Income Differences, Productivity and Input-Output Networks *

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Abstract

We study the role of input-output (IO) linkages and sectoral productivity (TFP) levels for cross-country income differences. Using data on IO tables and sectoral TFPs, we find important differences in IO structure and its interaction with TFP levels across countries: while highly connected sectors are more productive than the typical sector in poor countries, the opposite is true in rich ones. To quantitatively assess the role of IO linkages in cross-country income differences, we use tools from network theory to build a multi-sector general equilibrium model. Aggregate income is approximated by a simple function of the first and second moments of the joint distribution capturing interactions of IO linkages and sectoral TFPs. We then structurally estimate country-specific parameters of this distribution and simulate cross-country income differences. Our main finding is that incorporating IO linkages into a model with sectoral TFP differences significantly improves our ability to predict cross-country income variation.

KEY WORDS: input-output structure, networks, productivity, cross-country income differences, development accounting

JEL CLASSIFICATION: O11, O14, O47, C67, D85

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1 Introduction

Cross-country differences in income per capita are largely due to differences in aggregate total factor productivity (TFP), which account for at least 50% of income variation.[1] These cross-country differences in aggregate TFP stem from two sources: those due to differences in the technologies used and the efficiency with which they are operated and those due to differences in the so-called input-output (IO) structure of the economies that determines how sectoral TFPs add up at the country level. The role of the first source of aggregate TFP and income differences has been the focus of a large literature on endogenous growth and technology adoption,[2] while the importance of the second has been emphasized by a literature in development economics initiated by Hirschman (1958), with more recent contributions provided by Ciccone (2002) and Jones (2011 a,b). In this paper we contribute to the literature in development economics by establishing systematic and empirically relevant cross-country differences in (i) IO structure and (ii) its interaction with sectoral TFP levels . We then show that these elements are of first-order importance for explaining cross-country income differences.

Countries' IO structure, by means of the linkages between sectors, determines each sector's importance or "weight" in aggregate TFP. It can be effectively summarized using the distribution of sectoral IO multipliers. The (first-order) IO multiplier of a sector depends on the (i) number of sectors to which the sector supplies and (ii) the intensity with which the output of the sector is used as an input by other sectors.[3] It measures by how much aggregate income changes if productivity of a given sector changes by one percent. Thus, TFP levels in sectors with high multipliers have a larger impact on aggregate income compared to sectors with low multipliers.

By combining data from the World Input-Output Database (Timmer, 2012) and the Global Trade Analysis project (GTAP Version 6), we construct a unique dataset of IO tables and sectoral TFP levels (relative to those of the U.S.) for a large cross section of countries.[4] We first establish that the empirical distribution of sectoral multipliers has a fat right tail in all countries, so that the TFP levels of a few high-multiplier sectors have a large impact on aggregate outcomes. This feature is more pronounced in developing countries than in rich economies. Moreover, in developing countries, sectoral IO multipliers and TFP levels are positively correlated, while they are negatively correlated in rich economies.

To quantitatively assess the role of IO linkages and sectoral TFP levels for cross-country income differences, we then use network theory to build a neoclassical multi-sector model that admits a closed-form solution for aggregate income as a function of the first and second moments of the joint distribution

[1] See, e.g., Klenow and Rodriguez-Clare (1997), Hall and Jones (1999), Caselli (2005), Hsieh and Klenow (2010).

[2] See, e.g., Romer (1990), Aghion and Howitt (1992), Comin and Hobijn (2004, 2010).

[3] The intensity of input use is measured by the IO coefficient, which states the cents spent on that input per dollar of output produced. There are also higher-order effects, which depend on the number and the IO coefficients of the sectors to which the sectors that use the initial sector's output as an input supply.

[4] Data on sectoral TFPs are available for 36 countries and data on IO tables for 65 countries.

of sectoral IO multipliers and TFP levels.[5] Higher average IO multipliers and higher average sectoral TFP levels have a positive effect on income per capita. Moreover, a positive correlation between sectoral IO multipliers and TFP levels also increases income.

We then estimate a set of country-specific model parameters from the joint empirical distribution of IO multipliers and productivities with Maximum Likelihood and plug the parameter estimates into the model to simulate the cross-country income distribution. Our main finding is that the model featuring cross-country differences in the joint distribution of sectoral IO multipliers and TFP levels fares far better in terms of predicting the actual cross-country income variation than restricted versions of the model that: either (i) abstract from linkages and just allow for cross-country differences in sectoral TFP levels; or (ii) abstract from cross-country TFP differences and just allow for differences in IO structure; or (iii) allow for both linkages and sectoral TFP differences but abstract from cross-country variation in the IO structure.

In fact, the version of the model without IO linkages predicts too large cross-country income differences compared to the data given the estimated differences in country-specific TFP distributions. Intuitively, the large sectoral TFP differences are mitigated by countries' IO structures: low-productivity sectors tend to be poorly connected (have low multipliers) in developing countries and are thus less detrimental to aggregate outcomes, while high-productivity sectors have large multipliers.[6] By contrast, no such tendency exists in rich countries. Thus, if we measured aggregate productivity levels by just averaging sectoral TFPs without accounting for variation in linkages, income levels of developing countries would be significantly lower than they actually are.

Our statistical approach, that considers the moments of the distribution instead of the actual values, requires making some simplifying assumptions on the structure of the IO network in order to remain analytically tractable. However, it has a number of crucial advantages compared to feeding the full set of IO matrices and sectoral productivity levels of each country into a large-scale multi-sector model. First, it allows obtaining analytical results for how sectoral IO structure and TFP levels interact in their impact on the cross-country income distribution, thus capturing the key economic mechanisms in a simple and intuitive way. Second, since the whole economic structure is summarized by a small set of parameters, we can estimate the relevant parameters for each country and project them on per capita GDP. This enables us to obtain income predictions for the full set of countries in the Penn World Tables (155 countries), rather than being constrained to the 36 countries for which we can actually observe

[5] In our baseline model, we take the IO structure as exogenous. Moreover, due to Cobb-Douglas technology sectoral TFP levels are independent of IO structure. In robustness checks we account for possible endogeneity of IO linkages by: (i) allowing for sector-country-specific tax wedges; (ii) introducing CES production functions, which makes IO linkages endogenous to sectoral TFPs.

[6] An important exception is agriculture, which, in low-income countries, has a high IO multiplier and a below-average productivity level.

both sectoral TFP levels and IO tables. In doing so, we can compare the model-predicted *world* income distribution with actual data. Finally, this approach enables us to carry out counter-factuals by changing the parameters of the joint distributions of multipliers and TFPs.[7]

The role of linkages and their interaction with sectoral TFPs for income differences is further evaluated by performing a number of counter-factuals. First, we impose the IO structure of the U.S. on all countries. We find that using the dense IO network of the U.S. would significantly reduce income of low- and middle-income countries. For a country at 40% of the U.S. income level (e.g., Mexico) per capita income would decline by around 20% and income reductions would amount to up to 60% for the world's poorest economies (e.g., Congo). Intuitively, imposing the dense IO structure of the U.S. on poor countries makes their typical, low-productivity, sector much more connected to the rest of the economy and thus increases its impact on aggregate income. To some extent the sparseness of the IO network in low-income countries is thus good news: in these countries policies that focus on increasing productivity in just a few crucial sectors can have a large effect on aggregate income, while this is not true in rich economies.

Second, we impose that sectoral IO multipliers and productivities are uncorrelated. This scenario would again hurt low-income countries, which would lose up to 10% of their per capita income, because they would no longer have the advantage of having above-average TFP levels in high-multiplier sectors. By contrast, high-income countries would benefit, since for them the correlation between multipliers and TFP levels would no longer be negative.

In our baseline model, differences in IO structure across countries are exogenously given. However, one may be concerned that observed IO linkages are affected by tax wedges. In an extension, we thus identify sector-country-specific tax wedges as deviations of sectoral intermediate input shares from their cross-country average value: a below-average intermediate input share in a given sector identifies a positive implicit tax wedge. We show that poor countries tax their high-multiplier sectors relatively more, while the opposite is the case in rich economies. We find that the distribution of IO multipliers and their correlation with TFP levels are not significantly affected by allowing for wedges. Moreover, introducing wedges does not improve the model's explanatory power in terms of predicting cross-country income levels much. Removing the correlation between wedges and multipliers would also have relatively modest effects. If low-income countries did not have above-average tax rates in high-multiplier sectors,

[7] In the light of Hulten's (1978) results, one may be skeptical whether using a structural general equilibrium model and considering the statistical features of the IO matrices adds much compared to computing aggregate TFP as a weighted average of sectoral TFPs (where the adequate 'Domar' weights correspond to the shares of sectoral gross output in GDP). Absent distortions, Domar weights equal sectoral IO multipliers and summarize the direct and indirect effect of IO linkages. However, such a reduced-form approach does not allow to assess which features of the IO structure matter for aggregate outcomes or to compute counter-factual outcomes due to changes in IO structure, or productivities, as we do. Finally, as Basu and Fernald (2002) show, in the presence of sector-specific distortions (that we consider in an extension) the simple reduced-form connection between sectoral productivities and aggregate TFP breaks down.

they would gain up to 10% of per capita income.[8]

In a further robustness check, we relax the assumption of a unit elasticity of substitution between intermediate inputs, so that IO linkages become endogenous to prices. We show that an elasticity of substitution between intermediate inputs different from unity is hard to reconcile with the data because – depending on whether intermediates are substitutes or complements – it implies that sectoral IO multipliers and TFP levels should either be positively or negatively correlated in *all* countries. Instead, we observe a positive correlation between these variables in poor economies and a negative one in rich countries. Moreover, we extend our baseline model to incorporate cross-country differences in final demand structure and imported intermediate inputs; we also differentiate between skilled and unskilled labor inputs. We find that our results are robust to all of these extensions.

1.1 Literature

We now turn to a discussion of the related literature.

Our work is related to the literature on development accounting, which aims at quantifying the importance of cross-country variation in factor endowments – such as physical, human or natural capital – relative to aggregate productivity differences in explaining disparities in income per capita across countries. This literature typically finds that both are roughly equally important in accounting for cross-country income differences.[9] The approach of development accounting is to specify an aggregate production function for value added (typically Cobb-Douglas) and to back out productivity differences as residual variation that reconciles the observed income differences with those predicted by the model given the observed variation in factor endowments. Thus, this aggregate production function abstracts from cross-country differences in the underlying IO structure and is exactly identified. We contribute to this literature by (i) showing how an aggregate production function for value added can be derived in the presence of IO linkages and (ii) providing an over-identification test for the model, since sectoral TFP estimates are obtained independently. Most importantly, we show that incorporating cross-country variation in IO structure is of first-order importance for explaining cross-country income differences.

The importance of linkages and IO multipliers for aggregate income differences has been highlighted by Fleming (1955), Hirschmann (1958), and, more recently, by Ciccone (2002) and Jones (2011 a,b). The last two authors emphasize that if the intermediate share in gross output is sizable, there exist large multiplier effects: small firm (or industry-level) productivity differences or distortions that lead to misallocation of resources across sectors or plants can add up to large aggregate effects. These authors make this point in a purely theoretical context. While our setup in principle allows for a mechanism

[8] In the Supplementary Appendix we also study optimal taxation and the welfare gains from moving from the current tax wedges to an optimal tax system that keeps tax revenue constant and obtain a similar conclusion.

[9] See, e.g., Klenow and Rodriguez-Clare (1997), Hall and Jones (1999), Caselli (2005), Hsieh and Klenow (2010).

whereby intermediate linkages amplify small sectoral productivity differences, we find that there is little empirical evidence for this channel: cross-country sectoral TFP differences estimated from the data are even larger than aggregate ones, and the sparse IO structure of low-income countries actually helps to mitigate the impact of very low productivity levels in some sectors on aggregate outcomes.

Our finding that sectoral productivity differences between rich and poor countries are larger than aggregate ones is instead similar to those of the literature on dual economies and sectoral productivity gaps in agriculture.[10] Also closely related to our work is a literature on structural transformation. It emphasizes sectoral productivity gaps and transitions from agriculture to manufacturing and services as a reason for cross-country income differences (see, e.g., Duarte and Restuccia, 2010 for a recent contribution). However, most this literature abstracts from the role of linkages between industries.

In terms of modeling approach, our paper adopts the framework of the multi-sector real business cycle model with IO linkages of Long and Plosser (1983); in addition we model the input-output structure as a network, quite similarly to the setup of Acemoglu, Carvalho and Ozdaglar (2012).[11] In contrast to these studies, which deal with the relationship between sectoral productivity shocks and economic fluctuations, we are interested in the question how sectoral TFP *levels* interact with the IO structure to determine aggregate income *levels* and we provide corresponding structural estimation results.

Other recent related contributions are Oberfield (2013) and Carvalho and Voigtländer (2014), who develop an abstract theory of endogenous input-output network formation, and Boehm (2015), who focuses on the role of contract enforcement on aggregate productivity differences in a quantitative structural model with IO linkages. Differently from these papers, we do not try to model the IO structure as arising endogenously and we take sectoral productivity differences as exogenous. Instead, we aim at understanding how given differences in IO structure and sectoral productivities translate into aggregate income differences.

The number of empirical studies investigating cross-country differences in IO structure is quite limited. In the most comprehensive study up to that date, Chenery, Robinson, and Syrquin (1986) find that the intermediate input share of manufacturing increases with industrialization and – consistent with our evidence – that input-output matrices become less sparse as countries industrialize. Most closely related to our paper is the contemporaneous work by Bartelme and Gorodnichenko (2015). They also collect data on IO tables for many countries and investigate the relationship between IO linkages and aggregate income.[12] In reduced-form regressions of *aggregate* IO multipliers on income per worker, they

[10] See, e.g., Caselli (2005), Chanda and Dalgaard (2008), Restuccia, Yang, and Zhu (2008), Vollrath (2009), Gollin et al.(2014).

[11] Related to Acemoglu et al. (2012) empirical work by Barrot and Sauvagnat (2016) provides reduced-form evidence for the short-run propagation of exogenous firm-specific shocks in the production network of U.S. firms.

[12] Grobovsek (2015) performs a development accounting exercise in a more aggregate structural model with two final and two intermediate sectors.

find a positive correlation between the two variables. Moreover, they investigate how distortions affect IO linkages and income levels. Differently from the present paper, they neither use data on sectoral productivities nor network theory to represent IO tables. As a consequence, they do not investigate how differences in the distribution of sectoral multipliers and their correlations with productivities impact on aggregate income, which is the focus of our work.

The outline of the paper is as follows. In the next section we describe our dataset and present some descriptive statistics. In the following section, we lay out our theoretical model and derive an expression for aggregate GDP in terms of the IO structure and sectoral TFP levels. Subsequently, we turn to the estimation and model fit. We then present the counter-factual results and a number of robustness checks. The final section presents our conclusions.

2 Dataset and descriptive analysis

2.1 Data

IO tables measure the flow of intermediate products between different plants, both within and between sectors. The ji'th entry of the IO table is the value of output from establishments in industry j that is purchased by different establishments in industry i for use in production.[13] Dividing the flow of industry j to industry i by gross output of industry i, one obtains the IO coefficient γ_{ji}, which states the cents of industry j's output used in the production of each dollar of industry i's output.

To construct a dataset of IO tables for a range of low- and high-income countries, to compute sectoral TFP levels, and to get information on countries' aggregate income and factor endowments, we combine information from three datasets: the World Input-Output Database (WIOD, Timmer, 2012), the Global Trade Analysis Project (GTAP version 6, Dimaranan, 2006), and the Penn World Tables, Version 7.1 (PWT, Heston et al., 2012).

The first dataset, WIOD, contains IO data for 36 countries classified into 35 sectors in the year 2005. The list of countries and sectors is provided in the Supplementary Appendix Tables A-1 to A-3. WIOD IO tables are available in current national currency at basic prices.[14] In our main specification, IO coefficients are defined as the value of domestically produced plus imported intermediates divided by the value of gross output at basic prices.[15] As explained in more detail below, the WIOD data also

[13]While IO tables in principle record flows independently of whether they occur within the boundaries of the firm or between plants owned by different companies, intermediate output must usually be traded between establishments in order to be recorded in the IO tables. Flows that occur within a given plant are not measured.

[14]Basic prices exclude taxes and transport margins.

[15]In a robustness check, we separate domestically produced from imported intermediates and define domestic IO coefficients as the value of domestically produced intermediates divided by the value of gross output, while IO coefficients for imported intermediates are defined as the value of imported intermediates divided by the value of gross output. We show in the robustness section that this choice does not affect our results.

allow us to compute sectoral TFPs.

The second dataset, GTAP version 6, contains data for 65 countries and 37 sectors in the year 2004. We use GTAP data to obtain more information about IO tables of low-income countries. We construct IO coefficients for all 65 countries.[16]

Finally, the third dataset, PWT, includes data on income per capita in PPP, aggregate physical capital stocks (constructed from investment data with the perpetual inventory method) and labor endowments for 155 countries in the year 2005. In our analysis, PWT data is mainly used to make out-of-sample predictions with our model.

2.2 IO structure

To start with, we provide some descriptive analysis of the IO structure of the countries in our data. To this end, we consider the sample of countries from the GTAP database. First, we sum IO multipliers of all sectors to compute the aggregate IO multiplier. While a sectoral multiplier indicates the change in aggregate income caused by a one-percent change in productivity of one specific sector, the aggregate IO multiplier tells us by how much aggregate income changes due to a one-percent change in productivity of all sectors.[17] Figure 1 (left panel) plots aggregate IO multipliers for each country against GDP per capita (relative to the U.S.).

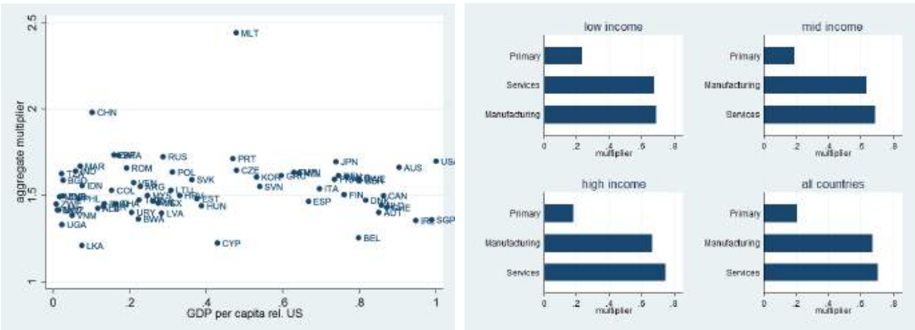

Figure 1: Aggregate IO-multipliers by country (left), sectoral IO-multipliers by income level (right)

We observe that aggregate multipliers average around 1.6 and are uncorrelated with the level of income. This implies that a one-percent increase in productivity of all sectors raises per-capita income by around 1.6 percent on average.[18]

Next, we separately compute the aggregate IO multipliers for the three major sector categories:

[16]Compared to the original GTAP classification, we aggregate all agricultural commodities in the GTAP data into a single sector. IO coefficients are computed as payments to intermediates (domestic and foreign) divided by gross output at purchasers' prices. Purchasers' prices include transport costs and net taxes on output (but exclude deductible taxes, such as VAT).

[17]We provide a formal definition of IO multipliers in section 3.3.

[18]Aggregate multipliers for the WIOD sample are somewhat larger (with a mean of around 1.8) and also uncorrelated with the level of per capita income. A simple regression of the aggregate multipliers from the GTAP sample on those from the WIOD data gives a slope coefficient of around 0.8 and the relationship is strongly statistically significant.

primary sectors (which include Agriculture, Coal, Oil and Gas Extraction and Mining), manufacturing and services. Figure 1 (right panel) plots these multipliers by income level. Here, we divide countries into low income (less than 10,000 PPP Dollars of per capita income), middle income (10,000-20,000 PPP Dollars of per capita income) and high income (more than 20,000 PPP Dollars of per capita income).

We find that multipliers are largest in services (around 0.65 on average), slightly lower in manufacturing (around 0.62) and smallest in the primary sector (around 0.2). As before, the level of income does not play an important role in this result: the comparison is similar for countries at all levels of income per capita.[19] We conclude that at the aggregate-economy level or for major sectoral aggregates there are no systematic differences in IO structure across countries.

Let us now look at differences in IO structure at a more disaggregate level. To this end, we compute sectoral IO multipliers separately for each sector and country. Figure 2 presents kernel density plots of the distribution of (log) sectoral multipliers for different levels of income per capita. The left panel presents the distributions of (log) multipliers for the GTAP sample (37 sectors) and the right panel the one for the WIOD sample (35 sectors).[20]

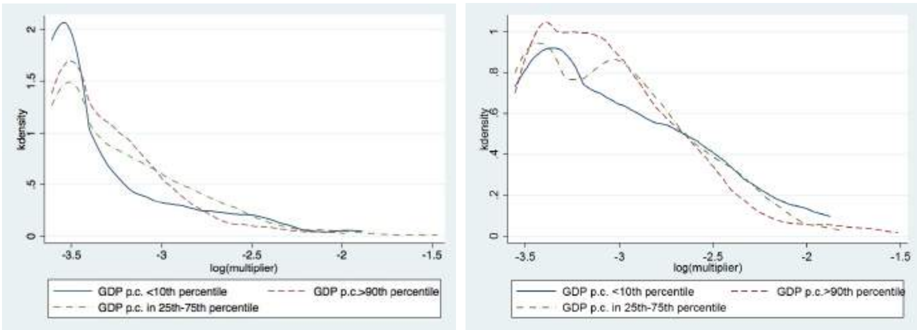

Figure 2: Distribution of sectoral log multipliers. GTAP sample (left panel); WIOD sample (right panel)

The following two facts stand out. First, for any given country the distribution of sectoral multipliers is *highly skewed*: while most sectors have low multipliers, a few sectors have multipliers way above the average. A typical low-multiplier sector (at the 10th percentile of the distribution of multipliers) has a multiplier of around 0.02 and the median sector has a multiplier of around 0.03. By contrast, a typical high-multiplier sector (at the 90th percentile of the distribution of multipliers) has a multiplier of around 0.065, while a sector at the 99th percentile has a multiplier of around 0.134.[21]

Second, the distribution of multipliers in low-income countries is *more skewed towards the extremes* than it is in high-income countries. In poor countries, almost all sectors have very low multipliers and a

[19] Very similar results are obtained for the WIOD sample. The only difference is that primary sectors are somewhat more important in low-income countries compared to others.

[20] We plot the distribution of log multipliers rather than the one of the level of multipliers in order to make the differences in the distributions more easily visible. Level multipliers follow an even more skewed distribution with most mass close to zero and a long right tail.

[21] These numbers correspond to the GTAP sample.

few sectors have very high multipliers. Differently, in rich countries the distribution of sectoral multipliers has significantly more mass in the center.[22]

Finally, we investigate which sectors tend to have the largest multipliers. We thus rank sectors according to the size of their multiplier for each country. The upper panels of Figure 3 plot sectoral multipliers for a few selected countries, which are representative for the whole sample: a very poor African economy (Uganda (UGA)), a large emerging economy (India (IND)) and a large high-income economy (United States (USA)). It is apparent that the distribution of multipliers in Uganda is such that the bulk of sectors have low multipliers, with the exception of Agriculture, Electricity, Trade and Inland Transport. By contrast, a typical sector in the U.S. has a larger multiplier, while the distribution of multipliers in India lies between the one of Uganda and the one of the U.S.[23]

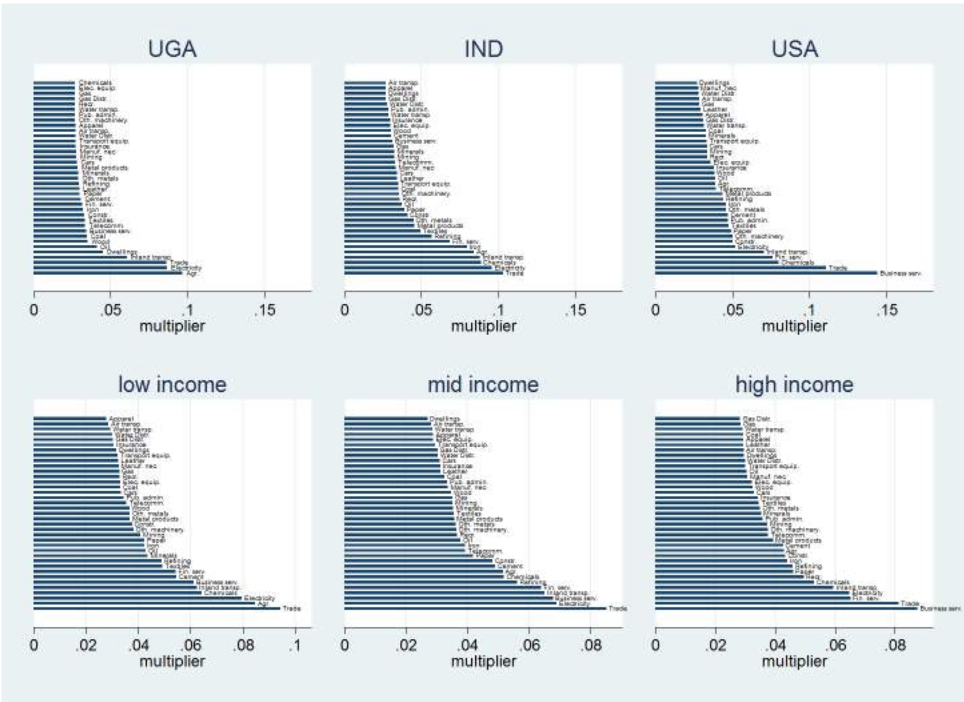

Figure 3: Sectoral IO-multipliers by country (top panel)/ income level (bottom panel)

In the lower panels of the same figure we plot sectoral multipliers averaged across countries by income level. Note that while the distributions of multipliers now look quite similar for different levels of income, this is an aggregation bias, which averages out much of the heterogeneity at the country level. From this figure we see that, in low-income countries, the sectors with the highest multipliers are Trade, Electricity,

[22] A non-parametric Kruskal-Wallis test for equality of the distributions across groups rejects the null of equal distributions across income groups at the one-percent level. We provide more detailed statistical analysis of the shape of the distributions in section 4.1.

[23] One might be concerned that the IO structure in poor countries is mismeasured due to the importance of the informal sector in these countries and that the size of linkages is thus understated (manufacturing census and survey data used to construct IO tables do not include the informal sector). However, the fact that estimated average multipliers do not differ with GDP per capita and that agriculture has strong IO linkages in developing countries, even though most agricultural establishments are in the informal sector, mitigates this concern. In addition, the largest firms in a sector (which operate in the formal economy) typically account for the bulk of sectoral output and inputs and even more so in developing countries (Alfaro et al., 2008), so that the mismeasurement in terms of aggregate output and intermediate input demand is probably small.

Agriculture, Chemicals, and Inland Transport, while in the set of middle- and high-income countries, the most important sectors in terms of multipliers are Trade, Electricity, Business Services, Inland Transport and Financial Services.

Thus, though in all income groups the sectors with the highest multipliers tend to be services, a notable difference between high-multiplier sectors of rich and poor countries is that the former contain exclusively service sectors, while the latter feature non-service sectors – Agriculture and Chemicals.[24] Moreover, the sectors with the lowest multipliers also differ across income levels and the differences in their composition across income groups are larger than those of the sectors with the highest multipliers.[25]

2.3 Productivities

We now explain the construction of a sectoral total factor productivity (TFP) relative to the U.S. and provide some descriptive evidence on sectoral TFPs as well as their correlation with sectoral multipliers. Here, we use the countries in the WIOD sample, because this information is available only for this dataset.

In particular, WIOD contains all the necessary information to compute gross-output-based sectoral total factor productivity: nominal gross output and material use, sectoral capital and labor inputs, sectoral factor payments to labor, capital and inputs for 35 sectors. Crucially, WIOD also provides purchasing power parity (PPP)-deflators (in purchasers' prices) for sector-level gross output that we use to convert nominal values into PPP units and which thus allow us to compute real TFPs at the sector level.[26] These deflators have been constructed by Inklaar and Timmer (2014) and are consistent in methodology and outcome with the latest version of the PWT. They combine expenditure prices and levels collected as part of the International Comparison Program (ICP) with data on industry output, exports and imports and relative prices of exports and imports from Feenstra and Romalis (2014). The authors use export and import values and prices to correct for the problem that the prices of goods consumed or invested domestically do not take into account the prices of exported products, while the prices of imported goods are included. To our knowledge, WIOD combined with these PPP deflators is the best available cross-country dataset for computing sector-level productivities using production data.

Given that we only have information on inputs and outputs in PPPs for a single year, we follow the development/growth accounting literature (e.g. Caselli, 2005; Jorgenson and Stiroh, 2000) and calibrate

[24] Agriculture is a high-multiplier sector in countries with an income level below 10,000 PPP dollars, where agricultural products are an input to many sectors.

[25] In general though, the sectors with the lowest multipliers are also mostly services: Apparel, Air Transport, Water Transport, Gas Distribution and Dwellings (Owner-occupied houses).

[26] WIOD data comprises socio-economic accounts that are defined consistently with the IO tables. We use sector-level data on gross output, physical capital stocks in constant 1995 prices, the price series for investment, and labor inputs in hours. Using the sector-level PPPs for gross output, we convert nominal gross output and inputs into constant 2005 PPP prices. Furthermore, using price series for investment from WIOD and the PPP price index for investment from PWT 7.1, we convert sector-level capital stocks from WIOD into constant 2005 PPP prices.

sector-level production functions. We compute TFP at the sector level relative to the U.S. (measured in constant 2005 PPPs) assuming constant-returns-to-scale Cobb-Douglas sectoral technologies for gross output with *country-sector-specific* input shares:

$$\Lambda_{ic}^{rel} \equiv \frac{\Lambda_{ic}}{\Lambda_{iUS}} = \frac{q_{ic}}{q_{iUS}} \frac{\left(k_{iUS}^{\alpha_{iUS}} l_{iUS}^{1-\alpha_{iUS}}\right)^{1-\gamma_{iUS}} d_{1iUS}^{\gamma_{1iUS}} d_{2iUS}^{\gamma_{2iUS}} \cdot \ldots \cdot d_{niUS}^{\gamma_{niUS}}}{\left(k_{ic}^{\alpha_{ic}} l_{ic}^{1-\alpha_{ic}}\right)^{1-\gamma_{ic}} d_{1ic}^{\gamma_{1ic}} d_{2ic}^{\gamma_{2ic}} \cdot \ldots \cdot d_{nic}^{\gamma_{nic}}}, \tag{1}$$

where i is the sector index and c is the country index. The notation uses Λ_{ic}^{rel} for TFP of sector i normalized relative to the U.S., q_{ic} for the gross output of sector i, k_{ic} and l_{ic} for the quantities of capital and labor inputs and d_{ji} for the quantity of intermediate good j used in the production of sector i; α_{ic}, $1-\alpha_{ic}$ are the empirical factor income shares in GDP, $\gamma_{jic} \in [0,1)$ are the intermediate input shares in gross output from the WIOD IO tables and $\gamma_{ic} = \sum_{j=1}^{n} \gamma_{jic}$.[27] The specification thus features cross-country differences in technology for a given sector, by allowing the output elasticity of any given input j in the production of sector i to vary by country c.

In Table 1 we report means and standard deviations of relative productivities by income level, as well as the correlation between sectoral multipliers and productivities. To compute the standard deviations and correlations, we consider deviations from country means, so they are to be interpreted as within-country variation.

Sample	N	avg. TFP	std. TFP (within)	corr. TFP, mult. (within)
low income	236	0.445	0.950	0.189***
mid income	340	0.619	0.667	0.065
high income	745	1.109	0.475	-0.135***
all	1,321	0.891	0.646	-0.026

Table 1: Descriptive statistics for sectoral TFPs and multipliers.
*** indicates statistical significance at the 1-percent level.

The following empirical regularities arise. First, average sectoral TFPs are highly positively correlated with income per capita. Second, the within-country standard deviation is highest for poor countries and lowest for rich countries, as is also apparent from the left panel of Figure 4, which plots histograms of log relative productivities by income level. Thus, low-income countries have much more dispersion in relative productivities across sectors than rich ones. Third, in low-income countries, TFP levels of high-multiplier sectors are above their average productivity level relative to the U.S., while in richer countries TFP levels

[27] Applying more sophisticated parametric estimation methods developed for plant-level data to obtain consistent estimates of output elasticities (e.g., Olley and Pakes, 1996) is not feasible, since it requires many observations for a given sector. These methods solve the simultaneity bias that arises when estimating the output elasticities of inputs with regression techniques by taking logs of (1), since unobserved TFP is correlated with input choice. Note, however, that using the empirical intermediate input shares γ_{jic} solves this simultaneity problem when the production function is Cobb-Douglas and intermediate inputs are freely adjustable. Under these assumptions the first-order conditions for profit maximization imply that intermediate input shares are independent of (unobserved) TFP.

in these sectors tend to be below average. This is demonstrated by the examples in the center and right panels of Figure 4. For instance, India (center panel) has productivity levels above its average in the high-multiplier sectors Chemicals, Inland Transport and Refining and Electricity, while its productivity levels in the low-multiplier sectors such as Car Retailing, Telecommunications and Business Services are below average. An exception is India's high-multiplier sector Agriculture, where the productivity level is very low. This confirms the general view that poor countries tend to have particularly low productivity levels in this sector. By contrast, rich European economies, such as Germany (right panel), tend to have below-average productivity levels in high-multiplier sectors such as Financial Services, Business Services and Transport.[28]

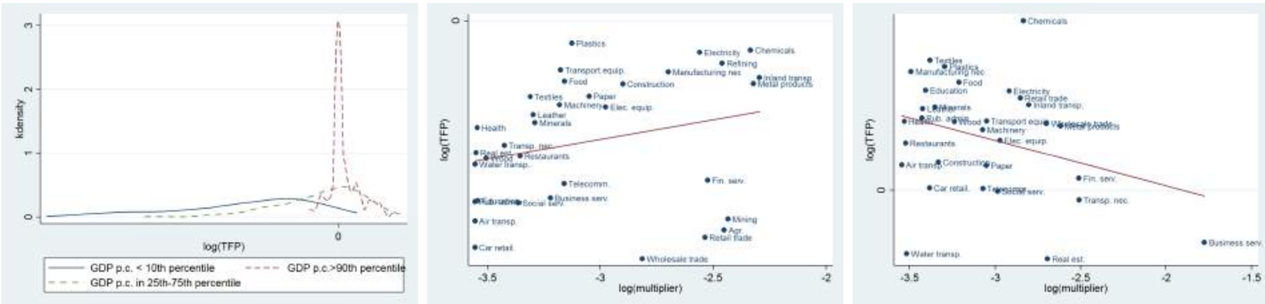

Figure 4: Distribution of sectoral log(TFP) relative to the U.S. (left panel). Correlation between IO-multipliers and productivities: India (middle panel) and Germany (right panel)

3 Theoretical framework

3.1 Model

In this section we present our theoretical framework, which will be used in the remainder of our analysis. Consider a static multi-sector economy. n competitive sectors each produce a distinct good that can be used either for final consumption or as an input for production. The technology of sector $i \in 1 : n$ is Cobb-Douglas with constant returns to scale. Namely, the output of sector i, denoted by q_i, is

$$q_i = \Lambda_i \left(k_i^{\alpha} l_i^{1-\alpha}\right)^{1-\gamma_i} d_{1i}^{\gamma_{1i}} d_{2i}^{\gamma_{2i}} \cdot \ldots \cdot d_{ni}^{\gamma_{ni}}, \tag{2}$$

where Λ_i is the exogenous total factor productivity of sector i, k_i and l_i are the quantities of capital and labor used by sector i and d_{ji} is the quantity of good j used in production of good i (intermediate good produced by sector j).[29] The exponent $\gamma_{ji} \in [0, 1)$ represents the share of good j in the production technology of firms in sector i, and $\gamma_i = \sum_{j=1}^{n} \gamma_{ji} \in (0, 1)$ is the total share of intermediate goods in

[28]While developing a full economic model that explains why in developing countries productivity gaps relative to the U.S. are smaller in high-multiplier sectors and the opposite is true in industrialized countries is beyond the scope of this paper, we provide a tentative explanation in section 4.1.

[29]In section 6 and in the Supplementary Appendix we consider the case of an open economy, where sectors' production technology employs both domestic and imported intermediate goods.

gross output of sector i. Parameters α, $1-\alpha \in (0,1)$ are the shares of capital and labor in the remainder of the inputs (value added).

Given the Cobb-Douglas technology in (2) and competitive factor markets, γ_{ji}'s also correspond to the entries of the IO matrix, measuring the value of spending on input j per dollar of production of good i. We denote this IO matrix by $\mathbf{\Gamma}$. Then the entries of the j'th row of matrix $\mathbf{\Gamma}$ represent the values of spending on a given input j per dollar of production of each sector in the economy. On the other hand, the elements of the i'th column of matrix $\mathbf{\Gamma}$ are the values of spending on inputs from each sector in the economy per dollar of production of a given good i.[30]

Output of sector i can be used either for final consumption, y_i, or as an intermediate good:

$$y_i + \sum_{j=1}^{n} d_{ij} = q_i \qquad i = 1:n \tag{3}$$

Final consumption goods are aggregated into a single final good through another Cobb-Douglas production function:

$$Y = y_1^{\frac{1}{n}} \cdot \ldots \cdot y_n^{\frac{1}{n}}. \tag{4}$$

This aggregate final good is used as households' consumption, C, so that $Y = C$. Note that the symmetry in exponents of the final good production function implies symmetry in consumption demand for all goods. This assumption is useful as it allows us to focus on the effects of the IO structure and the interaction between the structure and sectors' productivities in an otherwise symmetric framework. It is, however, straightforward to introduce asymmetry in consumption demand by defining the vector of demand shares $\boldsymbol{\beta} = (\beta_1, .., \beta_n)$, where $\beta_i \neq \beta_j$ for $i \neq j$ and $\sum_{i=1}^{n} \beta_i = 1$. The corresponding final good production function is then $Y = y_1^{\beta_1} \cdot \ldots \cdot y_n^{\beta_n}$. This more general framework is analyzed in section 6, where we consider extensions of our benchmark model.

Finally, the total supply of capital and labor in this economy are assumed to be exogenous and fixed at the levels of K and 1, respectively:

$$\sum_{i=1}^{n} k_i = K, \tag{5}$$

$$\sum_{i=1}^{n} l_i = 1. \tag{6}$$

To complete the description of the model, we provide a formal definition of a competitive equilibrium.

Definition A competitive equilibrium is a collection of quantities q_i, k_i, l_i, y_i, d_{ij}, Y, C and prices p_i, p, w, and r for $i \in 1:n$ such that

[30] According to our notation, the sum of elements in the i'th column of matrix $\mathbf{\Gamma}$ is equal to γ_i, the total intermediate share of sector i.

1. y_i solves the profit maximization problem of a representative firm in a perfectly competitive final good's market:

$$\max_{\{y_i\}} p y_1^{\frac{1}{n}} \cdot ... \cdot y_n^{\frac{1}{n}} - \sum_{i=1}^{n} p_i y_i,$$

taking $\{p_i\}, p$ as given.

2. $\{d_{ij}\}$, k_i, l_i solve the profit maximization problem of a representative firm in the perfectly competitive sector i for $i \in 1:n$:

$$\max_{\{d_{ji}\},k_i,l_i} p_i \Lambda_i \left(k_i^{\alpha} l_i^{1-\alpha}\right)^{1-\gamma_i} d_{1i}^{\gamma_{1i}} d_{2i}^{\gamma_{2i}} \cdot ... \cdot d_{ni}^{\gamma_{ni}} - \sum_{j=1}^{n} p_j d_{ji} - r k_i - w l_i,$$

taking $\{p_i\}$ as given (Λ_i is exogenous).

3. Households' budget constraint determines C: $C = w + rK$.

4. Markets clear:

   (a) r clears the capital market: $\sum_{i=1}^{n} k_i = K$,

   (b) w clears the labor market: $\sum_{i=1}^{n} l_i = 1$,

   (c) p_i clears the sector i's market: $y_i + \sum_{j=1}^{n} d_{ij} = q_i$,

   (d) p clears the final good's market: $Y = C$.

5. Production function for q_i is $q_i = \Lambda_i \left(k_i^{\alpha} l_i^{1-\alpha}\right)^{1-\gamma_i} d_{1i}^{\gamma_{1i}} d_{2i}^{\gamma_{2i}} \cdot ... \cdot d_{ni}^{\gamma_{ni}}$.

6. Production function for Y is $Y = y_1^{\frac{1}{n}} \cdot ... \cdot y_n^{\frac{1}{n}}$.

Note that households' consumption is simply determined by the budget constraints, so that there is no decision for the households to make. Moreover, total production of the aggregate final good, Y, which is equal to $\sum_{i=1}^{n} p_i y_i$, represents real GDP (total value added) per capita.

3.2 Equilibrium

The following proposition characterizes the equilibrium value of the logarithm of GDP per capita, which we later refer to equivalently as aggregate output or aggregate income or value added of the economy.

Proposition 1. *There exists a unique competitive equilibrium. In this equilibrium, the logarithm of GDP per capita, $y = \log(Y)$, is given by*

$$y = \sum_{i=1}^{n} \mu_i \lambda_i + \sum_{i=1}^{n} \sum_{j \ s.t. \ \gamma_{ji} \neq 0} \mu_i \gamma_{ji} \log \gamma_{ji} + \sum_{i=1}^{n} \mu_i (1-\gamma_i) log(1-\gamma_i) - \log n + \alpha \log K, \tag{7}$$

where

$$\begin{aligned} \boldsymbol{\mu} &= \{\mu_i\}_i = \frac{1}{n}[\boldsymbol{I} - \boldsymbol{\Gamma}]^{-1}\mathbf{1}, && n \times 1 \textit{ vector of multipliers} \\ \boldsymbol{\lambda} &= \{\lambda_i\}_i = \{\log \Lambda_i\}_i, && n \times 1 \textit{ vector of sectoral log-productivity coefficients} \end{aligned}$$

Proof. The proof of Proposition 1 is provided in the Supplementary Appendix.

Thus, due to the Cobb-Douglas structure of our economy, aggregate per capita GDP can be represented as a log-linear function of (i) terms representing aggregate productivity and summarizing the aggregate impact of sectoral productivities via the IO structure; and (ii) the capital stock per worker weighted by the capital share in GDP, α.

The proposition highlights two important facts. First, aggregate output is an increasing function of sectoral productivity levels. Second, and more importantly, the impact of each sector's productivity on aggregate output is proportional to the value of the sectoral IO multiplier μ_i, and hence, the larger the multiplier, the stronger the effect. This means that the positive effect of higher sectoral productivity on aggregate output is stronger in sectors with larger multipliers.[31]

The vector of sectoral multipliers, in turn, is determined by the features of the IO matrix through the Leontief inverse, $[\boldsymbol{I} - \boldsymbol{\Gamma}]^{-1}$.[32] The interpretation and properties of this matrix as well as a simpler representation of the vector of multipliers are discussed in the next section.

3.3 Intersectoral network. Multipliers as sectors' centrality

The input-output matrix $\boldsymbol{\Gamma}$, where a typical element γ_{ji} captures the value of spending on input j per dollar of production of good i, can be equivalently represented by a directed weighted network on n nodes. Nodes of this network are sectors and directed links indicate the flow of intermediate goods between sectors. Specifically, the link from sector j to sector i with weight γ_{ji} is present if sector j is an input supplier to sector i.

For each sector in the network we define the *weighted in-* and *out-degree.* The weighted in-degree of a sector is the share of intermediate inputs in its production. It is equal to the sum of elements in the corresponding *column* of matrix $\boldsymbol{\Gamma}$; that is, $d_i^{in} = \gamma_i = \sum_{j=1}^{n} \gamma_{ji}$. The weighted out-degree of a sector is the share of its output in the input supply of the entire economy. It is equal to the sum of elements in the corresponding *row* of matrix $\boldsymbol{\Gamma}$; that is, $d_j^{out} = \sum_{i=1}^{n} \gamma_{ji}$. Note that if the weights of all links that are present in the network are identical, the in-degree of a given sector is proportional to the number of sectors that supply to it and its out-degree is proportional to the number of sectors to which it is a

[31] The value of sectoral multipliers is positive due to a simple approximation result (9) in the next section.

[32] See Burress (1994).

supplier.

The interdependence of sectors' production technologies through the network of intersectoral trade helps to obtain some insights into the meaning of the Leontief inverse matrix $[\boldsymbol{I} - \boldsymbol{\Gamma}]^{-1}$ and the vector of sectoral multipliers $\boldsymbol{\mu}$.[33] A typical element l_{ji} of the Leontief inverse can be interpreted as the percentage increase in the output of sector i following a one-percent increase in productivity of sector j. This result takes into account all – direct and indirect – effects at work, such as for example, the effect of raising productivity in sector A that makes sector B more efficient and via this raises the output in sector C. Then multiplying the Leontief inverse matrix by the vector of weights $\frac{1}{n}\mathbf{1}$ adds up the effects of sector j on all the other sectors in the economy, weighting each by its share $\frac{1}{n}$ in GDP. Thus, a typical element of the resulting vector of IO multipliers reveals how a one-percent increase in productivity of sector j affects the overall value added in the economy.

In particular, for a simple one-sector economy, the multiplier is given by $\frac{1}{1-\gamma}$, where γ is a share of the intermediate input in the production of that sector. Moreover, $\frac{1}{1-\gamma}$ is also the value of the *aggregate* multiplier in an n-sector economy where only one sector's output is used (in the proportion γ) as an input in the production of all other sectors.[34] Thus, if the share of intermediate inputs in gross output of each sector is, for example, $\frac{1}{2}$ ($\gamma = \frac{1}{2}$), then a one-percent increase in TFP of each sector increases aggregate value added by $\frac{1}{1-\gamma} = 2$ percent. In more extreme cases, the aggregate multiplier – and hence, the effect of sectoral TFP improvements on aggregate value added – becomes infinitely large when $\gamma \to 1$ and it is close to 1 when $\gamma \to 0$. This is consistent with the intuition in Jones (2011b).

One important observation is that the vector of multipliers is closely related to the *Bonacich centrality* vector corresponding to the intersectoral network of the economy.[35] This means that sectors that are more "central" in the network of intersectoral trade have larger multipliers and hence, play a more important role in determining aggregate output.

To see what centrality means in terms of simple network characteristics, such as sectors' out-degree, consider the following useful approximation for the vector of multipliers. Since none of $\boldsymbol{\Gamma}$'s eigenvalues lie outside the unit circle (cf. footnote 33), the Leontief inverse and hence the vector of multipliers can be expressed in terms of a convergent power series:

$$\boldsymbol{\mu} = \frac{1}{n}[\boldsymbol{I} - \boldsymbol{\Gamma}]^{-1}\mathbf{1} = \frac{1}{n}\left(\sum_{k=0}^{+\infty}\boldsymbol{\Gamma}^k\right)\mathbf{1}.$$

[33]Observe that in this model the Leontief inverse matrix is well-defined since CRS technology of each sector implies that $\gamma_i < 1$ for any $i \in 1:n$. According to the Frobenius theory of non-negative matrices, this means that the maximal eigenvalue of $\boldsymbol{\Gamma}$ is bounded above by 1, and this, in turn, implies the existence of $[\boldsymbol{I} - \boldsymbol{\Gamma}]^{-1}$.

[34]Recall that aggregate multiplier is equal to the sum of all sectoral multipliers and represents the effect on aggregate income of a one-percent increase in the productivity of each sector.

[35]An analogous observation is made in Acemoglu et al. (2012), with respect to the *influence vector*. For the definition and other applications of the Bonacich centrality notion in economics see Bonacich, 1987; Jackson, 2008; and Ballester et al., 2006.

As long as the elements of $\mathbf{\Gamma}$ are sufficiently small, this power series is well approximated by the sum of the first terms. Namely, consider the norm of $\mathbf{\Gamma}$, $\|\mathbf{\Gamma}\|_\infty = \max_{i,j\in 1:n}\gamma_{ji}$, and assume that it is sufficiently small. Then

$$\frac{1}{n}\left(\sum_{k=0}^{+\infty}\mathbf{\Gamma}^k\right)\mathbf{1} \approx \frac{1}{n}(\boldsymbol{I}+\mathbf{\Gamma})\mathbf{1} = \frac{1}{n}\mathbf{1} + \frac{1}{n}\mathbf{\Gamma}\mathbf{1}.$$

Consider that $\mathbf{\Gamma}\mathbf{1} = \boldsymbol{d^{out}}$, where $\boldsymbol{d^{out}}$ is the vector of sectoral out-degrees, $\boldsymbol{d^{out}} = \left(d_1^{out}, .., d_n^{out}\right)'$. This leads to the following simple representation of the vector of multipliers:

$$\boldsymbol{\mu} \approx \frac{1}{n}\mathbf{1} + \frac{1}{n}\boldsymbol{d^{out}}, \tag{8}$$

so that for any sector i,

$$\mu_i \approx \frac{1}{n} + \frac{1}{n}d_i^{out}, \qquad i = 1:n. \tag{9}$$

Thus, larger multipliers correspond to sectors with larger out-degree, the simplest measure of sector's centrality in the network. In view of Proposition 1, this implies that sectors with the largest out-degree have the most pronounced impact on aggregate value added of the economy.

For the sample of countries in our data, both rich and poor, the approximation of sectoral multipliers by sectoral out-degree (times and plus $1/n$) turns out to be quite good, as demonstrated by Figure 5.

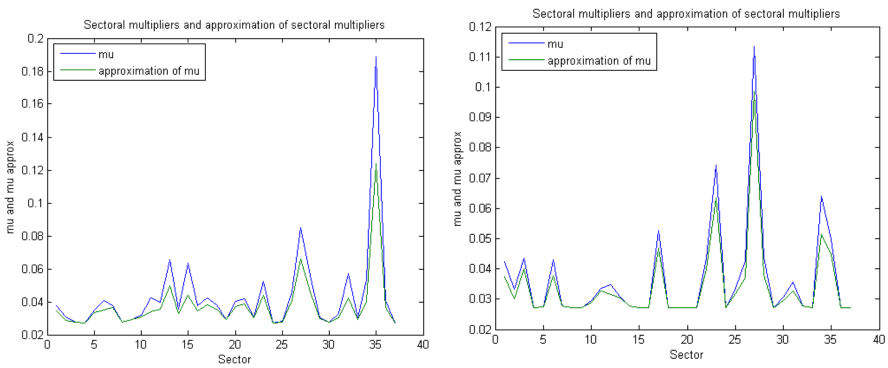

Figure 5: Sectoral multipliers in Germany (left) and Botswana (right). GTAP sample.

This close fit is further confirmed by the observation that – just like the empirical distribution of sectoral multipliers – the distribution of sectoral out-degrees in all countries possesses a fat tail: while putting most weight on small values of out-degrees, it assigns a non-negligible weight to the out-degrees that are way above the average. By contrast, the observed distribution of sectoral in-degrees (intermediate input shares) appears to be strongly peaked around the mean value. This suggests that while on the demand side sectors are rather homogeneous, i.e., they use intermediate goods in approximately equal proportions, this is in sharp contrast with the observed heterogeneity on the supply side: relatively few sectors supply their product to a large number of sectors in the economy, while many sectors supply to just a few. The left panel of Figure 9 in section 6 presents the empirical distributions of in-degrees for different levels of per capita income for the countries in the WIOD sample and Figure A-2 in the Supplementary Appendix plots the distributions of in- and out-degrees for the countries in the GTAP sample.

3.4 Expected aggregate output

To estimate our baseline model we use a statistical approach that allows us to represent aggregate income as a simple function of the first and second moments of the distribution of the IO multipliers and sectoral productivities. The distribution of multipliers, or sectors' centralities, captures the properties of the intersectoral network in each country, while the correlation between the distribution of multipliers and productivities captures the interaction of the IO structure with sectoral TFP levels.

Figures 2 and 4 in section 2 suggest that the *joint* distribution of sectoral log multipliers and log productivities (relative to the U.S.), $(\log(\mu_i), \log(\Lambda_i^{rel}))$, is close to *Normal*, so that the joint distribution of levels of the corresponding variables, (μ_i, Λ_i^{rel}), is *log-Normal*.[36] Here i refers to the sector and $\Lambda_i^{rel} = \frac{\Lambda_i}{\Lambda_i^{US}}$. In particular, the fact that the distribution of μ_i is log-Normal means that while the largest probability is assigned to relatively low values of a multiplier, a non-negligible weight is assigned to high values, too. That is, the distribution is positively skewed, or possesses a fat right tail. Empirically, we find that the tail is fatter in countries with lower income.[37]

Given the log-Normal distribution of (μ_i, Λ_i^{rel}), the expected value of aggregate output in each country can be evaluated using the expression for y in (7). This requires a few simplifying assumptions on our theoretical model. First, we consider that for each sector i the couple (μ_i, Λ_i^{rel}) is drawn from the *same* bivariate log-Normal distribution, that is, it is independent of the sector (but obviously country specific). Second, we assume that all variables on the right-hand side of (7), apart from μ_i and Λ_i^{rel}, are not random. Moreover, we consider that the in-degree γ_i is independent of the sector, $\gamma_i = \gamma$ for all i, which is broadly consistent with the empirical homogeneity of intermediate input shares across sectors (see previous section).[38] In the baseline model we also adopt a coarse approximation that all non-zero elements of the input-output matrix $\mathbf{\Gamma}$ are the same, that is, $\gamma_{ji} = \widehat{\gamma}$ for any i and j whenever $\gamma_{ji} > 0$. In the robustness checks we show that the empirical predictions of our baseline model for cross-country differences remain practically unchanged when the latter assumption is relaxed and γ_{ji} are considered as random draws from a log-Normal distribution (see section 6 and the Supplementary Appendix).[39]

[36] To be precise, the distribution of $(\log(\mu_i), \log(\Lambda_i^{rel}))$ is a *truncated* bivariate Normal, where $\log(\mu_i)$ is censored from below at a certain $a < 0$. This is taken into account in our empirical analysis. However, the difference from a usual, non-truncated Normal distribution turns out to be inessential. Therefore, for simplicity of exposition, in this section we refer to the distribution of $(\log(\mu_i), \log(\Lambda_i^{rel}))$ as Normal and to the distribution of (μ_i, Λ_i^{rel}) as log-Normal.

[37] See the distribution parameter estimates in the next section.

[38] The assumption of constant in-degree is also employed in Acemoglu et al. (2012) and in Carvalho et al.(2010).

[39] Note that our conditions on γ_{ji} and γ allow us to express $\sum_{j \text{ s.t. } \gamma_{ji} \neq 0} \mu_i \gamma_{ji} \log \gamma_{ji}$ as $\mu_i \gamma \log(\widehat{\gamma})$ since the number of non-zero elements in each column of $\mathbf{\Gamma}$ is equal to $\frac{\gamma}{\widehat{\gamma}}$, and $\sum_{i=1}^{n} \mu_i (1-\gamma_i) log(1-\gamma_i) = log(1-\gamma)$ since $\sum_{i=1}^{n} \mu_i (1-\gamma_i) = \mathbf{1}'[\boldsymbol{I} - \mathbf{\Gamma}]\cdot$

Finally, in order to express sectoral log productivity coefficients λ_i in terms of the relative productivity Λ_i^{rel}, we use the approximation $\lambda_i = \log(\Lambda_i) \approx \Lambda_i^{rel} + \big(\log(\Lambda_i^{US}) - 1\big)$, which, strictly speaking, is only good when Λ_i is sufficiently close to Λ_i^{US}.

Under these assumptions, the expression for the aggregate output y in (7) simplifies and can be written as:

$$y = \sum_{i=1}^{n} \mu_i \Lambda_i^{rel} + \sum_{i=1}^{n} \mu_i \gamma \log(\widehat{\gamma}) + \log(1-\gamma) - \log n + \alpha \log(K) - (1+\gamma) + \sum_{i=1}^{n} \mu_i \log(\Lambda_i^{US}). \qquad (10)$$

The expected aggregate output, $E(y)$, is then equal to :

$$\begin{aligned} E(y) &= n\Big(E(\mu)E(\Lambda^{rel}) + cov(\mu, \Lambda^{rel})\Big) + (1+\gamma)(\gamma \log(\widehat{\gamma}) - 1) + \\ &\quad + \log(1-\gamma) - \log n + \alpha \log(K) + E(\mu) \sum_{i=1}^{n} \log\left(\Lambda_i^{US}\right). \qquad (11) \end{aligned}$$

From this expression, we see that higher expected multipliers $E(\mu)$ lead to larger expected income $E(y)$ for the same fixed levels of $E(\Lambda^{rel})$ and covariance $cov(\mu, \Lambda^{rel})$. Moreover, since aggregate value added depends positively on the covariance term $cov(\mu, \Lambda^{rel})$, higher relative productivities have a larger impact if they occur in sectors with higher multipliers.

The expression for expected aggregate income in (11) can be written in terms of the parameters of the normally distributed $(\log(\mu), \log(\Lambda^{rel}))$, by means of the relationships between Normal and log-Normal distributions:[40]

$$\begin{aligned} E(y) &= n\left(e^{m_\mu + m_\Lambda + 1/2(\sigma_\mu^2 + \sigma_\Lambda^2) + \sigma_{\mu,\Lambda}}\right) + (1+\gamma)(\gamma \log(\widehat{\gamma}) - 1) + \\ &+ \quad \log(1-\gamma) - \log n + \alpha \log(K) + e^{m_\mu + 1/2\sigma_\mu^2} \sum_{i=1}^{n} \log\left(\Lambda_i^{US}\right), \qquad (13) \end{aligned}$$

where m_μ, m_Λ are the means and σ_μ^2, σ_Λ^2 and $\sigma_{\mu,\Lambda}$ are the elements of the variance-covariance matrix of the Normal distribution. This is the final expression that we use in the empirical analysis of the benchmark model in the next section.

$\frac{1}{n}[\boldsymbol{I}-\boldsymbol{\Gamma}]^{-1}\mathbf{1} = \frac{1}{n}\mathbf{1}'\mathbf{1} = 1$. Moreover, $\sum_{i=1}^{n} \mu_i \approx 1+\gamma$ because from (9) it follows that $\sum_{i=1}^{n} \mu_i \approx 1 + \frac{\sum_{i=1}^{n} d_i^{out}}{n} = 1 + \frac{\sum_{i=1}^{n} d_i^{in}}{n}$ and $d_i^{in} = \gamma_i = \gamma$ for all i.

[40] These relationships are:

$$E(\mu) = e^{m_\mu + 1/2\sigma_\mu^2}, \qquad E(\Lambda^{rel}) = e^{m_\Lambda + 1/2\sigma_\Lambda^2}, \qquad cov(\mu, \Lambda) = e^{m_\mu + m_\Lambda + 1/2(\sigma_\mu^2 + \sigma_\Lambda^2)} \cdot (e^{\sigma_{\mu,\Lambda}} - 1)\,. \qquad (12)$$

4 Empirical analysis

In this section we estimate the parameters of the Normal distribution of $(\log(\mu), \log(\Lambda^{rel}))$ for the sample of countries for which we have data. We allow parameter estimates to vary across countries in order to model the systematic underlying differences in IO structure and productivity that we have discussed in section 2. With the parameter estimates in hand we then use equation (13) to evaluate the predicted aggregate income in these countries and compare our baseline model with four simple alternatives which abstract from some of the elements present in our model: (i) sectoral TFP differences; (ii) IO linkages; (iii) country-specific IO structure. We show that all these elements are important for understanding cross-country income differences.

4.1 Structural estimation

We assume that the vector of log multipliers and log relative productivities $\mathbf{Z} \equiv (\log(\mu), \log(\Lambda^{rel}))$ is drawn from a (truncated) bivariate Normal distribution with country-specific parameters $\mathbf{\Theta} = (\mathbf{m}, \mathbf{\Sigma})$, where $\mathbf{m}$ is the vector of means and $\mathbf{\Sigma}$ denotes the variance-covariance matrix. In order to allow the distributions of log multipliers and productivities to differ across countries, we first estimate the parameters separately for each country using Maximum Likelihood.[41] Observe that in the estimation we do not impose any structure on the data except for assuming joint log-Normality. In a second step, we then regress the estimated country-specific parameters $\hat{\mathbf{\Theta}}$ on (log) per capita income in order to test if the parameters indeed systematically vary with countries' income level, as suggested by the evidence presented in section 2.[42]

We estimate the statistical model using the empirical data for log multipliers and log TFPs constructed from the WIOD dataset (35 sectors, 36 countries). In the panels of Figure 6 we plot the country-specific estimates of all parameters against (log) per capita GDP and in Table 2 we report the corresponding results of regressing each parameter on log per capita GDP. Because the coefficients are Maximum-Likelihood estimates, we report bootstrapped standard errors. We label the set of predicted values from these regressions $\tilde{\mathbf{\Theta}}$.

We find that m_μ does not vary systematically with the income level (column (1)). Instead, σ_μ decreases significantly in log per capita GDP with a slope of -0.076 (column (2)). Thus, in the WIOD

[41] The formula for the truncated bivariate Normal, where $\log(\mu)$ is censored from below at a is given by $f(\mathbf{Z}|log(\mu) \geq a) = \frac{1}{\sqrt{(2\Pi)^2|\mathbf{\Sigma}|}} exp[-1/2(\mathbf{Z}-\mathbf{m})'\mathbf{\Sigma}^{-1}(\mathbf{Z}-\mathbf{m})]/(1-F(a))$, where $F(a) = \int_{-\infty}^{a} \frac{1}{\sigma_\mu \sqrt{(2\Pi)}} exp[-1/2(\log(\mu)-m_\mu)^2/\sigma_\mu^2] d\log(\mu)$ is the cumulative marginal distribution of $\log(\mu)$ and where

$$\mathbf{m} = \begin{pmatrix} m_\mu \\ m_\Lambda \end{pmatrix}, \mathbf{\Sigma} = \begin{pmatrix} \sigma_\mu^2 & \sigma_{\mu,\Lambda} \\ \sigma_{\mu,\Lambda} & \sigma_\Lambda^2 \end{pmatrix}. \tag{14}$$

[42] We obtain very similar results by using an alternative, one-step procedure where we pool observations across countries and model coefficients as linear functions of (log) per capita income. Such approach is statistically more efficient than our two-step procedure, but it also imposes more structure on the data ex ante, which we would like to avoid.

sample, poor countries have a distribution of log multipliers with the same average but with more dispersion than rich countries. Average log productivity, m_Λ, increases strongly in log per capita GDP (with a slope of around 1.4, see column (3)), while the standard deviation of log productivity, σ_Λ, is a decreasing function of the same variable (column (4)). This implies that rich countries have much higher average productivity levels and less dispersion in relative productivities across sectors than poor economies. Finally, note that the covariance between log multipliers and log productivity, $\sigma_{\mu,\Lambda}$, has a positive intercept and is a decreasing function of log per capita GDP (column (5)). Hence, poor countries have above-average productivity levels in sectors with higher multipliers, and the opposite is the case in rich countries.[43]

While developing a full economic model that explains the difference in covariance signs across countries is beyond the scope of this paper, one potential explanation could be as follows. Consider a model where adoption of technology from a sector-specific frontier is costly, whereas the profitability of adoption depends on market size effects[44] and the IO structure is given. Observe that the country-sector-specific multiplier is a proxy for market size and thus profitability. Then all countries will adopt technologies that are relatively closer to the frontier in sectors with larger multipliers. However, since in industrialized countries the (exogenously given) IO structure is similar to the one in the U.S.,[45] their high- and low-productivity sectors will be similar, so that TFP levels *relative* to the U.S. appear uncorrelated with multipliers. Moreover, even given a similar IO structure, distortions that make technology adoption in specific sectors less profitable may induce particularly large productivity gaps of European countries relative to the U.S. in high-multiplier sectors, such as services. This could then even lead to negative correlations between relative TFP levels and multipliers. By contrast, in developing countries, where the IO structure is different from the one in industrialized countries, the set of high-productivity sectors will also be different from those of the U.S., generating a positive correlation between relative TFP levels and multipliers.

To obtain more information on the IO structure of low-income countries, we now redo the estimation using data for the GTAP sample (37 sectors, 65 countries). For this sample, we only have information on IO multipliers but not on productivity levels available. Therefore, we estimate a univariate (truncated) Normal distribution for m_μ and σ_μ for each country. The results of regressing the country-specific parameter estimates on log per capita GDP are reported in columns (6) and (7) of Table 2. The results

[43] The sign of the covariance changes at per capita GDP of approximately 22,026 ($= e^{10}$) PPP Dollars.

[44] Due to the standard economies-of-scale argument (Romer, 1990). Similarly, recent studies show a positive effect of the intensity with which a sector's output is used as input by other sectors on the speed of technology adoption (Comin and Hobijn, 2004; Magalhãesa and Afonso, 2017).

[45] The distributions of IO multipliers and the composition of top-multiplier sectors are similar across high-income countries and different from those of the low-income ones (see section 2.2). For example, Financial and Business services tend to have highest multipliers in industrialized countries but relatively low multipliers in developing countries, where sectors like Agriculture, Electricity and Chemicals posses the highest multipliers.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	WIOD sample					GTAP sample	
	m_μ	σ_μ	m_Λ	σ_Λ	$\sigma_{\mu,\Lambda}$	m_μ	σ_μ
Constant	-5.462***	1.461***	-14.216***	3.606***	2.320***	-8.749***	1.868***
	(1.125)	(0.392)	(2.119)	(0.619)	(0.478)	(2.959)	(0.443)
log(GDP p.c.)	0.168	-0.076*	1.396***	-0.303***	-0.234***	0.368	-0.100**
	(0.112)	(0.039)	(0.209)	(0.061)	(0.047)	(0.300)	(0.046)
R-squared	0.002	0.046	0.590	0.557	0.343	0.012	0.057
Observations	36	36	36	36	36	65	65

Table 2: Regression of estimated country-specific parameters on log per capita GDP. Bootstrapped standard errors in parentheses. Estimates significant at 1% (***), 5% (**), 10% (*) significance level.

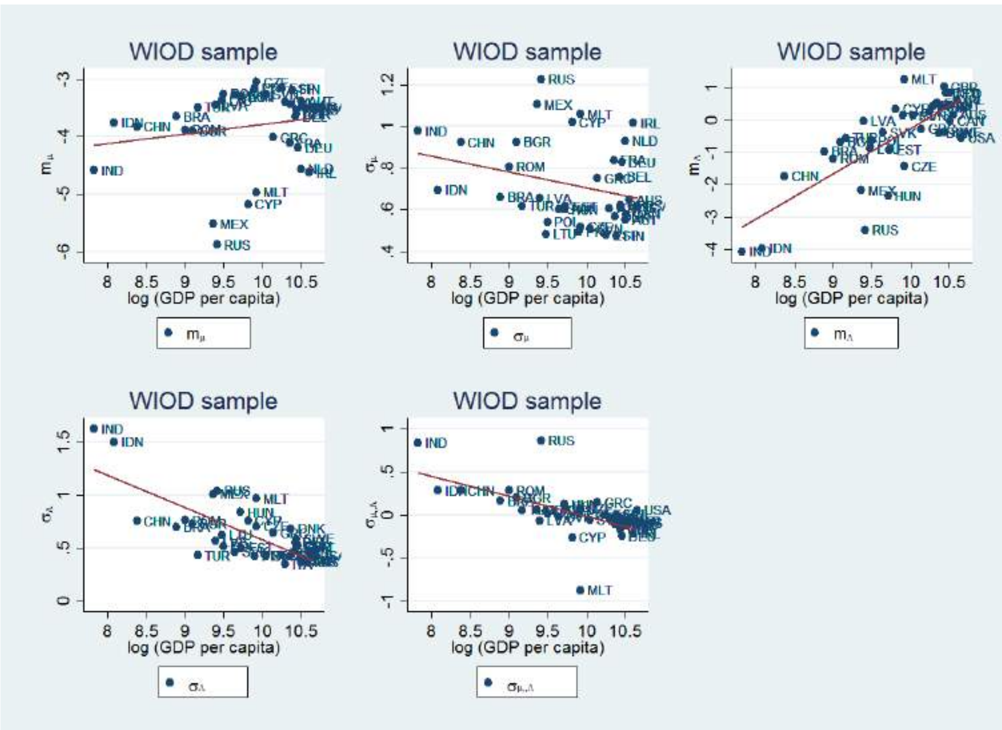

Figure 6: Correlation of country-specific coefficient estimates with log per capita GDP.

are quite similar to those for the WIOD sample: m_μ does not vary significantly with the income level (column (6)), while the standard deviation of log multipliers, σ_μ, is a decreasing function of (log) per capita income with a slope of -0.1 (column (7)). Again, this implies that in poor countries the average sector has the same log multiplier but there is more mass at the extremes of the distribution than in rich countries. We summarize these empirical findings below.

Summary of estimation results:

1. *The estimated distribution of log IO multipliers has a larger variance with more mass at the extremes in poor countries compared to rich ones.*

2. *The estimated distribution of log productivities has a lower mean and a larger variance in poor countries compared to rich ones.*

3. *Log IO multipliers and productivities correlate positively in poor countries and negatively in rich ones.*

4.2 Predicting cross-country income differences

We now plug the predicted values from the regressions of coefficient estimates on log per capita GDP, $\tilde{\mathbf{\Theta}}$, into the expression (13) for expected per capita GDP derived from the baseline model to forecast per capita income levels.[46] The remaining parameters are calibrated as follows. We set $(1-\alpha)$, the labor-income share in GDP, equal to 2/3 and we set n equal to 35, which corresponds to the number of sectors in the WIOD dataset.

4.2.1 Methodology

We compare our baseline model, which features country-specific IO linkages and sectoral productivity differences, with four simple alternatives. The first one has no IO structure and no productivity differences, so that $y = E(y) = \alpha log(K)$. The second model, by contrast, features sectoral productivity differences but no IO linkages. It is easy to show that under the assumption that sectoral productivities follow a log-Normal distribution, predicted log income in this model is given by $E(y) = e^{m_\Lambda + 1/2\sigma_\Lambda^2} + \alpha \log(K) + \frac{1}{n}\sum_{i=1}^{n}(\log(\Lambda_i^{US})) - 1$.[47] The third alternative model features sectoral productivity differences and IO linkages but keeps the IO structure constant across countries (by restricting the mean and the variance of the distribution of log multipliers and its covariance with log

[46] The expression for $E(y)$ for the *truncated* distribution of (μ_i, Λ_i^{rel}) is somewhat more complicated and less intuitive than (13). However, the results for aggregate income using a truncated normal distribution for μ are very similar to the estimation of (13) and we therefore use the formulas for the non-truncated distribution. The details can be provided by the authors.

[47] $Y = \prod_{i=1}^{n} \Lambda_i^{1/n}(K)^\alpha$, hence $y = \frac{1}{n}\sum_{i=1}^{n}\lambda_i + \alpha\log(K)$. Using our approximation for productivity relative to the U.S., taking expectations and assuming that Λ_i^{rel} follows a log-Normal distribution, we obtain the above formula.

productivities to be constant across countries). Finally, the last model allows for country-specific IO linkages but has no productivity differences.

To evaluate model performance, we provide several measures of fit. Our main measure of success in replicating cross-country income variation with the model is given by

$$\textbf{Success} \equiv \frac{\textit{coeff.var.}(Y)}{\textit{coeff.var.(GDP p.c.)}}, \tag{15}$$

where *coeff.var.(Y)* is the coefficient of variation (the standard deviation divided by the mean) of model-predicted income and *coeff.var.(GDP p.c.)* is the coefficient of variation of actual per capita GDP. Observe that the coefficient of variation is a standard scale-less measure of dispersion. **Success** compares the model-predicted variation in Y to the observed variation in GDP per capita, and the closer its value to one, the more successful the model at explaining cross-country income differences.[48] If the model generates less (more) variation in per capita income than is present in the data, **Success** will be smaller (larger) than unity.

Next, as a graphical measure for the goodness of fit, we plot model-predicted income relative to the U.S. against actual relative income (relative per capita GDP). Perfect fit would mean that the predicted relative income levels lie exactly on the 45-degree line. Finally, to statistically evaluate this graphical measure of fit, we regress model-predicted income relative to the U.S. on data for actual relative per capita GDP. If the model fits data perfectly, the estimate for the intercept should be zero *and* the regression slope *and* the R-squared should equal unity.

Note that these tests provide over-identification restrictions for our model, since there is no intrinsic reason for the model to fit data on relative per capita income well: we have not matched income data in order to estimate the parameters of the distribution of log IO multipliers and TFPs. Instead, we have just allowed their joint distribution to vary with the level of per capita income in the estimation procedure.

4.2.2 Analysis with WIOD sample

We first predict income levels for the sample of WIOD countries (36 countries), then for the GTAP sample (65 countries) and finally for the Penn-World-Table sample (155 countries). Starting with the WIOD sample, the results of **Success** and the regression statistics are reported in Table 3. In column (1), we report statistics for the model without TFP differences and IO structure. In column (2), we report results for the model with productivity differences but no IO structure. In column (3) we report

[48] Caselli (2005) instead uses the ratio of variances of log income generated by the model relative to the data as his main measure of success. While the variance of the log is also scale-less, it gives more weight to countries with small income levels. By contrast, we would like to weight observations equally.

results for our baseline model described by (13), where we take the parameter estimates obtained from the WIOD data.[49] In column (4) we report results for the baseline model when estimating the distribution of multipliers using the GTAP data.[50] In column (5), we force the distribution of multipliers (IO structure) to be the same across countries by restricting m_{μ}, σ_{μ}^2 and $\sigma_{\mu,\Lambda}$ to be constant . Finally, in column (6) we report results for the model with varying IO structure but without productivity differences.

We now present the results of this exercise. The model without TFP differences and IO structure fails to generate sufficient variation in per capita income (see column (1) of Table 3 and the green squares in the left panel of Figure 7). **Success** is 0.64, which means that this model can explain 64% of income variation in the sample. Not surprisingly, it over-predicts income levels for poor countries. By contrast, the model with productivity differences but no IO linkages (column (2)) generates *more* income variation than is present in the data (**Success** is 1.43) since it makes many countries significantly poorer than they actually are (red triangles in the upper panel of Figure 7). This implies that, when disregarding the role of the IO linkages, the TFP differences estimated from sectoral data are larger than those necessary to generate the observed cross-country income differences.

We now move to the specifications that include an IO structure. In column (3) we report results for our baseline model with productivity differences and varying IO structure, as estimated from WIOD data. This model indeed performs much better than the ones without IO structure in terms of predicting cross-country income variation: **Success** for this model is 1.10, so the model just slightly overpredicts cross-country income variation. A visual comparison of actual vs. predicted relative income in the left panel of Figure 7 confirms the substantially better fit of the model with IO linkages and productivity differences (blue circles) compared to the one without IO structure, which underpredicts relative income levels of most countries, and the one without IO structure and productivity differences, which overpredicts relative income levels for virtually all countries.[51] In column (5) we alternatively use the IO structure estimated from the GTAP sample in our baseline IO model. The GTAP data is more informative about cross-country differences in IO linkages than the WIOD data because it includes a much larger sample of low- and middle-income countries, which allows estimating differences in structure across countries more precisely. In particular, the estimates from the GTAP data indicate that poorer countries have a distribution of log multipliers with a significantly larger variance compared to rich countries. Using these estimates, we obtain a **Success** of 1.07. Thus, this specification performs comparably to the one with WIOD IO structure.

[49] We use predicted values of the parameters from Table 2, columns (1)-(5).

[50] We use predicted values for the distribution of log multipliers from Table 2, columns (6) and (7).

[51] This improved fit is confirmed by the regression statistics: for the baseline model, the intercept is not statistically different from zero, the slope coefficient equals 1.000 and the R-squared is 0.939. By contrast, the model in column (1) has an intercept of 0.371, a slope coefficient of 0.832 and an R-squared of 0.710; the model in column (2) has an intercept of -0.141, a slope coefficient of 0.967 and an R-squared of 0.927.

Next, we test if the inclusion of an IO structure per se or rather the interaction of cross-country differences in IO structure with productivity differences account for the improved model fit. In column (5) we thus restrict the parameters m_μ, σ_μ^2 and $\sigma_{\mu,\Lambda}$ to be the same for all countries. We find that this model fits the data significantly worse than the one with income-varying IO structure and very similarly to the model without IO structure: **Success** is now 1.45. This implies that cross-country variation in IO structure is crucial for predicting differences in income across countries given estimated productivity differences. Finally, we report results for the model with a varying IO structure but without productivity differences. This model does even worse than the model without TFP differences and IO structure. **Success** goes down to 0.48 since poor countries have more dispersion in log multipliers than rich ones, which exacerbates the problem of models without productivity differences that over-predict income levels of poor countries.[52]

Note that the good fit of the baseline model, with both IO structure and TFP differences, does not simply add up these two components but points to complementarities between them. **Success** of the baseline model (columns (3) and (4)) is 1.07 (1.10), which is an improvement of 36 (33) percentage points compared to the model with productivity differences and no IO structure (column (2)), that overpredicts income differences and has a **Success** of 1.43. Of this number, just introducing an IO structure without considering its interaction with sectoral TFPs (transition from column (1) to column (6)) reduces income differences and explains an improved fit of 16 percentage points (=0.64-0.48), while the rest is due to interaction effects between TFP differences and IO structure.

In conclusion, there are two main factors that determine the improved fit of the baseline model with IO structure compared to the models without IO structure or with constant structure. First, the differences in IO structure between low- and high-income countries: poor countries have only few highly connected sectors and many sectors that are relatively isolated, while rich countries have more intermediately connected sectors. Second, in contrast to rich countries, poor economies have above-average productivity levels in high-multiplier sectors. We will further investigate the impact of each of these factors in the section on counter-factuals.

4.2.3 Analysis with GTAP and PWT samples

Next, we turn to testing model fit in the sample of GTAP countries and the sample of countries in the Penn World Tables. The latter sample is usually employed for development accounting exercises. In Table 4, columns (1)-(4), we present results for the GTAP sample. In column (1) we report results for the model without productivity differences and without IO structure, which has a **Success** of 0.51. In column (2) we present results for the model with productivity differences but no IO structure. As before,

[52] Note that according to (13), larger σ_μ^2 displayed by poor countries increases predicted income in these countries.

	WIOD sample					
	(1)	(2)	(3)	(4)	(5)	(6)
	no IO structure no TFP diff.	no IO structure TFP diff.	WIOD IO structure TFP diff.	GTAP IO structure TFP diff.	constant IO structure TFP diff.	WIOD IO structure no TFP diff.
success	**0.64**	**1.43**	**1.10**	**1.07**	**1.45**	**0.48**
intercept	0.371***	-0.141***	-0.033	-0.023	-0.145***	0.625***
	(0.060)	(0.029)	(0.023)	(0.021)	(0.029)	(0.082)
slope	0.832***	0.967***	1.000***	1.040***	0.963***	0.572***
	(0.101)	(0.051)	(0.039)	(0.039)	(0.052)	(0.126)
R-squared	0.710	0.927	0.939	0.940	0.925	0.453
Observations	36	36	36	36	36	36

Table 3: Model fit: WIOD sample.
Standard errors in parentheses. Estimates significant at 1% (***), 5% (**), 10% (*) significance level.

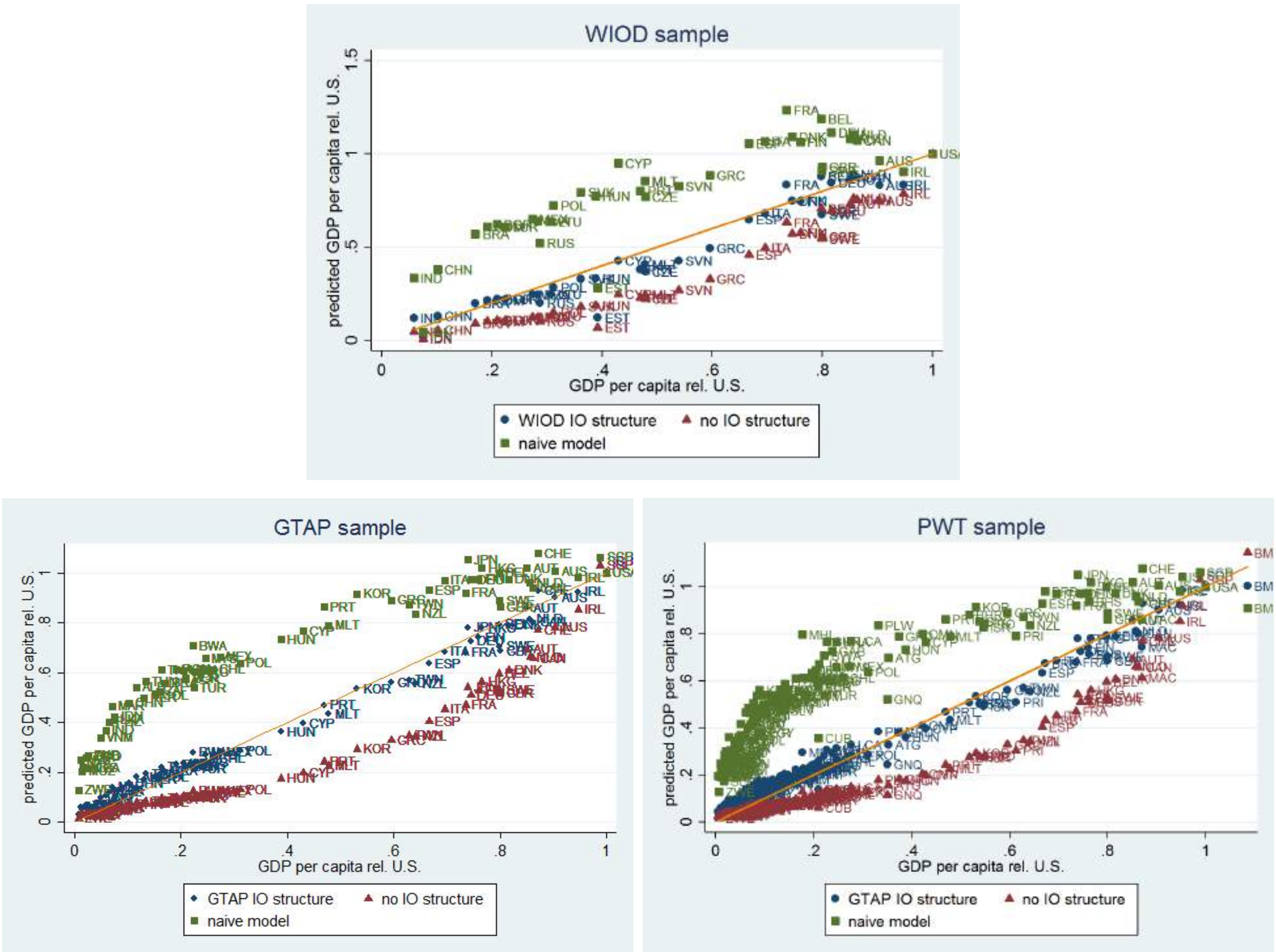

Figure 7: Predicted income per capita: model fit for different samples.

	GTAP sample				PWT sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	no IO structure no TFP diff.	no IO structure TFP diff.	WIOD IO structure TFP diff.	GTAP IO structure TFP diff.	no IO structure no TFP diff.	no IO structure TFP diff.	WIOD IO structure TFP diff.	GTAP IO structure TFP diff.
success	**0.51**	**1.27**	**0.92**	**0.95**	**0.43**	**1.19**	**0.77**	**0.85**
intercept	0.365***	-0.044***	0.054***	0.042***	0.342***	-0.018***	0.073***	0.051***
	(0.022)	(0.013)	(0.008)	(0.005)	(0.012)	(0.006)	(0.004)	(0.003)
slope	0.779***	0.804***	0.839***	0.918***	0.823***	0.763***	0.802***	0.897***
	(0.039)	(0.043)	(0.025)	(0.016)	(0.034)	(0.038)	(0.020)	(0.013)
R-squared	0.887	0.916	0.968	0.987	0.830	0.910	0.965	0.984
Observations	65	65	65	65	155	155	155	155

Table 4: Model Fit: GTAP and PWT Samples.
Standard errors in parentheses. Estimates significant at 1% (***), 5% (**), 10% (*) significance level.

this model overpredicts income variation across countries, with **Success** equal to 1.27. Next, turning to the baseline model with IO structure and productivity differences, in column (3) we report the results using parameter estimates from the WIOD sample. This model performs very well with a **Success** of 0.92. Similarly, the baseline model with parameter estimates from the GTAP sample (column (4)) has a **Success** of 0.95. The increased goodness of fit can also be seen from the left panel of Figure 7, where we plot predicted income against actual income for the baseline model (blue circles), the model without TFP differences and IO structure (green squares) and the model with TFP differences but no IO structure (red triangles). While the model without TFP differences and IO structure considerably over-predicts and the model without IO structure under-predicts relative income levels for most countries, the baseline model with productivity differences and IO structure is extremely close to the 45-degree line. Only for the poorest countries it slightly over-predicts their relative income levels.

Finally, we discuss model fit in the PWT sample (see columns (5)-(8)). This requires to predict not only TFP levels but also IO structure out of sample. As is well known, the performance of the model without productivity differences and IO structure is quite poor in this sample, with a **Success** of around 0.43, as this model strongly over-predicts income levels for poor countries (green squares in the right panel of Figure 7). In column (6) we report results for the model with TFP differences but without IO structure. It has a **Succcess** of 1.19 and thus over-predicts income variation across countries also in this sample (red triangles in the right panel of Figure 7). Turning to the models with both TFP differences and IO structure, they somewhat under-predict income variation in this sample. **Success** is 0.77 for the WIOD IO structure (column (7)) and 0.85 for the GTAP IO structure (column (8)). Still, as the right panel of Figure 7 and the regression statistics make clear, this model fits the data better than the other models: most blue circles are extremely close to the 45-degree line. The exception are very poor economies, whose income levels the model with IO structure over-predicts. Here, the extrapolation of IO structure seems to make too extreme predictions for the distribution of log multipliers and their covariance with TFP. Still, we conclude that including interaction effects between productivity and IO structure into the model helps to significantly improve model fit. To wrap up, we now present a summary of our findings.

Summary of model fit:

1. *The baseline model with estimated sectoral productivity differences and IO structure performs substantially better in terms of predicting cross-country income levels and their variation than a model without productivity differences (which under-predicts income variation) and a model with productivity differences but without IO structure (which over-predicts income variation).*

2. *The above results hold for three different samples of countries: the WIOD dataset (36 countries), the GTAP dataset (65 countries) and the Penn World Tables dataset (155 countries).*

5 Counter-factual experiments

We now present the results of a number of counter-factual experiments. We first investigate in more detail how differences in IO linkages – as summarized by the distribution of multipliers – matter for cross-country income differences. Thus, in our first counter-factual exercise we set the distribution of log multipliers in all countries equal to the U.S. one by fixing m_μ and σ^2_μ at the predicted values of a country at the U.S.-level of per capita income.[53] Note that given the Cobb-Douglas structure, our model allows us to separately identify sectoral TFP levels and IO structure and it thus makes sense to vary one of the two factors, while holding the other one fixed.[54] The result of this experiment is shown in the left panel of Figure 8. It plots the counter-factual percentage change in income per capita against GDP per capita relative to the U.S. As can be seen from the figure, virtually all countries would lose in terms of income if they had the U.S. IO structure. These losses are decreasing in income per capita and range from negligible levels for countries with income levels close to the U.S. one to more than 60 percent of per capita income for very poor countries such as Congo (ZAR) or Zimbabwe (ZWE).

[53]The experiment holds m_μ fixed and reduces σ_μ for virtually all countries, since, according to Table 2, σ_μ is a decreasing function of GDP per capita. For a log-normal distribution such a change shifts mass away from the lower and upper tails towards the center of the distribution.

[54]Note that productivity levels are also unaffected by changes in the distribution of IO multipliers even when technologies are not factor-neutral. To see this, note that labor-augmenting or intermediate-augmenting rather than Hicks-neutral technologies would imply:

$$\begin{aligned} q_i &= \left[k_i^\alpha (\Lambda_i l_i)^{1-\alpha}\right]^{1-\gamma_i} d_{1i}^{\gamma_{1i}} d_{2i}^{\gamma_{2i}} \cdot \ldots \cdot d_{ni}^{\gamma_{ni}}, \\ q_i &= \left(k_i^\alpha l_i^{1-\alpha}\right)^{1-\gamma_i} (\Lambda_i^{\gamma_i}) d_{1i}^{\gamma_{1i}} d_{2i}^{\gamma_{2i}} \cdot \ldots \cdot d_{ni}^{\gamma_{ni}} \end{aligned} \tag{16}$$

Under these assumptions, a change in the γ_{ji}s (reflecting a change in the distribution of multipliers) would potentially also affect measured productivity $\Lambda_i^{(1-\alpha)(1-\gamma_i)}$ or $\Lambda_i^{\gamma_i}$. While this is true in general, given our assumption that the intermediate share $\gamma_i = \sum_{j=1}^N \gamma_{ji}$ is constant across sectors, this is not a concern. Therefore, any change in the underlying IO structure that is implied by a change in the parameters m_μ or σ_μ leaves TFP levels unaffected.

The reason why most countries lose in this counter-factual experiment is the shape of the distribution of log multipliers in the U.S. compared to the one of low-income countries: the typical sector in the U.S. is intermediately connected (the mode of the distribution is larger than in poor countries) and the distribution of (log) multipliers has less mass in the right tail compared to poor countries. Formula (12) then makes it clear that assigning the U.S. distribution to other countries reduces both their average (level) multiplier and the absolute value of the correlation between TFP and multipliers. Given the positive correlation of TFP and multipliers in low-income countries, they thus perform much worse with their new IO structure: now their average multiplier is lower and so is the correlation between TFP and multipliers, preventing them to benefit from their “super-star” sectors.

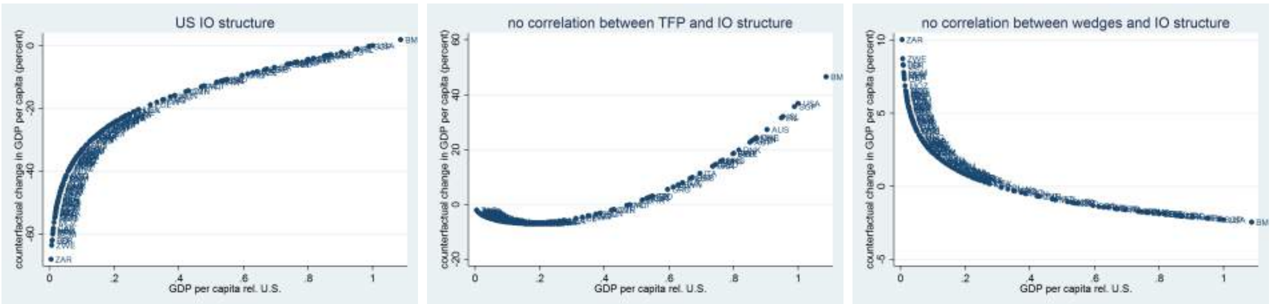

Figure 8: Counter-factuals

In the second counter-factual exercise, we keep the mean and the variance of log multipliers fixed and instead set the covariance between log multipliers and log productivities, $\sigma_{\mu,\Lambda}$, to zero. We can see from the central panel of Figure 8 that poor countries (up to around 40 percent of the U.S. level of income per capita) would lose up to 10 percent in terms of their initial income, while rich countries would gain up to 40 percent from this change. Why is this the case? From our estimates, poor countries have a positive covariance between log multipliers and log TFPs, while rich countries have a negative one. This implies that poor countries are doing relatively well despite their low average productivity levels, because they perform significantly better than average precisely in those sectors that have a large impact on aggregate performance. The opposite is true in rich countries, where the same covariance tends to be negative, so that highly connected sectors perform below average. Eliminating this link improves aggregate outcomes in rich economies further, while hurting poor countries.[55]

To sum up, recall that in low-income economies just a few sectors, such as Energy, Transport and Trade, provide inputs for most other sectors, while the typical sector provides inputs to only a few

[55] Note that as sectoral productivities are considered *relative* to the U.S., setting $\sigma_{\mu,\Lambda}$ to zero would actually not make any difference for the U.S. (it has zero correlation between multipliers and TFP by construction), but it would make a difference for a country with the U.S. level of GDP per capita (hence, label ”U.S.” on the figure), such as rich European countries. In these countries negative correlations arise due to particularly large productivity gaps with the U.S. in high-multiplier sectors, such as services (see more on this in section 4.1). Setting $\sigma_{\mu,\Lambda}$ to zero then effectively means bringing European productivity levels in the service sectors to the U.S. level. This would certainly have a large impact on GDP of European countries.

sectors. Thus, it suffices to have comparatively high productivity levels in those crucial sectors in order to obtain a relatively satisfactory aggregate outcome. By contrast, in the industrialized countries most sectors provide inputs for several other sectors (the IO network is quite dense), but there are hardly any sectors that provide inputs to most others. Thus, with such an IO structure increasing productivity levels in a few selected sectors is no longer enough to achieve a relatively good aggregate performance.

Finally, we conduct a counter-factual based on a model including sector-specific distortions or tax wedges that we consider in one of the robustness checks (see section 6.1). In this model, sector-specific wedges τ_i are assumed to reduce the value of sector i's production by a factor $(1-\tau_i)$, so that the profit maximization problem of a firm in sector i is given by

$$\max_{\{d_{ji}\}}(1-\tau_i)p_i\Lambda_i\left(k_i^{\alpha}l_i^{1-\alpha}\right)^{1-\gamma_i}d_{1i}^{\gamma_{1i}}d_{2i}^{\gamma_{2i}}\cdot\ldots\cdot d_{ni}^{\gamma_{ni}}-\sum_{j=1}^{n}p_jd_{ji}-rk_i-wl_i.$$

In section 6.1 we identify the sector-country-specific tax wedges as deviations of sectoral intermediate input shares from their cross-country average value. We then show that rich countries tend to have lower wedges in sectors with high multipliers, while the opposite is true in poor countries. The goal of our counter-factual experiment here is to check whether this cross-country variation in covariance between wedges and log multipliers has important quantitative implications. We thus set this covariance to zero for all countries. The right panel of Figure 8 plots the resulting changes in per capita income (in percent) against GDP relative to the U.S. level. Poor countries – which empirically exhibit a positive covariance between multipliers and wedges – experience moderate increases in income (up to 10 percentage points for Congo (ZAR)), while rich countries – which empirically have a negative covariance between multipliers and wedges – lose around one to two percentage points of per capita income. This implies that removing the positive covariance between wedges and multipliers in poor economies can lead to significant gains for them. However, cross-country income changes are smaller than those that would be induced by removing the covariance between productivities and multipliers.

Summary of counter-factual experiments:

1. *Imposing the dense IO structure of the U.S. on poor economies would reduce their income levels by up to 60 percent because a typical sector, which has a lower productivity level than the high-multiplier sectors in these economies, would become more connected.*

2. *If poor economies did not have above-average productivity levels in high-multiplier sectors, their income levels would be by up to 10 percent lower.*

3. *If poor economies did not have above-average wedges in high-multiplier sectors, their income levels would be by up to 10 percent higher.*

6 Robustness checks

In this section, we report the results of a number of robustness checks in order to show that our findings do not hinge on the specific restrictions imposed by the baseline model. We consider the following modifications of our benchmark setup. First, we allow IO multipliers to depend on implicit tax wedges. Second, we extend our model to sectoral CES production functions. Third, we generalize the final demand structure by introducing expenditure shares that differ across countries and sectors. Fourth, we explicitly account for imported intermediate inputs. Fifth, we allow for skilled and unskilled labor as separate production factors. Finally, we present a more general version of our structural model, which does not impose any symmetry on IO coefficients. We show that none of these modifications changes the basic conclusions of the baseline model. The formulas for aggregate income implied by these more general models as well as detailed derivations can be found in the Supplementary Appendix.

6.1 Wedges

One important concern is that empirically observed IO coefficients do not just reflect technological input requirements but also sector-specific distortions or wedges τ_i in the production of intermediates. To see this, consider the maximization problem of an intermediate producer:

$$\max_{\{d_{ji}\}}(1-\tau_i)p_i\Lambda_i\left(k_i^{\alpha}l_i^{1-\alpha}\right)^{1-\gamma_i}d_{1i}^{\gamma_{1i}}d_{2i}^{\gamma_{2i}}\cdot\ldots\cdot d_{ni}^{\gamma_{ni}}-\sum_{j=1}^{n}p_jd_{ji}-rk_i-wl_i,$$

taking $\{p_i\}$ as given (τ_i and Λ_i are exogenous). Sector-specific wedges are assumed to reduce the value of sector i's production by a factor $(1-\tau_i)$, so that $\tau_i > 0$ means an implicit tax and $\tau_i < 0$ means an implicit subsidy on the production of sector i's output.

The first-order condition w.r.t. d_{ji} is given by

$$(1-\tau_i)\gamma_{ji}=\frac{p_jd_{ji}}{p_iq_i}\quad j\in 1:n$$

Thus, a larger wedge in sector i implies lower observed IO coefficients in this sector since firms in a sector facing larger implicit taxes demand less inputs from all other sectors. Separately identifying wedges τ_i and technological IO coefficients γ_{ji} is an empirical challenge, which requires to impose some additional restrictions on the data. Observe that τ_i is the same for all inputs j demanded by a given sector i. Thus, introducing a country index c and summing across inputs j for a given country, we obtain

$$(1-\tau_{ic})\sum_j\gamma_{jic}\equiv(1-\tau_{ic})\gamma_{ic}=\sum_j\frac{p_{jc}d_{jic}}{p_{ic}q_{ic}}\quad i\in 1:n$$

Now, if we restrict the total technological intermediate share of sector i, γ_{ic}, to be the same across countries for a given sector i, we can identify country-sector specific wedges as

$$(1 - \tau_{ic}) = \sum_j \frac{p_{jc} d_{jic}}{p_{ic} q_{ic}} \frac{1}{\gamma_i} \quad i \in 1 : n \tag{17}$$

Observe that individual IO coefficients γ_{jic} are still allowed to differ across countries in an arbitrary way. According to equation (17), countries with below-average intermediate shares, $\sum_j \frac{p_{jc} d_{jic}}{p_{ic} q_{ic}}$, in a certain sector face an implicit tax in this sector, while countries with above-average intermediate shares receive an implicit subsidy. It is then straightforward to estimate γ_i using regression techniques. Taking logs of equation (17), we obtain:

$$\log\left(\sum_j \frac{p_{jc} d_{jic}}{p_{ic} q_{ic}}\right) = \log(\gamma_i) + \log(1 - \tau_{ic}) \tag{18}$$

Given (18), we regress the intermediate input shares of each country-sector pair on a set of sector-specific dummies to obtain estimates of the technological intermediate shares $\log(\gamma_i)$ and then back out $\log(1 - \tau_{ic})$ as the residual. The left panel of Figure 9 plots the distribution of intermediate input shares and the central panel plots the distribution of $\log(1 - \tau_{ic})$ by income level for the WIOD sample. Average intermediate shares do not vary systematically with per capita income, but poor countries have a larger fraction of sectors with very low intermediate shares and a lower fraction with high intermediate shares. Correspondingly, poor countries have a larger fraction of sectors with relatively high wedges, which corresponds to more mass in the left tail of the distribution of $\log(1 - \tau_{ic})$. Given wedges τ_{ic}, we construct IO coefficients adjusted for wedges as $\gamma_{ijc} = \frac{p_{jc} d_{jic}}{p_{ic} q_{ic}} \frac{1}{(1-\tau_{ic})}$. We then recompute sectoral productivities and IO multipliers using these adjusted IO coefficients. The right panel of Figure 9 plots the resulting distribution of (log) IO multipliers adjusted for wedges by income level. Observe that the distribution remains very similar to the one without wedges (compare with Figure 2).

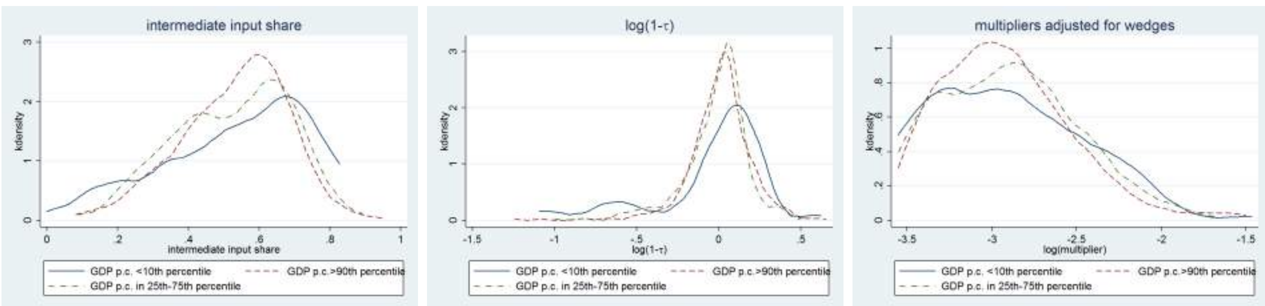

Figure 9: Intermediate input shares (left panel); wedges (central panel); IO multipliers adjusted for wedges (right panel).

One can show that in the presence of wedges which are considered as pure waste,[56] and under the

[56] In an unreported robustness check we verified that considering the revenues from tax wedges and rebating them lump sum to households does not make much difference for the results.

same simplifying restrictions used in our baseline model (cf. equation (10)), the expression for aggregate income can be written as:[57]

$$y = \sum_{i=1}^{n} \mu_i \Lambda_i^{rel} + \sum_{i=1}^{n} \mu_i (1-\tau_i) + \sum_{i=1}^{n} \mu_i \gamma \log(\widehat{\gamma}) + \log(1-\gamma) - \log n + \alpha \log K - 2(1+\gamma) + \sum_{i=1}^{n} \mu_i \log(\Lambda_i^{US}).$$

Now, assuming that sectoral multipliers, productivities and $(1-\tau_i)$ are stochastic, we obtain that expected aggregate output, $E(y)$, is given by:

$$\begin{aligned} E(y) &= n\Big(E(\mu)E(\Lambda^{rel}) + cov(\mu,\Lambda^{rel}) + E(\mu)E(1-\tau) + cov(\mu, 1-\tau)\Big) + (1+\gamma)(\gamma\log(\widehat{\gamma}) - 2) + \\ &+ \log(1-\gamma) - \log n + \alpha\log(K) + E(\mu)\sum_{i=1}^{n}\log\left(\Lambda_i^{US}\right). \end{aligned} \tag{19}$$

Again, this equation has an intuitive interpretation: higher average wedges τ are detrimental to aggregate income and more so if the average sector has higher multiplier; moreover, the negative impact of high wedges is particularly distorting if wedges co-vary positively with multipliers (i.e., $cov(\mu, 1-\tau) < 0$). If we impose joint log normality on the triple $(\mu, \Lambda_i^{rel}, 1-\tau)$, we obtain:

$$\begin{aligned} E(y) &= n\left(e^{m_\mu + m_\Lambda + 1/2(\sigma_\mu^2 + \sigma_\Lambda^2) + \sigma_{\mu,\Lambda}} + e^{m_\mu + m_{1-\tau} + 1/2(\sigma_\mu^2 + \sigma_{1-\tau}^2) + \sigma_{\mu,1-\tau}}\right) + (1+\gamma)(\gamma\log(\widehat{\gamma}) - 2) + \\ &+ \log(1-\gamma) - \log n + \alpha\log(K) + e^{m_\mu + 1/2\sigma_\mu^2}\sum_{i=1}^{n}\log\left(\Lambda_i^{US}\right), \end{aligned} \tag{20}$$

where m_μ, m_Λ, $m_{1-\tau}$ are the means and σ_μ^2, σ_Λ^2, $\sigma_{1-\tau}^2$, $\sigma_{\mu,\Lambda}$ and $\sigma_{\mu,1-\tau}$ are the elements of the variance-covariance matrix of the Normal distribution of $(\log(\mu), \log(\Lambda_i^{rel}), \log(1-\tau))$.

Given data on $(1-\tau)$, productivities Λ^{rel} and multipliers μ and imposing log-Normality on them, we re-estimate the parameters of their joint distribution separately for each country using Maximum Likelihood. We then regress these country-specific parameter estimates on (log) per capita GDP. Table 5 reports the result.[58] While the point estimates are quantitatively somewhat different from those of the baseline model (compare with Table 2), the qualitative features remain very similar: the average log multiplier, m_μ, does not vary with income, while σ_μ decreases in (log) per capita GDP. Again, this result implies that in poor countries the distribution of log multipliers has more mass at the extremes. Average log productivity, m_Λ, is again strongly increasing in income, while the standard deviation of

[57]With wedges equation (7) for aggregate income includes in addition the term $\sum_{i=1}^{n} \mu_i \log(1-\tau_i)$, which, for small enough τ_i, can be approximated by $-\sum_{i=1}^{n} \mu_i \tau_i = \sum_{i=1}^{n} \mu_i (1-\tau_i) - \sum_{i=1}^{n} \mu_i$. Then under the same simplifying restrictions as before, $\sum_{i=1}^{n} \mu_i \approx 1+\gamma$, and we obtain an equation very similar to (10).

[58]Note that we have less observations than in Table 2 (31 instead of 36) because the Maximum Likelihood estimation does not converge for all countries.

log productivity, σ_Λ, is decreasing. The mean of the distribution of $\log(1-\tau)$, $m_{1-\tau}$, does not change significantly with the income level, while its standard deviation, $\sigma_{1-\tau}$, decreases in (log) per capita GDP. Moreover, in rich countries wedges tend to be lower ($(1-\tau)$ is larger) in sectors with high multipliers, while the opposite is true in poor countries.[59] Finally, productivity levels correlate positively with log multipliers in poor countries, and the correlation decreases with the income level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	m_μ	σ_μ	m_Λ	σ_Λ	$\mathrm{m}_{1-\tau}$	$\sigma_{1-\tau}$	$\sigma_{\mu,\Lambda}$	$\sigma_{\mu,1-\tau}$
intercept	-2.868***	0.847**	-10.483***	4.002***	-0.116	0.670***	0.607*	-0.105*
	(0.341)	(0.156)	(1.908)	(0.877)	(0.306)	(0.154)	(0.317)	(0.063)
slope	-0.026	-0.035**	1.009***	-0.314***	-0.009	-0.049**	-0.049*	0.012*
	(0.035)	(0.016)	(0.187)	(0.087)	(0.030)	(0.023)	(0.025)	(0.006)
R-squared	0.010	0.151	0.610	0.579	0.008	0.321	0.153	0.287
Observations	31	31	31	31	31	31	31	31

Table 5: Regression of estimated country-specific parameters on log(GDP p.c.).
Bootstrapped standard errors in parentheses. Estimates significant at 1% (***), 5% (**), 10% (*) significance level.

Next, we plug the predicted parameter values into equation (20) to forecast income levels. **Success** of this model is 0.98, which means that the model with wedges predicts cross-country income variation almost perfectly and even better than the baseline model. We thus conclude that introducing wedges in addition to an IO structure helps to improve model fit in the WIOD sample by another 5 percentage points (0.98 instead of 1.07). The reason is that compared to the baseline model, this tends to reduce the income levels of poor economies, where $m_{1-\tau} < 0$ and $\sigma_{\mu,1-\tau} < 0$, which lowers predicted income.

In the Supplementary Appendix we study optimal taxation and the welfare gains from moving from the current tax wedges to an optimal tax system that keeps tax revenue constant. Our results suggest that when the government is concerned with maximizing GDP per capita subject to a given level of tax revenue, the actual distribution of tax rates in rich countries is close to optimum. By contrast, in poor countries, the mean of the distribution is too low and the variance is too high relative to the optimal values. Furthermore, for a given value of tax variance, a negative correlation of taxes with IO multipliers is optimal, while the actual correlation in poor countries is positive. Overall, we find that the poorest countries in the world could gain up to 10 % in terms of income per capita by moving to an optimal tax system.

6.2 CES production function

Another potential concern is that sectoral production functions are not Cobb-Douglas, but instead feature an elasticity of substitution between intermediate inputs different from unity. If this were the case, IO coefficients would no longer be sector-country-specific constants γ_{jic} but would instead be endogenous to equilibrium prices, which would reflect the underlying productivities of the upstream sectors. While

[59] The sign of the covariance changes at the level of per capita GDP of approximately 6311 ($= e^{0.105/0.012}$) PPP Dollars.

	(1) wedges	(2) demand	(3) open	(4) skill	(5) exact
success	**0.98**	**1.18**	**0.85**	**0.93**	**1.03**
intercept	0.031	-0.031	0.120***	0.092**	0.010
	(0.025)	(0.050)	(0.034)	(0.035)	(0.039)
slope	1.018***	0.791***	0.897***	1.030***	0.932***
	(0.045)	(0.081)	(0.053)	(0.069)	(0.059)
R-squared	0.927	0.826	0.887	0.83 2	0.899
Observations	36	36	36	36	36

Table 6: Robustness checks

it has been observed that for the U.S. the IO matrix has been remarkably stable over the last decades despite large shifts in relative prices (Acemoglu et al., 2012) – an indication of a unit elasticity – in this robustness check we briefly discuss the implications of considering a more general CES sectoral production function. The sectoral production functions are now given by:

$$q_i = \Lambda_i \left(k_i^{\alpha} l_i^{1-\alpha}\right)^{1-\gamma_i} M_i^{\gamma_i}, \tag{21}$$

where $M_i \equiv \left(\sum_{j=1}^{N} \gamma_{ji} d_{ji}^{\frac{(\sigma-1)}{\sigma}}\right)^{\frac{\sigma}{(\sigma-1)}}$. The rest of the model is specified as in section 3.1.

With CES production functions the equilibrium cannot be solved analytically, so one has to rely on numerical solutions. However, it is straightforward to show how IO multipliers are related to sectoral productivities in this case. From the first-order conditions it follows that the relative expenditure of sector i on inputs produced by sector j relative to sector k is given by:

$$\frac{p_j d_{ji}}{p_k d_{ki}} = \left(\frac{p_j}{p_k}\right)^{1-\sigma} \left(\frac{\gamma_{ji}}{\gamma_{ki}}\right) \tag{22}$$

Thus, if $\sigma > 1$ ($\sigma < 1$), each sector i spends relatively more on the inputs provided by sectors that charge lower (higher) prices. These sectors then have higher (lower) multipliers, as multipliers are proportional (up to a shift by $1/n$) to the sector's out-degree $d_j^{out} = \sum_{i=1}^{n} \frac{p_j d_{ji}}{p_i q_i}$ (see equation (9)). Moreover, since prices are inversely proportional to productivities, sectors with higher productivity levels charge lower prices. Consequently, when $\sigma > 1$, sectoral multipliers and productivities should be positively correlated in *all* countries, while when $\sigma < 1$, the opposite should be true. We confirm these results in unreported simulations. Observe that these predictions are not consistent with our empirical finding that multipliers and productivities are positively correlated in low-income countries, while they are negatively correlated in high-income ones. Consequently – unless the elasticity of substitution differs systematically across countries – the data on IO tables and sectoral productivities are difficult to reconcile with CES production functions.

6.3 Cross-country differences in final demand structure

So far we have abstracted from cross-country differences in the final demand structure, which also matter for the values of sectoral multipliers since sectors with higher final-expenditure shares have a larger impact on GDP. In the next robustness check, we thus consider a more general demand structure. More specifically, we now model the production function for the aggregate final good as $Y = y_1^{\beta_1} \cdot ... \cdot y_n^{\beta_n}$, where β_i is allowed to be country-sector-specific. The advantage of this specification is that it picks up differences in the final demand structure that may have an impact on aggregate income. The drawback is that with this specification multipliers reflect both the IO structure and final demand. Thus, this specification does not allow one to differentiate between the two channels. The vector of sectoral multipliers is now defined as $\boldsymbol{\mu} = \{\mu_i\}_i = [\boldsymbol{I} - \boldsymbol{\Gamma}]^{-1}\boldsymbol{\beta}$, where $\boldsymbol{\beta} = (\beta_1, .., \beta_n)'$. So, holding constant the IO structure $\boldsymbol{\Gamma}$, sectors with larger final-expenditure shares have larger multipliers. The interpretation of IO multipliers is identical to the one before: each sectoral multiplier μ_i reveals how a change in productivity of sector i affects total value added in the economy. Given the new multipliers, we re-estimate their joint distribution and predict income levels using the formula presented in the Supplementary Appendix.

The fit of this model can be found in column (2) of Table 6. **Success** is now 1.18, which is somewhat worse than the performance of our baseline model (1.07). Like the model without linkages, this model somewhat over-predicts cross-country income differences. This indicates that – within the context of our model – modeling differences in final demand structure does not help to understand differences in aggregate income. The reason is that modeling differences in final demand structure across countries introduces a lot of additional noise in the multiplier data, which makes it harder to estimate the systematic underlying features of the inter-industry linkages.

6.4 Imported intermediates

So far we have abstracted from international trade and we have assumed that all intermediate inputs have to be produced domestically. Imported intermediate inputs may to some extent mitigate low productivity of domestic firms in the upstream sector, by enabling domestic producers to source from foreign suppliers.[60] Here, we allow for both domestically produced and imported intermediates, which are imperfectly substitutable. We thus assume that sectoral production functions are given by:

$$q_i = \Lambda_i \left(k_i^{\alpha} l_i^{1-\alpha}\right)^{1-\gamma_i-\sigma_i} d_{1i}^{\gamma_{1i}} d_{2i}^{\gamma_{2i}} \cdot ... \cdot d_{ni}^{\gamma_{ni}} \cdot f_{1i}^{\sigma_{1i}} f_{2i}^{\sigma_{2i}} \cdot ... \cdot f_{ni}^{\sigma_{ni}}, \tag{23}$$

[60] See, e.g. Halpern, Koren and Szeidl (2015) for a recent micro-level study on the effect of importing intermediate inputs on the productivity levels of domestic producers.

where d_{ji} are domestically produced intermediate inputs and f_{ji} are imported intermediate inputs. γ_{ji} and σ_{ji} denote the shares of each domestic and imported intermediate, respectively, in the value of sectoral gross output. We change the construction of the IO tables accordingly by separating domestically produced from imported intermediates. We then re-estimate the joint distributions of IO multipliers and productivities.

The results for model fit with this specification are given in column (3) of Table 6. **Success** is now 0.85, which is slightly worse than the fit of the baseline model. The intuition for why results remain similar when considering imported inputs comes from the fact that most high-multiplier sectors tend to be services, which are effectively non-traded. Therefore, allowing for trade does not change the statistical distribution of multipliers and the implied predicted income much. We thus conclude that our results are quite robust to allowing for trade in intermediates.

6.5 Skilled labor

Finally, we split aggregate labor endowments into skilled and unskilled labor. Namely, let the technology of each sector $i \in 1:n$ in every country be described by the following Cobb-Douglas function:

$$q_i = \Lambda_i \left(k_i^{\alpha} u_i^{\delta} s_i^{1-\alpha-\delta} \right)^{1-\gamma_i-\sigma_i} d_{1i}^{\gamma_{1i}} d_{2i}^{\gamma_{2i}} \cdot \ldots \cdot d_{ni}^{\gamma_{ni}}, \tag{24}$$

where s_i and u_i denote the amounts of skilled and unskilled labor used by sector i, $\gamma_i = \sum_{j=1}^{n} \gamma_{ji}$ is the share of intermediate goods in the total input use of sector i and α, δ, $1-\alpha-\delta \in (0,1)$ are the respective shares of capital, unskilled and skilled labor in the remainder of the inputs. The total supply of skilled and unskilled labor in the economy is fixed at the exogenous levels of S and U, respectively. We define skilled labor as the number of hours worked by workers with at least some tertiary education and we define unskilled labor as the number of hours worked by workers with less than tertiary education. Information on skilled and unskilled labor inputs by sector is from WIOD. We recompute productivities Λ^{rel} assuming production-functions as given by (24) and then re-estimate all parameter values. We calibrate $\delta = 1/6$ to fit the college skill premium of the U.S. The results for fitting cross-country income variation with this model are provided in column (4) of Table 6. **Success** is now 0.93, which is comparable to the baseline model. This is not suprising: given the great fit of the baseline model, there is little room left for improving the explanatory power of the model by introducing human capital. We conclude that our results are not very sensitive to the definition of labor endowments.

6.6 Log-Normally distributed IO coefficients

In the baseline model we imposed the restrictive and unrealistic assumption that all non-zero elements of the input-output matrix $\mathbf{\Gamma}$ are the same, that is, $\gamma_{ji} = \widehat{\gamma}$ for any i and j whenever $\gamma_{ji} > 0$. Here we consider a more general version of the model where γ_{ji}'s are independent random draws from a log-Normal distribution and are thus allowed to vary across countries and sectors. Note that this distribution is appropriate due to three observations: (i) by equation (9), sectoral multipliers can be approximated by the sum of IO coefficients in the corresponding row of the IO matrix (shifted and multiplied by $1/n$), (ii) sectoral multipliers are log-Normally distributed, and (iii) the sum of independent log-Normal random variables is approximately log-Normal according to the Fenton-Wilkinson method (Fenton, 1960).

When IO coefficients are not constant, the term $\sum_{i=1}^{n}\sum_{j \text{s.t. } \gamma_{ji}\neq 0}\mu_i\gamma_{ji}\log\gamma_{ji}$ in equation(7) is no longer equal to $\sum_{i=1}^{n}\mu_i\gamma\log(\widehat{\gamma})$ (as in (10)). Instead, it is given by a longer and more complex expression that we derive in the Supplementary Appendix. The expectation of this term is a function of the parameters of the Normal distribution of $\log\gamma_{ji}$, $(\mu_\gamma, \sigma_\gamma^2)$. These parameters, in turn, are related to the parameters of the Normal distribution of $\log(\mu)$, (m_μ, σ_μ^2), due to the relationship established in (9): $\mu_j \approx \frac{1}{n} + \frac{1}{n}\sum_{i=1}^{n}\gamma_{ji}$.[61] This then leads to the following expression for the expected aggregate income:

$$\begin{aligned}
E(y) &= ne^{m_\mu+m_\Lambda+1/2(\sigma_\mu^2+\sigma_\Lambda^2)+\sigma_{\mu,\Lambda}} - (1+\gamma) + E\left[\sum_{i=1}^{n}\sum_{j=1}^{n}\mu_i\gamma_{ji}\log\gamma_{ji}\right] + \\
&+ \log(1-\gamma) - \log n + \alpha\log(K) + e^{m_\mu+1/2\sigma_\mu^2}\sum_{i=1}^{n}\log\left(\Lambda_i^{US}\right) = \\
&= ne^{m_\mu+m_\Lambda+1/2(\sigma_\mu^2+\sigma_\Lambda^2)+\sigma_{\mu,\Lambda}} - (1+\gamma) + \\
&+ x^{\frac{1}{2}}z[n + x^{\frac{1}{2}}z(n^2-1)](\log(x) + \log(z)) + x^2z^2(\log(z) + 2\log(x)) + \\
&+ \log(1-\gamma) - \log n + \alpha\log(K) + e^{m_\mu+1/2\sigma_\mu^2}\sum_{i=1}^{n}\log\left(\Lambda_i^{US}\right), \qquad (25)
\end{aligned}$$

where x and z are functions of (m_μ, σ_μ^2), which are provided in the Supplementary Appendix.

This expression for aggregate income depends only on the parameter estimates used in the baseline model without imposing any symmetry on the IO coefficients. It is similar to the one of the baseline model but includes additional terms that capture the effect of asymmetric linkages. We use it to predict cross-country income differences in this more general setting. While it is difficult to gain intuition for the expression summarizing the effect of asymmetric IO linkages, the predicted income levels from this

[61] Indeed, from this equation it follows that $E(\mu) = \frac{1}{n} + \frac{1}{n}\mu_{sum}$ and $var(\mu) = \frac{1}{n^2}\sigma_{sum}^2$, where μ_{sum}, σ_{sum}^2 are the mean and the variance of the distribution of the sum $\sum_{i=1}^{n}\gamma_{ji}$, which can be expressed in terms of $(\mu_\gamma, \sigma_\gamma^2)$, and $E(\mu)$, $var(\mu)$ can be expressed in terms of (m_μ, σ_μ^2) by means of the relationship between the Normal and log-Normal distributions ($E(\mu) = e^{m_\mu+1/2\sigma_\mu^2}$, $var(\mu) = e^{2m_\mu+m_\Lambda+\sigma_\mu^2}\cdot[e^{\sigma_\mu^2}-1]$). By the Fenton-Wilkinson method, the distribution of the sum $\sum_{i=1}^{n}\gamma_{ji}$ is approximately log-Normal with $\mu_{sum} = \log(ne^{\mu_\gamma}) + \frac{1}{2}\left(\sigma_\gamma^2 - \sigma_{sum}^2\right) = \log(ne^{\mu_\gamma}) + \frac{1}{2}\left(\sigma_\gamma^2 - \log\left(\frac{\left(e^{\sigma_\gamma^2}\right)-1}{n+1}.\right)\right)$, $\sigma_{sum}^2 = \log\left(\frac{\left(e^{\sigma_\gamma^2}\right)-1}{n+1}\right)$.

model are similar to those of the baseline model. In column (5) of Table 6 we report the results: **Success** is now slightly improved to 1.03 compared to 1.07 for the baseline model and the regression statistics remain also very similar. This justifies the use of the much simpler and more intuitive approximation in the baseline model.

7 Conclusions

In this paper we have studied the role of IO structure and its interaction with sectoral productivity levels in explaining income differences across countries. We have described and formally modeled cross-country differences in IO linkages and shown that they are important for understanding the income differences. Poor countries rely on a few highly connected sectors, which tend to have higher-than-average productivity levels. Their typical, low-productivity sectors are not strongly linked to the rest of the economy, mitigating their impact on aggregate income. By contrast, in rich countries the typical sector is intermediately connected and the economy is not dominated by a few "super-star" sectors. Thus, while increasing productivity levels in a few sectors can have a large positive impact on aggregate income in poor economies, this is not the case in medium-income and rich countries. In these more densely connected economies the productivity levels of many more sectors need to be sufficiently high in order to guarantee a high income level. These insights have important consequences for the design of development policies.

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