

Productivity, Networks and Input-Output Structure

PRELIMINARY AND INCOMPLETE.*

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Abstract

We consider a multi-sector general equilibrium model with IO linkages, sector-specific productivities and tax rates. Using tools from network theory, we investigate how the IO structure interacts with productivities and taxes in the determination of aggregate income. Employing a statistical approach, we show that aggregate income is a simple function of the first and second moments of the distribution of the IO multipliers, sectoral productivities and sectoral tax rates. We then estimate the parameters of the model to fit their joint empirical distribution, allowing these to vary with income per capita.

We find an important difference between rich and medium-low income countries. Poor countries have more extreme distributions of IO multipliers than rich economies: there are a few high multiplier sectors, while most sectors have very low multipliers; in contrast, rich countries have more sectors with intermediate multipliers. Moreover, the correlations of these with productivities and tax rates are positive in poor countries, while being negative in rich ones. The estimated model predicts cross-country income differences extremely well, also out-of-sample (up to 97% of the variation in relative income per capita). Finally, we perform a number of counterfactuals. First, we “impose” the dense IO structure of the U.S. on low- and middle-income countries and find a large damaging effect, up to 80 %. Second, we assume that sectoral IO multipliers and productivities are uncorrelated and find that low income countries would lose up to 50% of their per capita income while high income countries would gain.

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

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

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1 Introduction

One of the fundamental debates in economics is about how important differences in factor endowments – such as physical or human capital stocks – are relative to aggregate productivity differences in terms of explaining cross-country differences in income per capita. The standard approach to address this question is to specify an aggregate production function for value added (e.g., Caselli, 2005). Given data on aggregate income and factor endowments and the imposed mapping between endowments and income, one can back out productivity differences as a residual that explains differences between predicted and actual income. However, this standard approach ignores that GDP aggregates value added of many economic activities which are connected to each other through input-output linkages.¹ In contrast, a literature in development economics initiated by Hirschman (1958) has long emphasized that economic structure is of first-order importance to understand cross-country income differences.²

Consider, for example, a productivity increase in the Transport sector. This reduces the price of transport services and thereby increases productivity in sectors that use transport services as an input (e.g., Mining). Increased productivity in Mining in turn increases productivity of the Steel sector by reducing the price of iron ore, which in turn increases the productivity of the Transport Equipment sector. In a second-round effect, the productivity increase in Transport Equipment in turn improves productivity of the Transport sector and so on. Thus, input-output (IO) linkages between sectors lead to multiplier effects. The IO multiplier of a sector summarizes all these intermediate effects and measures by how much aggregate income will change if productivity of this sector changes by one percent. The size of the sectoral multiplier effect depends to a large extent on the number of sectors to which a given sector supplies and the intensity with which its output is used as an input by the other sectors.³ We document that there are large differences in IO multipliers across sectors – e.g., most infrastructure sectors, such as Transport and Energy, have high multipliers because they are used as inputs by many other sectors,⁴ while a sector such as Textiles – which does not provide inputs to many sectors – has a low multiplier. As a consequence, low productivities in different sectors will have very distinct effects on aggregate income, depending on the size of the sectoral IO multiplier.

¹An important exception that highlights sectoral TFP differences is the recent work on dual economies. This literature finds that productivity gaps between rich and poor countries are much more pronounced in agriculture than in manufacturing or service sectors and this fact together with the much larger value added or employment share of agriculture in poor countries can explain an important fraction of cross-country income differences.

²More recent contributions highlighting the role of economic structure for aggregate income are Ciccone, 2002 and Jones, 2011 a,b.

³The 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.

⁴The view that infrastructure sectors are of crucial importance for aggregate outcomes has also been endorsed by the World Bank. In 2010, the World Bank positioned support for infrastructure as a strategic priority in creating growth opportunities and targeting the poor and vulnerable. Infrastructure projects have become the single largest business line for the World Bank Group, with \$26 billion in commitments and investments in 2011 (World Bank Group Infrastructure Update FY 2012-2015).

In this paper, we address the question how differences in economic structure across countries – as captured by IO linkages between sectors – affect cross-country differences in aggregate income per capita. To this end, we combine data from the World Input-Output Database (Timmer, 2012) and the Global Trade Analysis project (GTAP Version 6), in order to construct a unique dataset of IO tables, sectoral total factor productivities and sectoral tax rates for a large cross-section of countries in the year 2005.⁵ With this data at hand, we investigate how the IO structure interacts with sectoral TFP differences and taxes to determine aggregate per capita income. First, we document that in all countries there is a relatively small set of sectors which have very large IO multipliers and whose performance thus crucially affects aggregate outcomes. Moreover, despite this regularity, we also find that there do exist substantial differences in the network characteristics of IO linkages between poor and rich countries. In particular, low income countries typically have a very small number of average and large multiplier sectors, while high income countries have a more dense input-output network. To visualize these differences, in Figure 1 we plot a graphical representation of the IO matrices of two countries: Uganda (a very low income country with a per capita GDP of 964 PPP dollars in 2005) and the U.S. (a major industrialized economy with a per capita GDP of around 42,500 PPP dollars in 2005). The columns of the IO matrix are the producing sectors, while the rows are the sectors whose output is used as an input. Thus, a dot in the matrix indicates that the column sector uses some of the row sector’s output as an input and a blank space indicates that there is no significant connection between the two sectors.⁶

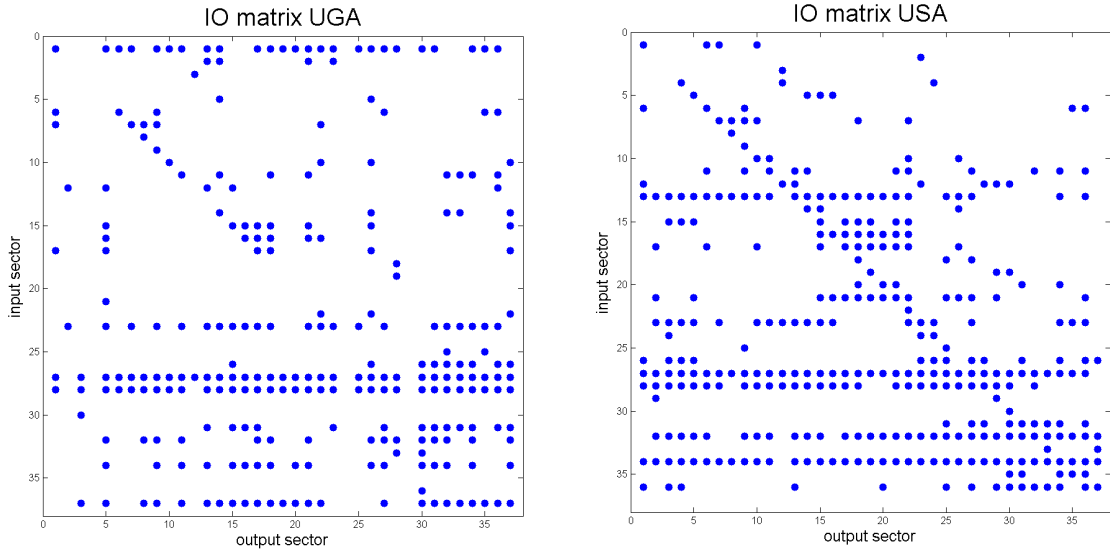


Figure 1: IO-matrices by country: Uganda (left), USA (right)

By comparing the matrices it is apparent that in Uganda there are only four sectors which supply

⁵We have data on sectoral TFPs and tax rates for 37 countries and data on IO tables for 70 countries.

⁶Data are from GTAP version 6, see the data appendix for details. The figure plots IO coefficients defined as cents of industry j output (row j) used per dollar of output of industry i (column i). To make the figure more readable, we only plot linkages with at least 2 cents per dollar of output.

to most other sectors.⁷ These are Agriculture (row 1), Electricity (row 23), Wholesale and Retail Trade (row 27), and Transport (row 28). These sectors are the high IO multiplier sectors, where a change in sectoral productivity has a relatively large effect on aggregate output. Most other sectors are quite isolated in Uganda, in the sense that their output is not used as an input by many sectors. In contrast, the U.S. has a much larger number of sectors that supply to many others: Chemicals (row 13), Electricity (row 23), Construction (row 26), (Wholesale and Retail) Trade (row 27), Transport (row 28), Financial Services (row 32), and Business Services (row 34), among others. This difference in IO structure between rich and poor countries has important implications for aggregate income differences: in Uganda changes in the productivity of a few crucial sectors have large effects on aggregate income, while productivity in most sectors does not matter much for aggregate per capita income, because these sectors are isolated. In contrast, in the U.S. productivity levels of many more sectors have a significant impact on aggregate income because the IO network is much denser. To some extent this is good news for low-income countries: in those countries policies that focus on a few crucial sectors can have a large impact on aggregate income, while this is not true for middle-income and rich countries.

We model countries' IO structures using tools from network theory. We analytically solve a multi-sector general equilibrium model with IO linkages, sector-specific productivities and tax rates. We then estimate this model using a statistical approach that employs the moments of the distributions instead of actual values. The crucial advantage of this approach is that it allows us to derive a simple closed-form expression for aggregate per capita income that conveniently summarizes the interactions between IO structure, productivities and tax rates, without having to deal with the complicated input-output matrices directly: aggregate income is a simple function of the first and second moments of the distribution of IO multipliers, sectoral productivities and sectoral tax rates. Higher average IO multipliers and average sectoral productivities have a positive effect on income per capita, while higher average tax rates reduce it. Moreover, a positive correlation between sectoral IO multipliers and productivities increases income, while a positive correlation between IO multipliers and tax rates has the opposite effect. This is intuitive: high sectoral productivities have a larger positive impact if they occur in high multiplier sectors, while high tax rates in high multiplier sectors are very distortionary. We estimate the parameters of the model to fit the joint empirical distribution of IO multipliers, productivities and tax rates for the countries in our sample, allowing them to vary with income per capita. We find that low income countries have more extreme distributions of IO multipliers: while most sectors have very low multipliers, there are a few very high multiplier sectors. In contrast, rich countries have relatively more sectors with intermediate multipliers. Moreover, while sectoral IO multipliers and productivities are positively correlated in low income countries, they are negatively correlated in high income ones.

⁷See Appendix Table 9 for the complete list of sectors.

Similarly, IO multipliers and tax rates are positively correlated in poor countries and negatively correlated in rich ones.

With the parameter estimates at hand, we use our closed-form expression for income per capita as a function of IO structure to predict income differences across countries. In contrast to standard development accounting, where the model is exactly identified, this provides an over-identification test, since we have not used any data on income to estimate the parameter values. We find that our model predicts cross-country income differences extremely well both within the sample of countries that we have used to estimate the parameter values and also out of sample, i.e., in the full Penn World Tables sample (around 150 countries). Our model predicts up to 99% of the cross-country variation in relative income per capita, which is extremely large compared to standard development accounting. Moreover, our model with IO linkages does much better in terms of predicting income differences than a model that just averages estimated sectoral productivities and ignores IO structure. In fact, such a model actually over-predicts cross-country income differences. The reason is that the large sectoral TFP differences that we observe in the data are mitigated by the IO structure, since very low productivity sectors tend to be isolated in low- and middle-income countries. Thus, if we measure aggregate productivity levels as an average of sectoral productivities, income levels of middle- and low-income countries would be significantly lower than they actually are.

Finally, we perform a number of counterfactuals. First, we impose the IO structure of the U.S. on all countries, which forces them to use the relatively dense U.S. IO network. We find that the U.S. IO structure 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 40% and income reductions would amount to up to 80 % for the world's poorest economies (e.g., Congo). The intuition for this result is that poor countries tend to have higher than average relative productivity levels (relative to those of the U.S. in the same sector) in precisely those sectors that have higher IO multipliers.⁸ This implies that they do relatively well given their really low productivity levels in some sectors. Consequently, if we impose the much denser IO structure of the U.S. on poor countries – which would make their really bad sectors much more connected to the rest of the economy – they would be significantly poorer.

Second, we impose that sectoral IO multipliers and productivities are uncorrelated. This scenario would again hurt low income countries, which would lose up to 50% of their per capita income, because they have above average productivity levels in high multiplier sectors. By contrast, high income countries would gain up to 50% in terms of income per capita, since they tend to have below average productivity

⁸An important exception is Agriculture, which, in low income countries, has a high IO multiplier and a below-average productivity level.

levels in high multiplier sectors.⁹

Third, reducing distortions from taxes on gross output would have more modest effects. If low income countries did not have above average tax rates in high multiplier sectors, they would gain up to 4% of per capita income, while imposing the U.S. tax structure on them (which has a relatively low variance of tax rates and lower tax rates in high multiplier sectors) would increase their income by up to 6%.

1.1 Literature

We now turn to a discussion of the related literature.

Our work is connected with the literature on development accounting (level accounting), which aims at quantifying the relative 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 (see, e.g., Hall and Jones (1999), Klenow and Rodriguez-Clare (1997), Caselli (2005)). 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 observed variation in factor endowments. Thus, this approach naturally abstracts from any cross-country differences in the underlying economic structure across countries. We contribute to this literature by showing how aggregate value added production functions can be derived in the presence of input-output linkages that differ across countries. Moreover, we show that incorporating cross-country variation in input-output structure is of first-order importance in explaining cross-country income differences.

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

⁹In particular, most industrialized countries tend to have relatively large productivity gaps relative to the U.S. in high-multiplier service sectors, e.g. Business Services or Financial Services. Differently, European productivity levels in manufacturing tend to be somewhat higher than the U.S. ones.

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 (Caselli, 2005; Restuccia, Yang, and Zhu, 2008; Chanda and Dalgaard, 2008; Vollrath, 2009, Gollin et al., 2014). Also closely related to our work – which focuses on changes in the IO structure as countries’ income level increases – a literature on structural transformation 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, this literature abstracts from intermediate 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 et. al. (2012). In contrast to these studies, which deal with the relationship between sectoral productivity shocks and aggregate fluctuations, we are interested in the question how sectoral productivity *levels* interact with the IO structure to determine aggregate income *levels*. Moreover, while the aforementioned papers are purely theoretical, we provide a comprehensive empirical study of the impact of cross-country differences in IO structure on income.

Other recent related contributions are Oberfield (2014), who develops an abstract theory of endogenous input-output network formation and Boehm (2014), 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 shares of manufacturing increase with industrialization and – consistent with our evidence – that input output matrices become less sparse as countries industrialize. The empirical study most closely related to our paper is the contemporaneous work by Bartelme and Gorodnichenko (2014). They also collect data on IO tables for many countries and investigate the relationship between IO linkages and aggregate income. In reduced form regressions of aggregate input-output multipliers on income per worker, they 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 do not use data on sectoral productivities and tax rates and they do not use network theory to represent IO-tables. As a consequence, they do not investigate how differences in the distribution of multipliers and their

correlations with productivities and tax rates impact on aggregate income, which is the focus of our work.

The outline of the paper is as follows. The next section describes 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 network characteristics. Subsequently, we turn to the estimation and model fit and finally, we present a number of counterfactual results. The final section presents our conclusion.

2 Dataset and descriptive analysis

2.1 Data

IO tables measure the flow of intermediate products between different plants or establishments, 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.¹⁰ 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 output used in the production of each dollar of industry i output.

To construct a dataset of input-output tables for a range of high and low income countries and to calculate sectoral total factor productivities, tax rates and 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 7.1, Heston et al., 2012).¹¹

The first dataset, WIOD, contains IO data for 39 countries classified into 35 sectors in the year 2005. The list of countries and sectors is provided in Appendix Tables 7 and 9. WIOD data also provides all the information necessary to compute gross-output based sectoral total factor productivity: real gross output, real sectoral capital and labor inputs, Purchasing Power Parity price indices for sectoral gross output and sectoral factor payments to labor and capital. Moreover, WIOD provides information on sectoral net tax rates (taxes minus subsidies) on gross output. The second dataset, GTAP version 6, contains data for 70 countries and 37 sectors in the year 2004. We use GTAP data to get more information about IO tables of low-income countries and we construct IO coefficients for all 70 countries. Finally, the third dataset, PWT 7.1, includes data on income per capita in PPP, aggregate physical capital stocks and labor endowments for 155 countries in the year 2005. In our analysis, PWT table data is used to make out of sample predictions with our model.

¹⁰Intermediate output must be traded between establishments in order to be recorded in the IO table, while flows that occur within a given plant are not measured.

¹¹In the main text we only provide a rough description of the datasets. Details can be found in the data Appendix.

2.2 IO structure

To begin with, we provide some descriptive analysis of the input-output structure of the set of 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 sector, the aggregate IO multiplier tells us by how much aggregate income changes due to a one percent change in productivity of all sectors. Figure 2 (left panel) plots aggregate IO multipliers for each country against GDP per capita (relative to the U.S.).

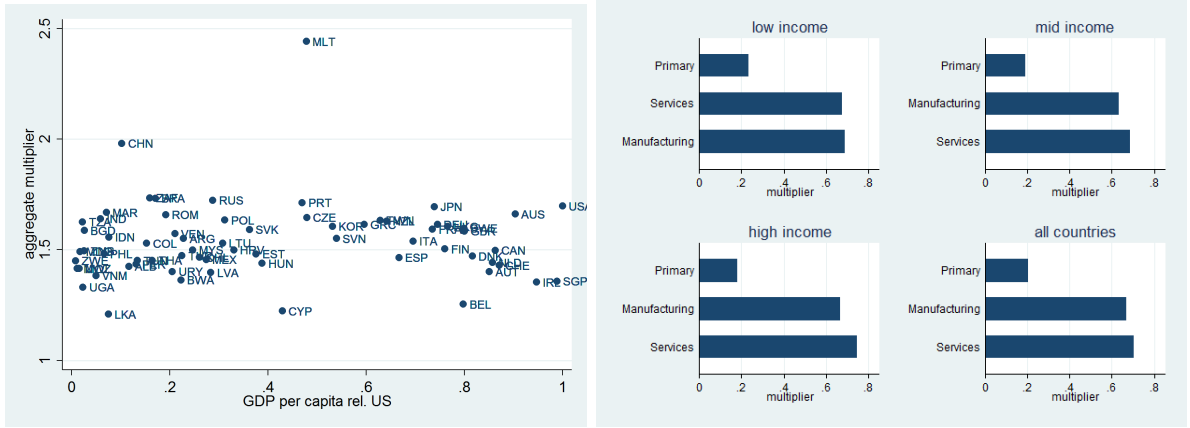


Figure 2: Aggregate IO-multipliers by country (left), sectoral IO-multipliers by income level (right)

We observe that aggregate multipliers for the GTAP sample 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.¹²

Next, we compute separately the aggregate IO multipliers for the three major sector categories: primary sectors (which include Agriculture, Coal, Oil and Gas Extraction and Mining), manufacturing and services. Figure 2 (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 primary sectors (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.¹³ We conclude that at the aggregate-economy level or for major sectoral aggregates there

¹²Aggregate 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 for the countries for which we can measure both gives a slope coefficient of around 0.8 and the relationship is strongly statistically significant

¹³Very 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.

are no systematic differences in IO structure across countries.

Let us now look at differences in IO structure at a more disaggregate level (37 sectors). To this end, we compute sectoral IO multipliers separately for each sector and country. Figure 3 presents kernel density plots of the distribution of (log) sectoral multipliers for different levels of income per capita.

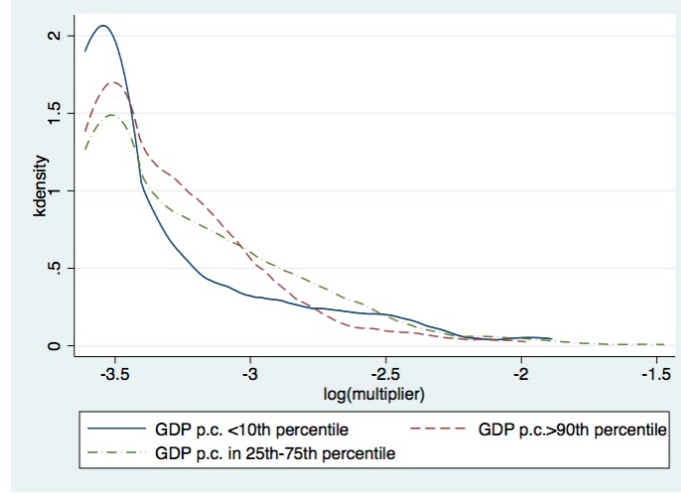


Figure 3: Distribution of sectoral log multipliers (GTAP sample)

The following two facts stand out. First, for any given country the distributions 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) has a multiplier of around 0.02 and the median sector has a multiplier of around 0.03. In contrast, a typical high multiplier sector (at the 90th percentile) has a multiplier of around 0.065, while a sector at the 99th percentile has a multiplier of around 0.134.

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

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. Figure 4 plots 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 country (United States (USA)). It is apparent that the distribution of multipliers of Uganda is such that the bulk of sectors have low multipliers, with the exception of Agriculture, Electricity, Trade and Inland Transport. In contrast, the typical sector in the U.S. has a larger multiplier, while the distribution of multipliers of India lies between the one of Uganda and the one of the U.S.

In the lower panels of the same figure we plot sectoral multipliers averaged across countries by income

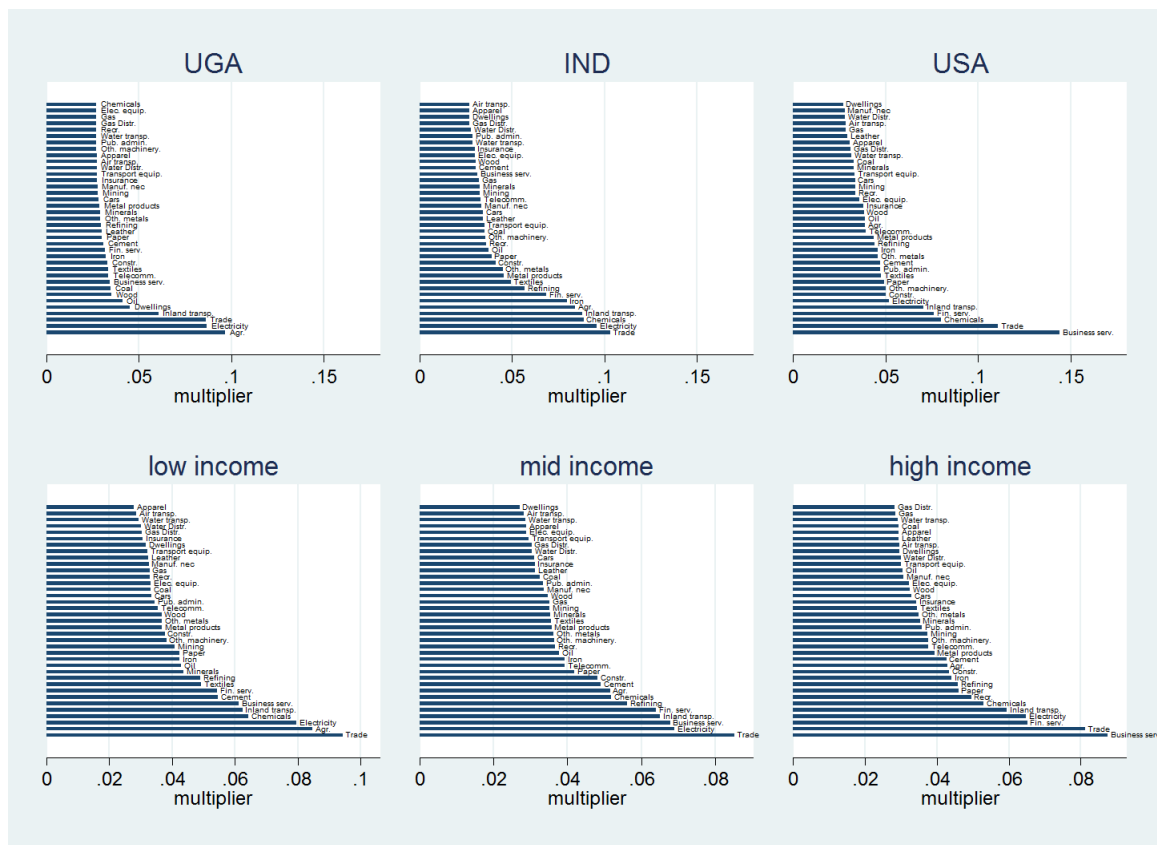


Figure 4: Sectoral IO-multipliers by country (top panel)/ income level (bottom panel)

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

Thus, overall the sectors with the highest multipliers are mostly service sectors. Agriculture is one notable exception for countries with an income level below 10,000 PPP dollars, where agricultural products are an input to many sectors. Moreover, in low-income countries Chemicals and Petroleum Refining tend to have a large multiplier, too. In general though, typical manufacturing sectors have intermediate multipliers (around 0.04). Finally, the sectors with the lowest multipliers are also mostly services: Apparel, Air Transport, Water Transport, Gas Distribution and Dwellings (Owner-occupied houses). Given the large number of sectors with low multipliers, the specific sectors differ more across income groups. The figures for individual countries confirm the overall picture.

2.3 Productivities and taxes

We now provide some descriptive evidence on sectoral total factor productivity (TFPs) relative to the U.S., tax rates as well as their correlations with sectoral multipliers. Here, we use the countries in the WIOD sample, because this information is available only for this dataset. In Table 1 we provide means and standard deviations of relative productivities and tax rates by income level, as well as the correlation between multipliers and productivities or tax rates. To compute the correlations, we consider deviations from country means, so they are to be interpreted as within-country correlations. Moreover, in Figure 5 we plot correlations between multipliers and log productivities and tax rates for two selected countries, which are representative for countries at similar income levels: India (IND) and Germany (DEU).

Table 1: Descriptive statistics for TFPs and tax rates

Sample	N	avg. TFP	std. TFP	avg. tax rate	std. tax rate	corr. TFP, mult. (within)	corr. tax, mult. (within)
low income	236	0.445	0.430	0.047	0.041	0.251	0.019
mid income	340	0.619	0.593	0.046	0.036	0.06	-0.092
high income	745	1.109	0.801	0.049	0.034	-0.156	-0.124
all	1,321	0.891	0.765	0.049	0.036	-0.101	-0.034

The following empirical regularities arise. First, average sectoral productivities are highly positively correlated with income per capita, while average tax rates are not correlated with income per capita. Second, in low-income countries productivity levels of high-multiplier sectors are above their average productivity relative to the U.S., while in richer countries productivities in these sectors tend to be below average. This is demonstrated by the examples in Figure 5. For instance, India has productivity levels above its average in the high-multiplier sectors – Chemicals, Inland Transport, 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. In contrast, rich European economies, such as Germany – which according to our data is absolutely more productive than the U.S. in manufacturing sectors – tend to have below average productivity levels in high-multiplier sectors such as Financial Services, Business Services and Transport. Qualitatively the same pattern of correlation is observed between sectoral multipliers and taxes. Low-income countries have above average tax rates in high-multiplier sectors, while high income countries have below average tax rates in these sectors. India, for example, taxes gross output in high-multiplier sectors such as Inland Transport, Chemicals and Refining relatively heavily compared to its average sector, while Germany taxes the high-multiplier sectors such as Financial or Business Services at below average rates.

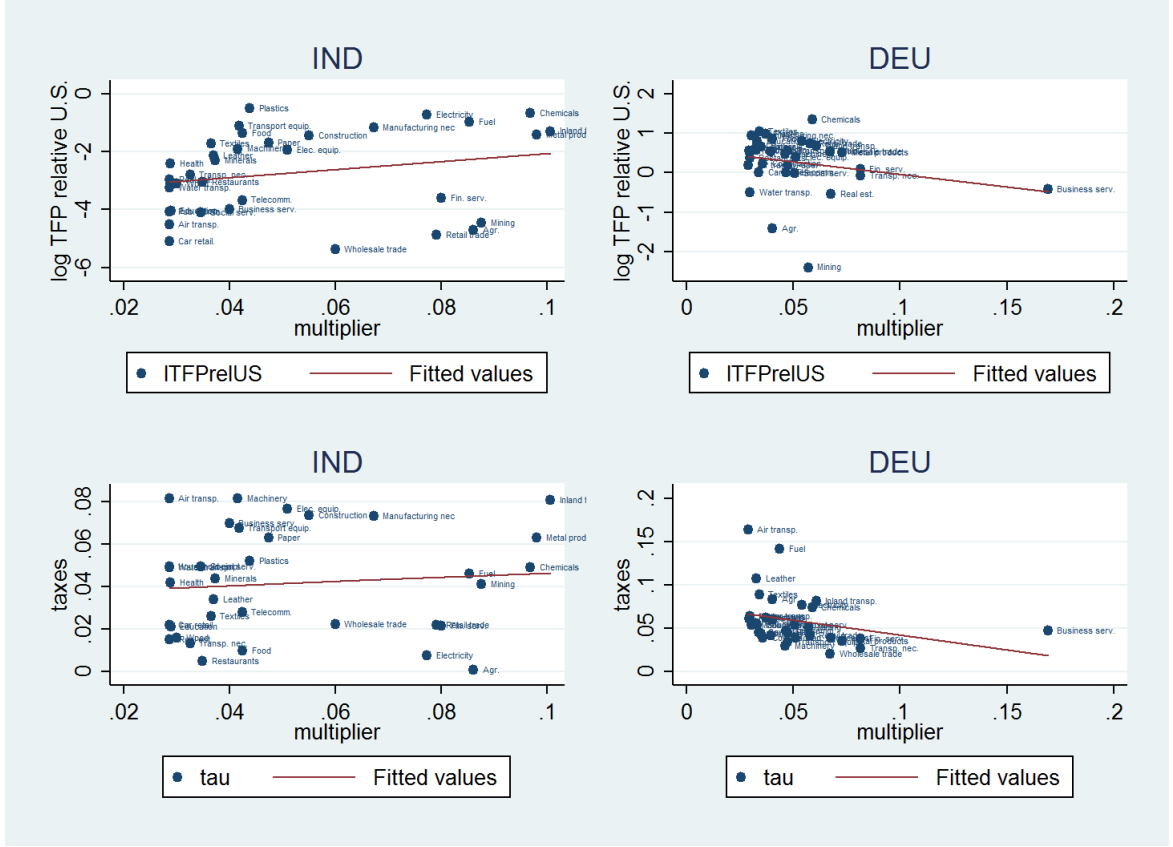


Figure 5: Correlation between IO-multipliers and productivity/taxes

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 with taxes. 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

$$q_i = \Lambda_i (k_i^\alpha l_i^{1-\alpha})^{1-\gamma_i} d_{1i}^{\gamma_{1i}} d_{2i}^{\gamma_{2i}} \dots d_{ni}^{\gamma_{ni}}, \quad (1)$$

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 goods produced by sector j).¹⁴ 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 gross output of sector i . Parameters $\alpha, 1 - \alpha \in (0, 1)$ are shares of capital and labor in the remainder of the inputs (value added).

¹⁴In section 4.4 and Appendix A we consider the case of an open economy, where sectors' production technology employs both domestic and imported intermediate goods.

Given the Cobb-Douglas technology in (1) 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 .¹⁵

Resources in the economy are allocated with distortions. In this paper distortions are regarded as sector-specific proportional taxes on gross output and modeled as exogenous reductions in firms' revenue. Revenue from taxation is spent on government expenditures. Throughout the paper taxes in sector i are denoted by τ_i . We assume that $\tau_i \leq 1$ and interpret negative taxes as subsidies.

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

$$y_i + \sum_{j=1}^n d_{ij} = q_i \quad i = 1 : n \quad (2)$$

Consumption increases households' wellbeing. But rather than specifying a utility function of households over n different consumption goods, we aggregate these final consumption goods into a single final good through another Cobb-Douglas production function:

$$Y = y_1^{\frac{1}{n}} \cdot \dots \cdot y_n^{\frac{1}{n}}. \quad (3)$$

This aggregate final good is used in two ways, as households' consumption, C , and government's consumption, G , that is, $Y = C + G$. Note that the symmetry in exponents of the final good production function implies the 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 and tax rates in an otherwise symmetric framework. It is, however, straightforward to introduce asymmetry in consumption demand by defining the vector of demand shares $\beta = (\beta_1, \dots, \beta_n)$, 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 $Y = y_1^{\beta_1} \cdot \dots \cdot y_n^{\beta_n}$. This more general framework is analyzed in section 4.4 and in Appendix A, 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

¹⁵According 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 .

at the levels of K and 1, respectively:

$$\sum_{i=1}^n k_i = K, \quad (4)$$

$$\sum_{i=1}^n l_i = 1. \quad (5)$$

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

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

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

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

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 $i \in 1 : n$:

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

taking $\{p_i\}$ as given (τ_i and Λ_i are exogenous).

3. 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: $Y = C + G$.

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

5. Government's budget constraint determines G : $G = \sum_{i=1}^n \tau_i p_i q_i$.

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

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

Note that the households' and government's consumption are simply determined by the budget constraints, so that there is no decision for the households or the government to be made. Moreover, the total production of the aggregate final good, Y , which is equal to $\sum_{i=1}^n p_i y_i$ due to the Cobb-Douglas technology in a competitive final good's market, represents 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 set of values $\bar{\tau}_i > 0$, $i = 1 : n$, such that for all $0 \leq \tau_i \leq \bar{\tau}_i \forall i$ there exists a unique competitive equilibrium. In this equilibrium, the logarithm of GDP per capita, $y = \log(Y)$, is given by*

$$\begin{aligned} y = & \sum_{i=1}^n \mu_i \lambda_i + \sum_{i=1}^n \mu_i \log(1 - \tau_i) + \sum_{i=1}^n \sum_{j \text{ s.t. } \gamma_{ji} \neq 0} \mu_i \gamma_{ji} \log \gamma_{ji} + \sum_{i=1}^n \mu_i (1 - \gamma_i) \log(1 - \gamma_i) - \log n + \\ & + \log \left(1 + \sum_{i=1}^n \tau_i \bar{\mu}_i \right) + \alpha \log K, \end{aligned} \quad (6)$$

where

$$\begin{aligned} \boldsymbol{\mu} &= \{\mu_i\}_i = \frac{1}{n} [\mathbf{I} - \boldsymbol{\Gamma}]^{-1} \mathbf{1}, & n \times 1 \text{ vector of multipliers} \\ \boldsymbol{\lambda} &= \{\lambda_i\}_i = \{\log \Lambda_i\}_i, & n \times 1 \text{ vector of sectoral log-productivity coefficients} \\ \boldsymbol{\tau} &= \{\tau_i\}_i, & n \times 1 \text{ vector of sector-specific taxes} \\ \bar{\boldsymbol{\mu}} &= \{\bar{\mu}_i\}_i = \frac{1}{n} [\mathbf{I} - \bar{\boldsymbol{\Gamma}}]^{-1} \mathbf{1}, & n \times 1 \text{ vector of multipliers corresponding to } \bar{\boldsymbol{\Gamma}} \\ \bar{\boldsymbol{\Gamma}} &= \{\bar{\gamma}_{ji}\}_{ji} = \left\{ \frac{\tau_i}{n} + (1 - \tau_i) \gamma_{ji} \right\}_{ji}, & n \times n \text{ input-output matrix adjusted for taxes} \end{aligned}$$

Proof. See Appendix.¹⁶

Thus, due to the Cobb-Douglas structure of our economy, aggregate per capita GDP can be represented as a log linear function of terms that represent aggregate productivity and summarize the aggregate impact of sectoral productivities and taxes via the IO structure, and the capital stock per worker weighted by the capital share in GDP, α .

Two important outcomes are suggested by the proposition. First, aggregate output is an increasing function of sectoral productivities and it is a decreasing function of sector-specific taxes, at least in the

¹⁶The set of upper bounds $\bar{\tau}_i > 0$, $i = 1 : n$, on tax values and the implied upper bound on government's consumption G ensure the existence of an equilibrium as it guarantees the existence of strictly positive equilibrium prices, wage and return on capital. The proof of Proposition 1 follows from the proof of the analogous result stated for a more general setting – with imported intermediate inputs, division into skilled and unskilled labor and unequal demand shares. This more general result, together with the explanation of its applicability to our benchmark model, is provided in the Appendix.

vicinity of small positive $\{\tau_i\}_i$.¹⁷ That is, larger sectoral productivities increase and larger taxes decrease aggregate output of the economy. Observe that the positive component of the effect of taxes, associated with the term $\log(1 + \sum_{i=1}^n \tau_i \bar{\mu}_i)$ in (6), accounts for the fact that larger taxes do not only reduce firms' revenues but also contribute to government expenditures and thereby increase GDP. Second, and more importantly, the impact of each sector's productivity and tax 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 and the negative effect of a higher tax on aggregate output are stronger in sectors with larger multipliers.¹⁸

The vector of sectoral multipliers, in turn, is determined by the features of the IO matrix through the Leontief inverse, $[\mathbf{I} - \mathbf{\Gamma}]^{-1}$.¹⁹ The interpretation and properties of this matrix as well as a simpler representation of the vector of multipliers are discussed in the next section. We show that sectoral multipliers can be directly expressed in terms of simple characteristics of the IO structure of the economy and have a straightforward interpretation as a measure of sectors' *centrality* in the IO network. Namely, larger IO multipliers correspond to sectors that are more central in a well-defined sense. Then in view of Proposition 1, this implies that the impact of sectoral productivities and taxes on aggregate output of the economy tends to be stronger for sectors that are located more centrally in the IO network.

3.3 Intersectoral network. Multipliers as sectors' centrality

The input-output matrix $\mathbf{\Gamma}$, 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. We will call this network the *intersectoral network* of the economy. 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, or simply the *in-degree*, is the share of intermediate inputs in its production. It is equal to the sum of elements in the corresponding *column* of matrix $\mathbf{\Gamma}$; that is, $d_i^{in} = \gamma_i = \sum_{j=1}^n \gamma_{ji}$. The weighted out-degree of a sector, or simply the *out-degree*, 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 $\mathbf{\Gamma}$; that is, $d_j^{out} = \sum_{i=1}^n \gamma_{ji}$. Note that if weights of all links that are present in the network are identical, the

¹⁷Note that the partial derivative of y with respect to τ_i is equal to:

$$\frac{\partial y}{\partial \tau_i} = \frac{-\mu_i}{1 - \tau_i} + \frac{\bar{\mu}_i}{1 + \sum_{i=1}^n \tau_i \bar{\mu}_i} = \frac{-\mu_i (1 + \sum_{i=1}^n \tau_i \bar{\mu}_i) + \bar{\mu}_i - \tau_i \bar{\mu}_i}{(1 - \tau_i) (1 + \sum_{i=1}^n \tau_i \bar{\mu}_i)} \approx \frac{-\mu_i \sum_{i=1}^n \tau_i \bar{\mu}_i - \tau_i \bar{\mu}_i}{(1 - \tau_i) (1 + \sum_{i=1}^n \tau_i \bar{\mu}_i)},$$

where the last equality employs the approximation $\bar{\mu}_i \approx \mu_i$ at low $\{\tau_i\}_i$.

¹⁸The value of sectoral multipliers is positive due to a simple approximation result (8) in the next section.

¹⁹See Burress, 1994.

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 supplier.

The interdependence of sectors' production technologies through the network of intersectoral trade, helps obtaining the insights into the meaning of the Leontief inverse matrix $[\mathbf{I} - \mathbf{\Gamma}]^{-1}$ and the vector of sectoral multipliers $\boldsymbol{\mu}$.²⁰ 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.²¹ 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 the value added by $\frac{1}{1-\gamma} = 2$ percent. In more extreme cases, the aggregate multiplier and hence, the effect of sectoral productivity increases on aggregate value added becomes infinitely large when $\gamma \rightarrow 1$ and it is close to 1 when $\gamma \rightarrow 0$. This is consistent with the intuition in Jones (2011b).

The important observation is that the vector of multipliers is closely related to the *Bonacich centrality* vector corresponding to the intersectoral network of the economy.²² 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. Thus, productivity changes and distortions in a sector that supplies its output to a larger number of direct and indirect customers should have a more significant impact on the overall economy.

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 $\mathbf{\Gamma}$'s eigenvalues lie outside the unit circle (cf. footnote 20), the Leontief inverse and hence the vector of multipliers can

²⁰Observe 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 then suggests that the maximal eigenvalue of $\mathbf{\Gamma}$ is bounded above by 1, and this, in turn, implies the existence of $[\mathbf{I} - \mathbf{\Gamma}]^{-1}$.

²¹Recall 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.

²²Analogous 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, 1986, Jackson, 2008, and Ballester et al., 2006.

be expressed in terms of a convergent power series:

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

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

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

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

$$\boldsymbol{\mu} \approx \frac{1}{n}\mathbf{1} + \frac{1}{n}\mathbf{d}^{out}, \quad (7)$$

so that for any sector i ,

$$\mu_i \approx \frac{1}{n} + \frac{1}{n}d_i^{out}, \quad i = 1 : n. \quad (8)$$

Thus, larger multipliers correspond to sectors with larger out-degree, the simplest measure of sector's centrality in the network. In view of the statement in the previous section, this implies that sectors with the largest out-degree have the most pronounced impact on aggregate value added of the economy. Thus, the changes in productivity and taxes in such "central" sectors affect aggregate output most.

For the sample of countries in our GTAP data, both rich and poor, the approximation of sectoral multipliers by sectors' out-degree (times and plus $1/n$) turns out to be quite good, as demonstrated by Figure 6 below.

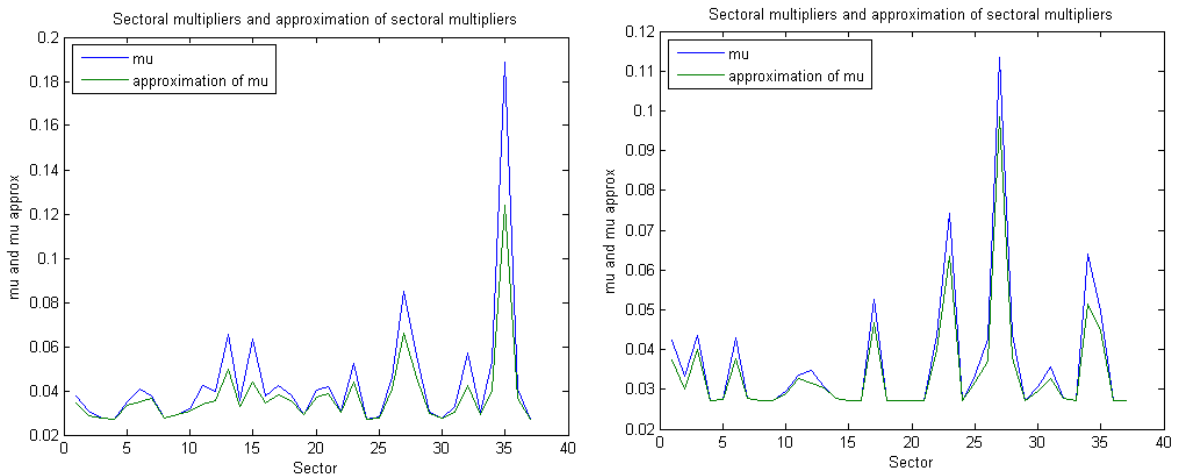


Figure 6: Sectoral multipliers in Germany (left) and Botswana (right). GTAP sample.

In what follows we will consider that the in-degree of all sectors is the same, $\gamma_i = \gamma$ for all i . While

clearly a simplification, this assumption turns out to be broadly consistent with the empirical distribution of sectoral in-degrees of countries from our GTAP sample. In fact, the distribution of in-degrees in all countries is strongly peaked around the mean value, which suggests that on the demand side sectors are rather homogeneous, i.e., they use intermediate goods in approximately equal proportions.²³ This is in sharp contrast with the observed distribution of sectoral out-degrees that puts most weight on small values of out-degrees but also assigns a non-negligible weight to the out-degrees that are way above the average, displaying a fat tail. That is, on the supply side sectors are rather heterogeneous: relatively few sectors supply their product to a large number of sectors in the economy, while many sectors supply to just a few. Figure 12 in the Appendix provides an illustration of empirical distributions of in- and out-degree for different levels of income per capita.

Note that the fat-tail nature of out-degree distribution is also inherent to the distribution of sectoral multipliers. Moreover, according to both distributions, the proportion of sectors with very low and very high out-degree and multiplier is larger in low-income countries. This similarity between the distribution of sectoral out-degrees and multipliers is consistent with the derived relationship (8) between d_i^{out} and μ_i for each sector.

3.4 Expected aggregate output

To estimate the 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, sectoral productivities and sectoral tax rates. 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 and between multipliers and distortions captures the interaction of the input-output structure with sectoral productivities and distortions.

In the next section, we show that the *joint* distribution of sectoral multipliers, productivities (relative to the U.S.) and taxes $(\mu_i, \Lambda_i^{rel}, \tau_i)$ is close to *log-Normal*, so that the joint distribution of log's of the corresponding variables, $(\log(\mu_i), \log(\Lambda_i^{rel}), \log(\tau_i))$ is *Normal*.²⁴ Here i refers to the sector and $\Lambda_i^{rel} = \frac{\Lambda_i}{\Lambda_{US}}$. 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 this tail is fatter and hence, the variance and the mean of μ_i are larger in countries with lower

²³Note that essentially the same assumption of constant in-degree ($\gamma_i = 1$) is employed in Acemoglu et al., 2012, and in Carvalho et al., 2010.

²⁴To be precise, the distribution of $(\log(\mu_i), \log(\Lambda_i^{rel}), \log(\tau_i))$ is a *truncated* trivariate 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 $(\log(\mu_i), \log(\Lambda_i^{rel}), \log(\tau_i))$ as Normal and to the distribution of $(\mu_i, \Lambda_i^{rel}, \tau_i)$ as log-Normal.

income.²⁵

Given the log-Normal distribution of $(\mu_i, \Lambda_i^{rel}, \tau_i)$, the expected value of the aggregate output in each country can be evaluated using the expression for y in (6). We first impose a few simplifying assumptions. First, we consider that for each sector i of a given country, the triple $(\mu_i, \Lambda_i^{rel}, \tau_i)$ is drawn from the *same* trivariate log-Normal distribution, as estimated for this country. Second, we assume that all variables on the right-hand side of (6), apart from μ_i , Λ_i^{rel} and τ_i , are not random. Moreover, all non-zero elements of the input-output matrix $\mathbf{\Gamma}$ are the same, that is, $\gamma_{ji} = \hat{\gamma}$ for any i and j whenever $\gamma_{ji} > 0$, and the in-degree $\gamma_i = \gamma$ for all i .²⁶ Third, to simplify the analysis of the benchmark model, we omit the positive term with taxes, $\log(1 + \sum_{i=1}^n \tau_i \bar{\mu}_i)$, on the right-hand side of (6). It is easy to show that such modification means treating distortions as pure waste, rather than taxes contributing to government budget. In section 4.4, we implement "full" estimation of the model, including the omitted term, and show that the difference between treating distortions as a pure waste or taxes is not empirically relevant. Furthermore, we regard the values of $\{\tau_i\}_i$ as sufficiently small, which allows approximating $\log(1 - \tau_i)$ with $-\tau_i$. Finally, in order to express a sectoral log-productivity coefficient λ_i in terms of the relative productivity Λ_i^{rel} , we use an approximation $\lambda_i = \log(\Lambda_i) \approx \Lambda_i^{rel} + (\log(\Lambda_i^{US}) - 1)$, 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 (6) simplifies and can be written as:

$$y = \sum_{i=1}^n \mu_i \Lambda_i^{rel} - \sum_{i=1}^n \mu_i \tau_i + \sum_{i=1}^n \mu_i \gamma \log(\hat{\gamma}) + \log(1 - \gamma) - \log n + \alpha \log(K) - (1 + \gamma) + \sum_{i=1}^n \mu_i \log(\Lambda_i^{US}). \quad (9)$$

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

$$\begin{aligned} E(y) &= n \left(E(\mu) E(\Lambda^{rel}) + cov(\mu, \Lambda^{rel}) - E(\mu) E(\tau) - cov(\mu, \tau) \right) + (1 + \gamma)(\gamma \log(\hat{\gamma}) - 1) + \\ &+ \log(1 - \gamma) - \log n + \alpha \log(K) + E(\mu) \sum_{i=1}^n \log(\Lambda_i^{US}). \end{aligned} \quad (10)$$

From this expression, we see that higher expected multipliers $E(\mu)$ lead to larger expected income $E(y)$ for the same fixed levels of $E(\Lambda^{rel})$, $E(\tau)$ and covariances, as soon as $E(\Lambda^{rel}) > E(\tau)$, which holds empirically for most countries. 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. Similarly, higher tax rates reduce aggregate income by more if they are set in

²⁵ See the distribution parameter estimates in the next section.

²⁶ These 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 $\mu_i \gamma \log(\hat{\gamma})$ since the number of non-zero elements in each column of $\mathbf{\Gamma}$ is equal to $\frac{\gamma}{\hat{\gamma}}$, and $\sum_{i=1}^n \mu_i (1 - \gamma_i) \log(1 - \gamma_i) = \log(1 - \gamma)$ since $\sum_{i=1}^n \mu_i (1 - \gamma_i) = \mathbf{1}'[\mathbf{I} - \mathbf{\Gamma}] \cdot \frac{1}{n}[\mathbf{I} - \mathbf{\Gamma}]^{-1} \mathbf{1} = \frac{1}{n} \mathbf{1}' \mathbf{1} = 1$. Moreover, $\sum_{i=1}^n \mu_i \approx 1 + \gamma$ because from (8) 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 .

sectors with higher multipliers, as indicated by $cov(\mu, \tau)$.

The expression for expected aggregate income in (10) can be written in terms of the parameters of the normally distributed $(\log(\mu), \log(\Lambda^{rel}), \log(\tau))$, by means of the relationships between Normal and log-Normal distributions:²⁷

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

where m_μ , m_Λ , m_τ are the means and σ_μ^2 , σ_Λ^2 , σ_τ^2 and $\sigma_{\mu,\Lambda}$ and $\sigma_{\mu,\tau}$ are the elements of the variance-covariance matrix of the Normal distribution.

This is the ultimate expression that we use in the empirical analysis of the benchmark model in section 4 below.

4 Empirical analysis

In this section we estimate the parameters of the Normal distribution of $(\log(\mu), \log(\Lambda^{rel}), \log(\tau))$ for the sample of countries for which we have data and evaluate the predicted aggregate income in these countries (relative to the one of the U.S.). In order to predict relative rather than absolute output, we use equation (13) differenced with the value of predicted aggregate income for the U.S.

4.1 Structural estimation

The vector of log multipliers, log relative productivities and log tax rates $\mathbf{Z} = (\log(\mu), \log(\Lambda^{rel}), \log(\tau))$ is drawn from a (truncated) trivariate Normal distribution.²⁸

The vector of parameters to be estimated using Maximum Likelihood estimation is $\Theta = (\mathbf{m}, \Sigma)$, where $\mathbf{m}$ is the vector of means and Σ denotes the variance-covariance matrix. In order to allow for structure, productivity and taxes to differ across countries we model both $\mathbf{m}$ and Σ as linear functions of $x = \log(\text{GDP per capita})$.

²⁷These relationships are:

$$E(\mu) = e^{m_\mu + 1/2\sigma_\mu^2}, \quad E(\Lambda^{rel}) = e^{m_\Lambda + 1/2\sigma_\Lambda^2}, \quad E(\tau) = e^{m_\tau + 1/2\sigma_\tau^2}, \quad (11)$$

$$cov(\mu, \Lambda) = e^{m_\mu + m_\Lambda + 1/2(\sigma_\mu^2 + \sigma_\Lambda^2)} \cdot (e^{\sigma_{\mu,\Lambda}} - 1), \quad cov(\mu, \tau) = e^{m_\mu + m_\tau + 1/2(\sigma_\mu^2 + \sigma_\tau^2)} \cdot (e^{\sigma_{\mu,\tau}} - 1) \quad (12)$$

²⁸The formula for the truncated trivariate Normal, where $\log(\mu)$ is censored from below at a is given by $f(\mathbf{Z}|\mu \geq a) = \frac{1}{\sqrt{(2\pi)^3|\Sigma|}} \exp[-1/2(\mathbf{Z} - \mathbf{m})'\Sigma^{-1}(\mathbf{Z} - \mathbf{m})]/(1 - F(a))$, 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

$$\mathbf{m} = \begin{pmatrix} m_\mu \\ m_\Lambda \\ m_\tau \end{pmatrix}, \quad \Sigma = \begin{pmatrix} \sigma_\mu^2 & \rho_{\mu\Lambda}\sigma_\mu\sigma_\Lambda & \rho_{\mu\tau}\sigma_\mu\sigma_\tau \\ \rho_{\mu\Lambda}\sigma_\mu\sigma_\Lambda & \sigma_\Lambda^2 & \rho_{\Lambda\tau}\sigma_\Lambda\sigma_\tau \\ \rho_{\mu\tau}\sigma_\mu\sigma_\tau & \rho_{\Lambda\tau}\sigma_\Lambda\sigma_\tau & \sigma_\tau^2 \end{pmatrix} \quad (14)$$

First, we estimate the statistical model on the WIOD sample (35 sectors, 39 countries). We find that m_μ is decreasing in $\log(\text{GDP per capita})$, while σ_μ is not a significant function of per capita GDP for this sample. We thus restrict the second parameter to be constant in the reported estimates. The point estimates and standard errors of all parameters are summarized in Table 2. m_μ is decreasing in $\log(\text{GDP per capita})$ with a slope of around -0.08. The log of σ_μ^2 is around -0.642. Hence, in the WIOD sample poor countries have a distribution of log multipliers with a slightly higher average than rich countries but with the same dispersion, implying that the distribution of the level of multipliers has a larger mean and a larger variance in poor countries (see formulas in footnote 30). Average log productivity, m_Λ is strongly increasing in $\log \text{GDP per capita}$ (with a slope of around 1.3), while the standard deviation of log productivity, σ_Λ is a decreasing function of the same variable. This implies that rich countries have higher average productivity levels and less variation in productivity (relative to the U.S.) across sectors than poor countries. Similarly, average log taxes, m_τ , are slightly increasing in $\log(\text{GDP per capita})$ (with a slope of 0.09), whereas the variability of tax rates, as described by $\log(\sigma_\tau^2)$, is decreasing with income. Finally, note that the correlation between log multipliers and log productivity, $\rho_{\mu\Lambda}$, is a decreasing function of $\log(\text{GDP per capita})$. Similarly, the correlation between log multipliers and log distortions, $\rho_{\mu\tau}$ is also decreasing in per capita income. These correlations imply that poor countries have above average productivity levels in sectors with higher multipliers, while rich countries have taxes which are lower than their average levels in these sectors. Figure 7 provides density plots of the empirical and estimated distributions of log multipliers, log productivity and log distortions. It is apparent that the estimated distributions fit the empirical ones quite well. Finally, Figure 8 plot the parameter estimates of the correlation coefficients $\rho_{\mu\Lambda}$ and $\rho_{\mu\tau}$ as functions of $\log(\text{GDP per capita})$.

To obtain more information on the IO structure of low-income countries, we now re-estimate our statistical model on the GTAP sample (37 sectors, 70 countries). For these countries, we only have information on IO multipliers but not on productivity levels and taxes. Therefore, we estimate a univariate Normal distribution for m_μ and σ_μ . Table 3 reports the results. We find that m_μ is now an insignificant function of income and we therefore report the estimate for constant m_μ . In contrast, for the larger sample the standard deviation of log multipliers, σ_μ is now significantly smaller for rich than for poor countries. This implies that both the mean and the standard deviation of the corresponding distributions of multipliers are larger in poor countries than in rich ones: in poor countries the average sector has a larger multiplier and there is more mass in the right tail of the distribution. We summarize these empirical findings below.

Summary of estimation results:

1. *The estimated distribution of IO multipliers has a larger variance and more mass in the right tail*

Table 2: Maximum likelihood

WIOD sample		
	Coef.	Std. Err.
$\mathbf{m}_\mu$:		
constant	0.648	0.431
log(gdp per capita)	-0.081*	0.047
$\log(\sigma_\mu^2)$:		
constant	-0.642***	0.145
$\mathbf{m}_\Lambda$:		
constant	-13.327***	1.287
log(gdp per capita)	1.287***	0.142
$\log(\sigma_\Lambda^2)$:		
constant	4.102***	0.735
log(gdp per capita)	-0.375***	0.074
$\mathbf{m}_\tau$:		
constant	-3.847***	0.464
log(gdp per capita)	0.090***	0.046
$\log(\sigma_\tau^2)$:		
constant	1.870***	0.617
log(gdp per capita)	-0.284***	0.062
z-transformed $\rho_{\mu\Lambda}$:		
constant	3.440***	0.813
log(gdp per capita)	-0.352***	0.083
z-transformed $\rho_{\mu\tau}$:		
constant	1.010*	0.607
log(gdp per capita)	-0.126**	0.061
Log likelihood	-107.885	
Observations	1281	

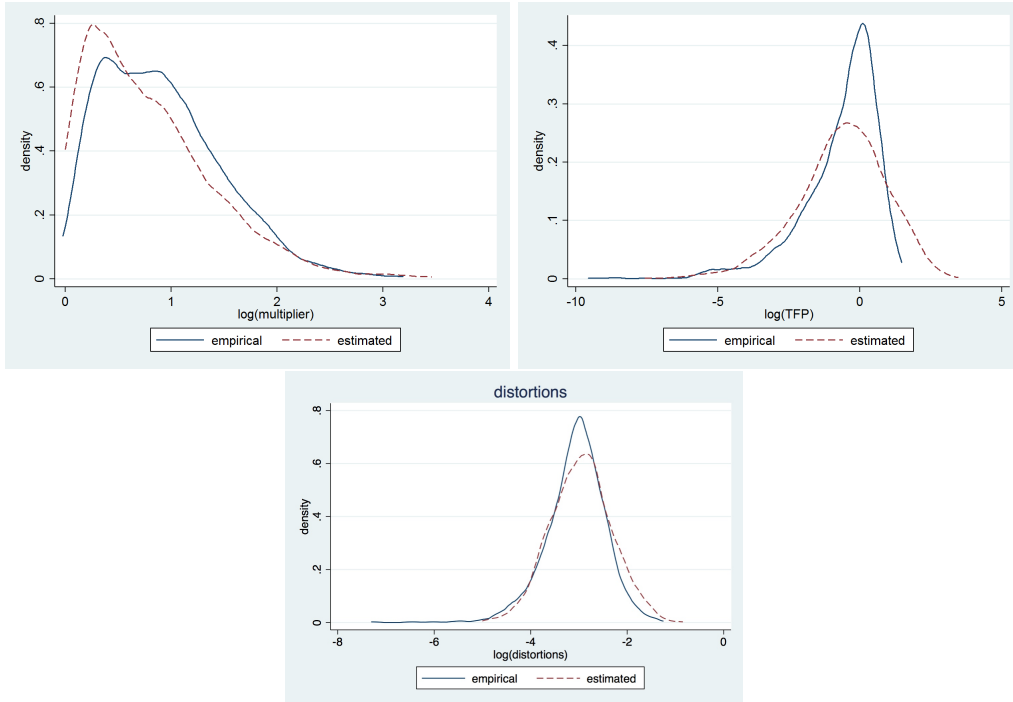


Figure 7: Estimated vs. actual distribution of log multipliers (left), log productivity (right), and log tax rates (bottom)

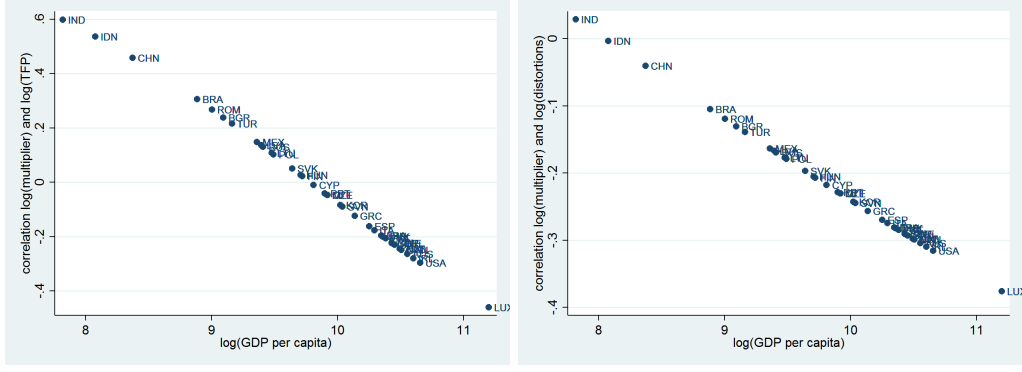


Figure 8: Estimated correlation between multiplier and productivity (left), distortions (right)

Table 3: Maximum Likelihood

GTAP sample		
	Coef.	Std. Err.
m_μ :		
constant	-3.274***	0.072
$\log(\sigma_\mu^2)$:		
constant	0.328***	0.029
$\log(\text{GDP per capita})$	-0.008***	0.003
Log likelihood	10,069.322	
Observations	2,553	

in poor countries compared to rich ones.

- The estimated distribution of productivities has a lower mean and a larger variance in poor countries compared to rich ones.*
- The estimated distribution of tax rates has a lower mean and a larger variance in poor countries compared to rich ones.*
- IO multipliers and productivities correlate positively in poor countries and negatively in rich ones.*
- IO multipliers and tax rates correlate positively in poor countries and negatively in rich ones.*

4.2 Predicting cross-country income differences

With the parameter estimates $\hat{\Theta}$ at hand, we now use equation (13) (differenced relative to the U.S.) to predict income per capita relative to the U.S.²⁹ We compare our baseline model which features IO linkages, sectoral productivity differences and taxes with two simple alternatives. The first one, which we label the 'naive model', has no IO structure, no productivity differences and no taxes, so that $y = E(y) = \alpha \log(K)$. The second model, in contrast, has sectoral productivity differences but no IO linkages.

²⁹The expression for $E(y)$ for the truncated distribution of $(\mu_i, \Lambda_i^{rel}, \tau_i)$ is somewhat more complicated and less intuitive. 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.

It is easy to show that under the assumption that sectoral productivities follow a log-Normal distribution predicted log income in the this model is given by $E(y) = e^{m_\Lambda + 0.5\sigma_\Lambda^2} + \alpha \log(K) + \frac{1}{n} \sum_{i=1}^n (\log(\Lambda_i^{US})) - 1$.³⁰ In addition to the estimated parameter values $\hat{\Theta}$, we need to calibrate a few other parameters. As standard, we set α , the labor income share in GDP, equal to 2/3. Moreover, we set γ , the share of intermediates in gross output, equal to 0.5, which corresponds to the average level in the WIOD dataset. Finally, we set n equal to 35, which corresponds to the number of sectors in the WIOD dataset.

To evaluate model fit, we provide the following tests: first, we regress income per capita relative to the U.S. predicted by the model on actual data for GDP per capita relative to the U.S. If the model fits perfectly the estimate for the intercept should be zero, while the regression slope and the R-squared should equal unity. Second, as a graphical measure for the goodness of fit, we also plot predicted income per capita relative to the U.S. against actual relative income. Note that these statistics provide over-identification tests for our model since there is no intrinsic reason for the model to fit data on relative per capita income: we have not tried to match income data in order to estimate the parameters of the distribution of IO multipliers, productivities or taxes. Instead, we have just allowed the joint distribution of these parameters to vary with the level of income per capita.

The results for the first test are reported in Table 4. In the first column, we report statistics for the 'naive' model. In the second column, we report results for the model with productivity differences but no IO structure. In column (3) we report results for the baseline model ((13)), where we take the parameter estimates as estimated from the WIOD data (using parameters for the distribution of multipliers from Table 2 above). In column (4), we force the distribution of multipliers to be the same across countries by restricting both m_μ and σ_μ^2 to be constant. Finally, in column (5) we report results for the baseline model when the distribution of multipliers is estimated from the GTAP dataset (using parameters for the distribution of multipliers from Table 3).

We now present the results of this exercise. The 'naive' model fails in predicting relative income across countries (column (1)). As is well known, a model without productivity differences predicts too little variation in income per capita across countries. Still, in the WIOD sample, which consists mostly of high-income countries, it does relatively well: the intercept is 0.426, the slope coefficient is 0.735 and the R-squared is 0.888. The simple model with productivity differences but no IO linkages (column (2)) performs better but it generates too much variation in income compared to the data, implying that aggregate productivity differences estimated from sectoral data are larger than what is necessary to generate the observed differences in income: the intercept is -0.155, the slope coefficient is 0.929 and the R-squared is 0.865. We now move to the first specification with IO structure. In column (3) we report

³⁰ $Y = \prod_{i=1}^n \Lambda_i^{1/n} (K)^\alpha$, 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 follows a log-Normal distribution, we obtain the above formula.

results for the baseline model with the IO structure estimated from WIOD data. This model indeed performs better than the one without IO structure: the intercept is no longer statistically different from zero, the slope coefficient equals 0.922 and the R-squared is 0.853. A visual comparison of actual vs. predicted relative income in Figure 9 confirms the substantially better fit of the model with IO linkages compared to the one without IO structure, which underpredicts relative income levels of most countries. Next, we test if cross-country differences in IO structure are part of the explanation of improved fit. In column (4) we restrict the coefficients of m_μ and σ_μ^2 to be the same for all countries but we continue to allow for cross-country differences in the correlation between productivity and IO structure as well as in the correlation between taxes and IO structure. We find that this model fits the data much worse than the one with income-varying IO structure: the intercept is 0.225, the slope coefficient drops to 0.843 and the R-squared to 0.738, thus indicating that cross-country differences in IO structure are important for predicting differences in income across countries. Finally, in column (5) we use the estimated IO structure from the GTAP sample in our baseline IO model. The GTAP data is more informative about cross-country differences in IO structure 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 much more precisely. The above estimates from the GTAP data indicate that poorer countries have a distribution of multipliers with a significantly fatter right tail compared to rich countries. Using these estimates, we find that the size of the intercept drops to 0.007 and is not statistically different from zero, while the slope coefficient is equal to 0.901 and the R-squared is 0.834. Thus, this specification outperforms both the model without IO structure and the one with constant IO structure in terms of predicting income differences and performs comparably to the one where the IO structure is estimated from the WIOD data.

Observe that there are three main factors that determine the improved fit of the baseline model with IO structure compared to the model without IO structure: first, the difference in the IO structure between high and low-income countries, where poor countries in the sample have only a few highly connected sectors and many sectors that are relatively isolated, while rich countries have more intermediately connected sectors; second, the fact that in contrast to rich countries poor economies have higher than average productivity levels in high-multiplier sectors; third, the fact that poor countries have relatively higher taxes in high-multiplier sectors. We will investigate the impact of each of these factors separately in the next section, but we first turn to the model fit in two alternative samples.

Using our model together with the parameter estimates obtained from the WIOD and GTAP data, we predict relative income for the sample of GTAP countries (70 countries) and the sample of countries in the Penn World Tables for which we have the necessary information on capital stocks (155 countries).

Table 4: Model Fit: World IO sample

	Naive model	No IO structure	WIOD IO structure	Constant IO structure	GTAP IO structure
constant	0.426*** (0.064)	-0.155*** (0.030)	-0.014 (0.021)	0.225** (0.038)	0.007 (0.023)
slope	0.735*** (0.117)	0.929*** (0.066)	0.922*** (0.057)	0.843*** (0.080)	0.907*** (0.061)
Observations	39	39	39	39	39
R-squared	0.557	0.865	0.853	0.738	0.834

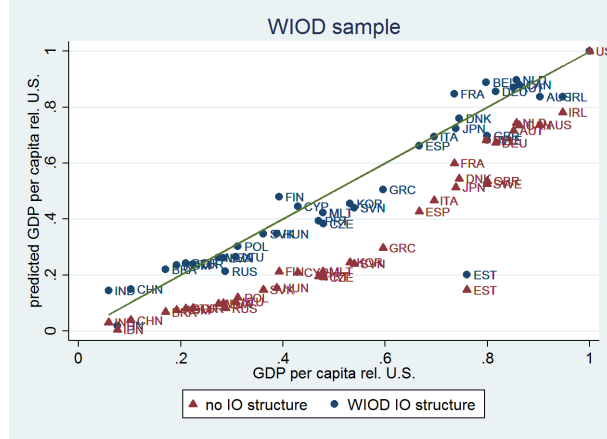


Figure 9: Predicted income per capita: baseline model with estimated IO structure

The latter sample is usually employed for development accounting exercises. In Table 5, columns (1)-(4), we present results for the GTAP sample. In column (1) we report results for the 'naive' model, which does relatively poorly in predicting relative income for this sample: the intercept is 0.363, the slope coefficient is 0.781 and the R-squared is 0.888. In column (2), by contrast, we present results for the model with productivity differences but no IO structure. Again, this model performs much better than the 'naive' one: the intercept drops to -0.067, the slope coefficient rises to 0.807 and the R-squared improves to 0.901. Now we turn to the baseline model with IO structure. In column (3) we report the results for the baseline model where we take the parameter estimates for the distribution of multipliers from the GTAP sample. This model does much better than the 'naive' one and also better than the model without IO structure in terms of fitting the regression of predicted on actual income: the intercept is 0.127, the slope coefficient is 0.812 and the R-squared is 0.977. The increased goodness of fit can also be seen from Figure 10, left panel, where we plot predicted income against actual income for the baseline model and the model without IO structure. While the second considerably underpredicts income for most countries, the model with IO structure is extremely close to the 45 degree line. Only for the poorest countries it overpredicts their relative income somewhat. Finally, in column (4) we report results for the baseline model where the estimates of the IO structure are derived from the WIOD sample: we now get the intercept of 0.084, the slope coefficient of 0.808 and the R-squared of 0.962. Thus, this model

performs slightly worse than the one where we have used the GTAP IO structure because it predicts somewhat smaller differences in IO structure across countries.

Finally, we discuss the results for the Penn World Tables sample (columns (5)-(8)). Here the performance of the 'naive' model is again quite poor and it strongly overpredicts income for poor countries, indicating that productivity differences matter for explaining aggregate income differences. In column (5) the intercept is 0.342 and the slope coefficient is 0.823 with an R-squared of 0.831. In column (6) we report results for the model without IO structure, which has a negative intercept (-0.037), an even smaller slope coefficient of 0.759 and an R-squared of 0.894. This model is again outperformed by our baseline model with the GTAP IO structure: the slope coefficient for this model is 0.775 and the R-squared increases substantially to 0.966. Thus, the model performs quite well in predicting relative income across countries, even in a sample that is much larger than the one from which we have estimated the parameters of the model. The good fit can also be seen clearly from the right panel of Figure 10, where most data points are extremely close to the 45 degree line. Again, the model overpredicts relative income levels somewhat for very low-income countries. Finally, in column (8), we report results for the baseline model when estimating the IO structure from the WIOD sample. This model does slightly worse than the previous one, but still performs better than the model without IO structure: the slope coefficient is 0.763, and the R-squared is 0.953. We conclude that including an IO structure into the model helps to substantially improve model fit. To wrap up, we now present a summary of our findings.

Summary of model fit:

1. *The baseline model with estimated IO structure performs substantially better in terms of predicting cross-country income differences than a model without technology differences (which underestimates income differences) and a model with technology differences but without IO structure (which overestimates income differences).*
2. *The baseline model with IO structure estimated from GTAP data performs slightly better than the same model with IO structure estimated from WIOD data.*
3. *The above results hold for three different samples of countries: the WIOD dataset (39 countries), the GTAP dataset (70 countries) and the Penn World Tables dataset (155 countries).*

Now that we have shown that the baseline model with IO structure performs very well in terms of predicting relative income levels across countries, we turn to several counterfactual exercises in order to understand better how the interplay between IO structure, sectoral productivity levels and taxes determines income differences across countries.

Table 5: Model Fit: Alternative Samples

	GTAP sample				PWT sample			
	Naive model	No IO structure	GTAP IO structure	WIOD IO structure	Naive model	No IO structure	GTAP IO structure	WIOD IO structure
constant	0.363*** (0.022)	-0.067*** (0.014)	0.127*** (0.093)	0.084*** (0.009)	0.342*** (0.012)	-0.037*** (0.007)	0.146*** (0.004)	0.110*** (0.005)
slope	0.781*** (0.039)	0.807*** (0.046)	0.812*** (0.019)	0.808*** (0.025)	0.823*** (0.034)	0.759*** (0.041)	0.775*** (0.016)	0.763*** (0.024)
Observations	70	70	70	70	155	155	155	155
R-squared	0.888	0.903	0.977	0.962	0.831	0.894	0.966	0.953

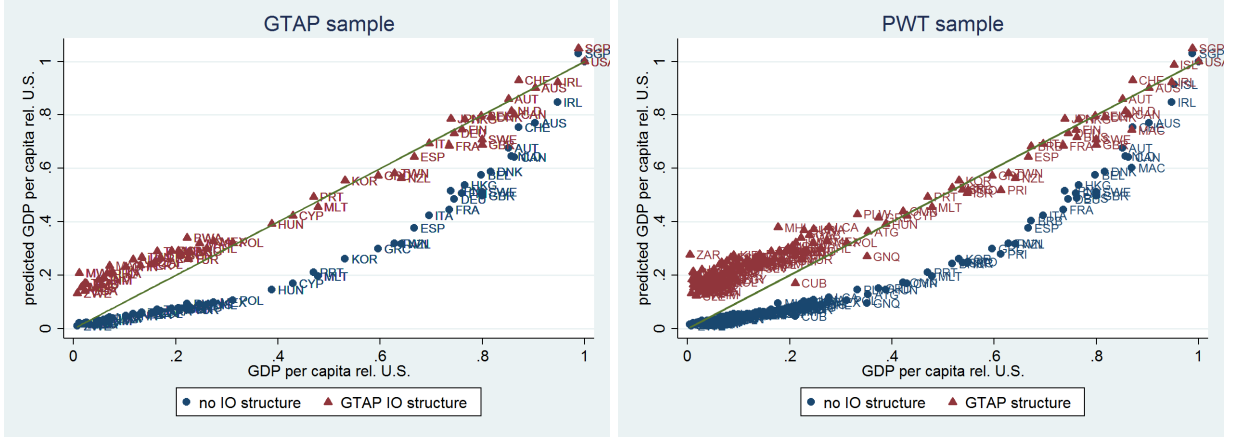


Figure 10: Predicted income per capita: baseline model with estimated IO structure

4.3 Counterfactual experiments

We first investigate how differences in IO structure – as summarized by the distribution of multipliers – matter for cross-country income differences. Thus, in our first counterfactual exercise we set the distribution of multipliers equal to the U.S. one. The result can be grasped from Figure 11, upper left panel, which plots the counterfactual change in income per capita (in percent of the initial level of income per capita) against GDP per capita relative to the U.S. It can be seen that 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 for countries with income levels close to the U.S. one, to 80 percent of per capita income for very poor countries such as Congo (ZAR) or Zimbabwe (ZWE).

The reason why most countries lose in this counterfactual experiment is the form of the distribution of multipliers in the U.S.: high-income countries have a distribution of multipliers with less mass in the right tail than poor countries but much more mass in the middle range of the distribution. This implies that a typical sector in the U.S. is intermediately connected. Given the distribution of productivities in low-income countries, which has a low mean, high variance and positive correlation with multipliers, they perform much worse with their new IO structure: now their typical sector – which is much less productive than in the U.S. – has a higher multiplier and thus is more of a drag on aggregate performance. Moreover, they can no longer benefit much from the fact that their super-star sectors are relatively productive

because the relative importance of these sectors for the economy has been reduced substantially. To put it differently, recall that in low-income economies, 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 sectors. Thus, it suffices to have comparatively high productivity levels in those crucial sectors in order to obtain a relatively satisfactory aggregate outcome. In 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 other sectors. Thus, with such dense IO structure fixing inefficiencies in a few selected sectors is no longer enough to achieve a relatively good aggregate performance.

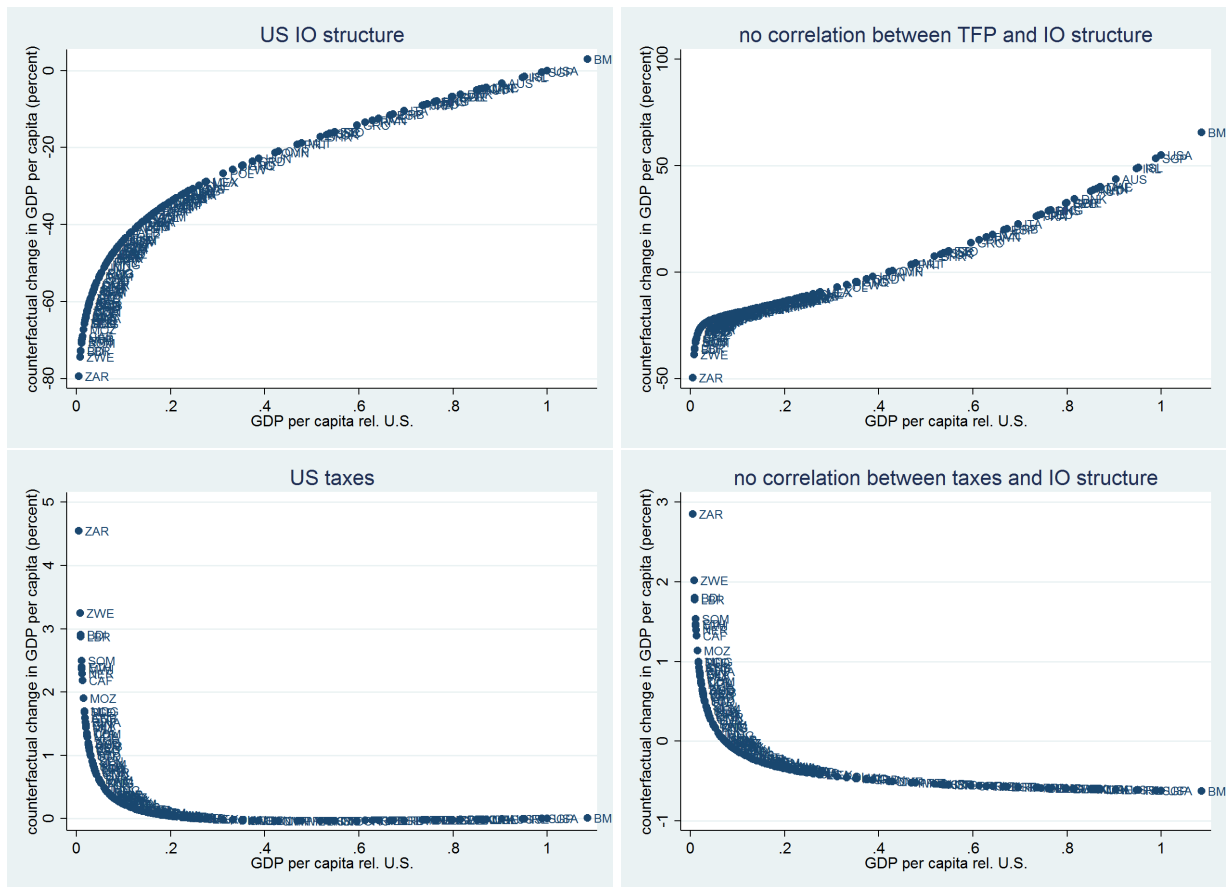


Figure 11: Counterfactuals

In the second counterfactual exercise, we set the correlation between log multipliers and log productivities, $\rho_{\mu\Lambda}$, to zero. We can see from the upper right panel of Figure 11 that poor countries (up to a around 40 percent of of the U.S. level income per capita) would lose substantially (up to 50 percent) in terms of their initial income, while rich countries would gain up to 60 percent. Why is this the case? From our estimates, poor countries have a positive correlation between log multipliers and log productivities, while rich countries have a negative one (see Figure 8). 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 correlation tends to be negative. Eliminating this link worsens aggregate outcomes in poor countries and improves those in rich countries further.

Next, we turn to a counterfactual where we set the distribution of log taxes as well as their correlation with log multipliers equal to the U.S. one. As can be seen from Table 2, average tax rates in rich countries are somewhat higher than in low-income countries, but they have a much lower variance across sectors and are thus less distortionary. Moreover, the correlation between multipliers and tax rates is negative for the U.S. The lower left panel of Figure 11 plots changes in income per capita (in percent) against GDP per capita relative to the U.S. One can see that setting distortions equal to the U.S. level provides negligible gains for most countries. Only countries with less than 20 percent of the U.S. income level gain significantly, with a maximum of around 5 percentage points for Congo (ZAR). Thus, income gains from reducing tax distortions to the U.S. level are modest for most countries.³¹

In the final experiment we set the correlation between log multipliers and log taxes to zero for all countries. The lower right panel of Figure 11 plots the resulting changes in per capita income (in percent) against GDP relative to the U.S. level. Again, income changes resulting from this experiment are relatively small. Poor countries – which empirically exhibit a positive correlation between multipliers and distortions – experience small increases in income (up to 3 percentage points for Congo (ZAR)), while rich countries – which empirically have a negative correlation between multipliers and tax rates – lose around one percentage point of income per capita.

Summary of counterfactual experiments:

1. *Imposing the dense IO structure of the U.S. on poor economies would reduce their income levels by up to 80 percent because the typical sector, which has a lower productivity 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 reduced by up to 40 percent.*
3. *Imposing the distribution of tax rates of the U.S. on poor economies would lead to moderate income gains of up to 5 percent.*
4. *If poor economies did not have above-average tax levels in high-multiplier sectors, their income levels would increase by up to 3 percent.*

³¹Observe that this does not imply that distortions which imply misallocation of resources across sectors are small. However, in our data – which uses information on actual tax rates on gross output – the bulk of these distortions are captured by low sectoral productivity levels rather than by high tax rates.

4.4 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 on the baseline model. We consider the following extensions. First, we estimate parameters using the approximated distribution of multipliers, where we employ the representation of multipliers in terms of sectoral out-degrees. Second, we allow for skilled and unskilled labor as separate production factors. Third, we generalize the final demand structure and introduce expenditure shares that differ across countries and sectors. Fourth, we generalize the model by introducing imported intermediate inputs. Finally, we consider taxes as government revenue instead of treating them as wasteful. We then show that none of these generalizations 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 Appendix.

4.4.1 Approximation of multipliers

We first provide results when estimating the distribution of log multipliers from a first and second-order approximation, instead of using the actual empirical distribution of log multipliers. Following the discussion in section 3.3, the first-order approximation of multipliers is $\boldsymbol{\mu} \approx \frac{1}{n} + \frac{1}{n}\boldsymbol{\Gamma}\mathbf{1}$, while the second-order approximation is $\boldsymbol{\mu} \approx \frac{1}{n} + \frac{1}{n}\boldsymbol{\Gamma}\mathbf{1} + \frac{1}{n}\boldsymbol{\Gamma}^2\mathbf{1}$. The first-order approximation abstracts from higher-order interconnectedness and only considers direct outward linkages (weighted out-degrees), while the second-order approximation also considers second-order interconnectedness (the weighted out-degree of sectors to which each sector delivers).

Empirically, there is little difference between the actual distribution of multipliers and the estimated distribution using the first and second-order approximation, as can be seen from Figure 13 in the Appendix. Columns (1) and (2) of Table 6 report model fit results for the first- and second-order approximation. It is apparent that the difference in performance between the models is relatively small. The intercepts are now -0.106 and -0.133 and the slope coefficients are 0.989 and 0.974, respectively, for the first- and second-order approximation, compared to -0.014 and 0.922 for the baseline model with IO structure estimated on the WIOD sample. Observe also that the first-order approximation, which is most consistent with the formula for aggregate income (13), performs slightly better than the second-order approximation, indicating that modeling second-order interconnectedness does not help to improve our understanding how differences in countries' IO structure affect aggregate income.

4.4.2 Cross-country differences in demand structure

So far we have abstracted from cross-country differences in the final demand structure, which also have an impact on sectoral multipliers because sectors with larger final expenditure shares will have a larger impact on GDP. In the next robustness check, we thus consider a more general demand structure. More specifically, we model the production function for the aggregate final good as $Y = y_1^{\beta_1} \cdot \dots \cdot y_n^{\beta_n}$, 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 now multipliers become functions of both differences in the IO structure and differences in final demand. Thus, this specification does not allow one to differentiate between the two channels. The vector of sectoral multipliers is now defined as $\boldsymbol{\mu} = \{\mu_i\}_i = [\mathbf{I} - \boldsymbol{\Gamma}]^{-1} \boldsymbol{\beta}$, where $\boldsymbol{\beta} = (\beta_1, \dots, \beta_n)'$. Its interpretation, however, is identical to the one before: each sectoral multiplier μ_i reveals how a change in productivity (or taxes) of sector i affects the overall value added in the economy.

The results for this model can be found in column (3) of Table 6. The intercept is now -0.12 and the slope coefficient is 0.901, which is somewhat worse than the performance of our baseline model. This indicates that – within the context of our model – modeling differences in the final demand structure does not help to understand differences in aggregate income. The reason seems to be that modeling differences in final demand structure introduces additional noise in the multiplier data, which makes it harder to estimate the systematic features of inter-industry linkages.

4.4.3 Skilled labor

Next, 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:

$$q_i = \Lambda_i \left(k_i^\alpha u_i^\delta s_i^{1-\alpha-\delta} \right)^{1-\gamma_i-\sigma_i} d_{1i}^{\gamma_{1i}} d_{2i}^{\gamma_{2i}} \cdot \dots \cdot d_{ni}^{\gamma_{ni}}, \quad (15)$$

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 $\alpha, \delta, 1 - \alpha - \delta \in (0, 1)$ 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 is from WIOD. We calibrate $\delta = 1/6$ to fit the college skill premium of the U.S. Results are provided in column (4) of Table 6. The intercept is -0.055 and the slope coefficient is 0.943, which is very close to the baseline model. We conclude that the results are not

sensitive to the definition of labor endowments.

4.4.4 Imported intermediates

So far we have abstracted from international trade and we have assumed that all goods have to be produced domestically. Here, we instead allow for both domestically produced and imported intermediates. We thus assume that sectoral production functions are given by:

$$q_i = \Lambda_i (k_i^\alpha l_i^{1-\alpha})^{1-\gamma_i-\sigma_i} d_{1i}^{\gamma_{1i}} d_{2i}^{\gamma_{2i}} \cdot \dots \cdot d_{ni}^{\gamma_{ni}} \cdot f_{1i}^{\sigma_{1i}} f_{2i}^{\sigma_{2i}} \cdot \dots \cdot f_{ni}^{\sigma_{ni}}, \quad (16)$$

where d_{ji} are domestically produced intermediate inputs and f_{ji} are imported intermediate inputs. Domestic and imported intermediate inputs are assumed to be imperfectly substitutable, and γ_{ji} , σ_{ji} denote the shares of domestic and imported intermediates, respectively, in the value of sectoral gross output. We change the construction of the IO tables accordingly by separating domestically produced from imported intermediates and then re-estimating the distribution of IO multipliers.

The results for fitting the model with this specification are given in column (5) of Table 6. The slope coefficient is now 1.004, which is even closer to one than with the baseline specification. The intuition for why results remain very similar comes from the fact that most important, 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 in every country very much. We thus conclude that our results are quite robust to allowing for trade in intermediates.

4.4.5 Taxes as government revenue

As a final robustness check, we rebate tax revenues collected by the government lump sum to households instead of considering them as wasted. The results for this model are presented in column (6) of Table 6. We find that the results are basically equivalent to those in the baseline model: the intercept is 0.017 and not statistically different from zero, while the slope coefficient is 0.920. Thus, rebating government revenue to households does not make a difference. We therefore conclude that our baseline model is pretty robust to a number of extensions and alternative assumptions.

5 Conclusions

In this paper we have studied the role of input-output structure of the economy and its interaction with sectoral productivities and tax distortions in explaining income differences across countries. In contrast to the typical approach in the literature on development accounting and on dual economies and structural transformation, we model input-output linkages between sectors and the difference in

Table 6: Robustness: World IO sample

	1st order approximation	2nd order approximation	Expenditure shares	Human capital	Imported intermediates	No waste
constant	-0.106*** (0.022)	-0.133** (0.059)	-0.128*** (0.027)	-0.055*** (0.002)	-0.153*** (-0.026)	0.017 (0.021)
slope	0.989*** (0.056)	0.974*** (0.059)	0.901*** (0.064)	0.943*** (0.055)	1.004*** (0.063)	0.920*** (0.057)
Observations	39	39	39	39	39	39
R-squared	0.883	0.884	0.865	0.845	0.884	0.852

these linkages across countries explicitly. Moreover, our approach is to a large extent empirical, which complements the predominantly theoretical analysis of previous studies on cross-country differences in IO structure.

We first develop and analytically solve a multi-sector general equilibrium model with IO linkages, sector-specific productivities and taxes. We then estimate this model using a statistical approach that allows us to derive a simple closed-form dependence of aggregate per capita income on the first and second moments of the joint distribution of IO multipliers, sectoral productivities and tax rates. We estimate the parameters of this distribution to fit the corresponding empirical distribution of IO multipliers, productivities and tax rates for the countries in our sample, allowing them to vary with income per capita. The estimates suggest some important cross-country differences in countries' IO structure and in the interaction between IO structure and sectoral productivities and taxes. First, in low-income countries the distribution of IO sectoral multipliers is more extreme: while most sectors have very low multipliers, the multipliers of a small number of sectors are very high compared to the average. In contrast, the distribution of sectoral multipliers in rich countries allocates a relatively large weight to intermediate values of multipliers. Moreover, while in poor countries sectoral IO multipliers and productivities are positively correlated, in rich countries the correlation is negative. Similarly, the correlation of IO multipliers and tax rates is positive in poor countries but negative in rich.

These cross-country differences in the distribution of IO multipliers and their interaction with productivities and taxes lead to the difference in predicted income. We find that our (over-identified) model predicts cross-country income differences extremely well both within and out of sample. In fact, the generated predictions are much more accurate than those of the standard development accounting model and of the model that measures aggregate productivity as an average of the estimated sectoral productivities and ignores IO structure. While the former model (which does not factor in productivity differences between countries) heavily underpredicts the variation in per capita income, the latter model overpredicts it. The reason for the overprediction of the income gap in the model with the simple productivity averaging and no IO structure is that the empirically large sectoral TFP differences are

actually mitigated by the IO structure, as very low-productivity sectors in poor countries tend to be badly connected and hence, "unimportant" for the aggregate economy.

Finally, our counterfactual experiments suggest that if we impose the much denser IO structure of the U.S. on poor countries and thereby increase the overall significance of their worst-productivity sectors, the per capita income of these countries could decline by as much as 80%. That is, given the very low productivity levels of many sectors in poor countries, having these sectors largely isolated effectively benefits these economies. Similarly, eliminating the correlation of sectoral multipliers and productivities would hurt poor countries but benefit the rich ones, due the fact that the correlation of multipliers and productivities is positive in poor countries and negative in rich countries. At last, reducing distortions from taxes on gross output would improve the aggregate economic performance of poor countries and worsen that of rich economies. However, the overall income changes in all countries would be relatively small.

Appendix A: Extensions of the benchmark model

5.1 Skilled labor

Consider the economy of our benchmark model where we introduce the distinction between skilled and unskilled labor. This distinction implies that the technology of each sector $i \in 1 : n$ in every country can be described by the following Cobb-Douglas function:

$$q_i = \Lambda_i \left(k_i^\alpha u_i^\delta s_i^{1-\alpha-\delta} \right)^{1-\gamma_i-\sigma_i} d_{1i}^{\gamma_{1i}} d_{2i}^{\gamma_{2i}} \cdot \dots \cdot d_{ni}^{\gamma_{ni}}, \quad (17)$$

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 $\alpha, \delta, 1 - \alpha - \delta \in (0, 1)$ 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.

In this case, the logarithm of the value added per capita, $y = \log(Y/(U + S))$, is given by the expression (27) of Proposition 2, adopted to our framework here. In fact, it is only slightly different from the expression for y in our benchmark model (cf. Proposition 1), where $\delta = 0$ and the total supply of labor is normalized to 1. With skilled and unskilled labor, the aggregate output per capita is given by:

$$\begin{aligned} y &= \sum_{i=1}^n \mu_i \lambda_i + \sum_{i=1}^n \mu_i \log(1 - \tau_i) + \sum_{i=1}^n \sum_{j \text{ s.t. } \gamma_{ji} \neq 0} \mu_i \gamma_{ji} \log \gamma_{ji} + \sum_{i=1}^n \mu_i (1 - \gamma_i) \log(1 - \gamma_i) - \log n + \\ &+ \log \left(1 + \sum_{i=1}^n \tau_i \bar{\mu}_i \right) + \alpha \log K + \delta \log U + (1 - \alpha - \delta) \log S - \log(U + S). \end{aligned}$$

Then the approximate representation of y is also similar to the corresponding representation of y in the benchmark model (cf. (9)):

$$\begin{aligned}
y &= \sum_{i=1}^n \mu_i \Lambda_i^{rel} - \sum_{i=1}^n \mu_i \tau_i + \sum_{i=1}^n \mu_i \gamma \log(\hat{\gamma}) + \log(1 - \gamma) - \log n + \alpha \log(K) + \\
&+ \delta \log U + (1 - \alpha - \delta) \log S - \log(U + S) - (1 + \gamma) + \sum_{i=1}^n \mu_i \log(\Lambda_i^{US}), \tag{18}
\end{aligned}$$

where the same assumptions and notation as before apply.

We now employ this representation of y to find the predicted value of aggregate output $E(y)$. Note that since the new framework, with skilled and unskilled labor, does not modify the definition of the sectoral multipliers, the distribution of the triple $(\mu_i, \Lambda_i^{rel}, \tau_i)$ in every country remains the same. It is a trivariate log-Normal distribution with parameters $\mathbf{m}$ and $\mathbf{\Sigma}$ that have been estimated for our benchmark model. Using these parameters, together with the equations (11) – (12) (see footnote 27), we derive the expression for the predicted aggregate output $E(y)$ in terms of the estimated parameters:

$$\begin{aligned}
E(y) &= n \left(e^{m_\mu + m_\Lambda + 1/2(\sigma_\mu^2 + \sigma_\Lambda^2) + \sigma_{\mu,\Lambda}} - e^{m_\mu + m_\tau + 1/2(\sigma_\mu^2 + \sigma_\tau^2) + \sigma_{\mu,\tau}} \right) + (1 + \gamma)(\gamma \log(\hat{\gamma}) - 1) + \\
&+ \log(1 - \gamma) - \log n + \alpha \log(K) + \delta \log U + (1 - \alpha - \delta) \log S - \log(U + S) + \tag{19}
\end{aligned}$$

$$+ e^{m_\mu + 1/2\sigma_\mu^2} \sum_{i=1}^n \log(\Lambda_i^{US}). \tag{20}$$

This equation for the predicted aggregate output is analogous to the equation (13) that we employed in our estimation of the benchmark model.

5.2 Sector-specific expenditure shares

Consider now the economy that is identical to our benchmark economy in all but demand shares for final goods. Namely, let us generalize the production function for the aggregate final good to accommodate arbitrary, sector-specific demand shares:

$$Y = y_1^{\beta_1} \cdot \dots \cdot y_n^{\beta_n},$$

where $\beta_i \geq 0$ for all i and $\sum_{i=1}^n \beta_i = 1$. As before, suppose that this aggregate final good is fully allocated to households' consumption and government's spending, that is, $Y = C + G$.

Using the generic expression for the aggregate output (27) of Proposition 2 and adopting this ex-

pression to the case of our economy here, we obtain the following formula for y :

$$\begin{aligned}
y &= \sum_{i=1}^n \mu_i \lambda_i + \sum_{i=1}^n \mu_i \log(1 - \tau_i) + \sum_{i=1}^n \sum_{j \text{ s.t. } \gamma_{ji} \neq 0} \mu_i \gamma_{ji} \log \gamma_{ji} + \sum_{i=1}^n \mu_i (1 - \gamma_i) \log(1 - \gamma_i) + \\
&+ \sum_{i=1}^n \beta_i \log(\beta_i) + \log \left(1 + \sum_{i=1}^n \tau_i \bar{\mu}_i \right) + \alpha \log K.
\end{aligned}$$

In this formula the vector of sectoral multipliers is defined differently than before, to account for the arbitrary demand shares. The new vector of multipliers is $\boldsymbol{\mu} = \{\mu_i\}_i = [\mathbf{I} - \boldsymbol{\Gamma}]^{-1} \boldsymbol{\beta}$. Its interpretation, however, is identical to the one before: each sectoral multiplier μ_i reveals how a change in productivity (or distortion) of sector i affects the overall value added in the economy.

Given this expression for y , we now derive the approximate representation of the aggregate output to be used in our empirical analysis. For this purpose, we employ the same set of simplifying assumptions as before, which results in:

$$\begin{aligned}
y &= \sum_{i=1}^n \mu_i \Lambda_i^{rel} - \sum_{i=1}^n \mu_i \tau_i + \sum_{i=1}^n \mu_i \gamma \log(\hat{\gamma}) + \log(1 - \gamma) + \sum_{i=1}^n \beta_i \log(\beta_i) + \alpha \log(K) - \\
&- (1 + \gamma) + \sum_{i=1}^n \mu_i \log(\Lambda_i^{US}).
\end{aligned} \tag{21}$$

Following the same procedure as earlier, we use this expression to find the predicted value of y . First, we estimate the distribution of the triple $(\mu_i, \Lambda_i^{rel}, \tau_i)$ in every country. We find that even though the definition of sectoral multipliers is now different from the one in our benchmark model, the distribution of $(\mu_i, \Lambda_i^{rel}, \tau_i)$ is still log-Normal.³² Then, using the estimates of the parameters of this distribution, $\mathbf{m}$ and $\boldsymbol{\Sigma}$, together with the equations (11) – (12) (see footnote 27), we find the predicted aggregate output $E(y)$ as a function of these parameters:³³

$$\begin{aligned}
E(y) &= n \left(e^{m_\mu + m_\Lambda + 1/2(\sigma_\mu^2 + \sigma_\Lambda^2) + \sigma_{\mu, \Lambda}} - e^{m_\mu + m_\tau + 1/2(\sigma_\mu^2 + \sigma_\tau^2) + \sigma_{\mu, \tau}} \right) + (1 + \gamma)(\gamma \log(\hat{\gamma}) - 1) + \log(1 - \gamma) + \\
&+ \sum_{i=1}^n \beta_i \log(\beta_i) + \alpha \log(K) + e^{m_\mu + 1/2\sigma_\mu^2} \sum_{i=1}^n \log(\Lambda_i^{US}).
\end{aligned} \tag{22}$$

The resulting expression for $E(y)$ is similar to (13) in our benchmark model.

5.3 Imported intermediates

Another extension of the benchmark model allows for trade between countries. The traded goods are used as inputs in production of the n competitive sectors, so that both domestic and imported intermediate

³²In fact, differently from the benchmark model, the distribution is "exactly" log-Normal and not *truncated* log-Normal as it was before.

³³As before, we also assume for simplicity that all other variables on the right-hand side of (21) are non-random.

goods are employed in sectors' production technology. Then the output of sector i is determined by the following production function:

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

where d_{ji} is the quantity of the domestic good j used by sector i , and f_{ji} is the quantity of the imported intermediate good j used by sector i . The imported intermediate goods are assumed to be different, so that domestic and imported goods are not perfect substitutes. Also, with a slight abuse of notation, we assume that there are n different intermediate goods that can be imported.³⁴ The exponents γ_{ji} , $\sigma_{ji} \in [0, 1)$ represent the respective shares of domestic and imported good j in the technology of firms in sector i , and $\gamma_i = \sum_{j=1}^n \gamma_{ji}$, $\sigma_i = \sum_{j=1}^n \sigma_{ji} \in (0, 1)$ are the total shares of domestic and imported intermediate goods, respectively.

As in our benchmark economy, each domestically produced good can be used for final consumption, y_i , or as an intermediate good, and all final consumption goods are aggregated into a single final good through a Cobb-Douglas production function, $Y = y_1^{\frac{1}{n}} \cdot \dots \cdot y_n^{\frac{1}{n}}$. Now, in case of an open economy considered here, the aggregate final good is used not only for households' consumption and government's spending but also for export to the rest of the world; that is, $Y = C + G + X$. The exports pay for the imported intermediate goods and are defined by the balanced trade condition:

$$X = \sum_{i=1}^n \sum_{j=1}^n \bar{p}_j f_{ji}, \quad (24)$$

where $\bar{p}_j$ is the exogenous world price of the imported intermediate goods. Note that the balanced trade condition is reasonable to impose if we consider our static model as describing the steady state of the model.

The aggregate output y is determined by the equation (27) of Proposition 2, adopted to our framework here:

$$\begin{aligned} y = & \frac{1}{\sum_{i=1}^n \mu_i (1 - \gamma_i - \sigma_i)} \left(\sum_{i=1}^n \mu_i \lambda_i + \sum_{i=1}^n \mu_i \log(1 - \tau_i) + \sum_{i=1}^n \sum_{j \text{ s.t. } \gamma_{ji} \neq 0} \mu_i \gamma_{ji} \log \gamma_{ji} + \right. \\ & + \sum_{i=1}^n \sum_{j \text{ s.t. } \sigma_{ji} \neq 0} \mu_i \sigma_{ji} \log \sigma_{ji} - \sum_{i=1}^n \sum_{j=1}^n \mu_i \sigma_{ji} \log \bar{p}_j + \sum_{i=1}^n \mu_i (1 - \gamma_i - \sigma_i) \log(1 - \gamma_i - \sigma_i) - \log n \Big) + \\ & + \log \left(1 + \sum_{i=1}^n \tau_i \bar{\mu}_i + \sum_{i=1}^n (1 - \tau_i) \sigma_i \bar{\mu}_i \right) + \alpha \log K, \end{aligned}$$

where vector $\{\bar{\mu}_i\}_i = \frac{1}{n}[\mathbf{I} - \bar{\Gamma}]^{-1}\mathbf{1}$ is a vector of multipliers corresponding to $\bar{\Gamma}$ and $\bar{\Gamma} = \{\gamma_{ji}\}_{ji} =$

³⁴This is consistent with the specification of input-output tables in our data.

$\{\frac{1}{n}\tau_i + \frac{1}{n}(1 - \tau_i)\sigma_i + (1 - \tau_i)\gamma_{ji}\}_{ji}$ is an input-output matrix adjusted for taxes and shares of imported intermediate goods.³⁵

In the empirical analysis we use an approximate representation of the aggregate output, where a range of simplifying assumptions is imposed. First, to be able to compare the results with the results of the benchmark model, we employ the same assumptions on in-degree, elements of matrix $\mathbf{\Gamma}$ and distortions as earlier. In particular, distortions are treated as pure waste, which simplifies the definition of matrix $\bar{\mathbf{\Gamma}}$, so that $\bar{\mathbf{\Gamma}} = \{\gamma_{ji}\}_{ji} = \{\frac{1}{n}\sigma_i + \gamma_{ji}\}_{ji}$, and this results in term $\log(1 + \sum_{i=1}^n \sigma_i \bar{\mu}_i)$ instead of a longer term $\log(1 + \sum_{i=1}^n \tau_i \bar{\mu}_i + \sum_{i=1}^n (1 - \tau_i)\sigma_i \bar{\mu}_i)$ in the above expression for y .³⁶ Second, in the new framework with open economies we also impose some conditions on imports. We assume that the total share of imported intermediate goods used by any sector of a country is sufficiently small and identical across sectors, that is, $\sigma_i = \sigma$ for any sector i .³⁷ We also regard any non-zero elements of the vector of import shares of sector i as the same, equal to $\hat{\sigma}_i$ (such that $\sum_{j \text{ s.t. } \sigma_{ji} \neq 0} \hat{\sigma}_i = \sigma$). Then we obtain the following approximation for the aggregate output y :

$$\begin{aligned} y = & \frac{1}{(1 - \sigma(1 + \gamma))} \left(\sum_{i=1}^n \mu_i \Lambda_i^{rel} - \sum_{i=1}^n \mu_i \tau_i + \sum_{i=1}^n \mu_i \gamma \log \hat{\gamma} + \sum_{i=1}^n \mu_i \sigma \log \hat{\sigma}_i - \right. \\ & \left. - \sum_{i=1}^n \mu_i \hat{\sigma}_i \sum_{j \text{ s.t. } \sigma_{ji} \neq 0} \log \bar{p}_j - \log n \right) + \log(1 - \gamma - \sigma) + \sigma(1 + \gamma + \sigma) + \alpha \log K - \\ & - \frac{1 + \gamma}{(1 - \sigma(1 + \gamma))} + \frac{1}{(1 - \sigma(1 + \gamma))} \sum_{i=1}^n \mu_i \log(\Lambda_i^{US}). \end{aligned}$$

Now, using equations (11) – (12) (see footnote 27) for the parameters of the trivariate log-Normal distribution of $(\mu_i, \Lambda_i^{rel}, \tau_i)$, we can derive the predicted aggregate output $E(y)$:

$$\begin{aligned} E(y) = & \frac{n}{(1 - \sigma(1 + \gamma))} \left(e^{m_\mu + m_\Lambda + 1/2(\sigma_\mu^2 + \sigma_\Lambda^2) + \sigma_{\mu,\Lambda}} - e^{m_\mu + m_\tau + 1/2(\sigma_\mu^2 + \sigma_\tau^2) + \sigma_{\mu,\tau}} \right) + \\ & + \frac{1}{(1 - \sigma(1 + \gamma))} \sum_{i=1}^n \left(\sigma \log \hat{\sigma}_i - \hat{\sigma}_i \sum_{j=1, j \text{ s.t. } \sigma_{ji} \neq 0}^n \log \bar{p}_j + \log(\Lambda_i^{US}) \right) e^{m_\mu + 1/2\sigma_\mu^2} + \\ & + \frac{(1 + \gamma)\gamma \log \hat{\gamma}}{(1 - \sigma(1 + \gamma))} - \frac{\log n}{(1 - \sigma(1 + \gamma))} + \log(1 - \gamma - \sigma) + \sigma(1 + \gamma + \sigma) + \alpha \log(K) - \frac{1 + \gamma}{(1 - \sigma(1 + \gamma))}. \end{aligned}$$

We bring this expression to data and evaluate predicted output in all countries of our data sample. We note, however, that the vector of world prices of the imported intermediates $\{\bar{p}_j\}_{j=1}^n$ is not provided in

³⁵Observe that $(\mathbf{I} - \bar{\mathbf{\Gamma}})^{-1}$ exists because the maximal eigenvalue of $\bar{\mathbf{\Gamma}}$ is bounded above by 1. The latter is implied by the Frobenius theory of non-negative matrices, that says that the maximal eigenvalue of $\bar{\mathbf{\Gamma}}$ is bounded above by the largest column sum of $\bar{\mathbf{\Gamma}}$, which in our case is smaller than 1: $\sum_{j=1}^n (\frac{1}{n}\tau_i + \frac{1}{n}(1 - \tau_i)\sigma_i + (1 - \tau_i)\gamma_{ji}) = \tau_i + (1 - \tau_i)\sigma_i + (1 - \tau_i)\gamma_i = \tau_i + (1 - \tau_i)(\sigma_i + \gamma_i) < 1$ for any $\sigma_i + \gamma_i < 1$ and any $\tau_i < 1$.

³⁶Details are available from the authors.

³⁷This allows approximating $\log(1 + \sum_{i=1}^n \sigma_i \bar{\mu}_i)$ with $\sigma \sum_{i=1}^n \bar{\mu}_i = \sigma(1 + \gamma + \sigma)$, where the equality follows from $\bar{\mu}_i \approx \mu_i + \frac{1}{n} \sum_{j=1}^n \frac{1}{n} \sigma_j$. The latter, in turn, is a result of the approximation of $\{\bar{\mu}_i\}_i$ by the first elements of the convergent power series $\frac{1}{n} \left(\sum_{k=0}^{+\infty} \bar{\mathbf{\Gamma}}^k \right) \mathbf{1}$ and the analogous approximation for $\{\mu_i\}_{i=1}^n$ (see section 3.3).

the data. Then to make the comparison of aggregate income in different countries possible, we assume that for any sector i , the value of $\hat{\sigma}_i \sum_{j=1, j \text{ s.t. } \sigma_{ji} \neq 0}^n \log \bar{p}_j$ is the same across countries, so that this term cancels out when the difference in countries' predicted output is considered. For this purpose we assume that in all countries, the vector of shares of the imported intermediate goods used by sector i is the same and that all countries face the same vector of prices of the imported intermediate goods $\{\bar{p}_j\}_{j=1}^n$.

5.4 Taxes as government revenue

As a final extension, consider our benchmark model in which taxes are regarded not as waste but as government revenue. This means that taxes do not only decrease aggregate income through a reduction in firms' revenues but they also increase it through an increase in government expenditures. Therefore, (9) used for the estimation in the benchmark model should contain an additional term $\log(1 + \sum_{i=1}^n \tau_i \bar{\mu}_i)$, which is positive and increasing in taxes. In approximation at small taxes, when $\log(1 + \sum_{i=1}^n \tau_i \bar{\mu}_i) \approx \sum_{i=1}^n \tau_i \bar{\mu}_i$, this leads to

$$\begin{aligned} y = & \sum_{i=1}^n \mu_i \Lambda_i^{rel} + \sum_{i=1}^n \mu_i \gamma \log(\hat{\gamma}) + \log(1 - \gamma) - \log n + \alpha \log(K) - (1 + \gamma) + \\ & + \sum_{i=1}^n \mu_i \log(\Lambda_i^{US}) + \frac{1}{n^2} \left(\sum_{i=1}^n \tau_i^2 + \sum_{i=1}^n \sum_{j \neq i} \tau_i \tau_j \right). \end{aligned} \quad (25)$$

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

$$\begin{aligned} E(y) = & n \left(e^{m_\mu + m_\Lambda + 1/2(\sigma_\mu^2 + \sigma_\Lambda^2) + \sigma_{\mu, \Lambda}} - \gamma^2 e^{m_\mu + m_\tau + 1/2(\sigma_\mu^2 + \sigma_\tau^2) + \sigma_{\mu, \tau}} \right) + (1 + \gamma)(\gamma \log(\hat{\gamma}) - 1) + \\ & + \log(1 - \gamma) - \log n + \alpha \log(K) + e^{m_\mu + 1/2\sigma_\mu^2} \sum_{i=1}^n \log(\Lambda_i^{US}) + \\ & + \left(\frac{1}{n} - \hat{\gamma} \right) e^{2m_\tau + \sigma_\tau^2} \left(e^{\sigma_\tau^2} + n - 1 \right), \end{aligned} \quad (26)$$

where as before, we employed equations (11) – (12) (see footnote 27) and the new relevant equation $var(\tau) = (e^{\sigma_\tau^2} - 1) e^{2m_\tau + \sigma_\tau^2}$ for the relationship between the parameters of the Normal and log-Normal distributions.³⁸

Appendix B: Proofs for the benchmark model and its extensions

Proposition 1 and formulas for aggregate output stated in Appendix A are particular cases of Proposition 2 that applies in a generic setting – with open economies, division into skilled and unskilled labor and unequal demand shares. A brief description of this economy, as well as Proposition 2 and its proof are

³⁸In calculating $E(\tau_i \tau_j)$ for $i \neq j$, we also employed the assumption that random draws of τ_i are independent across sectors.

provided below.

- The technology of each of n competitive sectors is Cobb-Douglas with constant returns to scale. Namely, the output of sector i , denoted by q_i , is

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

where s_i and u_i are the amounts of skilled and unskilled labor, d_{ji} is the quantity of the domestic good j and f_{ji} is the quantity of the imported good j used by sector i . $\gamma_i = \sum_{j=1}^n \gamma_{ji}$ and $\sigma_i = \sum_{j=1}^n \sigma_{ji}$ are the respective shares of domestic and imported intermediate goods in the total input use of sector i and $\alpha, \delta, 1 - \alpha - \delta$ are the respective shares of capital, unskilled and skilled labor in the remainder of the inputs.

- A good produced by sector i can be used for final consumption, y_i , or as an intermediate good:

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

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

$$Y = y_1^{\beta_1} \cdot \dots \cdot y_n^{\beta_n},$$

where $\beta_i \geq 0$ for all i and $\sum_{i=1}^n \beta_i = 1$.

- This aggregate final good can itself be used in one of three ways, as households' consumption, government expenditures or as export to the rest of the world:

$$Y = C + G + X.$$

- Exports pay for the imported intermediate goods, and we impose a balanced trade condition:

$$X = \sum_{i=1}^n \sum_{j=1}^n \bar{p}_j f_{ji},$$

where $\bar{p}_j$ is the exogenous world price of the imported intermediate goods.

- Households finance their consumption through income:

$$C = w_U U + w_S S + rK.$$

- Government finances its expenditures through tax revenues:

$$G = \sum_{i=1}^n \tau_i p_i q_i.$$

- The total supply of physical capital, unskilled and skilled labor are fixed at the exogenous levels of K , U and S , respectively:

$$\begin{aligned} \sum_{i=1}^n k_i &= K, \\ \sum_{i=1}^n u_i &= U, \\ \sum_{i=1}^n s_i &= S. \end{aligned}$$

For this "generic" economy, the competitive equilibrium with distortions is defined by analogy with the definition in section 3.1. The solution is described by Proposition 2.

Proposition 2. *There exists $\bar{G} > 0$ such that for any $0 \leq G \leq \bar{G}$ there exists a unique competitive equilibrium. In this equilibrium, the logarithm of GDP per capita, $y = \log(Y/(U + S))$, is given by*

$$\begin{aligned} y = & \frac{1}{\sum_{i=1}^n \mu_i (1 - \gamma_i - \sigma_i)} \left[\sum_{i=1}^n \mu_i \lambda_i + \sum_{i=1}^n \mu_i \log(1 - \tau_i) + \sum_{i=1}^n \sum_{j \text{ s.t. } \gamma_{ij} \neq 0} \mu_i \gamma_{ji} \log \gamma_{ji} + \sum_{i=1}^n \sum_{j \text{ s.t. } \sigma_{ij} \neq 0} \mu_i \sigma_{ji} \log \sigma_{ji} - \right. \\ & \left. - \sum_{i=1}^n \sum_{j=1}^n \mu_i \sigma_{ji} \log \bar{p}_j + \sum_{i=1}^n \beta_i \log \beta_i + \sum_{i=1}^n \mu_i (1 - \gamma_i - \sigma_i) \log(1 - \gamma_i - \sigma_i) \right] + \log \left(1 + \sum_{i=1}^n \tau_i \bar{\mu}_i + \sum_{i=1}^n (1 - \tau_i) \sigma_i \bar{\mu}_i \right) + \\ & + \alpha \log K + \delta \log U + (1 - \alpha - \delta) \log S - \log(U + S). \end{aligned} \quad (27)$$

where

$$\boldsymbol{\mu} = \{\mu_i\}_i = [\mathbf{I} - \boldsymbol{\Gamma}]^{-1} \boldsymbol{\beta}, \quad n \times 1 \text{ vector of multipliers}$$

$$\boldsymbol{\lambda} = \{\lambda_i\}_i = \{\log \Lambda_i\}_i, \quad n \times 1 \text{ vector of sectoral log-productivity coefficients}$$

$$\bar{\boldsymbol{\mu}} = \{\bar{\mu}_i\}_i = [\mathbf{I} - \bar{\boldsymbol{\Gamma}}]^{-1} \boldsymbol{\beta}, \quad n \times 1 \text{ vector of multipliers corresponding to } \bar{\boldsymbol{\Gamma}}$$

$$\bar{\boldsymbol{\Gamma}} = \{\bar{\gamma}_{ji}\}_{ji} = \{\beta_j \tau_i + \beta_j (1 - \tau_i) \sigma_i + (1 - \tau_i) \gamma_{ji}\}_{ji}, \quad n \times n \text{ input-output matrix adjusted for taxes and trade}$$

Proof. Part I: Calculation of $\log w_U$.

Consider the profit maximization problems of a representative firm in the final goods market and in each sector. For a representative firm in the final goods market the FOCs allocate to each good a spending share that is proportional to the good's demand share β_i :

$$p_i y_i = \beta_i Y = \beta_i (C + G + X) = \beta_i (w_U U + w_S S + rK) + \beta_i \sum_{i=1}^n \tau_i p_i q_i + \beta_i \sum_{i=1}^n \sum_{j=1}^n \bar{p}_j m_{ji} \quad \forall i \in 1 : n$$

where the price of the final good is normalized to 1, $p = 1$. For a firm in sector i the FOCs are:

$$(1 - \tau_i)\alpha(1 - \gamma_i - \sigma_i)\frac{p_i q_i}{r} = k_i \quad (28)$$

$$(1 - \tau_i)\delta(1 - \gamma_i - \sigma_i)\frac{p_i q_i}{w_U} = u_i \quad (29)$$

$$(1 - \tau_i)(1 - \alpha - \delta)(1 - \gamma_i - \sigma_i)\frac{p_i q_i}{w_S} = s_i \quad (30)$$

$$(1 - \tau_i)\gamma_{ji}\frac{p_i q_i}{p_j} = d_{ji} \quad j \in 1 : n \quad (31)$$

$$(1 - \tau_i)\sigma_{ji}\frac{p_i q_i}{\bar{p}_j} = f_{ji} \quad j \in 1 : n \quad (32)$$

Substituting the left-hand side of these equations for the values of k_i , u_i , s_i , $\{d_{ji}\}$ and $\{f_{ji}\}$ in firm i 's log-production technology and simplifying the obtained expression, we derive:

$$\begin{aligned} \delta \log w_U &= \frac{1}{1 - \gamma_i - \sigma_i} \left(\lambda_i + \log(1 - \tau_i) + \log p_i - \sum_{j=1}^n \gamma_{ji} \log p_j + \sum_{j \text{ s.t. } \gamma_{ji} \neq 0} \gamma_{ji} \log \gamma_{ji} - \right. \\ &\quad \left. - \sum_{j=1}^n \sigma_{ji} \log \bar{p}_j + \sum_{j \text{ s.t. } \sigma_{ji} \neq 0} \sigma_{ji} \log \sigma_{ji} \right) - \alpha \log r - (1 - \alpha - \delta) \log(w_S) + \\ &\quad + \log(1 - \gamma_i - \sigma_i) + \alpha \log(\alpha) + \delta \log \delta + (1 - \alpha - \delta) \log(1 - \alpha - \delta) \end{aligned} \quad (33)$$

Next, we use FOCs (28) – (32) and market clearing conditions for labor and capital to express r and w_S in terms of w_U :

$$w_U = \frac{1}{U} \delta \sum_{i=1}^n (1 - \tau_i)(1 - \gamma_i - \sigma_i)(p_i q_i) \quad (34)$$

$$w_S = \frac{1}{S} (1 - \alpha - \delta) \sum_{i=1}^n (1 - \tau_i)(1 - \gamma_i - \sigma_i)(p_i q_i) = \frac{w_U U}{S} \frac{1 - \alpha - \delta}{\delta} \quad (35)$$

$$r = \frac{1}{K} \alpha \sum_{i=1}^n (1 - \tau_i)(1 - \gamma_i - \sigma_i)(p_i q_i) = \frac{w_U U}{K} \frac{\alpha}{\delta} \quad (36)$$

Substituting these values of r and w_S in (33) we obtain:

$$\begin{aligned} \log w_U &= \frac{1}{1 - \gamma_i - \sigma_i} \left(\lambda_i + \log(1 - \tau_i) + \log p_i - \sum_{j=1}^n \gamma_{ji} \log p_j + \sum_{j \text{ s.t. } \gamma_{ji} \neq 0} \gamma_{ji} \log \gamma_{ji} - \sum_{j=1}^n \sigma_{ji} \log \bar{p}_j + \right. \\ &\quad \left. + \sum_{j \text{ s.t. } \sigma_{ji} \neq 0} \sigma_{ji} \log \sigma_{ji} \right) + \alpha \log K - (1 - \delta) \log U + (1 - \alpha - \delta) \log S + \log(1 - \gamma_i - \sigma_i) + \log \delta \end{aligned}$$

Multiplying this equation by the i th element of the vector $\boldsymbol{\mu}' \mathbf{Z} = \boldsymbol{\beta}' \mathbf{1}' [\mathbf{I} - \boldsymbol{\Gamma}']^{-1} \cdot \mathbf{Z}$, where $\mathbf{Z}$ is a

diagonal matrix with $Z_{ii} = 1 - \gamma_i - \sigma_i$, and summing over all sectors i gives

$$\begin{aligned} \sum_{i=1}^n \mu_i (1 - \gamma_i - \sigma_i) \log w_U &= \sum_{i=1}^n \mu_i \lambda_i + \sum_{i=1}^n \mu_i \log(1 - \tau_i) + \sum_{i=1}^n \beta_i \log p_i + \sum_{i=1}^n \sum_{j \text{ s.t. } \gamma_{ji} \neq 0} \mu_i \gamma_{ji} \log \gamma_{ji} - \\ &- \sum_{j=1}^n \mu_j \sigma_{ji} \log \bar{p}_j + \sum_{j \text{ s.t. } \sigma_{ji} \neq 0} \mu_j \sigma_{ji} \log \sigma_{ji} + \sum_{i=1}^n \mu_i (1 - \gamma_i - \sigma_i) \log(1 - \gamma_i - \sigma_i) + \\ &+ \sum_{i=1}^n \mu_i (1 - \gamma_i - \sigma_i) (\alpha \log K - (1 - \delta) \log U + (1 - \alpha - \delta) \log S + \log \delta) \end{aligned}$$

Next, we use the relation between the price of the final good p (normalized to 1) and prices of each sector goods, derived from a profit maximization of the final good firm that has Cobb-Douglas technology.³⁹ This relation implies that $\prod_{i=1}^n (p_i)^{\beta_i} = \prod_{i=1}^n (\beta_i)^{\beta_i}$, so that $\sum_{i=1}^n \beta_i \log p_i = \sum_{i=1}^n \beta_i \log \beta_i$, and the above equation becomes:

$$\begin{aligned} \log w_U &= \frac{1}{\sum_{i=1}^n \mu_i (1 - \gamma_i - \sigma_i)} \left[\sum_{i=1}^n \mu_i \lambda_i + \sum_{i=1}^n \mu_i \log(1 - \tau_i) + \sum_{i=1}^n \beta_i \log \beta_i + \sum_{i=1}^n \sum_{j \text{ s.t. } \gamma_{ji} \neq 0} \mu_i \gamma_{ji} \log \gamma_{ji} - \right. \\ &- \sum_{j=1}^n \mu_j \sigma_{ji} \log \bar{p}_j + \sum_{j \text{ s.t. } \sigma_{ji} \neq 0} \mu_j \sigma_{ji} \log \sigma_{ji} + \left. \sum_{i=1}^n \mu_i (1 - \gamma_i - \sigma_i) \log(1 - \gamma_i - \sigma_i) \right] + \\ &+ \alpha \log K - (1 - \delta) \log U + (1 - \alpha - \delta) \log S + \log \delta \end{aligned} \quad (37)$$

Part II: Calculation of y .

Recall that our ultimate goal is to find $y = \log(Y/(U + S)) = \log(C + G + X) - \log(U + S)$. From the households' and government's budget constraints and from the balanced trade condition, $C + G + X = w_U U + w_S S + rK + \sum_{i=1}^n \tau_i p_i q_i + \sum_{i=1}^n \sum_{j=1}^n \bar{p}_j f_{ji}$, where in the last term, $\bar{p}_j f_{ji} = (1 - \tau_i) \sigma_{ji} p_i q_i$ (cf. (32)). Below we show that $p_i q_i$ can be expressed as a product of $w_U U + w_S S + rK$ and another term that involves distortions and structural characteristics. Then using (35) and (36), we obtain the representation of $C + G + X$ as a product of w_U and another term determined by exogenous variables. This representation, together with (37), will then allow us to solve for y .

Consider the resource constraint for sector j , with both sides multiplied by p_j :

$$p_j y_j + \sum_{i=1}^n p_j d_{ji} = p_j q_j$$

Using FOCs of the profit maximization problem of the final good's firm and a firm in sector i , this can

³⁹Profit maximization of the final good's firm implies that $\frac{\partial Y}{\partial y_i} = \frac{p_i}{p}$. On the other hand, since $Y = y_1^{\beta_1} \cdot \dots \cdot y_n^{\beta_n}$, we have $\frac{\partial Y}{\partial y_i} = \beta_i \frac{Y}{y_i}$. Hence, $\beta_i \frac{Y}{y_i} = \frac{p_i}{p}$, or $y_i = \beta_i \frac{pY}{p_i}$. Substituting this in the production technology of the firm in final good market, we obtain:

$$Y = \prod_{i=1}^n \left(\beta_i \frac{pY}{p_i} \right)^{\beta_i} = pY \prod_{i=1}^n \left(\beta_i \frac{1}{p_i} \right)^{\beta_i}.$$

So, $p \prod_{i=1}^n \left(\beta_i \frac{1}{p_i} \right)^{\beta_i} = 1$. Now, since we used the normalization $p = 1$, it must be that $\prod_{i=1}^n (p_i)^{\beta_i} = \prod_{i=1}^n (\beta_i)^{\beta_i}$.

be written as:

$$\beta_j Y + \sum_{i=1}^n (1 - \tau_i) \gamma_{ji} p_i q_i = p_j q_j$$

or

$$\beta_j (w_U U + w_S S + rK) + \sum_{i=1}^n [\beta_j \tau_i + (1 - \tau_i) \gamma_{ji}] p_i q_i + \beta_j \sum_{i=1}^n \sum_{j=1}^n (1 - \tau_i) \sigma_{ji} p_i q_i = p_j q_j.$$

Using the fact that $\sum_{j=1}^n \sigma_{ji} = \sigma_i$ and combining terms, we obtain:

$$\beta_j (w_U U + w_S S + rK) + \sum_{i=1}^n [\beta_j \tau_i + \beta_j (1 - \tau_i) \sigma_i + (1 - \tau_i) \gamma_{ji}] p_i q_i = p_j q_j.$$

Denote by $a_j = p_j q_j$ and by $\bar{\gamma}_{ji} = \beta_j \tau_i + \beta_j (1 - \tau_i) \sigma_i + (1 - \tau_i) \gamma_{ji}$. Then the above equation in the matrix form is:

$$(w_U U + w_S S + rK) \boldsymbol{\beta} + \bar{\mathbf{\Gamma}} \mathbf{a} = \mathbf{a}$$

where $\boldsymbol{\beta} = (\beta_1, \dots, \beta_n)'$, $\bar{\mathbf{\Gamma}} = \{\bar{\gamma}_{ji}\}_{ji}$ and $\mathbf{a} = \{a_j\}_j$. Hence,

$$\mathbf{a} = (\mathbf{I} - \bar{\mathbf{\Gamma}})^{-1} (w_U U + w_S S + rK) \boldsymbol{\beta} = (w_U U + w_S S + rK) \bar{\boldsymbol{\mu}}$$

where $\bar{\boldsymbol{\mu}} = (\mathbf{I} - \bar{\mathbf{\Gamma}})^{-1} \boldsymbol{\beta}$.⁴⁰ So, $a_i = p_i q_i = (w_U U + w_S S + rK) \bar{\mu}_i$ and therefore,

$$\begin{aligned} Y &= C + G + X = w_U U + w_S S + rK + \sum_{i=1}^n \tau_i p_i q_i + \sum_{i=1}^n \sum_{j=1}^n (1 - \tau_i) \sigma_{ji} p_i q_i = \\ &= (w_U U + w_S S + rK) \left(1 + \sum_{i=1}^n \tau_i \bar{\mu}_i + \sum_{i=1}^n (1 - \tau_i) \sigma_i \bar{\mu}_i \right) \end{aligned}$$

Using (35) and (36), this leads to

$$Y = \frac{w_U U}{\delta} \left(1 + \sum_{i=1}^n \tau_i \bar{\mu}_i + \sum_{i=1}^n (1 - \tau_i) \sigma_i \bar{\mu}_i \right).$$

so that

$$y = \log Y - \log(U + S) = \log w_U + \log U + \log \left(1 + \sum_{i=1}^n \tau_i \bar{\mu}_i + \sum_{i=1}^n (1 - \tau_i) \sigma_i \bar{\mu}_i \right) - \log \delta - \log(U + S).$$

⁴⁰Notice that $(\mathbf{I} - \bar{\mathbf{\Gamma}})^{-1}$ exists because the sum of elements in each column of $\bar{\mathbf{\Gamma}}$ is less than 1: $\sum_{j=1}^n (\beta_j \tau_i + \beta_j (1 - \tau_i) \sigma_i + (1 - \tau_i) \gamma_{ji}) = \tau_i + (1 - \tau_i) \sigma_i + (1 - \tau_i) \gamma_i = \tau_i + (1 - \tau_i) (\sigma_i + \gamma_i) < 1$ for any $\sigma_i + \gamma_i < 1$ and any $\tau_i < 1$.

Finally, substituting $\log w_U$ with (37) yields our result:

$$\begin{aligned}
y = & \frac{1}{\sum_{i=1}^n \mu_i(1 - \gamma_i - \sigma_i)} \left[\sum_{i=1}^n \mu_i \lambda_i + \sum_{i=1}^n \mu_i \log(1 - \tau_i) + \sum_{i=1}^n \sum_{j \text{ s.t. } \gamma_{ji} \neq 0} \mu_i \gamma_{ji} \log \gamma_{ji} + \sum_{i=1}^n \sum_{j \text{ s.t. } \sigma_{ij} \neq 0} \mu_i \sigma_{ji} \log \sigma_{ji} - \right. \\
& - \sum_{i=1}^n \sum_{j=1}^n \mu_i \sigma_{ji} \log \bar{p}_j + \sum_{i=1}^n \mu_i(1 - \gamma_i - \sigma_i) \log(1 - \gamma_i - \sigma_i) + \sum_{i=1}^n \beta_i \log \beta_i \left. \right] + \log \left(1 + \sum_{i=1}^n \tau_i \bar{\mu}_i + \sum_{i=1}^n (1 - \tau_i) \sigma_i \bar{\mu}_i \right) + \\
& + \alpha \log K + \delta \log U + (1 - \alpha - \delta) \log S - \log(U + S).
\end{aligned}$$

This completes the proof. $\square$

Application of Proposition 2 to the case of the benchmark economy:

Proof. (Proposition 1) In case of our benchmark economy, we assume that: i) there is no distinction between skilled and unskilled labor, so that $\delta = 1 - \alpha$ and the total supply of labor is normalized to 1; ii) demand shares for all final goods are the same, that is, $\beta_i = \frac{1}{n}$ for all i ; iii) the economies are closed, so that no imported intermediate goods are used in sectors' production, that is, $\sigma_{ji} = 0$ for all $i, j \in 1 : n$ and $\sigma_i = 0$ for all i . This simplifies the expression for y in Proposition 2 and produces:

$$\begin{aligned}
y = & \frac{1}{\sum_{i=1}^n \mu_i(1 - \gamma_i)} \left(\sum_{i=1}^n \mu_i \lambda_i + \sum_{i=1}^n \mu_i \log(1 - \tau_i) + \sum_{i=1}^n \sum_{j \text{ s.t. } \gamma_{ji} \neq 0} \mu_i \gamma_{ji} \log \gamma_{ji} + \sum_{i=1}^n \mu_i(1 - \gamma_i) \log(1 - \gamma_i) - \log n \right) + \\
& + \log \left(1 + \sum_{i=1}^n \tau_i \bar{\mu}_i \right) + \alpha \log K,
\end{aligned}$$

Now, observe that $\sum_{i=1}^n \mu_i(1 - \gamma_i) = \mathbf{1}'[\mathbf{I} - \mathbf{\Gamma}] \cdot \frac{1}{n}[\mathbf{I} - \mathbf{\Gamma}]^{-1} \mathbf{1} = \frac{1}{n} \mathbf{1}' \mathbf{1} = 1$. Then the expression simplifies even further and leads to the result of Proposition 1:

$$\begin{aligned}
y = & \sum_{i=1}^n \mu_i \lambda_i + \sum_{i=1}^n \mu_i \log(1 - \tau_i) + \sum_{i=1}^n \sum_{j \text{ s.t. } \gamma_{ji} \neq 0} \mu_i \gamma_{ji} \log \gamma_{ji} + \sum_{i=1}^n \mu_i(1 - \gamma_i) \log(1 - \gamma_i) - \log n + \\
& + \log \left(1 + \sum_{i=1}^n \tau_i \bar{\mu}_i \right) + \alpha \log K,
\end{aligned}$$

where

$$\begin{aligned}
\boldsymbol{\mu} &= \{\mu_i\}_i = \frac{1}{n}[\mathbf{I} - \mathbf{\Gamma}]^{-1} \mathbf{1}, & n \times 1 \text{ vector of multipliers} \\
\boldsymbol{\lambda} &= \{\lambda_i\}_i = \{\log \Lambda_i\}_i, & n \times 1 \text{ vector of sectoral log-productivity coefficients} \\
\boldsymbol{\tau} &= \{\tau_i\}_i, & n \times 1 \text{ vector of sector-specific taxes} \\
\bar{\boldsymbol{\mu}} &= \{\bar{\mu}_i\}_i = \frac{1}{n}[\mathbf{I} - \bar{\mathbf{\Gamma}}]^{-1} \mathbf{1}, & n \times 1 \text{ vector of multipliers corresponding to } \bar{\mathbf{\Gamma}} \\
\bar{\mathbf{\Gamma}} &= \{\bar{\gamma}_{ji}\}_{ji} = \left\{ \frac{\tau_i}{n} + (1 - \tau_i) \gamma_{ji} \right\}_{ji}, & n \times n \text{ input-output matrix adjusted for taxes}
\end{aligned}$$

$\square$

Appendix D: Data construction

WIOD: IO tables are available in current national currency at basic prices and are separated into domestically produced and imported intermediates. 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. Basic prices exclude taxes and transport margins. In the robustness checks, domestic IO coefficients are defined as the value of domestically produced intermediates divided by the value of gross output, and IO coefficients for imported intermediates are defined as the value of imported intermediates divided by the value of gross output. The IO tables also provide separate information about net taxes (taxes minus subsidies) on gross output.

WIOD data also includes socio-economic accounts that are defined consistently with the IO tables. We use sector-level data on gross output in current national currency, physical capital stocks in constant 1995 national currency, price series for investment, and labor inputs in hours by skill category. We define skilled labor as workers with at least some tertiary education and unskilled labor as those with less than tertiary education. WIOD also provides purchasing power parity (PPP)-deflators (in purchasers' prices) for sector-level gross output.

Using sector-level PPPs for gross output from WIOD and exchange rates from PWT 7.1, 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 into constant 2005 PPP prices.

Total factor productivity (TFP) at the sector level relative to the U.S. is computed from WIOD data (measured in constant 2005 PPPs) assuming Cobb-Douglas sectoral technologies for gross output with country-sector-specific input shares:

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

where i is the sector index and c is the country index. The notation uses Λ_{ic} for TFP of sector i , q_{ic} for the output of sector i , k_{ic} and l_{ic} for the quantities of capital and labor and d_{ji} for the quantity of intermediate good j used in the production of sector i ; α_{ic} , $1 - \alpha_{ic}$ and $\gamma_{ji} \in [0, 1)$ are the respective input shares.

GTAP version 6, contains data for 70 countries and 37 sectors in the year 2004. Compared to the original GTAP classification, all agricultural goods in the GTAP data are aggregated into a single good, produced by a single sector agriculture. 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).

PWT 7.1 includes data on GDP per capita in 2005 PPPs, aggregate physical capital stocks constructed with the perpetual inventory method, the PPP price level of investment, exchange rates, and employment for 155 countries in the year 2005.

Appendix E: Additional Figures and Tables

Table 7: Countries: WIOT Sample

(countries)	
AUS	IND
AUT	IRL
BEL	ITA
BGR	JPN
BRA	KOR
CAN	LTU
CHN	LUX
CYP	LVA
CZE	MEX
DEU	MLT
DNK	NLD
ESP	POL
EST	PRT
FIN	ROM
FRA	RUS
GBR	SVK
GRC	SVN
HUN	SWE
IDN	TUR
	USA

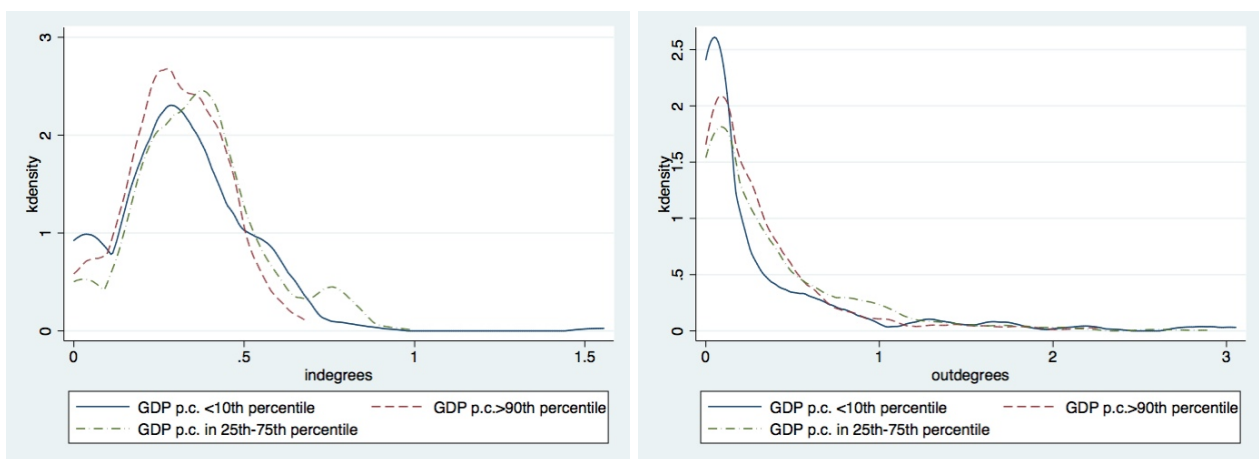


Figure 12: Distribution of sectoral in-degrees (left) and out-degrees (right) (GTAP sample)

Table 8: Countries: GTAP Sample

countries	
ALB	LTU
ARG	LUX
AUS	LVA
AUT	MDG
BEL	MEX
BGD	MLT
BGR	MOZ
BRA	MWI
BWA	MYS
CAN	NLD
CHE	NZL
CHL	PER
CHN	PHL
COL	POL
CYP	PRT
CZE	ROM
DEU	RUS
DNK	SGP
ESP	SVK
EST	SVN
FIN	SWE
FRA	THA
GBR	TUN
GRC	TUR
HKG	TWN
HRV	TZA
HUN	UGA
IDN	URY
IND	USA
IRL	VEN
ITA	VNM
JPN	ZAF
KOR	ZMB
LKA	ZWE

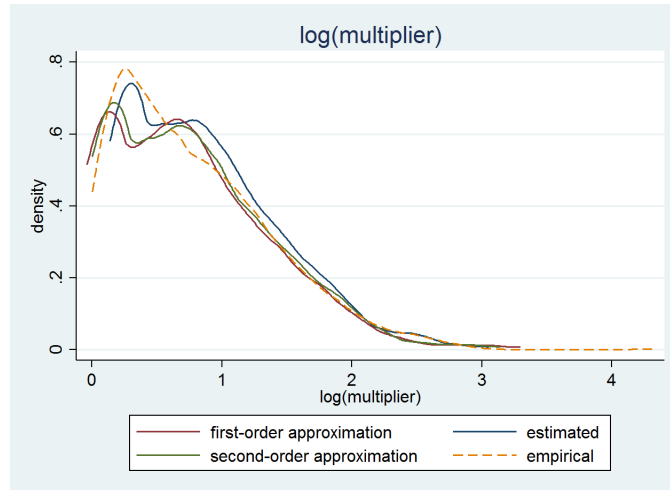


Figure 13: Approximation of distribution of log multipliers

Table 9: Sector List

WIOD sectors		GTAP sectors	
1	Agriculture	1	Agriculture
2	Mining	2	Coal
3	Food	3	Oil
4	Textiles	4	Gas
5	Leather	5	Mining
6	Wood	6	Food
7	Paper	7	Textiles
8	Refining	8	Apparel
9	Chemicals	9	Leather
10	Plastics	10	Wood
11	Minerals	11	Paper
12	Metal products	12	Refining
13	Machinery	13	Chemicals
14	Elec. equip.	14	Minerals
15	Transport equip.	15	Iron
16	Manufacturing nec	16	Oth. metals
17	Electricity	17	Metal products
18	Construction	18	Cars
19	Car retail.	19	Transport equip.
20	Wholesale trade	20	Electric equip.
21	Retail trade	21	Oth. Machinery
22	Restaurants	22	Manuf. nec
23	Inland transp.	23	Electricity
24	Water transp.	24	Gas Distr.
25	Air transp.	25	Water Distr.
26	Transp. nec.	26	Construction
27	Telecomm.	27	Trade
28	Fin. serv.	28	Inland transp.
29	Real est.	29	Water transp.
30	Business serv.	30	Air transp.
31	Pub. admin.	31	Telecomm.
32	Education	32	Financial serv.
33	Health	33	Insurance
34	Social serv.	34	Business serv.
35	Household empl.	35	Recreation
		36	Education, Health
		37	Dwellings

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