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Peer Effects in Productivity and Differential Growth: A Global Value-Chain Perspective

Philipp Mundt[1], Ivan Savin[2,3,*], Uwe Cantner[4,5], Hiroyasu Inoue[6] and Simone Vannuccini[7]

[1]Economics Institute, University of Bamberg, Feldkirchenstraße 21, Bamberg D-96052, Germany. e-mail: philipp.mundt@uni-bamberg.de, [2]ESCP Business School, C. de Arroyofresno, 1, Madrid 28035, Spain. e-mail: isavin@escp.eu, [3]Graduate School of Economics and Management, Ural Federal University, Yekaterinburg, Russia, [4]Faculty of Economics and Business Administration, Friedrich Schiller University of Jena, Carl-Zeiss-Strasse 3, Jena D-07743, Germany. e-mail: uwe.cantner@uni-jena.de, [5]Department of Marketing and Management, University of Southern Denmark, Denmark, [6]Graduate School of Information Science, University of Hyogo, 7-1-28 Minatojima-minamimachi, Chuo-ku, Kobe, Hyogo 650-0047, Japan. e-mail: inoue@gsis.u-hyogo.ac.jp and [7]GREDEG, CNRS, Université Côte d'Azur, Campus Azur du CNRS—250 rue Albert Einstein—CS 10269, Sophia Antipolis Cedex F06905, France. e-mail: simone.vannuccini@univ-cotedazur.fr

*Main author for correspondence.

Abstract

Using multinational input–output data, we analyze how the productivity of countries adjusted for participation in global value chains affects their output growth in manufacturing sectors. Based on parametric and non-parametric methods, we find that value-chain linkages are critical to the productivity–growth nexus and help to explain cross-country differences in sectoral output growth rates compared to the situation where these linkages are ignored. Our results have implications for macroeconomics, where they point to peer effects in productivity as drivers of growth, and for economic development, where they illustrate how the participation in global value chains may outweigh disadvantages in productive performance at the level of individual countries. They may also encourage future empirical tests of replicator dynamics to verify whether global value chains can explain the weak evidence of selection forces at the firm level.

JEL classification: C67, D22, L14, L16, L20

1. Introduction

Fueled by the growing availability of multinational input–output data, the last years have seen a surge of interest in global value chains (GVC) and the role of input linkages in explaining economic outcomes. Accordingly, pertinent literature has started to approach the production of output from a network perspective (see, e.g., Bernard and Moxnes, 2018; Carvalho, 2014, for recent reviews). This view acknowledges that firms or disaggregated sectors do not operate in isolation, transforming anonymously supplied inputs into final products, but source raw materials, parts, and supporting services from upstream suppliers, convert them to new goods, and sell the output to other sectors and end consumers domestically and abroad.

In this paper, we analyze how the productivity of countries adjusted for GVC participation affects their output growth in manufacturing sectors, finding that input linkages increase the explanatory power of productivity on growth compared to the situation where GVC are ignored. Our analysis builds on network panel data from the World Input Output Database (WIOD; see Timmer *et al.*, 2015), which provides sector-level information on input linkages within and across 43 major economies over the period 2000–2014. Using these data, we employ standard input–output accounting (Leontief, 1936) and a model of vertical production in the spirit of Pasinetti (1973) to compute direct and indirect input and value-added contributions of all suppliers participating in the GVC of a given country-sector. We then use these quantities to estimate (labor) productivity of the entire value chain, which represents a more thorough measure of productive performance than the idiosyncratic productivity of an individual country. The explicit comparison between the two measures enables us to assess the gains in explanatory power of productivity on growth arising from the shift of attention away from individual countries and toward GVC.

To highlight the role of input linkages in output growth, our empirical analysis proceeds in three steps. First, we assess the relation between productivity and growth in panel regressions, incorporating cross-country differences in productivity levels and changes in productivity as explanatory variables. Distinguishing between idiosyncratic and value-chain productivity, our analysis testifies to the importance of input linkages as value-chain productivity can explain more variation in output growth than the productivity of individual countries.

Second, we employ a spatial regression approach that explains output growth of a country in a given industry with its individual productivity level and productivity change and the spatial averages of these variables across its suppliers. We find that both individual productivity improvement and productivity improvement of the GVC partners contribute positively to output growth of the focal country in the end-consumer market. We also find that the joint explanatory power of the individual and spatial productivity terms is almost identical to that of the value-chain productivity measure in our first regression and that the spatially lagged productivity terms can explain at least as much variation in growth as individual productivity. This implies that the productive performance of the GVC partners is actually more important than the productivity of the focal country, and neglecting the influence of the former would lead to a downward bias in the productivity–growth relationship.

Third, we consider global labor productivity in a given sector and decompose its change over time into within and between components. While the within effect encompasses the influence of individual technological improvement within countries, the between effect captures the change in average sectoral productivity arising from the reallocation of market shares (approximated either by the amount of labor employed or output produced) between countries. We run this decomposition for individual and value-chain productivity and find that the within component accounts for most of the productivity change when input linkages are ignored. The consideration of input linkages reverses the relative importance of the two effects and leads to a dominant between component, suggesting that market reallocation outweighs productivity improvement as the main driver of productivity change in the setting of GVC. Interpreting this finding jointly with the decomposition result for idiosyncratic productivity, this implies that global competition reallocates labor and production to countries embedded in more productive GVC, but not necessarily to countries with the highest individual productivity in a given sector.

Our study relates to different strands of literature. First, it relates to the literature that explores and explains GVC. The latter was rapidly growing in recent years because production processes increasingly rely on foreign value added, typically exhibiting complex topologies that go beyond the prototypical example of "snake-like" structures (Antràs, 2020). Analytical models of GVC are variations of trade models with sequential production (Antràs and Chor, 2013; Costinot *et al.*, 2013). These models shed light on the mechanisms behind the allocation of production stages to firms or countries (Chor, 2019; Alcacer and Delgado, 2016) and on the geographical location of given stages of production in the presence of trade barriers (Antràs and De Gortari, 2020). Parallel to the theoretical study of GVC, the literature has progressed on the fronts of developing GVC governance models (Gereffi *et al.*, 2005), empirical investigations into the determinants and consequences of participating in GVC (Amador and Cabral, 2016; Antràs, 2020), and the measurement of GVC (Johnson, 2018; Mundt, 2021). Main research topics in this field are to "slice up" GVC in order to understand the distribution of value added across countries (Timmer *et al.*, 2014) and the measurement of "upstreamness" and "downstreamness" of producers to assess their distance to final consumers (Antràs *et al.*, 2012; Antràs and Chor, 2018). For empirical investigations, the growing availability of global input–output data such as WIOD (Timmer *et al.*, 2015) has been particularly valuable. For example, López González *et al.* (2019) use WIOD data to study the interplay between inter-industry linkages and patterns of specialization, while Amoroso and Martino (2020) employ the same data to compute firms' distance to the technology frontier and study the efficacy of capital, labor, and product market policies in the technological catch-up process. Our work contributes to this literature by discussing the application of input—output data to productivity measurement and the analysis of market share reallocation between countries in global manufacturing.

Since our work highlights the influence of supply-chain partners on the growth of individual countries, the present study also relates to the literature that explains how network structure shapes economic outcomes. Peer effects have been explored in different research trajectories, ranging from abstract network games where individual payoffs depend on the peer group (Galeotti *et al.*, 2010) to concrete applications in the fields of, e.g., labor markets (Cornelissen *et al.*, 2017), consumption (Moretti, 2011), education (Epple and Romano, 2011), inequality perceptions (Schulz *et al.*, 2022), and innovation economics (Savin, 2021). Recent macroeconomic literature describes how input–output linkages contribute to aggregate fluctuations (Acemoglu *et al.*, 2012; Carvalho and Tahbaz-Salehi, 2019b; Carvalho and Grassi, 2019). More closely related to the present investigation, McNerney *et al.* (2022) analyze the role of input linkages in productivity spillovers. They find that technological improvement accumulates along input linkages so that longer value chains for a country bias it toward faster growth. Accounting for vertical relationships in production is also important for industrial policy, development, and international trade. For example, Liu (2019) describes how sales distortions may compound through input linkages and thus provide an incentive to subsidize upstream sectors because they are prone to these distortions. Laursen and Meliciani (2000) explain sectors' export shares based on upstream and downstream industrial linkages and demonstrate that these linkages are an important channel for innovation spillovers, which determine competitiveness in international markets. The present paper relates to this literature by illustrating the role of GVC partners in explaining excessive growth of focal producers.

Last but not the least, our finding that value-chain productivity better determines growth outcomes than individual productivity might have implications for evolutionary studies of market selection and industry dynamics (e.g., Dosi *et al.*, 2010; Metcalfe, 1994), analyzing whether differential productive performances of individual firms lead to differential market success. According to the selection hypothesis, often formalized in terms of a replicator dynamics model (Taylor and Jonker, 1978; van den Bergh *et al.*, 2019; Foramitti *et al.*, 2021), competition ensures that the "fittest" (e.g., most productive) firms display above-average growth. Despite its intuitive appeal, however, empirical support for the selection hypothesis on the firm level is typically weak (e.g. Bottazzi *et al.*, 2010; Dosi *et al.*, 2015; Savin, 2020). Cantner *et al.* (2019) extend the replicator dynamics model to GVC and argue theoretically that value chain instead of individual fitness determines the growth of the final producer in the end-consumer market. In other words, their model predicts that market selection works properly at the bottom layer of the value chain under the condition that the productive performance of all value-chain partners is accounted for, while it may fail when only the final producer's individual productivity is considered. Our work might thus stimulate future empirical research to verify whether GVC play a role not only in reallocation effects across countries but also in explaining the weak evidence of selection forces operating at the firm level reported in prior work. In this respect, the idea to shift the focus on entire value chains might also help to explain the lack of cleansing effects during episodes of economic crises as in Domini and Moschella (2022) who report that productivity-enhancing reallocation of labor has been slower in France during the Great Recession of 2008–2010. In particular, due to the trade collapse associated with the crisis, value-chain productivity of the fittest producers could have lost its competitive edge.

The remainder of this paper is structured as follows. Section 2 describes the data and explains the measurement of productivity in GVC based on world input–output tables. Section 3 introduces our empirical strategy and discusses the results of our analysis, while Section 4 summarizes and concludes.

2. Data

Our analysis employs network panel data on global production input linkages sampled across 43 countries for the period 2000–2014. These countries include the current 27 member states of the European Union and 16 additional large economies such as the United States, China, Japan, India, Russia, Brazil, the United Kingdom, and Canada, which together account for approximately 85% of world GDP at the end of the sample period. These data are obtained from the 2016 release of WIOD reporting annual trade flows in intermediate goods between 56 sectors (see Timmer *et al.*, 2015, for a comprehensive introduction to the WIOD database). Thus, a major advantage of the WIOD data is not only its global coverage but also the fact that these data capture the full range of economic activities in the value chain, including all pre- and post-production phases before the output is sold to final consumers.

The input–output network in Figure 1 illustrates intra- and inter-sectoral trade in intermediate inputs within and across these countries. From 2000 to 2014 the number of production input linkages increased by almost 69% from 370,912 to 625,937, testifying to the rising complexity of the global production network over time. The importance of GVC is also reflected in the share of total output sold to downstream sectors. Averaging across all sectors, this share increased from 52% in 2000 to 58% in 2014, suggesting that trade in intermediate inputs accounts for the majority of trade and became even more important over time, which motivates our interest in GVC and their effect on the productivity–growth nexus in the first place.

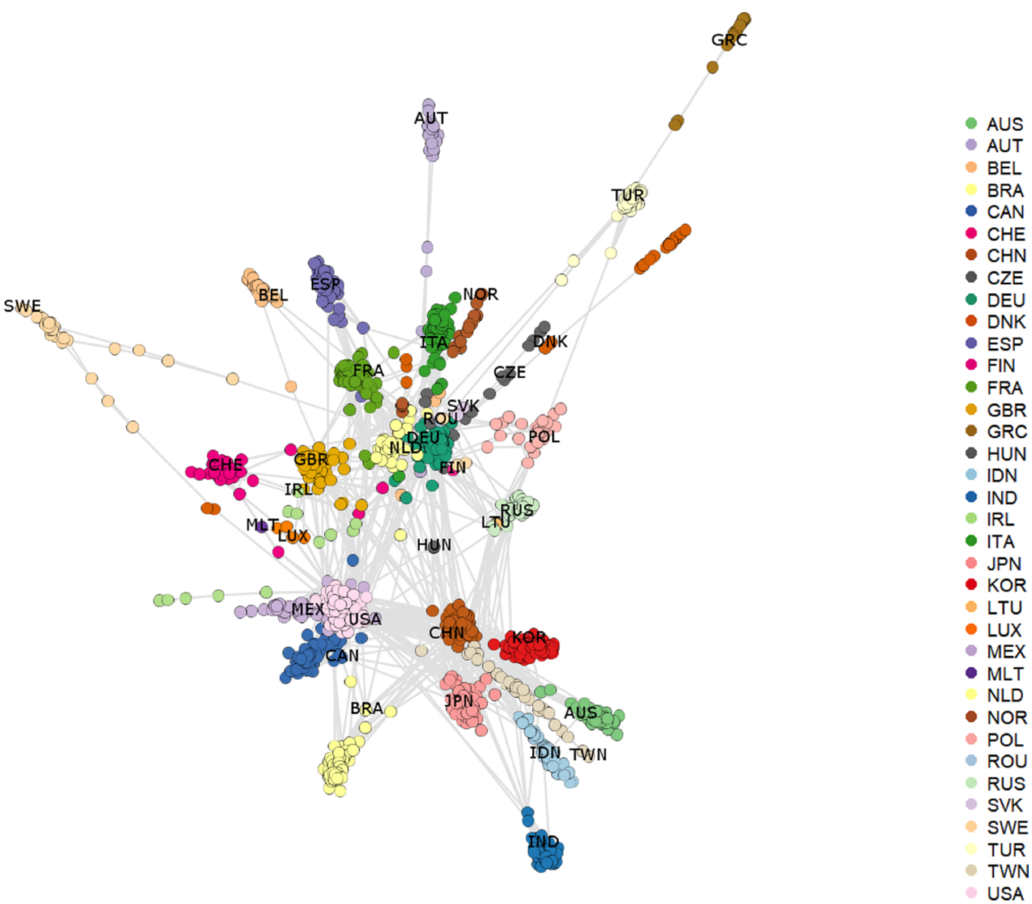

Figure 1. The global input–output network in 2014. Nodes represent country-sectors and edges illustrate trade in intermediate inputs. Colors represent the 43 countries. Edges with a weight below 1 billion USD have been removed to simplify the graphical exposition.

In addition to these input–output data, WIOD provides information on the quantity of goods and services sold to end consumers domestically and abroad, which enables us to distinguish output by its utilization. It also includes data on total gross output, value added, and employment via the supplementary Socio-Economic Accounts. The data are converted into USD and adjusted for inflation using national price indexes with base year 2010.

Throughout this study our measure of productivity is value added per labor hour. To assess the relation between productivity and growth and to compare our network perspective to the situation where input linkages are ignored, we consider two variations of labor productivity: (i) the individual labor productivity of each country in a given sector (idiosyncratic productivity) and (ii) the productivity of its entire value chain (value-chain productivity). The latter incorporates the focal country-sector that sells output to final consumers and all its direct and indirect suppliers along the GVC.

Value-chain productivity is computed as the ratio of the sum of value added across all layers of the GVC to the sum of both direct and indirect labor demand for producing the final output. Since the accounting identity implies that the sum of value added across all contributing country-sectors equals the output sold to end consumers, we measure the former as final demand. To compute the total labor demand across all layers of the GVC, we combine standard methodology in input–output analysis (Leontief, 1936) with the model of vertical production initially proposed by Pasinetti (1973) and later applied to productivity measurement by Timmer and Ye (2018).[1] Building on this approach, the labor requirements matrix is given by

$$\mathbf{L} = \mathbf{l}(\mathbf{I} - \mathbf{A})^{-1}\mathbf{f}, \tag{1}$$

where $(\mathbf{I} - \mathbf{A})^{-1}$ is the Leontief inverse with the identity matrix $\mathbf{I}$. $\mathbf{A} = (a_{i,j}(x,y))$ is a matrix of technical coefficients, defined as the output shipped from sector x in country i to sector y in country j, divided by the output of the receiving country-sector. $\mathbf{l}$ is a diagonal matrix of direct labor coefficients. These direct labor coefficients reflect the labor demand of a particular country-sector, measured in terms of labor hours, per unit of gross output. If we post-multiply these direct labor coefficients with the Leontief inverse, we obtain the direct and indirect labor requirements of each country-sector per unit of final output. Finally, we derive the matrix of direct and indirect labor requirements, $\mathbf{L}$, by post-multiplying the previous result with the diagonal matrix $\mathbf{f}$, capturing the final demand of each country-sector. The column sum of $\mathbf{L}$ measures the quantity of direct and indirect labor necessary to produce the final output of a given country-sector, while its row sum quantifies the total hours worked in this country-sector. Notice that the latter includes labor to produce intermediate inputs for other domestic and foreign sectors.[2]

In addition to the value-chain productivity measure, we consider the idiosyncratic labor productivity of a country in a given sector to compare our network perspective to the situation where value-chain linkages are ignored. To this end, we compute the ratio of a country's gross output in an industry minus its demand for intermediate inputs to total hours worked. Thus, the crucial difference between value-chain and idiosyncratic productivity is that the former sums up the labor and value-added contributions of all domestic and foreign sectors in the value chain to produce final output, while the latter focuses on the target country-sector and thus disregards that a significant share of output is sold to other country-sectors. The explicit comparison of the two measures enables us to assess the gain in explanatory power originating in the consideration of value-chain linkages.

While the value-chain productivity incorporates labor and value-added contributions from all 56 sectors, we restrict our subsequent empirical analysis of the productivity–growth nexus to the 19 manufacturing industries included in our sample. We do so for several reasons. First, output in manufacturing is tradable (e.g., OECD, 2018), which is an important prerequisite for the

[1] Unlike our study, Timmer and Ye (2018) construct a measure of total factor productivity (TFP) for value chains. Since TFP might be biased in the presence of technologically heterogeneous producers and input complementarities (Dosi and Grazzi, 2006), we focus on labor productivity.

[2] The Leontief inverse adopts a demand perspective on input–output relationships and thus focuses on backward linkages. Therefore, our value-chain productivity measure, which builds on the Leontief inverse, incorporates the influence of the focal country and its upstream suppliers. An alternative to the Leontief inverse that captures the role of forward linkages is the Ghoshian inverse (Ghosh, 1958).

reallocation of market shares across countries. Second, manufacturing industries provide more reliable estimates of output and value added, without resorting to income data as in, e.g., services. Third, manufacturing industries exhibit long value chains (McNerney *et al.*, 2022), which makes it worthwhile to compare the two productivity measures for this subset of sectors (for a discussion of other economic sectors, e.g., mining, services, and construction, see Savin and Mundt, 2022).

Table 1 presents descriptive statistics for output growth rates and the two productivity measures. The mean growth rate varies between -1% in textiles and 5% in pharmaceuticals, computer and electronic, and motor vehicles, with a cross-sectional average of 3%. The most volatile industry is coke and petroleum with a standard deviation of 24%, while food exhibits the lowest dispersion in our sample with a standard deviation of merely 10%. Estimates of the dispersion of idiosyncratic productivity vary between 0.75 (repair and installation) and 1.33 (coke and petroleum), with a cross-sectional average of 0.94. Our results imply that a country which is one standard deviation above the mean is about $\exp(0.94+0.94) \approx 6.5$ times more productive than a country whose productivity is one standard deviation below the mean. It is worth noting, however, that value-chain productivity is less dispersed than idiosyncratic productivity, consistent with the view that the participation in GVC leads to convergence in productivity because the vast majority of country-sectors are directly or indirectly connected via input linkages (e.g., Carvalho and Tahbaz-Salehi, 2019a; Mundt, 2021). Yet, even at the value-chain level, there is large variation of productivity across countries to warrant a meaningful analysis of its effect on differential growth. We will turn to this question in the next section.

3. Empirical strategy and results

In this section, we present three related sets of results on differential growth in GVC, testing if countries embedded in more productive GVC for a sector experience faster growth. To investigate whether our value-chain perspective increases the explanatory power of productivity on growth, we compute and compare results for the two productivity measures from Section 2.

3.1 Regression analysis of the output growth–productivity relationship

We start to assess the productivity–growth nexus by estimating the following static linear panel model with country-level fixed effects

$$g_{i,t}(x) = a + b_t + c_i + \beta_\Delta \Delta\pi_{i,t}(x) + \beta_m \bar{\pi}_{i,t}(x) + \epsilon_{i,t}, \tag{2}$$

where $g_{i,t}(x)$ denotes the (log) growth rate of output of country i in sector x from year $t-1$ to t.[3] b_t is a time dummy. $\Delta\pi_{i,t}(x)$ stands for the (log) growth rate of labor productivity (as a proxy of innovation). $\bar{\pi}_{i,t}(x)$ is the level of productivity (as a proxy of technology), measured in terms of the time average over the years t and $t-1$. c_i represents country fixed effects, and $\epsilon_{i,t}$ is the error term. Since we estimate Eq. (2) individually for each sector, the presence of time dummies is equivalent to consider the deviation of individual productivity from the sectoral average in a given year, implying that countries' relative efficiency within those sectors serves as the explanatory variable of output growth. Note that here and later we focus on productivity terms as explanatory variables and abstain from adding controls like labor costs or size of the economy. Since our main interest is not the extent to which growth is explained by productivity but the marginal improvement in explanatory power when considering value-chain instead of idiosyncratic productivity, our results are robust to omitted variable bias.

[3] The Hausmann test supports our modeling strategy because it favors the fixed over the random effects model in all except one (or 95%) of the industries on the 5% significance level. We also confirm that there is no sign of omitted dynamics in the productivity–growth relationship because the Breusch–Godfrey test cannot reject the null hypothesis of no serial correlation among the within-group errors in 17 out of 19 (or 89%) industries at the 5% significance level.

Table 1. Descriptive statistics for growth rates and (log) labor productivity.

	Growth			Productivity					
				Idiosyncratic			Value chain		
Sector	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
Food	0.03	0.03	0.10	34.99	28.01	0.84	37.24	34.55	0.77
Textiles	−0.01	0.01	0.13	23.30	15.47	1.06	28.54	25.12	0.86
Wood	0.02	0.03	0.14	24.17	20.87	0.95	31.30	29.05	0.83
Paper	0.02	0.03	0.14	35.98	29.48	0.85	41.69	39.11	0.73
Printing	0.02	0.02	0.14	28.87	25.29	0.80	36.70	33.85	0.69
Coke and petroleum	0.03	0.03	0.24	176.99	115.02	1.33	89.44	75.27	0.95
Chemicals	0.03	0.04	0.19	66.60	47.95	0.98	57.59	51.08	0.74
Pharmaceuticals	0.05	0.05	0.13	90.86	58.93	1.04	63.53	57.72	0.74
Rubber and plastic	0.04	0.05	0.14	30.69	26.20	0.89	40.23	38.00	0.70
Other non-metallic	0.03	0.04	0.15	33.58	29.05	0.90	41.31	38.45	0.75
Basic metals	0.03	0.05	0.18	45.56	39.29	0.93	49.92	51.82	0.69
Fabricated metals	0.04	0.05	0.16	29.47	27.28	0.86	37.82	36.23	0.66
Computer and electronic	0.05	0.05	0.19	46.36	35.33	1.07	48.15	45.82	0.79
Electrical	0.04	0.04	0.18	38.39	30.68	0.92	44.57	42.08	0.71
Machinery	0.04	0.06	0.17	34.33	27.70	0.91	39.86	38.59	0.69
Motor vehicles	0.05	0.06	0.21	34.63	28.21	0.84	41.02	39.40	0.64
Other transport	0.04	0.06	0.21	41.75	33.39	0.98	42.20	39.93	0.71
Furniture	0.02	0.03	0.16	31.09	19.12	1.03	35.47	30.46	0.82
Repair and installation	0.05	0.05	0.17	33.58	28.11	0.75	41.44	35.95	0.64
Mean	0.03	0.04	0.17	46.38	35.02	0.94	44.63	41.18	0.74
Median	0.03	0.04	0.16	34.63	28.21	0.92	41.31	38.59	0.73

Note: Productivity is defined in USD per labor hour and is measured in constant prices as of 2010 as explained in the main text. SD stands for standard deviation.

Table 2. Estimation results for the fixed effects model in Eq. (2).

Sector	Idiosyncratic		Value chain	
	β_Δ	β_m	β_Δ	β_m
Food	0.40***	−0.03	0.62***	−0.04*
Textiles	0.35***	−0.08**	0.63***	−0.11***
Wood	0.38***	−0.02	0.61***	−0.02
Paper	0.21***	−0.03	0.58***	−0.06*
Printing	0.33***	−0.02	0.60***	0
Coke and petroleum	0.16***	−0.03	0.55***	−0.01
Chemicals	0.45***	−0.02	0.45***	−0.01
Pharmaceuticals	0.30***	−0.01	0.42***	−0.03
Rubber and plastic	0.28***	−0.08***	0.67***	−0.1***
Other non-metallic	0.42***	−0.01	0.69***	−0.06*
Basic metals	0.24***	0.01	0.28***	−0.06*
Fabricated metals	0.41***	−0.05*	0.76***	−0.03
Computer and electronic	0.39***	−0.07***	0.88***	0.04
Electrical	0.41***	−0.02	0.75***	−0.03
Machinery	0.40***	−0.08***	0.65***	−0.07**
Motor vehicles	0.44***	−0.01	0.70***	0
Other transport	0.36***	−0.03	0.47***	−0.02
Furniture	0.54***	−0.06*	0.73***	−0.04
Repair and installation of machinery	0.48***	−0.06	0.83***	−0.03

*Note: Entry 0 stands for values $< 5 \times 10^{-3}$. ***, **, and * indicate statistical significance at the 0.1%, 1%, and 5% level, respectively.*

We estimate Eq. (2) for the two different measures of productivity and rely on the Shapley decomposition of the pertinent R^2 to determine the explanatory power of $\bar{\pi}_{i,t}(x)$ and $\Delta\pi_{i,t}(x)$ from

$$S^2 = \frac{\text{Var}(\beta_\Delta \Delta\pi_{i,t}(x) + \beta_m \bar{\pi}_{i,t}(x))}{\text{Var}(g_{i,t}(x))}, \tag{3}$$

which measures the share of the growth variance explained by the two productivity terms.

Table 2 summarizes the estimation results. While the influence of the level of productivity seems negligible and is often insignificant, we find that the coefficient of the change in productivity is positive and statistically significant at the 0.1% level across all sectors. The dominant role of the dynamic productivity component on growth is confirmed by the Shapley decomposition in Table 3 and its graphical illustration in Figure 2, which show that the explanatory power of the change in productivity is twice as high as that of the productivity level across all sectors. The median share of the growth variance explained by Eq. (2) amounts to 57% for the idiosyncratic productivity measure, and 29 percentage points of which pertain to the two productivity terms. Turning to the value-chain productivity measure, we find that the median share of the growth variance explained by Eq. (2) rises from 57% to 62%, and 41% points of which must be attributed to the value-chain productivity terms. Thus, peer effects in productivity are quantitatively important and help to explain cross-country differences in sectoral output growth rates.

A potential concern about our regression analysis is that the use of global output growth and value-chain productivity data in the panel model in Eq. (2) may lead to cross-sectional dependence, with potential implications on parameter estimation and inference. Cross-sectional dependence may arise in our study when countries are exposed to common shocks or when regressors are correlated across countries due to the network structure of input–output linkages from which we derive the value-chain productivity measure. Indeed, we obtain evidence for cross-sectional dependence in 3 out of 19 sectors based on Pesaran (2021) cross-sectional dependence test when the level and change of idiosyncratic productivity serve as regressors, which we attribute to the presence of common external shocks. The number of affected sectors rises to 16 when we consider value-chain productivity instead of idiosyncratic productivity. This increase can be explained with the additional dependence introduced through our measure of value-chain

Table 3. Shapley decomposition for the fixed effects model in Eq. (2).

Sector	Idiosyncratic			Value chain		
	R^2	$S^2_{\Delta\pi}$	S^2_{π}	R^2	$S^2_{\Delta\pi}$	S^2_{π}
Food	0.64	0.26	0.13	0.74	0.35	0.20
Textiles	0.58	0.15	0.26	0.66	0.22	0.30
Wood	0.64	0.26	0.09	0.64	0.32	0.08
Paper	0.52	0.14	0.09	0.60	0.25	0.17
Printing	0.50	0.19	0.06	0.54	0.32	0.01
Coke and petroleum	0.22	0.07	0.04	0.42	0.26	0.02
Chemicals	0.48	0.21	0.07	0.34	0.14	0.03
Pharmaceuticals	0.41	0.20	0.05	0.43	0.20	0.08
Rubber and plastic	0.62	0.13	0.24	0.72	0.26	0.28
Other non-metallic	0.68	0.28	0.04	0.73	0.31	0.19
Basic metals	0.57	0.17	0.03	0.54	0.12	0.13
Fabricated metals	0.69	0.22	0.17	0.76	0.41	0.09
Computer and electronic	0.56	0.18	0.18	0.62	0.36	0.10
Electrical	0.59	0.27	0.07	0.64	0.35	0.10
Machinery	0.72	0.21	0.23	0.75	0.31	0.19
Motor vehicles	0.64	0.32	0.02	0.62	0.36	0.01
Other transport	0.40	0.17	0.08	0.31	0.15	0.02
Furniture	0.55	0.22	0.19	0.53	0.28	0.13
Repair and installation of machinery	0.39	0.17	0.11	0.52	0.33	0.06
Mean	0.55	0.20	0.11	0.58	0.28	0.12
Median	0.57	0.20	0.09	0.62	0.31	0.10

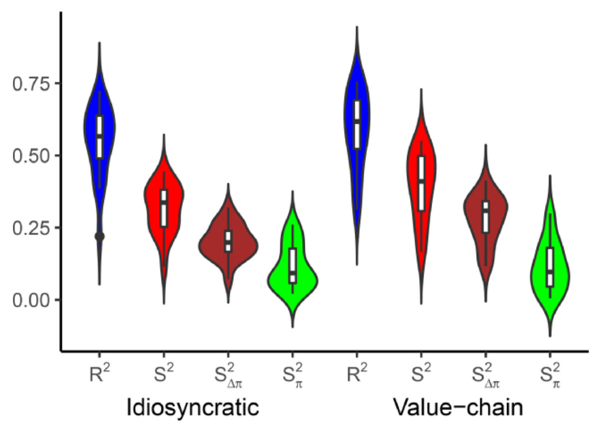

Figure 2. Distribution of the Shapley decomposition for the fixed effects model in Eq. (2).

productivity that uses information from the input–output matrix. To confirm that our results are not an artifact of cross-sectional dependence, we have also estimated the relationship between output growth and productivity using the common correlated effects mean group estimator proposed by Pesaran (2006), which considers the cross-sectional averages of output growth and productivity as additional explanatory variables. The results, which are reported in Tables A2–A3 in the Appendix, confirm that our findings remain valid and are not driven by these correlations.

Since the sector-by-sector analysis limits the number of cross-sectional observations to $43 \times 15 = 645$, we also estimated a pooled model with ordinary least squares, which has good small sample properties. To account for sectoral differences, we adjust growth and productivity variables by subtracting their sectoral means across all countries prior to the estimation. The results in Table A4 in the Appendix are consistent with those obtained from the static linear panel model with fixed effects. In particular, we obtain a positive and highly statistically significant

Table 4. Estimation results for the spatial panel regression model in Eq. (4).

Sector	β_Δ	β_m	γ_Δ	γ_m
Food	0.24***	0.01	0.55***	−0.06***
Textiles	0.25***	−0.03	0.59***	−0.03
Wood	0.31***	0	0.44***	−0.03
Paper	0.12***	0.01	0.81***	−0.01
Printing	0.24***	0	0.67***	0.01
Coke and petroleum	0.15***	−0.03	0.21	−0.09
Chemicals	0.42***	−0.01	0.30**	−0.05
Pharmaceuticals	0.26***	0.01	0.51***	−0.06
Rubber and plastic	0.10***	−0.01	0.90***	−0.11***
Other non-metallic	0.21***	0.02	0.83***	−0.01
Basic metals	0.19***	0.02	0.57***	−0.01
Fabricated metals	0.25***	−0.04	0.75***	0.06
Computer and electronic	0.34***	−0.05**	0.54***	−0.07
Electrical	0.35***	0.01	0.51***	−0.13*
Machinery	0.33***	−0.07**	0.47***	0.04
Motor vehicles	0.37***	0	0.70***	0.03
Other transport	0.29***	0.02	0.76***	−0.15**
Furniture	0.46***	−0.06·	0.36***	0.04
Repair and installation of machinery	0.47***	−0.04	0.17	−0.03

Note: Entry 0 stands for values $< 5 \times 10^{-3}$. ****, **, and * indicate statistical significance at the 0.1%, 1%, and 5% level, respectively.*

coefficient for the change in both productivity measures, and a $R^2 = 0.29$ for value-chain productivity compared to $R^2 = 0.21$ for the idiosyncratic productivity.

3.2 Spatial regression analysis

Our second test considers whether the (idiosyncratic) productivity of suppliers of the focal country i in a given sector x has an effect on output growth of i in that sector. It employs a spatial panel model with fixed effects for growth that incorporates the spatial lags of the two productivity terms in Eq. (2) as additional explanatory variables. Thus, this augmented regression model does not only test whether output growth of i at time t is determined by its own idiosyncratic productivity but also by the weighted average idiosyncratic productivity of its value-chain partners. Formally, we estimate

$$g_{i,t}(x) = a + b_t + c_i + \beta_\Delta \Delta\pi_{i,t}(x) + \beta_m \bar{\pi}_{i,t}(x) + \gamma_\Delta SL(\Delta\pi_{i,t}(x)) + \gamma_m SL(\bar{\pi}_{i,t}(x)) + \epsilon_{i,t}, \quad (4)$$

where the spatial lag $SL(\Delta\pi_{i,t}(x))$ represents the weighted average productivity change and $SL(\bar{\pi}_{i,t}(x))$ is the weighted average productivity level, respectively, of i's suppliers. We determine the weights of these suppliers based on their labor contributions to the focal country in a given sector. Specifically, the weights are obtained from Eq. (1) by dividing the elements in each column of the matrix **L** by the respective column sum. Since the typical country-sector consumes a significant portion of its own output, however, idiosyncratic productivity and the spatially lagged productivity terms would be highly correlated without further corrections. To avoid biased results due to collinearity, we set the elements on the main diagonal of **L** equal to zero before computing the column sum and the pertinent weights. This correction excludes domestic intra-industry transactions and thus separates the focal producer from the set of its suppliers.

Table 4 presents the estimation results for the spatial regression model in Eq. (4). We find that our main results from Section 3.1 remain valid as the change in productivity is quantitatively still more important for growth than the productivity level. Even more importantly, the spatial lag of the change in productivity is positive and statistically significant at the 5% level in 17 out of 19 manufacturing industries.[4] Thus, we obtain direct empirical evidence for the idea that countries

[4] Repair and installation of machinery and equipment exhibits the weakest dependence on suppliers in the sample, with a ratio of direct and indirect labor contributions from upstream suppliers in percentage of total labor demand of

Table 5. Shapley decomposition results for the spatial panel model in Eq. (4).

Sector	R^2	$S^2_{\Delta\pi}$	$S^2_{\bar{\pi}}$	$S^2_{SL(\Delta\pi_{i,t})}$	$S^2_{SL(\bar{\pi}_{i,t})}$
Food	0.74	0.14	0.04	0.23	0.20
Textiles	0.63	0.12	0.14	0.18	0.05
Wood	0.67	0.21	0.01	0.18	0.09
Paper	0.62	0.09	0.04	0.31	0.03
Printing	0.57	0.15	0.00	0.23	0.04
Coke and petroleum	0.22	0.05	0.03	0.02	0.05
Chemicals	0.49	0.17	0.02	0.07	0.08
Pharmaceuticals	0.47	0.14	0.03	0.13	0.12
Rubber and plastic	0.73	0.05	0.04	0.27	0.23
Other non-metallic	0.75	0.13	0.10	0.30	0.03
Basic metals	0.60	0.12	0.07	0.18	0.02
Fabricated metals	0.74	0.13	0.12	0.23	0.11
Computer and electronic	0.58	0.13	0.13	0.10	0.10
Electrical	0.62	0.16	0.03	0.11	0.19
Machinery	0.74	0.17	0.20	0.13	0.06
Motor vehicles	0.67	0.23	0.01	0.21	0.06
Other transport	0.46	0.09	0.04	0.11	0.14
Furniture	0.56	0.17	0.16	0.09	0.06
Repair and installation of machinery	0.39	0.15	0.08	0.03	0.04
Mean	0.59	0.14	0.07	0.16	0.09
Median	0.62	0.14	0.04	0.18	0.06

grow not only because their own productive performance is above the average but also because they have value-chain partners with superior productivity.

Considering the results for goodness of fit and the Shapley decomposition in Table 5 and Figure 3, we find that the median share of the growth variance explained by the spatial model amounts to 62% across all sectors, which is identical to the result obtained for the value-chain productivity measure in Table 3. We thus conclude that the explanatory power of the aforementioned value-chain productivity measure can be decomposed into two terms: (i) a country's idiosyncratic productivity and (ii) the productivity of its GVC partners. Neglecting the latter thus leads to a downward bias in the productivity–growth relationship since the spatial productivity terms explain at least as much variation in growth as the individual productivity terms in most sectors.

We have also investigated how the explanatory power of the spatially lagged productivity terms depends on the quantitative importance of upstream suppliers for the focal country. To this end, we estimate the relationship between the growth variance explained by the spatial lags divided by the variance explained by all productivity terms in Eq. (4) as the dependent variable and the aforementioned measure of dependence on the upstream suppliers in terms of labor as the explanatory variable (see footnote 4). Fitting a linear model to this relationship using (weighted) ordinary least squares yields a slope of 0.54 ± 0.27 with a p-value of 0.06 and $R^2 = 0.19$.[5] This suggests that the more labor the upstream suppliers contribute, the higher the importance of peer effects in productivity tends to be.

3.3 Decomposition of global sectoral productivity change

Evolutionary studies of market selection consider the relation between productivity and growth on the firm level, hypothesizing that more productive firms will display above-average growth

41%, which might explain the insignificant influence of suppliers in this sector. The median realization of this ratio across the manufacturing sectors is 55%.

5 Observations are weighted by the relative size of each sector in terms of labor.

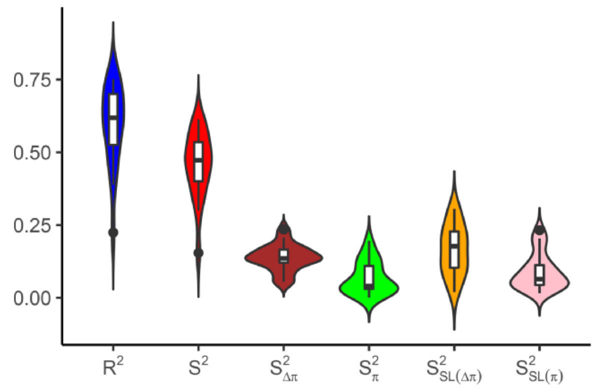

Figure 3. Distribution of the Shapley decomposition for the spatial panel model in Eq. (4).

(e.g., Dosi *et al.*, 2010; Metcalfe, 1994). To encourage the consideration of our value-chain productivity measure as an alternative to individual productivity in empirical firm-level tests of market selection as suggested by Cantner *et al.* (2019), we also apply a productivity decomposition because it is frequently used in this literature. To this end, we decompose the global labor productivity in sector *x* at time *t*,

$$\Pi_t(x) = \sum_i s_{i,t}(x)\pi_{i,t}(x), \tag{5}$$

where $\pi_{i,t}(x)$ denotes the productivity of country *i* in that sector. $s_{i,t}(x)$ is the country's market share, measured in terms of *i*'s labor hours in percentage of the global labor demand in that sector. To decompose the productivity index in Eq. (5), we employ the method proposed by Griliches and Regev (1995).[6] This decomposition splits the change in aggregate productivity into

$$\Delta\Pi_t(x) = \sum_i \bar{s}_{i,t}(x)\Delta\pi_{i,t}(x) + \sum_i \Delta s_{i,t}(x)\bar{\pi}_{i,t}(x), \tag{6}$$

where a bar over a variable stands for its average over two consecutive years $t-1$ and t.

The first term on the right-hand side of Eq. (6) represents the so-called *within effect*, i.e. the sum of country-specific changes in productivity in a given sector, weighted by the share of each country. This component captures the change in productivity resulting from idiosyncratic efforts (e.g., due to innovation). The second term on the right-hand side of Eq. (6) is the so-called *between effect*, i.e. the sum of changes in countries' market shares in a given sector, weighted by the productivity levels of these countries. Since the sum of shares is constant and equal to unity by construction, a positive between term suggests that market shares are reallocated to countries operating above the sectoral average productivity level. Therefore, it can explain why a rise in aggregate productivity is consistent with a situation where individual productivity remains unchanged for each country but global competition reallocates market shares to more productive countries. Moreover, if the between effect is larger for the value chain than for the idiosyncratic productivity measure, this suggests that input linkages are relevant for market selection and must be taken into consideration. Notice that a negative between term would speak against the selection mechanism in the sense that less productive countries gain a larger share in the global market. On the other hand, a negative sign of the within effect would imply that countries shift their production from more to less valuable (e.g., less technologically intensive) activities.[7]

Given that the WIOD dataset covers a period of 15 years, we are interested in the aggregate effects over multiple years. To this end, we compute the overall contribution of the within and

[6] In the Appendix, we discuss an alternative decomposition that separates out the covariance between changes in market shares and productivity.

[7] These interpretations hold as long as global productivity change in a given sector is strictly positive.

Table 6. Decomposition of productivity change according to Griliches and Regev (1995) with market shares measured in terms of employment (labor hours).

	Idiosyncratic		Value chain	
Sector	**Within**	**Between**	**Within**	**Between**
Food	−12.01	13.01	−8.30	9.30
Textiles	0.80	0.20	0.54	0.46
Wood	1.27	−0.27	0.85	0.15
Paper	−1.19	2.19	−0.05	1.05
Printing	19.73	−18.73	−1.81	2.81
Coke and petroleum	1.07	−0.07	1.04	−0.04
Chemicals	0.68	0.32	0.74	0.26
Pharmaceuticals	0.58	0.42	0.54	0.46
Rubber and plastic	24.36	−23.36	−0.39	1.39
Other non-metallic	1.01	−0.01	0.15	0.85
Basic metals	0.16	0.84	1.03	−0.03
Fabricated metals	−6.58	7.58	−0.43	1.43
Computer and electronic	−0.30	1.30	0.20	0.80
Electrical	−1.96	2.96	0.03	0.97
Machinery	−1.91	2.91	−0.16	1.16
Motor vehicles	−0.61	1.61	0.07	0.93
Other transport	−0.18	1.18	0.11	0.89
Furniture	1.69	−0.69	1.46	−0.46
Repair and installation	2.12	−1.12	2.50	−1.50
Mean	1.51	−0.51	−0.10	1.10
Median	0.58	0.42	0.15	0.85

between components by running the decomposition for different pairs of consecutive years and summing the results over the years, which yields

$$\sum_t \Delta\Pi_t(x) = \sum_t \sum_i \bar{s}_{i,t}(x)\Delta\pi_{i,t}(x) + \sum_t \sum_i \Delta s_{i,t}(x)\bar{\pi}_{i,t}(x). \tag{7}$$

To ease the comparison of the relative importance of between and within effects obtained from Eq. (7), we report percentage shares of the two components for total productivity change. For example, for the between effect we have

$$\left(\sum_t \sum_i \Delta s_{i,t}(x)\bar{\pi}_{i,t}(x)\right) / \left(\sum_t \Delta\Pi_t(x)\right) = \sum_t \left[\left(\frac{\sum_i \Delta s_{i,t}(x)\bar{\pi}_{i,t}(x)}{\Delta\Pi_t(x)}\right)\left(\frac{\Delta\Pi_t(x)}{\sum_t \Delta\Pi_t(x)}\right)\right]. \tag{8}$$

In Table 6, we find that the median within effect amounts to 58%, while the median between effect is merely 42% for the idiosyncratic productivity measure. If we consider value-chain instead of idiosyncratic productivity, however, the median between effect rises to 85%, implying that the consideration of input linkages facilitates the identification of stronger selection effects. Considering the mean instead of the median qualitatively confirms these results and leads to more extreme realizations in some sectors due to outliers. The box plots in Figure 4 illustrate the rising importance of market reallocation in GVC and further suggest that input linkages reduce the dispersion of within and between effects across sectors due to the high connectivity of the global production network.

A potential critique of our application of productivity decomposition to multinational input-output data is that limitations to labor mobility might prevent the reallocation of market shares across countries. To check if our findings are materially affected by frictions in the reallocation of labor, we weighted productivity not only by labor shares but also by shares in gross output as in Bottazzi *et al.* (2010). As Table A5 in the Appendix shows, our main conclusions remain valid

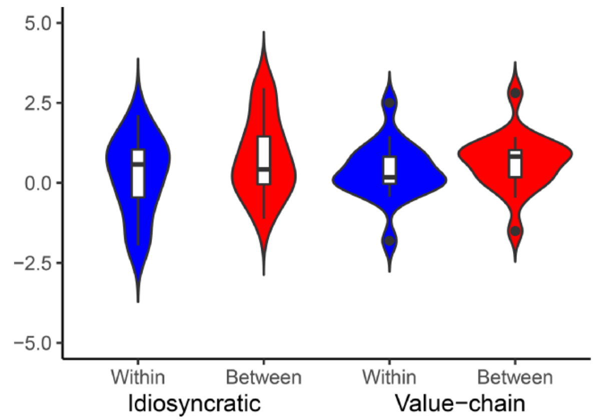

Figure 4. Distribution of sectoral within and between components.

across alternative market share measures.[8] Specifically, the median contribution of the between effect now increases by a factor of four compared to two for labor shares.

To sum up, the decomposition analysis testifies to stronger reallocation effects at the level of GVC. So it seems worthwhile to apply our methodology to firm-level data, testing if GVC do not only shape reallocation effects across countries but can also explain the weak evidence of selection forces at the firm level.

4. Conclusion

Using WIOD data to map the network of sectoral input–output linkages within and between countries, this paper employs regression analyses and productivity decomposition to study differential growth driven by heterogeneous production efficiency in the setting of GVC. We find that the influence of value-chain partners' productivity on the output growth of individual countries is not only significant but also quantitatively more important than the individual productivity of the focal country. The superior explanatory power of value-chain productivity in growth regressions suggests that input linkages are relevant in explaining individual growth, and our decomposition analysis shows that global competition reallocates market shares to countries embedded in more productive GVC, but not necessarily to the most productive countries. While we do not deny other influencing factors of growth including policy, our main contribution is to show empirically that the consideration of input linkages, ceteris paribus, improves the explanatory power of productivity on growth compared to the situation where input linkages are ignored.

Our empirical results have implications for macroeconomics, where they point to peer effects in productivity as drivers of growth, and for economic development, where they illustrate how GVC participation can outweigh disadvantages in the productive performance of individual countries. Our finding that network structure matters for growth outcomes might also be relevant for the literature on industry dynamics, especially for evolutionary studies of market selection that predict the "survival of the fitter" and typically rely on the replicator dynamics model as their standard workhorse. Although the selection hypothesis offers an intuitive explanation of differential growth driven by heterogeneity in production efficiency, it seems fair to say that pertinent literature has barely succeeded in the task to turn theoretical predictions into compelling empirical evidence (e.g., Bottazzi *et al.*, 2010; Dosi *et al.*, 2015; Savin *et al.*, 2020). Prior work discussed several potential reasons why empirical evidence does not lend much support to the selection hypothesis on the firm-level, including mismatch between industry classifications and actual markets and the choice of irrelevant fitness measures. Consistent with our empirical finding that input linkages are crucial for the measurement of reallocation effects, Cantner *et al.* (2019)

[8] A potential explanation is that 27 out of 43 countries in our sample are members of the EU for which labor mobility has considerably increased since monetary unification (Arpaia *et al.*, 2016).

provide an alternative explanation. They argue that GVC may undermine the selection mechanism at the level of individual producers in the sense that less efficient producers may gain market share if they are linked to superior value-chain partners in related markets, even if their own productive performance is relatively poor (and vice versa). In other words, their model predicts that market success is not only determined by the firm's individual fitness but also by the fitness of its value-chain partners. So we hope that the results presented in this paper will encourage further research investigating whether GVC linkages can also explain the weak evidence of selection forces operating at the firm level. Assessing the explanatory power of our approach based on more granular data would certainly enhance our understanding of competition in value chains, provided that one could compile a data set that includes both the identity of customers and suppliers and transaction volumes in a multinational setting. Another promising future research trajectory would be to evaluate and compare the relative contributions of suppliers' and customers' fitness on individual growth. This paper approaches value chains from the last producer that sells output to final consumers. To generalize this perspective, one could study and compare the role of forward and backward linkages. We hope that our study will stimulate more empirical work in this direction.

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References

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

Alcacer, J. and M. Delgado (2016), 'Spatial organization of firms and location choices through the value chain', *Management Science*, **62**(11), 3213–3234.

Amador, J. and S. Cabral (2016), 'Global value chains: A survey of drivers and measures', *Journal of Economic Surveys*, **30**(2), 278–301.

Amoroso, S. and R. Martino (2020), 'Regulations and technology gap in Europe: the role of firm dynamics', *European Economic Review*, **129**(103551), 103551.

Antràs, P. (2020), 'Conceptual Aspects of Global Value Chains'. *World Bank Economic Review*, **34**(3), 551–574.

Antràs, P. and D. Chor (2013), 'Organizing the global value chain', *Econometrica*, **81**(6), 2127–2204.

Antràs, P. and D. Chor (2018), 'On the measurement of upstreamness and downstreamness in global value chains', *World Trade Evolution: Growth, Productivity and Employment*, 126–194.

Antràs, P., D. Chor, T. Fally and R. Hillberry (2012), 'Measuring the upstreamness of production and trade flows', *American Economic Review*, **102**(3), 412–416.

Antràs, P. and A. De Gortari (2020), 'On the geography of global value chains', *Econometrica*, **88**(4), 1553–1598.

Arpaia, A., A. Kiss, B. Palvolgyi and A. Turrini (2016), 'Labour mobility and labour market adjustment in the EU', *IZA Journal of Migration*, **5**(21).

Bernard, A. and A. Moxnes (2018), 'Networks and trade', *Annual Review of Economics*, **10**(1), 65–85.

Bottazzi, G., G. Dosi, N. Jacoby, A. Secchi and F. Tamagni (2010), 'Corporate performances and market selection: some comparative evidence', *Industrial and Corporate Change*, **19**(6), 1953–1996.

Cantner, U., I. Savin and S. Vannuccini (2019), 'Replicator dynamics in value chains: explaining some puzzles of market selection', *Industrial and Corporate Change*, **28**(3), 589–611.

Carvalho, V. M. (2014), 'From micro to macro via production networks', *The Journal of Economic Perspectives*, **28**(4), 23–47.

Carvalho, V. M. and B. Grassi (2019), 'Large firm dynamics and the business cycle', *American Economic Review*, **109**(4), 1375–1425.

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

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

Chor, D. (2019), 'Modeling global value chains: approaches and insights from economics', in *Handbook on Global Value Chains*. Edward Elgar Publishing: Cheltenham.

Cornelissen, T., C. Dustmann and U. Schönberg (2017), 'Peer effects in the workplace', *American Economic Review*, **107**(2), 425–256.
Costinot, A., J. Vogel and S. Wang (2013), 'An elementary theory of global supply chains', *Review of Economic Studies*, **80**(1), 109–144.
Domini, G. and D. Moschella (2022), 'Reallocation and productivity during the Great Recession: evidence from French manufacturing firms', *Industrial and Corporate Change*, **31**(3), 783–810.
Dosi, G., G. Fagiolo and A. Roventini (2010), 'Schumpeter meeting Keynes: a policy-friendly model of endogenous growth and business cycles', *Journal of Economic Dynamics and Control*, **34**(9), 1748–1767.
Dosi, G. and M. Grazzi (2006), 'Technologies as problem-solving procedures and technologies as input-output relations: some perspectives on the theory of production', *Industrial and Corporate Change*, **15**(1), 173–202.
Dosi, G., D. Moschella, E. Pugliese and F. Tamagni (2015), 'Productivity, market selection and corporate growth: comparative evidence across US and Europe', *Small Business Economics*, **45**(3), 643–672.
Epple, D. and R. Romano (2011), *Handbook of Social Economics, Chapter Peer Effects in Education: A Survey of the Theory and Evidence*. Elsevier: Amsterdam, pp. 1053–1163.
Foramitti, J., I. Savin and J. van den Bergh (2021), 'Regulation at the source? Comparing upstream and downstream climate policies', *Technological Forecasting and Social Change*, **172**, 121060.
Foster, L., J. C. Haltiwanger and C. J. Krizan (2001), 'Aggregate productivity growth. Lessons from microeconomic evidence', in *New Developments in Productivity Analysis*. University of Chicago Press: Chicago, pp. 303–372.
Galeotti, A., S. Goyal, M. O. Jackson, F. Vega-Redondo and L. Yariv (2010), 'Network games', *The Review of Economic Studies*, **77**(1), 218–244.
Gereffi, G., J. Humphrey and T. Sturgeon (2005), 'The governance of global value chains', *Review of International Political Economy*, **12**(1), 78–104.
Ghosh, A. (1958), 'Input-output approach to an allocation system', *Economica*, **25**(97), 58–64.
Griliches, Z. and H. Regev (1995), 'Firm productivity in Israeli industry: 1979-1988', *Journal of Econometrics*, **65**(1), 175–203.
Johnson, R. C. (2018), 'Measuring global value chains', *Annual Review of Economics*, **10**(1), 207–236.
Laursen, K. and V. Meliciani (2000), 'The importance of technology-based intersectoral linkages for market share dynamics', *Review of World Economics*, **136**(4), 702–723.
Leontief, W. (1936), 'Quantitative input-output relations in the economic system of the United States', *Review of Economics and Statistics*, **18**(3), 105–125.
Liu, E. (2019), 'Industrial policies in production networks', *The Quarterly Journal of Economics*, **134**(4), 1883–1948.
López González, J., V. Meliciani and M. Savona (2019), 'When Linder meets Hirschman: inter-industry linkages and global value chains in business services', *Industrial and Corporate Change*, **28**(6), 1555–1586.
McNerney, J., C. Savoie, F. Caravelli, V. Carvalho and D. Farmer (2022) 'How production networks amplify economic growth,' *Proceedings of the National Academy of Sciences*, 119(1), 1–11.
Metcalfe, J. S. (1994), 'Competition, Fisher's principle and increasing returns in the selection process', *Journal of Evolutionary Economics*, **4**(4), 327–346.
Moretti, E. (2011), 'Social learning and peer effects in consumption: evidence from movie sales', *Review of Economic Studies*, **78**(1), 356–393.
Mundt, P. (2021), 'The formation of input-output architecture: evidence from the European Union', *Journal of Economic Behavior and Organization*, **183**, 89–104.
OECD. (2018), 'Productivity and jobs in a globalised world: how can all regions benefit?' *Chapter thinking global, developing local: tradable sectors, cities and their role for catching up*, OECD Publishing: Paris, pp. 57–93.
Pasinetti, L. (1973), 'The notion of vertical integration in economic analysis', *Metroeconomica*, **25**(1), 1–29.
Pesaran, H. (2006), 'Estimation and inference in large heterogeneous panels with a multifactor error structure', *Econometrica*, **74**(4), 967–1012.
Pesaran, H. (2021), 'General diagnostic tests for cross-sectional dependence in panels', *Empirical Economics*, **60**(1), 13–50.
Savin, I. (2020), 'Studying market selection in Russia and abroad: Measurement problems, national specificity and stimulating methods', *Journal of the New Economic Association*, **48**(4), 197–204.
Savin, I. (2021), 'On optimal regimes of knowledge exchange: a model of recombinant growth and firm networks', *Journal of Economic Interaction and Coordination*, **16**(3), 497–527.
Savin, I., O. Mariev and A. Pushkarev (2019), 'Survival of the fittest? Measuring the strength of market selection on the example of the Urals Federal District', *HSE Economic Journal*, **23**(1), 90–117.
Savin, I., O. Mariev and A. Pushkarev (2020), 'Measuring the strength of market selection in Russia: When the (firm) size matters', *Voprosy Ekonomiki*, **2**(2), 101–124.
Savin, I. and P. Mundt (2022), 'Drivers of productivity change in global value chains: Reallocation vs. innovation', *Economics Letters*, **220**, 110878.

Schulz, J., D. Mayerhoffer and A. Gebhard (2022), 'A network-based explanation of inequality perceptions', *Social Networks*, **70**, 306–324.
Taylor, P. and L. Jonker (1978), 'Evolutionary stable strategies and game dynamics', *Mathematical Biosciences*, **40**(1-2), 145–156.
Timmer, M. P., E. Dietzenbacher, B. Los, R. Stehrer and G. J. De Vries (2015), 'An illustrated user guide to the world input–output database: the case of global automotive production', *Review of International Economics*, **23**(3), 575–605.
Timmer, M. P., A. A. Erumban, B. Los, R. Stehrer and G. J. de Vries (2014), 'Slicing up global value chains', *The Journal of Economic Perspectives*, **28**(2), 99–118.
Timmer, M. and X. Ye (2018), *The Oxford Handbook of Productivity Analysis, Chapter Productivity and Substitution Patterns in Global Value chains*, Oxford University Press: New York.
van den Bergh, J., I. Savin and S. Drews (2019), 'Evolution of opinions in the growth-vs-environment debate', *Futures*, **109**, 84–100.

Appendix 1

As a robustness check to the productivity decomposition in Section 3.3, we also consider the alternative decomposition by Foster *et al.* (2001) (see p. 315, Eq. (2) for details). Apart from entry and exit effects that are not relevant for the present data and are thus omitted, its main difference to the decomposition in Eq. (6) is an additional covariance term that captures the relation between market share reallocation and productivity improvement.[9] For the idiosyncratic productivity measure, the results in Table A1 imply median within, between, and covariance components of 0.65, 0.63, and −0.61, respectively. They change to 0.50, 1.05, and −0.61 for the value-chain productivity measure, consistent with the argument that input linkages facilitate the identification of selection effects. Closer inspection of these results shows, however, that the absolute covariance effect is consistently negative and substantial in size for all industries under consideration, which would suggest that economies with decreasing productivity gain market shares and vice versa. Foster *et al.* (2001) explain that a negative covariance might be spurious because their method is sensitive to measurement errors in inputs and outputs, which are common in aggregated macroeconomic data. In particular, random measurement error in man-hours implies that production units with spuriously high measured man-hours will have spuriously low measured productivity, leading to a negative covariance between changes in productivity and changes in shares and a spuriously high within effect.[10] Since the decomposition by Griliches and Regev (1995) averages labor shares over time, their method is less sensitive to random measurement error in output or inputs, which supports our preference for the Griliches and Regev (1995) decomposition reported in the main text.

Table A1. Decomposition of productivity change according to Foster *et al.* (2001) with market shares measured in terms of employment (labor hours).

	Idiosyncratic			Value chain		
Sector	Within	Between	Covar	Within	Between	Covar
Food	1.65	26.68	−27.33	3.89	21.48	−24.37
Textiles	0.65	0.05	0.29	0.44	0.35	0.21
Wood	0.80	−0.74	0.93	0.55	−0.15	0.60
Paper	0.39	3.77	−3.16	0.62	1.71	−1.33
Printing	6.79	−31.67	25.89	−0.50	4.12	−2.63
Coke and petroleum	1.24	0.09	−0.33	1.19	0.10	−0.29

(continued)

[9] While the decomposition in Eq. (6) does not separate out the covariance effect, it is straightforward to show that it splits the covariance term equally between the within and the between component (see Savin *et al.*, 2019).
[10] Interestingly, the covariance is higher (though still negative) for value-chain productivity than for idiosyncratic productivity, suggesting that the former measure helps to wash out these measurement errors to some extent.

Table A1. (Continued)

Sector	Idiosyncratic			Value chain		
	Within	Between	Covar	Within	Between	Covar
Chemicals	0.99	0.63	−0.61	0.95	0.48	−0.44
Pharmaceuticals	0.62	0.46	−0.08	0.61	0.53	−0.15
Rubber and plastic	6.50	−41.23	35.73	0.49	2.28	−1.78
Other non-metallic	0.30	−0.73	1.43	−0.68	0.01	1.68
Basic metals	1.75	2.43	−3.17	1.59	0.53	−1.12
Fabricated metals	−1.61	12.56	−9.96	0.22	2.09	−1.30
Computer and electronic	0.38	1.97	−1.34	0.45	1.05	−0.50
Electrical	0.36	5.28	−4.64	0.55	1.49	−1.04
Machinery	0.02	4.84	−3.86	0.43	1.76	−1.19
Motor vehicles	0.35	2.58	−1.93	0.50	1.35	−0.86
Other transport	0.40	1.76	−1.17	0.41	1.20	−0.61
Furniture	0.78	−1.60	1.82	0.43	−1.50	2.06
Repair and installation	1.26	−1.98	1.72	1.55	−2.46	1.90
Mean	1.24	−0.78	0.54	0.72	1.92	−1.64
Median	0.65	0.63	−0.61	0.50	1.05	−0.61

Table A2. Estimation results for the common correlated effects mean group model.

Sector	Idiosyncratic		Value chain	
	β_Δ	β_m	β_Δ	β_m
Food	0.40***	0.01	0.59***	−0.02
Textiles	0.38***	−0.03	0.61***	−0.08
Wood	0.42***	0.03	0.62***	0.03
Paper	0.26***	−0.02	0.53***	−0.10·
Printing	0.36***	0.01	0.59***	0.03
Coke and petroleum	0.16***	−0.02	0.50***	0.03
Chemicals	0.38***	0.02	0.44***	−0.03
Pharmaceuticals	0.29***	−0.01	0.41***	−0.03
Rubber and plastic	0.29***	0.02	0.66***	−0.02
Other non-metallic	0.39***	0.07	0.64***	−0.03
Basic metals	0.23***	0.05	0.38***	−0.04
Fabricated metals	0.39***	0.06	0.70***	0.09·
Computer and electronic	0.39***	−0.03	0.79***	−0.01
Electrical	0.40***	−0.01	0.74***	−0.01
Machinery	0.36***	−0.04	0.54***	−0.04
Motor vehicles	0.42***	0.02	0.67***	0.03
Other transport	0.39***	0.01	0.52***	−0.01
Furniture	0.47***	−0.08	0.65***	−0.07
Repair and installation	0.45***	0.02	0.79***	0.15*

*Note: In addition to the productivity level and productivity change, Pesaran (2006) common correlated effects mean group estimator includes the cross-sectional averages of the dependent and independent variables as additional regressors (estimates not shown) to account for cross-sectional dependence. ***, **, and * indicate statistical significance at the 0.1%, 1%, and 5% level, respectively.*

Table A3. Shapley decomposition for the common correlated effects mean group model.

Sector	Idiosyncratic			Value chain		
	R^2	$S^2_{\Delta\pi}$	$S^2_{\bar{\pi}}$	R^2	$S^2_{\Delta\pi}$	$S^2_{\bar{\pi}}$
Food	0.69	0.23	0.12	0.77	0.23	0.19
Textiles	0.67	0.14	0.20	0.72	0.18	0.22

(continued)

Table A3. (Continued)

Sector	Idiosyncratic			Value chain		
	R^2	$S^2_{\Delta\pi}$	$S^2_{\bar{\pi}}$	R^2	$S^2_{\Delta\pi}$	$S^2_{\bar{\pi}}$
Wood	0.72	0.25	0.09	0.71	0.26	0.11
Paper	0.59	0.16	0.04	0.66	0.22	0.16
Printing	0.59	0.18	0.09	0.59	0.27	0.05
Coke and petroleum	0.32	0.08	0.05	0.62	0.24	0.01
Chemicals	0.55	0.19	0.07	0.56	0.15	0.06
Pharmaceuticals	0.50	0.20	0.04	0.50	0.19	0.09
Rubber and plastic	0.70	0.09	0.22	0.75	0.21	0.21
Other non-metallic	0.73	0.27	0.04	0.76	0.26	0.16
Basic metals	0.63	0.15	0.02	0.64	0.11	0.11
Fabricated metals	0.76	0.21	0.13	0.80	0.35	0.09
Computer and electronic	0.64	0.15	0.17	0.70	0.31	0.07
Electrical	0.68	0.25	0.07	0.71	0.28	0.10
Machinery	0.75	0.17	0.18	0.77	0.25	0.16
Motor vehicles	0.70	0.28	0.03	0.67	0.29	0.01
Other transport	0.49	0.16	0.08	0.49	0.18	0.01
Furniture	0.61	0.20	0.15	0.59	0.26	0.11
Repair and installation	0.46	0.12	0.12	0.60	0.32	0.05
Mean	0.62	0.18	0.10	0.66	0.24	0.10
Median	0.64	0.18	0.09	0.67	0.25	0.10

Table A4. Results from pooled ordinary least squares estimation.

Measure	α	β	γ	R^2
Idiosyncratic productivity	-0**	0.32***	-0.01***	0.21
Value-chain productivity	0	0.56***	0	0.29

*Note: The regression equation is $g_i = \alpha + \beta\Delta\pi_i + \gamma\bar{\pi}_i + \epsilon_i$. Entry 0 stands for values $< 5 \times 10^{-3}$. ***, **, and * indicate statistical significance at the 0.1%, 1%, and 5% level, respectively.*

Table A5. Decomposition of productivity change according to Griliches and Regev (1995) with market shares measured in terms of gross output.

Sector	Idiosyncratic		Value chain	
	Within	Between	Within	Between
Food	0.76	0.24	0.47	0.53
Textiles	0.67	0.33	−1.75	2.75
Wood	0.84	0.16	−0.44	1.44
Paper	0.88	0.12	0.43	0.57
Printing	0.93	0.07	0.37	0.63
Coke and petroleum	1.07	−0.07	1.20	−0.20
Chemicals	1.41	−0.41	0.80	0.20
Pharmaceuticals	0.82	0.18	1.86	−0.86
Rubber and plastic	0.86	0.14	1.21	−0.21
Other non-metallic	0.73	0.27	0.40	0.60
Basic metals	0.64	0.36	0.38	0.62
Fabricated metals	0.87	0.13	−0.25	1.25
Computer and electronic	0.79	0.21	−9.60	10.60
Electrical	0.79	0.21	−0.05	1.05
Machinery	0.88	0.12	0.19	0.81
Motor vehicles	0.87	0.13	−0.34	1.34
Other transport	0.95	0.05	−0.34	1.34
Furniture	0.86	0.14	−0.37	1.37
Repair and installation of machinery	0.80	0.20	0.92	0.08
Mean	0.86	0.14	−0.26	1.26
Median	0.86	0.14	0.37	0.63