Production Network Diversification and Economic Development*

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Abstract

We provide empirical evidence and a theoretical analysis of the influence of production network diversification on countries' economic performance, reflected in their GDP per-capita levels. Using a panel sample of 55 countries, we find a strong positive association between the number of active links in the input-output network of a country and its GDP per-capita over time, even after controlling for several country characteristics. To complement and scrutinize our empirical finding, we advance economic theory on the link between network diversity and economic development by proposing a multisector model with input-output linkages, non-unitary elasticity of substitution in production, and a love of variety in the bundle of intermediate inputs that rationalize our empirical results. In the long run, when labor and intermediates are substitute inputs, denser production structures enjoy higher productivity in the intermediate input bundle, which generates a larger input-output multiplier that more strongly amplifies a given sequence of sectoral productivity. Hence, our model predicts that economies with denser production structures display higher income.

JEL codes: 011, 014, 041, 047

Keywords: Production network structure, GDP per capita, productivity, substitutability between inputs

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1 Introduction

One of the key features of a country's economy is how its production system operates and what it generates. Input-output (I-O) tables have been historically and widely used to map the interconnections of productive systems and to measure the economic impacts of changes in their structures. I-O data allow us to observe the interlinkages between industries and sectors, from which we can assess how well or poorly diversified the productive systems of an economy are. By analyzing these interlinkages, in this paper, we provide empirical and theoretical analyses of how a denser production network structure can support higher levels of economic output in a country. In particular, we explore the question: How important is the organization of production in explaining the large differences in income per capita observed across countries? This is a long standing question in the economic development literature (see, for example, Hirschman, 1958; Hidalgo, Klinger, Barabási, and Hausmann, 2007; Jones, 2011; McNerney, Savoie, Caravelli, and Farmer, 2018) because its answer has important implications for industrial policies and for the development of nations and regions (see, for example, Liu, 2019; Choi and Levchenko, 2021).

In this paper, we study the relationship between the diversification of intermediate inputs traded across economic sectors of a country and the country's economic performance measured by its level of GDP per capita. We start by exploring empirical evidence on a panel of 55 countries for the period 1995-2011; using this evidence, we then propose a formal theoretical model displaying a network of producers trading intermediate inputs. Our empirical results and theoretical construct present novel evidence on the effect that intermediate input diversification can have on GDP per capita levels. Empirically, we document a strong fact using different specifications: countries with higher production network density—that is, a higher number of non-zero intermediate input links among sectors—present higher levels of GDP per capita. To complement this empirical observation, we build a relatively simple theoretical model of a detailed network structure that shows, intuitively, that under certain conditions, in denser production networks, a given productivity shock could spill over more easily to the rest of the economy, generating higher output, as observed in the data.

In our empirical approach, we use different econometric specifications that aim to explore whether and to what extent production network density influences the GDP per capita level of a country. Our data are sourced from the OECD databases and contain detailed information on production linkages for 33 industries for each of the 55 countries in our sample. We calculate network density following influential network science research that aims to capture the complexity of network interconnections (see, for example, Gai, Haldane, and Kapadia, 2011; Acemoglu, Ozdaglar, and Tahbaz-Salehi, 2015; Herskovic, 2018). In particular, production network density is built to capture the proportional amount of active connections within the productive input-output structure of a country, which allows us to measure network diversification as in Miranda-Pinto (2021), while capturing the notion of economic sparsity analyzed in Dupor (1999), Acemoglu et al. (2012), and Acemoglu et al. (2015).

We test the relevance of network density to a country's economic performance using a number of cross-country fixed-effect panel regressions that include different sets of drivers of economic growth commonly used in the literature such as years of schooling, quality of institutions, service share, and an index of economic complexity, among others. Across our specifications, we find a consistent positive effect of network density on a country's level of GDP. Our most conservative estimate indicates that a 10% increase in network density (85 new links, among 1,056 possible links) is associated with a 3.5% increase in GDP per capita (on average, $726 PPP US dollars, which corresponds to Cambodia's GDP per capita in 1995). The results suggest that network connections among domestic industries drive most of the effect (77%) and that the number of imported intermediates also plays a role in accounting for differences in GDP per capita across countries.[1]

To support our empirical observation, we formally propose a theoretical model in which network density could generate higher levels of output in a country. In our model we assume that the topology of the production network is exogenous (active links), while the intensity of the connections is endogenous to changes in relative input prices. We use the model to study how different network structures affect the level of GDP via shaping the strength of the propagation and amplification of sectoral productivity shocks. To this end, we assume that sectoral productivity follows the same stochastic process across sectors and countries and that the elasticity of substitution between inputs is non-unitary and common across sectors and economies. Therefore, the main difference among economies is the production network structure—namely, the network density, sectoral intermediate input shares, and sectoral consumption shares.

Our main theoretical result indicates that the role of production network density in shaping the level of GDP in an economy depends on the specifics of sectoral production function. Under standard Cobb-Douglas production functions, which assume unitary elasticity of substitution between inputs, network density plays no role in shaping aggregate GDP. However, production network density does have a role in affecting GDP when sectoral production function displays non-unitary elasticities of substitution in production and a love of variety in the bundle of intermediate inputs. The mechanism in which a higher network density results in higher output works as follows. Within the intermediate

[1] Kasahara and Rodrigue (2008) document that importing intermediate inputs is associated with higher productivity and, therefore, output, which is consistent with the results in our empirical section.

input bundle of CES production technologies, the number of intermediate inputs used in production affects how productive a given mix of intermediate inputs is. The difference in intermediate input productivity embedded in the diversification of the intermediate input bundle then shapes firms' equilibrium input shares, as long as the elasticity of substitution between labor and intermediate inputs is different from one. If intermediate inputs and labor/capital are substitutes, the love of variety effect makes intermediates more attractive in denser production networks, implying that denser networks are also more connected networks that display a larger input-output multiplier. In this case, a given level of sectoral productivity generates higher output in denser networks, all else equal.

We conclude our theoretical construct with a numerical simulation that calibrates our model to match each of the 55 countries production structure in 1995. We simulate the model with a sequence of sectoral productivity shocks and show that the model is successful at replicating the structure of our empirical observation. In our model, a 10% increase in network density is associated with a 5.6% increase in GDP, which is in line with our empirical estimates.[2]

The rest of the paper is organized as follows. Section 2 discusses the literature on the role that production diversification and complexity play in shaping the economic performance of countries and regions. Section 3 describes data sources and methodology, including the design of our network density variable. Section 4 presents our empirical findings. Section 5 expands our empirical analysis by developing a theoretical framework that rationalizes our results and we propose and quantify the mechanism for the influence of network density on GDP per capita. Finally, Section 6 concludes, including a discussion of policy implications. Additional analysis, data considerations and proofs are provided in the Appendix.

2 Related literature

Our paper contributes to the literature that studies the role that production network structures play in shaping countries' average income. In this sense, the papers that are closest to our study are Jones (2011), Bartelme and Gorodnichenko (2015), McNerney et al. (2018), and Fadinger et al. (2021).

Jones (2011) studies the role that intermediate input linkages and input complementarity play in amplifying distortions and depressing aggregate productivity and GDP (*misallocation*). Their model assumes a unitary elasticity of substitution between in-

[2] Our empirical estimates for a 10% increase in $Density$ vary from 0.28 to 0.68, depending on the controls and the threshold used to define an "active connection."

termediate inputs and labor-capital, and the key production network moment shaping GDP is the share of intermediate inputs in production (assumed to be common across sectors). Jones (2011) empirically analyzes the cross-country correlation between the intermediate input share and GDP per capita, finding no significant association.

Bartelme and Gorodnichenko (2015), McNerney et al. (2018), and Fadinger et al. (2021) study the empirical association between the average input-output multiplier and aggregate productivity to account for the differences in cross-country income per capita. These papers find a positive correlation between the average input-output multiplier and log of GDP per capita. The theoretical framework proposed by these authors and Jones (2011) assume unitary elasticity of substitution between intermediates and labor-capital, which implies that the intensity of input-output connections is the key metric in determining how productivity or frictions propagate and amplify along the production chain. In their framework, there is no role for the network density.

Different from Jones (2011), Bartelme and Gorodnichenko (2015), McNerney et al. (2018) and Fadinger et al. (2021), we emphasize the role played by a particular network structure—network density—in amplifying productivity shocks in the presence of non-unitary elasticity of substitution between intermediates and labor-capital, including a love of variety in the bundle of intermediate inputs. In this sense, we provide empirical and theoretical support for the role of the proportion of positive I-O connections in shaping the input-output multiplier and, therefore, GDP.

A significant number of other studies in different disciplines have used the interconnections of input-output tables to also explore productive structures and their relation to economic performance (e.g., Bartelme and Gorodnichenko, 2015; Sonis and Hewings, 1998; Xu, Allenby, and Crittenden, 2011; Blöchl, Theis, Vega-Redondo, and Fisher, 2011). In the context of a single country, Choi and Levchenko (2021) study the successful role that industrial policies played in the development of Korea. In their model, the industrial policy generates manufacturing hubs in which firms become more productive due to having easier access to credit and learning by doing, thus generating higher diversification among the I-O structure of the country. In relation to this, although we do not model industrial policies (and their costs) or other factors that determine a country's network structure, we show in our theoretical framework that a higher number of active I-O links (denser network) alone can improve a country's output via multipliers.[3]

Explaining the intricacies and economic outcomes of input-output networks, Acemoglu and Azar (2020) model the evolution of the production network of a country to understand how the endogenous reshaping of networks can support long-term economic growth. The authors show that denser networks arise due to sectoral improvements in

[3] Choi and Levchenko (2021) do not evaluate this, as their model does not connect firms.

productivity. However, they also show that, given productivity, a higher density of the network increases output via providing more possibilities of efficient input combinations. In our case, the network structure in our theoretical analysis is exogenous, but the positive relationship between network density and income does arise from the fact that input diversification improves input productivity (love of variety). In this way, our paper complements Acemoglu and Azar (2020) by documenting the empirical relationship between network density and GDP per capita and by rationalizing this relationship with a relatively simple extension of existing exogenous production network models with CES technologies, as in Papageorgiou and Saam (2008) and Atalay (2017).[4]

Hidalgo and Hausmann (2009) and Hausmann and Hidalgo (2011) propose novel ways to empirically study the influence of production structures in the economic performance of nations. The authors develop indexes of economic complexity based on exports diversification to understand how complexity supports economic development. Their measure of economic complexity is constructed using the number of different products a country exports and the uniqueness of those products compared to other exporters' products. Thus, their measure captures the ability to diversify shocks (number of products) and comparative advantage (the ability to produce a unique product). Different from these papers, our network density measure is more aggregated at the industry level and captures how shocks transmit along the production chain by considering the number of active industry connections. In addition, the relationship between production complexity and development in Hidalgo and Hausmann (2009) and Hausmann and Hidalgo (2011) resides in the fact that a more complex production structure is the result of unobserved capabilities. Expanding on this notion, our paper explicitly develops a model that displays a direct connection between the production network structure and GDP per capita.

Production and export diversification has also been widely studied as a feature of economic resilience, with researchers arguuing that diversified economies support a better buffer to shocks. Indeed, the 2008-09 global economic crisis spawned a number of studies on economic diversity, stability and the ability to recover from downturns (e.g., Han and Goetz, 2015; Deller and Watson, 2016). Looking at link volatility and development, Koren and Tenreyro (2013) explore the role of input diversification, although the authors do not offer a framework with input-output linkages and provide no

[4] It is worth noting that Acemoglu and Azar (2020) use a Cobb-Douglas production function. In addition, the love-of-variety effect in their model is different from ours. In particular, in their model, the arrival of new varieties increases the amount of inputs in production and, all else equal, increases output. In our model, the CES function imposes weights on the intermediate inputs, which add up to one; therefore, when adding a new variety, the process does not necessarily increase output, as it requires reallocating other intermediates.

empirical evidence linking network density and GDP per capita.[5] In a similar analysis, Krishna and Levchenko (2013) show a negative relationship between the number of intermediates used in production and GDP volatility; however, the authors do so only by exploring information from manufacturing industries and, thus, miss all the other interconnections that occur in an economy that can be also relevant to explaining growth. Miranda-Pinto (2021) expands on Acemoglu et al. (2012) and Krishna and Levchenko (2013) by exploring the empirical and theoretical relationship between the economy's wide intermediate input diversification and the service share in driving GDP volatility. We expand the econometric and theoretical approaches developed by Miranda-Pinto (2021), and, rather than focusing on the relationship between the production network structure and short-term macroeconomic volatility, we focus on the role of production structure in shaping the average income of a country.

3 Data and methodology

We piece together a cross-country panel dataset consisting of 55 countries over seventeen years (1995-2011), forming a full balanced panel of 935 observations.[6] To evaluate the economic effects of production network density, we construct panel models using GDP per capita as the dependent variable and a set of different drivers of economic development as independent variables. For the dependent variable, we collect data on GDP per capita at purchasing power parity (PPP) at current international dollars from the World Bank's World Development Indicators.[7] From this same database, we obtain data on population and years of schooling, key determinants of income per capita according to Mankiw et al. (1992).

Motivated by the resource curse literature (e.g., Sachs and Warner, 1995; Mehlum, Moene, and Torvik, 2006), on the one hand, we control for the size of the commodity sector in each economy (as a share of total output). On the other hand, motivated by Calderón and Liu (2003) and Beck et al. (2014), who study the relationship between the size of the financial sector and economic growth, we use the output share of the financial sector as a control. Broadberry (1998) and Moro (2015) study the relationship between the service sector share and GDP growth. Hence, we also control for the service share of different countries. Moreover, following Acemoglu et al. (2017), we control for the degree

[5] The authors provide evidence for eight OECD economies showing that for the period 1970-2007, the diagonal shares of the input-output table have become smaller, on average, (indicating more reliance on other sectors.)

[6] We select these 55 countries because they are the only ones with available data, across our different sources.

[7] data.worldbank.org

of sectoral dominance in the production network.[8] These four measures are obtained from the OECD input-output tables.

An open economy has long been touted as a necessary element to growing an economy as first discussed in the seminal paper of Frankel and Romer (1999). Thus, we control for this by introducing *trade to GDP* data in our dataset, where trade is the sum of a country's exports and imports. Additionally, high quality institutions have been shown to have significant effects on GDP per capita (Acemoglu and Robinson, 2012). Therefore, to control for the quality of institutions and governance, we retrieve data from the World Governance Indicators (also via the World Bank) on *Rule of Law*, *Control of corruption*, *Government effectiveness*, *Voice and accountability*, *Political stability*, and *Regulatory quality*.

We also use data from the *Economic Complexity Index* (ECI+) of MIT's Observatory of Economic Complexity (`atlas.media.mit.edu`) (from Hidalgo and Hausmann, 2009; Albeaik, Kaltenberg, Alsaleh, and Hidalgo, 2017a). ECI+ is a measurement of how sophisticated an economy's production is. This is assessed by taking into account the diversity of a nation's exports and the uniqueness of the products that are exported. This is a preferred measure of economic complexity since ECI+ performs better than the original ECI as a predictor of growth (Albeaik et al., 2017a).

Finally, in order to calculate our main variable of interest, network density, we collect input-output data from the OECD. We detail how this variable is measured and analyzed next.[9]

3.1 Measuring Production Network Diversification

Following Acemoglu et al. (2015) and Miranda-Pinto (2021), we define production network diversification using network density. The production network density, which from now on we refer as $Density$, of a country measures how interconnected its industries are. To estimate this, we use the formula

$$Density = \frac{\sum_{i=1}^{N} \sum_{j}^{N} 1\left[\tilde{\omega}_{ij} > \underline{\omega}\right]}{N(N-1)}, \tag{1}$$

[8] Acemoglu et al. (2017) show that economies with larger sectoral dominance display sharper downturns. Dominance is defined as the ratio between the largest Domar weight (supplier centrality) in the network and the variability in sectoral supplier importance. A symmetric and simple network with no dominant sector displays a value of 1, while a network with only one extremely important supplier of intermediates will display a very large value of dominance.

[9] The OECD input-output data have two different sources: first, the 'ISIC Revision 3' that covers 33 industries over the period 1995-2011; and, the 'ISIC Revision 4' that covers 35 industries from 2005 to 2015. For consistency, we decided to use the ISIC Revision 3, to have comparable network density measures over time. Source: `http://www.oecd.org/sti/ind/input-outputtables.htm`.

where $\tilde{\omega}_{ij}$ is an input-output share that can be observed. It captures the portion of intermediate input that originated from sector i and subsequently shipped to sector's j total expenditure on intermediates. These input-output relationships are not symmetrical; there may be situations, for example, in which sector i provides inputs to sector j, but sector j does not supply intermediates to sector i. $1\left[\tilde{\omega}_{ij} > 0\right]$ is a function that determines input-output connections that are larger than a tiny threshold of $\underline{\omega} \in [0.00001, 0.001]$. N is the number of sectors. If $Density$ is equivalent to 0, this indicates that no sectors in the economy rely on others for production. However, if $Density$ equals 1, then each sector relies on all other sectors for production purposes.

Table 1 displays descriptive statistics for total $Density$ (assuming $\underline{\omega} = 0.001$), its variation across countries and over time, and GDP per capita.[10] Across all our observations, $Density$ has a mean of 0.811, implying that the average country in our sample, in an average year, will have about 856 network connections out of a possible 1,056 connections (81.1 per cent of possible connections). Delving into the average standard deviation (SD) of $Density$ within countries (over time), we see an average of 0.022, which tells us that a single deviation from the mean within a given country would create roughly 20 extra network linkages. With regard to the average standard deviation of $Density$ across countries, we observe a variation of around 96 production network linkages. This demonstrates that there is a healthy variation in network densities throughout the 55 countries' data and over time. Focusing on GDP per capita (US PPP dollars), we see that there is also a decent amount of variability in income per capita across countries, given a standard deviation ($13,219) that is more than half the average national income ($20,743).

Table 1. Descriptive statistics

Variable	Obs.	Mean	Median	Std. Dev.	Min.	Max.
$Density$ (Production network density)	935	0.811	0.825	0.094	0.498	0.98
SD of $Density$ across countries	55	0.094	0.096	0.003	0.088	0.098
SD of $Density$ within countries	17	0.022	0.017	0.016	0.003	0.091
GDP per capita ($ US int. dollars)	935	20,743	19,386	13,219	789	75,113

Figure 1 provides an illustrative example of $Density$. The figure shows the production network structure of Thailand and Denmark in 1995. The size of each node represents the relative share of that particular sector in the economy. Each number represents a sector (see details in Table 7 in the Appendix). For example, sector s20 (Construction) and sector s21 (Wholesale trade) are among the largest sectors in both economies. There is also clear heterogeneity in sectoral composition, consistent with each country's stage

[10]Throughout the paper we use total $Density$ which includes domestic linkages and imported intermediates. In our Appendix we show the same results hold for domestic linkages only. In Table 5 of our Appendix we show the correlation of measures of network density using different threshold values.

of development. While the Agriculture and Textile sectors (sectors s1 and s4, respectively) are among the largest sectors in Thailand, the Real Estate and Health sectors (sector s26 and s32, respectively) are among the largest sectors in Denmark.

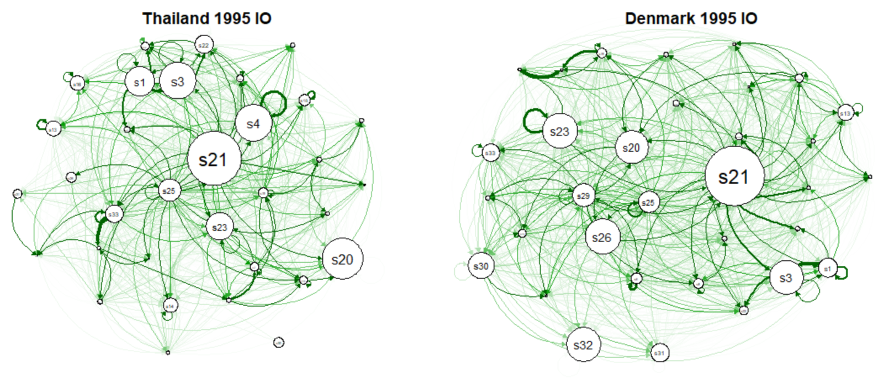

Figure 1. Input-output network in Thailand and Denmark in 1995

Note: This figure shows the production network of Thailand and Denmark in 1995 using the ISIC rev. 3 sectoral classification (source OECD). Each node (circle) is a different sector in the economy, and the size of the node represents sectoral output shares (the labels in the nodes are linked to sectors in Table 7 of our Appendix). An arrow from sector i to sector j represents intermediate inputs flowing from i to j. The intensity of the arrow (darkness and width) indicates how much sector i is buying from j as a fraction of total intermediate input expenses. Source: Authors with data from OECD –see footnote 9.

A network link is represented by an edge from sector i pointing to sector j, which represents intermediate inputs supplied from sector i to sector j. The width of the edge represents the intensity of the connection (intermediate input purchases) as a share of sectors' total sales. Visually, one can see that Denmark has a denser production network than Thailand. Indeed, in 1995, 86% of sectoral connections in Denmark were non-zero ($Density = 0.86$), while in Thailand, only 62% of sectoral connections were active ($Density = 0.62$). To put these numbers into perspective, in 1995, the Danish economy had about 250 extra linkages compared to Thailand. Part of this difference comes from the highly connected service sector in Denmark. We can see that the Financial Intermediation sector (s25) resides in the center of the network, and, even though it does not rank among the largest sectors, it is one of the sectors with the largest number of edges pointing to other sectors. Two additional service sectors are central in the Danish network (but not in the Thai network). These sectors are the Real Estate sector (s26) and the R&D and Professional Services sector (s29).

Figure 2 presents a scatter plot with countries' production network density in 1995 on the horizontal axis and countries' log GDP per capita in 2011 on the vertical axis. As the figure shows, there is a strong positive association between $Density$ and GDP per capita. An increased network density from 0.79 to 0.8 —about ten new links among sectors— in 1995 is associated with a 4.8% higher GDP per capita in 2011.[11]

[11] Even though Cambodia appears as an outlier in the data, all of our estimates are consistent, even when

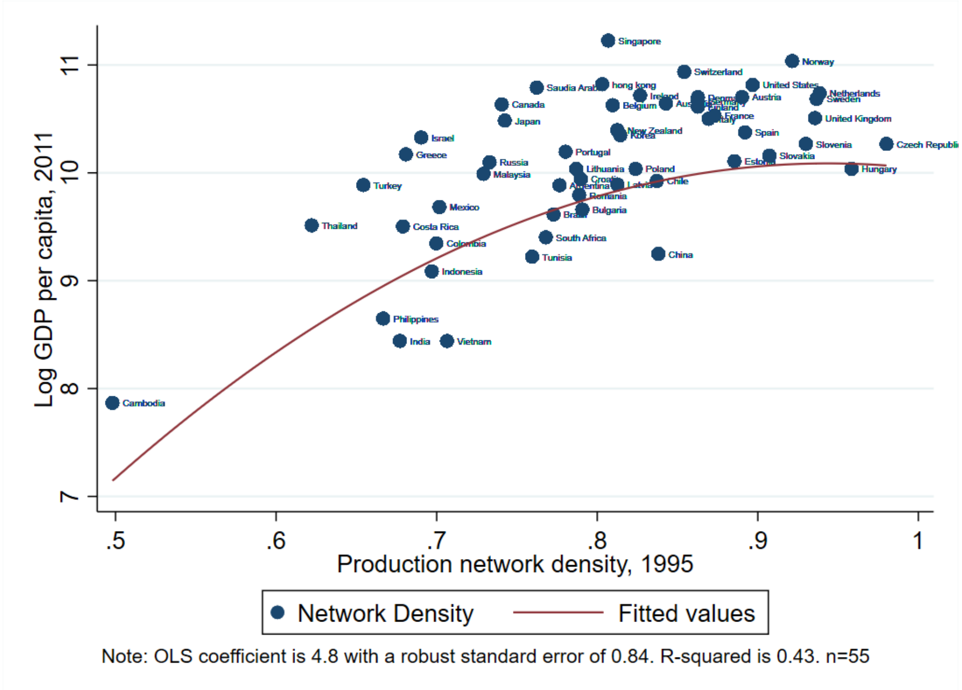

Figure 2. Production network density ($Density$) 1995 and development 2011

To study the robustness of the association between $Density$ and GDP per capita in Figure 2, the next section specifies the econometric strategy we use to control for additional covariates, including unobserved and time-invariant country characteristics.

3.2 Econometric strategy

We use within estimators in order to develop a robust understanding of the relationship between $Density$ and GDP per capita. This form of estimation helps us to deal with any endogeneity stemming from time-invariant country characteristics. Taking into account the insights from Figure 2, we estimate Equation 2 below.

$$Ln(Y_{ct}) = \alpha_0 + \beta Ln(Density_{ct}) + \gamma \Psi'_{ct} + \epsilon_{ct}. \tag{2}$$

Here, c is a country and t a given year between 1995 and 2011. The dependent variable Y_{ct} is GDP per capita PPP adjusted in international dollars. β is our main coefficient of interest and captures the elasticity of $Density$ on GDP per capita. Ψ' is a vector that includes the drivers of economic development discussed above. These control variables include measures of institutional quality; market share of the financial, service and commodity sectors; a measure of the degree of sectoral dominance in the network; population growth; trade to GDP ratio; years of schooling; and the economic complexity

Cambodia is excluded from the analysis.

index (ECI+). Table 6 in the Appendix presents the relevant descriptive statistics for the full sample of country-year observations.

4 Empirical Results

The results from the panel regressions are presented in Table 2. The table contains three columns, each adding a separate set of controls. Column 1 shows the parsimonious model results, where $Density$ reaches a statistically significant elasticity of 1.98. The within R-squared that measures the fit of the regression within a country over time is 6%, while the between R-squared that measures the fit of the regression across countries is 32%, more in line with the cross-sectional regression in Figure 2.

Column 2 presents results of a model including additional country production characteristics, and column 3 expands the analysis to include trade openness, years or schooling, population growth, and institutional and governance characteristics. From the complete regression results (column 3), we see that our estimation accounts for roughly 94% of the within-country variation in GDP per capita for the 55 countries in our sample.

Across the three set of results, we see that $Density$ has a consistent positive significant effect. This is in line with theory (explained later) and the intuition taken from Figure 2. The $Density$ elasticity in column 3 implies that a 10% increase in the network density of the average country will increase its GDP per capita by roughly \$800 PPP international dollars. In our Appendix (Table 3), we show that the same result holds when using only domestic input-output connections. In this case, a 10% increase in domestic connections is associated with an increase in GDP per capita of roughly \$600 PPP international dollars. Similarly, if we use a different threshold to define an active connection, $\tilde{\omega} = 0.00001$ instead of $\tilde{\omega} = 0.001$, we observe an even larger coefficient (see Table 4 in the Appendix). In this case, a 10% increase in $Density$ is associated with an average increase in GDP per capita of about \$1000 PPP international dollars.

As in previous related studies, such as Albeaik et al. (2017b) and Hidalgo and Hausmann (2009), we find that a higher level of export complexity in a country, represented by the ECI+ coefficient, is associated with higher levels of GDP per capita. The elasticities of trade and services shares are statistically significant predictors of GDP per capita, reflecting the importance of trade openness and the increasingly relevant role of services in more-modernized and growing economies, as in Frankel and Romer (1999) and Moro (2015). As expected, education (years of schooling) also affects GDP per capital positively, as evidenced in multiple empirical studies (see, for example, Mankiw, Romer, and Weil, 1992).

In line with the 'Resource Curse' hypothesis (Sachs and Warner, 2001), our variable

Table 2. Panel Fixed Effects results, 1995-2011

VARIABLES	(1) Ln GDP pc	(2) Ln GDP pc	(3) Ln GDP pc
Ln *Density*	1.982**	0.513**	0.363**
	(0.782)	(0.229)	(0.164)
ECI+		0.138	0.143**
		(0.098)	(0.067)
Ln *Sectoral dominance*		-0.110	-0.125
		(0.117)	(0.076)
Ln *Financial sector share*		0.0882*	0.134**
		(0.053)	(0.056)
Ln *Service sector share*		0.157	0.379**
		(0.174)	(0.154)
Ln *Natural resources share*		-0.572***	-0.455***
		(0.016)	(0.022)
Ln *Trade to GDP*			0.287***
			(0.042)
Years of schooling			0.040***
			(0.001)
Control of corruption			0.036
			(0.034)
Voice and accountability			-0.071**
			(0.037)
Rule of law			0.056
			(0.039)
Government effectiveness			0.102***
			(0.029)
Political stability			0.013
			(0.018)
Regulatory quality			-0.084**
			(0.041)
Population growth			-1.25*
			(0.734)
Constant	10.10***	9.225***	8.005***
	(0.169)	(0.209)	(0.288)
Observations	935	935	703
R-squared	0.061	0.895	0.940
Number of countries	55	55	55

Note: This table presents a panel fixed-effect regression using log GDP per capita as the dependent variable and several time-variant country characteristics as independent variables. Robust standard errors in parentheses. *** Significant at the 1-percent level; ** Significant at the 5-percent level; * Significant at the 10-percent level.

capturing dependence on natural resource extraction shows a negative effect on GDP level of a country. Such a negative effect can come from different 'resource curse' channels, such as Dutch disease effects or temporary loss of learning by doing (Van der Ploeg (2011); Fleming et al. (2015)).

Government effectiveness is another statistically significant predictor of higher levels of GDP per capita, pointing to the relevance of a modern public sector to economic progress. Interestingly, we find a negative correlation between measures of *voice and accountability* and *regulatory quality* over time with development, which can point to short-term adjustments and investors' uncertainty in economic systems as countries attempt to enhance these processes.[12]

5 A Simple Theoretical Rationale

In this section, we propose one channel in which a denser production network could generate higher output. In this case, the production network is exogenous and we study how different network structures affect the propagation and amplification of sectoral productivity shocks.

The model in this section differs from those of Jones (2011), Bartelme and Gorodnichenko (2015), and Fadinger et al. (2015) in the following respects. First, the model economy displays non-unitary elasticity of substitution between intermediate inputs and labor. Second, as implied by standard CES production technologies, the productivity of the intermediate input bundle depends on how diversified the mix of intermediates is. Due to these two elements, absent from the papers cited above, the model in this section delivers a role for network density in shaping aggregate GDP.[13]

Firms

The economy is composed by N sectors. In each sector, there is a continuum of homogeneous firms that behave competitively. The CES production technology of firms in sector j is

$$Q_j = Z_j\Big(a_j L_j^{\frac{\epsilon_Q - 1}{\epsilon_Q}} + (1-a_j) M_j^{\frac{\epsilon_Q - 1}{\epsilon_Q}}\Big)^{\frac{\epsilon_Q}{\epsilon_Q - 1}}, \tag{3}$$

in which the intermediate input bundle is

$$M_j = \Big(\sum_{i=1}^{N} \omega_{ij}^{\varrho_M} M_{ij}^{\frac{\epsilon_M - 1}{\epsilon_M}}\Big)^{\frac{\epsilon_M}{\epsilon_M - 1}}. \tag{4}$$

Gross output of the representative firm in sector j is Q_j. Sectoral total factor productivity is Z_j; labor is L_j; M_j is the intermediate input bundle of sector j; and M_{ij} is the

[12] See Ash et al. (2020) and Han et al. (2014) for a discussion of the heterogeneous effects of regulatory quality and voice and accountability in income per capita

[13] The model is similar to the one in Miranda-Pinto (2021). However, the author focuses on the relationship between the production network structure and short-term macroeconomic volatility, while this paper studies the relationship between the structure of the production network and the long-term GDP level.

amount of intermediates that sector j purchases from sector i. The parameter a_j represents how important labor is in the total value of production. The element ω_{ij} reflects the importance of sector i as an input supplier to sector j. Hence, the square matrix Ω—of dimension N and typical element ω_{ij}—defines the input-output structure of the economy. The elasticity of substitution between labor and intermediates is denoted by ϵ_Q, and the elasticity of substitution among material varieties is ϵ_M. The parameter ρ_M captures the love of variety in the bundle of intermediates. As we explain later, the elasticities of substitution between inputs and the love-of-variety parameters are crucial in determining the relationship between the production network structure and GDP.

Households

The representative household maximizes utility

$$U(C_1, ..., C_N) = \Big(\sum_{j=1}^{N} \beta_j C_j^{\frac{\epsilon_D - 1}{\epsilon_D}}\Big)^{\frac{\epsilon_D}{\epsilon_D - 1}}, \tag{5}$$

subject to the budget constraint

$$w\bar{L} + \sum_{j=1}^{N} \pi_j = \sum_{j=1}^{N} P_j C_j, \tag{6}$$

in which C_j is the household's consumption of sector j's output. The parameter β_j represents the importance of sectoral consumption in aggregate consumption expenditure. We have that $\sum_{j=1}^{N} \beta_j = 1$. The elasticity of substitution between consumption goods is ϵ_D. We assume that labor is supplied inelastically; π_j is profit from firms in sector j; w is the wage rate; and P_j represents the price of sector j's good.

Let us assume that sectoral productivity follows the following autoregressive process:

$$\log Z_{jt} = \log \bar{Z} + \rho_z \log Z_{jt-1} + \kappa_{jt}, \tag{7}$$

where κ is a productivity shock that follows a normal distribution with mean zero and standard deviation σ_j. Proposition 1 provides the solution for the competitive equilibrium of the model.[14]

Proposition 1 *Assume that* $\epsilon_Q = \epsilon_M \neq 1$*;* $\epsilon_D = 1$*; and a labor endowment* $\bar{L} = 1$*. Then, log real GDP* ($GDP = C$) *in this economy is*

[14]Competitive equilibrium is defined as follows. Firms and households take prices as given, and given prices maximize their objective functions subject to constraints, such that the goods market and the labor market clear.

$$\log C = \sum_{j=1}^{N} \beta_j \log\Big(\frac{\beta_j}{P_j}\Big), \tag{8}$$

while the vector of sectoral prices is

$$P^{1-\epsilon_Q} = [I - Z^{\epsilon_Q - 1} \circ \big((1-a)^{\epsilon_Q} 1' \circ \Omega'^{\varrho_M \epsilon_Q}\big)]^{-1}(Z^{\epsilon_Q - 1} \circ a^{\epsilon_Q}). \tag{9}$$

Proof: See Appendix.

Proposition 1 shows that log GDP depends on sectoral prices, which, in turn, are a function of the production network structure (Ω, a), sectoral productivity Z, the elasticity of substitution between inputs ϵ_Q, and the love-of-variety parameter ϱ_M. As we will see next, log GDP is a function of the production network density, and their relationship depends crucially on the value of $\varrho_M \epsilon_Q$. Bartelme and Gorodnichenko (2015) and Fadinger et al. (2021) obtain a related result for the relationship between the input-output structure and log GDP. However, the authors explore the case of unitary elasticity of substitution, in which, as we will see below, the relationship between network density and GDP is non-existent.

The role of production diversification

To better examine the role of production network diversification, we study two symmetric networks. As mentioned before, in symmetric networks, the matrix Ω, which represents the input-output network of the economy, displays homogeneous row sums (first-order outdegree). Thus, when a, ϵ_Q, and ϵ_M are common across sectors, sectoral prices are the same across sectors, within the network. Let us define the following symmetric networks:

$$\Omega^{sparse} = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \qquad \text{and} \qquad \Omega^{denser} \begin{bmatrix} 1/2 & 1/2 \\ 1/2 & 1/2 \end{bmatrix}.$$

Assume that steady state productivity is $Z = 1$ for all sectors and networks. Also, assume that $a = [0.6, 0.6]$ and $\beta = [1/2, 1/2]$ are common across networks. Use Proposition 1 and assume that $\epsilon_Q = 1.2$ and $\varrho_M = 0.6$ (so, $\varrho_M \epsilon_Q < 1$). The implied vector of sectoral prices in the sparse network is

$$\log P^{sparse} = \frac{1}{1-\epsilon_Q} \log\Big([I - ((1-a) \circ \Omega^{sparse})^{\varrho_M \epsilon_Q}]^{-1}(a^{\epsilon_Q})\Big) = [0.74 \quad 0.74]'$$

and the vector of sectoral prices in the dense network is

$$\log P^{dense} = \frac{1}{1-\epsilon_Q} \log \left([I - ((1-a) \circ \Omega^{dense})^{\varrho_M \epsilon_Q}]^{-1} (a^{\epsilon_Q}) \right) = [-0.02 \quad -0.02]'.$$

Having solved for prices, equation (8) implies

$$\log C^{dense} - \log C^{sparse} = - \sum_{j=1}^{N} \beta_j \log P_j^{dense} + \sum_{j=1}^{N} \beta_j \log P_j^{sparse} > 0. \tag{10}$$

Equation (10) indicates that, in the presence of high flexibility between intermediate inputs and labor ($\epsilon_Q > 1$) and a love of variety in the bundle of intermediates (implied by $\varrho_M \epsilon_Q < 1$, as discussed next), a denser production network displays a larger GDP. The denser network has a more efficient combination of inputs and is, therefore, able to produce more given productivity levels. In other words, a denser production network displays a larger input-output multiplier, which then spills over a given sequence of sectoral productivities more strongly.

Note that, as Dupor (1999), Acemoglu et al. (2012), Bartelme and Gorodnichenko (2015), and Fadinger et al. (2021) predict, when $\epsilon_Q = 1$ or when $\epsilon_Q = \frac{1}{\varrho_M}$, both networks behave the same. Two symmetric networks, which differ only in terms of their production diversification, display the same sectoral centralities and aggregate GDP. In such a case, the extensive margin of connections does not affect the equilibrium intensity of sectoral connections, which, in the end, determines how shocks propagate along the production chain.

5.1 The mechanism

Here, we explain the mechanism by which production network density affects the level of GDP. We discuss the trade-off between a concentrated intermediate input bundle (sparse network) versus a diversified one (dense network). Consider a firm in sector j that uses only one intermediate input in production, as well as a firm in sector j that uses all of the N intermediate inputs available in production (in equal proportion). Hence, the sparse firm has $\omega_{ij} = 1$ for the main input and $\omega_{kj} = 0$ for all other inputs $k \neq i$, whereas the diversified firm displays $\omega_{ij} = 1/N$ for all i. Moreover, assume that the firm with the non-diversified intermediate input bundle uses $M_{ij} = M_1 > 0$ and $M_{kj} = 0$ for all $k \neq i$, while the diversified firm uses $M_{ij} = M_2 = \frac{1}{N} M_1$ for all i.

From Equation (4) we can see that the non-diversified firm's intermediate input bundle becomes $M_j^1 = M_1$. The diversified firm's intermediate input bundle is

$$M_j^2 = (\omega_{1j}^{\varrho_M} \cdot M_2^{\rho_M} + ... + \omega_{Nj}^{\varrho_M} \cdot M_2^{\rho_M})^{1/\rho_M},$$

in which $\rho_M = \frac{\epsilon_M - 1}{\epsilon_M}$. Using the fact that, for the diversified firm, $\omega_{ij} = \frac{1}{N}$ for all i and that $M_2 = \frac{1}{N} M_1$, we obtain

$$M_j^2 = \big((\frac{1}{N})^{\varrho_M} M_2^{\rho_M} N\big)^{1/\rho_M} = M_2 N^{\frac{1-\varrho_M}{\rho_M}} = M_1 N^{\frac{1-\varrho_M-\rho_M}{\rho_M}}.$$

We can now compare the productivity of the intermediate input bundles of both firms. We can see that if $\frac{1-\varrho_M-\rho_M}{\rho_M} > 0$, there exists a love of variety in the intermediate input bundle. In this case, the diversified firm produces $M_j^2 = M_1 N^{\frac{1-\varrho_M-\rho_M}{\rho_M}}$ more than M_1 (when $N > 1$). More generally, there is a love of variety when $\varrho_M < \frac{1}{\epsilon_M}$ if $\epsilon_M > 1$, or $\varrho_M > \frac{1}{\epsilon_M}$ when $\epsilon_M < 1$. This implies that the diversified firm faces a cheaper relative cost of intermediates (due to higher productivity of the bundle). We can further see the implications of the love of variety in the optimality conditions for M_j:

$$\frac{P_j^M M_j}{P_j Q_j} = (1 - a_j)^{\epsilon_Q} \Big(\frac{P_j^M}{Z_j P_j}\Big)^{1-\epsilon_Q}. \tag{11}$$

Assuming that $\epsilon_Q > 1$, and for a given value of a_j and Z_j, firms in a denser network demand more intermediates relative to firms in a sparse network. Hence, a denser network displays a larger intermediate input share, which then amplifies the effect of sectoral shocks along the production chain, as implied by Equation (10). The resulting relationship between intermediate input shares, input-output multiplier and GDP is reminiscent of Jones (2011), Bartelme and Gorodnichenko (2015), and Fadinger et al. (2015). Our results complement theirs by establishing a relationship between the extensive margin of connections ($Density$) and GDP that is mediated by the equilibrium input-output multiplier of the economy.[15]

5.2 Calibration

In this section, we study the ability of the model to replicate the quantitative relationship between $Density$ and GDP observed in the data. We calibrate the model to match each country's production structure in 1995. We calibrate a_j, the importance of intermediate inputs in production, using an iterative process that matches the data and the model's implied intermediate input share. We calibrate the input-output shares ω_{ij} using the

[15] Note that the role played by ϱ_M in this paper differs from that in Miranda-Pinto (2021), who focuses on short-term volatility. In this paper, we focus on the long-run relationship between $Density$ and the level of GDP. In this context, ϱ_M reflects that, in the long run, a denser production of producers arises from the fact that a more diversified intermediate input mix provides higher input productivity, which relates to the endogenous mechanism in Acemoglu and Azar (2020).

observed intermediate input shares in the data.[16] The model is highly non-linear when ϵ_Q and ϵ_M are different from one. Our simulation assumes that $\epsilon_Q = \epsilon_M = 1.05$ and $\varrho_M = 0.9$, such that $\epsilon_Q \varrho_M < 1$. In this situation, as discussed in the previous section, a diversified intermediate input bundle is more productive. Thus, when intermediates and labor are substitute inputs, in the long run, firms are able to take advantage and use more of the more-productive input, which then increases the input-output multiplier of the economy.

Our quantitative exercise works as follows. For each country, we solve an $N = 33$ equations system for equilibrium prices, and then obtain equilibrium GDP. Using the process for productivity in Equation (7), assuming $\rho_z = 0.5$ and $\log \bar{Z} = 0.1$, we simulate the economy $T = 15$ years. We repeat the process $S = 50$ times and obtain the average (across S) value of log GDP.

Figure 3 plots the average value of log GDP at T (across the S simulations) against $Density$ in 1995. We observe that the model is able to replicate the observed positive relationship between log GDP and production network density. A simple OLS regression using log GDP at T as the dependent variable and log $Density$ as the independent variable yields an GDP-density elasticity of 0.56 (standard error of 0.21), which is close to the upper bound of the empirical estimates that fluctuate between 0.28 and 0.46.

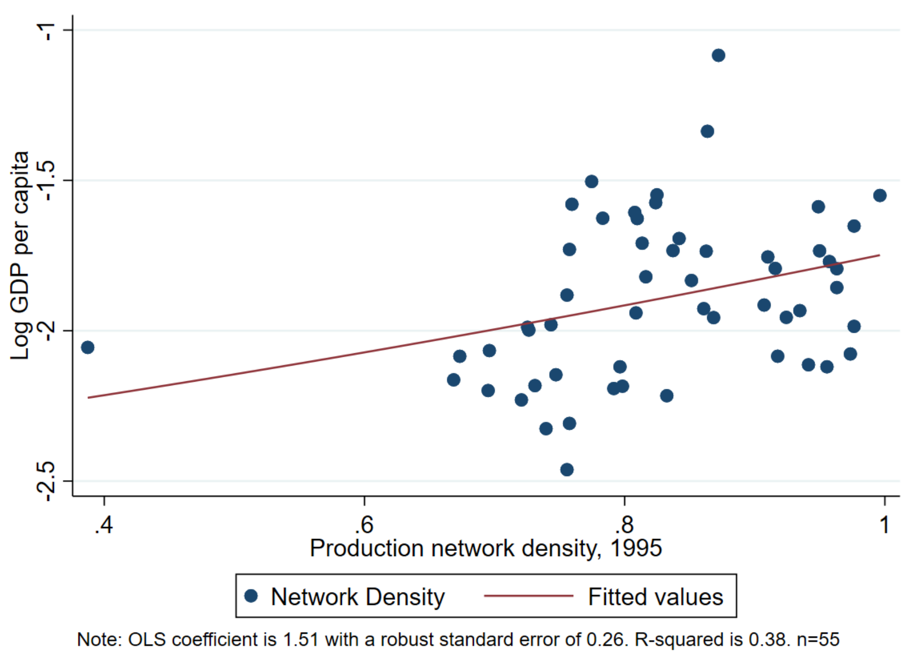

Figure 3. $Density$ and log GDP model

[16] Note that, ideally, we should reproduce the iterative process used to calibrate a_j. However, to simplify computation, we assume that ω_{ij} equals the observed intermediate input share. Given that our focus is on the number of non-zero ω_{ij}, this assumption maintains consistency between the model implied $Density$ and the observed one.

In this section, we have shown that a relatively simple extension of the production network model in Acemoglu et al. (2012) is able to rationalize the observed relationship between production network density and income per capita. While the production structure of our model is exogenous, we show that cross-country heterogeneity in $Density$ does play a role in shaping average income, given a sequence of productivity innovations.

6 Conclusion

We show that the details of countries' production network structure—specifically, the number of active links in the production network ($Density$)—are strongly associated with their level of GDP per capita. Even after controlling for key country characteristics that are generally used in the economic growth literature, we show that countries with denser production structures display higher average income. The empirical results also provide strong support for the role of institutions, education, and economic complexity in attaining higher income.

We extend the standard production network model in Acemoglu et al. (2012)— displaying input-output linkages, perfect competition and idiosyncratic sectoral productivity shocks—to rationalize the evidence we document. The model indicates that, in the long run, sectoral productivity levels are amplified in denser production structures, as long as intermediate inputs and labor are easily substitutable, and a more diversified input mix provides higher input productivity.

Our paper contributes to the literature that explores the role of production diversification in economic development by documenting a strong cross-country correlation and also highlighting the theoretical benefits of having a more diversified production network structure. However, we should point out that our evidence and theoretical construct should not be interpreted as the only causal mechanism. In other words, even though we show that higher diversity in the use of intermediary inputs across sectors supports higher levels of a country's GDP per capita, we do not explicitly study the costs of diversifying production systems. Nor do we explore the idea that to reach high diversification, a country might first need to reach high income and minimum levels of other assets, such as educational attainment and institutional quality. The determinants and costs of higher levels of $Density$ are important topics for future research.

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Appendix—Supporting Information

Proof Proposition 1

To ease notation define $\rho_Q = \frac{\epsilon_Q - 1}{\epsilon_Q}$, $\epsilon_Q = \frac{1}{1-\rho_Q}$, $\rho_M = \frac{\epsilon_M - 1}{\epsilon_M}$, $\epsilon_M = \frac{1}{1-\rho_M}$. Also, let $b_j = 1 - a_j$ the importance of materials in production. The firms first order conditions with respect to inputs are:

$$
\begin{aligned}
L_j : P_j Z^{\rho_Q} a_j \big(\frac{Q_j}{L_j}\big)^{1-\rho_Q} &= w \\
M_j : P_j Z^{\rho_Q} b_j \Big(\frac{Q_j}{M_j}\Big)^{1-\rho_Q} &= P_j^M \\
M_{ji} : P_i Z_i^{\rho_Q} Q_i^{1-\rho_Q} (1-a_i) M_i^{\rho_Q - \rho_M} M_{ji}^{\rho_M - 1} \omega_{ji}^{\varrho_M} &= P_j
\end{aligned}
$$

Similarly, firms minimize the cost of the bundle of intermediates $\sum_{i=1}^N P_i M_{ij}$ subject to $M_j = \big(\sum_{i=1}^N \omega_{ij}^{\varrho_M} M_{ij}^{\rho_M}\big)^{1/\rho_M}$. In competitive markets, I obtain:

$$
P_j^M = \Big(\sum_{i=1}^N \omega_{ij}^{\varrho_M \epsilon_M} P_i^{1-\epsilon_M}\Big)^{\frac{1}{1-\epsilon_M}}.
$$

Assuming common sectoral elasticities, the production function of firms in sector j can be expressed as:

$$
Z_j^{-\rho_Q} = a_j \Big(\frac{L_j}{Q_j}\Big)^{\rho_Q} + b_j \Big(\frac{M_j}{Q_j}\Big)^{\rho_Q},
$$

which combined with the FONC gives:

$$
P_j^{1-\epsilon_Q} = Z_j^{\epsilon_Q - 1} a_j^{\epsilon_Q} w^{1-\epsilon_Q} + Z_j^{\epsilon_Q - 1} b^{\epsilon_Q} \Big(\sum_{i=1}^N \omega_{ij}^{\varrho_M \epsilon_M} P_i^{1-\epsilon_M}\Big)^{\frac{1-\epsilon_Q}{1-\epsilon_M}},
$$

assuming $\epsilon_Q = \epsilon_M$ we have, in matrices, the solution for prices:

$$
P^{1-\epsilon_Q} = [I - Z^{\epsilon_Q - 1} \circ \big((1-a)^{\epsilon_Q} 1' \circ \Omega'^{\varrho_M \epsilon_Q}\big)]^{-1} (Z^{\epsilon_Q - 1} \circ a^{\epsilon_Q}) \tag{12}
$$

To obtain GDP we use the household budget constraint and first order conditions. From the budget constraint, and assuming labor is the numeraire good, we have $P_c C = 1$, implying that $\log GDP = -\log P_c$. We further assume $\epsilon_D = 1$ and by minimizing the consumption expenditure we obtain

$$
P_c = \prod_{j=1}^N \Big(\frac{P_j}{\beta_j}\Big)^{\beta_j}.
$$

Thus, as we already solved for prices, we have

$$\log GDP = \sum_{j=1}^{N} \beta_j \log\left(\frac{\beta_j}{P_j}\right).$$

Empirical Appendix - Robustness tests

Here we present alternative regression results considering different $Density$ measures, one measuring the network density across only domestic sectors (i.e., excluding connections to sectors from other countries), and one considering a different minimum threshold to define $\underline{\omega}$ ($\underline{\omega} = 0.00001$). We finish by showing the summary statistics of $Density$, GDP per capita, and control variables for the 55 countries in our sample.

Domestic Network Density

Table 3. Panel Fixed effects results using Domestic Density, 1995-2011

VARIABLES	(1) Ln GDP pc	(2) Ln GDP pc	(3) Ln GDP pc
ln *Density Domestic*	0.758	0.276*	0.280**
	(0.659)	(0.158)	(0.130)
ECI+		0.132*	0.147**
		(0.068)	(0.066)
Ln *Sectoral dominance*		-0.113	-0.123
		(0.092)	(0.075)
Ln *Financial sector share*		0.085	0.133**
		(0.064)	(0.058)
Ln *Service sector share*		0.468***	0.400**
		(0.168)	(0.158)
Ln *Natural resources share*		-0.505***	-0.455***
		(0.021)	(0.023)
Ln *Trade to GDP*		0.400***	0.305***
		(0.061)	(0.043)
Years of schooling			0.040***
			(0.010)
Control of corruption			0.040
			(0.034)
Voice and accountability			-0.0791**
			(0.038)
Rule of law			0.058
			(0.041)
Government effectiveness			0.100***
			(0.029)
Political stability			0.011
			(0.019)
Regulatory quality			-0.083**
			(0.042)
Population growth			-1.275*
			(0.729)
Constant	9.894***	7.734***	7.933***
	(0.194)	(0.291)	(0.273)
Observations	935	935	703
R-squared	0.014	0.924	0.940
Number of countries	55	55	55

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Network Density considering different thresholds

Table 4. Panel FE Total Density Threshold: 0.00001, 1995-2011

VARIABLES	(1) Ln GDP pc	(2) Ln GDP pc	(3) Ln GDP pc
Ln *Density*	6.014***	0.524**	0.459**
	(1.343)	(0.248)	(0.220)
ECI+		0.116	0.131*
		(0.071)	(0.066)
Ln *Sectoral dominance*		-0.110	-0.116
		(0.098)	(0.081)
Ln *Financial sector share*		0.076	0.125*
		(0.069)	(0.063)
Ln *Service sector share*		0.457***	0.391**
		(0.168)	(0.155)
Ln *Natural resources share*		-0.498***	-0.453***
		(0.022)	(0.025)
Ln *Trade to GDP*		0.385***	0.288***
		(0.062)	(0.044)
Years of schooling			0.039***
			(0.011)
Control of corruption			0.0433
			(0.035)
Voice and accountability			-0.075*
			(0.040)
Rule of law			0.036
			(0.041)
Government effectiveness			0.104***
			(0.029)
Political stability			0.015
			(0.020)
Regulatory quality			-0.086*
			(0.045)
Population growth			-1.191
			(0.748)
Constant	9.890***	7.721***	7.932***
	(0.0490)	(0.288)	(0.278)
Observations	935	935	703
R-squared	0.248	0.924	0.939
Number of countries	55	55	55

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Summary Statistics and Sectoral Definition

Table 5. Density Cross-correlation

Variables	Density 1	Density 2	Density 3	Density 4
Density 1	1.000			
Density 2	0.982	1.000		
Density 3	0.836	0.886	1.000	
Density 4	0.655	0.596	0.504	1.000

Table 6. Summary statistics

Variable	Obs	Mean	Std. Dev.
GDP pc	935	20743.48	13219.94
Density	935	.811	.094
ECI+	935	.818	.468
Dominance	935	2.504	.394
Financial sector share	935	.044	.022
Trade	935	.882	.622
Service share	935	.613	.106
Years of schooling	935	9.569	2.385
Population growth (in %)	935	0.741	0.958
Natural resources share	935	.318	.326
Control of corruption	715	.735	1.014
Voice and accountability	715	.64	.858
Rule of law	747	.721	.883
Government effectiveness	715	.862	.832
Political stability	715	.373	.862
Regulatory quality	715	.845	.746

Table 7. Sectors in OECD Database

Sector Number	Sector Name
S1	DOM C01T05: Agriculture, hunting, forestry and fishing
S2	DOM C10T14: Mining and quarrying
S3	DOM C15T16: Food products, beverages and tobacco
S4	DOM C17T19: Textiles, textile products, leather and footwear
S5	DOM C20: Wood and products of wood and cork
S6	DOM C21T22: Pulp, paper, paper products, printing and publishing
S7	DOM C23: Coke, refined petroleum products and nuclear fuel
S8	DOM C24: Chemicals and chemical products
S9	DOM C25: Rubber and plastics products
S10	DOM C26: Other non-metallic mineral products
S11	DOM C27: Basic metals
S12	DOM C28: Fabricated metal products
S13	DOM C29: Machinery and equipment, nec
S14	DOM C30T33X: Computer, Electronic and optical equipment
S15	DOM C31: Electrical machinery and apparatus, nec
S16	DOM C34: Motor vehicles, trailers and semi-trailers
S17	DOM C35: Other transport equipment
S18	DOM C36T37: Manufacturing nec; recycling
S19	DOM C40T41: Electricity, gas and water supply
S20	DOM C45: Construction
S21	DOM C50T52: Wholesale and retail trade; repairs
S22	DOM C55: Hotels and restaurants
S23	DOM C60T63: Transport and storage
S24	DOM C64: Post and telecommunications
S25	DOM C65T67: Financial intermediation
S26	DOM C70: Real estate activities
S27	DOM C71: Renting of machinery and equipment
S28	DOM C72: Computer and related activities
S29	DOM C73T74: R&D and other business activities
S30	DOM C75: Public administration and defence; compulsory social security
S31	DOM C80: Education
S32	DOM C85: Health and social work
S33	DOM C90T93: Other community, social and personal services