A Networked Global Economy: The Role of Social Capital in Economic Growth

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Abstract. Understanding the drivers of economic growth is one of the fundamental questions in Economics. While the role of the factors of production—capital and labor—is well understood, the mechanisms that underpin Total Factor Productivity (TFP) are not fully determined. A number of heterogeneous studies point to the creation and transmission of knowledge, factor supply, and economic integration as key aspects; yet a need for a systematic and unifying framework still exists. Both capital and labor are embedded into a complex network structure through global supply chains and international migration, and it has been shown that the structure of global trade plays an important role in economic growth. Additionally, recent research has established a link between types of social capital and different network centralities. In this paper we explore the role of these measures of social capital as drivers of the TFP. By leveraging the EORA Multi Regional Input Output and the UN International Migration databases we build the complex network representation for capital and labor respectively. We compile a panel data set covering 155 economies and 26 years. Our results indicate that social capital in the factors of production network significantly drives economic output through TFP.

Keywords: Economic growth · Total factor productivity · Social capital · Economic complexity · Complex networks · Panel data

1 Introduction

Understanding growth is one of the fundamental questions in Economics. From the seminal work of Solow [1], economic output has been understood as a monotonically increasing function of the factors of production—land, labor and capital—and an additional term called Total Factor Productivity (TFP). This term was introduced to account for additional unknown factors, and was initially connected to technology and human capital [2]. And despite being the key determinant of the long run growth rate (per worker) [3], the drivers of TFP remain unclear.

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Diverse studies have further investigated the fundamental drivers of TFP. Knowledge creation through innovation plays a key role [4], but also knowledge transfers occurring through Foreign Direct Investments (FDI) [5–9], trade (under the condition of having the necessary human capital to absorb it) [10], and reception of skilled migrants [11]. Skilled emigration also drives TFP through knowledge transfers to the original community [12,13]. Moreover, it has been identified that friendly economic environment and policies lead to economic prosperity for companies, so political and economic freedom have a positive effect on TFP [14]. Finally, the literature also identifies that financial openness leads to TFP growth [15].

Many of these factors rely on the fact that the two main factors of production—labor and capital—flow across the globe through global supply chains and international migration networks respectively. On the trade side, traditional economics reveals that export diversification of products leads to growth [16], and especially for developing countries [17,18]. On the migration side, studies have found that the macroeconomic and fiscal consequences of international migration are positive for OECD countries [19], and the information contained in bilateral migration stocks suggests that migration diversity has a positive impact on real GDP [11]. Also, it has been found that when international asylum seekers become permanent residents, their macroeconomic impacts are positive [20]. Nonetheless, classical methods use local, first-neighbour metrics (usually Herfindahl-Hirschman Index or similar). Therefore they are not able to exploit the information at higher-order neighbours contained in the full network structure. These highly complex datasets contain reverse causality, non-linear and variable interaction effects that call for advanced modelling techniques.

The global financial and migratory flows can be interpreted as having a complex network structure where nodes are countries and links are flows of labor and capital, and this requires sophisticated tools to be fully understood [21]. At the macro level, it has been shown that rich countries display more intense trade links and are more clustered [22]. In this trade network, node-statistic distributions and their correlation structure have remained surprisingly stable in the last 20 years [23]. At the micro level, there is evidence that node centrality on the Japanese inter-firm trading network significantly correlates with firm size and growth [24]. Also, the country-level migration stock network has been found to have a small world structure [25,26], and another study found a network homophily effect that could be explained in terms of cultural similarities [27].

On another line of work, recent advances on complex network theory link network centrality measures to social capital types [28]. This concept has mainly been tested on social networks, linking social capital to information diffusion [29], innovation [30] and even personal economic prosperity [31]. Social capital studies point out that individual traders in Africa with more contacts have higher output and growth [32].

The purpose of this work is to unify these different strands of literature under one framework. We proxy different types of social capital with two centrality measures: incoming (out-coming) information capital with hubs (authorities) score, and favor capital with favor centrality. In order to proxy the relationship of social capital with TFP, we estimate a model based on an augmented Cobb-Douglass production function [33]. In this way, we give social capital a role in growth theory. To test this model, we build the network representations for the networks of the factors of production; On the one hand, we build two representations of the capital flows network leveraging the EORA World Multi-Regional Input Output database [34], one for capital and another for goods and services. On the other hand we build the labor flow network using the UN's International Migration Database. This results on a panel data set covering 155 economies from 2000 to 2016, including seven different social capital measures for each country.

The rest of this work is structured as follows: in Sect. 2 we describe the proposed framework, the model and the data, in Sect. 3 we lay out the obtained results, and in the last section we summarize our conclusions.

2 Materials and Methods

2.1 Network Centralities as Proxy for Types of Social Capital

Recent advances interpret social capital as a topological property of networks that can be proxied with different centrality measures [28]. Our focus is on two different social capital types. The first one is information capital, a proxy for the ability to acquire valuable information and/or to spread it to others. The second one is favor capital, which is defined as having neighbours that are supported by a neighbour in common.

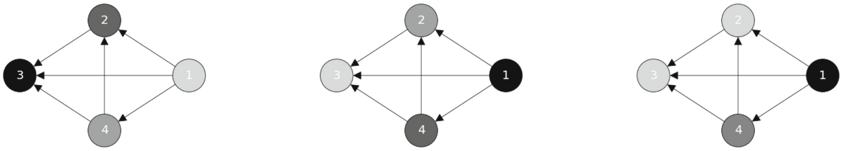
Information capital (I) is related to diffusion centrality [35], which converges to eigenvector centrality in infinite iterations [36]. As both of our networks are directed, we leverage the HITS algorithm to proxy inwards (I^{in}) and outwards (I^{out}) information capital with the hubs and authorities centralities respectively [37]. On the other hand, the favor capital of node i in an un-weighted network $\mathbf{g}$ as been previously proxied with favor centrality as follows [28]:

$$F_i(\mathbf{g}) = |j \in N_i(\mathbf{g}) : [\mathbf{g}^2]_{ij} > 0|. \tag{1}$$

Where $N_i(\mathbf{g})$ is the set of i's neighbours—notice that the term $[\mathbf{g}^2]_{ij} > 0$ is restricting the set to neighbors of i that are connected to at least another neighbor of i. Thus, we extend this definition to a weighted network in the following way:

$$F_i(\mathbf{g}) = \sum_j [\mathbf{g}^2]_{ij} \tag{2}$$

In Fig. 1 we show the proposed social capital measures over a toy model network with link weights equal to one. We observe that node 3 (node 1) has the highest inwards (outwards) information capital, because it is the target (source) of many links. On the other hand, We see that nodes 2 and 3 have the lowest favor capital, since they do not have any neighbours with neighbours in common.



(a) Inwards information capital (b) Outwards information capital (c) Favor capital

Fig. 1. Toy model of the three social capital indicators, where nodes with higher values are colored darker. In this example all link weights are equal to one.

2.2 Link Between Social Capital Types and TFP Factors

As we pointed out in the introduction, foreign sources of knowledge and technology are linked to TFP and in turn to growth. Knowledge from abroad may flow through a variety of channels. On the one hand, knowledge on how to efficiently use the factors of production is key for productivity. And in that way, knowledge transfers among countries help develop technology and therefore drive TFP. The first channel for knowledge transfers is Foreign Direct Investments (FDI), helping knowledge spillovers from industrialised to developing countries [5–9]. The second channel is through imports of sophisticated goods and services with high technological content [10]. And the third channel is through international migration [11,13] that works both through the reception of skilled migrants in developed economies, and through migrants' attachment to their original countries. On the other hand, availability of human capital is key to absorbing knowledge shocks, so access to foreign labor can be key to TFP growth.

We propose a direct association between this factors and different types of social capital. We link knowledge transfers due to Foreign Direct Investments (FDI) with information capital on the monetary network, knowledge transfers associated with importing sophisticated goods and services to information capital on the goods and services network, and knowledge transfers associated to migration with information capital on the migration network. On the other hand, another factor playing a relevant role is the availability of a human capital supply. We link this factor to favor capital in the migration network, understanding it as the belonging to country partnerships of free movement of people. The proposed links between the types of social capital and drivers of TFP are summarised in Table 1.

2.3 Social Capital and Economic Growth

Macroeconomic theory generally describes a country's output through the aggregate production function [1,2] for which one widely used functional form is the Cobb-Douglas function [33]:

$$Q = A \cdot K^{\alpha} \cdot L^{\beta}, \tag{3}$$

Table 1. Relationship between different TFP growth factors and the different types of social capital in the different networks.

Contribution to total factor productivity	Social capital	
	Type	Network
Knowledge transfer through FDI	Information capital	Financial
Knowledge transfer through trade	Information capital	Goods and services
Knowledge transfer through migration	Information capital	Migration
Human capital supply	Favor capital	Migration

where Q represents total production, A stands for the Total Factor Productivity, K is capital and L is labor. We propose an augmented Cobb-Douglas production function including the human and financial social capitals:

$$Q = \bar{A} \cdot K^{\alpha} \cdot L^{\beta} \cdot S(K)^{\kappa} \cdot S(L)^{\lambda}, \tag{4}$$

where $S(x)$ stands for the social capital of the factor of production x. Notice that the key difference with respect to Eq. 3 is that we factor out the social capital contributions from the TFP as follows:

$$A = \bar{A} \cdot S(K)^{\kappa} \cdot S(L)^{\lambda} \tag{5}$$

2.4 Global Network Data

The two main factors of production—capital and labor—can be interpreted as having a complex network structure. In general, we interpret global transnational interactions (both financial and migratory) as a network ($\mathcal{G}$), with n countries indexed by $i \in \{1, ..., n\}$. This graph is described by the adjacency matrix $\mathbf{g} \in [0, 1]^{n \times n}$, where the $g_{ij} > 0$ represents the weight of the interaction between i and j. Since these are directed graphs, $\mathbf{g}$ is not symmetrical for any of them.

There is a growing body of literature interpreting the global financial flows as a complex network [38,39]. Although interpreted in a different way, the adjacency matrix of the financial network has been thoroughly studied in the field of Input-Output economics [40] under the name of technical coefficient matrix, and thus there are many open data-sources providing this information. In particular, we used EORA's World Multi-Regional Input Output database [34] to proxy the amount of trade between pairs of countries. On the one hand, we extracted the adjacency matrix of the financial network ($\mathcal{G}_F$), where link weights represent the percentage of country's economic output (measured in dollars) that is paid to any other country in exchange of goods and services exported. On the other hand, we built the goods and services network ($\mathcal{G}_G$) by weighting the links with the proportion of the total production of goods and services that a country exports to any other country.

We build the migration network's ($\mathcal{G}_M$) adjacency matrix by leveraging the UN's International Migration Database [41]. This database contains information for the yearly number of people migrating from one country to another. Using skilled migrants data would be the best approach, however at the time of writing we have no access to such dataset. Thus, we defined the weights of $\mathcal{G}_M$ as the migrant stock living in a given host country, relative to the working population of the home country.

3 Results

3.1 Panel Data Set

We combine the social capital indicators described in Sect. 2.4 with some extra economic information; economic output is modeled with GDP (in current US dollars) provided by the World Bank, capital is modeled as Gross Fixed Capital Formation (in current US dollars) provided by the World Bank and labor as total working population (in millions) provided by the OECD. The result is a panel data set covering 155 economies from 1990 to 2016. In Fig. 2 we show the distributions of the different variables as well as their pairwise Spearman correlations and R^2 coefficients of a linear regression model with intercept.

3.2 Social Capital Contribution to Economic Output

We model the relationship of social capital with GDP of country i at time t in a linear fashion by taking logs in Eq. 4:

$$\log(GDP_{it}) = A + \alpha \cdot \log(K_{it}) + \beta \cdot \log(L_{it})$$
$$+ \xi \cdot \log(F_{it\mathcal{M}}) + \sum_{n \in \mathcal{N}} \mu_n \cdot \log(I_{itn}^{in}) + \nu_n \cdot \log(I_{itn}^{out}) \tag{6}$$

where A is the intercept, K_{it} is the gross capital formation, L_{it} is the total working population, $\mathcal{N}$ is the set of networks $\{\mathcal{G}_F, \mathcal{G}_G, \mathcal{G}_M\}$, F_{itn} is the favor capital, and I_{itn}^{in} and I_{itn}^{out} are the in and out information capitals respectively.

We first estimate the model coefficients through Ordinary Least Squares (OLS). To account for unobserved entity and time effects, we leverage a Fixed Effects (FE) estimator including both country and year effects. We performed a Hausman test in order to test consistency of Random Effect estimates—which we rejected with a 1% significance level. Additionally, we use heteroskedasticity and autocorrelation consistent (HAC) errors in our estimation. Results are shown in Table 2.

Notice that the adjusted R^2 of the models including the social capital indicators raise with respect to the base models, so that the new model is capturing a stronger signal. This is consistent with the clear uni-variate relationships between the social capital indicators and $\log(GDP)$ (Fig. 2). Also, results in

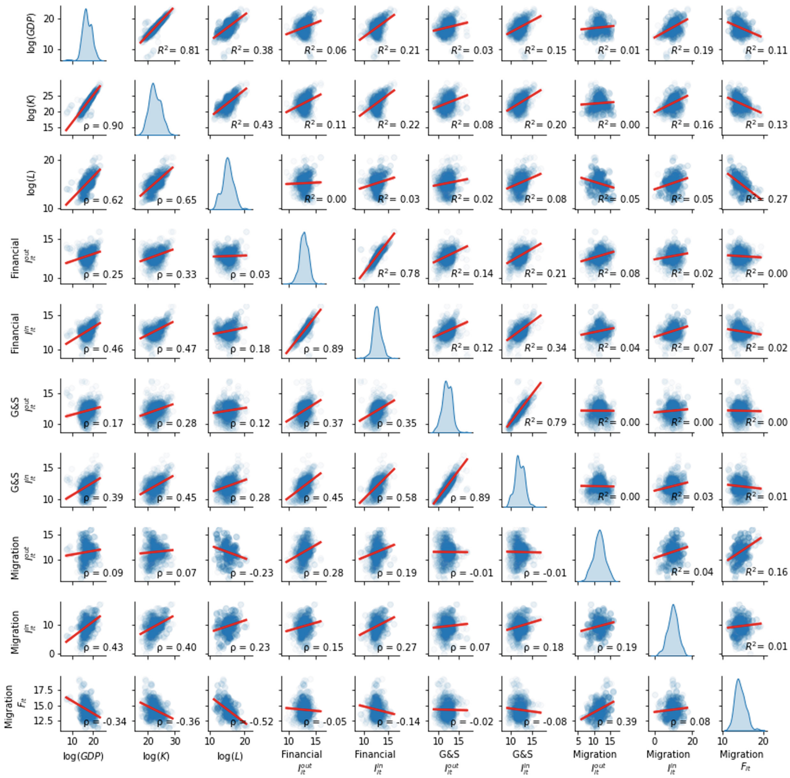


Fig. 2. Pairwise distribution matrix for economic output ($\log(GDP)$), capital ($\log(K)$), labor ($\log(L)$) and the developed social capital indicators: inwards/outwards information capital (I^{in}/I^{out}), and favour capital F for the financial, goods and services, and migration networks. Each observation corresponds to one country and year. Spearman correlations (ρ) are shown in the lower triangular matrix, while the R^2 of a linear regression model with intercept is shown in the upper triangular matrix.

Table 2 indicate that most of the significant effects of the social capital variables are positive.

However, we observe that some of the introduced variables have unexpected negative effects. This result could be due to different issues in the model specification; first, network centrality measures generally tend to correlate [42]. This is confirmed by the correlations in Fig. 2, but also by high Variance Inflation Factors[1] (the minimum is $VIF = 15.8$ for inwards information capital in the migratory network, and the maximum is $VIF = 2915.7$ for the outwards information capital in the financial network). Therefore, we can expect the regression model to suffer from a multicollinearity problem. Second, we don't capture either

[1] The variance inflation factor (VIF) quantifies the severity of multicollinearity in an ordinary least squares regression analysis. To calculate the VIF of every feature, we regress it against all other features and compute $VIF_i = 1/(1 - R_i^2)$.

Table 2. Regression results for the model specification in Eq. 6. The panel data model specification is p-value notation is ***, ** and * for significance at the 1%, 5% and 10% levels respectively, and standard errors are shown in parenthesis. For each model we show number of observations N, R^2, adjusted R^2 and F-statistic.

Model	OLS base	OLS extended	FE base	FE extended
N	3397	3397	3397	3397
R^2	0.839	0.885	0.156	0.390
Adj R^2	0.839	0.884	0.108	0.353
F	8819.1	2884.3	297.35	227.48
A	−4.7402*** (0.1642)	−0.2960 (1.2994)	11.388*** (1.2792)	15.724*** (2.3497)
α	0.9264*** (0.0169)	0.8616*** (0.0229)	0.3516*** (0.0285)	0.3028*** (0.0209)
β	0.0535*** (0.0184)	−0.0045 (0.0202)	−0.1470 (0.1005)	−0.3292*** (0.1211)
$\nu_{\mathcal{F}}$		−1.2268*** (0.1979)		−0.8433*** (0.2491)
$\mu_{\mathcal{F}}$		1.1802*** (0.1835)		0.6904*** (0.1488)
$\nu_{\mathcal{G}}$		−0.2107* (0.1185)		0.1111* (0.0626)
$\mu_{\mathcal{G}}$		0.0474 (0.1206)		−0.0597 (0.0543)
$\nu_{\mathcal{M}}$		0.0922*** (0.0116)		0.0203 (0.0365)
$\mu_{\mathcal{M}}$		0.0385*** (0.0058)		0.0019 (0.0096)
ξ		−0.0582*** (0.0219)		0.0482** (0.0240)

non-linear nor interaction terms. These could be of special relevance given the complex nature of the data in hand. And last, our model specification could be prune to suffer from simultaneity bias due to a reverse causality channel; higher social capital enhances productivity, however higher GDP could attract trade and migration and therefore leading to higher social capital.

4 Conclusions

In this work we interpret capital and labour as two factors of production traveling across the globe via the mobility networks of trade and migration. Leveraging recent advances in the intersection of social capital and network theory, we proxy types of social capital with different network centrality measures. This provides an intuitive way of interpreting the topological importance of each country in the different factors of production networks.

We then identify different channels in which social capital may affect Total Factor Productivity—and therefore GDP. On the one hand, information capitals in the financial, goods and services and migration networks are linked respectively to knowledge transfers through FDI, goods and services and migration. On the other hand, favor capital on the migration network is linked to human capital supply. Then, the contributions of the multiple factors are linearly modeled by means of an extended Cobb-Douglass production function (Eq. 4).

To test our model, we build two representations of the trade network—one for money and other for goods and services—based on EORA's World Multi-Regional Input Output database, and one representation of the migration network based on the UN's International Migration Database. We compiled a panel dataset with seven different social capital indicators for 155 countries across 26 years.

Overall, we find significant positive relationships between social capital and economic performance. To combine all the effects, we estimate the extended Cobb-Douglass model coefficients using both OLS and a Fixed Effects estimators. In both cases the model fit is enhanced by the inclusion of the indicators. This yields significant coefficients for some of the indicators. We observe positive Spearman correlations of $\log(GDP)$, $\log(K)$ and $\log(L)$ with the new variables, and most of the regression coefficients are positive and significant.

We identify the existence of three possible issues in the estimation; multicollinearity, non-linear and interaction effects, and reverse causality bias. Although out of scope of this work, these issues could be tackled in future research. A common solution to multicollinearity is to apply dimensionality reduction techniques such as Principal Component Analysis (PCA) [43]. Non-linear and interaction effects could be captured by using more sophisticated machine learning techniques such as gradient boosting trees or neural networks. These could be applied in combination to regularization techniques that would also limit the impact of multicollinearity. And last, a possible way to remove the simultaneity bias and capture a causal effect could be to estimate a gravity model [44] of trade and migration as an instrumental variable approach.

This work provides two different types of contribution. First, the presented indicators are very rich signals for policy-making—despite the issues related to estimation. Social capital is a latent variable which is difficult to quantify, yet it contributes to productivity and growth. We provide different indicators for information social capital such as knowledge and migration hubs, which identify knowledge exporters. Moreover, considering social capital in its favor exchange function we quantify the level of integration and openness of countries in the global economic and migratory flows. Moreover, this work contributes to enlarge the discussion in the intersection of complex systems, economic and network theory, as they are all needed to understand the patterns of mobility and the factors of production.

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