences. The black line TFP uses the data estimate from the Penn World Tables for $d\,log\,TFP^{*}_{r,t}$. The red line uses the adjusted model-based TFP with varying weights $\phi_{r,t} + d\,log\,TFP_{r,t}$. The purple line fixes both the matrices Ω_x an β at their 1965 levels and uses them to estimate a set of weights λ and χ that are used to estimate $d\,log\,TFP_{r,t}$. The blue line fixes the matrices β at their 1965 level, allows Ω_x to follow the observed variation, and uses them to estimate a set of weights λ and χ that are used to estimate $d\,log\,TFP_{r,t}$. The blue line fixes the matrices Ω_x at their 1965 level, allows β to follow the observed variation, and uses them to estimate a set of weights λ and χ that are used to estimate $d\,log\,TFP_{r,t}$.

Figure 13: Conterfactuals with 1965 Global Network

A. France



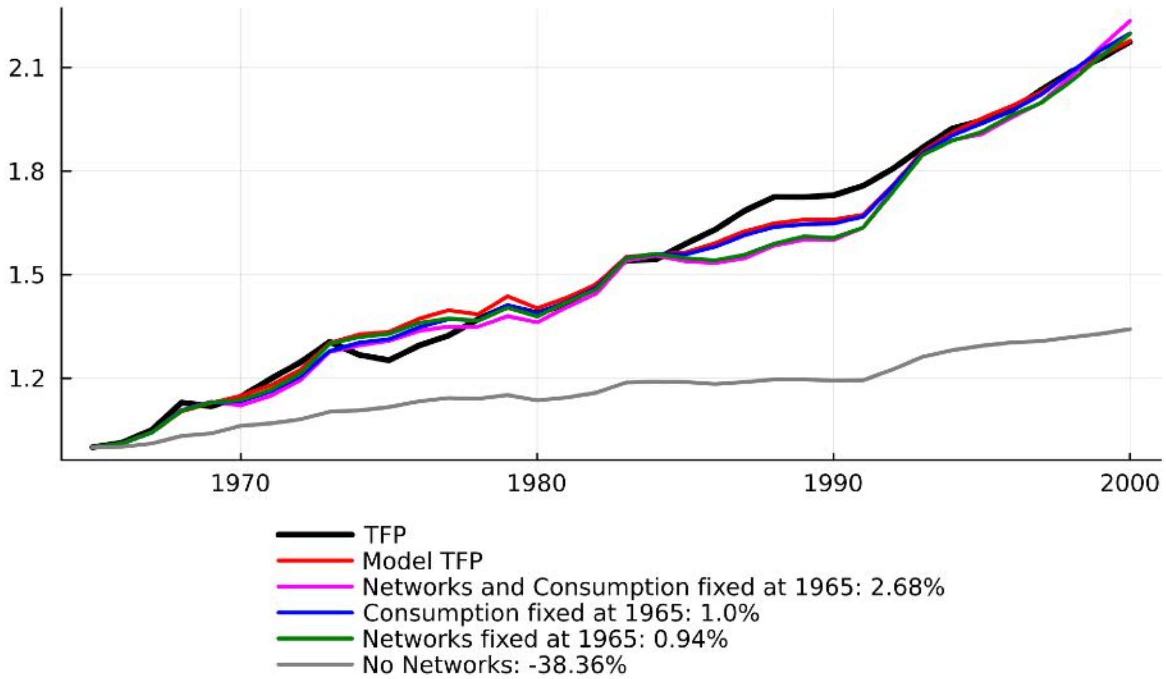
B. Germany



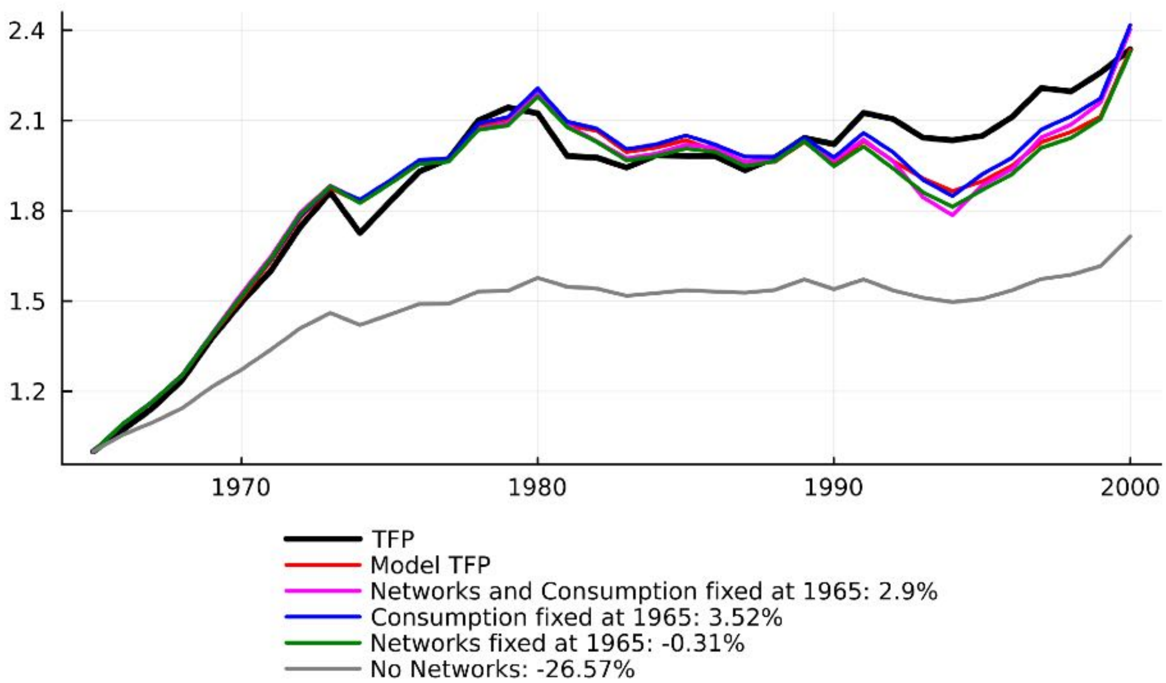
Note: $TFP_{r,1965}$ is normalized at 1 $\forall r \in \mathscr{R}$. Each line estimates $TFP_{r,t}$ introducing a a different sequence for $\{d\,log\,TFP_{r,t}\}_{t=1966}^{2000}$ in the equation $TFP_{r,t} = \prod_{s=1966}^{t}(1 + d\,log\,TFP_{r,s})$. All estimates utilize the same sectoral productivity sequences. The black line TFP uses the data estimate from the Penn World Tables for $d\,log\,TFP^{*}_{r,t}$. The red line uses the adjusted model-based TFP with varying weights $\phi_{r,t} + d\,log\,TFP_{r,t}$. The purple line fixes both the matrices Ω_x an β at their 1965 levels and uses them to estimate a set of weights λ and χ that are used to estimate $d\,log\,TFP_{r,t}$. The blue line fixes the matrices β at their 1965 level, allows Ω_x to follow the observed variation, and uses them to estimate a set of weights λ and χ that are used to estimate $d\,log\,TFP_{r,t}$. The blue line fixes the matrices Ω_x at their 1965 level, allows β to follow the observed variation, and uses them to estimate a set of weights λ and χ that are used to estimate $d\,log\,TFP_{r,t}$.

Figure 14: Conterfactuals with 1965 Global Network

A. Great Britain



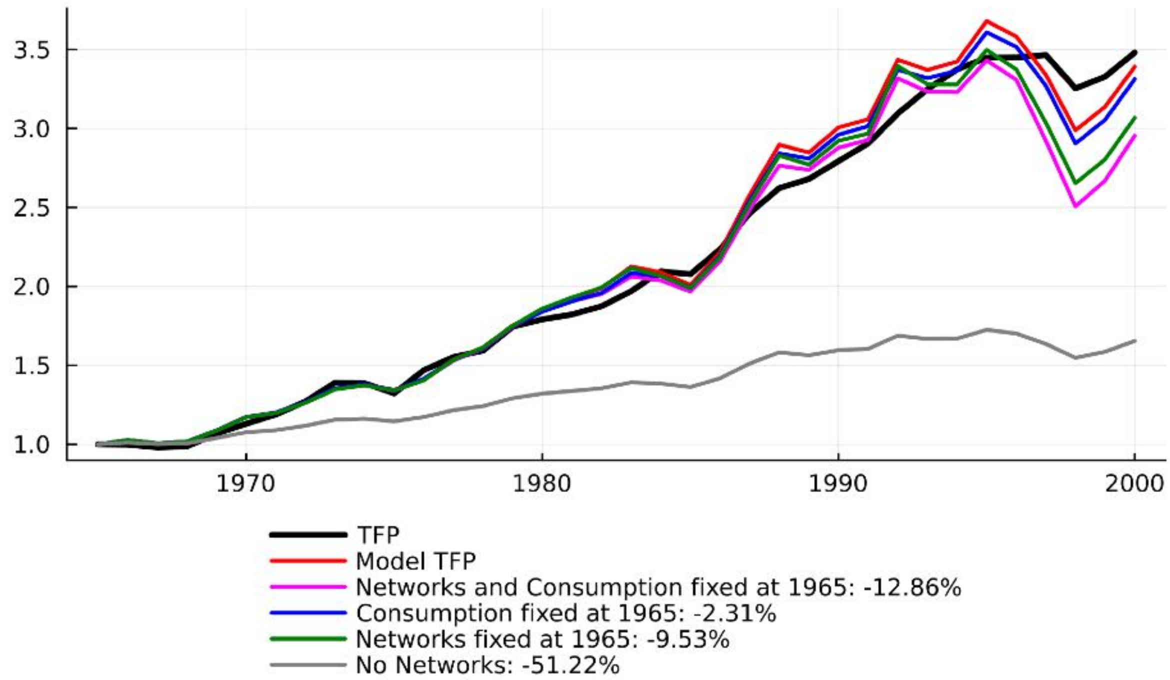
B. Greece



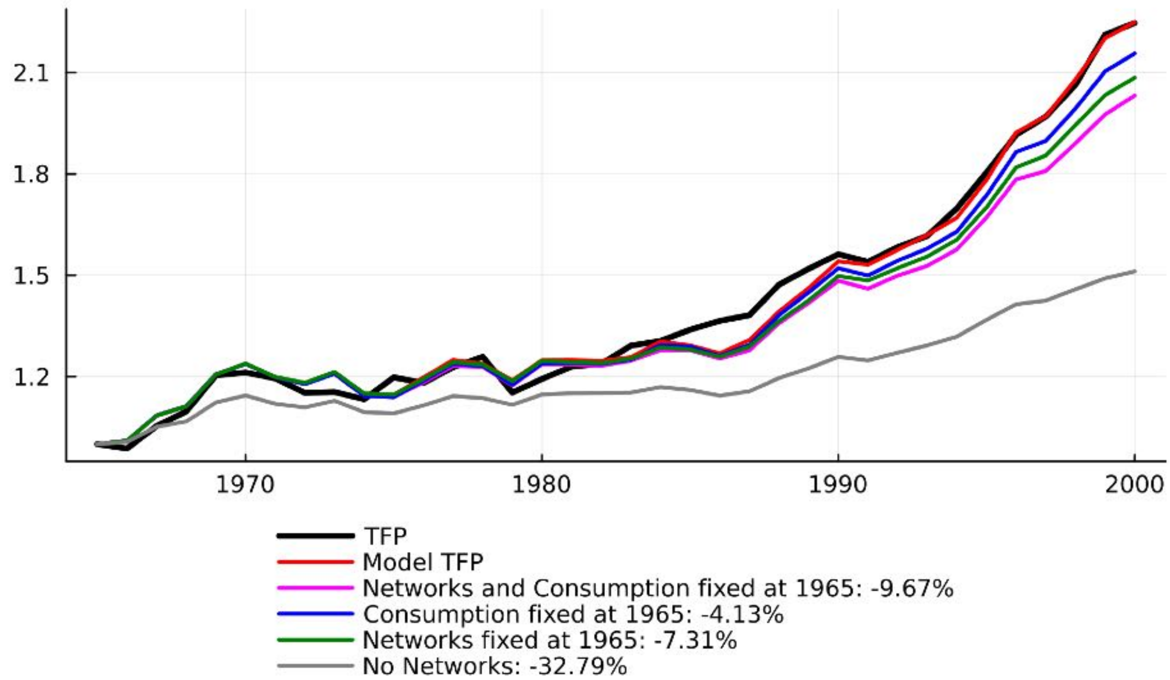
Note: $TFP_{r,1965}$ is normalized at 1 $\forall r \in \mathscr{R}$. Each line estimates $TFP_{r,t}$ introducing a a different sequence for $\{d\,log\,TFP_{r,t}\}_{t=1966}^{2000}$ in the equation $TFP_{r,t} = \prod_{s=1966}^{t}(1 + d\,log\,TFP_{r,s})$. All estimates utilize the same sectoral productivity sequences. The black line TFP uses the data estimate from the Penn World Tables for $d\,log\,TFP^{*}_{r,t}$. The red line uses the adjusted model-based TFP with varying weights $\phi_{r,t} + d\,log\,TFP_{r,t}$. The purple line fixes both the matrices Ω_x an β at their 1965 levels and uses them to estimate a set of weights λ and χ that are used to estimate $d\,log\,TFP_{r,t}$. The blue line fixes the matrices β at their 1965 level, allows Ω_x to follow the observed variation, and uses them to estimate a set of weights λ and χ that are used to estimate $d\,log\,TFP_{r,t}$. The blue line fixes the matrices Ω_x at their 1965 level, allows β to follow the observed variation, and uses them to estimate a set of weights λ and χ that are used to estimate $d\,log\,TFP_{r,t}$.

Figure 15: Conterfactuals with 1965 Global Network

A. Hong Kong



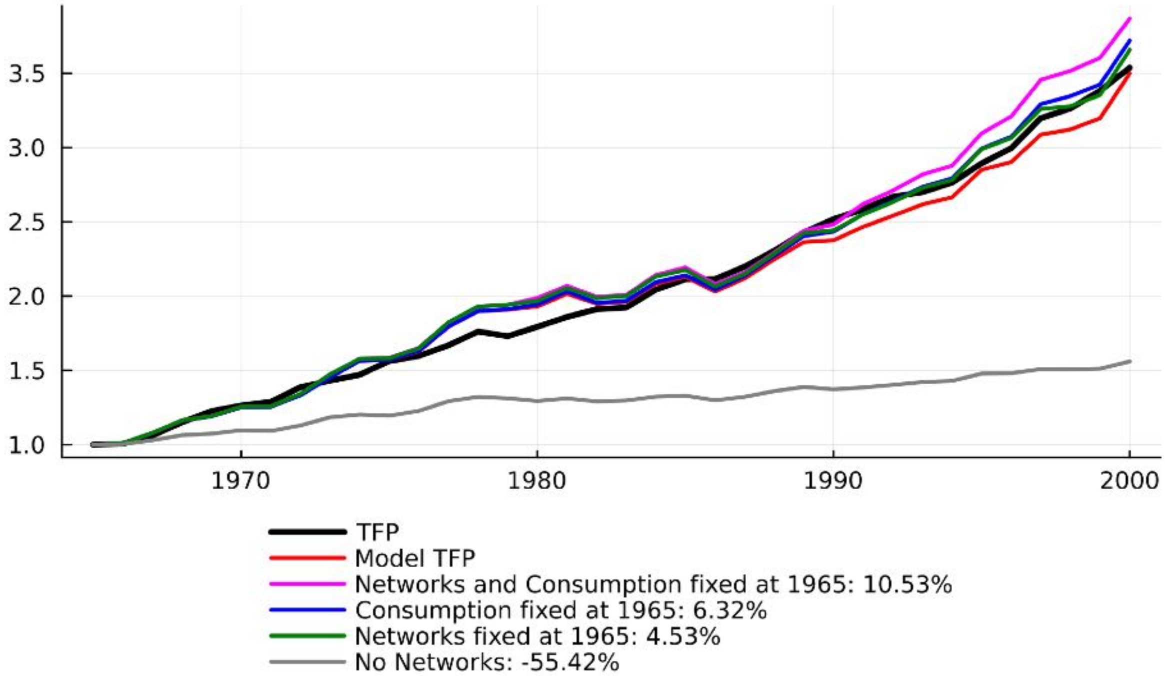
B. India



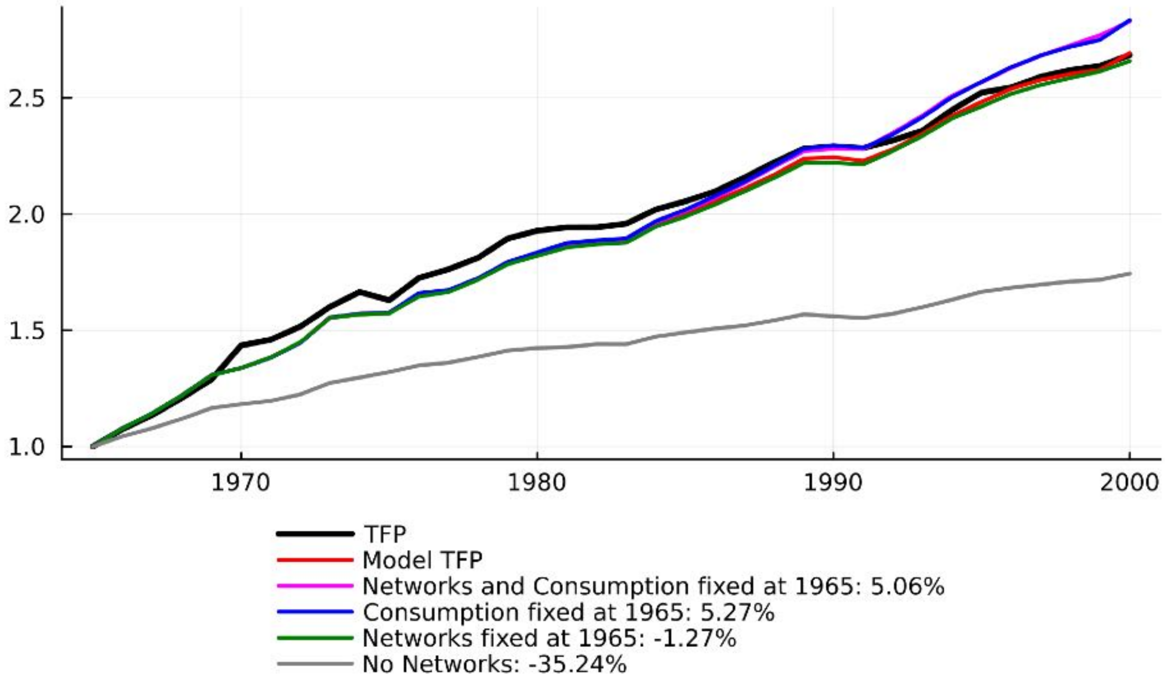
Note: $TFP_{r,1965}$ is normalized at 1 $\forall r \in \mathscr{R}$. Each line estimates $TFP_{r,t}$ introducing a a different sequence for $\{d\,log\,TFP_{r,t}\}_{t=1966}^{2000}$ in the equation $TFP_{r,t} = \prod_{s=1966}^{t}(1 + d\,log\,TFP_{r,s})$. All estimates utilize the same sectoral productivity sequences. The black line TFP uses the data estimate from the Penn World Tables for $d\,log\,TFP^{*}_{r,t}$. The red line uses the adjusted model-based TFP with varying weights $\phi_{r,t} + d\,log\,TFP_{r,t}$. The purple line fixes both the matrices Ω_x an β at their 1965 levels and uses them to estimate a set of weights λ and χ that are used to estimate $d\,log\,TFP_{r,t}$. The blue line fixes the matrices β at their 1965 level, allows Ω_x to follow the observed variation, and uses them to estimate a set of weights λ and χ that are used to estimate $d\,log\,TFP_{r,t}$. The blue line fixes the matrices Ω_x at their 1965 level, allows β to follow the observed variation, and uses them to estimate a set of weights λ and χ that are used to estimate $d\,log\,TFP_{r,t}$.

Figure 16: Conterfactuals with 1965 Global Network

A. Ireland



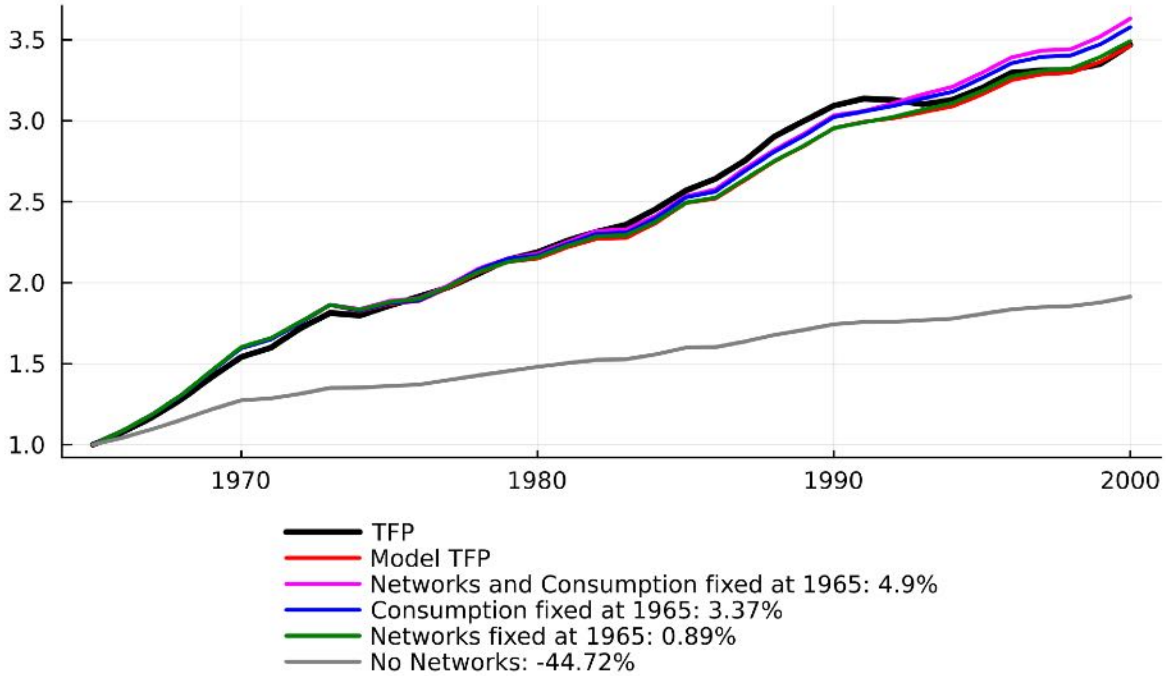
B. Italy



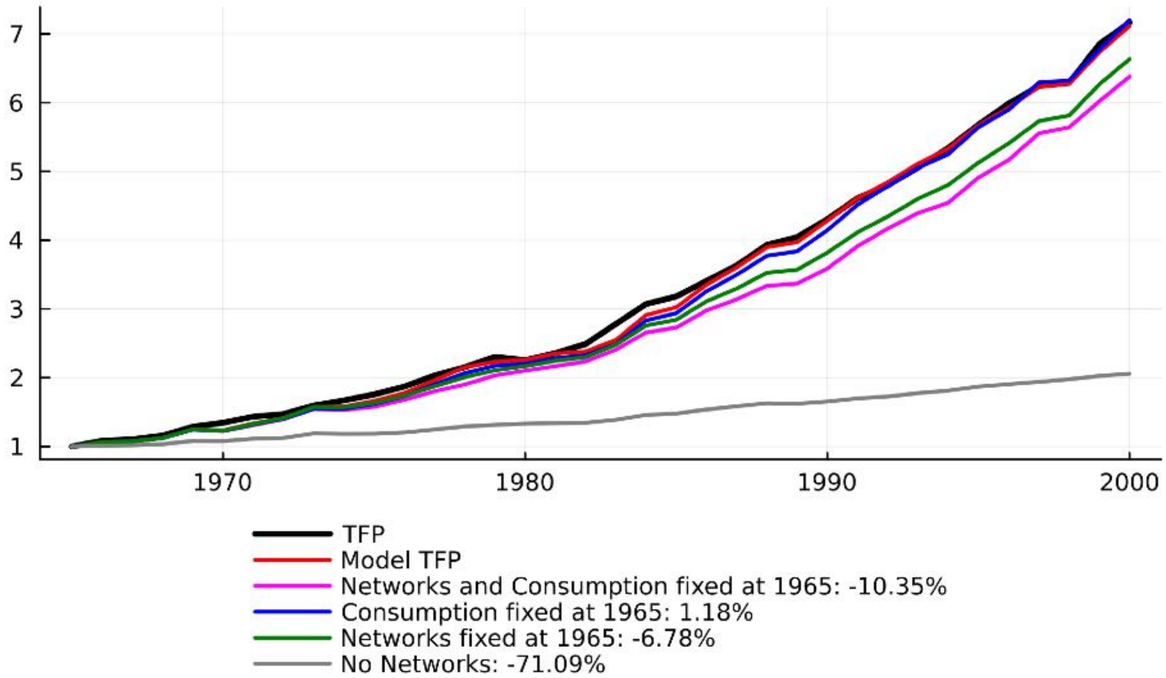
Note: $TFP_{r,1965}$ is normalized at 1 $\forall r \in \mathscr{R}$. Each line estimates $TFP_{r,t}$ introducing a a different sequence for $\{d\,log\,TFP_{r,t}\}_{t=1966}^{2000}$ in the equation $TFP_{r,t} = \prod_{s=1966}^{t}(1 + d\,log\,TFP_{r,s})$. All estimates utilize the same sectoral productivity sequences. The black line TFP uses the data estimate from the Penn World Tables for $d\,log\,TFP^{*}_{r,t}$. The red line uses the adjusted model-based TFP with varying weights $\phi_{r,t} + d\,log\,TFP_{r,t}$. The purple line fixes both the matrices Ω_x an β at their 1965 levels and uses them to estimate a set of weights λ and χ that are used to estimate $d\,log\,TFP_{r,t}$. The blue line fixes the matrices β at their 1965 level, allows Ω_x to follow the observed variation, and uses them to estimate a set of weights λ and χ that are used to estimate $d\,log\,TFP_{r,t}$. The blue line fixes the matrices Ω_x at their 1965 level, allows β to follow the observed variation, and uses them to estimate a set of weights λ and χ that are used to estimate $d\,log\,TFP_{r,t}$.

Figure 17: Conterfactuals with 1965 Global Network

A. Japan



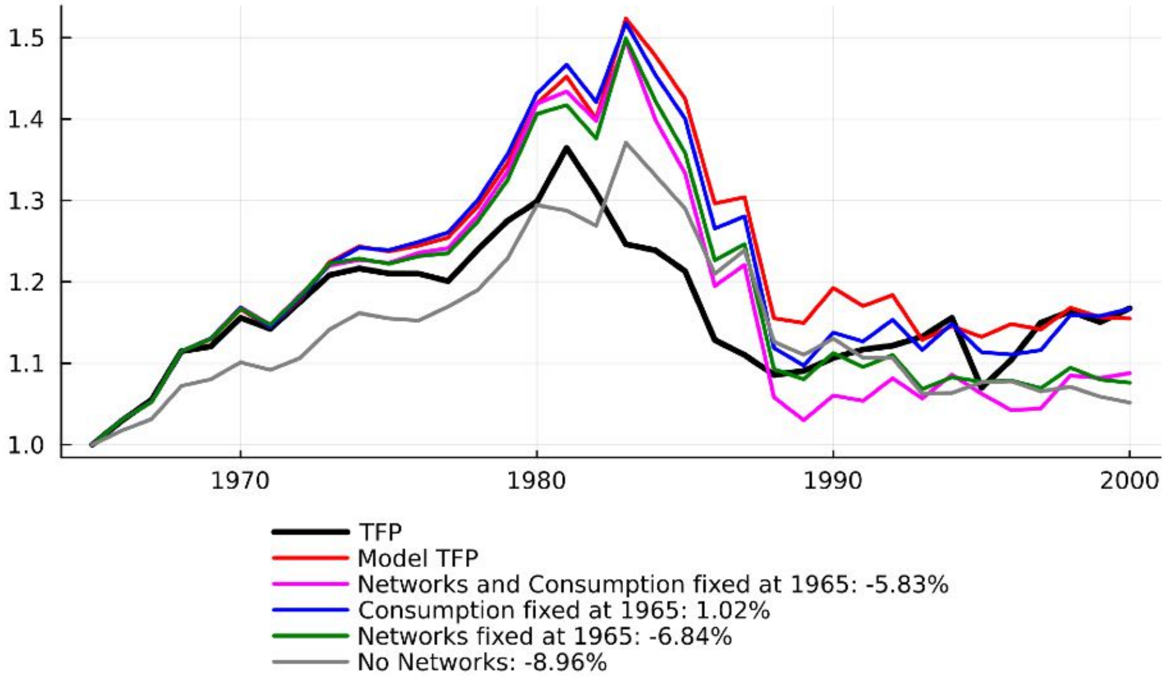
B. Korea



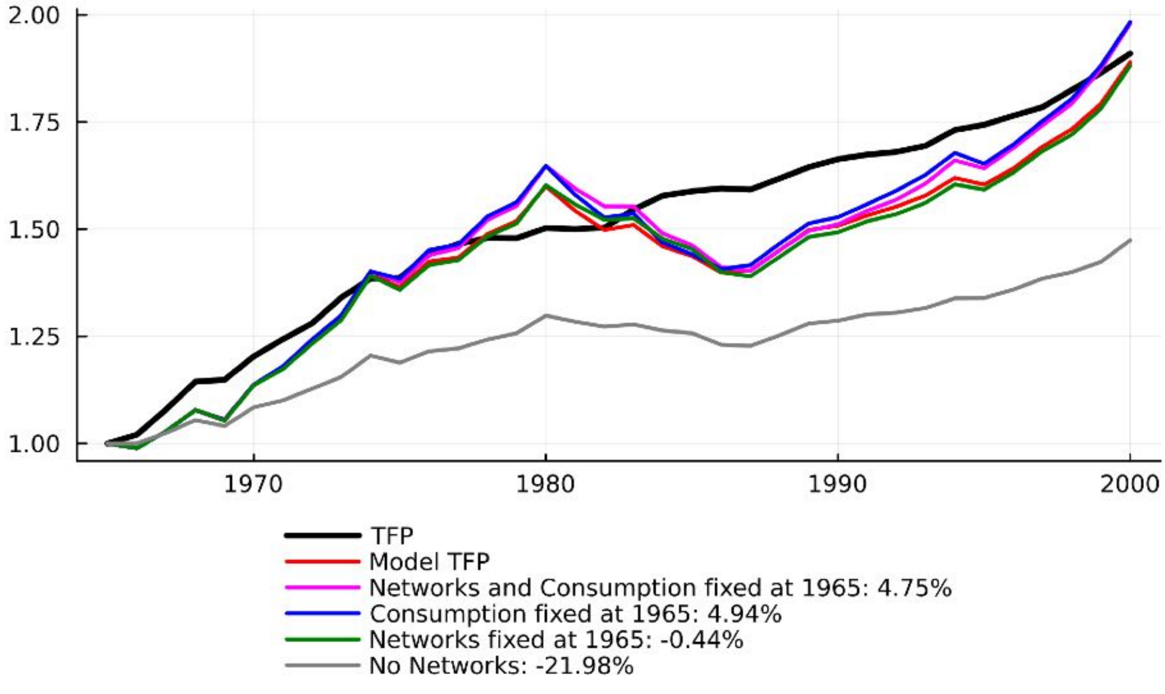
Note: $TFP_{r,1965}$ is normalized at 1 $\forall r \in \mathscr{R}$. Each line estimates $TFP_{r,t}$ introducing a a different sequence for $\{d\,log\,TFP_{r,t}\}_{t=1966}^{2000}$ in the equation $TFP_{r,t} = \prod_{s=1966}^{t}(1 + d\,log\,TFP_{r,s})$. All estimates utilize the same sectoral productivity sequences. The black line TFP uses the data estimate from the Penn World Tables for $d\,log\,TFP^{*}_{r,t}$. The red line uses the adjusted model-based TFP with varying weights $\phi_{r,t} + d\,log\,TFP_{r,t}$. The purple line fixes both the matrices Ω_x an β at their 1965 levels and uses them to estimate a set of weights λ and χ that are used to estimate $d\,log\,TFP_{r,t}$. The blue line fixes the matrices β at their 1965 level, allows Ω_x to follow the observed variation, and uses them to estimate a set of weights λ and χ that are used to estimate $d\,log\,TFP_{r,t}$. The blue line fixes the matrices Ω_x at their 1965 level, allows β to follow the observed variation, and uses them to estimate a set of weights λ and χ that are used to estimate $d\,log\,TFP_{r,t}$.

Figure 18: Conterfactuals with 1965 Global Network

A. Mexico



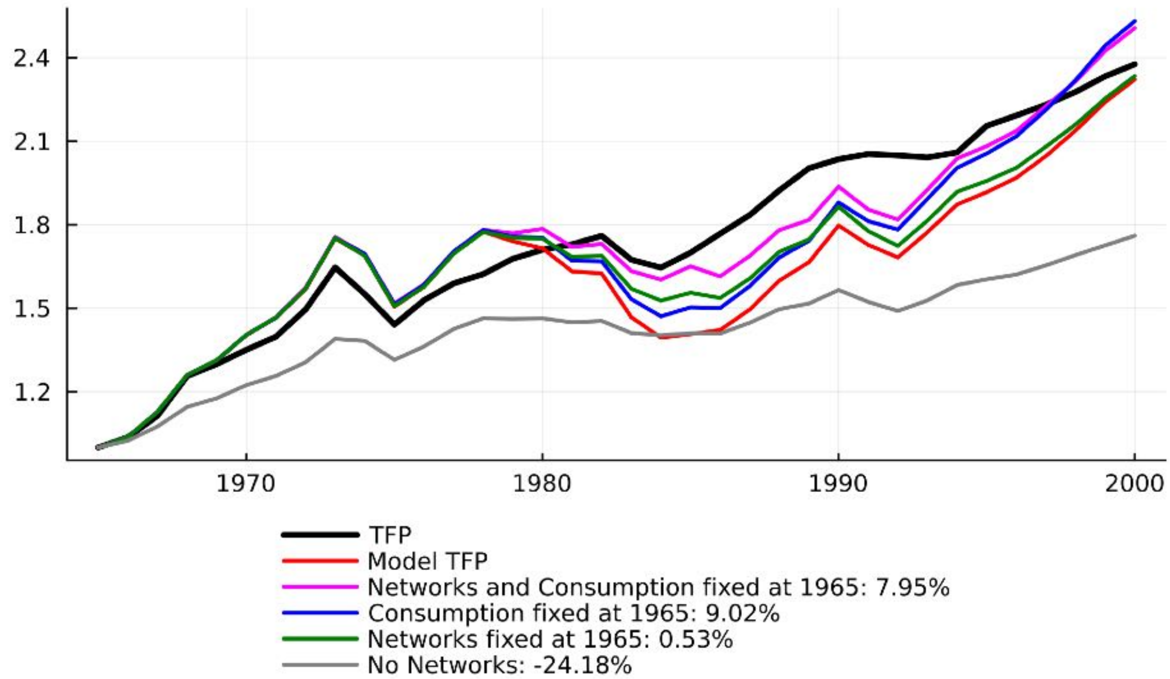
B. Netherlands



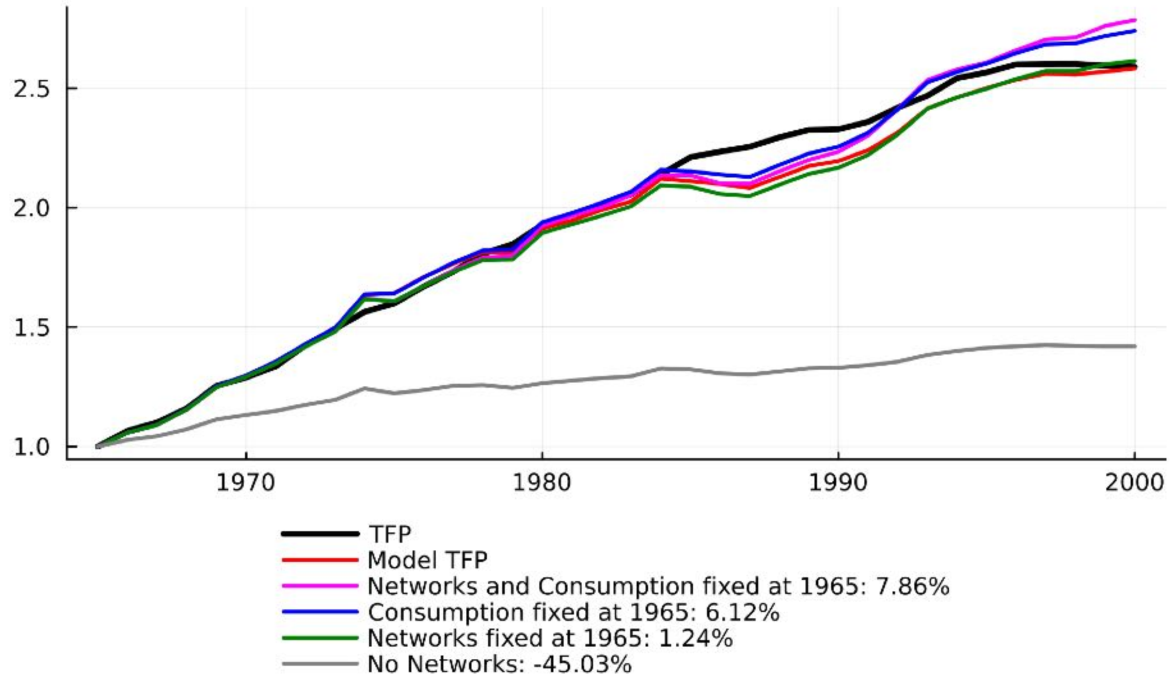
Note: $TFP_{r,1965}$ is normalized at 1 $\forall r \in \mathscr{R}$. Each line estimates $TFP_{r,t}$ introducing a a different sequence for $\{d\,log\,TFP_{r,t}\}_{t=1966}^{2000}$ in the equation $TFP_{r,t} = \prod_{s=1966}^{t}(1 + d\,log\,TFP_{r,s})$. All estimates utilize the same sectoral productivity sequences. The black line TFP uses the data estimate from the Penn World Tables for $d\,log\,TFP^{*}_{r,t}$. The red line uses the adjusted model-based TFP with varying weights $\phi_{r,t} + d\,log\,TFP_{r,t}$. The purple line fixes both the matrices Ω_x an β at their 1965 levels and uses them to estimate a set of weights λ and χ that are used to estimate $d\,log\,TFP_{r,t}$. The blue line fixes the matrices β at their 1965 level, allows Ω_x to follow the observed variation, and uses them to estimate a set of weights λ and χ that are used to estimate $d\,log\,TFP_{r,t}$. The blue line fixes the matrices Ω_x at their 1965 level, allows β to follow the observed variation, and uses them to estimate a set of weights λ and χ that are used to estimate $d\,log\,TFP_{r,t}$.

Figure 19: Conterfactuals with 1965 Global Network

A. Portugal



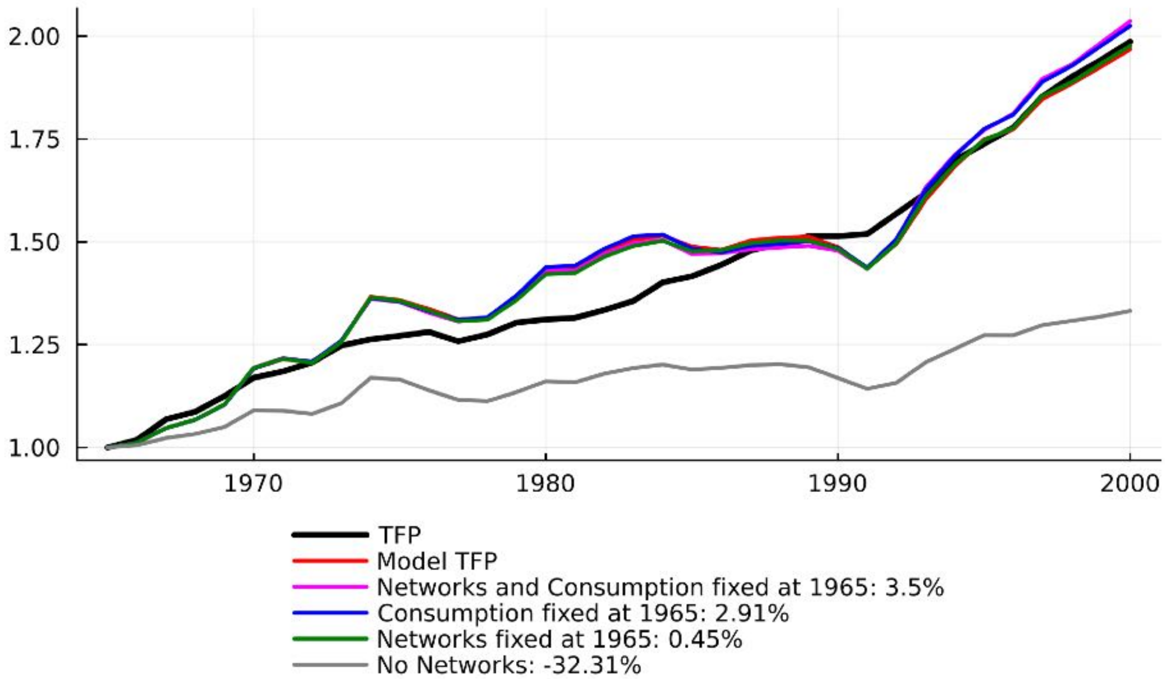
B. Spain



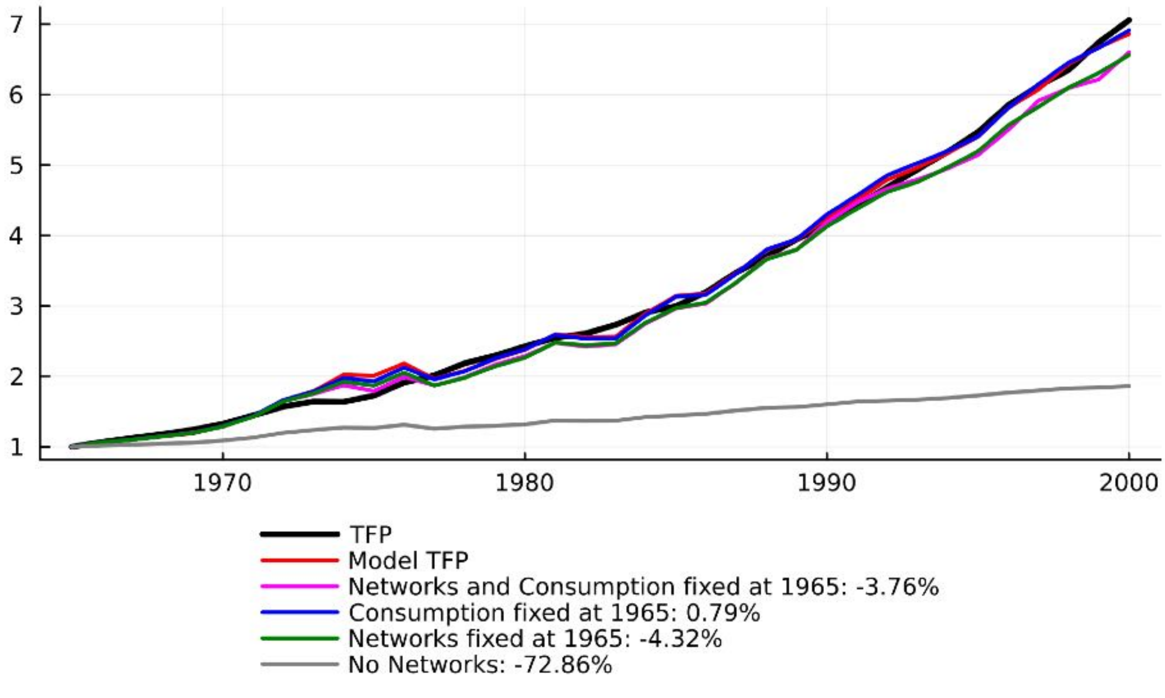
Note: $TFP_{r,1965}$ is normalized at 1 $\forall r \in \mathscr{R}$. Each line estimates $TFP_{r,t}$ introducing a a different sequence for $\{d\,log\,TFP_{r,t}\}_{t=1966}^{2000}$ in the equation $TFP_{r,t} = \prod_{s=1966}^{t}(1 + d\,log\,TFP_{r,s})$. All estimates utilize the same sectoral productivity sequences. The black line TFP uses the data estimate from the Penn World Tables for $d\,log\,TFP^{*}_{r,t}$. The red line uses the adjusted model-based TFP with varying weights $\phi_{r,t} + d\,log\,TFP_{r,t}$. The purple line fixes both the matrices Ω_x an β at their 1965 levels and uses them to estimate a set of weights λ and χ that are used to estimate $d\,log\,TFP_{r,t}$. The blue line fixes the matrices β at their 1965 level, allows Ω_x to follow the observed variation, and uses them to estimate a set of weights λ and χ that are used to estimate $d\,log\,TFP_{r,t}$. The blue line fixes the matrices Ω_x at their 1965 level, allows β to follow the observed variation, and uses them to estimate a set of weights λ and χ that are used to estimate $d\,log\,TFP_{r,t}$.

Figure 20: Conterfactuals with 1965 Global Network

A. Sweden

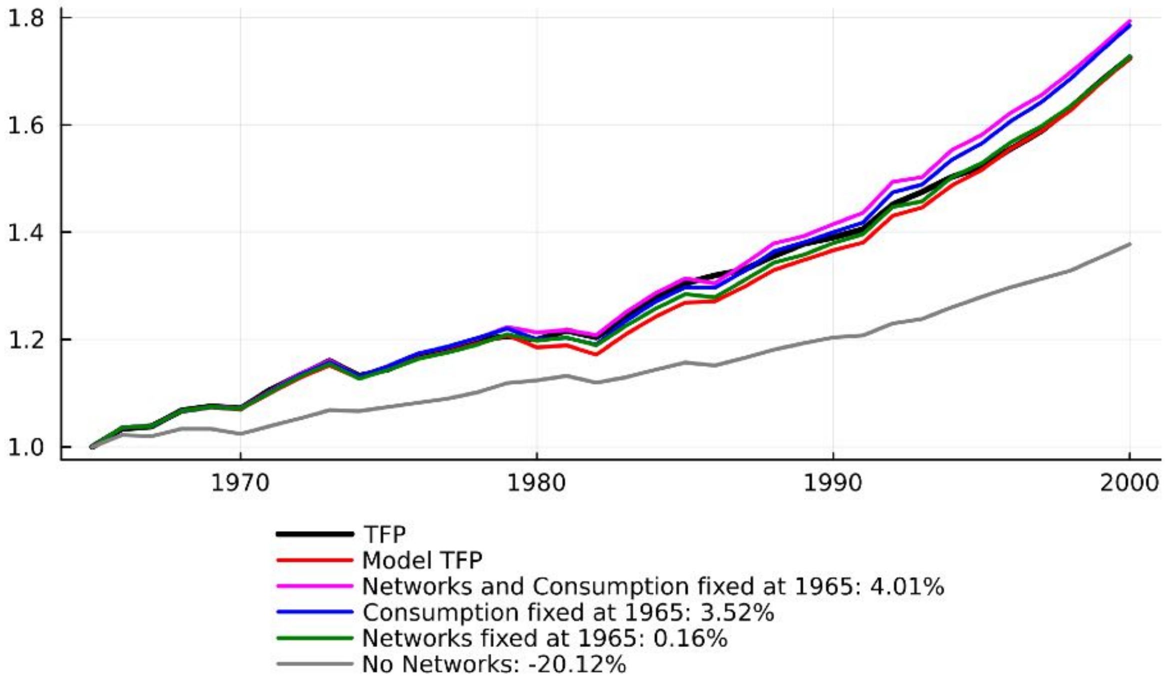


B. Taiwan



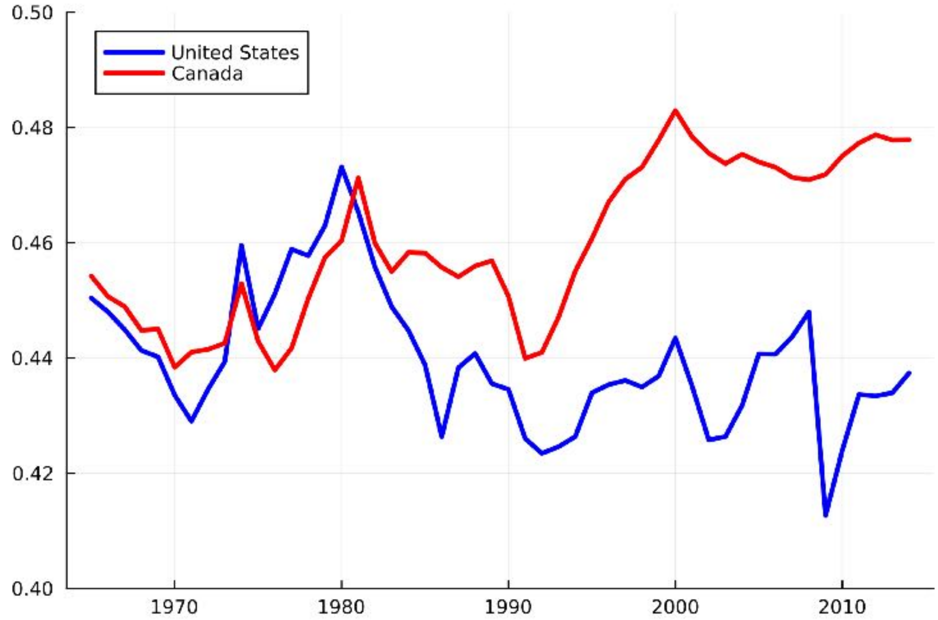
Note: $TFP_{r,1965}$ is normalized at 1 $\forall r \in \mathscr{R}$. Each line estimates $TFP_{r,t}$ introducing a a different sequence for $\{d\,log\,TFP_{r,t}\}_{t=1966}^{2000}$ in the equation $TFP_{r,t} = \prod_{s=1966}^{t}(1 + d\,log\,TFP_{r,s})$. All estimates utilize the same sectoral productivity sequences. The black line TFP uses the data estimate from the Penn World Tables for $d\,log\,TFP^{*}_{r,t}$. The red line uses the adjusted model-based TFP with varying weights $\phi_{r,t} + d\,log\,TFP_{r,t}$. The purple line fixes both the matrices Ω_x an β at their 1965 levels and uses them to estimate a set of weights λ and χ that are used to estimate $d\,log\,TFP_{r,t}$. The blue line fixes the matrices β at their 1965 level, allows Ω_x to follow the observed variation, and uses them to estimate a set of weights λ and χ that are used to estimate $d\,log\,TFP_{r,t}$. The blue line fixes the matrices Ω_x at their 1965 level, allows β to follow the observed variation, and uses them to estimate a set of weights λ and χ that are used to estimate $d\,log\,TFP_{r,t}$.

Figure 21: Conterfactuals with 1965 Global Network for the United States



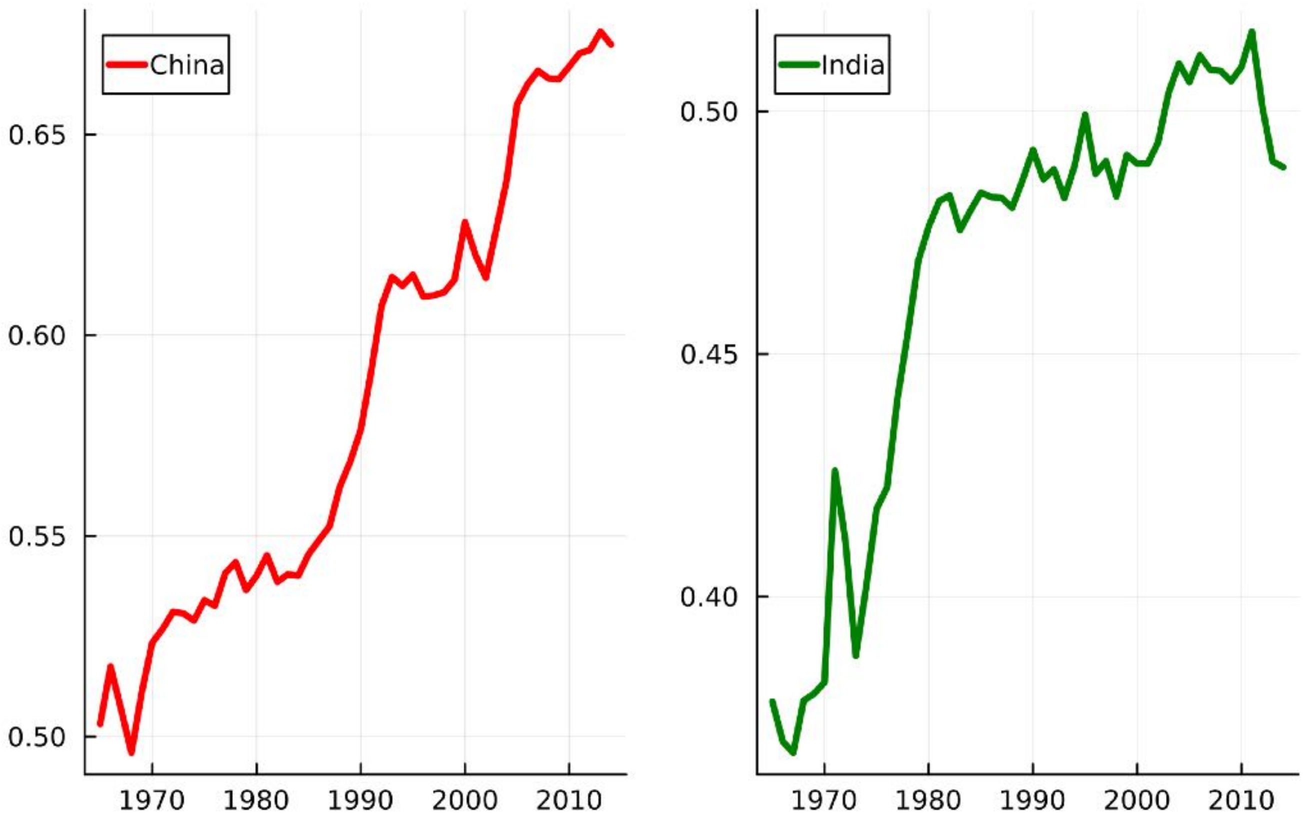
Note: $TFP_{r,1965}$ is normalized at 1 $\forall r \in \mathscr{R}$. Each line estimates $TFP_{r,t}$ introducing a a different sequence for $\{d\,log\,TFP_{r,t}\}_{t=1966}^{2000}$ in the equation $TFP_{r,t} = \prod_{s=1966}^{t}(1 + d\,log\,TFP_{r,s})$. All estimates utilize the same sectoral productivity sequences. The black line TFP uses the data estimate from the Penn World Tables for $d\,log\,TFP^{*}_{r,t}$. The red line uses the adjusted model-based TFP with varying weights $\phi_{r,t} + d\,log\,TFP_{r,t}$. The purple line fixes both the matrices Ω_x an β at their 1965 levels and uses them to estimate a set of weights λ and χ that are used to estimate $d\,log\,TFP_{r,t}$. The blue line fixes the matrices β at their 1965 level, allows Ω_x to follow the observed variation, and uses them to estimate a set of weights λ and χ that are used to estimate $d\,log\,TFP_{r,t}$. The blue line fixes the matrices Ω_x at their 1965 level, allows β to follow the observed variation, and uses them to estimate a set of weights λ and χ that are used to estimate $d\,log\,TFP_{r,t}$.

Figure 22: Intermediate Input Share for the United States and Canada



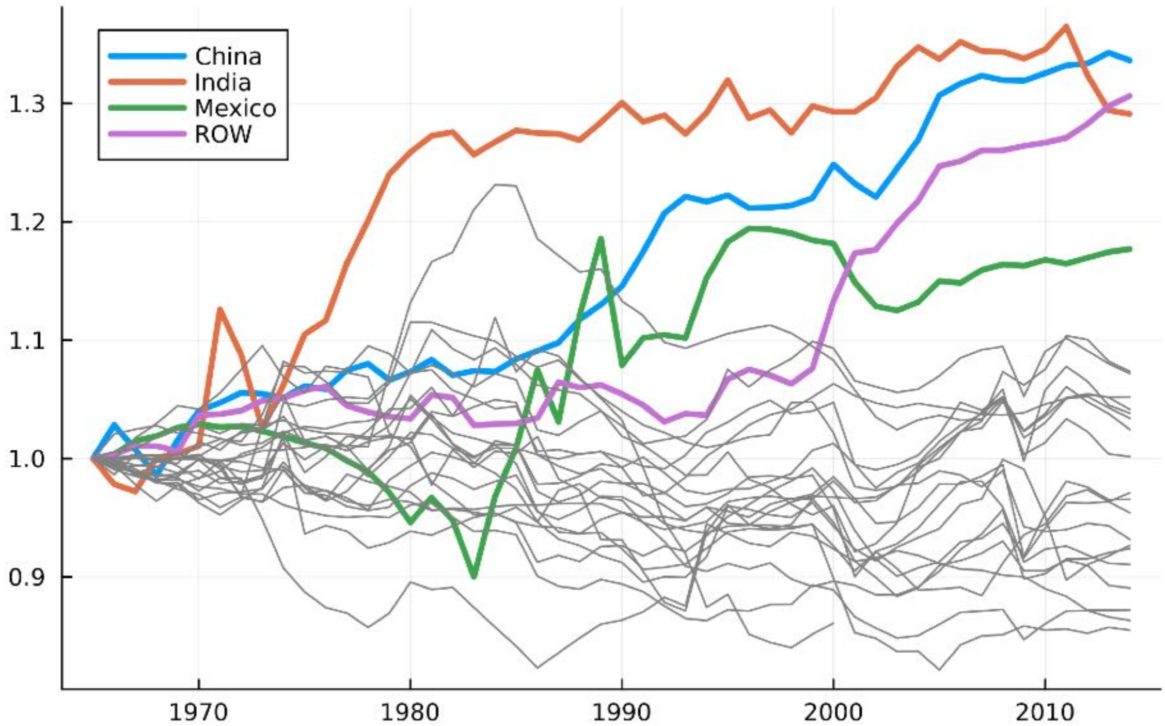
Note: Intermediate Input Costs over Total Costs.

Figure 23: Intermediate Input Share for China and India



Note: Intermediate Input Costs over Total Costs.

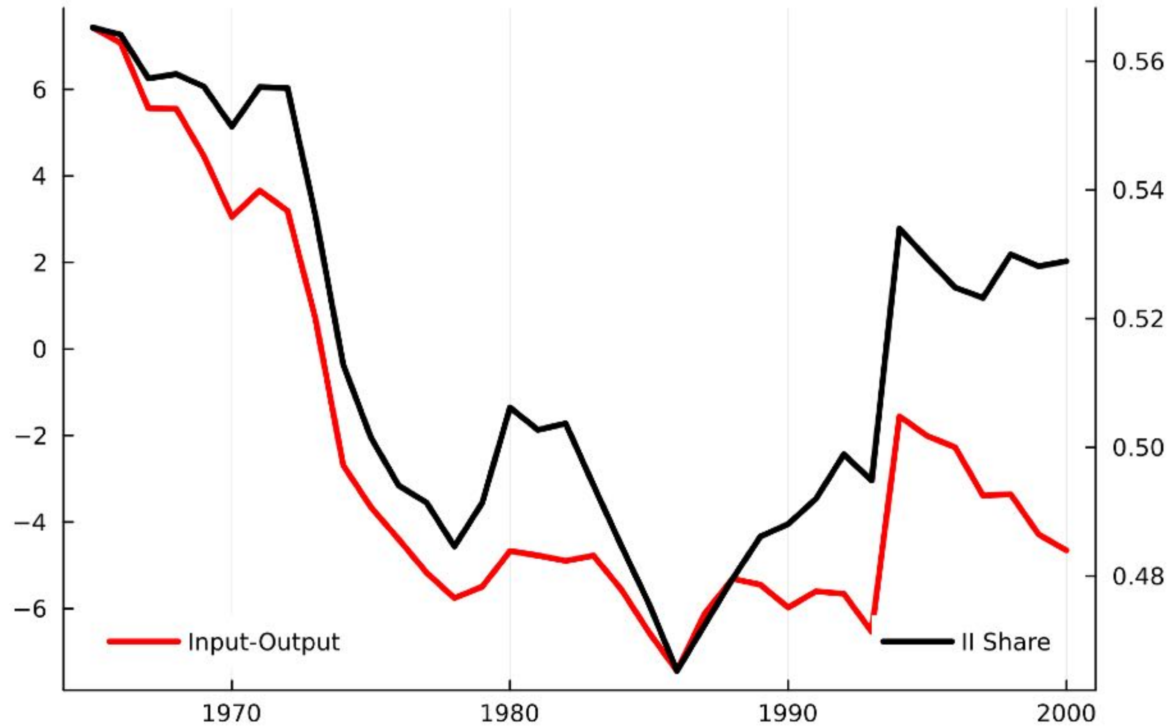
Figure 24: Relative Growth in Intermediate Input Share



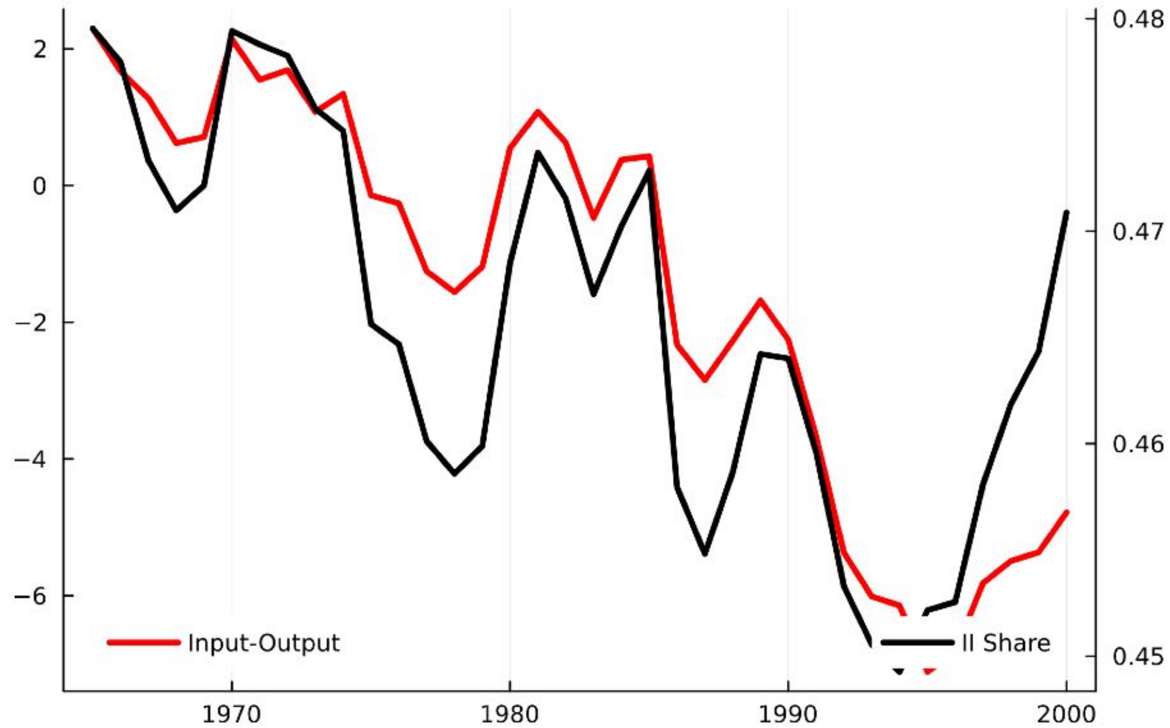
Note: Intermediate Input Costs over Total Costs. 1965 levels are normalized at 1 for all countries.

Figure 25: Conterfactuals with Global Intermediate Input Network for each year and IIS

A. Australia



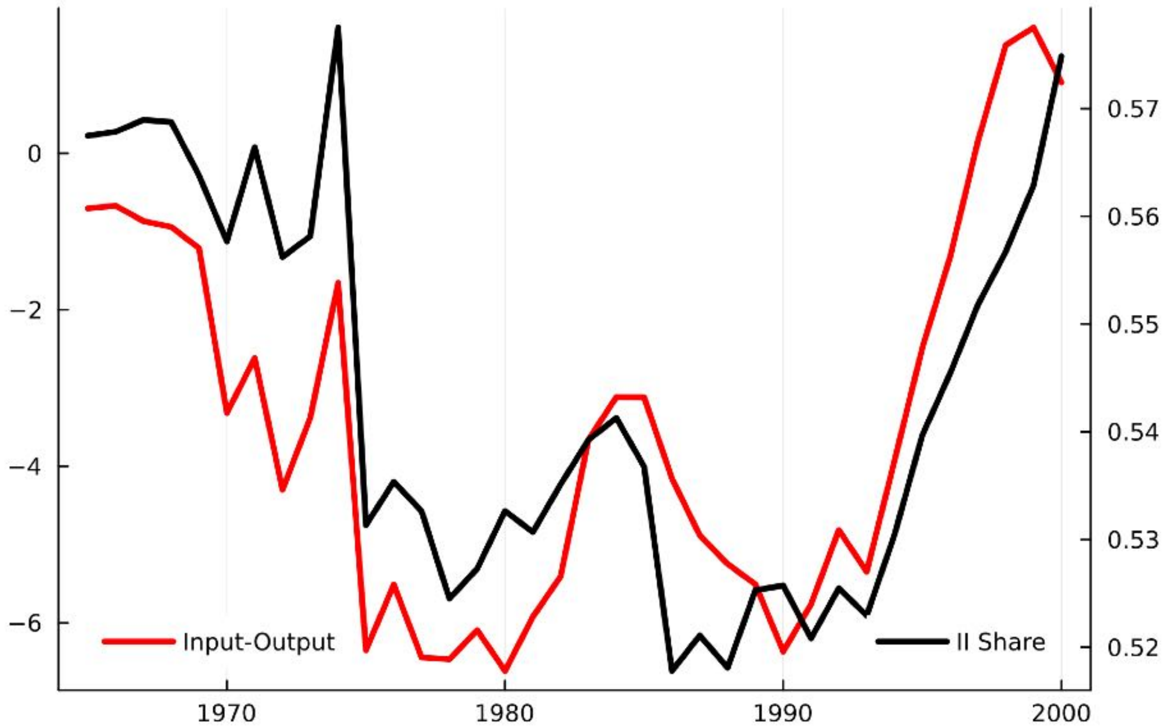
B. Austria



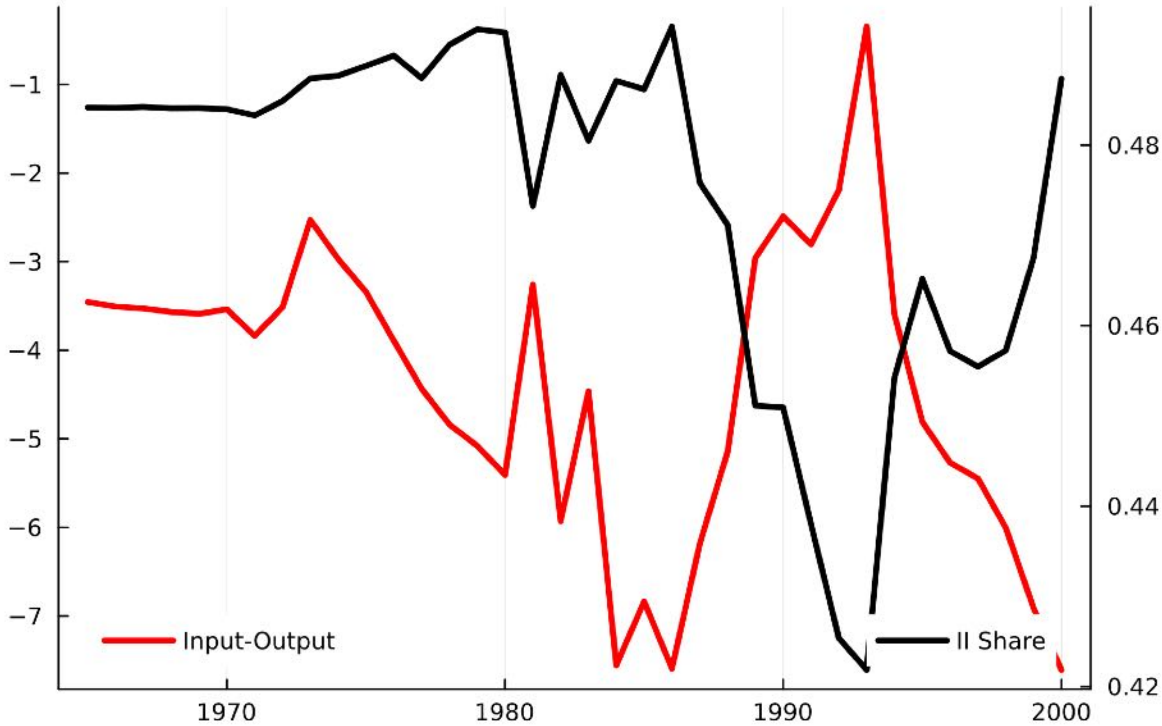
Note:

Figure 26: Conterfactuals with Global Intermediate Input Network for each year and IIS

A. Belgium



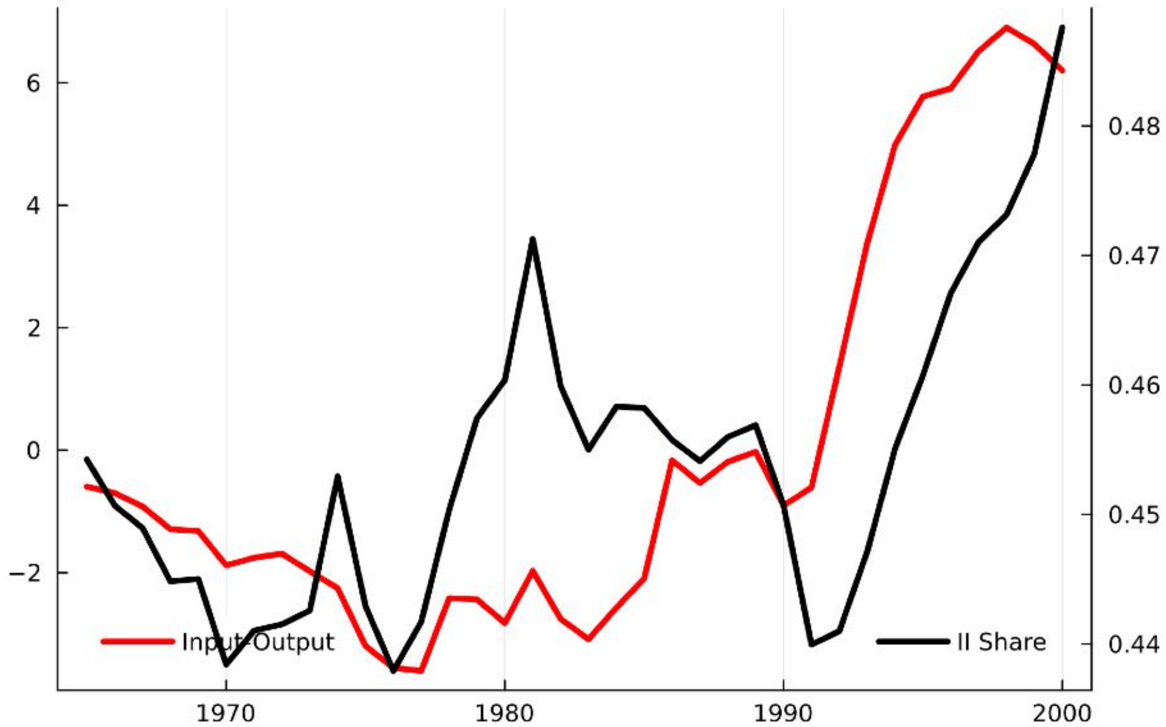
B. Brazil



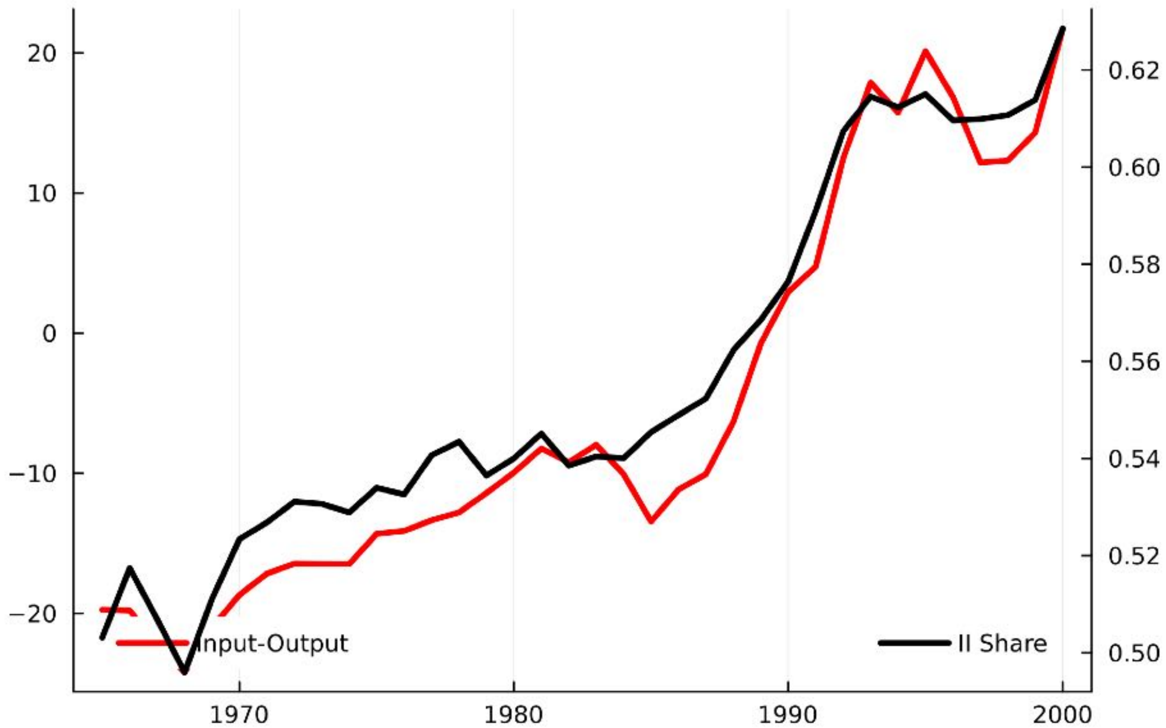
Note:

Figure 27: Conterfactuals with Global Intermediate Input Network for each year and IIS

A. Canada



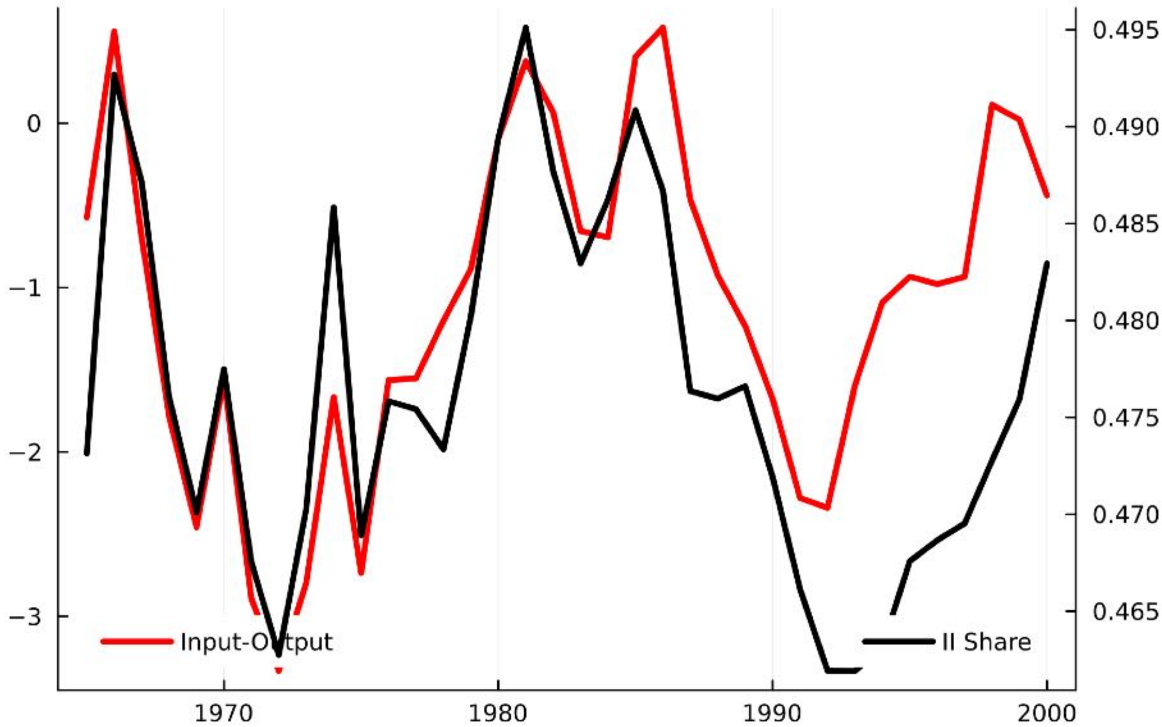
B. China



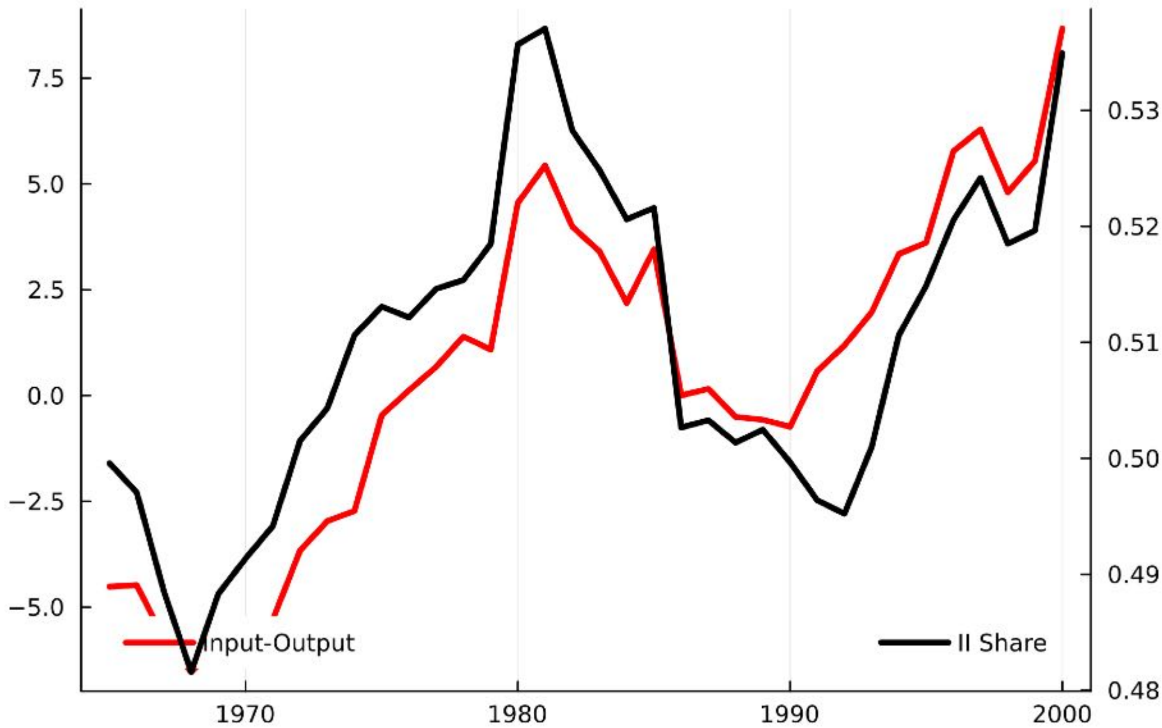
Note:

Figure 28: Conterfactuals with Global Intermediate Input Network for each year and IIS

A. Denmark



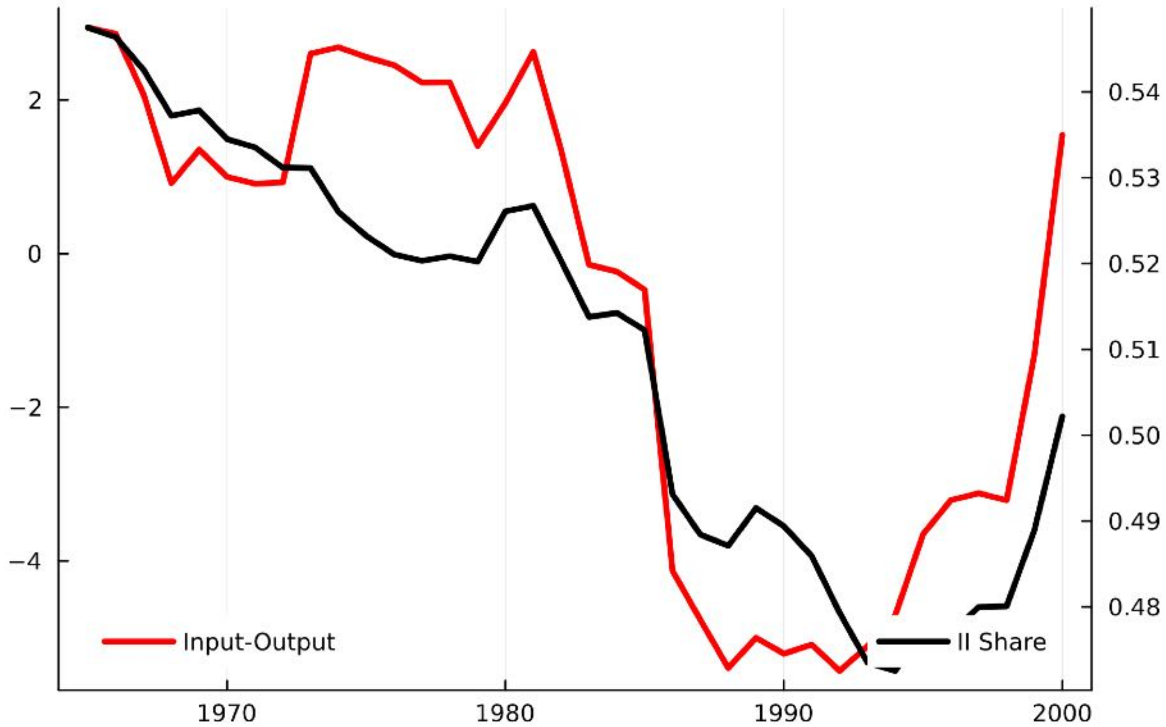
B. Finland



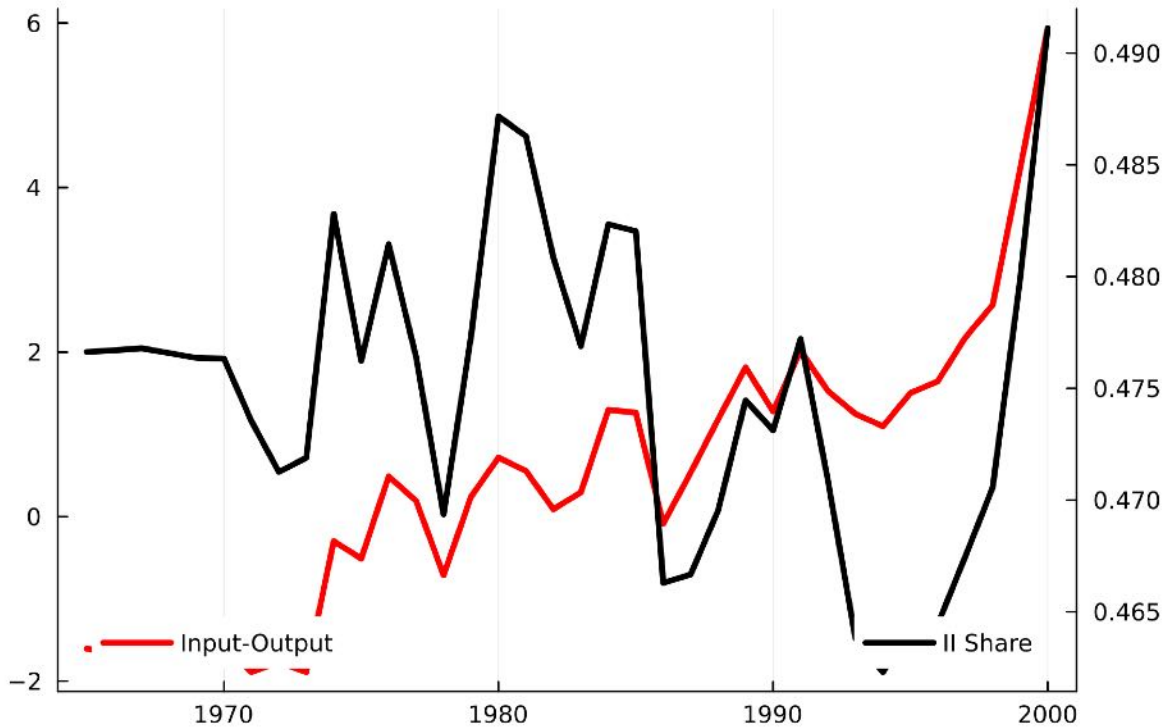
Note:

Figure 29: Conterfactuals with Global Intermediate Input Network for each year and IIS

A. France



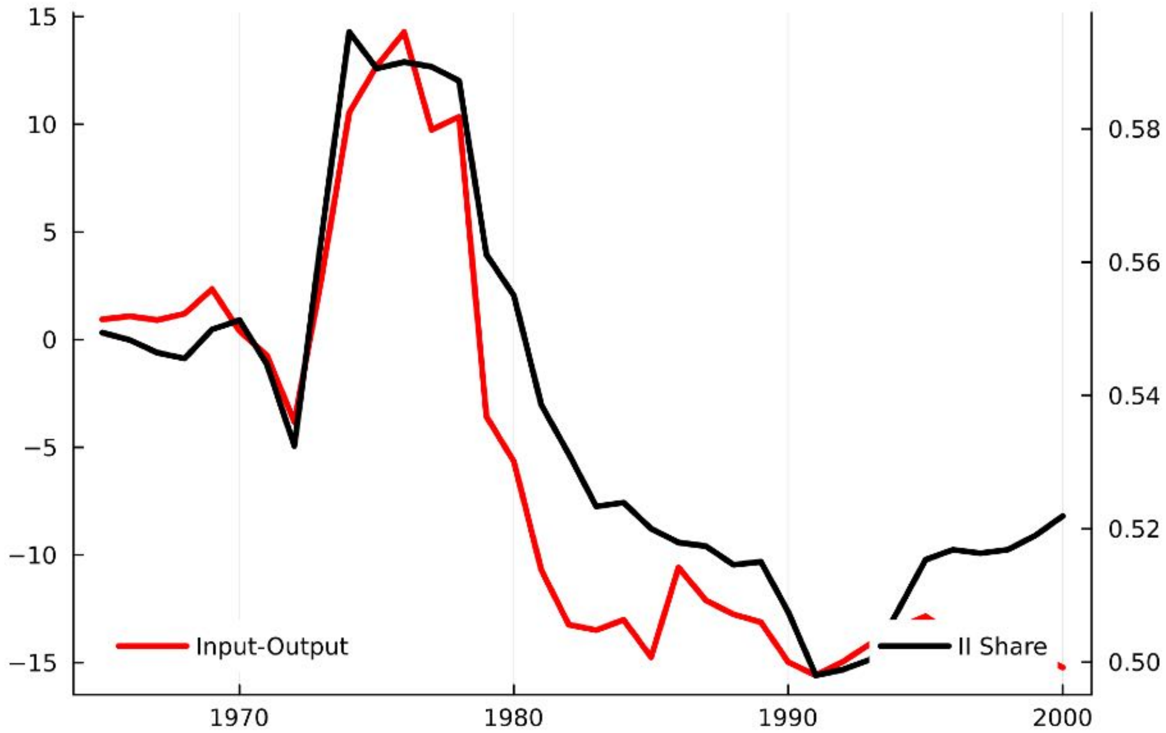
B. Germany



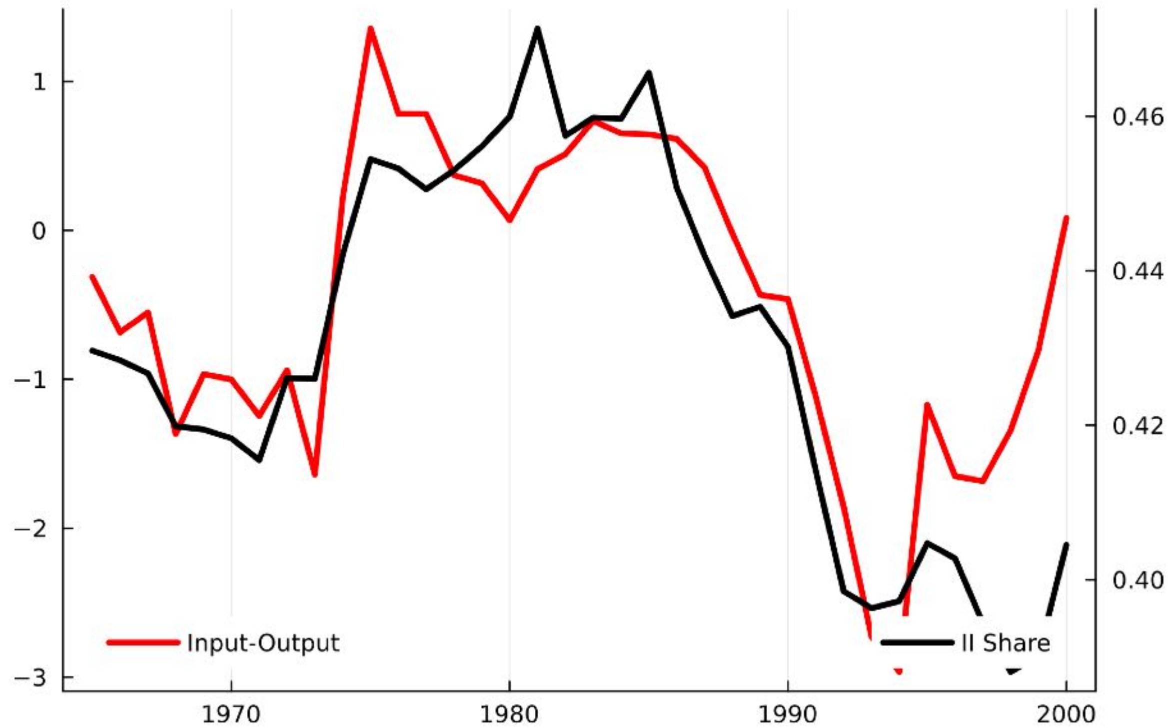
Note:

Figure 30: Conterfactuals with Global Intermediate Input Network for each year and IIS

A. Great Britain



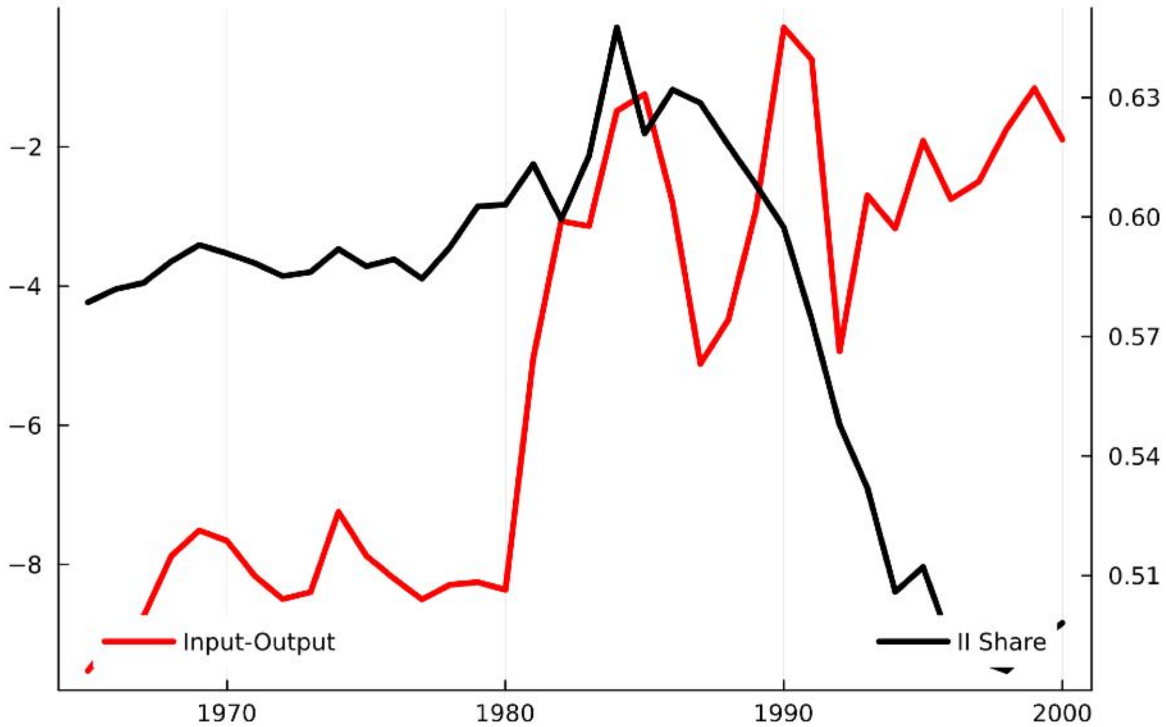
B. Greece



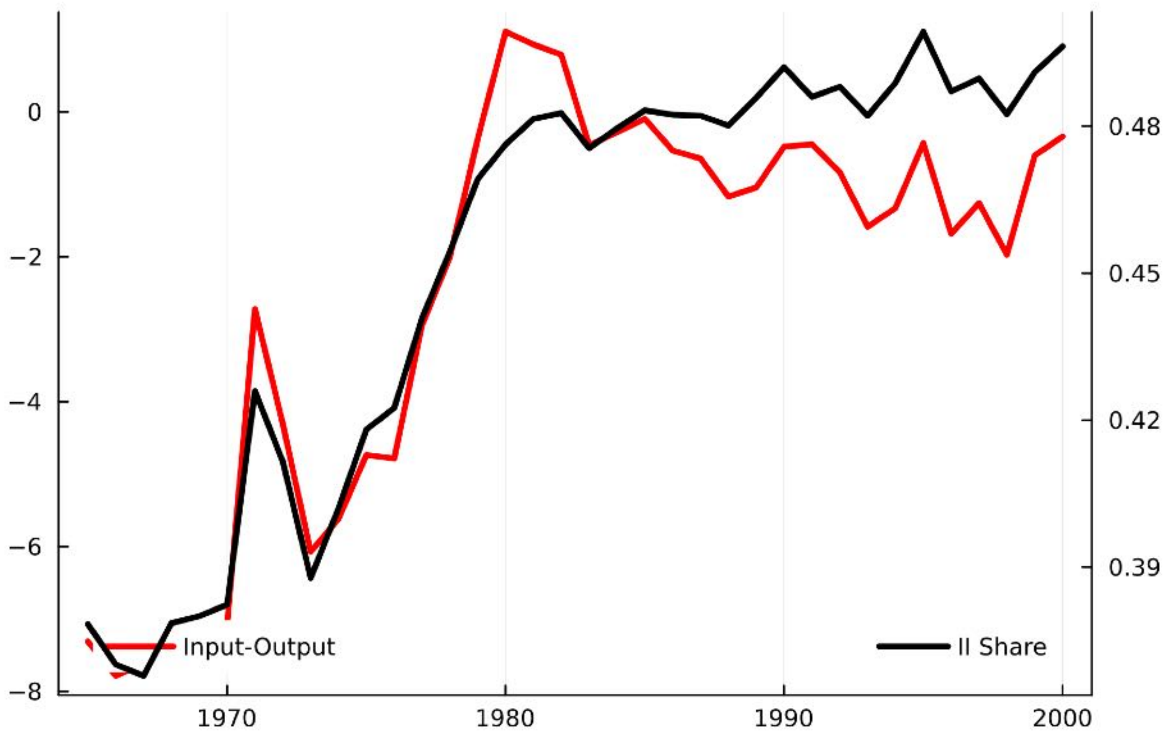
Note:

Figure 31: Conterfactuals with Global Intermediate Input Network for each year and IIS

A. Hong Kong



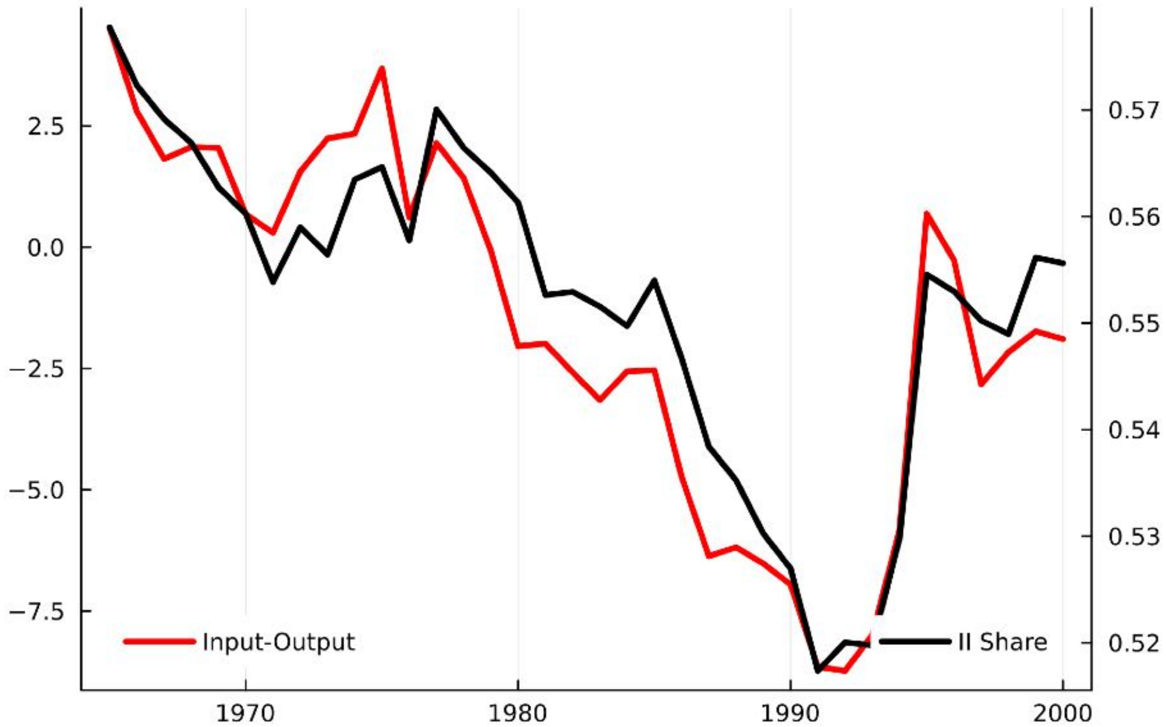
B. India



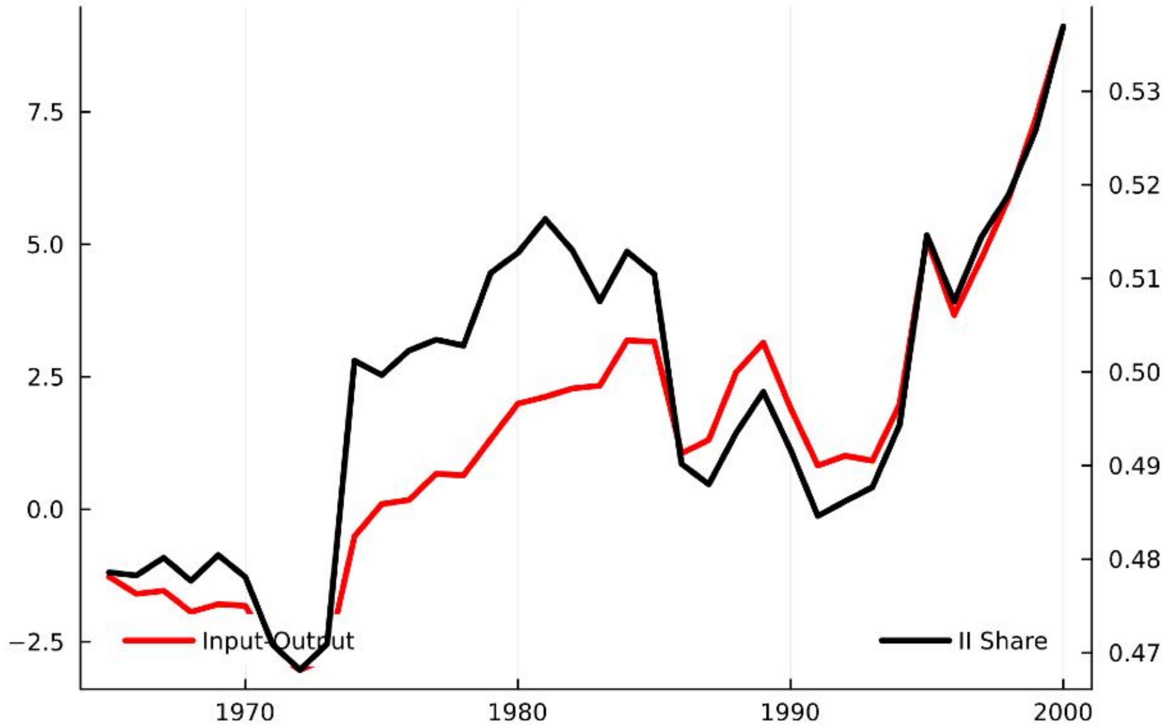
Note:

Figure 32: Conterfactuals with Global Intermediate Input Network for each year and IIS

A. Ireland



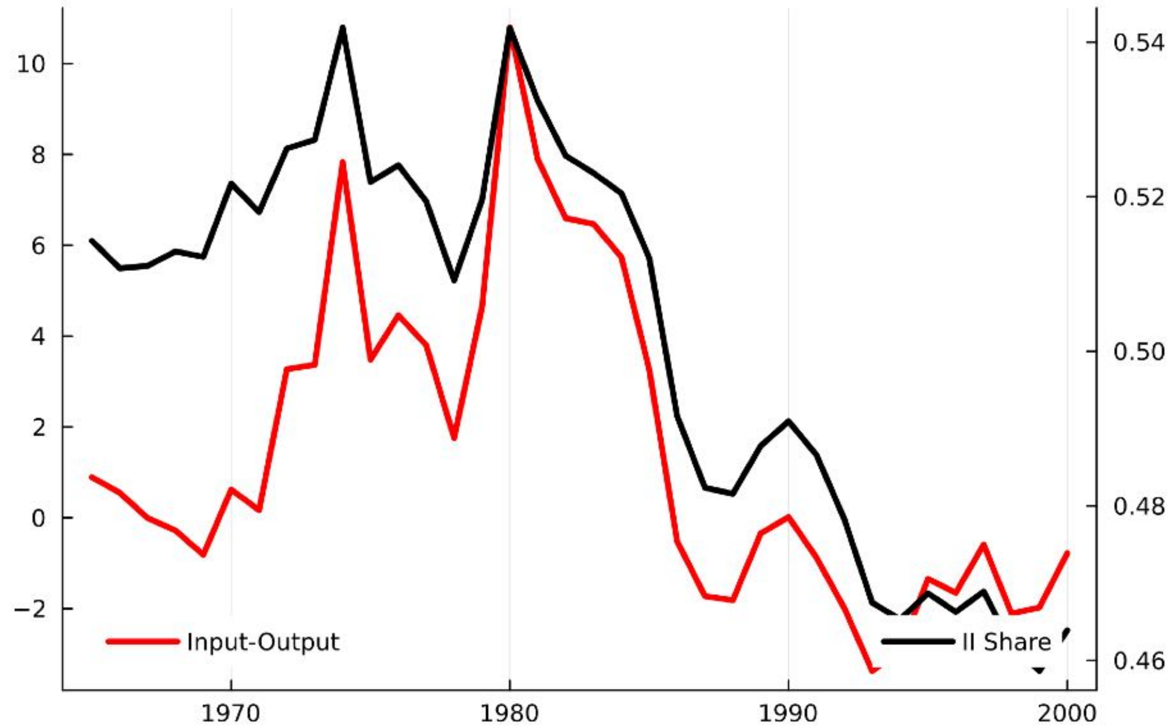
B. Italy



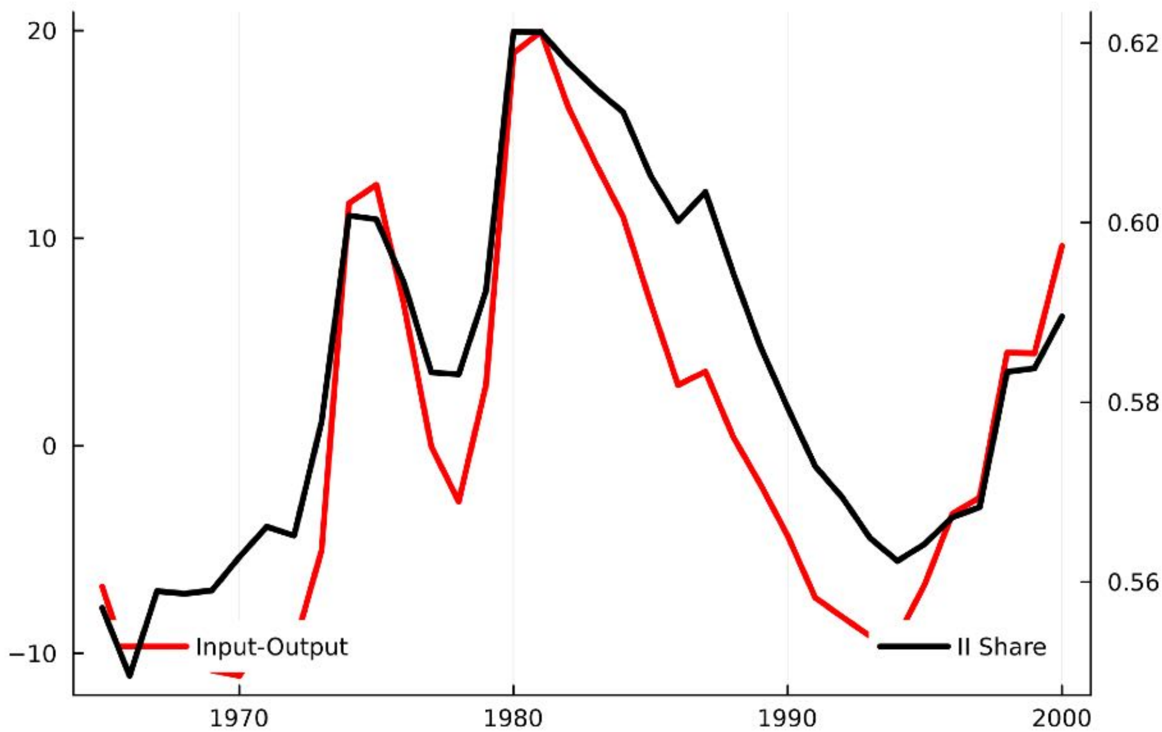
Note:

Figure 33: Conterfactuals with Global Intermediate Input Network for each year and IIS

A. Japan



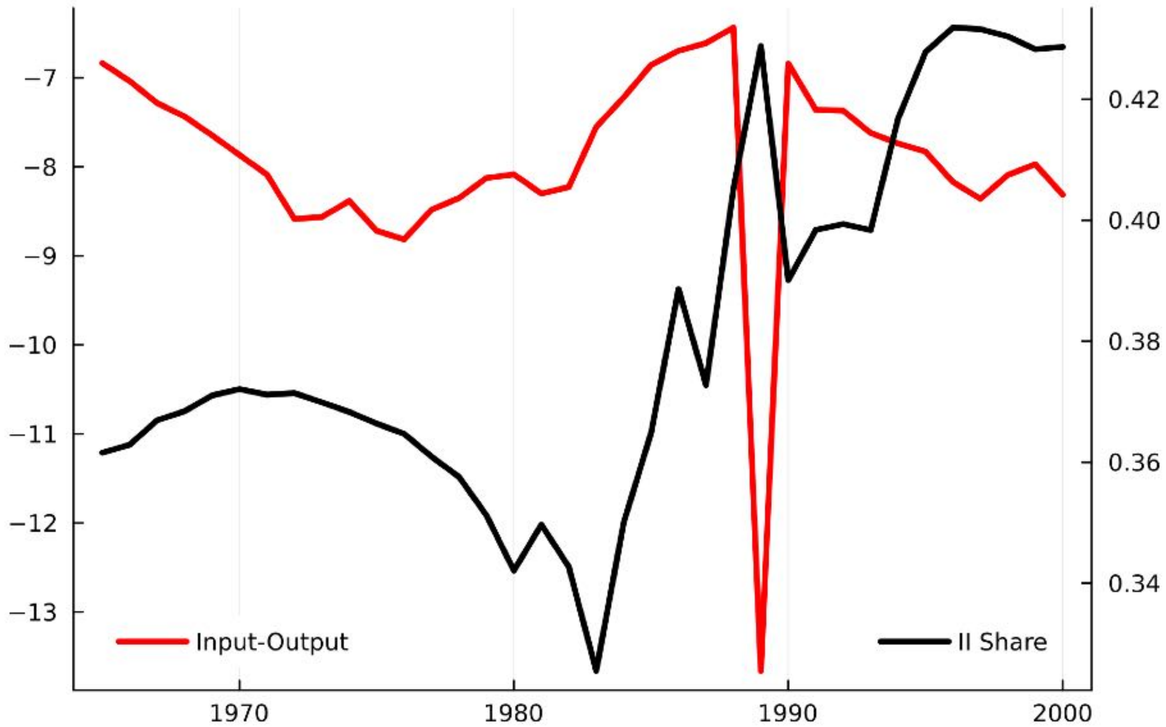
B. Korea



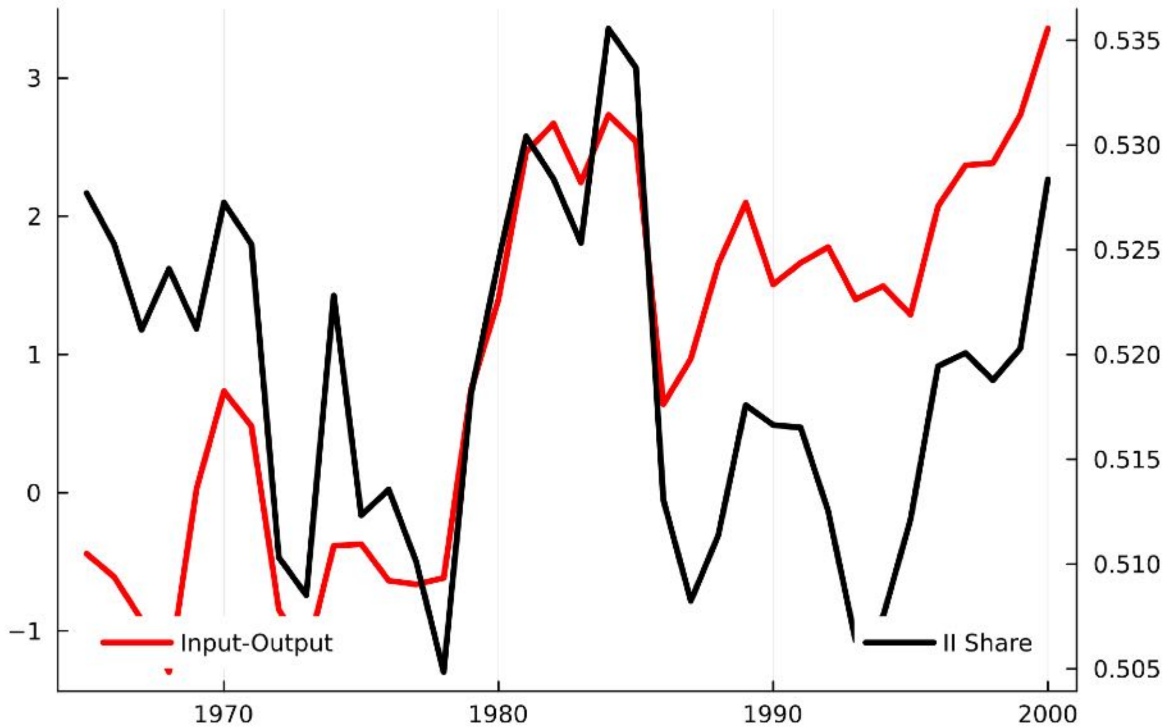
Note:

Figure 34: Conterfactuals with Global Intermediate Input Network for each year and IIS

A. Mexico



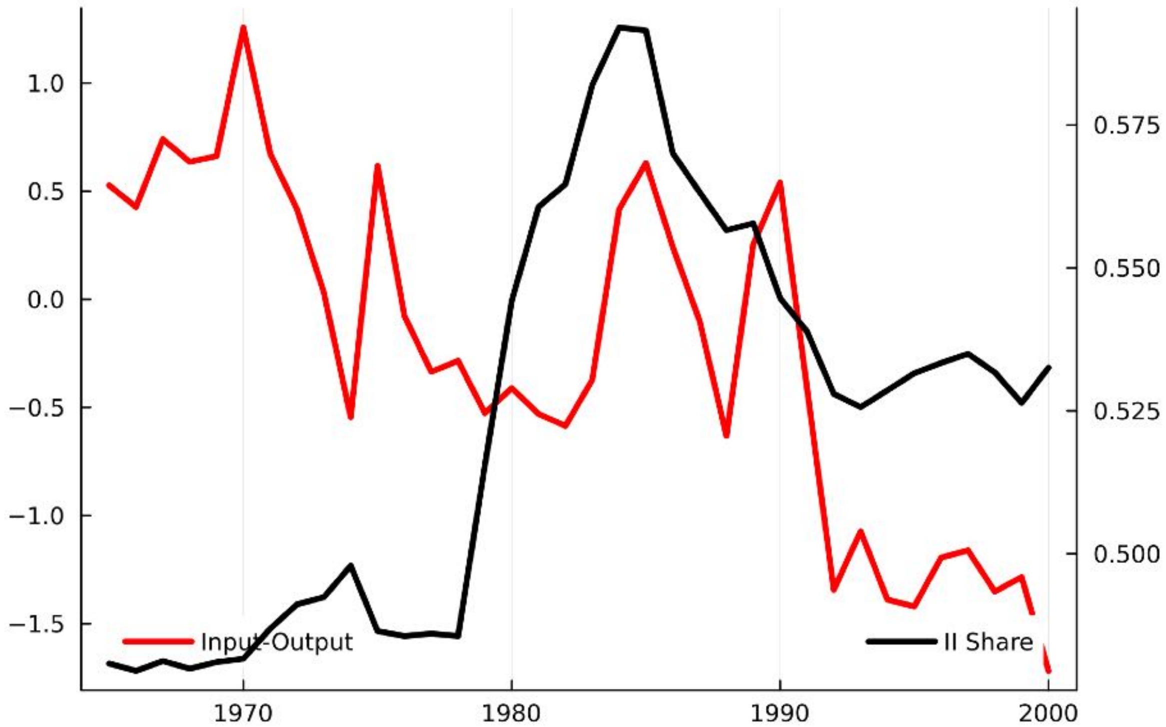
B. Netherlands



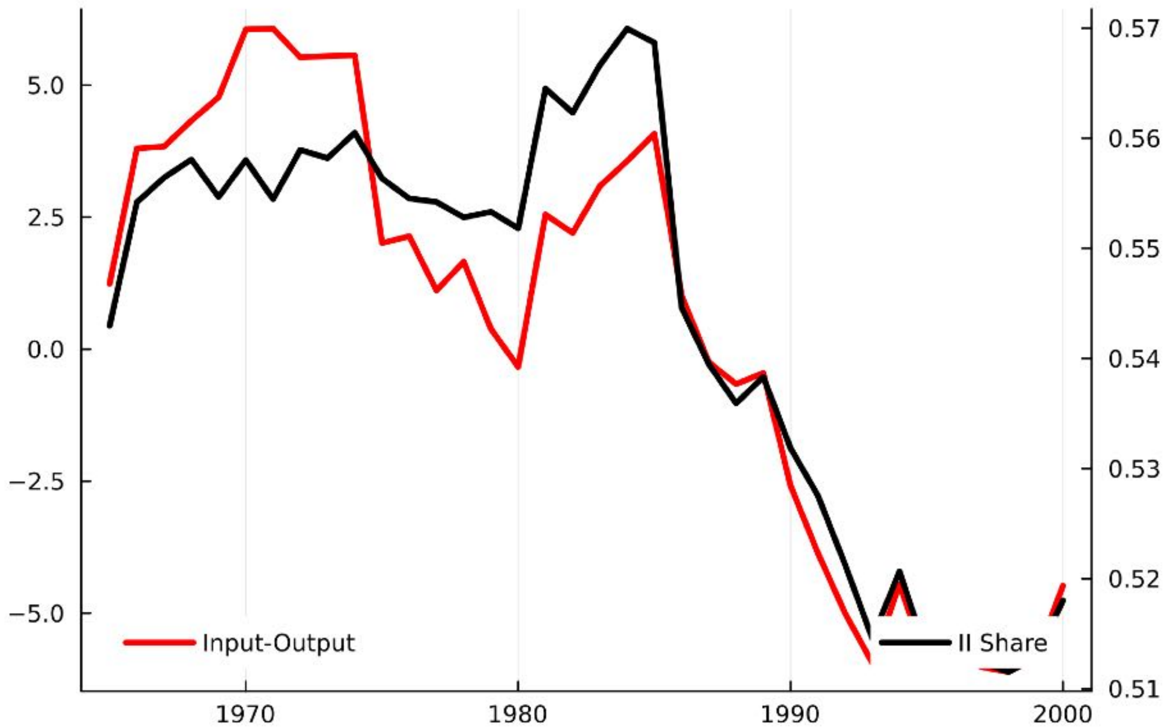
Note:

Figure 35: Conterfactuals with Global Intermediate Input Network for each year and IIS

A. Portugal



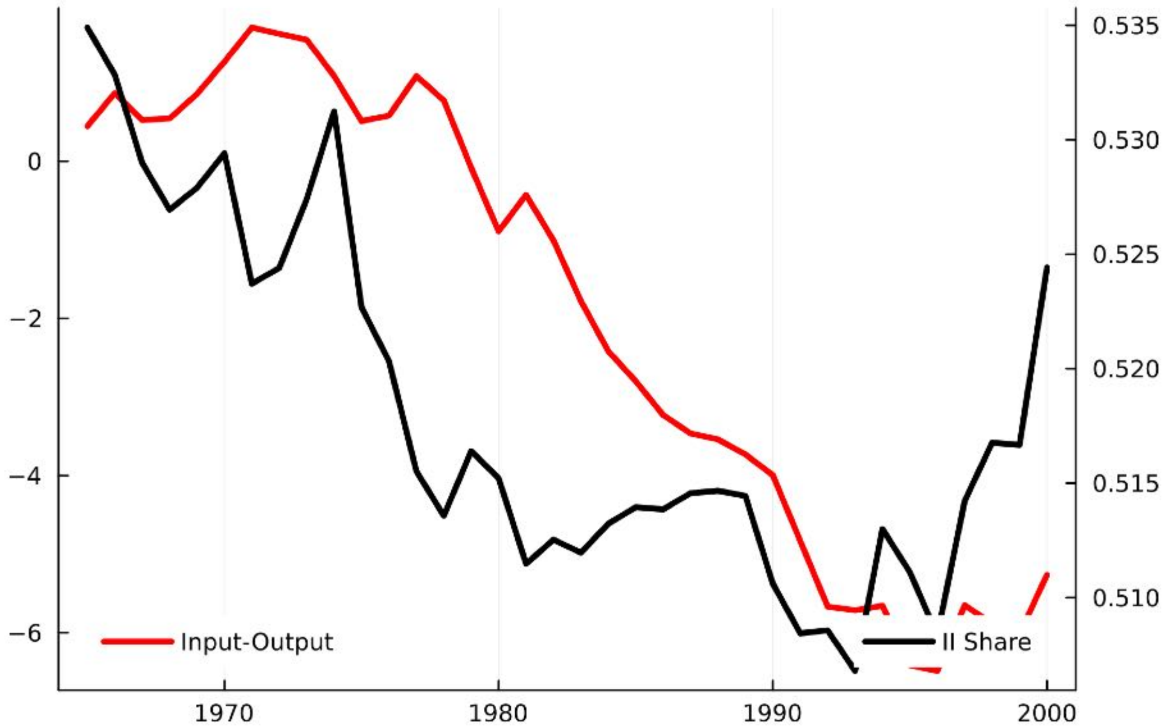
B. Spain



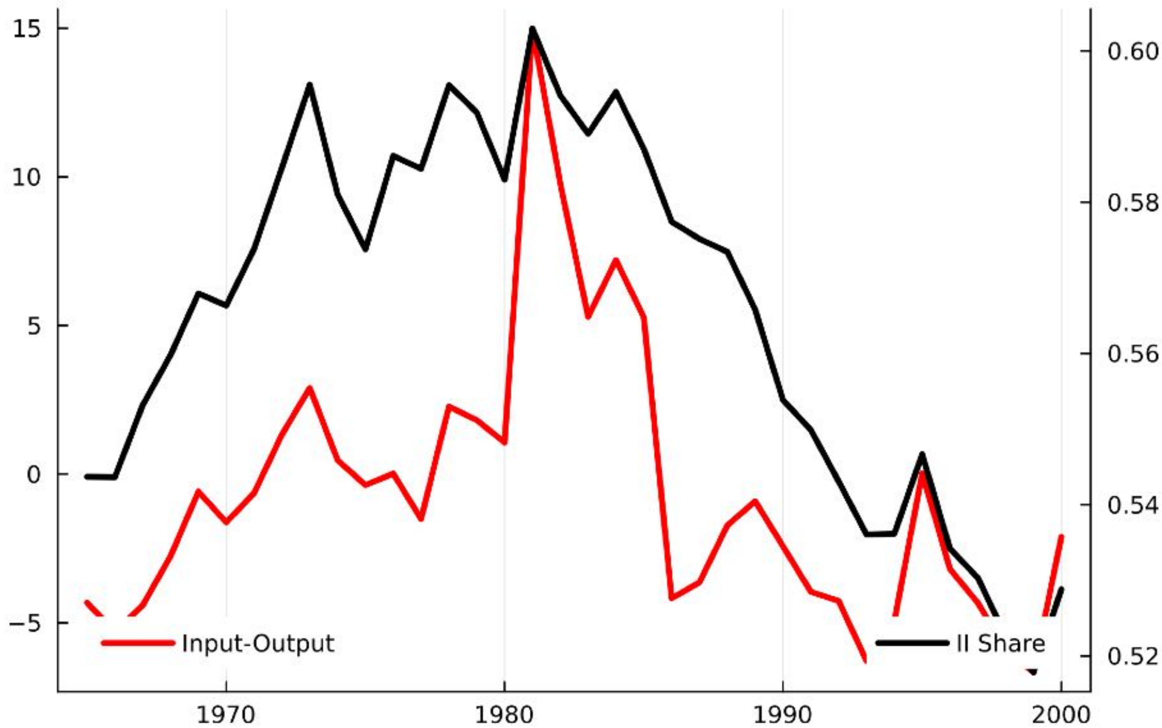
Note:

Figure 36: Conterfactuals with Global Intermediate Input Network for each year and IIS

A. Sweden

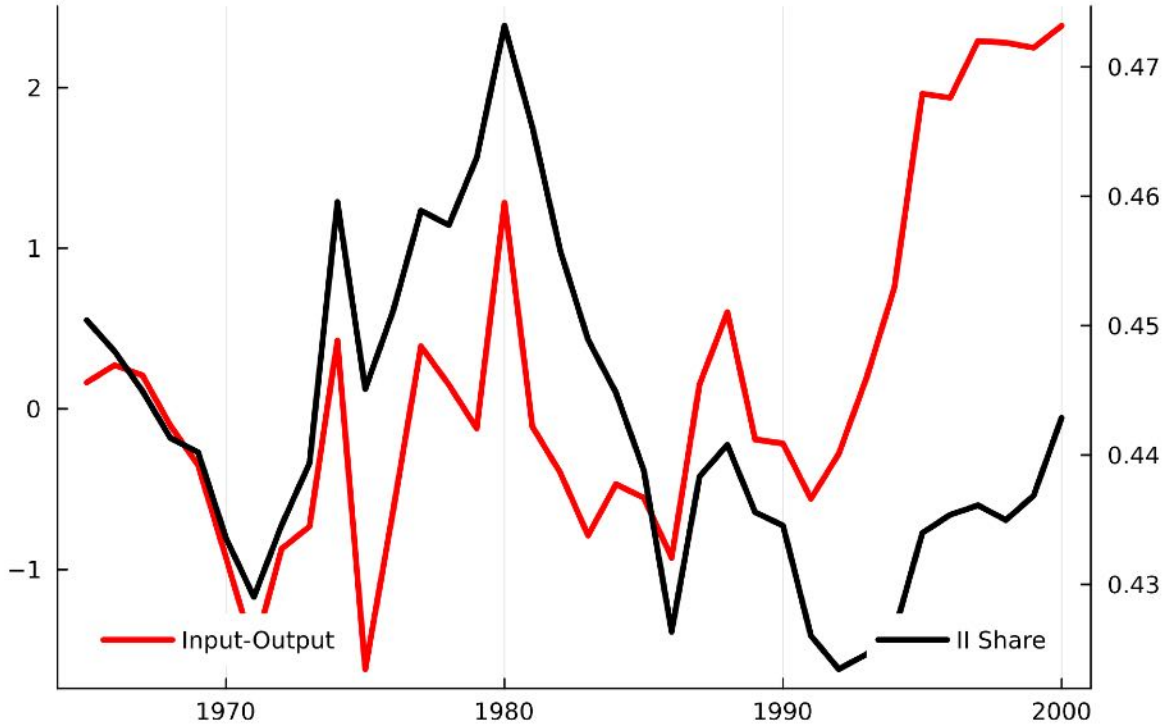


B. Taiwan



Note:

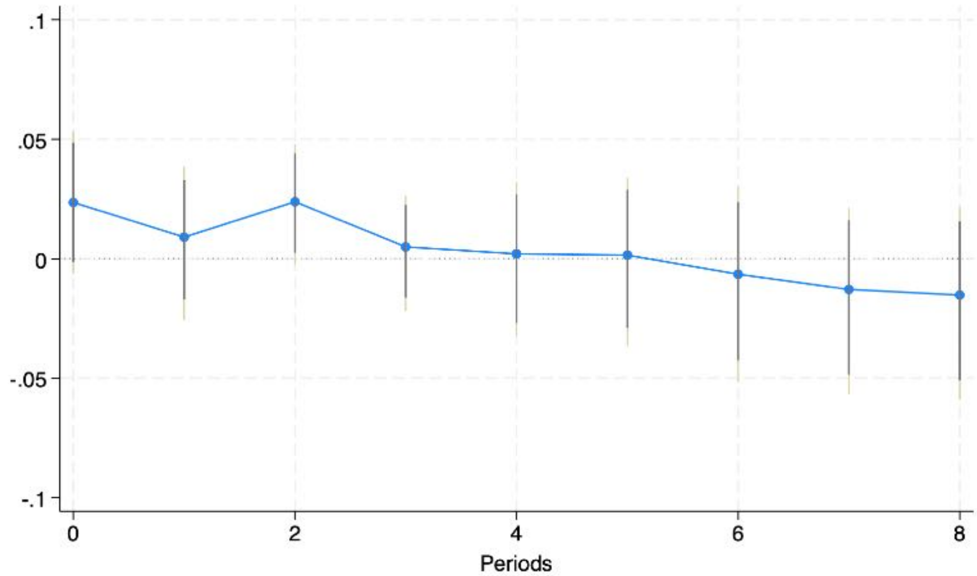
Figure 37: Conterfactuals with Global Intermediate Input Network for each year and IIS for the United States



Note:

Figure 38: Impulse Responses of Country Domestic Intermediate Input Cost Share to Sectoral Productivity Shocks

A. Chemicals and Chemical Products



B. Other Non-Metallic Mineral

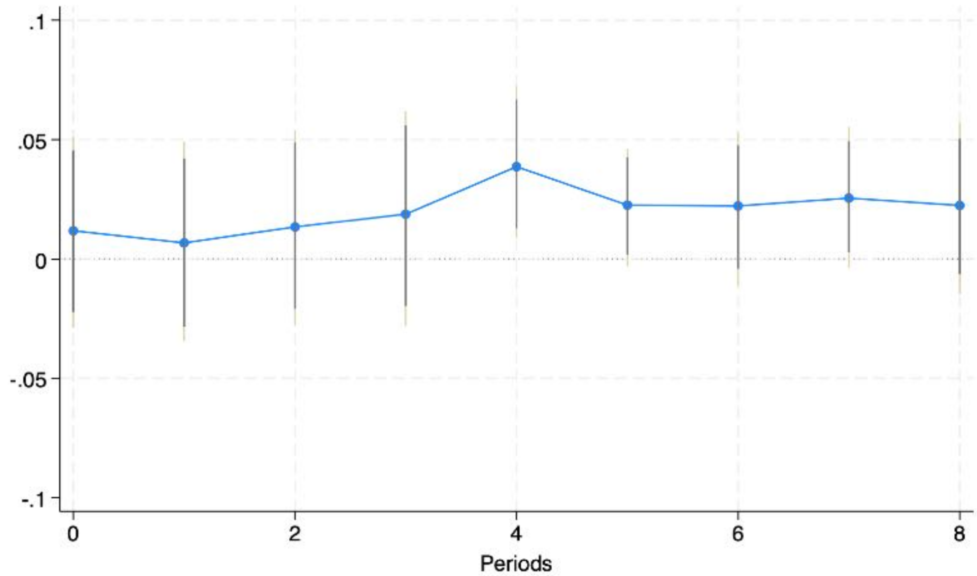
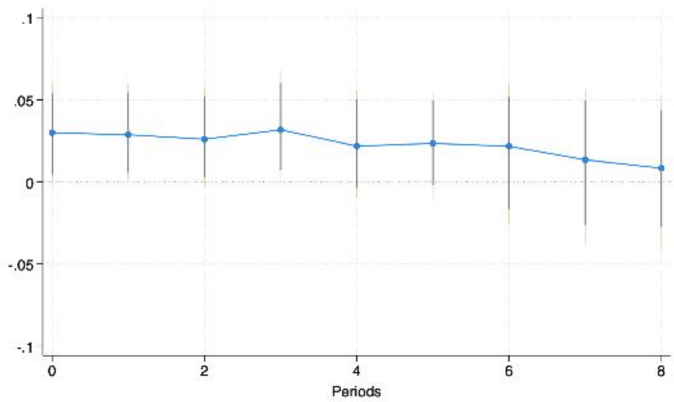
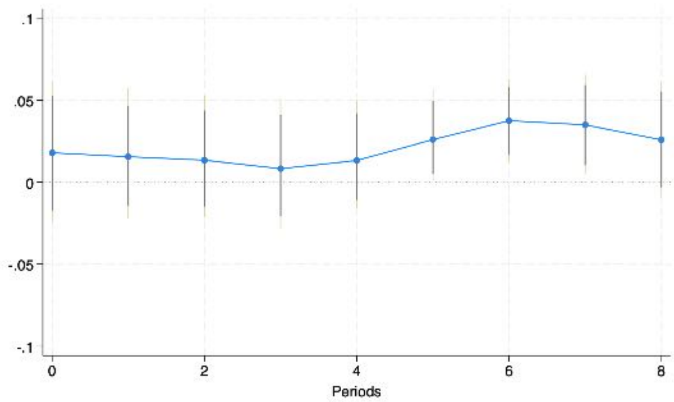


Figure 39: Impulse Responses of Country Domestic Intermediate Input Cost Share to Sectoral Productivity Shocks

A. Electrical and Optical Equipment



B. Manufacturing, Nec; Recycling



C. Real Estate, Renting and Business Activities

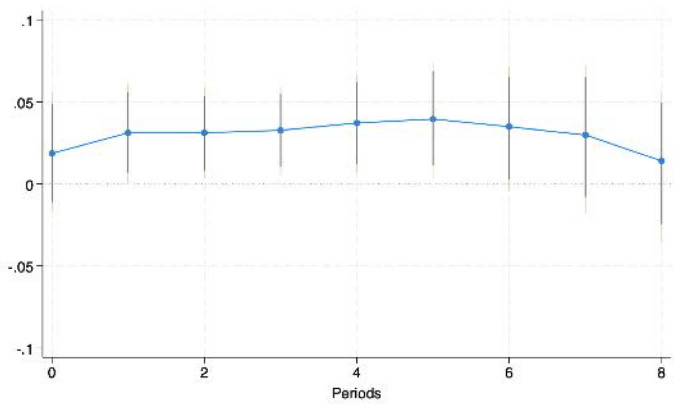
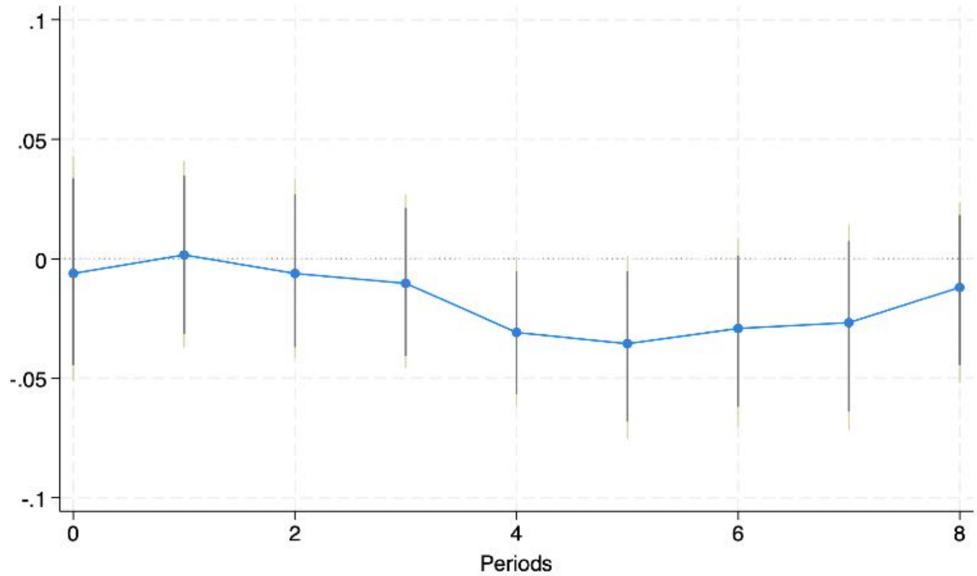


Figure 40: Impulse Responses of Country Domestic Intermediate Input Cost Share to Sectoral Productivity Shocks

A. Basic Metals and Fabricated Metal



B. Electricity, Gas and Water Supply

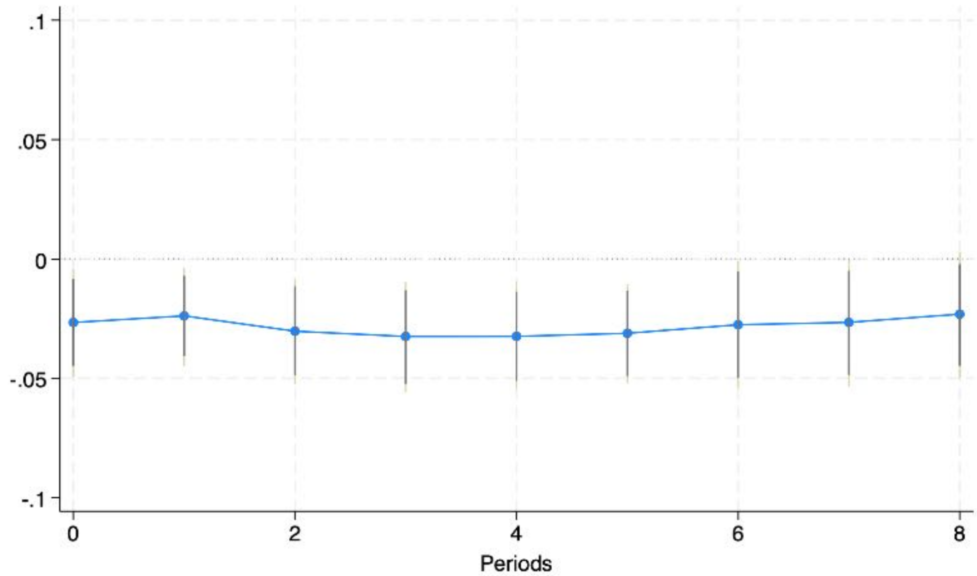
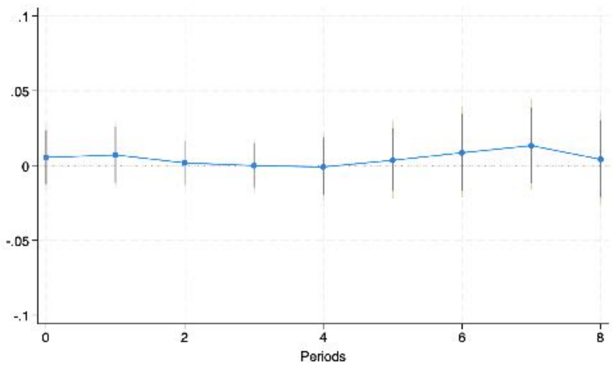
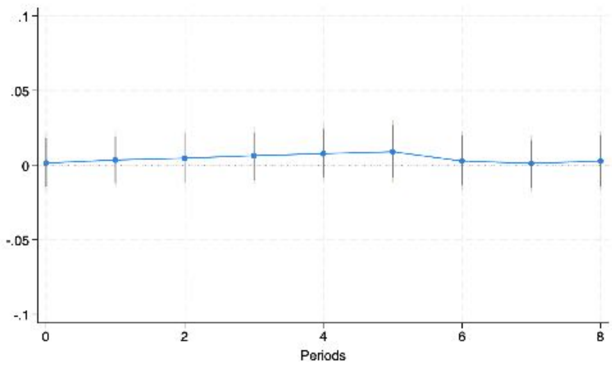


Figure A1: Impulse Responses of Country Domestic Intermediate Input Cost Share to Sectoral Productivity Shocks

A. Agriculture, Hunting, Forestry and Fishing



B. Mining and Quarrying



C. Food, Beverages and Tobacco

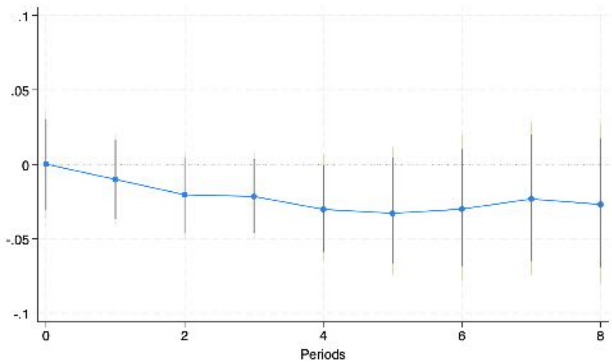
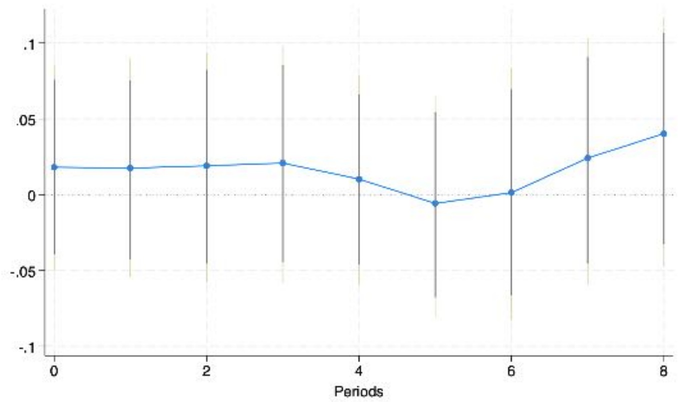
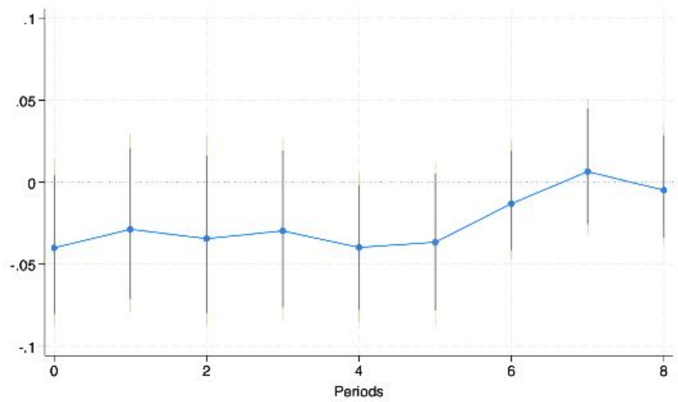


Figure A2: Impulse Responses of Country Domestic Intermediate Input Cost Share to Sectoral Productivity Shocks

A. Textiles, Textile, Leather and Footwear



B. Pulp, Paper, Paper, Printing and Publishing



C. Coke, Refined Petroleum and Nuclear Fuel

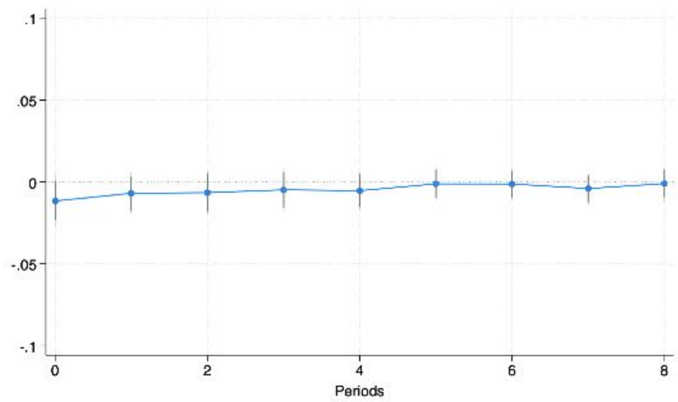
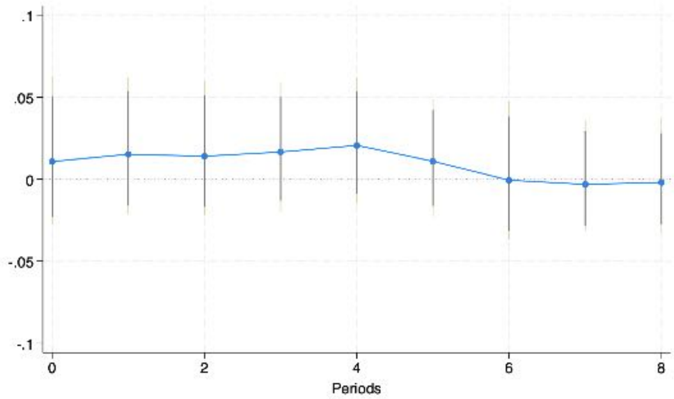
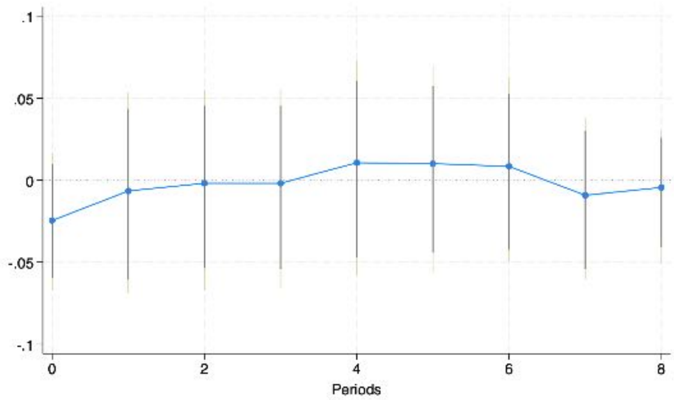


Figure A3: Impulse Responses of Country Domestic Intermediate Input Cost Share to Sectoral Productivity Shocks

A. Rubber and Plastics



B. Machinery, Nec



C. Transport Equipment

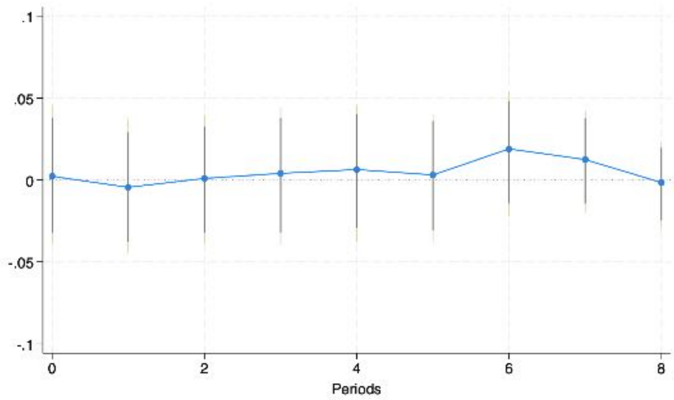
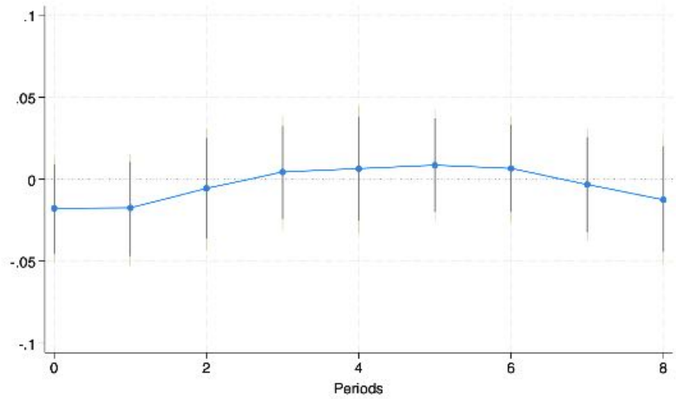
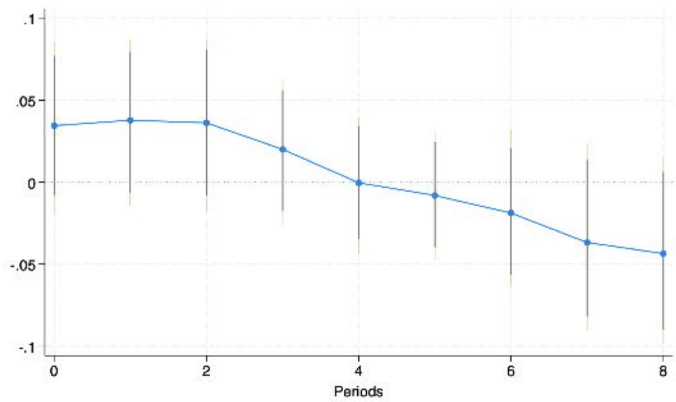


Figure A4: Impulse Responses of Country Domestic Intermediate Input Cost Share to Sectoral Productivity Shocks

A. Construction



B. Wholesale and Retail Trade



C. Hotels and Restaurants

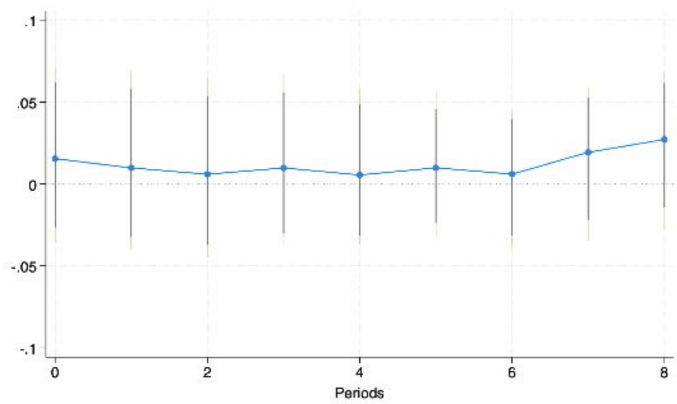
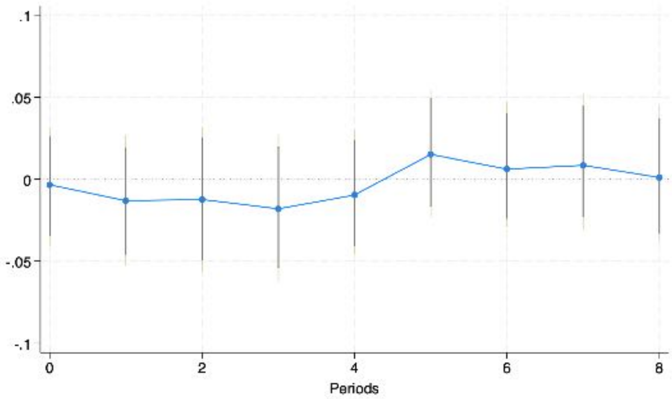
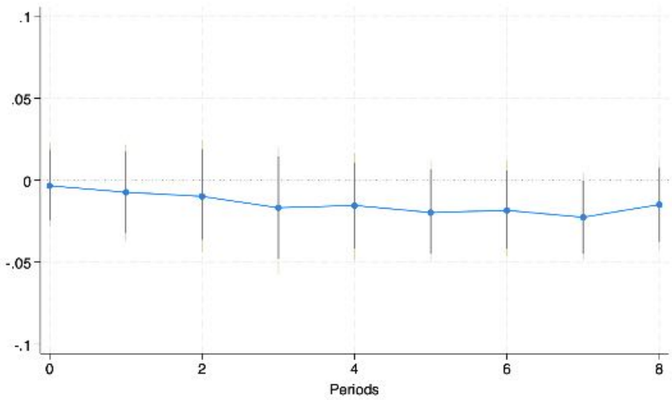


Figure A5: Impulse Responses of Country Domestic Intermediate Input Cost Share to Sectoral Productivity Shocks

A. Transport and Storage



B. Post and Telecommunications



C. Financial Intermediation

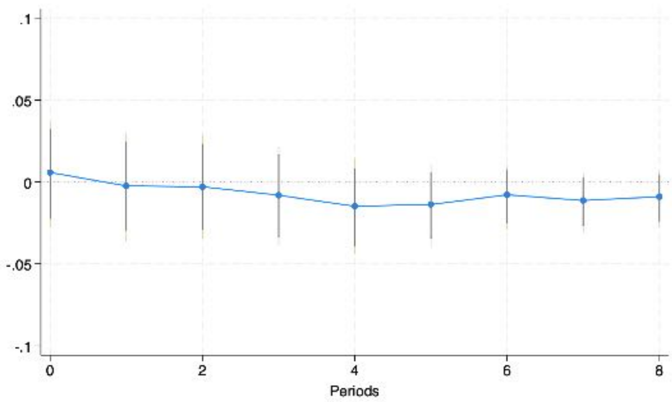
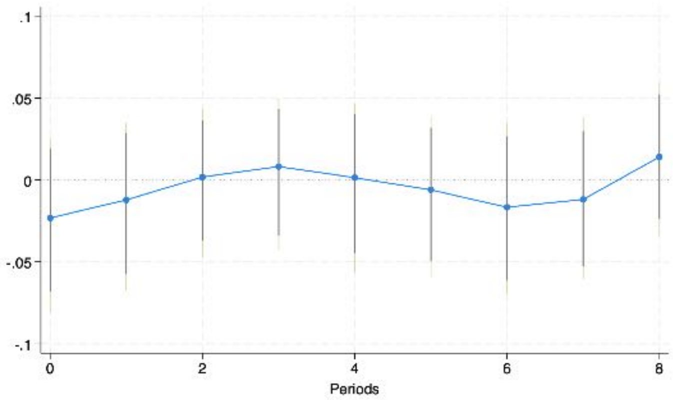


Figure A6: Impulse Responses of Country Domestic Intermediate Input Cost Share to Sectoral Productivity Shocks

A. Community Social and Personal Services



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