Production network and GDP growth: a decomposition approach

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Abstract

We propose a novel decomposition of the input-output linkage impact into linkage efficiency and linkage strength. We show that, for standard multisectoral models, countries' GDP growth rates are related to the average total backward linkages in the economy, which we call linkage strength, and to the covariance between sectoral backward linkages and the sectoral shares in final demand, which we call linkage efficiency. Using the World Input-Output Database, we further demonstrate that what matters for GDP growth is the linkage efficiency.

Keywords: economic growth; input-output linkages; economic structure;
JEL Class: C67, O4, E2, L1, D57.

1 Introduction

At least since Leontief (1963) and Hirschman (1958), persistent and significant cross-country differences in GDP growth rates have been traced back to differences in input-output (I-O) networks.[1] In this paper, we show that the relationship between growth and I-O networks is mostly due to what we call 'linkage efficiency', an indicator dependent on the correlation between sector's final demand shares and I-O multipliers.

Very few papers have attempted to understand how the joint structure of the sectoral shares and I-O multipliers matters for aggregate growth. Acemoglu et al. (2016) evaluate how industry-level shocks interact with input and output multipliers and find that supply-side shocks mostly propagate downstream (to costumers) whereas upstream effects (to suppliers) are more related with demand-side shocks. Fadinger et al. (2021) find that in poor countries large sectors tend to be the most productive, whereas in rich countries the sectors with the high I-O multipliers tend to have lower productivity levels McNerney et al. (2018) show a solid empirical relationship between a country's weighted I-O multiplier and its future growth rate.

Here we propose to decompose the relationship between growth and the I-O network into an effect due to the average sectoral multiplier (linkage strength) and an effect dependent on the correlation between sector's final

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[1] See Yotopoulos and Nugent (1973) and the debates in the *QJE* 1976 (90:2) issue on balanced-growth hypothesis.

demand shares and sectoral multipliers (linkage efficiency). This decomposition of the *weighted* sectoral multipliers as a sum of the *linkage efficiency* and *linkage strength*, to the best of our knowledge, is new in the literature. Based on the proposed decomposition, we then undertake a series of statistical exercises to highlight the importance of linkage efficiency in understanding economic growth.

2 Economic structure and growth under uniform sectoral shocks

We motivate our empirical results on the economic structure and economic growth by several standard multisectoral models. In spite of their differences, they all lead to the conclusion that the interplay between the I-O multipliers and the sectoral final demand shares plays a major role in growth performance. This interplay is captured by the Domar weights, which link sectoral shocks and aggregate growth. After summarizing the standard multisectoral models, we propose a novel decomposition of the sum of the Domar weights into *linkage strength* and *linkage efficiency*. We assume a closed economy with no government, and n sectors producing single commodities.[2]

2.1 Domar aggregation and Hulten's theorem

With the objective to understand how total factor productivity (TFP) growth happening at individual economic units (firms and sectors) affects the economic growth across different aggregation levels, Domar (1961) designs an aggregation procedure where the aggregated growth rate of TFP is a weighted average of each sectors' TFP growth rates. This weighting scheme is called the *Domar weights*.

In Domar's model, sector j produces commodity q_j using primary inputs and other sectors' outputs with constant returns to scale (CRS) Cobb-Douglas (C-D) production functions

$$q_j = c_j L_j^{\omega_j} K_j^{\beta_j} Q_{1j}^{a_{1j}} \cdot \ldots Q_{nj}^{a_{nj}} \quad (j \in N),$$

where c_j is the Hicks-neutral productivity shock, L_j and K_j are labor and capital, the Q_{ij} are the intermediate inputs produced by sectors $i \in N$, and $(\omega_j, \beta_j, a_{ij})$ are the labor, capital and intermediate inputs shares in outputs' value. Based on this set-up and some desirable properties, Domar proposes an aggregation method in which the growth rate of TFP of the whole economy ($\widehat{TFP}$) is obtained as:

$$\widehat{TFP} = \sum\nolimits_{j=1}^{n} \hat{\epsilon}_j \vartheta_j, \tag{1}$$

$$\vartheta_j \equiv \frac{x_j}{GDP} \quad (j \in N), \tag{2}$$

where $\epsilon_j \equiv \ln c_j$, the ϑ_j are the Domar weights, and $x_j \equiv p_j q_j$ is the output value, where p_j is its price. As long as there is a $Q_{ij} > 0$, $\sum_{i=1}^{n} \vartheta_j > 1$. National accounting expresses (in matrix notation) the sectors' output value and GDP as

$$\mathbf{x} = \mathbf{Ze} + \mathbf{f} \tag{3}$$

$$GDP = \sum\nolimits_{i=1}^{n} f_i, \tag{4}$$

where $\mathbf{x} \equiv [x_i]$, $\mathbf{Z} \equiv [Z_{ij}] \equiv [p_i Q_{ij}]$ is the value of intermediate consumption, $\mathbf{e} \equiv [1]$, and y_i $(i \in N)$ and $\mathbf{f} \equiv [f_i] \equiv [p_i y_i]$ are the final demand output and value.

[2] Let N be the set of indices $1, \ldots, n$. Boldfaced letters refer to vectors (lower cased) and (squared) matrices (upper cased). Vectors have dimensions $n \times 1$. Transpose vectors are indicated with tilde and vectors within $\langle\cdot\rangle$ are diagonal matrices. $\bar{\cdot}$ refers to averages across sectors whereas $\hat{\cdot}$ refers to growth rates.

Hulten (1978) arrives at (1) based on a neoclassical multisector production model under competitive equilibrium conditions and using CRS production functions:

$$q_j = F_j(Q_{1j}, \dots, Q_{nj}, J_{1j}, \dots, J_{mj}, t),$$

where J_{kj} $(k = 1, \dots, m)$ are the primary inputs used.

The recent literature on production network arrives at similar results starting instead from the multisector static real business cycle model of Long and Plosser (1983). Carvalho and Tahbaz-Salehi (2019) takes a CRS C-D technology

$$q_j = c_j L_j^{\omega_j} \prod\nolimits_{i=1}^{n} Q_{ij}^{a_{ij}} \quad \text{for} \quad j \in N$$

and shows that the log GDP is the weighted average of ϵ_j:

$$\ln GDP = \sum\nolimits_{j=1}^{n} \epsilon_j \vartheta_j. \tag{5}$$

Fadinger et al. (2021) use the CRS C-D production function

$$q_j = c_j \left(\frac{L_j^{\omega} K_j^{\omega}}{\gamma_j}\right)^{1-\gamma_j} \prod\nolimits_{i=1}^{n} \left(\frac{Q_{ij}}{a_{ij}}\right)^{a_{ij}} \quad j \in N$$

and obtain a similar expression but for labor productivity

$$\ln(GDP/L) = \sum\nolimits_{j=1}^{n} \epsilon_j \vartheta_j + (1 - \omega) \ln K, \tag{6}$$

where $K = \sum_{j=1}^{n} K_j$.

These results are not exclusive to the models that assume production functions. Under the assumption that labor is the only primary factor and the constancy of the labor and intermediate inputs shares, the growth accounting exercise of McNerney et al. (2018) shows that

$$\widehat{GDP/L} = \sum\nolimits_{j=1}^{n} \hat{\epsilon}_j \vartheta_j. \tag{7}$$

2.2 The composition of Domar weights

The common feature of (1) and (5)-(7) is that sectoral productivity shocks ϵ_j have multiplicative effects in the aggregate due to $\sum_{j=1}^{n} \vartheta_j > 1$. These multiplicative effects in turn result from the interaction of two features of the productive structure: the I-O multipliers and the final demand shares. To see this, suppose the constancy of the inputs shares $a_{ij} = \frac{Z_{ij}}{x_j}$ $(i, j \in N)$ and the final demand shares, $\psi_i \equiv \frac{p_i y_i}{GDP}$ $(i \in N)$. Hence, $\mathbf{Z}\langle\mathbf{x}\rangle^{-1} \equiv \mathbf{A} \equiv [a_{ij}]$ and $\mathbf{f} = \boldsymbol{\psi} \cdot GDP$. Therefore, (3) is:

$$\mathbf{x} = \mathbf{A}\mathbf{x} + \mathbf{f}. \tag{8}$$

Assuming further that matrix $\mathbf{A}$ is productive, then matrix $(\mathbf{I} - \mathbf{A})$ is nonsingular and its inverse is semipositive $(\mathbf{I} - \mathbf{A})^{-1} \equiv \mathbf{D} \equiv [d_{ij}] \geq \mathbf{0}$ (Takayama, 1974, p. 392). Coefficients d_{ij} are the I-O multipliers, which show how the output value of sector i increases as an effect of variations in final demand in sector j. Now, we solve $(\mathbf{I} - \mathbf{A})\mathbf{x} = \mathbf{f}$ in (8) for $\mathbf{x}$ as

$$\mathbf{x} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{f} = \mathbf{D}\boldsymbol{\psi} \cdot GDP, \tag{9}$$

where $\boldsymbol{\psi} \equiv [\psi_i]$, and express the vector of Domar weights $\mathbf{x}GDP^{-1} \equiv \boldsymbol{\vartheta} \equiv [\vartheta_i]$ as $\boldsymbol{\vartheta} = \mathbf{D}\boldsymbol{\psi}$, or $\boldsymbol{\vartheta}' = \boldsymbol{\psi}'\mathbf{D}'$, so

$$\vartheta_j = \boldsymbol{\psi}'\mathbf{D}'_{(j)} = \sum\nolimits_{i=1}^{n} d_{ji}\psi_i \quad j \in N \tag{10}$$

$$\sum\nolimits_{i=1}^{n} \vartheta_i = \mathbf{e}'\boldsymbol{\vartheta} = \mathbf{e}'\mathbf{D}\boldsymbol{\psi} = \mathbf{b}'\boldsymbol{\psi} = \sum\nolimits_{j=1}^{n} b_j\psi_j, \tag{11}$$

where $\mathbf{e}'\mathbf{D} \equiv \mathbf{b}' \equiv [b_j]$ are the so-called backward linkages.

Given the covariance definition,

$$\mathrm{Cov}(\hat{\epsilon}, \vartheta) = \frac{1}{n}\sum\nolimits_{j=1}^{n} \hat{\epsilon}_j\vartheta_j - \bar{\hat{\epsilon}}\bar{\vartheta}, \tag{12}$$

we can decompose $\sum_{j=1}^{n} \hat{\epsilon}_j\vartheta_j$ as

$$\sum\nolimits_{j=1}^{n} \hat{\epsilon}_j\vartheta_j = n\mathrm{Cov}(\hat{\epsilon}, \vartheta) + \bar{\hat{\epsilon}} \cdot \sum\nolimits_{j=1}^{n} b_j\psi_j. \tag{13}$$

This full decomposition result in (13) suggests that the propagation mechanism of productivity shocks $\hat{\epsilon}_j$ can be mitigated or enhanced depending on how sector's I-O multipliers and final demand shares interact. For instance, given that $\hat{\epsilon}_j\vartheta_j = \hat{\epsilon}_j \sum_{i=1}^{n} d_{ji}\psi_i$, the potentially high macro impacts brought by a high shock $\hat{\epsilon}_k$ could be nullified if the high-valued multipliers in sector k (d_{ki}) are associated with small shares in final demand ψ_i. Hence, the stronger the positive relationship between the structural parameters d_{ji} and ψ_i, the higher the effect of individual shocks on aggregated output.

2.3 Linkage strength and linkage efficiency

In order to study further how the sector I-O multiplier-relative size interaction is related to economic growth, we assume an economy whose shocks are uniform across sectors, $\hat{\epsilon}_i = \hat{\epsilon}$, so that $\mathrm{Cov}(\hat{\epsilon}, \vartheta) = 0$ and $\bar{\hat{\epsilon}} = \hat{\epsilon}$. Hence, $\widehat{TFP}$, $\widehat{GDP}$, or $\widehat{GDP/L}$ are then proportional to what we call *total linkages* (TL), i.e, the weighted average of the sectoral backward linkages, $\sum_{j=1}^{n} b_j\psi_j$. To separate the interaction between the backward linkages b_j and the final demand shares ψ_j from the standalone linkage effect $\bar{b}$, we use the same decomposition approach as in (12)-(13). Since the average final demand share is $1/n$ ($\bar{\psi} = 1/n$) due to $\sum_{j=1}^{n} \psi_j = 1$, we can decompose the TL as

$$\underbrace{\sum\nolimits_{j=1}^{n} b_j\psi_j}_{\text{Total linkages (TL)}} = \underbrace{n\mathrm{Cov}(b, \psi)}_{\text{Linkage Efficiency (LE)}} + \underbrace{\bar{b}.}_{\substack{\text{Linkage Strength} \\ \text{(LS)}}} \tag{14}$$

The term $n\mathrm{Cov}(b, \psi) = \sum_{j=1}^{n}(b_j - \bar{b})(\psi_j - \bar{\psi})$ captures the effects on aggregate output derived from the (linear) relationship between backward linkages and sectoral shares. We call this effect *linkage efficiency* (LE) since it measures how efficiently the linkages of the sectors are wired to the relative importance in the final demand of the economy. The LE is higher when higher linkage sectors have a larger size and lower linkage sectors have a smaller size in the economy. When sectors with large size are associated with *low*-linkages sectors then linkage efficiency will be negative. The term $\bar{b}$ is the average standalone linkage effect or the economy-wide average output multiplier, which we call the *linkage strength* (LS). Based on this decomposition, we can empirically examine which linkage variable between LE and LS has more explanatory power for the cross-country GDP growth.[3]

[3] Fadinger et al. (2021) also use (13) but without considering our proposed decomposition (14). They showed that high-income countries tend to have $\mathrm{Cov}(\epsilon, \vartheta) < 0$.

3 Empirical results

The positive relationship between the I-O multipliers and growth has been well-documented (e.g. Acemoglu et al., 2016; Fadinger et al., 2021; McNerney et al., 2018). However, no attempt has been made to measure this relationship for the decomposed linkage variables in (14). To conduct this alternative exercise, we carry out a panel regression analysis to examine the effect of LS and LE on $\widehat{GDP}$ across countries.

3.1 Data and descriptive result

Two data sources are used for our statistical exercises: the World Input-Output Database (WIOD, Timmer et al., 2015; Dietzenbacher et al., 2013), and the Penn World Table, version 9.0, (PWT9, Feenstra et al., 2015). We use the WIOD to construct the backward linkages and the final demand shares, and use the PWT9 to get the measures on GDP, TFP, and government spending. We choose 40 countries between 2000 and 2014 for our sample.[4]

Income Level	Total Linkage	Linkage Strength	Linkage Efficiency	Efficiency Ratio (%)	Per capita GDP ($)	GDP Growth (%)
Low	2.139	2.142	-0.004	-0.39	14,036	4.10
	(0.298)	(0.264)	(0.065)	(2.82)	(4,947)	(4.42)
Middle	2.103	2.15	-0.046	-2.56	28,857	1.75
	(0.219)	(0.168)	(0.107)	(5.08)	(5,141)	(3.18)
High	2.016	2.13	-0.115	-5.87	46,211	1.67
	(0.157)	(0.131)	(0.07)	(3.73)	(11,312)	(2.27)

Table 1: Averages of linkage and GDP measures. The numbers in the parenthesis are the standard deviation.

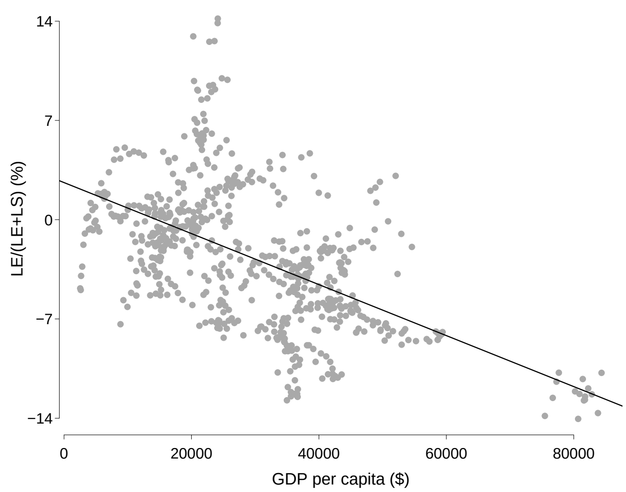

Figure 1: GDP per capita vs. Contribution of linkage efficiency. Each dot is for a given country in a given year.

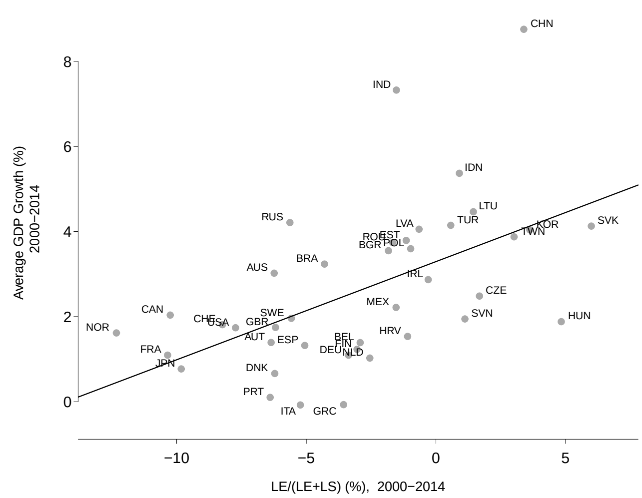

Figure 2: Average contribution of linkage efficiency vs. Average GDP growth from 2000 to 2014.

Table 1 summarizes the time averages of the linkage structure (TL, LE, LS, and efficiency ratio (ER), defined as ER = LE/(LE+LS)), GDP growth rates, and income per capita levels for three different income groups. Whereas the

[4] The WIOD has 43 countries but we do not include city/island nations whose population is smaller than 1 million (Cyprus, Malta, and Luxembourg). This exclusion does not lead to a qualitative difference in the result.

country group-level difference in LS is relatively small given the scale of the variable with no particular pattern, the difference in LE and the ER is noticeable and shows that the higher the income per capital the lower the efficiency indicators. To highlight this point, Figure 1 shows a clear negative relationship between the income level and the ER ($\rho = -0.553$), suggesting a process of increased inefficiency in the linkages-relative size coordination as countries climb the ladder of development.

Finally, we show in Figure 2 that there exists an overall positive correlation between the average $\widehat{GDP}$ (GDP growth) and the average ER for all 40 countries ($\rho = 0.533$).

3.2 Regression model and estimation results

To empirically test the relationship between the linkage variables and the GDP growth ($\widehat{GDP}$), we compare regression results of models with the total linkage (TL), the linkage strength (LS), the linkage efficiency (LE), and the efficiency ratio (ER) as the main predictor. We use a Bayesian panel regression model with the following specification:

$$
\begin{aligned}
\widehat{GDP}_k &\sim \text{Normal}\,(\mu_k, \sigma) \\
\mu_k &= \beta_1 \text{Linkage}_k + \beta_2 \text{Shock}_k + \\
&\quad\ \gamma_{c[k]} + \alpha_{t[k]} \\
\gamma_c &\sim \text{Normal}(0,\ \sigma_\gamma) \quad \text{for } c \in C \\
\alpha_t &\sim \text{Normal}(0,\ \sigma_\alpha) \quad \text{for } t \in T \\
\zeta, \beta_1, \beta_2 &\sim \text{Normal}(0, 10) \\
\sigma, \sigma_\gamma, \sigma_\alpha &\sim \text{Half-Cauchy}(0, 5)
\end{aligned}
$$

where subscript k represents the k-th observation/unit in the data, Linkage is the linkage indicator (TL, LS, LE, and ER), Shock is the TFP growth or the government spending change, γ_c and α_t are the country- and time-varying intercepts (fixed effects), and C and T are the set of country and time indices. We use a shrinkage prior on the varying intercepts, which is known to perform better in out-of-sample prediction (Stein, 1956; James and Stein, 1961; Hastie et al., 2009). Both country- and time-varying intercepts are given a normal prior distribution centered at 0 with unknown standard deviations, $\sigma_\gamma, \sigma_\alpha$ to be directly estimated from the data.[5] Priors on unknown parameters are given a weakly informative distribution such as a normal distribution for slope parameters, ψ, β_1, β_2 and a one-sided Cauchy distribution for scale parameters, $\sigma, \sigma_\gamma, \sigma_\alpha$. These regularizing prior distributions help fast and efficient estimation of the model without affecting the estimation results substantially.

Table 2 summarizes the regression results for the models with four different linkages variables and with two different aggregated shocks. We focus on the slope parameter of the linkage index, β_1. There are two key findings: First, the result confirms a positive relationship between the TL and economic growth known in the literature (e.g. Acemoglu et al., 2016; McNerney et al., 2018) as shown by the positive mean estimate of the slope in both models. The 5% left tail of the posterior distribution of β_1 does not include zero. The source of shocks, whether it is a supply-side (TFP growth) or a demand-side (government spending change), does not change the qualitative results even though the magnitude of the impact tends to be higher in the latter.

[5] The normal prior is centered at zero because our independent variables are mean-centered.

	Total Linkage		Linkage Strength		Linkage Efficiency		Efficiency Ratio	
	TFP Shock	Gov. Spending Shock	TFP Shock	Gov. Spending Shock	TFP Shock	Gov. Spending Shock	TFP Shock	Gov. Spending Shock
Linkage index, β_1	**0.022**	**0.026**	**0.016**	**0.019**	**0.046**	**0.07**	**0.102**	**0.151**
	[0.007,0.038]	**[0.009,0.044]**	**[-0.002,0.033]**	**[-0.002,0.038]**	**[0.011,0.081]**	**[0.03,0.108]**	**[0.026,0.183]**	**[0.065,0.237]**
Shock	0.945	0.422	0.952	0.427	0.946	0.426	0.946	0.426
	[0.866,1.025]	[0.339,0.505]	[0.873,1.035]	[0.342,0.514]	[0.867,1.03]	[0.347,0.511]	[0.864,1.028]	[0.338,0.513]
SD country	0.012	0.011	0.012	0.012	0.012	0.01	0.012	0.01
	[0.009,0.017]	[0.008,0.016]	[0.009,0.017]	[0.009,0.017]	[0.009,0.016]	[0.007,0.015]	[0.009,0.016]	[0.007,0.014]
SD year	0.012	0.025	0.011	0.025	0.011	0.025	0.011	0.024
	[0.007,0.021]	[0.016,0.042]	[0.007,0.019]	[0.016,0.041]	[0.007,0.019]	[0.015,0.041]	[0.007,0.02]	[0.015,0.042]
Observations	560	560	560	560	560	560	560	560
Bayes R2	0.831	0.671	0.83	0.669	0.83	0.669	0.83	0.669
	[0.817,0.843]	[0.641,0.697]	[0.816,0.841]	[0.638,0.695]	[0.817,0.842]	[0.638,0.695]	[0.817,0.841]	[0.639,0.695]

Table 2: Estimated parameters of the growth regression for 40 WIOD countries using linkage variables as the main predictor. The mean and the 99% uncertainty interval (in bracket) are shown for each parameter.

Second, the parameter of LS is estimated to be positive but is not sufficiently large so that the 99% uncertainty interval of the posterior distribution includes zero. In contrast, the parameter of LE is estimated to be positive and is sufficiently large. This contrasting effect between LS and LE can also be confirmed in the model with the ER where the slope parameter is positive and sufficiently large. This result implies that, given the same total linkage, the economy with a higher degree of linkage efficiency tends to achieve higher $\widehat{GDP}$. The overall result, especially the higher statistical significance of the LE over LS and the positive slope of the ER variable, is robust to a wide range of different model specifications, including the model with both LS and LE as the main linkage indicators[6], models with lagged independent variables, and a model with a GDP level as an additional control variable. The same result holds for GDP per capita growth.

Overall, the result suggests that the economic structure captured by LE tends to have a positive relationship with $\widehat{GDP}$: the more efficiently the I-O network is wired, the higher the economic growth. In contrast, the LS does not seem to directly affect $\widehat{GDP}$.

4 Discussion and conclusion

This paper fills the gap in the production network literature where the focus has been put on the impact of the total linkage on the GDP growth. Our paper, for the first time in the literature, proposed a novel decomposition of the total linkage impact into linkage efficiency and linkage strength and demonstrated that what matters for the GDP growth is the linkage efficiency, which depends on the covariance of the sector-level linkage effects and the final demand shares.

While we cannot claim to measure causality, our analysis suggests that as countries develop their linkage efficiency drops, which lowers GDP growth. This may be related to the process of diversification over the course of development (Imbs and Wacziarg, 2003). For example, low-income countries that grow faster (as shown in Table 1) are specialized in central sectors such as manufacturing. As development progresses, they diversify -

[6] The baseline model does not include LE and LS simultaneously due to potential multicollinearity: LE and LS tend to be positively related conditional on the year group because countries with higher total linkage have higher LE and LS simultaneously. In contrast, they tend to have a mild negative relationship conditional on the country group because a high LE implies a low LS in each country especially when the total linkage does not change substantially over time.

necessarily in less central sectors, before eventually re-specializing in sectors that do not have particularly high backward linkages, such as services. We leave this important question for future research.

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