Network Origin of Industrial Comovement

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Abstract

This paper provides empirical evidence on the importance of production networks configuration in accelerating industry-specific perturbations. Recent theoretical literature has brought back a classical question: can industry specific perturbations result into aggregate fluctuations? According to this literature, whether industry-specific perturbations are able to persist and to reach the aggregate economy depends on the capacity of inter-industrial diffusion mechanism to amplify such perturbations. Empirical studies aiming at validating this hypothesis have focused on exploring the origins of aggregate output variance, without reaching a consensus. In this study, we investigate whether the strength of inter-industrial diffusion mechanism depends on the organization of production networks. We address this question by approximating the inter-industrial diffusion process through a measure of industry-industry co-movement. Based on the cross-country World Input-Output Database, we characterize the topology of production networks through a set of indicators for 40 countries and for the period 1995-2009. Our results suggest that the diffusion mechanism is stronger in more asymmetric production networks.

Keywords: *Production Networks, Aggregate Fluctuations, Industry Comovement*

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1 INTRODUCTION

The configuration of inter-industrial markets, called production networks, might play a key role in amplifying and accelerating micro-economic shocks. According to recent propositions, whether some economies exhibit micro-to-macro events more often than others depend on how heterogeneous is the distribution of industries' influence within production networks. The aim of this paper is to test empirically these recent theoretical propositions.

This paper follows a recent line of research that brought back a classical debate to the macroeconomic arena: the possibility that aggregate fluctuations may result from micro-economic shocks. This literature claims that macro-economic swings may be induced from perturbations suffered by non-aggregated entities such as sectors and firms. This debate dates back (at least) to Lucas (1977), which states that industries or firms are too granular to influence aggregate activity. According to this author, specific perturbations experienced by micro-economic entities might not be perceptible at aggregate scale since their effects would tend to average out. This is known as the diversification argument. Since then, several theoretical and empirical works has been developed with the aim of evaluating the pertinence of Lucas' argument, and more recently, some propositions highlight that the occurrence of micro-to-macro events cannot be completely disregarded. Rather, production networks might play a central role in the persistence and amplification of idiosyncratic perturbations (Gabaix (2011), Acemoglu et al (2012), Carvalho (2014)).

This paper contributes to this literature by studying the contagion mechanism within production networks. This mechanism seems to be relevant, since a non-negligeable fraction of aggregate volatility in most advanced economies is explained by industry covariance. Figure 1 presents a decomposition of aggregate volatility for the period 1995-2009 and for 38 most advanced economies.[1] It shows that in most cases, interindustrial comovement remains the main source of aggregate volatility by explaining at least 50 percent of aggregate volatility. Thus, whatever is affecting aggregate volatility, the inter-industry channel may be key in diffusing, and perhaps, in accelerating shocks. This paper shed light on how the share of industry covariance on aggregate volatility may be due to the very structure of production networks.

In particular, we are interested in testing empirically recent theoretical propositions presented by Acemoglu et al (2012), relating the topology of production networks to the capacity of industries to induce aggregate fluctuations. According to these claims, theoretically, economies having more asymmetric production networks (i.e. those in which the influence of input suppliers is strongly heterogeneous) would be more likely to experience

[1] See more details in the Appendix A.

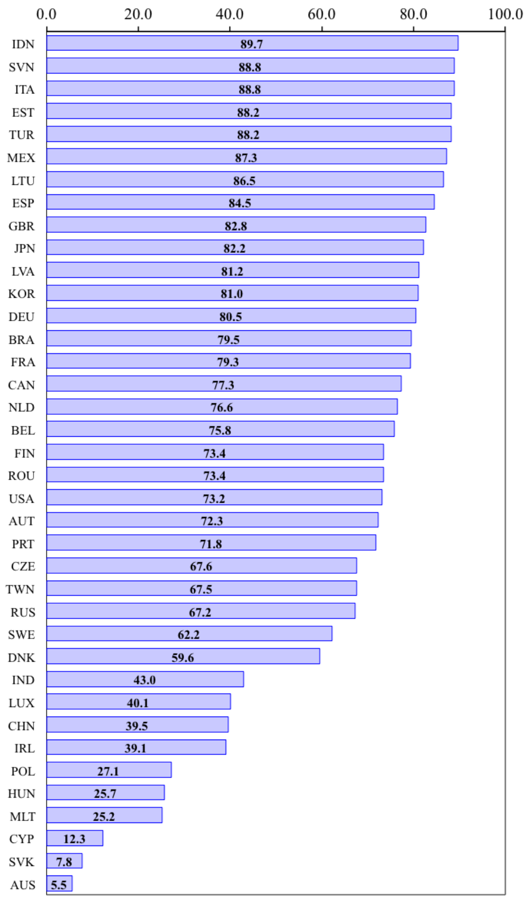

Figure 1: Share of Aggregate Volatility due to Industry Comovement (1995-2009). Figures represent estimates of the share of industry covariance on aggregate volatility. The latter is measured through the variance of aggregate value added growth rates. *Source:* Authors' calculation based on World Input-Output Database.

aggregate fluctuations triggered by industry-specific perturbations. This is because, under highly asymmetric configurations, key input suppliers concentrate a degree of influence such that they may induce large and persistent multipliers.

Do more asymmetric production networks exhibit stronger inter-industrial propagation mechanisms? To what extent interindustry transmission channels depends on industry-specific or country-specific characteristics? We treat these questions empirically by studying the short term dynamics of aggregate production, and by approximating the production networks contagion mechanism through a measure of interindustrial comovement. By focalizing on domestic industries; we evaluate whether or not the distribution of influence inside the network have an impact on industry synchronization. By using the World Input-Output Database (WIOD), we implement a cross-country analysis over the period 1995-2009.

Our results suggest that in average, production networks asymmetry has a positive impact on the level of general synchronization among domestic industries' activity. We observe that indicators that are not traditionally used in macroeconomics may be useful in the characterization of industrial co-movement, such as network distance.

The remaining of the paper is organized as follows. In section 2, we present a rephrase of the *asymmetric economy notion* that motivates this paper. In Section 3, we present a theoretical framework to justify why theoretical propositions presented by Acemoglu et al (2012) can be tested empirically by studying the short term dynamics of aggregate production. In Section 4, we introduce the indicators used in the empirical characterization of production network diffusion mechanism. In section 5, we introduce the regression techniques adopted to study the force of contagion of production networks. Results are presented in this same section. Finally, in section 6 a concluding discussion si presented.

2 THE ASYMMETRIC ECONOMY

Input requirements lead industries to develop interdependence. By changing prices, or by suffering large disruptions on the delivery process, industries are able to transmit perturbations downstream via vertical linkages. As a result, in the absence of short run substitutes, highly specialized sectors are more likely to endure perturbations suffered by main input suppliers. The collection of these inter-industrial interactions is known as *production networks*, and their configuration is thought to play an important role in the diffusion of industry-specific disturbances.

More generally, throughout production networks, industries may develop complex and unsuspected forms of interdependency. This is because their interconnected nature allow idiosyncratic shocks to induce adjustments (directly and indirectly) at several scales through a *network multiplier*. New insights in macro-economic literature suggest that aggregate fluctuations may be a consequence of large network multipliers, which in turn depend upon the organization of network linkages. In particular, it would depend on the capacity of network interactions to amplify industry specific shocks. When this amplification process is strong enough, perturbations originated within production networks may propagates across the economy and potentially induce aggregate perturbations. [Acemoglu et al (2012) and Carvalho (2014)]

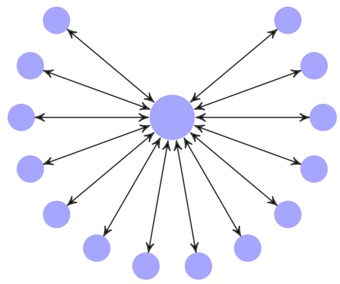

Figure 2: The Extreme Case: A Star-like Topology

According to these propositions, large networks multipliers would be more likely to take place in economies whose production networks configuration approximates to star-like network. Figure 2 illustrates the topology of these extreme configuration, which are characterized by having a central input supplier to which the rest of industries are connected. Under this hypothetical production network configuration, all non-central industries would be only indirectly connected to each other through a central node, and the internal diffusion mechanism would have two main peculiarities. Firstly, central supplier would be able to affect the global activity of the network rapidly, and may be potentially the main source of volatility at network scale. Secondly, this structure would imply the presence of a powerful channel by which idiosyncratic shocks taking place in the periphery may propagate easily across the network. In latter case, indirect linkages would allow non-central industries to potentially induce global fluctuations, and increase the likelihood that network scale fluctuations arise from non-central entities. In sum, the network multiplier obtained under Star Economy configuration would be always higher than that observed under any other kind of network configuration [Carvalho (2014)].

How close are modern economies from the hypothetical star-like configuration? and how investigating interindustry comovement may shed light on the contagion mechanism within production networks ? In its seminal work, Acemoglu et al (2012) demonstrates theoretically that the speed of dissipation of industry specific shocks decreases as the economy get closer to a star-like configuration; easing the propagation of idiosyncratic shocks, and increasing their chances of attaining aggregate activity. In this paper, we hold that whether network configuration effectively makes industry disturbances more persistent, it would be reflected in most cases as higher interindustry comovement. This is because as shocks propagate across the network, vertical complementarities ensure that adjustments are made gradually and at different scales, inducing synchronization among industrial activity. Thus, were the configuration of production networks accelerate their inner diffusion mechanism, it should also accelerate industry comovement.

In this paper, we investigate empirically how close are economies to the star-like configuration by studying industries' centrality probability distribution. The more asymmetric the distribution of centrality within production networks, the closer they are from the star-like configuration; and thus, the stronger the internal propagation mechanism.[2] We compute an indicator of *network asymmetry* for 40 economies to study empirically whether this characteristic helps understanding interindustry co-movement.

3 MODELING THE INTER-INDUSTRY PROPAGATION MECHANISM

In this section, we present a simplified version of a model firstly developed by *Long and Plosser (1983)*, and which is commonly used in the literature to study the granular origin of aggregate business cycles. We take the core of the inter-industry diffusion mechanism, and demonstrate that theoretical propositions highlighting the link between the organization of production networks, and the force of contagion of industry-specific shocks, can be tested by studying the short-term aggregate fluctuations.

Consider an economy composed by n industries, and whose the production process of the *ith* industry is characterized by the following production function:

$$Y_{i,t} = e_{i,t} \prod_{j}^{n} (Y_{j,t}^{\omega_{ij}})^{\alpha} \tag{1}$$

where $Y_{j,t}$ represents intermediate goods provided by industry $j \epsilon \{1...n\}$ at time t, and where $\omega_{ij} \epsilon (0,1)$ denotes the level of specialization of industry i on the technology provided by industry j. Under this framework, it is also assumed that industry i's production is subjected to orthogonal and identically distributed idiosyncratic technological shocks, denoted by $e_{i,t}$.

Equation (1) characterizes the engines of production networks. Under this setting, technological linkages allow industries to interact and to become interdependent, by allowing idiosyncratic disturbances to be transmitted downstream through the production chain. In what follows, we demonstrate that under this framework, the organization of technological linkages may condition the contagion mechanism of industry-specific perturbations.

Proposition 1: *The capacity of industries to induce short-term spillovers is determined by their level of network centrality, denoting how essential they are within production networks.*

[2] Centrality distribution is said asymmetrical when a handful of industries are strongly central, whereas the rest of industries are weakly influential.

To see this, let study the inter-industrial diffusion mechanism of short term through the *Variance-Covariance* matrix of the system composed by industrial production growth rates:

$$\Sigma_{\mathrm{Y}} = [\mathrm{I} - \alpha \mathrm{W}]^{-1} \Sigma_{\mathrm{Z}} [\mathrm{I} - \alpha \mathrm{W}]^{-1(T)}$$

where Σ_{Y} and Σ_{Z} denote the variance-covariance matrix of the industry production growth rates vector (Y) and the industry-specific shocks growth rates vector (Z), respectively.[3] Moreover, W is a squared matrix whose (i, j) entries correspond to ω_{ij}. [4] It is worth noting that even if idiosyncratic shocks are assumed orthogonal, industries are able to transfer idiosyncratic shocks, and to induce network spillovers thanks to technological ties via the term $[I - \alpha \mathrm{W}]^{-1}$. This implies that the short term dynamics of industrial production is subjected to the properties of production networks expressed through the matrix W.

Let *aggregate volatility* be defined as the variance of the weighted sum of industrial production growth rates (g_{y_i}) as follows:

$$\sigma_Y^2 = Var(\sum_{i=1}^{n} \mathrm{w}_i \cdot g_{y_i})$$

where w_i denotes the share of aggregate production that is produced by industry i. Let $\mathrm{w}_i = 1/n$ for $\forall i$, and by taking the structure characterizing industries' production process proposed by equation (1), then aggregate volatility equals:

$$\sigma_Y^2 = v^T \cdot \Sigma_Z \cdot v \tag{2}$$

where $v = 1/n \cdot [I - \alpha W^T]^{-1} \cdot \vec{1}$ corresponds a to the *influence vector* highlighted by *Acemoglu et al (2012)* and *Carvalho(2014)*. This is a well-known notion on *social network analysis*, where v is called *Eigenvector* centrality, and is used to identify more interconnected or influential network members. In this context, the presence of this vector suggests that the industries' capacity to generating short-run fluctuations depends on how well interconnected they are within production networks. This result is parallel to what was firstly proposed by *Acemoglu et al (2012)*, where in a general equilibrium framework, the capacity of industries to induce aggregate fluctuations is proportional to v, their level of *network influence*.

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[3]This equation is obtained by computing $\Sigma_X = E\left([X - E(X)] \cdot [X - E(X)]^T\right)$, for $X = \{Y, Z\}$ where $Y^T = \begin{bmatrix} g_{y_1} & g_{y_2} & \cdots & g_{y_n} \end{bmatrix}^T$ and $Z^T = \begin{bmatrix} g_{e_1} & g_{e_2} & \cdots & g_{e_n} \end{bmatrix}^T$, such that $g_{y_i} = \partial(log(Y_i))/\partial(t)$ and $g_{e_i} = \partial(log(e_i))/\partial(t)$.

[4]Matrix W corresponds to the transposed Input-Output tables. That is, W is such that columns contain intermediate production of industry j, rows contain intermediate consumption of industry i.

Proposition 2: *The organization of production networks conditions the force of contagion of short-term spillovers. Higher levels of heterogeneity (or asymmetry) in industry centrality are related to higher levels of short-term fluctuations.*

To illustrate this, we study aggregate volatility in (a) absence of inter-industrial trade, and (b) in presence of technological linkages. In both cases, let aggregate volatility be computed by using the first order approximation of variance-covariance matrix of industrial production growth rates, $\Sigma_{\mathrm{Y}} = [\mathrm{I} + \alpha \mathrm{W}] \, \Sigma_{\mathrm{Z}} \, [\mathrm{I} + \alpha \mathrm{W}]^T$.

(a) Without of Inter-Industrial Trade. Under this scenario, the matrix containing the inter-industrial transactions, W, is empty. Since industry-specific shocks are supposed orthogonal and identically distributed, aggregate volatility equals:

$$\sigma_Y^2 = \frac{1}{n} \cdot \sigma_z^2$$

where σ_z^2 denotes the variance of idiosyncratic shocks growth rates, (g_e). In this case, idiosyncratic shocks are not transmitted among industries due to the absence of technological ties. Therefore, there is no contagion effect, and aggregate variance is simply the average of the variance idiosyncratic shocks.

(b) With Inter-industrial Trade. In this case, industries are interdependent and idiosyncratic perturbations propagate downstream through production chain. The *variance-covariance* matrix Σ_Y is therefore conditioned by the organization of inter-industry linkages through the matrix W. Aggregate volatility would be defined by:

$$\sigma_Y^2 = \frac{1}{n} \cdot \sigma_z^2 \left[1 + \mu \left(\alpha, CV(d)^2 \right) \right] \tag{3}$$

where μ denotes a network multiplier, which in turn, is positively linked to $CV(d)$, the coefficient of variation of the first order *outdegree* centrality, such that

$$CV(d) = \frac{1}{\overline{d}} \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (d_i - \overline{d})^2}$$

where d_i denotes the first order outdegree of the *ith* industry and $\overline{d} = \frac{1}{n} \sum_{i=1}^{n} d_i$. This result implies in presence of vertical linkages, aggregate volatility is augmented by a network multiplier, that in turn, is stronger for more asymmetric centrality distributions.

Proposition 3: *The acceleration of aggregate volatility induced by higher levels of network asymmetry is mostly due to a reinforcement of Industry Covariance.*

The network multiplier (μ) affecting aggregate volatility can be decomposed as function of *Industry Variance* and *Industry Covariance*. To see this, let aggregate volatility be re-expressed as follows:

$$\sigma_Y^2 = \frac{1}{n} \cdot \sigma_z^2 \left[1 + (1-\tau) \cdot \mu(\alpha, CV) + \tau \cdot \mu(\alpha, CV)\right]$$

where $\mu(\alpha, CV)$ denotes the network multiplier introduced in equation (3), and $\tau = \sigma_{yy}/\mu(\alpha, CV(d))$ is the share of the network multiplier due to *Industry Covariance*. The higher τ, the higher is the effect enhanced by higher network asymmetry passing through *Industry Covariance*. By using information from the World-Input Database, it turns out that for most advanced economies, this parameter τ in average 0.87. This result indicates that most part of the acceleration effect induced over aggregate volatility - and resulting from the organization of production networks, might be passing through the inter-industrial channel. Thus, the role played by the organization of production networks on aggregate fluctuations may be studied empirically by exploring inter-industrial synchronization.

4 EMPIRICAL CHARACTERIZATION OF PRODUCTION NETWORKS

This section introduces the indicators used in the empirical characterization of industry comovement and its main drivers.

4.1 Industry Synchronization

We study the Industry covariance through a finer measure of synchronization: the industry pairwise *Pearson* correlation. There are two reasons justifying this procedure. Firstly, the pairwise correlation allows us to differentiate negatively from positively synchronized industry couples. Ultimately, stronger interindustry propagation channels would be expressed as tighter synchronization, whether this is negative or positive. Moreover, using *Pearson* correlation instead of industry covariance allows us to work with a free-units indicator, and yields a better measure of comovement.

Our variable of interest is then the industry pairwise *Pearson* correlation, which is computed as follows:

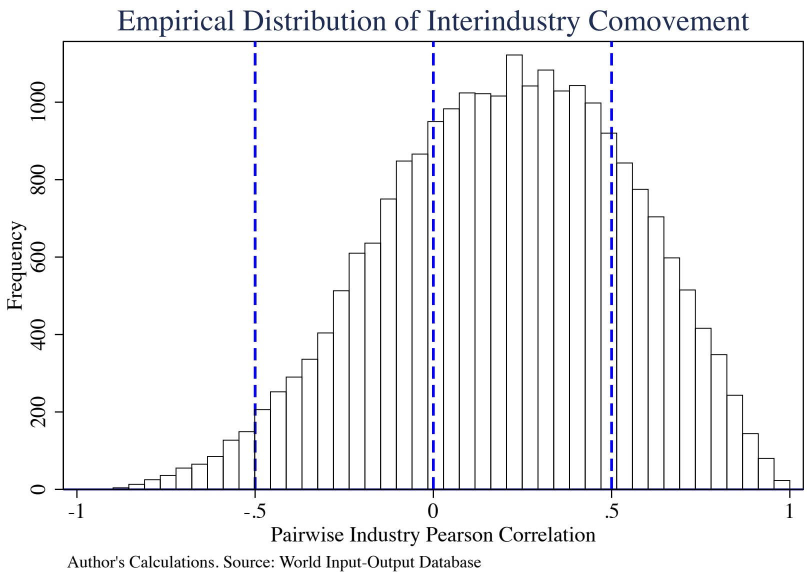

Figure 3: Empirical Distribution: Pairwise Industry Pearson Correlation. Period: 1995-2009. *Source:* Authors' calculation based on World Input-Output Database.

$$\rho_{jq} = \frac{\sigma_{jq}(\mathrm{w}_{jt} \cdot g_{jt}, \mathrm{w}_{qt} \cdot g_{qt})}{\sqrt{\sigma_j^2(\mathrm{w}_{jt} \cdot g_{jt}) \cdot \sigma_q^2(\mathrm{w}_{qt} \cdot g_{qt})}} \tag{4}$$

where σ_{jq} denotes the observed covariance between value added growth rates of industries j and q within the period 1995-2009. We implement our analysis by using data from the World Input-Output Database, which provides time-series of harmonized Input-Output tables for 40 countries covering the period 1995-2011 based on official *Socio-Economic* and *Environmental Accounts*. In particular, industry value added growth rates are computed from Input-Output tables available in a disaggregation basis of 35 industries according to ISIC Rev.3 code. In our empirical analysis, ρ_{jq} is computed for every pair of different domestic industries (i.e. $j \neq q$) and for 40 countries available in the World Input Output Database. This yields a sample size of 23800 industry couples (595 industry pairs by country). Figure 3 shows the empirical distribution of our pairwise Pearson correlation indicator. We observe that, in average, industry couples have a positive and moderate level of synchronization. Moreover, we also observe that a non-negligible proportion (30 percent) of total industry pairs in our sample have a negative co-variance. Later in this paper, we dedicate a section to study this observation.

The theoretical framework presented above yields a frame of reference about the potential sources of parwirse comovement. From the aggregate *Variance-Covariance* matrix, Σ_Y, it follows that the covariance between any pair of industries i and j can be characterized as follows:

$$Cov(y_i, y_j) = \sigma_z^2 f\left(\alpha, \omega_{ij}, \omega_{ji}, CV(d)\right)$$

According to this expression, pairwise industry comovement might be induced by tighter *vertical linkages* (ω) as well as higher level of *network asymmetry*. The remaining of this section aims at giving details about the empirical characterization of these potential sources of comovement.

4.2 Vertical Specialization

The first indicator is a measure of industry inter-dependency , denoted ω_{ij} in the theoretical framework presented above. Its role is to characterize the intensity of direct vertical linkages within production networks. This indicator is computed as follows:

$$\omega_{ij} = \frac{InputDemand_{i,j}}{\sum_i^n InputDemand_{i,j}} \tag{5}$$

where $InputDemand_{i,j}$ denotes the value of inputs supplied from j to i, and $\sum_j^n InputDemand_{i,j}$ is the total intermediary consumption of industry i. The higher ω_{ij}, the higher the contribution of industry j's output on total intermediate consumption of industry i. Alternatively, this measure can be interpreted as the level of input specialization of industry i on inputs produced by industry j. That is, if $\omega_{ij} = 1$, it implies that industry j is the only input supplier of industry i; when $\omega_{ij} = 0$, in contrast, industry i does not require industry j to produce.

We use a second indicator allowing to compute vertical dependency in a broader sense. In some cases, two industries may be weakly and directly related within the network, while being strongly connected via indirect linkages. To control for this feature, we computed the technological proximity for each pair of industries as follows:

$$Proxy = max\{\omega_{ij}, NetDist^{-1}\}$$

where $NetDist$ denotes the network distance computed from the *Floyd-Marshall* algorithm, which finds the shortest path linking two industries within production networks. Since higher proximity may translate into major feedback, industries being closer within the network might present higher co-movement. We would expect *Proxy* to be related positively to pairwise synchronization.

Table 1: Network Complementarities

Industry (i)	Industry (j)	Vertical Specialization (ω_{ij}) Average	Standard Deviation	Min	Max	Average Pairwise Comovement
Agriculture	Food & Beverages	33.9%	9.0%	18.9%	55.7%	5.8%
Construction	Real Estate Activities	29.4%	20.2%	1.1%	81.9%	35.5%
Mining	Coke & Petroleum	28.4%	27.8%	0.0%	90.7%	0.0%
Food & Beverages	Hotels & Restaurants	27.6%	11.5%	1.2%	58.2%	26.3%
Metals	Machinery	22.8%	9.0%	2.4%	38.3%	55.6%
Agriculture	Wood & Cork	19.6%	12.8%	0.1%	47.6%	5.4%
Financial Intermediation	Real Estate Activities	16.4%	11.2%	1.7%	40.5%	9.2%
Chemicals	Rubber & Plastics	16.2%	12.9%	0.1%	45.9%	40.4%
Renting Of Machinery & Eq	Other Services	15.9%	7.7%	1.7%	31.0%	36.0%
Wood & Cork	Manufacturing	15.4%	9.7%	1.2%	43.4%	50.0%
Renting Of Machinery & Eq	Public Admin	15.3%	7.3%	1.1%	29.1%	-2.1%
Metals	Transport Eq.	14.6%	7.4%	0.6%	46.6%	50.9%
Other Mineral	Construction	13.4%	6.6%	5.5%	31.7%	59.1%
Mining	Electricity & Gas & Water	13.2%	12.7%	0.0%	41.8%	27.0%
Metals	Electrical & Optical Eq.	12.5%	7.6%	0.3%	33.3%	52.8%
Electricity & Gas & Water	Education	12.3%	9.4%	0.8%	47.2%	10.3%
Coke & Petroleum	Other Inland Transport	12.2%	11.4%	0.0%	43.4%	4.1%
Renting Of Machinery & Eq	Education	11.7%	6.9%	1.3%	26.7%	1.5%
Mining	Other Mineral	11.1%	7.8%	0.4%	45.6%	14.1%
Other Inland Transport	Other Transport Activities	10.9%	9.3%	1.2%	37.3%	37.4%
Coke & Petroleum	Other Air Transport	10.8%	9.3%	0.0%	42.0%	11.2%
Metals	Manufacturing	10.7%	6.1%	0.8%	26.1%	47.6%
Renting Of Machinery & Eq	Health & Social Work	10.4%	5.8%	0.2%	24.0%	12.7%
Metals	Construction	10.2%	5.5%	0.7%	28.0%	46.2%

Author's calculations. *Source*: WIOD.

In Table 1 we present an overview of results obtained after computing the *vertical specialization* indicator. By exploring intermediary consumption profile of industries, we identify the 25 most specialized industries, i.e. those industries for which production relies the most on direct input suppliers. Our results indicate that, in average, the most specialized industry is *Food Beverages*, whose 33,9 percent of total intermediary consumption is provided by *Agriculture*, followed by *Real State Activities* whose 29 percent of total intermediary consumption relies on *Construction*. *Table 1* also allows us to infer indirect relationships as well. For instance, at the bottom of first column, we observe that *Metals* is an important input supplier of *Construction*, which in turn is an important input supplier of *Real State Activities*. From this observation, we deduce that *Metals* and *Real State Activities* are indirectly related within production networks, through a *2nd order* relationship.

4.3 Network Asymmetry

Our main indicator is the *Asymmetry Index*. Its purpose is to characterize how close are economies from the star-like configuration, and to assess the potential of interindustry channel to accelerate industry-specific perturbations. In a broad sense, the Asymmetry notion highlights how heterogeneous is the distribution of influence among industries within the network. In the context of this paper, for instance, a network is asymmetric when a large proportion of total network intermediate consumption is satisfied by a handful of industries.[5] This characteristic is a well known notion in networks theory, and its computation consists on fitting the empirical probability distribution of a network *centrality* notion, to the most adapted *theoretical probability law.* In order to compute this characteristic, we firstly define the notions of *network centrality.*

Network Centrality

In the context of this paper, *Centrality* indicators attributes higher levels of influence to those industries on which production networks relies the most directly and indirectly, at least in the short run. The simplest version is the *first order Outdegree*:

$$d_i^{(1)} = \sum_{j=1}^{n} \omega_{ji} \tag{6}$$

where ω_{ij} denotes vertical specialization indicator defined above. *Outdegree* centrality is defined as the total direct input contributions made by industry i to the network. It is possible to thing of $d_i^{(1)}$ as an indicator of how necessary is industry i's technology in i's direct neighbors production process.[6] We pay particular attention to more extended versions of *Outdegree* centrality. In particular, we modify the *Outdegree* notion by considering how well connected are direct neighbors. Ultimately, industries possessing strongly connected direct neighbors are more likely to transfer shocks downstream through the production chain, and to induce comovement. This is reflected by the *second-order Outdegree* :

$$d_i^{(2)} = \sum_{j=1}^{n} \omega_{ji} \cdot d_j^{(1)} \tag{7}$$

where ω_{ij} denotes the measure of vertical specialization defined above and $d_j^{(1)}$ denotes the first-order outdegree of the jth neighbor. According to this indicator, industry i might have a higher level of influence when its direct neighbors are themselves important input suppliers.

Following these notions, we focus on a more comprehensive measure of centrality that defines network influence as the capacity of industries to transfer shocks k steps downstream through the production chain. This

[5]This is simplistic definition, since as we will see later in this paper, stronger differences in network influence are observed when studying indirect linkages.

[6]When two industries interact directly within inter-industrial markets, we will denote them as *first order neighbors*, or simply *direct neighbors.* More generally, when the minimum quantity of transactions relating (directly or indirectly) a couple of industries is equal to k, we will refer to them as *k-order neighbors*; and the set of *k-order neighbors* of industries will be denoted as the *k-order neighborhood.*

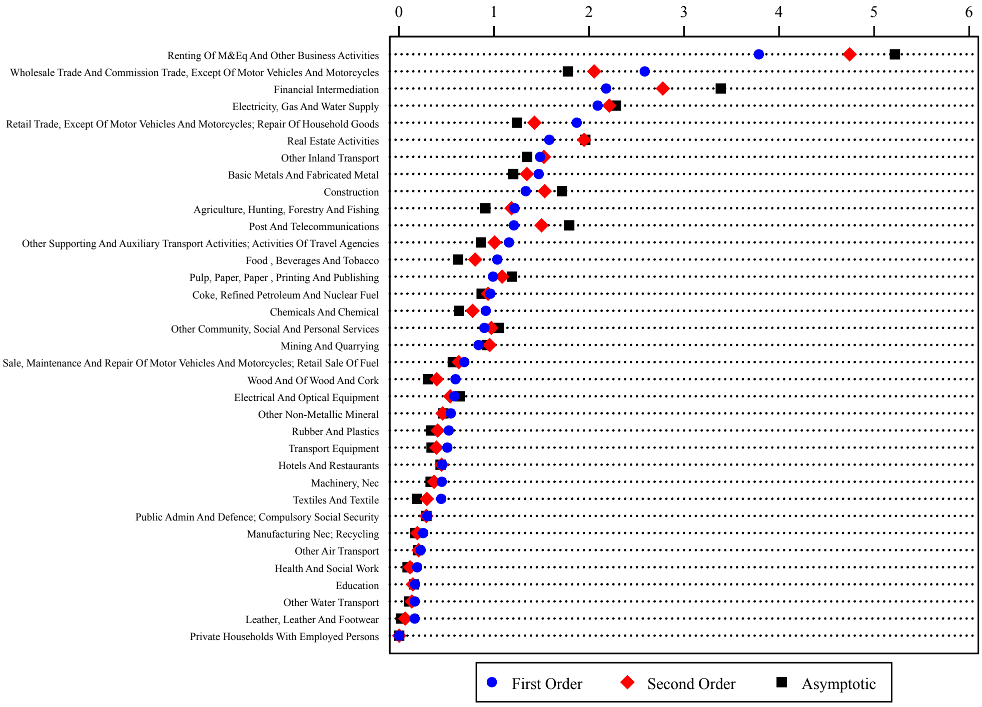

Figure 4: *Outdegree Centrality*: Several Orders. The centrality indicators were computed by using input-output tables from the WIOD, which are available at a disaggregation level of 35 industries and for 40 countries. The level of centrality of each industry in the figure was computed in two stages. Firstly, we computed the average centrality level of each industry for the period 1995-2011. Secondly, we computed the average level of each type of industry across the 40 countries. Authors' calculation. *Source:* WIOD.

can be obtained through a generalization of *Outdegree*, called the *k-order Outdegree*:

$$d_i^{(k)} = \sum_{j=1}^{n} \omega_{ji} \cdot d_j^{k-1} \tag{8}$$

$$\text{with } d_j^{(0)} = 1$$

where $d_j^{(k-1)}$ denotes the *k-1 order Outdegree* of the jth neighbor. This indicator characterize network centrality by considering the potential influence exerted by industry i over its first k neighborhoods.

Who is who in production networks? Figure 4 presents a list of 35 industries contained in the WIOD in descending order according to their

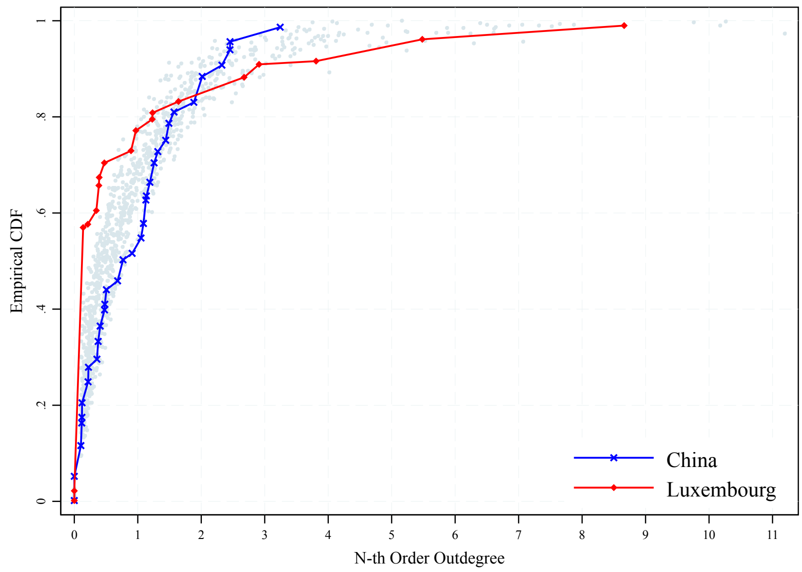

Figure 5: Fitting Empirical CDF of Centrality to Weibull. In the figure the CDF for 40 countries contained in the WIOD are taken together. Horizontal axis represent the 30th Outdegree, and vertical axis represent the empirical CDF of network centrality. Author's calculations *Source*: WIOD

first-order Outdegree, and provides information on their *2th* and *30th order Outdegree*. In average, the top 5 list of general purpose industries among the 40 economies considered in our data is conformed by : (1) Renting of Machinery and Equipment, (2) Wholesale Trade, (3) Financial Intermediation, (4) Electricity, Gas and Water Supply and (5) Retail Trade. These industries can be though as key direct input suppliers within production networks. We observe that *Renting of Machinery and Equipment* and *Financial Intermediation* present considerable gains on centrality when considering their indirect level of influence within production networks. This characteristic reflects the fact that these industries not only provide inputs directly to a large part of the network, but also they provide inputs to important input suppliers. In contrast, among the top 5 more central industries, *Wholesale Trade* and *Retail Trade* industries exhibit lower levels of influence when considering indirect influence. This suggests that, even if these industries are key *direct input suppliers*, their neighbors are not, limiting their capacity for generate large network multipliers.

Asymmetry Indicators

In the theoretical framework presented above, network asymmetry appears in the model through the coefficient of variation of *first order Outdegree* centrality, $CV(d)$. In estimations, we study network asymmetry not only through the $CV(d)$ coefficient, but also through an *Asymmetry Index.* The latter is constructed by fitting the empirical probability distribution of *k-order Outdegree* to a *Weibull* propability law, which seems be the most adapted for data provided by World Input-Output Database (WIOD).[7] Then, we construct an asymmetry index which is simply defined as the inverse of the shape parameter (γ) of *Weibull* distribution:

$$Asymmetry = 1/\widehat{\gamma} \tag{9}$$

where $\widehat{\gamma}$ represent the (estimated) shape parameter of the Weibull distribution, s.t. $P(X < x) = 1 - exp\{(x/\lambda)^{\gamma}\}$ for $x \sim Weibull(\lambda, \gamma)$. Lower values of γ are associated to more skewed distributions. In particular, a random variable generated by a Weibull probability law will present a heavy-tail behavior only when γ is less than 1. Moreover, when $\gamma < 1$, there exist a monotonic and negative relationship between γ and $CV(d)$. Therefore; strongly asymmetrical production networks should be characterized by a empirical CDF having a low shape parameter, eventually lower that 1.

Empirical Issues

We observed that the level of disaggregation of IO tables have an influence on the metrics used in the study of production networks. Particularly, highly aggregated data tends to show more homogenous centrality distributions among industries, which subsequently affects indicators such as the *Asymmetry Index.* We also observe that outdegree distribution become less homogenous at higher-order outdegree. In order to deal with the homogeneity of industries induced by the level of disaggregation, we will consider the *30th outdegree* to compute *Asymmetry index*, since is considered to be more accurate in reflecting the true centrality distribution of domestic industries. In the remainder of this work, this is simply denoted as *Asymmetry.*

Figure 5 illustrates the empirical CDF associated to the *30-th order Outdegree* centrality. Empirical CDF is computed for 40 countries contained in the WIOD, but highlighted graphically only for the least asymmetric (China) and the most asymmetric production network in the sample (Luxembourg). In the case of China, for instance, Figure 1 suggests that roughly 50 percent

[7]Acemoglu et al (2012, 2013) and Carvalho (2011, 2014) show that for the United States, the tail of industries' centrality CDF approximates a power law. However, when using IO tables made available by most statistical offices, it is not possible to characterize production networks' centrality distribution through this particular distribution. This difference is mainly due to the level of disaggregation of IO tables used in the calculation of centrality indicators. The authors use data having a disaggregation level of nearly 400 industries, in our case; however, IO tables go until 35 industries.

Table 2: Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
Asymmetry	1.340	0.306	0.876	2.302
Land Size	0.110	0.224	0.000	1.000
Openness	0.858	0.483	0.232	2.754
Economy Size	0.081	0.164	0.001	1.000
A-Centrality	0.967	0.903	0.000	7.582
D-Centrality	1.165	1.451	0.000	11.194
A-Proximity	0.041	0.033	0.000	0.464
D-Proximity	0.040	0.053	0.000	0.887
A-Vertical	0.025	0.035	0.000	0.497
A-Vertical^2	0.002	0.007	0.000	0.247
D-Vertical	0.035	0.057	0.000	0.994
A-Industry Size	0.029	0.019	0.000	0.171
D-Industry Size	0.029	0.028	0.000	0.241

Author's calculations. Sorce: WIOD

of industries have a level of centrality inferieur to 1, in Luxumbourg; in contrast, this percentage is about 80 percent. This implies that in Luxembourg, network centrality is relatively more concentrated than in China.

4.4 Additional Controls

We incorporate in our empirical analysis other potential sources of interindustry comovement. For instance, we analyze whether the fact of belonging to different sectors –Primary, Secondary or Tertiary– may determine industry comovement. We also incorporate a dummy indicating whether industry couples belong to one of Eurozone economies (denoted by EURO). Our estimations also include a measure of openness to trade (denoted by *Openness*), a variable controlling for the size of geographic territory (denoted *LandSize*), and the relative size of the economy (denoted *EconomySize*). More details are presented in the Annex.

5 EXPLORING THE SOURCES OF INDUSTRY SYNCHRONIZATION

Our empirical analysis is implemented in two stages. The first and main part consists on studying the sources of pairwise industry synchronization (ρ_c) and by implementing a *Beta* regression. The second part of the empirical analysis aims at further our understanding of industry comovement. We classify industry couples according to the degree and sign of comovement, and use a Multinomial Logit to identify what lead industry couples to exhibit a particular pattern of comovement.

5.1 First Stage: Beta Regression

Our first and main objective is to study whether the configuration of production networks determine interindustry synchronization, which is approximated here via ρ_c. This indicator has the particularity that is bounded to (-1,1) interval. This implies that classical techniques of regression cannot be applied to study this variable, since non-linear behavior may be induced over regressors. We deal with this limitation by implementing *Beta Regression*. This approach allows the study of variables that are bounded to (0,1) interval, and more generally, allows the study of any bounded variable not defined in the interval (0,1) after applying a transformation. In our case, we transform industry pairwise correlation so that it is defined within the (0,1) interval as follows:

$$\widehat{\rho_c} = \frac{\rho_c + 1}{2} \tag{10}$$

where index $c \in$ 23,800 denotes industry couples contained in our sample. Thus, we study the force of interindustry comovement through the transformed pairwise correlation, $\widehat{\rho_c}$, and by implementing a Beta regression. The latter is based on maximum likelihood estimation according to the following specification:

$$log(\frac{\theta_X}{1-\theta_X}) = \delta_i + \delta_j + \delta_l + X\beta + Z\lambda + \varepsilon_c \tag{11}$$

where θ_X denotes $E(\widehat{\rho_c}/X)$ such that $\widehat{\rho_c}$ is assumed to follow a $Beta(\theta_X)$ distribution.[8] Variable X denotes a vector of industry pair-wise characteristics, and Z denotes a vector of control variables specified at country level. Moreover, we include fixed effects by industry (δ_i, δ_j) and by country (δ_l).

In particular, *beta regression* allow us to study our variable of interest ($\widehat{\rho_c}$) by studying its conditional mean parameter (θ_X). However, as implied by Equation (11) , $\widehat{\beta}$ assesses the linear relationship between X and $log(\frac{\theta_X}{1-\theta_X})$, implying that *Beta regression* estimation does not yield a direct estimator of the relationship between $E(\widehat{\rho_c}/X)$ and explanatory variables. Therefore, in order to get a estimator of the marginal relationship of the form $\partial E(\widehat{\rho}/X)/\partial X$, we compute the Average Marginal Effects (AME).[9] In particular, when presenting and interpreting results for *beta regression*, we will mainly focus on the average marginal effects (AME) presented in table (4). Alternatively, we present estimates of Equation (11) in table (3) to show that estimations are robust in most cases.

[8] This specification implies that θ and the vector of explanatory variables, X, are related by a *Logit* link function, that is, $\theta = \frac{e^{X\beta}}{1+e^{X\beta}}$. See more details in the Annex.

[9] See more details in the Annex.

5.2 Results

Our main objective is to study whether the diffusion mechanism within production networks is reinforced in more asymmetrical configurations. This claim is studied through the *Asymmetry Index*, which yields a measure of how heterogeneous is the distribution of centrality among domestic industries. We would expect that more asymmetric economies posses more powerful diffusion mechanisms, and thus, stronger interindustry comovement. Our results indicate that higher levels of network asymmetry are associated to higher levels of industry synchronization: an increase in *Asymmetry* by one standard deviation (i.e. 0.306) would lead to an increase of about 16 percent on the level of industry synchronization.[10] This effect is robust and statistically significant at 1 percent across all our specifications (see table (3)). This indicates that on average, industries' activity co-moves more closely in economies having more asymmetrical production networks. We consider that this is evidence of a general reinforcement on the diffusion channels by which industry-specific shocks propagate throughout production networks. Moreover, such reinforcement is a necessary condition for production networks to be at the core of aggregate fluctuations, as proposed by *Acemoglu et al (2012)*.

Comovement is also induced by industry specific characteristics. In particular, the intensity of network interactions is related to positive comovement: an increase in the average vertical specialization (denoted by $A - Vertical$) by one standard deviation (i.e. 0.035) have a positive impact on the synchronization of industries' activity of about 3 percent. This is in line with what is expected from a production networks perspective: the higher the average direct network interdependency, the higher the synchronization between two industries.

Interestingly enough, other control variables have the expected sign and may be useful in the characterization of industry synchronization. At industry level, for instance, we observe that the sector is a good predictor of synchronization. Our results suggest that couples whose both industries are classified as either *Secondary* or *Tertiary* exhibit a level of synchronization at least 30 percent higher than couples formed by two *Primary* industries. We also find that industry couples from Eurozone economies exhibit higher levels of industry synchronization of about 21 percent higher than the average. This is in line with literature suggesting that economic activity is

[10] This effect is obtained by re-transforming $\widehat{\rho_c}$ ϵ (0,1) into ρ_c ϵ (-1,1), and by computing:

$$AME(\rho_c) = \frac{\partial E(\rho_c/X)}{\partial X_k} = \frac{\partial E(\rho_c/X)}{\partial E(\widehat{\rho_c}/X)} \cdot \frac{\partial E(\widehat{\rho_c}/X)}{\partial X_k} = 2 \cdot \frac{\partial \widehat{\theta_X}}{\partial X_k} = 2 \cdot AME(\widehat{\rho_c})$$

where $AME(\widehat{\rho_c})$ represents the Marginal Effect induced by one unit change on the *k-th* variable over the transformed correlation $\widehat{\rho_c}$.

Table 3: Beta Reg: Explaining industry pairwise comovement 1995-2009

Estimated Equation: $log(\frac{\theta_X}{1-\theta_X}) = \delta_i \iota + \delta_j \iota + \delta_l \iota + X\beta + Z\lambda + \varepsilon_c$

where $\theta_X = E(\widehat{\rho_c}/X_k)$ such that $\widehat{\rho_c} \sim Beta(\theta_X)$

	(1)	(2)	(3)	(4)	(5)	(6)
$Asymmetry$	1.225***	1.225***	1.090***	1.176***	1.156***	
	(0.0141)	(0.0141)	(0.0109)	(0.0115)	(0.0172)	
$CV(d)$						0.832***
						(0.0114)
$EURO$		0.544***	0.657***	0.473***	0.467***	0.393***
		(0.00292)	(0.00390)	(0.00303)	(0.00411)	(0.00481)
$LandSize$			0.255***	-2.225***	-2.213***	-2.483***
			(0.00775)	(0.0147)	(0.0203)	(0.0226)
$Openness$				-1.364***	-1.348***	-1.273***
				(0.0100)	(0.0161)	(0.0146)
$EconomySize$					0.00488	0.0572***
					(0.00366)	(0.00338)
$Secondary \times Secondary$	0.690***	0.690***	0.690***	0.690***	0.690***	0.708***
	(0.139)	(0.139)	(0.139)	(0.139)	(0.139)	(0.139)
$Tertiary \times Tertiary$	0.877***	0.877***	0.877***	0.877***	0.877***	0.852***
	(0.111)	(0.111)	(0.111)	(0.111)	(0.111)	(0.109)
$Secondary \times Tertiary$	0.230	0.230	0.230	0.230	0.230	0.388***
	(0.184)	(0.184)	(0.184)	(0.184)	(0.184)	(0.120)
$Primary \times Secondary$	-0.000320	-0.000320	-0.000320	-0.000320	-0.000320	0.0128
	(0.102)	(0.102)	(0.102)	(0.102)	(0.102)	(0.103)
$Primary \times Tertiary$	-0.157	-0.157	-0.157	-0.157	-0.157	-0.00134
	(0.179)	(0.179)	(0.179)	(0.179)	(0.179)	(0.0924)
$A - Vertical$	1.854***	1.854***	1.854***	1.854***	1.854***	
	(0.668)	(0.668)	(0.668)	(0.668)	(0.668)	
$(A - Vertical)^2$	-4.865***	-4.865***	-4.865***	-4.865***	-4.865***	
	(1.761)	(1.761)	(1.761)	(1.761)	(1.761)	
$D - Vertical$	-0.315	-0.315	-0.315	-0.315	-0.315	
	(0.242)	(0.242)	(0.242)	(0.242)	(0.242)	
$A - Proximity$						0.450
						(0.613)
$(A - Proximity)^2$						-1.271
						(1.798)
$A - IndSize$	-1.367	-1.367	-1.367	-1.367	-1.367	-1.232
	(1.423)	(1.423)	(1.423)	(1.423)	(1.423)	(1.444)
$D - IndSize$	0.522	0.522	0.522	0.522	0.522	0.462
	(0.366)	(0.366)	(0.366)	(0.366)	(0.366)	(0.364)
N	22340	22340	22340	22340	22340	22273
δ_i, δ_j and δ_l	YES	YES	YES	YES	YES	YES

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Note: All regressions include dummy variables at country level and clustered standard errors by country.

Table 4: Average Marginal Effects (AME) of transformed ($\widehat{\rho_c}$) and non transformed pearson correlation (ρ_c). OLS estimations are obtained by regressing transformed $\widehat{\rho_c}$.

	Beta Regression		*OLS*	
	AME($\widehat{\rho_c}$)	AME(ρ_c)*σ_X	β	β*σ_X
Asymmetry	0.268*** (0.00353)	0.164	0.244*** (0.00141)	0.149
EURO	0.108*** (0.000911)	0.216	0.106*** (0.000611)	0.212
LandSize	-0.513*** (0.00396)	-0.229	-0.501*** (0.00124)	-0.224
Openness	-0.313*** (0.00329)	-0.302	-0.296*** (0.000974)	-0.285
EconomySize	0.00113 (0.000850)		0.00880*** (0.000451)	
$Secondary \times Secondary$	0.160*** (0.0319)	0.32	0.158*** (0.0331)	0.316
$Tertiary \times Tertiary$	0.203*** (0.0253)	0.406	0.211*** (0.0249)	0.422
$A - Vertical$	0.430*** (0.155)	0.03	0.382** (0.143)	0.026
$(A - Vertical)^2$	-1.128*** (0.408)		-1.024** (0.397)	
N	22340	22343		

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Note: Marginal Effects result from Beta regression estimates including Fixed Effects and clustered standard errors by country. **Interpretation:** Coefficients correspond to the average effect from one-unit change in the *k-th* variable over industry comovement.

closely synchronized among countries from euro zone.

Our results also point out that external and geographical drivers should be considered when characterizing the inter-industrial diffusion mechanism. Our results indicate that industry couples from economies having levels of *Openness* of about one standard deviation higher than the average exhibit 30 percent less synchronization. This result may suggest that the more exposed the economy to external factors, the less correlated domestic industries. Moreover, the territory size expressed through *LandSize* is found to play a potential role in the diffusion of shocks. Our results indicate that one standard deviation increase on the relative country territory (i.e. 0.224) is related to a decrease in industry synchronization of about 23 percent.

5.3 Second Stage: Multinomial Logit

Our second objective is to study further the nature of interindustry comovement. Why some industries are strongly synchronized while most industries have a moderate level of synchronization? Or even more, what determines the strongly negative synchronization observed in some industry couples?

For this purpose, we classified industry pairs into m categories, according to the direction and the size of co-movement. We use a Multinomial Logit Regression (MLR) to analyze the probability for industry pairs of belonging to the *m-th* category, and to observe to what extent this probability is determined by a set of characteristics. This regression technique uses maximum likelihood estimation according to the following specification:

$$log(\frac{Pr(\rho_c = m)}{Pr(\rho_c = m_0)}) = \delta_l + X\beta^{(m)} + Z\lambda^{(m)} + \varepsilon_c \tag{12}$$

where m denotes the synchronization category such that

$$m = \begin{cases} Strong^{+} & if\ \rho_c \,\epsilon\, (0.5, 1] \quad (High\, and\, positive) \\ Weak^{+} & if\ \rho_c \,\epsilon\, (0, 0.5] \quad (Weak\, and\, positive) \\ Weak^{-} & if\ \rho_c \,\epsilon\, [-0.5, 0] \quad (Weak\, and\, negative) \\ Strong^{-} & if\ \rho_c \,\epsilon\, [-1, -0.5) \quad (High\, and\, negative) \end{cases}$$

where index $c \,\epsilon$ 23,800 denotes industry couples contained in our sample, X denotes a vector of industry pair-wise characteristics, and Z denotes a vector of control variables specified at country level. The ratio $\frac{Pr(\rho_c=m)}{Pr(\rho_c=m_0)}$ is also called the relative risk-ratio (RRR), and represents the relative probability for an industry couple of belonging to category m, with respect to the base category m_0.

The Multinomial Logit estimation yields an estimator for β and λ vectors, which represents the marginal impact of one-unit changes in the set of characteristics, on the logarithm of the risk-relative ratio. Since we are interested in predicting variations of the form $\frac{\partial Pr(p_c=m)}{\partial x_k}$, results are interpreted via the Average Marginal Effects presented in Table 5.[11]

Figure 3 shows how industry couples are distributed across these categories. In particular we observe that a non-negligible proportion (30 percent) of total industry pairs in our sample have a negative co-variance. This could correspond to couples of industries that are counter-cyclical by nature, or being the result of input substitutions within production networks. However, negative covariance can be also due to less intuitive sources. For instance, we observe that some rich economies such as Germany, United States or France exhibit a high proportion of negatively synchronized industries, while a group of developing countries conformed by India, China, Turkey and Mexico have a very high proportion of positively synchronized industries. This lead us to think that the proportion of positively and negatively synchronized industry couples might not being produced randomly, but instead, it may be associated institutional or structural conditions. Therefore, studying the factors leading an industry couple to exhibit a particular sign on covariance may also be informative about the functioning of the inner propagation mechanism of economies.

5.4 Results

As mentioned earlier, we classified industry couples into four categories according to the strength (weak or strong) and sign of synchronization (negative or positive). Then, we apply a Multinomial Logit to identify what lead industry couples to belong to one of these four types of synchronization.

Our results suggest that network asymmetry is related to *strong and positive* correlation category. We find that important levels of network asymmetry make industries more likely to be strongly synchronized: an increase of one standard deviation on *Asymmetry Index* (i.e. 0.302) would increase the probability for industry couples of being positively and strongly synchronized by about 16 percent. At the contrary, the probability of being negative and strongly correlated decreases considerably in more asymmetric configurations.

At industry level, we found that technological distance is a good predictor of the sign of interindustry co-movement. Two indicators are used to this purpose: the vertical specialization ω_{ij} (denoted by *A-Vertical*) and the network proximity (denoted by *A-Proxy*). Higher values on the average vertical specialization imply that either both industries are highly and directly dependent, or there is a relatively important input supplier between them. Our results indicate that one standard deviation increase on average vertical specialization (i.e. 0.035) would increase the probability for industry

[11] Estimates of equation (12) are also available in the Annex.

Table 5: Multinomial Logit: Explaining the interindustry comovement by degree of synchronization (ρ_c). Average Marginal Effects by category of comovement

	$Pr(\rho_c = Strong^{+})$	$Pr(\rho_c = Weak^{+})$	$Pr(\rho_c = Weak^{-})$	$Pr(\rho_c = Strong^{-})$
Asymmetry	0.514***	-0.0688***	0.0553***	-0.500***
	(0.00508)	(0.00546)	(0.00216)	(0.00606)
EURO	0.230***	-0.0489***	-0.0122***	-0.169***
	(0.00296)	(0.00319)	(0.00114)	(0.00375)
LandSize	-1.020***	0.00333	0.158***	0.859***
	(0.00598)	(0.00675)	(0.00232)	(0.00449)
Openness	-0.577***	-0.00448	0.0404***	0.541***
	(0.00455)	(0.00524)	(0.00169)	(0.00499)
EconomySize	0.120***	-0.101***	-0.0158***	-0.00326
	(0.00213)	(0.00209)	(0.000606)	(0.00256)
$Secondary \times Secondary$	0.475***	-0.263**	-0.0534***	-0.159*
	(0.159)	(0.123)	(0.0157)	(0.0816)
$Tertiary \times Tertiary$	0.309**	-0.231*	-0.0372***	-0.0412
	(0.157)	(0.127)	(0.0132)	(0.0775)
$Secondary \times Tertiary$	0.338**	-0.212*	-0.0434***	-0.0828
	(0.156)	(0.124)	(0.0142)	(0.0773)
$Primary \times Secondary$	0.205	-0.171	-0.0286**	-0.00559
	(0.160)	(0.122)	(0.0133)	(0.0795)
$Primary \times Tertiary$	0.193	-0.199	-0.0330**	0.0393
	(0.161)	(0.125)	(0.0135)	(0.0769)
$A - Centrality$	-0.0248**	0.0271**	-0.0106**	0.00834
	(0.0125)	(0.0131)	(0.00464)	(0.0126)
$D - Centrality$	0.00790	-0.00817	0.00174	-0.00147
	(0.00509)	(0.00675)	(0.00194)	(0.00662)
$A - Proxy$	1.805***	-0.692	0.0490	-1.161***
	(0.509)	(0.613)	(0.207)	(0.390)
$D - Proxy$	-0.993***	0.292	-0.0200	0.721***
	(0.232)	(0.274)	(0.0829)	(0.227)
$A - Vertical$	1.724***	-0.804	0.184	-1.103***
	(0.547)	(0.538)	(0.170)	(0.408)
$(A - Vertical)^2$	-9.082***	4.098**	-0.151	5.135***
	(2.316)	(1.613)	(0.238)	(1.145)
$D - Vertical$	0.202	0.0193	-0.0900	-0.131
	(0.239)	(0.254)	(0.0620)	(0.162)
$A - IndSize$	-0.319	-0.370	0.157	0.532
	(0.469)	(0.440)	(0.145)	(0.414)
$D - IndSize$	-0.0404	0.0224	0.00887	0.00911
	(0.239)	(0.226)	(0.0629)	(0.225)
N	22276	22276	22276	22276

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. **Note**: Marginal Effects results from Multinomial Logit including Fixed effects and clustered standard errors by country. **Interpretation:** Coefficients correspond to the average effect from one-unit change in the *k-th* variable over the probability for industry pairs of belonging to each comovement category.

couples of being positive and strongly correlated by about 6 percent, while reducing the probability of being negative and strongly correlated by about 4 percent.

The second indicator, *Proxy*, represents a more general measure of technological linkage. In particular, it assess how nearby are industries within inter-industrial networks, independently on whether these interact directly or indirectly. The effect of the average proximity on industry comovement is similar to that obtained by the average vertical specialization. However, contrary to the latter, the effect of network proximity on comovement is subjected to reciprocity. That is, network proximity induce synchronization only when both industries are mutually near from each other (i.e. lower *D-Proxy*). Our result suggests that an increase of one standard deviation on $D - Proxy$ (i.e. 0.053) would reduce the probability for industry couples of being positively and strongly correlated in about 5 percent, while increasing the probability of being negatively and strongly correlated in about 4 percent.

Other control variables were found useful in characterizing interindustry comovement. At country level, for instance, industries belonging to Eurozone are more likely to be positive and strongly synchronized. We also found that external sector could play a central role in explaining interindustry comovement. Our results indicate that the openness to trade of economies makes industries less likely to exhibit positive and strong levels of comovement. Another factor seems to be the geography. Industries belonging to countries having relatively big territories are less likely to be positive and strongly synchronized, while increasing considerably the probability of being negatively and strongly correlated. The production dispersion as well as the transportation costs in big territories might be behind these results.

6 Conclusion

This work aimed at testing empirically recent theoretical propositions highlighting production networks as an important accelerator of microeconomic shocks [*Acemoglu et al (2012)*, *Carvalho(2014)*]. According to these, economies having more asymmetric production networks tend to have more persistent idiosyncratic shocks, due mainly to stronger network multipliers. Therefore, in a context of strongly asymmetrical production networks, idiosyncratic shocks may be diffused more easily throughout the economy, and potentially resulting in aggregate fluctuations.

Our approach consists in demonstrating that these claims can be tested empirically by studying the short term dynamic of aggregate production. In particular, we demonstrate that most part of the (theoretical) acceleration effect induced by more asymmetric production networks might be passing through the inter-industry channel. Thus, were more asymmetric configurations render idiosyncratic shocks more persistent via stronger network multiplier, it should necessarily be reflected as higher industry synchronization.

We focus on studying the sources of pairwise industry co-movement. Our results suggest that in average, production networks asymmetry effectively increases the level of general synchronization among domestic industries' activity. After controlling for country-specific and industry-specific characteristics, this effect is robust and statistically significant across all our specification. This is interpreted as a reinforcement of the inter-industry propagation mechanism as implied by propositions presented by *Acemoglu et al (2012).* Moreover, we also observe that higher levels of vertical linkages lead to higher levels of industry synchronization.

This approach is alternative to that presented by other studies in the field, in which researchers are typically interested on searching the microeconomic origin of aggregate fluctuations. Instead, we focus the propagation mechanism itself, i.e. that required by industry-specific perturbations to induce large fluctuations. We find that the underling propagation mechanism of production networks does react, and may be reinforced, by organization of technological linkages, which is a necessary condition on the granular origin of aggregate fluctuations hypothesis. Finally, more recherche is needed to explore how the structure of international production networks could be shaping comovement among domestic industries.

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Appendices

A Industry Comovement

The decomposition of aggregate volatility presented in Figure (1) is obtained by following Shea (2002), which decomposes aggregate volatility into the weighted sum of industry variance and industry covariance. By taking aggregate value added as a representative measure of total production, we let aggregate value added growth rates (g_t) be defined as a weighted average of industrial value added growth rates (g_{jt}):

$$g_t = \sum_{j=1}^{N} \mathrm{w}_{jt} \cdot g_{jt}$$

where N is the number of industries, and w_{jt} is the share of industry's j value added on aggregate value added at period t. Then, aggregate volatility is approximated by the weighted sum of variance and covariance of industry value added growth rates as follows :

$$\sigma_i^2(g_t) = \sum_{j=1}^{N} \sigma_j^2(\mathrm{w}_{jt} \cdot g_{jt}) + 2 \sum_{1 \leq j < q \leq n} \sigma_{jq}(\mathrm{w}_{jt} \cdot g_{jt}, \mathrm{w}_{qt} \cdot g_{qt})$$

where σ_i^2 and σ_{jq} denote variance and covariance operators, respectively. This equation yields a decomposition of aggregate volatility into variance and covariance of domestic industries production. We apply these notions over 40 economies for the period 1995-2009 by using information from the WIOD dataset. Table 6 below presents the observed aggregate volatility, as well as the estimated aggregate volatility computed through Equation (2). We observe that, in general, this decomposition yields a good approximation of the aggregate dynamics. Moreover, as presented prevously in Figure 1, industry comovement remains the main source of volatility for aggregate value added series. This is in line with what is observed in other studies using different datasets and different periods of time. In particular, our results suggest that in 28 out of the 40 countries considered in the sample, interindustry comovement represents the main source of aggregate volatility, by explaining at least 50 percent of total volatility. This observation may indicate that, to some extent, interindustry channel could play an important role on shaping aggregate dynamics.

Table 6: Volatility of Aggregate Value Added (1996-2009)

Country	*Observed Std. Dev.* $\sigma(g_t)$	*Estimated Std. Dev* $\overline{\sigma(g_t)}$	*Due to Comovement* (÷)
AUS	0.9	0.88	5.5
AUT	2.06	1.84	72.3
BEL	1.62	1.74	75.78
BGR	4.82	3.31	-
BRA	1.99	1.97	79.52
CAN	1.32	1.36	77.25
CHN	1.9	2.62	39.54
CYP	1.86	2.66	12.32
CZE	3.49	4.54	67.57
DEU	2.16	2.17	80.47
DNK	2.14	2.07	59.59
ESP	2.1	2.05	84.48
EST	6.96	7.83	88.21
FIN	3.68	4.54	73.42
FRA	1.55	1.79	79.32
GBR	2.21	2.52	82.75
GRC	1.87	2.2	-
HUN	3.26	4.08	25.72
IDN	5.88	5.3	89.65
IND	2.13	2.11	43.01
IRL	4.35	4.09	39.09
ITA	2.11	2.1	88.8
JPN	2.81	3.02	82.2
KOR	3.89	4.02	80.97
LTU	6.35	5.78	86.46
LUX	3.08	2.9	40.06
LVA	6.99	6.76	81.19
MEX	3.28	3.7	87.26
MLT	3.35	4.94	25.24
NLD	2.1	2.12	76.56
POL	1.8	2.39	27.12
PRT	2.01	2.3	71.79
ROU	5.25	5.92	73.41
RUS	6.41	5.38	67.19
SVK	3.97	65.74	7.76
SVN	3.53	3.52	88.83
SWE	2.74	4.19	62.22
TUR	5.84	5.69	88.17
TWN	3.12	2.98	67.52
USA	1.97	2.19	73.2

Authors calculations. *Source:* WIOD

B Average Marginal Effect

As mentioned earlier, the regression techniques used in this paper does not provide direct measures of the relationship between the regressors (X_k) and our variable of interest, ρ_c. In particular, contrary to linear regression, beta coefficients cannot be directly interpreted as the marginal variation of the form $\frac{\partial(\rho_c)}{\partial(X_k)}$. We deal with this by computing the Marginal Effects. This approach consists in computing the theoretical form of marginal derivative, and use observed values to obtain a numeric estimation of $\frac{\partial(\rho_c)}{\partial(X_k)}$. In this paper, our variables of interest are:

(a) $P(\rho_c = m)$: the probability for industry pairs to belong to category m, and

(b) θ_X: the conditional mean of industry synchronization (ρ_c), such that $\rho_c \sim Beta(\theta_X)$.

According to Multinomail Logit Regression and Beta regression, our variables of interest are linked to explanatory variables as follows:

$(a.1)\ \pi_c^{(m)} = P(\rho_c = m) = \frac{e^{\beta_i^{(m)} X_i^{(m)}}}{\sum_{j=1}^{m} e^{\beta_i^{(m)} X_i^{(m)}}}$

$(b.1)\ \theta_X = \frac{e^{\sum_{i=1}^{k} \beta_i X_i}}{1+e^{\sum_{i=1}^{k} \beta_i X_i}}$

The theoretical form of marginal derivatives of (a.1) and (b.1) with respect to X_k are defined as follows:

$$\frac{\partial(\pi_c^{(m)})}{\partial X_k} = \pi_c^{(m)} \cdot [\beta_k^{(m)} - \sum_{m=1}^{J} \beta_k^{(m)} \cdot \pi_c^{(m)}]$$

$$\frac{\partial \theta_X}{\partial X_k} = \beta_k \cdot \theta_X(1 - \theta_X)$$

We obtain an estimation of marginal derivative based on these theoretical forms, denoted Margin Effect (ME), by replacing estimated values of β_k and observed X_k. Estimates of ME are computed for each observation within the sample, and average values are used as a representative measure of marginal effects:

$$AME_k^{(m)} = \frac{1}{n} \sum_{c=1}^{n} \frac{\partial(\widehat{\pi}_c^{(m)})}{\partial X_k}$$

$$AME_k = \frac{1}{n} \sum_{c=1}^{n} \frac{\partial \widehat{\theta}_X}{\partial X_k}$$

C The Model

Modeling Interindustry Comovement with industry-specfic shocks

Consider an economy composed by **n** industries, and whose the production process of the *ith* industry is characterised by the following production function:

$$Y_i = e_i \prod_{j}^{n} (Y_j^{\omega_{ij}})^{\alpha} \tag{13}$$

where Y_j represents intermediate goods provided by industry $j \, \epsilon \, \{1...n\}$, and where $\omega_{ij} \, \epsilon \, (0,1)$ denotes the level of specialization of industry i on the technology provided by industry j. Through this function, it is also assumed that industry i's production is subjected to orthogonal and identically distributed idiosyncratic technological shocks, denoted by e_i.

The production function presented above characterizes production networks at its finest level. Under this setting, technological linkages allow industries to interact and to become interdependent, by allowing idiosyncratic disturbances to be transmitted downstream through the production chain. Recent propositions highlight the role of production network in accelerating micro-economic shocks, by pointing out that under some conditions, the organization of technological linkages may be such that it admits a strong contagion mechanism [Acemoglu et al (2012), Carvalho (2014)].

In this paper, we are interested in testing empirically whether the transmission of industry-specific shocks is conditioned by the organization of production networks. This analysis is implemented by studying the synchronization of industry production growth rates. In what follows, we show how the organization of production networks may determine the force of inter-industry spillovers, expressed through the strength of growth rates comovement.

Let the production function presented above be expressed in growth rates form as follows:

$$g_{y_i} = g_{e_i} + \alpha \sum_{j=1}^{n} \omega_{ij} \cdot g_{y_j}$$

where $g_{y_i} = \frac{\partial(log(Y_i))}{\partial(t)}$ and $g_{e_i} = \frac{\partial(log(e_i))}{\partial(t)}$. It can be noticed that the mechanism of vertical transmission characterizing production networks is maintained after this transformation. Moreover, the equation system formed by the **n** transformed production functions implies a multiplier mechanism having the following form:

$$\mathrm{Y} = \left[\mathrm{I} - \alpha \cdot \mathrm{W}\right]^{-1} \cdot \mathrm{Z}$$

where $\mathrm{Y} = \begin{bmatrix} g_{y1} & g_{y2} & \cdots & g_{y_n} \end{bmatrix}^T$, $\mathrm{Z} = \begin{bmatrix} g_{e1} & g_{e2} & \cdots & g_{e_n} \end{bmatrix}^T$ and W is a squared matrix whose (i,j) entries correspond to ω_{ij}. We study the link between the strength of the network multiplier and the organization or production networks, by studying the *Variance-Covariance* matrix of the vector containing the industry production growth rates (Y):

$$\Sigma_{\mathrm{Y}} = [\mathrm{I} - \alpha \mathrm{W}]^{-1} \Sigma_{\mathrm{Z}} [\mathrm{I} - \alpha \mathrm{W}]^{-1(T)} \tag{14}$$

where Σ_{Y} and Σ_{Z} denote the variance-covariance matrix of industry production and idiosyncratic shocks growth rates, respectively. It is worth noting that since idiosyncratic shocks are assumed orthogonal, Σ_Z is diagonal.

By following the property of *power series expansion* such that $[\mathrm{I} - \alpha \mathrm{W}]^{-1} = \sum_{k=0}^{\infty} \alpha^k \mathrm{W}^k$, for $\alpha < 1$, we can study the *variance-covariance* matrix of industry production growth rates through its first order approximation:

$$\Sigma_{\mathrm{Y}} = [\mathrm{I} + \alpha \mathrm{W}] \Sigma_{\mathrm{Z}} [\mathrm{I} + \alpha \mathrm{W}]^T$$

or simply,

$$\Sigma_{\mathrm{Y}} = \left(\mathrm{I} + \alpha \cdot \mathrm{W}^{\mathrm{T}} + \alpha \cdot \mathrm{W} + \alpha^2 \mathrm{W} \cdot \mathrm{W}^T\right) \Sigma_{\mathrm{Z}}$$

It can be noticed that even if industry-specific shocks are assumed orthogonal, the variance-covariance matrix of industry production growth rates (Σ_{Y}) is not diagonal, as long as off-diagonal elements of W are different from zero. That is to say, inter-industry linkages allow industry production growth rates to comove as a result of the vertical transmission of idiosyncratic shocks, even if the latter are independent.

D Proofs

PROOF OF PROPOSITION 1: Let aggregate production growth rate (g_Y) be defined as a weighted sum of industrial production growth rates (g_y) as follows:

$$g_Y = \sum_{i=1}^{n} \mathrm{w}_i \cdot g_{y_i}$$

where w_i denotes the share of aggregate production that is produced by industry i. In addition, let aggregate volatility be defined by

$$\sigma_{\mathrm{Y}}^2 = \frac{1}{n^2} \cdot Var(\sum_{i=1}^{n} g_{yi})$$

where $\sigma_{\mathrm{Y}}^2 = Var(g_{\mathrm{Y}})$, and by setting $\mathrm{w}_i = 1/n$ for $\forall i$.

By following the theoretical framework presented above, it is possible to attribute an analytic form to $Var(\sum_{i=1}^{n} g_{yi})$. This term is equivalent to summing up the elements of the *variance-covariance* matrix of industrial production growth rates, Σ_{Y}. Therefore, aggregate volatility can be re-expressed as follows:

$$\sigma_Y^2 = \frac{1}{n^2} \cdot (\vec{1})^T \cdot \Sigma_{\mathrm{Y}} \cdot \vec{1}$$

where $\vec{1}$ denotes the all-ones vector of order n. It is possible to highlight the network properties of the inter-industrial diffusion channel by using the general form for Σ_z expressed through equation (14); and by letting aggregate volatility be redefined by:

$$\sigma_Y^2 = v^T \cdot \Sigma_Z \cdot v$$

where $v = 1/n \cdot [I - \alpha W^T]^{-1} \cdot \vec{1}$ corresponds a to a vector of *Eigenvector* centrality. This concept is used in *social network theory* to identify more interconnected network members. In this case, the presence of this vector suggests that the industries' power of diffusion relies on how well interconnected are these are within production networks. This result is parallel to what was firstly proposed by *Carvalho(2009)* and *Acemoglu et al (2012)*, where in a general equilibrium framework, the capacity of industries to induce aggregate fluctuations is proportional to v, their level *network influence*.

PROOF OF PROPOSITION 2: Let aggregate volatility be characterized by its first order approximation of Σ_{Y}:

$$\sigma_Y^2 = \frac{1}{n^2} \cdot (\vec{1})^T \cdot \Big(\Sigma_{\mathrm{Z}} + \alpha\Sigma_{\mathrm{Z}} \cdot \mathrm{W}^T + \alpha\mathrm{W} \cdot \Sigma_{\mathrm{Z}} + \alpha^2\mathrm{W} \cdot \Sigma_{\mathrm{Z}} \cdot \mathrm{W}^T\Big) \cdot \vec{1}$$

where Σ_{Z} denote the variance covariance matrix of idiosyncratic shocks, and W whose (i, j) entries correspond to ω_{ij}. To study how the organization of production networks may determine the way idiosyncratic shocks propagate, lets study what happen to aggregate volatility in (a) absence of inter-industrial trade, and (b) in presence of technological linkages.

(a) Without of Inter-Industrial Trade

Under this scenario, the matrix containing the inter-industrial transactions, W, is empty. Aggregate volatility is then defined by:

$$\sigma_Y^2 = \frac{1}{n^2} \cdot (\vec{1})^T \cdot \Big(\Sigma_{\mathrm{Z}}\Big) \cdot \vec{1}$$

Since industry-specific shocks are supposed orthogonal and identically distributed, aggregate volatility equals:

$$\sigma_Y^2 = \frac{1}{n} \cdot \sigma_z^2$$

where σ_Y^2 denotes the variance of idiosyncratic shocks, e_i.

(b) With Inter-industrial Trade

Under this scenario, industries are interdependent and idiosyncratic perturbations are allowed to propagate downstream in the production chain and across the technological plan. The *variance-covariance* matrix of industry growth rates, Σ_Z, is conditioned by the properties of production networks through the matrix W. To see this, let the first order approximation of aggregate volatility be re-expressed as a function of industries' centrality as follows:

$$\sigma_Y^2 = \frac{1}{n^2}\left((\vec{1})^T \Sigma_Z \vec{1} + \alpha (\vec{1})^T \Sigma_Z \cdot \vec{d} + \alpha (\vec{d})^T \cdot \Sigma_Z \vec{1} + \alpha^2 (\vec{d})^T \cdot \Sigma_Z \cdot \vec{d} \right)$$

where $\vec{d} = W^T \cdot \vec{1}$ represents a vector containing the first order *Outdegree centrality*, such that $d_j = \sum_{i=1}^n \omega_{ij}$. This notion attributes higher levels of centrality to more important input suppliers. That is, those satisfying directly a large proportion of the network's total intermediate consumption. Last equation suggests, in addition, that under this framework the capacity of industries to diffuse idiosyncratic shocks downstream within the network would depend on their level of *Outdegree* centrality. That is to say, on how dependent is the network as a whole to a particular technology.

By developing further, aggregate volatility can be re-expressed as follows:

$$\sigma_Y^2 = \frac{1}{n^2}\left[\sum_{j=1}^n \sigma_{z_j}^2 + 2\alpha \cdot \sum_{j=1}^n \sigma_{z_j}^2 \cdot d_j + \alpha^2 \cdot \sum_{j=1}^n \sigma_{z_j}^2 \cdot d_j^2 \right] \tag{15}$$

Since industry-specific shocks are assumed independent and identically distributed, it implies $\sum_{j=1}^n \sigma_{z_j}^2 = n \cdot \sigma_z^2$, and aggregated volatility would equal:

$$\sigma_Y^2 = \frac{1}{n} \cdot \sigma_z^2 \left[1 + 2\alpha \cdot \overline{d} + \alpha^2 \cdot \overline{d^2} \right] \tag{16}$$

where $\overline{d} = \left(\frac{1}{n}\right) \sum_{j=1}^n d_j$, and $\overline{d^2} = \left(\frac{1}{n}\right) \sum_{j=1}^n d_j^2$.

Since by definition $\overline{d} = 1$, it follows that $\overline{d^2} = \text{Var}(d) + 1$. Then, aggregate volatility would be redefined as

$$\sigma_Y^2 = \frac{1}{n} \cdot \sigma_z^2 \Big[1 + \mu\left(\alpha, CV(d)\right) \Big] \tag{17}$$

where μ denotes the production networks multiplier such that

$$\mu\left(\alpha, CV(d)\right) = \left[2\alpha + \alpha^2\left(1 + \mathrm{CV(d)}^2\right)\right]$$

where $CV(d) = \sigma_d/\mu_d$ denotes the coefficient of variation of the first order outdegree centrality, d, with $\sigma_d = \sqrt{Var(d)}$ and $\mu_d = \overline{d}$. This result implies that higher levels of heterogeneity in industry centrality (i.e. higher CV(d)) are directly related to higher levels of aggregate volatility.

PROOF OF PROPOSITION 3: Before presenting the proof, we introduce two definitions regarding *Industry Variance and Covariance.*

Definition 3.1: *Industry Variance* (σ_y^2) equals the sum of diagonal elements of the first order approximation of Variance-Covariance matrix:

$$\sigma_y^2 = \frac{1}{n^2}(\vec{1})^T \cdot \mathrm{Diag}(\Sigma_Y) \cdot \vec{1}$$

$$\Leftrightarrow \sigma_y^2 = \frac{1}{n^2}\Big(\sum_{j=1}^{n} \sigma_{z_j}^2 + 2\alpha \sum_{j=1}^{n} \sigma_{z_j}^2 \omega_{jj} + \alpha^2 \sum_{j=1}^{n}\sum_{k=1}^{n} \sigma_{z_j}^2 \omega_{kj}^2\Big)$$

Definition 3.2: *Industry Covariance* (σ_{yy}) equals the sum of the off-diagonal elements of Variance-Covariance matrix Σ_Y:

$$\sigma_{yy} = \sigma_Y^2 - \sigma_y^2$$

$$= \frac{1}{n^2}\left(\sum_{j=1}^{n} \sigma_{z_j}^2 + 2\alpha \cdot \sum_{j=1}^{n} \sigma_{z_j}^2 \cdot d_j + \alpha^2 \cdot \sum_{j=1}^{n} \sigma_{z_j}^2 \cdot d_j^2\right)$$

$$-\frac{1}{n^2}\left(\sum_{j=1}^{n} \sigma_{z_j}^2 + 2\alpha \sum_{j=1}^{n} \sigma_{z_j}^2 \omega_{jj} + \alpha^2 \sum_{k=1}^{n}\sum_{j=1}^{n} \sigma_{z_j}^2 \omega_{kj}^2\right)$$

$$\sigma_{yy} = \frac{2\alpha}{n^2}\left(\sum_{j=1}^{n} \sigma_{z_j}^2 \cdot d_j - \sum_{j=1}^{n} \sigma_{z_j}^2 \omega_{jj}\right) + \frac{\alpha^2}{n^2}\left(\sum_{j=1}^{n} \sigma_{z_j}^2 \cdot d_j^2 - \sum_{k=1}^{n}\sum_{j=1}^{n} \sigma_{z_j}^2 \omega_{kj}^2\right)$$

This proof is presented in two stages. The first part consists on proving that the Network Asymmetry has a non-negative impact on the level of industry synchonization. The second part of the proof, in turn, shows that the acceleration of aggregate volatility can be separated into the effect induced over Industry Variance, and that induced over Industry Covariance.

(a) First Part: Consider the *Definition 3.2.* Since industry-specific shocks are assumed independently and identically distributed with variance σ_z^2, *Industry Covariance* may be expressed as follows:

$$= \frac{\sigma_z^2}{n^2}\left[2\alpha\left(\sum_{j=1}^{n} d_j - \sum_{j=1}^{n}\omega_{jj}\right) + \alpha^2\left(\sum_{j=1}^{n} d_j^2 - \sum_{k=1}^{n}\sum_{j=1}^{n}\omega_{kj}^2\right)\right] \tag{18}$$

or,

$$= \frac{1}{n}\cdot\sigma_z^2\left[2\alpha\cdot\left(\overline{d} - \overline{\omega_{jj}}\right) + \alpha^2\left(\overline{d^2} - (n)\cdot\overline{\omega^2}\right)\right]$$

where $\overline{d} = \frac{1}{n}\sum_{j=1}^{n} d_j$, $\overline{d^2} = \frac{1}{n}\sum_{j=1}^{n} d_j^2$, $\overline{\omega_{jj}} = \frac{1}{n}\sum_{j=1}^{n}\omega_{jj}$ and $\overline{\omega^2} = \frac{1}{n^2}\sum_{k=1}^{n}\sum_{j=1}^{n}\omega_{kj}^2$. Since par definition $\overline{d} = 1$ and $\overline{\omega} = 1/n$, it follows that $\overline{d^2} = \mathrm{Var}(d) + 1$, and $\overline{\omega^2} = Var(\omega) + (1/n)^2$. Then,

$$= \frac{1}{n}\cdot\sigma_z^2\left[2\alpha\left(1 - \overline{\omega_{jj}}\right) + \alpha^2\left(Var(d) + 1 - n\cdot\left[Var(\omega) + (1/n)^2\right]\right)\right]$$

$$= \frac{1}{n}\cdot\sigma_z^2\left[2\alpha\left(1 - \overline{\omega_{jj}}\right) + \alpha^2\left(CV(d)^2 - \frac{CV(\omega)^2}{n} + \frac{n-1}{n}\right)\right]$$

where $CV(d)$ and $CV(\omega)$ represent the coefficient of variation of the first order outdegree centrality and the coefficient of variation of direct input flows. Last equation implies that the network asymmetry is positively linked to the *Industry Covariance.* More importantly, it can be shown that this effect is non-negative. To see this, consider Equation (18):

$$= \frac{2\alpha\cdot\sigma_z^2}{n^2}\left[\left(\sum_{j=1}^{n} d_j - \sum_{j=1}^{n}\omega_{jj}\right) + \alpha^2\left(\sum_{j=1}^{n} d_j^2 - \sum_{k=1}^{n}\sum_{j=1}^{n}\omega_{kj}^2\right)\right]$$

$$= \frac{2\alpha\cdot\sigma_z^2}{n^2}\left[\sum_{j=1}^{n}\sum_{\substack{i=1\\ i\neq j}}^{n}\omega_{ij} + \alpha^2\left(\sum_{j=1}^{n}\left(\sum_{k=1}^{n}\omega_{kj}\right)^2 - \sum_{k=1}^{n}\sum_{j=1}^{n}\omega_{kj}^2\right)\right]$$

$$= \frac{2\alpha \cdot \sigma_z^2}{n^2} \left[\sum_{j=1}^{n} \sum_{\substack{i=1 \\ i \neq j}}^{n} \omega_{ij} + \alpha^2 \sum_{j=1}^{n} \left(\left(\sum_{k=1}^{n} \omega_{kj} \right)^2 - \sum_{k=1}^{n} \omega_{kj}^2 \right) \right]$$

since $\bigvee j \epsilon \{1, ..., n\}$:

$$\begin{aligned} \left(\sum_{k=1}^{n} \omega_{kj}\right)^2 - \sum_{k=1}^{n} \omega_{kj}^2 &= (\omega_{1j} + \omega_{2j} + ... + \omega_{nj})(\omega_{1j} + \omega_{2j} + ... + \omega_{nj}) - \sum_{k=1}^{n} \omega_{kj}^2 \\ &= \left[\sum_{k=1}^{n} \omega_{kj}^2 + 2\sum_{1 \leqslant k < i \leqslant n} \omega_{kj}\omega_{ij}\right] - \sum_{k=1}^{n} \omega_{kj}^2 \\ &= 2\sum_{1 \leqslant k < i \leqslant n} \omega_{kj}\omega_{ij} \\ \left(\sum_{k=1}^{n} \omega_{kj}\right)^2 - \sum_{k=1}^{n} \omega_{kj}^2 &\geq 0 \end{aligned}$$

We conclude that the impact of the network asymmetry over *Industry Covariance* is always positive in presence of interindustrial trade.

(b) Second Part: According to Equation (17), higher production network asymmetry implies stronger network spillovers, and thus, higher aggregate volatility. This is because more heterogenous centrality distribution implies stronger inter-industry diffusion mechanisms. In this context, it is possible to decompose the network multiplier as a weighted sum of the accelerator effect induced over *Industry Variance*, and that induced over *Industry Covariance*. To see this, consider the aggregate volatility definition presented Equation (16):

$$\sigma_Y^2 = \frac{1}{n} \cdot \sigma_z^2 \left[1 + \frac{2\alpha}{n} \cdot \sum_{j=1}^{n} d_j + \frac{\alpha^2}{n} \cdot \sum_{j=1}^{n} d_j^2 \right]$$

where $d_j = \sum_{i=1}^{n} \omega_{ij}$ the *Outdegree* centrality indicator.

By taking the *Definitions (3.1)* and *(3.2)*, aggregate volatility can be re-expressed as follows:

$$\sigma_Y^2 = \sigma_y^2 + \sigma_{yy}$$

such that:

$$\sigma_y^2 = \frac{1}{n} \cdot \sigma_z^2 \left[1 + \frac{2\alpha}{n} \sum_{j=1}^{n} \omega_{jj} + \frac{\alpha^2}{n} \sum_{j=1}^{n} \sum_{i=1}^{n} \omega_{ij}^2 \right]$$

and

$$\sigma_{yy} = \frac{2}{n} \cdot \sigma_z^2 \left[\frac{\alpha}{n} \sum_{j=1}^{n} \sum_{\substack{i=1 \\ i \neq j}}^{n} \omega_{ij} + \frac{\alpha^2}{n} \sum_{1 \leq i < k \leq n} \omega_{ij}\omega_{kj} \right]$$

Finally, aggregate volatility can be re-expressed in terms of the network multiplier as follows:

$$\sigma_Y^2 = \frac{1}{n} \cdot \sigma_z^2 \left[1 + (1-\tau) \cdot \mu(\alpha, CV) + \tau \cdot \mu(\alpha, CV)\right]$$

where $\mu(\alpha, CV)$ denotes the network multiplier introduced in equation (17), and $\tau = \sigma_{yy}/\mu(\alpha, CV(d))$ is the share of the network multiplier induced by a reinforcement of the *Industry Covariance*.

Table 7: Control Variables Description

Class	Label	Variable	Description
Country-Specific	Asymmetry	$\frac{1}{15}\sum_{t=1995}^{2009} Asymmetry_{(l,t)}$	Measure of industry heterogeneity with respect to production network centrality. See Section 3
	LandSize	$\frac{Land_{(l)}}{Land_{(RUS)}}$	Country's total area relative to Russia's territory. Author's calculations *Source*: World Bank
	EURO	$Dummy$	Dummy variable denoting industry couples from Eurozone economies. *Source*: Eurostat
	EconomySize	$\frac{1}{15}\sum_{t=1995}^{2009} \frac{VA_{l,t}}{VA_{(USA,t)}}$	Economy size relative to USA economy. VA denotes aggregate detrended value added. *Source*: WIOD
	Openness	$\frac{1}{15}\sum_{t=1995}^{2009} \frac{Exp_{(l,t)} + Imp_{(l,t)}}{GDP_{(l,t)}}$	Computed as the sum of Exports and Imports for each economy divided by total GDP. *Source*: World Bank
Industry-Specific	$Vertical_{(i,j)}$	$\frac{1}{15}\sum_{t=1995}^{2009} \omega_{ij,t}$	Direct Vertical Specialization (j on i). See Section 3.
	$Centrality_{(i)}$	$\frac{1}{15}\sum_{t=1995}^{2009} Out_{i,t}^{30th}$	Outdegree Centrality of Order 30th. See Section 3
	$Proxy_{(i,j)}$	$\frac{1}{15}\sum_{t=1995}^{2009} (Distance_{(ij,t)})^{-1}$	Computed by using Floyd-Warshall algorithm. Denotes the network proximity between industries i and j.
	$IndSize_{(i)}$	$\frac{1}{15}\sum_{t=1995}^{2009} \frac{VA_{i,t}}{\sum_j^n VA_{j,t}}$	The share of industry's i value added on total aggregate value added. *Source*: WIOD
Pair-Wise	$A - Vertical$	$Avg(\omega_{ij}, \omega_{ji})$	Average Vertical Specialization.
	$D - Vertical$	$Abs(\omega_{ij} - \omega_{ji})$	Absolute Difference of Vertical Specialization.
	$A - Centrality$	$Avg(Out_i^{(30th)}, Out_j^{(30th)})$	Average Outdegree Centrality
	$D - Centrality$	$Abs(Out_i^{(30th)} - Out_j^{(30th)})$	Absolute Difference of Network Centrality
	$A - Proximity$	$Avg(Proxy_{(ij)}, Proxy_{(ji)})$	Average Network Proximity
	$D - Proximity$	$Abs(Proxy_{(ij)} - Proxy_{(ji)})$	Absolute Difference of Network Proximity
	$A - IndSize$	$Avg(IndSize_{(i)}, IndSize_{(j)})$	Average Industry Size
	$D - IndSize$	$Abs(IndSize_{(i)} - IndSize_{(j)})$	Absolute Difference of Industry Size

Table 8: Multinomial Logit: Explaining comovement by degree of synchronization ρ_c in the period 1995-2009

Estimated Equation: $log(\frac{Pr(\rho_c = m)}{Pr(\rho_c = m_0)}) = \delta_l \iota + X\beta^{(m)} + Z\lambda^{(m)} + \varepsilon_c$

$where\ m_0$: $\rho_c \ \epsilon \ (0, 0.5)$ and $\delta_l \iota$: Fixed effects by country

	$log(\frac{Pr(\rho_c = Strong^+)}{Pr(\rho_c = Weak^+)})$	$log(\frac{Pr(\rho_c = Weak^-)}{Pr(\rho_c = Weak^+)})$	$log(\frac{Pr(\rho_c = Strong^-)}{Pr(\rho_c = Weak^+)})$
$Asymmetry$	2.962***	2.166***	-2.064***
	(0.0491)	(0.110)	(0.0397)
$EURO$	1.355***	-0.533***	-0.669***
	(0.0213)	(0.0553)	(0.0198)
$LandSize$	-5.645***	7.195***	3.902***
	(0.0746)	(0.134)	(0.0421)
$Openness$	-3.180***	2.048***	2.430***
	(0.0459)	(0.0985)	(0.0329)
$EconomySize$	0.842***	-0.493***	0.153***
	(0.0151)	(0.0233)	(0.0142)
$Secondary \times Secondary$	3.088***	-1.896***	-0.277
	(1.070)	(0.659)	(0.412)
$Tertiary \times Tertiary$	2.113**	-1.198**	0.198
	(1.064)	(0.578)	(0.400)
$Secondary \times Tertiary$	2.240**	-1.518**	-0.0237
	(1.057)	(0.609)	(0.393)
$Primary \times Secondary$	1.434	-0.915	0.257
	(1.079)	(0.560)	(0.378)
$Primary \times Tertiary$	1.416	-1.026*	0.502
	(1.086)	(0.573)	(0.373)
$A - Centrality$	-0.185**	-0.494**	-0.0170
	(0.0806)	(0.206)	(0.0721)
$D - Centrality$	0.0580*	0.0875	0.00884
	(0.0336)	(0.0864)	(0.0390)
$A - Proximity$	11.19***	2.600	-3.909
	(3.611)	(9.331)	(2.480)
$D - Proximity$	-6.000***	-0.928	2.676**
	(1.588)	(3.670)	(1.356)
$A - Vertical$	10.94***	8.540	-3.374
	(3.711)	(7.413)	(2.430)
$(A - Vertical)^2$	-57.39***	-10.52	15.52***
	(15.52)	(10.29)	(4.873)
$D - Vertical$	1.083	-3.931	-0.672
	(1.667)	(2.789)	(0.999)
$A - IndSize$	-1.117	7.646	3.104
	(2.975)	(6.583)	(2.392)
$D - IndSize$	-0.262	0.343	0.00677
	(1.572)	(2.762)	(1.202)
N	22276	22276	22276

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. **Note**: Regression estimates includes Fixed Effects and clustered standard errors by country