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Input-Output Networks and Growth Performances across Countries

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**Input-Output Networks and Growth Performances across
Countries**

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Input-Output Networks and Growth Performances across Countries

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Abstract

This paper investigates the relationship between economic growth performances of countries and their structural input-output network characteristics. We employ a new centrality measure developed by Blöchl *et al.* (2011) for directed networks with self-loops to determine sectoral heterogeneities in IO tables of 33 OECD countries over the period 1995-2011. Relating the gini indices of these centrality measures to output growth reveals that countries with less heterogeneous IO networks tend to grow faster. Such finding implies a key role for the inter-linkages across sectors in economic growth, and underlines the importance of designation of sectoral policy measures to counteract heterogeneity of IO networks.

Keywords: input-output tables, networks, centrality, economic growth, heterogeneity

Jel Classification: C67; O50

1. Introduction

Input-Output (IO) tables were central to old school development economists, in particular to Leontief and Hirschman. Leontief (1936) revealed the technical nature of national production structures through IO tables. Hirschman (1958) developed his well-known arguments of "forward and backward linkages" employing the IO analysis. After a long period of obscurity, interest on IO tables have been revived recently, because of the understanding of the importance of their network structure, which enables sectoral connections to be explored, producing insights with the potential to shape aggregate economic outcomes. In fact, IO tables are directed weighted networks in which each sector is a vertex and the flow of economic activity from one sector to another constitutes an edge. They contain nodes with self loops, and are almost completely connected.

After the financial crisis of 2007-2008, understanding the characteristics of IO networks has become the key element in exploring the propagation of sectoral shocks throughout the economy. There are a number of theoretical and empirical papers focusing on the exploration

of IO networks.¹ The theory side builds on macroeconomics fluctuations literature, such as Basu (1995), Horvath (1998), Dupor (1999) and Conley and Dupor (2003), all closely related to the original work of Long and Plosser (1984) in which a multi-sector real business cycle model is built to demonstrate that transmission of sectoral shocks through IO networks can have important overall effects on aggregate output volatilities. Ciccone (2002) derives an intermediate goods multiplier formula for a triangular IO model, and demonstrates that this multiplier can be quite large. More recently, Carvalho (2010) builds a general equilibrium model on the IO network structure to show that sectors acting as hubs propagate individual sectoral shocks through the whole network without decay. Acemoglu *et al.* (2010) and Acemoglu *et al.* (2012) suggest that aggregate fluctuations decay much more slowly in an economy with fewer "dominant" (central) sectors and verify this finding with an extrapolation exercise based on US IO data. Jones (2011a) focuses on the critical role of intermediate inputs flowing across sectors in an IO network. His findings suggest that the effects of a sector-specific shock associated with the misallocation of resources will become multiplied through the IO network, leading to potential large income differences across countries. . Moreover, Jones (2011b) highlights that misallocation of resources at the micro level can be amplified through the input-output structure of the economy.

On the empirical side, McNerney (2009) analyzes 20 OECD country IO networks over time, and observes no difference among countries in terms of the flow size and strength distributions of sectors. He further argues that there is a striking difference between the largest sectors and the most central sectors. Contreras (2014) investigate the propagation of shocks through IO networks in European economies, and find an association between the centrality of the sector and the impact of the shock. They further argue that the importance of a sector relies more on its position in the network than its economic size. Assuming that the movement of goods between the sectors of an economy is best modeled as a random walk, Blöchl *et al.* (2011) propose two new measures for sector centralities, both having interpretations as propagation of shocks, and apply these centrality measures to IO networks of 37 countries. They demonstrate that the rankings of the sectors based on these measures are highly related to the development status of the national economies.

Common to all mentioned studies is the idea that the more heterogeneous the structure of the IO network, which is to say, the more important the role of a few central sectors in the IO network, the greater the impact of a sector-specific shock on the aggregate economy. This finding has important implications for the current lack of understanding of economic performance differences across countries and this paper attempts to make a preliminary contribution in this path. Our paper is most closely related to Blöchl *et al.* (2011). We borrow their counting betweenness measure, which identifies the central or key sectors in directed IO

¹There is also a burgeoning literature on international trade networks and the corresponding effects of their structure on income and growth. For example, Hausman *et al.* (2007) and Hidalgo and Hausman (2009) show that economic complexity, an indicator quantified by a method based on the trade network structures of the countries and the products they export with revealed comparative advantage, is the key determinant in explaining economic growth and development. Here, we focus on papers that examine IO networks.

networks with self loops. Specifically, the higher the counting betweenness measure of a sector in an IO network, the more central the sector, and the higher numbers of transactions and periods of time required for a shock to decay. With fewer key sectors in an IO network, the distribution of the IO network will be more unequal, and as Jones (2011) suggests, a sector-specific shock related with the misallocation of resources will have a greater impact on the aggregate economy, leading to weaker economic growth performance. Thus, we expect the economic performances of the countries to be negatively associated with the heterogeneity of the distribution of sectors in their IO networks.

In this vein, we extend the study of Blöchl *et al.* (2011) in three ways. First, we apply the counting betweenness measure to IO tables of 33 countries for 1995-2011 period, rather than 1 year period, and determine the centrality of the sectors in each economy and for each time period. Second, we use these measured centralities of the sectors to construct gini coefficients for each IO network. We employ these indices, reflecting mainly the inequality among sectors in terms of time spent in individual sectors, as a proxy for the heterogeneity of weighted links and loops in each network. Lastly, we employ a fixed-effect model for panel data to test whether there is an association between economic growth performances of countries and heterogeneity of their input-output networks, controlling for major variables such as investment, employment, life expectancy, government effectiveness, and trade flows.

Our paper is a step towards explaining economic growth disparities across countries through the differences in their structural IO network characteristics. The findings of this study provide cross-country evidence that countries with less heterogeneous IO networks tend to grow faster. This result may provide insights to the policy makers in designing and implementing specific sectoral policy measures needed to correct for heterogeneity across sectors revealed in the network structures of IO tables.

The rest of the paper is organized as follows. Section 2 describes counting betweenness centrality measure and its interpretation. Section 3 presents data and methodology. Section 4 discusses empirical approach and results. Section 5 presents robustness checks. Finally, Section 5 concludes.

2. IO Networks and the Measure of Counting Betweenness

An IO table A is an $n \times n$ adjacency matrix of a network consisting of n vertices and a set of edges where each vertex corresponds to a sector and each edge represents an economic flow from one sector to another. The (i, j) th element A_{ij} indicates the flow from sector j to sector i . IO tables contain self loops representing flows from one sector to itself, and they are weighted networks.

The path followed by a sectoral flow in the IO network, as it wanders from a source vertex to a target vertex, can be considered as a random walk (Newman, 2005). At some point in this walk, the probability of the flow to move from its current position on the IO network, namely vertex i , to one of the adjacent vertices, vertex j , is given by

$$M_{i,j} = \frac{A_{i,j}}{k_j}, \text{ for } j \neq t, \quad (1)$$

where A_{ij} is an element of the adjacency matrix and $k_j = \sum_i A_{ij}$ is the degree of vertex j . Note that probability is determined according to the edge weight. In matrix notation, equation (1) can be written as

$$M = D^{-1} A$$

where D is the diagonal matrix with elements $D_{ii}=k_i$ and M is the transition matrix. Random walk betweenness measure of Newman (2005) averages all possible source-target pairs in a network. Yet, random walk betweenness has two deficiencies as an IO centrality measure. First, it is designed for undirected networks whereas IO tables represent directed networks. Second, it does not account for self loops. Nonetheless, output of a sector can be used as its input, meaning that IO tables contain self loops.

Blöchl *et al.* (2011) adapted random walk betweenness measure of Newman (2005) to directed networks with self loops. Their measure, the so-called 'counting betweenness', is defined as the number of times that a flow visits a vertex on first passage walks, averaged over all possible source-target pairs. Starting from the source vertex s , the probability of being at vertex i , which is different from the target vertex t after r steps is given by $(M_{-t})_{si}^r$ and the probability of being at an adjacent vertex j is $m_{ij}(M_{-t})_{st}^r$ where m_{ij} is the probability of passing from vertex i to vertex j . Summing over r yields the expected frequency of using the edge (i,j)

$$N_{ij}^{st} = m_{ij} \sum_r ((M - t)^r)_{st} = m_{ij} (M - t)^r_{st} = m_{ij} ((I - M_{-t})^{-1})(M - t)^r_{st}.$$

Then the number of times that a random walker passes through the edge (i,j) and back through the edge (j,i) is equal to $N_{ij}^{st} + N_{ji}^{st}$. Since this measure allows for self loops, a walker may visit the edge (i,i) , passing through vertex i twice. Hence, the number of times that a random walker passes through the edge (i,j) must be divided by two in all cases. Therefore, the number of times that a flow on its travel from s to t passes through vertex i is given by the following equation

$$N^{st}(i) \sum_{j \neq t} (N_{ij}^{st} + N_{ji}^{st} / 2).$$

However, two special cases must be mentioned:

$$N^{st}(i) \sum_{j \neq t} (N_{ij}^{st} + N_{ji}^{st} / 2) + 1 \quad \text{if } i = s$$

$$N^{st}(i) = 1 \quad \text{if } i = t$$

If $i=s$, vertex s is visited one more time and if $i=t$, the flow reaches its target at the very first time on its path.

In brief, counting betweenness of vertex i is defined as the average number of times that a flow visits this vertex over all possible source-target pairs:

$$C(i) = \frac{\sum_{s \in V} \sum_{t \in (V \setminus \{s\})} N^{st}(i)}{n(n-1)}$$

Counting betweenness of sector i can be interpreted as the expected period of time that an economic transaction spends in this sector.

Because an economic transaction has both the real side and the monetary side, it can either be a flow of goods and services from the source sector to the target sector, or a flow of dollars as a payment for these goods and services from the target sector to the source sector. The higher the counting betweenness of this sector, the more central the sector is, and therefore, the longer the dollar transaction will remain here, meaning that a supply shock to the economy will be extended, as this sector will impede transactions in the economy.

We use counting betweenness centrality measures to derive the gini index of each country at each year. Gini index of centrality measures is computed as follows:

$$G = \frac{\sum \sum |x_i - x_j|_i}{2n^2 \mu}$$

where μ is the mean of the counting betweenness centrality measures for each country at each year, and n is the number of the unordered observations of the sectoral counting betweenness centrality measures. These derived gini indices reflect the heterogeneity of input output network connections among sectors. The gini index varies from 0 to 1. A gini coefficient of 1 means perfect equality of measured outcomes across the observations. Conversely, a gini coefficient very close to 0 implies that the observational outcomes are dispersed unequally. Therefore, we expect the heterogeneity of input-output networks to impact negatively on economic growth.

3. Data and Methodology

We analyze the effect of the heterogeneity of the input-output networks on economic growth, controlling for traditional determinants of growth. We employ the following regression equation with fixed effects

$$g_{i,t} = \beta_0 + \beta_1 cbgini_{i,t} + \beta_2 gdpcap_{i,t} + \beta_3 trade_{i,t} + \beta_4 labor_{i,t} + \beta_5 credit_{i,t} + \beta_6 goveffect_{i,t} + \beta_7 life_{i,t} + e_{i,t} + u_{i,t}$$

where g is the GDP per capita growth rate and i is the index of countries and t represents the index of years. Variable $cbgini$ captures the gini index of centrality measures, i.e. the heterogeneity of IO tables explained in the previous section.

The variables are annual and the time period covers the years from 1995 to 2011. Since we use the annual growth rate of GDP per capita, the initial year is 1996. Our data for *cbgini* is taken from the World Input-Output Database (WIOD) which provides annual time-series of world input-output tables from 1995 onwards (Timmer *et al.* 2015). These tables have been constructed in a clear conceptual framework based on the system of national accounts. They are derived from officially published IO tables. The database covers 40 countries, including all 27 EU members, and 13 other major economies: Australia, Brazil, Canada, China, India, Indonesia, Japan, Mexico, Russia, South Korea, Taiwan, Turkey and the USA. The countries that make up the database fulfill two requirements: they provide data of sufficient quality and they represent a major proportion of the world economy. We apply counting betweenness measure of Blöchl *et al.* (2011) to IO tables of 33 countries.² Then we derive gini indices of these centrality measures. We include gini indices denoted by *cbgini* as well as a set of control variables which are likely to influence economic growth. Although there are many potential control variables in the literature, we follow Sala-i-Martin *et al.* (2004), which focuses on Bayesian post-estimation strength of the potential control variables.

The income variable is the GDP per capita level (*gdpcap*), which is in terms of constant 2000 dollars. Gross Fixed Capital Formation denoted by *gfcf* is used as a proxy for investment as a percentage of GDP. Credits to the private sector (*credit*) are used to take the efficiency of the financial sector into account. This variable measures the volume of private sector credit as a percentage of GDP. *Trade* is the sum of exports and imports as a percentage of GDP. Total employment (*labor*) and life expectancy (*life*) are included in log form.

Table 1: Descriptive Statistics

	N	Mean	Standard Deviation	Minimum	Maximum
<u>gdpcap</u> (\$)	551	21,859.510	14,833.370	469.470	52,924.820
<u>gdpcapgrowth</u> (%)	547	2.792	3.765	-14.573	13.600
<u>gfcf</u> (%)	552	23.713	4.943	5.385	45.332
<u>credit</u> (%)	523	78.046	49.757	6.695	227.753
<u>trade</u> (%)	552	76.796	37.761	15.580	178.254
<u>life</u> (years)	561	75.762	4.473	60.189	82.931
<u>gov</u> (%)	552	18.547	3.627	10.253	28.064
<u>labor</u> (million)	561	56,25	143,44	0,68	782,42
<u>goveffect</u>	429	1.017	0.744	-0.766	2.357
<u>cbcgini</u>	561	0.488	0.060	0.370	0.677

These variables capture the human capital aspect of the growth performances of countries. Government effectiveness (*goveffect*) measures the institutional quality and is extracted from

² The reason we exclude 8 countries from our sample is that these countries contain zeros in more than 15 % of their total IO table cells. The countries included in our empirical analysis are listed in the Appendix.

the World Governance Indicators database compiled by the World Bank. We take all data for variables other than the *cbcgini* and *goveffect* from the World Development Indicators (WDI) database. Finally, e is the unobserved country heterogeneity and u denotes idiosyncratic disturbances.

The summary statistics of independent variables are shown in Table 1. We observe a high level of diversity across countries and across years. The mean GDP per capita growth is 2.8 % per annum, but the standard deviation is much higher: 3.7%. The minimum is -14.5 % and the maximum is 13.6 %. For instance *goveffect* varies considerably, from -0.76 to +2.36 and *gdpcap* varies from 470 dollars to almost 53 thousand dollars.

Figure 1: Economic Performances and Betwenness Centrality Gini Indices

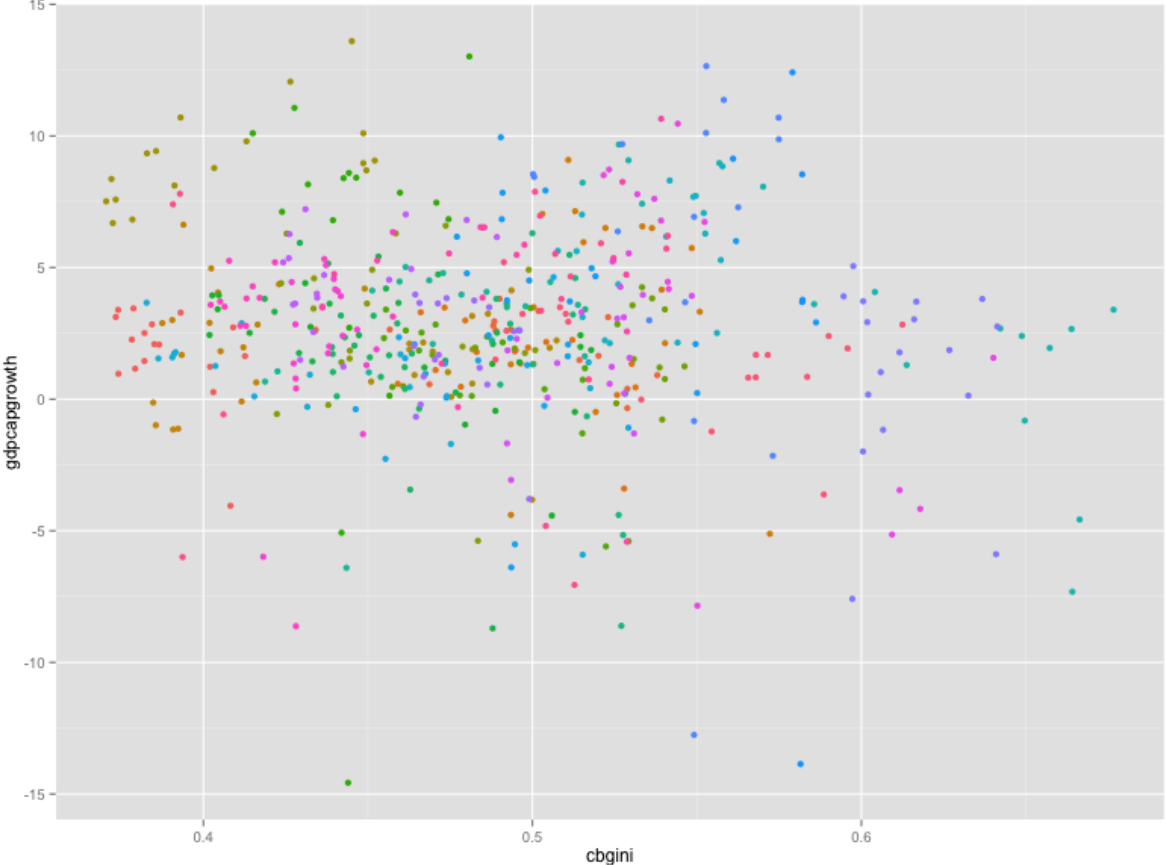


Figure 1 illustrates the relation between economic growth (*gdpcapgrowth*) and gini index of betweenness centrality (*cbgini*). Each country is represented with a different color. There is a negative, albeit weak, relationship between these two variables, not a very strong one.

We focus on the β_1 parameter estimations as these coefficients will imply that economic growth performances of countries are related to the degree of inequality in IO networks.

4. Empirical Results

Columns 1 to 6 in Table 2 display results from our fixed-effect regressions. We sequentially add conventional variables step-by-step in each regression displayed in columns 1 to 6. For example, the second regression includes labor while the third contains both labor and trade variables. In the fourth, we add the credit variable, and in the fifth, government effectiveness is added to the previous variables. The last column displays the most comprehensive regression, which forms the basis for the discussion of the results.

Table 2: Fixed Effect Regressions

log(gdpcap)	2.540*** (0.871)	-1.025 (1.003)	-5.149*** (1.256)	-1.855 (1.254)	-3.137* (1.674)	0.753 (1.881)
gfcf	0.358*** (0.051)	0.350*** (0.051)	0.439*** (0.052)	0.386*** (0.051)	0.406*** (0.058)	0.290*** (0.064)
cbgini	- 21.234*** (4.829)	- 16.002*** (5.103)	- 18.435*** (4.997)	- 15.382*** (4.830)	-13.617** (5.906)	-12.475** (5.780)
log(labor)		-8.424*** (2.827)	-7.290*** (2.765)	-1.674 (2.816)	1.673 (3.740)	11.069** (4.289)
goveffect					1.938* (1.076)	2.555** (1.062)
life						-1.062*** (0.253)

trade			0.078***	0.067***	0.084***	0.106***
			(0.015)	(0.015)	(0.017)	(0.017)
credit				-0.046***	-0.054***	-0.043***
				(0.007)	(0.008)	(0.009)
Observations	541	541	541	513	398	398
R2	0.123	0.138	0.182	0.232	0.261	0.295
Adjusted R2	0.115	0.129	0.170	0.215	0.235	0.265
F Statistic	23.624***	20.214***	22.483***	23.878***	18.068***	18.734***
	(df = 3; 506)	(df = 4; 505)	(df = 5; 504)	(df = 6; 475)	(df = 7; 359)	(df = 8; 358)

Note: * p<0.1; ** p<0.05; *** p<0.01

The coefficients of *cbgini* are negative and statistically significant in all fixed-effect panel regressions. We consider the results of regression (6) displayed in the last column as its R^2 is the highest. Accordingly, a one unit increase in *cbgini*, i.e. an increase from 0 to 1, leads to a 12.5 percentage points decrease in GDP per capita growth. The unit increase is, however, nonsensical, as it implies a change from a perfectly equal and symmetric IO network to a totally unequal and asymmetric IO one. One standard deviation is 0.06, so we can conclude that a one standard deviation increase in *cbgini* is associated with a 0.75 percentage point decrease in GDP per capita growth. This is a large effect; given the mean values of GDP per capita and growth rates, the loss would be as much as 2000 dollars per person over ten years.³

As expected, the coefficient of the *gfcf* variable which is a proxy for capital is statistically significant and positive. A one percentage increase in investment to GDP ratio is associated with a 0.29 percentage point increase in annual GDP per capita growth. The coefficients of the labor variable also confirm the conventional expectations; for example, from the column (6) we can infer that a one percent increase in total employment is related to a 0.11 percentage increase in annual GDP per capita growth.

These results are in line with those of Kubik (2015) in which the findings point to statistically significant and high effects of capital stock and human capital on economic growth. In addition we control for other macroeconomic variables as well as institutional quality.

The control variable *goveffect* is statistically significant in relation to the annual GDP per capita growth. A one unit increase in *goveffect* score is associated with a 2.55 percentage point increase in annual GDP per capita growth, as indicated in column (6). A unit percentage

³ We apply a cumulative growth of 2.75% and 2 % respectively to mean GDP per capita level of 20 thousand dollars, and find the corresponding levels of GDP per capita after 10 years. Then we take the difference.

point rise in trade is correlated with a 0.1 percentage point increase in the annual GDP per capita growth. Apart from the credit variable, which points to a negative relationship between credit and growth, all the other results concerning the control variables confirm conventional expectations: see Sala-I Martin *et al.* (2004).

5. Robustness Check

Finally, we added interaction dummies for the global crisis years of 2008 and 2009 to our regressions to determine whether our results were affected by the events of period. The interaction dummy is the product of *cbcgini* variable and the dummy in each year. Hence the interaction dummies capture the effect of the unequal distribution of the IO network in crisis years on economic growth. Table 3 displays our results. All the coefficients of the *cbcgini* and interaction variables remain negative and statistically significant. The coefficients of the interaction dummies in year 2009 take on greater negative values than those of the *cbcgini* variable in all columns meaning that countries with higher heterogeneity levels of IO networks were more adversely affected by the global crisis.

These results confirm our argument that highly unequal sectoral linkages in IO networks amplify negative shocks, and hence, harm economic growth performance. In a wider perspective, our results are in line with those of Acemoğlu *et al.* (2012) and Hausman and Hidalgo (2009) as these two papers also emphasize the importance of network effects on economic growth.

The coefficients on the control variables keep their significance and expected signs in Table 3. We consider again column (6) of Table 3. The coefficients of capital, labor, trade and government effectiveness remain similar to the values found in Table 2.

Our findings are important as they underline the significance of structural features of the IO networks for economic growth performance, as Albert Hirschmann originally argued. The inter-linkages among different sectors in the IO networks have significant consequences for economic growth. Policy makers and economists need to determine sectoral policies that will enable firms in different sectors to improve the evenness of distribution in IO networks.

Table 3: Fixed Effect Regressions with Interaction Terms

	Dependent Variable					
	gdpcapgrowth					
	(1)	(2)	(3)	(4)	(5)	(6)
log(gdpcap)	0.500 (0.736)	0.893 (0.831)	-2.030* (1.055)	0.142 (1.062)	-0.668 (1.313)	1.570 (1.480)
gfcf	0.303*** (0.042)	0.301*** (0.042)	0.369*** (0.044)	0.340*** (0.043)	0.358*** (0.046)	0.292*** (0.050)
cbcgini	-12.25*** (3.961)	-10.87*** (4.185)	-12.65*** (4.132)	-10.58*** (4.063)	-8.074* (4.609)	-7.553* (4.556)

log(labor)	-2.387 (2.344)	-1.709 (2.308)	2.448 (2.381)	6.370** (2.928)	11.874*** (3.381)	
goveffect				1.351 (0.839)	1.729** (0.837)	
life					-0.635*** (0.202)	
trade		0.055*** (0.013)	0.050*** (0.012)	0.059*** (0.014)	0.073*** (0.014)	
credit			-0.036*** (0.006)	-0.041*** (0.007)	-0.035*** (0.007)	
cbcgini2008	-5.861*** (0.951)	-5.755*** (0.956)	-6.231*** (0.946)	-5.853*** (0.915)	-6.181*** (0.863)	-6.197*** (0.853)
cbcgini2009	-14.77*** (0.940)	-14.63*** (0.950)	-13.93*** (0.947)	-12.68*** (0.947)	-12.85*** (0.895)	-12.39*** (0.896)
Observations	541	541	541	513	398	398
R²	0.426	0.427	0.448	0.462	0.555	0.567
Adjusted R²	0.396	0.397	0.416	0.426	0.498	0.507
F Statistic	74.676***	62.408***	58.156***	50.863***	49.442***	46.592***

Note: * p<0.1, ** p<0.05, *** p<0.01

6. Conclusion

In this paper we employ a new centrality measure developed by Blöchl *et al.* (2011) for directed networks with self loops to determine sectoral heterogeneities in IO tables of 33 OECD countries over the 1995-2011 period. Then, a fixed-effect model for panel data was used to examine the link between economic growth performances of countries and heterogeneity of their input-output networks, controlling for factors known to affect growth.

Our findings provide evidence of a negative association between heterogeneity of the IO networks and economic growth. Such finding implies a key role for the inter-linkages across sectors in economic growth, and underlines the importance of designation of sectoral policy measures to counteract heterogeneity of IO networks. Extending this finding onto other countries and time periods are the aims for future research.

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Appendix

Sample Countries

Australia	Estonia	Japan	Netherlands
Austria	Finland	Korea	Russia
Belgium	France	Latvia	Slovak Republic
Brazil	Germany	Slovenia	Turkey
Bulgaria	Greece	Spain	Czech Republic
Canada	Hungary	Ireland	Sweden
China	India	Mexico	Taiwan
Poland	Italy	Portugal	United States
Denmark			