Structural Transformation, Input-Output Networks, and Productivity Growth*

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Abstract

The income differences between rich and poor countries are enormous. Development accounting breaks down these differences into differences in aggregate factor inputs and into aggregate TFP. Sectoral development accounting also reveals how these factor inputs are allocated across sectors and the contribution of sector TFPs to aggregate TFP. Most of these analyses are based on the use of value-added production functions, which assume away cross-sectoral input-output relationships. However, most recent theoretical and empirical research revealed that input-output relationships matter for aggregate TFP and output. This paper reviews the existing literature, its key findings, and discusses their relevance for structural transformation, industrialisation in developing countries, and potential avenues for further research.

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1 Introduction

The differences in income per person between rich and poor countries are enormous. Development accounting decomposes these differences into differences in aggregate factor inputs and differences in aggregate total factor productivity (TFP) (see Caselli, 2005). The literature finds that about half of the cross-country income differences are accounted for by aggregate TFP differences. The natural next step is to refine development accounting and to disaggregate either the factor inputs or the aggregate output, or both. Here we focus on the disaggregation of aggregate output into the output of different sectors. One standard disaggregation of output in development accounting is to break down the economy into agriculture and non-agriculture sectors. Such a disaggregation is motivated by the observation that most poor countries are agrarian with a high proportion of workers employed in agriculture. The main finding of the literature on cross-country labour productivity (see Restuccia et al., 2008, and Gollin et al., 2014, among others) is that labour productivity in agriculture is lower than aggregate labour productivity. Hence, the primary reason why income levels are low in poor countries is that their agricultural TFP is very low and most of their workforce is employed in this sector. However, there are alternative disaggregations. Hsieh and Klenow (2007) quantify a two-sector model with an investment and a consumption good, and find that sectoral TFP differences between rich and poor countries are larger in the investment sector than aggregate TFP differences. Herrendorf and Valentinyi (2012) disaggregate the economy into five sectors and find that sectoral TFP differences between rich and poor countries are larger than aggregate TFP differences in the sectors producing equipment, construction, and food. In contrast, sectoral TFP differences in manufactured consumption are about the same and sectoral TFP differences in services are much smaller than aggregate TFP differences.

Differences in sectors do not only manifest themselves in differences in productivity levels but also in differences in sectoral productivity growth and volatility. The differences in sector productivity growth are one of the key drivers of structural transformation. An important feature of structural transformation is the hump-shaped relationship between employment share of manufacturing and GDP per capita. However, structural transformation does not appear to be homogeneous across countries. In countries where industrialisation started more recently, the late developers, the peak of the hump-shape occurs at a lower GDP per capita then in countries where industrialisation started early, the early bloomers, the current developed countries. Rodrik (2016) argues that this is "premature deindustrialisation" where employment share rises in low-productivity services in many low- or middle-income countries. Huneeus and Rogerson (2020) present an alternative view by arguing that agricultural productivity growth plays a crucial role in the variation of the peak of the manufacturing employment share. The two views may not be mutually exclusive. Could input-output relationships between firms and sectors within countries, the production network, and across countries, the trade network, connect the two views?

The broad open question this pathfinding paper is concerned with is whether there is a link between the TFPs of different sectors. Is it possible that the low productivity in agriculture affects the productivity of the other sectors in poor countries? Or that some sectors perhaps affect the productivity of agriculture? Or that imports of intermediate inputs led to faster measured value-added TFP growth in agriculture? Are there bottleneck sectors which may not be large in terms of employment share, but are crucially important for the other sectors of the economy? Answers to these questions only exist for high-income countries at the moment, primarily for the US. However, the very same questions should be asked for developing countries.

Intersectoral linkages come in different shapes and forms. Sectors shipping intermediate inputs to other sectors for production, intersectoral linkages, give rise to the 'production network'. Sectors shipping investment goods to other sectors give rise to the 'investment network'. Sectors in one country shipping goods or services to sectors in another country give rise to the 'trade network'. If a spatial structure within a country is considered, input-output linkages may refer to linkages between sectors separated by space forming a 'spatial network'. The broad term 'input-output network', or input-output linkages, encompasses a broad set of potential linkages which are each of potential relevance. In this survey I primarily focus on production and trade networks. Spatial networks are also important, and there is a significant theoretical literature on regional growth and development. However, empirical work in the spirit of production and trade networks is non-existent because of data constraints. Within-country flows of goods and services across regions and sectors are usually not available. One exception is the US where the Commodity Flow Survey allows construction of bilateral trade flows across sectors, and regions (see Caliendo et al., 2018, for an application).

We will start the survey by presenting a canonical framework of a production network which allows for an equilibrium relationship between aggregate output (GDP) and the production network. This is important because the framework that is usually employed by the development accounting literature and the structural transformation literature uses value-added production functions. By construction, it cannot be used to assess the importance of input-output networks because multi-sector models with value-added production functions assume it away. This formulation is tantamount to the assumption that each sector produces its own intermediate inputs. This seem to be inconsistent with the idea that one important source of productivity growth is the division of labour across firms and sectors. In this sense productivity growth appears to be intimately linked to ever more complex input-output networks. To study such networks we need to build a framework of multi-sector models with gross-output production functions.

The rest of the paper is organised as follows. Section 2 informally discusses the role of input-output networks in an economy. This is followed by a simple model of an input-output network which is suitable for development accounting. Section 3 presents some cross-country stylised facts and some cross-country features of input-output networks using the model developed in Section 2. Section 4 reviews the literature on input-output networks and discusses how it is linked to development and growth. Section 5 discusses avenues for future research. Section 6 concludes.

2 A simple model of a production network

2.1 Input-output networks: an informal description

The input-output model has a long tradition in economics starting with Leontief (1936), but it was primarily confined to the realm of statistics and the construction of national income accounts. The input-output model has not been viewed as a candidate for serious quantitative macroeconomic analysis. But one of the early applications of input-output models developed for statistical analysis can be found in the area of structural transformation, Chenery et al.

(1986). In a context of multi-sector models the authors found that the input-output analysis is indispensable in shedding light on the pattern of industrialisation. For example, they suggest the right sequencing of industrialisation, that is, starting with capital-good industries instead of moving to labour-intensive industries is key to successful export-led industrialisation. More recently, the growing interest in international vertical specialisation has generated interest in studying trade networks using tools of input-output analysis to 'slice' the global value chains generated by vertical specialisation and to understand how much value added is actually generated at various points in the chain. However, formal macroeconomic models with input-output networks, in particular with a production network, have only been developed more recently to analyse the microeconomic origins of aggregate shocks (see Acemoglu et al., 2012, for a key contribution and Carvalho and Tahbaz-Salehi, 2019, for a survey).

A model with a production network is built on the idea that intersectoral linkages are an essential part of an economy. Sectors use products of other sectors to produce their own products. Therefore, outputs from one sector become inputs to another. For example, manufacturing a car requires inputs from many sectors. It uses steel, plastic, electronics, rubber, and textile products, among others. Therefore, when we buy a car we affect the demand for steel, plastic, electronics, rubber, and textile products. It is important to realise that this is only the first-order effect, that is, the direct effect of purchases of cars on the demand for inputs used to produce the cars. When the demand for textile products increases due to car sales this leads to an increase in demand for cotton. This is a second-order, or in general, a higher-order effect of car sales. The effect of a car purchase percolates through the economy generating additional demands. The total effect of product i is the sum of the first-order effect and the higher-order effects on GDP, and it is measured by the multiplier of product or sector i, λ_i. We can collect all of these effects in a vector $\boldsymbol{\lambda}$. which the more recent literature calls an influence vector. I will use the term 'multiplier' which is the term the traditional statistical literature on input-output analysis uses (see ten Raa, 2005, Chapter 3 or Miller and Blair, 2009, Chapter 6 for examples).

This percolation of the effect of car purchases through the economy opens the door for the network structure to play a role in the propagation of shocks or distortions. Carvalho (2014) gives three simple examples to illustrate the role of the network structure. In a horizontal economy each sector produces its own intermediate inputs with capital and labour. This is equivalent to the more traditional multi-sector models with value-added production functions. The multiplier is one in this case, $\lambda_h = 1$. There is no additional demand created by the sale of one sector's product because they are not linked. In a vertical economy intermediate goods flow from upstream to downstream firms unidirectionally. The sale of one product of the most downstream sector generates higher order effects through the input-output chain, and thus $\lambda_v > \lambda_h$. The final example of Carvalho (2014) is the so-called 'star economy' where one sector, the hub, produces a vital intermediate input for every other sector, and the hub purchases intermediate inputs from all the other sectors. This structure has the highest multiplier because the sale of the product of any non-hub sector generates demand for the hub sector's product which in turn generates demand for all other sectors' product. Also note that low productivity of the hub sector or a large distortion in that sector can have a rather detrimental effect on all the other sectors (see vom Lehn and Winberry, 2021, for a recent example of investment hubs).

2.2 The environment

I turn now to the formal model of an input-output network. The aim is to describe a simple model which can be used for development accounting in a closed economy. As such the model will be static, and therefore, it will include only a production network and no investment network.

There are n sectors in the economy. Sector j's output, q_{jt}, is produced with capital, k_{jt}, labour, l_{jt}, and intermediate inputs, z_{ijt}, $i = 1, \ldots, n$, according to a Cobb-Douglas technology:

$$q_{jt} = A_{jt}\xi_j k_{jt}^{\theta_k} l_{jt}^{\theta_l} \prod_{i=1}^{n} z_{ij,t}^{\theta_{ij}}, \quad \theta_k, \theta_l \in (0,1), \quad \theta_{ij} \in [0,1), \quad \theta_k + \theta_l + \sum_{i=1}^{n} \theta_{ij} = 1, \tag{1}$$

where ξ_j is a normalising constant:

$$\xi_j \equiv (\theta_k + \theta_l)^{-(\theta_k+\theta_l)} \prod_{i=1}^{n} \theta_{ij}^{-\theta_{ij}}. \tag{2}$$

θ_k, θ_l and θ_{ij} are the elasticity of output of sector j with respect to capital, labour and intermediate input i, respectively. The assumption that θ_k and θ_l are the same across sectors facilitates the analytical solution. The assumption that $\theta_{ij} \in [0,1)$ allows them to vary across sectors. The only restriction is that $\sum_{i=1} \theta_{ij}$ is the same across sectors, implying we allow for a wide variety of potential network configurations. The introduction of the normalising constant, ξ_j, allows us to simplify some of the equilibrium relationships without the loss of generality. Output of sector i can be sold for intermediate use or final use, y_{it}. To keep the framework simple, we assume that goods sold for final use are combined into an aggregate output index with a Stone-Geary aggregator:

$$Y_t = \prod_{i=1}^{n} \alpha_i^{-\alpha_i} (y_{it} + \bar{y}_i)^{\alpha_i}, \quad \sum_{i=1}^{n} \alpha_i = 1, \quad \alpha_i \in (0, 1). \tag{3}$$

α_i governs the elasticity of the aggregate output index, Y_t, with respect to the final use of sector i's output, y_{it}. If $\bar{y}_i = 0$, α_i is the elasticity. If $\bar{y}_i > 0$, the elasticity depends both on the parameters α_i and $\bar{y}_i$, and on the level of final use, y_{it}. Note that because of the Stone-Geary specification $Y_t \neq GDP_t$. The Stone-Geary aggregator is one of the most frequently used in the development literature. Hence, it is useful to explore its potential implications in the presence of an input-output network.

The market-clearing conditions are:

$$q_{it} = y_{it} + \sum_{j=1}^{n} z_{ij,t}, \tag{4a}$$

$$K_t = \sum_{i=1}^{n} k_{it}, \tag{4b}$$

$$1 = \sum_{i=1}^{n} l_{it}. \tag{4c}$$

We made several simplifying assumptions. The production technology was assumed to be Cobb-Douglas which is equivalent to assuming that the gross-output share of intermediate inputs is constant. These shares are crucial because they define the production network. In the context of development this is counterfactual because these shares tend to change with the level of development. For example, as the country develops, the intermediate input share in agriculture rises. The technology is relatively easy to generalise for the more general constant elasticity of substitution (CES) technology at the expense of analytical tractability. The production network derived from CES sector technologies would depend both on the parameters of the technology and on the relative prices. Since these relative prices are equilibrium objects, we could not solve the model explicitly.

We also assumed that the final expenditure aggregator is of Stone-Geary type (non-homothetic Cobb-Douglas). Hence, our framework departs from the existing models of production networks in an important way. All of the models of production networks assume a homothetic aggregator, either CES or Cobb-Douglas. This is a good assumption in many contexts. However, we know that non-homotheticicities play an important role in development. In particular, it is impossible to reconcile cross-country data on final expenditures with homothetic preferences. Hence, I opted for this departure from the standard production network frameworks because this is the most relevant in the context of development.

2.3 Equilibrium with production network

Under the Cobb-Douglas assumptions, the first-order conditions are that the factor price equals the factor's share in output divided by the factor quantity:

$$r_t = \frac{\theta_k p_{jt} q_{jt}}{k_{jt}}, \tag{5a}$$

$$w_t = \frac{\theta_l p_{jt} q_{jt}}{l_{jt}}, \tag{5b}$$

$$p_{it} = \frac{\theta_{ij} p_{jt} q_{jt}}{z_{ij,t}}, \tag{5c}$$

$$p_{it} = \frac{\alpha_i p_t Y_t}{y_{it} + \bar{y}_i}, \tag{5d}$$

where p_t is the price level of GDP.

We can use (5d) to substitute $\alpha_i p_t Y_t / p_{it}$ for $y_{it} + \bar{y}_i$ in the aggregate output index, (3), to obtain the expression for the price of aggregate output:

$$p_t = \prod_{i=1}^{n} p_{it}^{\alpha_i} \equiv 1, \tag{6}$$

which we normalise to 1. It is important to note that the Stone-Geary aggregator is the only non-homothetic aggregator that allows for a regular price index which does not depend on the level of output. (5a) and (5b) imply that:

$$\frac{w_t}{r_t} = \frac{k_{jt}}{l_{jt}} = K_t, \tag{7}$$

which is the implication of our assumption that θ_k and θ_l are the same across sectors.

Next we derive the so-called 'Domar-weights', the sector output to GDP ratio. Restating (5d) as:

$$p_{it}(y_{it} + \bar{y}_i) = \alpha_i Y_t,$$

and summing it over i implies that:

$$Y_t = \sum_{i=1}^{n} p_{it} y_{it} + \sum_{i=1}^{n} p_{it} \bar{y}_i = GDP_t + \sum_{i=1}^{n} p_{it} \bar{y}_i. \tag{8}$$

Using (5d), the demand for y_{it} can be expressed as:

$$y_{it} = \frac{\alpha_i GDP_t}{p_{it}} + \frac{\alpha_i \sum_{j=1}^{n} p_{jt} \bar{y}_j - p_{it} \bar{y}_i}{p_{it}}. \tag{9}$$

Substituting this equation into the market clearing condition, (4a), and rearranging yields:

$$\lambda_{it} = \bar{\alpha}_{it} + \sum_{j=1}^{n} \theta_{ij} \lambda_{jt}, \tag{10}$$

where λ_{it} is the multiplier of sector i:

$$\lambda_{it} \equiv \frac{p_{it} q_{it}}{GDP_t},$$

and

$$\bar{\alpha}_{it} \equiv \alpha_i + \frac{\alpha_i \sum_{j=1}^{n} p_{jt} \bar{y}_j - p_{it} \bar{y}_i}{GDP_t}.$$

λ_{it} is the Domar-weight of sector i. Equation (10) is one of the key equations of the framework. It says that the Domar-weight of sector i, the gross output of sector i relative to GDP, is the value added of sector i relative to GDP plus the weighted average of the Domar-weights across all sectors where the weights are the share of intermediate input shipment from sector j to i.

Intuitively, the contribution of the gross output of sector i to GDP is the sum of the direct effect of sector i on GDP which is the value added of sector i *plus* all the indirect effects that the other sectors' gross output has on GDP via sector i.

Expression (10) can be written in matrix form as:

$$\boldsymbol{\lambda}_t = \bar{\boldsymbol{\alpha}}_t + \boldsymbol{\Theta}\boldsymbol{\lambda}_t, \tag{11}$$

where $\boldsymbol{\lambda}_t = (\lambda_1, \ldots, \lambda_n)'$ and $\bar{\boldsymbol{\alpha}}_t = (\bar{\alpha}_{1t}, \ldots, \bar{\alpha}_{nt})'$ are $(n \times 1)$ column vectors and $\boldsymbol{\Theta} = [\theta_{ij}]$ is an $n \times n$ square matrix of the intermediate input share parameters. Note that the definition of the technologies in (1) implies that θ_{ij} is the cost share of intermediate input j in the output of sector i. Thus, a column of the matrix is the cost shares of all sellers in a particular buyer's output, while a row of the matrix is cost shares of a particular seller in all buyers' output. This definition is consistent with the structure of the input-output tables as published by statistical agencies. This matrix represents the production network.

Equation (11) can be solved for $\boldsymbol{\lambda}_t$:

$$\boldsymbol{\lambda}_t = (\boldsymbol{I} - \boldsymbol{\Theta})^{-1}\bar{\boldsymbol{\alpha}}_t, \tag{12}$$

where $(\boldsymbol{I} - \boldsymbol{\Theta})^{-1} = [\ell_{ij}]$ is the so-called 'Leontief-inverse'. Gale (1960, Chapter 9) shows that a non-negative Leontief-inverse, $(\boldsymbol{I} - \boldsymbol{\Theta})^{-1} \geq 0$, exists if and only if there is a non-negative vector $\boldsymbol{\lambda} \geq 0$ such that $\boldsymbol{\lambda} > \boldsymbol{\Theta}\boldsymbol{\lambda}$. A non-negative matrix that satisfies this condition is called a productive matrix. It follows from equation (11) that if $\alpha_i > 0$ for all i, $\boldsymbol{\lambda} > \boldsymbol{\Theta}\boldsymbol{\lambda}$ holds. Thus, the matrix is productive. For future reference it is also useful to restate equation (12) for sector i as:

$$\lambda_{jt} = \sum_{i=1}^{n} \ell_{ji}\bar{\alpha}_{it}. \tag{13}$$

Finally, we derive the expression for aggregate output, and thus, for GDP. We first take the log of the production function, (1). We then substitute K_t for k_{jt}/l_{jt} and the first-order conditions for all remaining quantities. Lastly, we use the formula of the log of the price index, (6). After some manipulations, we obtain the key development accounting equation with production network:

$$\log GDP_t = \sum_{j=1}^{n}\left(\lambda_{jt}\log A_{jt} - \frac{p_{jt}\bar{y}_j}{GDP_t}\log p_{jt}\right) + \frac{\theta_k}{\theta_k+\theta_l}\log K_t. \tag{14}$$

There are few remarks in order. First, the multipliers, λ_{it}, as we discussed earlier, are the Domar-weights, that is, the sectoral output to GDP ratios. The Domar-weights capture that sectors with small value added or employment shares can have a large effect on GDP when they have large sectoral output. The total effect of a shock or a distortion originating in sector i can be decomposed into a direct and indirect effect:

$$\frac{p_{jt}q_{jt}}{GDP_t} = \frac{p_{jt}y_{jt}}{GDP_t} + \left(1 - \frac{p_{jt}y_{jt}}{p_{jt}q_{jt}}\right)\frac{p_{jt}q_{jt}}{GDP_t}. \tag{15}$$

The first term is the direct effect which may well be small, but the second term can be substantially larger depending on how much the sector's intermediate input share raises the importance of sector i for the aggregate economy.

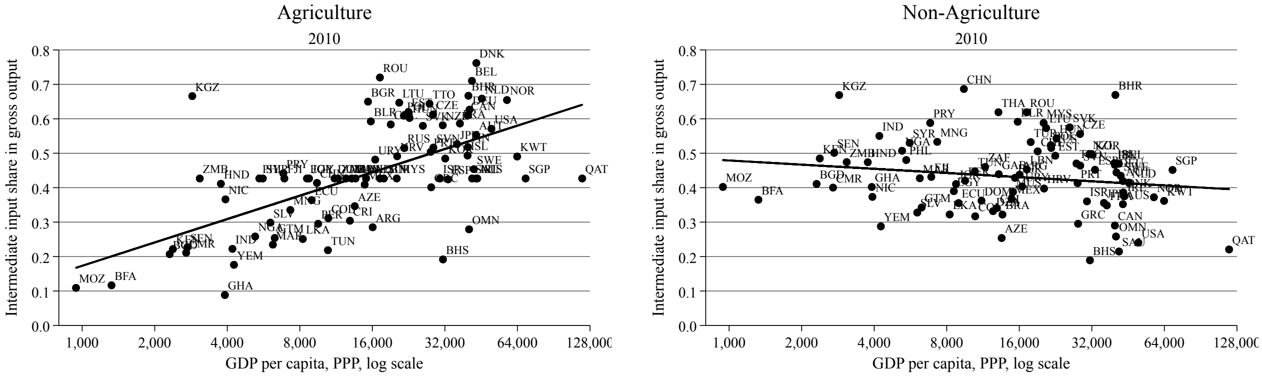
Second, equations (12)-(13) give a structural interpretation of the Domar-weights. Namely, equation (13) highlights that they depend both on the parameters of the production function captured by ℓ_{ji} and on the parameters of the GDP aggregator $\bar{\alpha}_{it}$.

Third, (14) suggests that aggregate TFP, the TFP associated with GDP is given by:

$$\log B_t \equiv \log GDP_t - \frac{\theta_k}{\theta_k+\theta_l}\log K_t = \sum_{j=1}^{n}\left(\lambda_{jt}\log A_{jt} - \frac{p_{jt}\bar{y}_j}{GDP_t}\log p_{jt}\right). \tag{16}$$

If $\bar{y}_j = 0$, then aggregate TFP is equal to the sum of sectoral TFPs weighted with the Domar-weights. This is the result of the celebrated Hulten Theorem, which states that if there are no distortions and the final demand function is homogeneous of degree zero, then we only need the Domar-weights to calculate aggregate TFP from the sectoral TFPs (see Hulten, 1978). However, if $\bar{y}_j > 0$ for at least one j, the final demand is not homogeneous of degree one, and thus Hulten's Theorem fails (see Baqaee and Farhi, 2019, for a detailed analysis of the conditions under which Hulten's Theorem fails).

Figure 1: Intermediate input shares

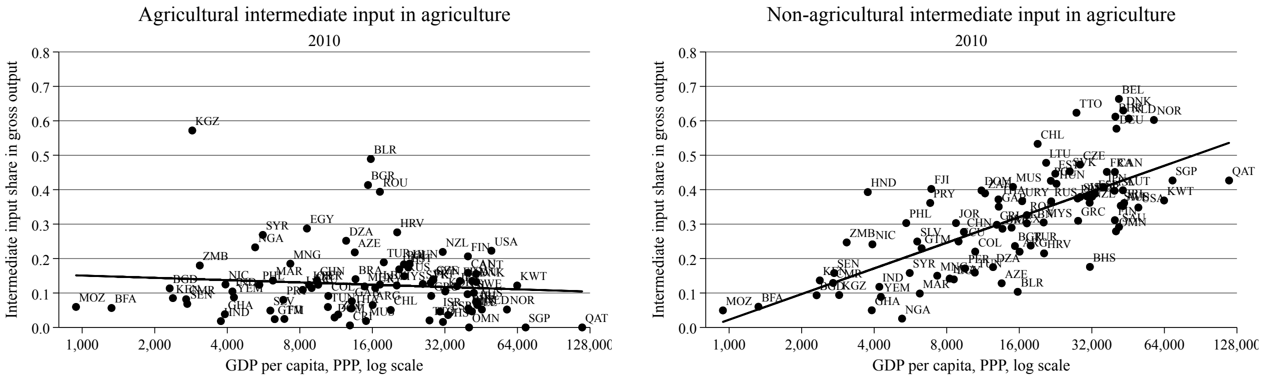


3 Cross-country Stylised Facts

In this section, I present stylised facts about a few specific features of the production network focusing primarily on the role of agriculture. The dataset consist of an unbalanced panel of input-output tables of 91 countries for the period 1970-2013 constructed at the Growth and Development Centre of the University of Groningen and generously provided by Stefan Pahl (Groningen). The data have 19 sectors for most countries. In 12 countries, the data have only 17 sectors. The service sector is well integrated as a supplier of goods for other sectors but much less so as a purchaser of intermediate inputs from other sectors. The data cover a number of developing countries, including 11 sub-Saharan African countries. As far as I know, this is the only dataset of input-output tables which includes a number poor countries. However, it also has some problems besides that it is not publicly available. Since it was constructed to analyse global value chains, the service sector is not disaggregated, and in most countries it is not fully integrated into the input-output tables. This limits its potential use. These data are used to calculate various statistics on the production network. GDP per capita is from Penn World Tables 9.1. In all graphs I display cross-sectional relationships for the year 2010.

Figure 1 plots the intermediate share in output in agriculture and non-agriculture against GDP per capita. The important take away from the two graphs in Figure 1 is that the intermediate input share in output rises with GDP per capita. However, this is entirely attributable to the rising intermediate input share in agriculture. As the economy develops, agriculture uses

Figure 2: Intermediate input shares in agriculture sector

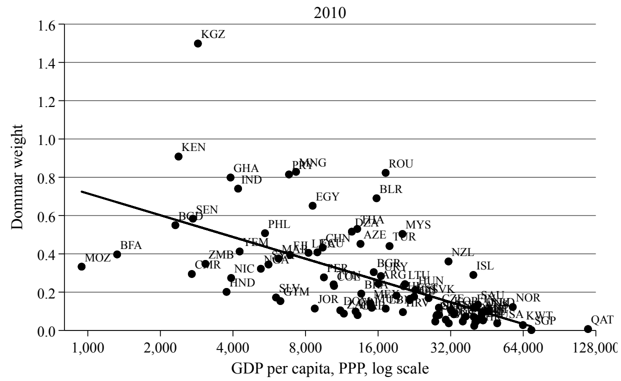


more and more intermediate inputs and, as we know from sector development accounting, the TFP in agriculture rises. To verify this hypothesis, in Figure 2 I break down the intermediate input share in agriculture into the intermediate inputs agriculture buys from itself and the intermediate inputs agriculture buys from other sectors. Again, the shares are plotted against GDP per capita. The interesting feature of the data is that agriculture does not use more inputs from agriculture as the economy develops, but instead uses more inputs from non-agriculture. This feature of the data is one of the motivating stylised facts of Donovan (2021). This pattern suggests more severe contractual problems (Acemoglu et al., 2007) or missing insurance markets (Donovan, 2021) in poor countries.

We turn now to some stylised facts which are now directly related to the network structure of the economy. We start with the cross-country patterns of Domar-weights. Figure 3 shows that the Domar-weight of agriculture is strongly negatively related to GDP per capita. The strong negative pattern suggests that the importance of agriculture declines with the level of development. This seems to be a well-known result as the value-added share of agriculture in GDP declines with level of development. However, the Domar-weights tell us something more. It is still the case that the cross-country variation in the value-added share in GDP contributes to the variations in the Domar-weights. But the Domar-weights also vary because of how important agriculture is as a buyer and seller of intermediate goods for the rest of the economy.

To gauge information about how important agriculture is as an intermediate good supplier

Figure 3: Domar-weights in agriculture



for the rest of the economy at different stages of development, we calculate the so-called 'out-degree' for the production network. We start with the definition of the outdegree. Consider the matrix $\mathbf{\Theta}$. Recall that each element θ_{ij} measures the share of intermediate input i in the output of sector j. We normalise this matrix in such a way that $\hat{\theta}_{ij}$ measures the share of intermediate input i in the total intermediate input use of sector j. Thus,

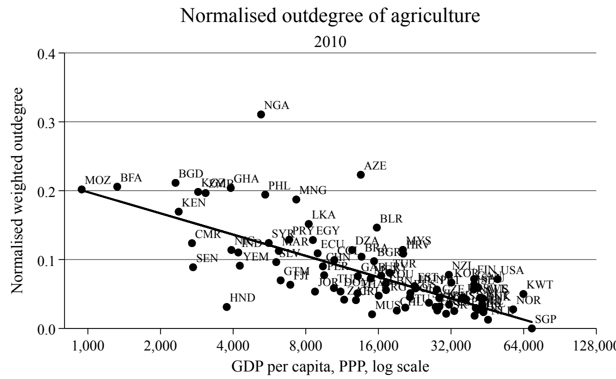
$$[\hat{\theta}_{ij}] = \widehat{\mathbf{\Theta}} = \frac{1}{1 - \theta_k - \theta_l}\mathbf{\Theta}.$$

The (weighted) outdegree of $\widehat{\mathbf{\Theta}}$ is defined by:

$$d_i = \sum_{j=1}^{n} \hat{\theta}_{ij}.$$

Note that $\sum_{i=1}^{n} \hat{\theta}_{ij} = 1$, which is called the indegree of $\widehat{\mathbf{\Theta}}$. But $d_i \neq 1$ in general, and it can be smaller or larger than unity. d_i measures the first-order importance of sector i for the economy as an intermediate input input supplier. If $\hat{\theta}_{ij} = 0$ for some j, then sector i is unimportant at the first order for sector i. If sector i produces all the intermediate goods for every other sector, then $\hat{\theta}_{ij} = 1$ for all i and $d_i = n$. This is just the first-order effect. One can calculate higher-order effects as well, but here we only focus on the first-order effect which is shown in Figure 4. Since 12 countries have 17 sectors, and the others 19, I plotted the outdegree normalised with the number of sectors, d_i/n. Agriculture is not only important in poor countries because it has

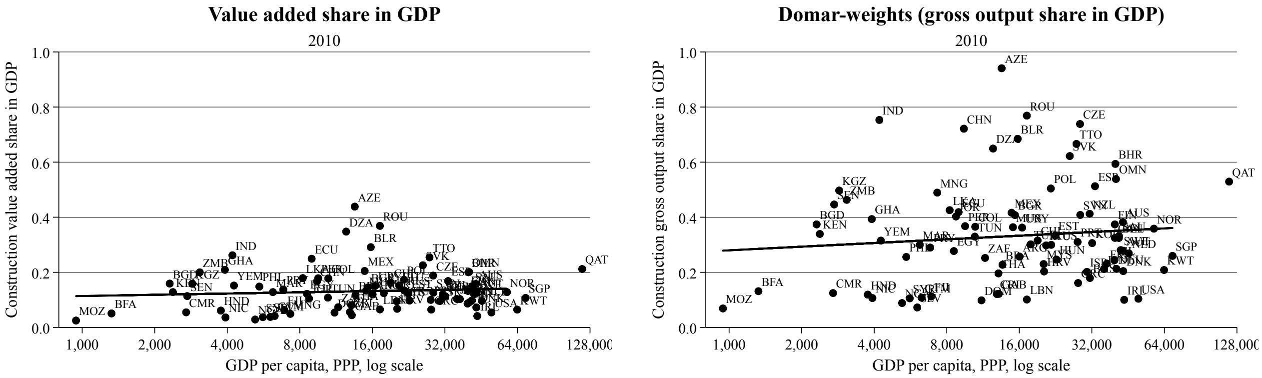
Figure 4: Agricultural and non-agricultural intermediate input shares in agriculture



a high value-added share in GDP or a high employment share in the total, but also because it is an important source of intermediate good supply for the other sectors. This matters because it affects the productivity of all other sectors as well.

The purpose of the final cross-country stylised facts highlights how important it can be to focus on the Domar-weights, sector gross-output share in GDP, instead of sector value-added share in GDP. The former includes all the indirect effects a sector has on GDP via the production network in addition to the direct effect, that is the effect of sector value added on GDP. As an example sector, I chose construction as it tends to deliver to almost all sectors of the economy. The cross-country pattern is displayed in Figure 5. The less important takeaway from the graph is that neither the value-added share nor the gross-output share of construction in GDP varies significantly with the level of development. However, the most important takeaway is that the overall importance of construction for GDP measured by the Domar-weights (gross-output share in GDP) can be very different from the value-added share in GDP. Hence, without considering the whole production network we could arrive to the wrong conclusion about what sectors have the largest effect on GDP, or on what sectors policymakers should focus when they design industrial policies. A sector can became a bottleneck for the economy if it is very centrally measured with the Domar-weight and it has low productivity. For example, the Domar-weight of construction in India is about three times higher than the share of construction in value added. Since productivity of construction is comparatively low, construction is likely to contribute significantly to the low aggregate productivity.

Figure 5: Construction



4 Input-output networks, development and growth

4.1 Aggregate productivity

The contribution of Jones (2011) was perhaps the first that integrated intermediate goods into the neoclassical development accounting framework. His analysis addresses two questions. First, how the production network amplifies the effect of sector TFPs on GDP per capita. Second, how the degree of complementarity across intermediate inputs alters the effect of sector TFPs on GDP per capita in the presence of distortions. The first question can be answered by our model. The amplification of sector TFPs on GDP are measured by our multipliers λ_{it}. With a homothetic aggregator, $\bar{y}_j = 0$, and in symmetric equilibrium, $A_{jt} = A_t$, we have that (11) and (14) imply:

$$\log B_t = \frac{1}{\theta_k + \theta_l} \log A_t.$$

Assuming that $\theta_k + \theta_l = 0.5$, we conclude that a doubling of sector TFPs leads to a fourfold increase in aggregate TFP. Notice, however, that B_t is the TFP associated with GDP. Thus, it is a value-added TFP while A_t is a gross-output TFP. Since $\theta_k + \theta_l$ is the value-added share in sector gross output, what the previous equation really does is to rewrite gross-output TFP in terms of value-added TFP, but they are fundamentally the same.

However, even our simple model suggests this assertion only holds under a very specific assumption. If the aggregator is non-homothetic, then converting gross-output sectoral TFP into value-added TFP will not give us the aggregate TFP. Another reason why the above assertion does not hold is distortions. Since Jones (2011) is interested in the interplay between distortions and complementarity, he assumes that both GDP and the intermediate input aggregator are of CES form. This opens up the door for complementarities to have an effect on GDP per capita. Strong complementarity increases the importance of the sectors with a lower TFP because more resources get allocated to these sectors in equilibrium. The quantitative exercise of the paper finds a multiplier effect of a factor of four to six for an intermediate good share of one half in the presence of distortions and complementarities.

The model of Jones (2011) has had two limitations. First, the model assumed identical sector technologies except for the sector TFP which allowed to solve the model for averages. Second, cross-country TFP data at the sector level were not available at the time of writing. Hence, the model was calibrated to aggregate data or averages of micro data. This approach allowed for the study of the effect of intermediate input shares on aggregate TFP but it did not provide insights as to how the production network affects it.

Fadinger et al. (2021) uses a framework which is the same as in Section 2 with $\bar{y}_i = 0$ for all i. The paper aims to provide a decomposition of the cross-country variation in GDP per capita (in the spirit of Caselli, 2005) into variation in the product of the average Domar-weights and average sector TFPs, the aggregate capital stock, and the covariance between Domar-weights and sector TFPs. They use the World Input-Output Database (WIOD) of 38 countries for 2005 and the corresponding database of sector productivities for 2005 to quantify the production side of the economy. In addition, they also use the GDP per capita, and aggregate capital stock data from the Penn World Tables. All three databases were constructed by the Groningen Growth and Development Centre. The first important finding is that the variance decomposition explains 92% of the variation in GDP per capita. This is remarkable because the GDP and capital data on the one hand and Domar-weights and sector productivity levels on the other come from a different dataset. Although the underlying national accounts and price datasets are either identical or largely overlap, still the result suggests that the model can account for the data well. The second important finding is that the product of the average Domar-weight and sector TFPs accounts for about half of the variation in GDP per capita and variation in the capital stock accounts for the other half, while the covariance term is negative and accounts for 6% which brings down the total to 90%. The interpretation of the finding about the covariance is that poor countries tend to have low Domar-weights in sectors with below-average productivity while rich countries tend to have high Domar-weights in sectors with below-average productivity.

Building a two-by-two sector model with intermediate and final goods, Grobovšek (2018) turns to a classic question of development economics, namely which sector makes poor countries so unproductive. The model has two intermediate and two final sectors producing goods and services using intermediate inputs and labour. This setup and the corresponding data work makes it possible to distinguish between TFP in final and intermediate output production. Using the 1997 and 2005 productivity and price-level data from the Groningen Growth and Development Center, the paper establishes that the price of intermediate inputs relative to final output declines with level of development, and thus, producers in poor countries have to pay more for their intermediate inputs than those in rich countries. In addition to this new finding, it also finds that intermediate input shares are fairly stable across countries, similar to what we have found for non-agriculture in Figure 1. The final interesting empirical finding is that poor countries are particularly inefficient at producing intermediate inputs. This is a particularly interesting result as it complements the findings of Hsieh and Klenow (2007) and Herrendorf and Valentinyi (2012), who used value-added models and data. The quantitative model reveals that the elasticity of GDP per capita with respect to TFP is high, implying high Domar-weights (multipliers) similar to those used by Jones (2011).

The common problem that these papers face is data issues. There are no cross-country databases of harmonised input-output tables that include poor, particularly sub-Saharan, countries. It is common practice to use the WIOD data which consists of only 40 countries. It includes India and China, but no poor countries. This limits the scope of the quantitative analysis of these papers. The exception is Bartelme and Gorodnichenko (2015) who compile a large set of input-output tables which include several sub-Saharan countries. However, it is unclear to what extent the industry structure is consistently defined across countries. Nevertheless, the paper presents a set of interesting facts including evidence about large multipliers.

4.2 Growth and Volatility

The papers reviewed in the previous section explored the implications of input-output linkages in the context of development accounting. Carvalho and Gabaix (2013) ask the question to what extent aggregate volatility can be attributed to sector-level volatility. They utilise the idea that if preferences are homothetic and there are no distortions, Hulten's Theorem implies that aggregate TFP can be written as:

$$\log B_t = \sum_{j=1}^{n} \lambda_{jt} \log A_{jt}.$$

Thus, aggregate TFP is the Domar-weighted aggregate of sector TFPs. Applying the framework to US data, they find that the Domar-weighted aggregate of sector TFPs tracks well the measured aggregate TFP. More importantly, they find that changes in aggregate TFP volatility are entirely driven by changes in the Domar-weights and the contribution of changes in sector-level volatility is not significant. In particular, the decline in aggregate volatility after the early 1980s, the Great Moderation, was driven by the decline in the Domar-weights associated with various highly volatile manufacturing sectors. This highlights that structural transformation matters not only for aggregate growth (if sector TFPs are growing at a different rate), but also matters for aggregate volatility (if the volatility of sector TFP growth is different). Moro (2012) also asks the question to what extent structural transformation can contribute to changes in aggregate volatility. Instead of using the disaggregated data directly, he constructs a model with goods and services, and intermediate inputs, and calibrates it to the US. He finds that structural transformation accounts for about 30% of the decline in volatility. Since Carvalho and Gabaix (2013) find on disaggregated sector data that almost all changes in aggregate volatility are due to structural changes, the difference between the two results highlights that aggregation issues are having a potentially important effect on the findings.

Moro (2015) links volatility to growth. He establishes empirically that growth and volatility are negatively related. This finding is rationalised with a two-sector model with goods and services in which both can be used as final expenditure or as intermediate inputs. The paper particularly emphasises the multiplier effects in a production network.

Despite these studies, how structural transformation affects growth and volatility is still not well understood. It is well known that agriculture is volatile. Therefore, if the economy is dominated by agriculture, aggregate output is naturally volatile. Koren and Tenreyro (2007) document that poor countries tend to specialise in more volatile sectors and aggregate fluctuations are highly correlated with the shocks to the sectors they specialise in. As countries initially develop they diversify and later specialise again, but in low-volatility sectors. It is not well understood, however, what theoretical mechanism generates these data patterns, or how this might be related to premature industrialisation, for example.

To gauge a better understanding of how input-output networks affect growth and volatility, we need more data, in particular more input-output tables to construct time series of production networks and capital flow tables to construct time series of investment networks. Long time series of annual input-output tables are available only for the US. In addition, there are also detailed sector investment data available for the US that allows for construction of capital flow tables. Foerster et al. (2019) explore the effect of the production and investment network on growth slowdown. In particular, they estimate that the trend of GDP growth declined about two percentage points since 1950, and ask the question what is the fundamental cause of this decline. To answer this question they build a multi-sector growth model with a production and investment network. They use the production and investment network for one particular year only to quantify the model. They find that 0.6 percentage points of the slowdown can be directly attributed to the construction sector alone, and another 0.6 percentage points to professional and business services, and non-durable goods production. To understand the mechanism of how these effects come about, it is useful to restate our development accounting equation, (14), for the homothetic case, $\bar{y}_i = 0$, and in terms of growth rates defined by log differences, $\Delta \log X_{t+1} \equiv \log X_{t+1} - \log X_t$. This gives:

$$\Delta \log GDP_t = \sum_{j=1}^{n} \lambda_j \Delta \log A_{jt} + \frac{\theta_k}{\theta_k + \theta_l} \Delta \log K_t. \tag{17}$$

The model of the production network states that the growth rate of GDP per capita depends on the Domar-weighted average of sector TFP growth rates and on the growth rate of the aggregate capital stock per capita. Adding an investment network to the model allows us to express the growth rate of the capital stock as a function of sector TFP growth rate:

$$\Delta \log K_t = \sum_{j=1}^{n} \lambda_j^x \Delta \log A_{jt},$$

where λ_j^x are the weights representing the effect of the investment network. Consolidating the two equations, we obtain:

$$\Delta \log GDP_t = \sum_{j=1}^{n} (\lambda_j + \lambda_j^x) \Delta \log A_{jt}. \tag{18}$$

This formula implies that a sector's contribution to the growth of GDP per capita depends on the multiplier, $(\lambda_j + \lambda_j^x)$, and on sectoral TFP growth. The quantitative results of Foerster et al. (2019) highlight the importance of the multiplier in comparison to the sector value-added share in GDP. Construction and business services are major drivers of aggregate GDP growth because both have a large multiplier, 0.17 and 0.25 respectively. These numbers are significantly larger than their value-added shares in GDP which are only 0.05 and 0.09 respectively.

Instead of growth rates, vom Lehn and Winberry (2021) focus on the volatility of GDP growth. Moreover, they assume away the production network, and focus only on the investment network which they construct for the postwar US. They find several results. First, they find that the investment network is dominated by four sectors. Construction, machinery manufacturing, motor vehicle manufacturing, and professional and technical services produce about two thirds of the investment commodities. These sectors are called 'investment hubs' and they are highly volatile. Second, their calibrated multi-sector model with an investment network implies that shocks to these four sectors are the primary source of aggregate fluctuations after 1984 while aggregate shocks were more important before 1984. Among other things, the increasing importance of the sector-specific shocks is the source of the declining cyclicality of labour productivity. One lesson for developing countries is that volatility of specific sectors can easily be amplified by the investment network. But the crucial question is how this will play out in developing countries if they import most of their machineries and they only have a small and relatively inefficient business service sector. How much volatility is then imported via machinery import for investment? Can business services also be imported?

4.3 Misallocation

Misallocation of factors of production across production units (e.g. plots of land, production plants) has been widely studied since Restuccia and Rogerson (2008) laid out a framework to analyse the effect of distortions on aggregate outcomes. Since the work of Hsieh and Klenow (2007), the empirical works on distortions were primarily based on micro data focusing on distortions of capital and labour allocations. Occasionally, when the data is sufficiently rich, such as in the case of Gollin and Udry (2021), heterogeneity across production units can also be considered. The standard question was by how much aggregate TFP increases if the distortions are eliminated.

Models of production networks provide a complementary framework to define and measure distortion using sector data. The idea is that the link between the matrix $\mathbf{\Theta}$ and the Domar-weights breaks down in the presence of distortions. Let

$$\boldsymbol{\mu}_t = (I - \mathbf{\Theta})^{-1} \bar{\boldsymbol{\alpha}}_t$$

be called the vector of multipliers. We established earlier that in the absence of distortions the Domar-weights are equal to the multipliers, $\boldsymbol{\lambda}_t = \boldsymbol{\mu}_t$. Now consider a tax on sector gross output τ_j, and let $\bar{\mathbf{\Theta}} \equiv [(1 - \tau_j)\theta_{ij}]$. Then one can show that the Domar-weights satisfy

$$\boldsymbol{\lambda}_t = (I - \bar{\mathbf{\Theta}})^{-1} \bar{\boldsymbol{\alpha}}_t. \tag{19}$$

Clearly, $\boldsymbol{\mu}_t = \boldsymbol{\lambda}_t$ if and only if $\tau_i = 0$ for all i. Hence, the ratio of the multipliers over the Domar-weights $\boldsymbol{\mu}_t / \boldsymbol{\lambda}_t$ can be used as a measure of distortion.

This idea was first explored by Jones (2013) who constructed an open-economy model with a production network and distortions. Using input-output tables of OECD countries he concludes that they look remarkably similar across countries. However, he emphasises the difficulty identifying $\boldsymbol{\mu}_t$ and $\boldsymbol{\lambda}_t$ separately because we only observe $\bar{\mathbf{\Theta}}$. Nevertheless, since the variation in $\bar{\mathbf{\Theta}}$ is relatively small across countries, he "tentatively" concludes that the distortions are not particularly large. One may well suspect that under some condition such an identification can be made. Bigio and La'O (2020) show for near-efficient allocation that distortions have zero first-order effects on aggregate TFP, but they have a significant effect on the labour wedge where the size of the effect is the measured Domar-weights. Thus, the Domar-weights identify the labour wedge, and consequently, the distortions. Moreover, their quantitative exercise implies that the production network amplified the financial distortions by a factor of two during the 2007-08 financial crisis. This result suggests that production networks could also play an important role in poor countries in amplifying the effects of financial distortions.

The central question of the paper of Liu (2019) is what sectors should industrial policy target in the presence of distortions. The naive intuition based on a model of value-added production would suggest that the government should target the most distorted sectors. However, by now we know that such policy might be unwise. One of the reasons is that the aggregate effect of a sector-specific distortion also depends on its position in the production network. If a sector is very central in the network, a small distortion can do a lot of damage. Another reason is that the sector size matters for the effect of the distortion. It is shown that, with a given level of sectoral distortions, upstream firms have the highest so-called 'distortion centrality' which is expressed in terms of our simple framework by $\boldsymbol{\mu}_t/\boldsymbol{\lambda}_t$. To identify the distortion centrality, the author deploys a range of strategies. It turns out that distortion centrality strongly correlates across all specifications, and it also correlates with the standard measure of the degree of upstreamness of sectors. The application of the model to evaluate industrial policies in South Korea and in China suggests that policy interventions in upstream sectors might have generated a positive net effect at the aggregate.

Hang et al. (2020) make a particularly important contribution to the misallocation literature by showing that it potentially makes a lot of difference whether one studies the misallocation in a value-added or in a gross-output framework. They establish that in the absence of intermediate input distortions, the gross-output and value-added models are theoretically isomorphic. Subject to some adjustment, the value-added TFP can be recovered from the gross-output TFP and misallocation leads to the same efficiency loss when measured from the same data. However, if there are intermediate input distortions, the equivalence breaks down and the value-added model cannot rationalise the data generated by a gross-output model. Therefore the value-added model will give a biased estimate of the effect of misallocation. Bridgman and Herrendorf (2021) use a framework with a production network to derive an aggregate markup from sectoral ones, and provide a decomposition of the change in aggregate markup into the change in goods and services markups and the reallocation from goods to services. To study markups requires one to assume that firms within sectors are monopolistically competitive. Hence, intermediate input allocations are distorted by design. In the spirit of Hang et al. (2020), the production network leads to double marginalisation in their framework: intermediate inputs are marked up both when they are used and when they are produced. Since intermediate input shares are different across goods and services, namely the share in goods is higher than in services in the US, the production network and structural transformation interact in determining aggregate markups. Bridgman and Herrendorf (2021) find that sector markups are smaller than the aggregate difference being accounted for by double marginalisation. In addition, since the intermediate input share is higher in goods then in services, the effect of double marginalisation on aggregate markups declines as goods share is reduced during structural transformation.

4.4 Trade

In the last several decades, we have witnessed a dramatic change in production processes. Stages of production are increasingly scattered across different countries with each country specialising in a particular stage of the production process where it imports intermediate goods to produce exports (see Hummels et al., 2001). This phenomenon has been called 'vertical specialisation', 'fragmentation of production', 'outsourcing' or 'global value chains' (GVCs). Production, in general, involves selling output for intermediate uses to other sectors or firms, and realising value added (income) on these sales. This fundamental feature of production does not change if sellers and buyers are in different countries, but the measurement of the transactions and of value added becomes more complicated. Input-output accounts give a good description of the production and value chains within countries but they do not go beyond the border. We do not know how exported commodities are used abroad, how the intermediate goods are produced abroad, and even the domestic use of imports is determined more by assumptions than by measurement. The traditional data sources do not provide enough information to map out the value chain stretching across many countries generated by vertical specialisation. Although these sources allow for a limited analysis of international specialisation patterns, we would need to complement the domestic *production network* with the *trade network* to get a complete picture of vertical specialisation and value chains. The primary database that contains such information is the WIOD. This database includes 40 countries and 56 sectors for the period 2000-2014 (see Timmer et al., 2015, for a detailed description). Unfortunately, although the countries included in the database produce 85% of world GDP, not one of them is a developing country. Hence, the WIOD is of limited use if we want to understand how developing countries participate in vertical specialisation. But even an analysis of a more limited scope requires national input-output tables. Such data make it possible to measure the degree of participation in international vertical integration or a country's contribution to GVCs. Interestingly, one of the early applications of input-output analysis was the factor content calculation of US exports and imports by Leontief (1953) which gave rise to the term "Leontief-paradox". Leontief's calculations were very similar in terms of their spirit to what we see below. He found that US imports were more capital intensive than US exports. This was paradoxical at the time because capital is more abundant than labour in the US. Therefore, one would have expected that US exports are more capital intensive than imports. Revisiting the Leontief-paradox on the 1997 input-output data, Valentinyi and Herrendorf (2008) found that the result depends on where one values exports and imports. If we follow Leontief and take exports at producer prices and imports at the port of entry, then we find US imports to be more capital intensive than US exports. In contrast, if we measure exports at purchaser prices and imports at the port of exit (foreign port), then we find exports more capital intensive than imports. All in all these calculations and the calculations below are very similar in terms of their spirit to Leontief's original calculations. In a way we still ride on Leontief's coattail.

Vertical specialisation has important implications for structural transformation as it affects the share of manufacturing both in value added and employment, and it also influences productivity growth. To shed more light on its patterns, Pahl and Timmer (2019) construct an unbalanced panel of 91 countries for the period of 1970-2013, which we have used earlier in the paper. It includes several sub-Saharan African countries and several poor countries from other parts of the world. The paper asks the questions what are the long-terms trends of vertical specialisation and how it correlates with GDP per capita. A natural measure of vertical specialisation is the import content of exports (see Hummels et al., 2001). The higher this ratio, the more vertically specialised is the country. The authors use a variant of this measure. They find that vertical specialisation has been a steady ongoing process occasionally interrupted by short periods of vertical integration. There is also evidence that poorer countries tend to be less vertically specialised than rich ones. Additionally, the process of vertical specialisation is uneven across countries. Periods of vertical integration are less frequent for rich countries and more frequent for poor countries. The empirical analysis focuses exclusively on the manufacturing sectors, it does not investigate how the process of vertical specialisation interacts with other sectors of the economy. It would be interesting to know more about how this specialisation affects structural change or plays any role in premature deindustrialisation, if any.

The work of Pahl and Timmer (2020) sheds more light on this interaction. Here, the question is how participation in GVCs affects productivity growth and manufacturing in a country. Again, the data are key. They construct data of manufacturing employment and value added for 58 countries between 1970 and 2008. In addition, they take the input-output tables of these 58 countries from the dataset they used in Pahl and Timmer (2019). The paper uses the previous indicator of vertical specialisation, the import content of exports, to measure the GVC participation of a country. First, the authors find evidence that GVC participation has a positive effect on productivity growth. In addition, this effect is stronger the further away the country is from the productivity frontier. This result is consistent with the idea that GVC participation makes technological upgrading in manufacturing easier.

Second, the paper also finds that GVC participation has no effect on manufacturing employment growth. This is more in line with the idea of premature deindustrialisation put forward by Rodrik (2016). However, we would need more empirical work to be able to give a more definitive answer. The paper focuses on manufacturing employment growth generated either directly or indirectly by GVC participation. However, structural transformation is jointly determined by reallocation across three major sectors. For example, Huneeus and Rogerson (2020) argue that the peak of manufacturing employment share is well explained by the cross-country productivity growth differences in agriculture. If that were the case, one of the crucial questions is whether trade in intermediate inputs for agriculture plays any role in observed productivity growth. On the other hand the quantitative analysis of Sposi (2019) suggests that about three quarters of the curvature of the hump-shape is due to cross-country variation in the production network. However, he focuses on cross-country variations with country- and sector-specific productivity shocks. Hence, it is hard to gauge how productivity growth and the presence of production networks would interact.

5 Future research

5.1 Data requirement

Considerable progress has been made in the last decade in developing analytical frameworks with input-output networks. However, the main constraint on making more progress in understanding the role of input-output networks in economic development in general, and in structural transformation in particular, is data constraints. Currently the main cross-country database on input-output networks is the WIOD which includes 43 countries which produce about 85% of world GDP. The advantage of this database is that it does not only include the production network but also the trade network which requires that industries are consistently defined across countries. Moreover, it is also consistent with the productivity level database of the Groningen Growth and Development Centre. This database provides PPP levels for the gross output of the 35 industries the WIOD uses. This makes it possible to analyse how productivity of a sector in one country affects productivity in another country via the trade and production network. The disadvantage of this database is that it includes 27 members of the European Union and 16 major countries in the world between only 2000 and 2014, and no low-income countries. Thus, there are no low-income sub-Saharan African, Latin American or Asian countries in the database. The lack of poor countries in the sample makes it unsuitable to study questions of economic development. The time period is also a constraint as a longer panel of production networks could provide more information about the interaction between structural transformation and production networks.

The database of 91 countries, which was used earlier to present some cross-country stylised facts about production networks, and which is not available publicly, has the advantage that it includes a number of low-income countries and is a panel covering the period 1970-2013. The major disadvantage of this database is that service industries are not fully integrated into the production network. First, the service sector is only disaggregated into two subsectors:

transport, telecommunications and all other services. Second, the subsector “all other services” is not properly integrated into the production network in the sense that all of its intermediate inputs are set to zero. The database was originally created to analyse GVCs. However, the lack of detail for the service industries makes it unsuitable to ask broader questions about the cross-sectional properties of the production network and its interaction with structural transformation.

To make further progress on understanding the role of production networks in economic development and in structural transformation, we need a good quality, publicly available panel of input-output tables for a large set of countries which includes as many low-income countries as possible. Coverage of 35 industries consistently defined across countries similar to the WIOD measured from 1970 to the near-present would be ideal as far as data on production networks are concerned. It would also greatly enhance the research potential of such a database if it was complemented by a productivity-level database with gross-output PPP productivity levels for the 35 industries, and industry-level employment data. These latter two datasets would make it possible to use measured productivity levels in research. If such data is not available, one could still construct sector-level productivities using data on aggregate productivity, data on relative prices, and a theoretical model.

5.2 Open questions

We learned from both the development accounting and structural transformation literature that non-homothetic preferences play a crucial role in rationalising data with models. The main reason is that along neither the cross-sectional or time series development path, relative price changes are not large enough to account for changes in expenditure share alone. Hence, the models have to rely on income effects, and thus, on non-homothetic preferences. However, we have shown in our simple framework that if preferences are non-homothetic, aggregate TFP is not simply the Domar-weighted average of gross-output sector TFPs. This is because the non-homothetic preferences create a wedge between GDP on the one hand and the Domar-weighted aggregate of sector TFPs and aggregate capital stock on the other. The effect of non-homotheticity on measured aggregate TFP is similar to distortions between sectors because income affects the sectoral allocation. However, it is unclear how non-homotheticity interacts with distortions between sectors. It may magnify it or offset it. In the latter case, some form of distortions may not matter as much as one would conclude with homothetic preferences. But this is both a theoretical and empirical question. Since parameters governing non-homotheticity can be estimated, one can quantify this effect if input-output tables and PPP-adjusted industry productivity levels are available. This is an important question to which we have no answer at the moment.

The existing papers on production networks and development use the WIOD data for quantitative analysis, which excludes low-income countries. For example, Grobovšek (2018) is unable to identify the inefficient sectors in poor countries producing intermediate inputs because the quantitative results depend on definition sectors and on sample size. Since the 'poor countries' in the database are actually emerging countries, it is not that surprising that it is more difficult to identify problem sectors in the data. The dataset of 91 countries, which includes low-income countries, allows us to learn something about the production network of poor countries. The share of agriculture value added in GDP is high and productivity of agriculture is low in poor countries. This direct contribution of agriculture to low GDP per capita in poor countries has been known for a long time. The dataset of 91 countries allows us to look beyond this direct contribution. In particular, it allows us to identify sectors of so-called 'high-centrality measure', which are important for other sectors and, indirectly, for the whole economy. The Domar-weights are such a centrality measure. Figure 3 suggests that agriculture is a problem sector in low-income countries. In addition, Figure 4 shows the so-called 'normalised outdegree', which tells us that agriculture in low-income countries ships relatively more intermediate inputs to other sectors than agriculture in high-income countries. Hence, low agricultural productivity also has a negative effect on other sectors of the economy. However, we do not know how important the service sectors are for other sectors in low-income countries because there are no low-income countries in the WIOD data where service sectors are sufficiently disaggregated and integrated into the input-output tables, and because the database with 91 countries, which includes low-income countries, does not sufficiently disaggregate services or integrate them into input-output tables either. It remains an open question which other sectors matter most for aggregate output beyond agriculture in low-income countries.

The key question is what are the problem sectors that remain on the table if we turn our attention directly to structural transformation. Uneven sector TFP growth plays an important role in generating structural change. We do not know how this plays out in the presence of production networks where value-added TFP growth at the sector level interacts with gross-output TFP growth of all the other sectors. Similarly, premature deindustrialisation due to labour saving technological progress in manufacturing and trade or due to uneven technological progress across sectors may not be mutually exclusive. Labour saving technological progress is not the only form of technological progress in a gross-output model. The change in the composition of intermediate inputs is also a form of technological change. Manufacturing may well be more labour intensive than it appears if it uses more labour-intensive services as intermediate inputs. Similarly, faster productivity growth in agriculture may be attributed partially to faster technological progress in intermediate input producing sectors used by agriculture. These are empirical questions which cannot be answered without good data on production networks.

Finally, structural transformation as a process of industrialisation sometimes fails to start, gets stuck somewhere, or occurs prematurely. This may open up the possibility of government intervention in the form of industrial policy. But what industry or sector should get special government attention? Where should government start dismantling distortions? The work of Liu (2019) suggests that distorted upstream sectors should be targeted by industrial policies. Which sectors those are is again an empirical question that cannot be answered without data on production networks.

6 Conclusion

We reviewed the literature on input-output networks to understand how considering such network structures allows us to better understand economic development and structural transformation. One key insight from the existing literature is that cross-country differences in the structure of networks contribute to differences in productivity levels, growth rates and volatility. It also shapes how and which various countries trade with each other. However, much of the role of input-output networks in economic development, economic growth and structural transformation remains unexplored.

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