Research Paper

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Production Networks, Sectoral Shocks and Aggregate Volatility in a Developing Economy: Insights From Morocco

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The role of the production network in shock propagation has been an issue of considerable interest since the Great Recession. However, the empirical literature has only focused on advanced and emerging countries. This paper aims to contribute to filling this gap by examining the case of Morocco, a developing country belonging to the lower-middle-income group. The question is whether its production network is a factor in amplifying idiosyncratic industry-level shocks or, conversely, a resilience factor. Overall, the findings indicate that this network is relatively sparse and balanced, compared to the sample of 66 countries for which input-output tables were published by the OECD in 2022. Idiosyncratic industry-level shocks have therefore a limited influence on aggregate volatility. In these conditions, it is unlikely that the Moroccan production network would serve as a significant propagation factor for sectoral shocks to the rest of the economy.

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RESEARCH PAPER

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1. INTRODUCTION

The role of industries in economic performance has long been a concern for economists, as evidenced by the groundbreaking work of Leontief (1941) in establishing input-output systems. The contribution of sectors to overall economic fluctuations has also received attention since the seminal work of Long and Plosser (1983). The Great Recession of 2008, partly caused by the financial sector's difficulties, brought this question back to the fore in economic debates. This has led to new literature (e.g. Acemoglu *et al*., 2016, 2012; Carvalho, 2014; Carvalho and Tahbaz-Salehi, 2019; Grassi and Sauvagnat, 2019; Jones, 2013), which has challenged the diversification hypothesis, once widely accepted, showing that sectoral shocks can propagate throughout the economy.

It is worth recalling that the diversification hypothesis suggests that shocks experienced in one industry will be offset due to the presence of a large number of industries within an economy, resulting in no significant impact on aggregate volatility (Acemoglu *et al*., 2012). However, empirical observations have demonstrated that not all industries contribute equally to the aggregate business cycle. The asymmetry at the industry level plays a vital role in determining whether idiosyncratic industry-level shocks can propagate throughout the economy.

These insights were gained by combining the economic framework with network theory. The interactions within the economy can be represented as a network, and this new framework has proven to be relevant for analyzing the role of idiosyncratic sectoral shocks and the mechanism of their propagation. The development of this corpus has, of course, benefited from statistical data in the input-output format that has become increasingly available, both over time and space.

However, empirical investigations in this area have been conducted in advanced and emerging countries. So far, developing countries have not been the subject of this kind of research. To address this gap, we determine whether the production network in Morocco, a lower-middle-income country, amplifies industry-level shocks or contains elements of resilience. Indeed, it will be insightful to investigate whether the patterns described in the literature also hold for these countries, and may explain their relatively high volatility (Agénor *et al*., 2000).

To achieve that, we analyzed Morocco's production network. We gauged the distribution of its centrality measures (importance of its sectors) by fitting power-law distributions. The robustness of our results was validated using alternative data (OECD's SUT) and simulations of theoretical networks. Our investigation highlights the Moroccan production network's structural characteristics as relatively sparse and balanced when compared to a sample of 66 countries' input-output tables published by the OECD. As a result, shocks at the industry level have a limited impact on overall volatility. Therefore, it is unlikely that the Moroccan production network would act as a significant propagator of sectoral shocks to the broader economy.

This paper is organized as follows: after reviewing the literature in section 2, we provide a theoretical section explaining the economic model underlying the link between the structure of production networks and the propagation of shocks. We then present the key elements of network theory. Empirical investigations are presented in section 4, followed by the discussion of our results in section 5. The final section concludes.

2. RELATED LITERATURE

The recognition of the existing interconnections between economic sectors as a necessity for understanding economic fluctuations is longstanding. Beyond the early writings of Leontief (1941) on these propagation mechanisms, this literature was relaunched with the consideration of production networks (interconnections between sectors) in the analysis of fluctuations following the great crisis of 2007 in the U.S.A. It was observed that a shock, localized at a sectoral or lower level, can spread and generate negative developments at the national economy level.

This new literature on the link between sectoral structure and economic volatility has been propelled notably by the works of Acemoglu *et al*. (2015, 2012) and Jones (2013). These authors showed that shocks emanating from sectors can propagate via the links between them with potentially significant consequences on the overall volatility of the economy and its growth. In particular, Acemoglu *et al*. (2015) argued that the links between the different sectors of the economy can play a leading role in determining the magnitude and frequency of major economic slowdowns. The *"puzzle of small shocks and large cycles"* of Bernanke *et al*. (1996) finds a new solution here, via the interaction between the underlying structure of the production network and the shape of the distribution of microeconomic shocks.

In their seminal paper, Acemoglu *et al*. (2012) showed that when the economy becomes more disaggregated (the number of industries is large), the rate at which overall volatility decreases is determined by the structure of the production network. This structure is illustrated by the centrality of the sectors as suppliers. More specifically, significant overall volatility is obtained from idiosyncratic sectoral shocks only if there is a significant asymmetry in the roles that sectors play as suppliers.

In the same vein, Carvalho and Tahbaz-Salehi (2019) explicitly modeled the role of linkages as a propagation channel in the economy, and a transmitter of microeconomic and sectoral shocks to aggregate fluctuations, via a benchmark model and its variants. While this paper was generally consistent with the conclusions of Acemoglu *et al*. (2012), it differed in the centrality measure to be considered.

The mechanism of shock propagation between sectors was empirically tested by Acemoglu *et al*. (2016). Their investigation showed that productivity shocks propagate downstream, and demand shocks do so upstream (in accordance with theoretical predictions). Overall, they highlighted that the multiplier effect of the production network is substantial (the overall effect is up to six times the initial shock).

Basic models incorporating production networks have undergone several extensions. In this regard, endogenous intersectoral exchanges have been considered (Acemoglu and Azar, 2020; Oberfield, 2018), and the representative agent assumption has been surpassed. Production technology has been generalized to capture factor substitutability (Baqaee and Farhi, 2018), or financial frictions and distortions (Bigio and La'O, 2020, 2016). Furthermore, the role of production networks in the understanding of fiscal policy, industrial policy, and finance was discussed by Grassi and Sauvagnat (2019). The work of Acemoglu *et al*. (2016b) showed how innovation policies can be used to improve economic performance by encouraging the formation of more-efficient production networks.

Acemoğlu *et al*. (2016) introduced a formal and unifying theoretical framework for the global link between production networks and macroeconomics from a canonical perspective. Beyond the nature of actors' reactions and preferences, the authors emphasized that the aggregation of sectoral choices is another determining factor in the role of idiosyncratic shocks on aggregate volatility. According to them, taking into account this second factor allows the differences observed in the literature's results to be explained.

Since the first investigations into the U.S.'s production network, a large literature has been developed around the world. The possibility that the production network can lead to significant effects of sectoral shocks on global fluctuations has been documented, among others, for Australia (Anufriev *et al*., 2016), Poland (Gradzewicz, 2020), Brazil (Gonçalves *et al*., 2020), China (Hu *et al*., 2017; Yu *et al*., 2022), Ecuador (Romero *et al*., 2018), Japan (Chakraborty *et al*., 2018; Fujita *et al*., 2019), and for European Union countries (Alatriste-Contreras, 2015; Contreras and Fagiolo, 2014; Giammetti *et al*., 2020). Others have revisited the case of the United States (for example, Foerster and Choi, 2017; Hou, 2021; Molnár and Csala, 2022; Sungki *et al*., 2018). The consequences and transmission of certain economic shocks have been revisited by incorporating production networks. This is the case for oil shocks, for which Caraiani (2019) and Caraiani *et al*., (2022) have shown that the links between sectors of activities amplify the consequences of these shocks.

3. METHODOLOGICAL BACKGROUND

3.1. Canonical Model

In its standard version, the underlying model of the production network that we borrow from Acemoglu *et al* (2012) and Carvalho and Tahbaz-Salehi (2019) is a static version of the sectoral general equilibrium model of Long and Plosser (1983). This basic model assumes an economy composed of N sectors, in which pure and perfect competition reigns. Each sector produces a unique product. The production technology is modeled via a Cobb-Douglas function with constant returns to scale. For a sector i, the production y_i is obtained (via a representative firm) by transforming, on the one hand, the quantity of labor l_i and, on the other hand, the intermediate inputs x_{ij} it purchases from other sectors of the economy:

$$y_i = z_i \zeta_i l_i^{\alpha_i} \prod_{j=1}^{N} x_{ij}^{a_{ij}} \tag{1}$$

With α_i the labor share in sector i, z_i is the productivity shock (in the Hicks sense), ζ_i is a normalisation constant that depends on the model parameters only. x_{ij} is the quantity consumed of product j for the production of sector *i*. Physical capital is absent as it has no impact on the results deduced (Acemoglu *et al*., 2016a). The constancy of returns to scale implies that the technological parameters α_i and a_{ij} satisfy the condition $\alpha_i + \sum_{j=1}^{N} a_{ij} = 1$. Since preferences are expressed in Cobb-Douglas, maximising producer profit implies that the coefficients a_{ij} coincide with the technical coefficients from the input-output analysis. This gives them an economic interpretation. Indeed, producer equilibrium implies that the weight (in value) of an input *j* in the output (in value) of sector i is fixed and equal to the corresponding exponent in the production function. The technology adopted results in equilibrium in the equality[1] $\frac{p_j x_{ij}}{p_i x_i} = a_{ij}$.

The economy is populated by a representative household that sells its labor inelastically with logarithmic preferences for the N goods produced by the economy:

$$u(c_i, \cdots, c_N) = \sum_{i=1}^{N} \beta_i \log\left(\frac{c_i}{\beta_i}\right) \tag{2}$$

With c_i the final consumption of product i. The parameter β_i translates the weight of good i in the preferences of the representative household (with the normalization $\sum_{i=1}^{N} \beta_i = 1$).

The general equilibrium in this economy under pure and perfect competition consists of a quantity vector and a price vector guaranteeing optimized behavior and equilibrium in the markets. The producer maximizes his profit : $\pi_i = p_i y_i - w l_i - \sum_{j=1}^{N} p_j x_{ij}$ by taking the prices of products p_j and labour w as given. The first-order conditions imply :

$$\begin{aligned} x_{ij} &= a_{ij} p_i y_i / p_j \\ l_i &= \alpha_i p_i y_i / w \end{aligned} \tag{3}$$

By replacement, we can obtain the relative prices[2] :

$$log\left(\frac{p_i}{w}\right) = \sum_{j=1}^{N} a_{ij} log\left(\frac{p_j}{w}\right) - \varepsilon_i \tag{4}$$

With $\varepsilon_i = \log(z_i)$. This means that relative prices (wages as numeraire) are expressed as a function of productivity shocks (in the log). In matrix form, the last equation system can be rewritten as follows:

$$\hat{p} = A\hat{p} - \varepsilon \tag{5}$$

With $\hat{p}$ the vector of relative prices and ε the vector of shocks. In the end, relative prices can be deduced as a function of sectoral productivity shocks and the production network:

$$\hat{p} = -(I - A)^{-1}\varepsilon \tag{6}$$

[1] For this reason, this basic model is considered more sensible than other variants that incorporate the exponents of x_{ij} in the production function as a proportion of x_{ij} in total intermediate consumption (as in Carvalho, 2014), or as a proportion of x_{ij} in value added, i.e. $y_i - x_i$ (as in Acemoglu *et al.*, 2012).

[2] Note in passing the negative effect of the productivity (supply) shock on the (relative) price.

On the other hand, the consumer maximizes his utility (equation 2) under his budget constraint $\sum_{i=1}^{N} p_i c_i \leq w$. This leads to his demand function for good i: $c_i = \beta_i w / p_i$.

The market equilibrium of product i is satisfied by the equality between the quantity demanded and the quantity offered : $y_i = \sum_{j=1}^{N} x_{ij} + c_i$ or -by substitution :

$$p_i y_i = \beta_i w + \sum_{j=1}^{N} a_{ij} p_j y_j \tag{7}$$

Dividing by GDP, here equal to w (resulting from the budget constraint according to which w is equal to final consumption, the only demand item in this '*Robinson Crusoe*' economy), we obtain :

$$\lambda_j = \beta_j + \sum_{i=1}^{N} a_{ij} \lambda_i \tag{8}$$

With λ_i is the weight of *Domar*, defined, for sector i, by the ratio of its sales to the GDP of the aggregate economy, i.e. $\lambda_i = p_i y_i / PIB$. Written more compactly, this last equality leads to : $\lambda = (I - A^{'})^{-1} \beta = L' \beta$. Under these conditions, the sectoral productions in equilibrium are defined (in the log) by :

$$\log(y_i) = \sum_{j=1}^{N} l_{ij} \varepsilon_j + \delta_i \quad ou \quad log(y) = L\varepsilon + \delta \tag{9}$$

With δ_i is a shock-independent constant.

This last relationship shows that the output of one sector depends on the shocks experienced by the others, which implies that inter-sector trade can play the role of the propagation mechanism of sectoral shocks. This propagation is captured by the inverse Leontief matrix L matrix (and not A), incorporating direct and indirect effects between sectors. It should also be noted that the impact on sector i of the shock experienced by sector j, captured by l_{ij}, propagate from a sector to its customers (*downstream*). Recall that l_{ij} measures the importance of sector j, as an input seller, for sector i, which means, by ricochet, that sector i is all the more affected by ε_j of sector j, the latter is more important as one of its customers (l_{ij} important).

This mechanism is economically intuitive. A negative productivity shock in a sector i generates an increase in the price of that sector's product (p_i), as follows from the (price) equation. The sectors that will be affected first are those that purchase directly its products as inputs. In a second step, these primary customer sectors will, in turn, affect their customer sectors and so on. All the effects are captured by the matrix L which adds up the direct and indirect effects of a shock.

In the same vein, it is useful to note that the weight of Domar, as seen previously by the relation $\lambda = L'\beta$ is a function of the preferences β and the structure of the sectoral links (production network), materialized by the Leontief matrix L. It is thus independent of productivity shocks, which means that, *in fine,* quantities and prices adjust so that the structures remain identical.

The second consequence of this model is that aggregate GDP is a weighted average of sectoral productivity shocks:

$$\log(PIB) = \sum_{i=1}^{N} \lambda_i \varepsilon_i \quad ou \quad \log(PIB) = \lambda' \varepsilon \tag{10}$$

The weights are nothing other than Domar weights, which make them sufficient, as a measure and statistic, to know how a (productivity) shock in a sector impacts overall GDP (output). They thus summarize the transition from industry-level shocks to aggregate GDP[3].

3.2. Conditions for Shock Propagation

The theoretical background we have outlined demonstrates the production network's function as a transmission mechanism, facilitating the propagation of sectoral shocks throughout the entire economy via the exchange between industries of production inputs. Nevertheless, it remains crucial to check whether this transmission mechanism can generate additional volatility at the level of aggregate GDP. In other words, it is imperative to ascertain the conditions under which a sectoral shock can give rise to a significant and observable fluctuation at the aggregated level. It is noteworthy that addressing this question is crucial, as a sectoral shock may not necessarily yield measurable repercussions at aggregate level.

To answer these questions, we take the basic model but with regularity assumptions. These assumptions ultimately allow the responses to be subtracted through comparative reasoning. Thus, we assume that productivity shocks ε_i are independently and identically distributed with zero mean and unique variance σ. Likewise, the share of labor in production is the same for all sectors ($\alpha_i = \alpha$). The aggregated volatility σ_{agg} can, in these conditions, be formulated as follows:

$$\sigma_{agg} = \sqrt{var(\log(PIB))} = \sigma \, ||\lambda|| \tag{11}$$

With $||\lambda|| = \left(\sum_{i=1}^{N} \lambda_i^2\right)^{1/2}$ and the (not demeaned) second-order norm or moment of the Domar weights. Since [4]$\sum_{i=1}^{N} \lambda_i = 1/\alpha$ then we can rewrite the aggregate volatility by[5]:

$$\sigma_{agg} = \frac{\sigma/\alpha}{\sqrt{N}} \sqrt{1 + N^2 \alpha^2 var(\lambda)} \tag{12}$$

[3] i.e. the theorem of Hulten (1978).

[4] This equality is deduced from the equilibrium of the markets $\lambda_j = \beta_j + \sum_{i=1}^{N} a_{ij} \lambda_i$. Summing up the two sides, we obtain $\sum_{j=1}^{N} \lambda_j = 1 + \sum_{j=1}^{N} \sum_{i=1}^{N} a_{ij} \lambda_i = 1 + \sum_{i=1}^{N} \lambda_i \sum_{j=1}^{N} a_{ij}$ because $\sum_{j=1}^{N} \beta_j = 1$. Knowing that $\sum_{j=1}^{N} a_{ij} = 1 - \alpha_i = 1 - \alpha$, then $\sum_{j=1}^{N} \lambda_j = 1 + (1-\alpha) \sum_{i=1}^{N} \lambda_i$, which implies that $\sum_{i=1}^{N} \lambda_i = 1/\alpha$.

[5] Given that $E(\lambda) = \alpha^{-2}$ then $\sum_{i=1}^{N} \lambda_i^2 = N \times E(\lambda) = N \times (var(\lambda) + (N\alpha)^{-2})$. Then $\sigma_{agg} = \sigma \, ||\lambda|| = \sigma\sqrt{Nvar(\lambda) + 1/N\alpha^{-2}}$ which leads to equation 12.

Thus, aggregate volatility depends closely on the heterogeneity of the sectors in terms of weight. With this last writing of σ_{agg} we find, moreover, that the diversification argument is only valid if all sectors have the same weight[6] . This is because, in this special case, the overall volatility is proportional to $1/\sqrt{N}$.

To isolate the role of the production network (equality $\lambda = L'\beta$ informs us that Domar weights also depend on consumer preferences), we adopt another regularity assumption, namely $\beta_i = \frac{1}{N}$. In this case, the variations in Domar weights will be due exclusively to changes in the production network. In this case, $\lambda = L'\mathbb{1}/N$ with $\mathbb{1}$ is the identity vector. It follows that $\lambda_i = v_i/N$ with $v_i = \sum_{j=1}^{N} l_{ji}$. Being defined by the sum of the $i^{ème}$ column of L, v_i reflects the importance of sector i as a seller (directly and indirectly) to the productive system.

Under these conditions and assuming the vector v= $[v_i]$ the aggregate volatility is written as follows:

$$\sigma_{agg} = \frac{\sigma}{\sqrt{N}}\sqrt{\alpha^{-2} + var(v)} \tag{13}$$

This formulation is the main contribution of the seminal paper by Acemoglu *et al.* (2012): sufficient heterogeneity of the industries within an economy in terms of supply power can lead to a significant contribution of sectoral shocks to aggregate volatility. This contrasts with the assumption of diversification, where industries are relatively homogeneous. Equation 13 reflects the transition mechanism from sectoral volatility to aggregate volatility. Specifically, if v is distributed according to a power-law with parameter $\gamma \in [1,2]$, then σ_{agg} is proportional to $N^{(1/\gamma-1)}$ when N is large. The argument for diversification only holds when $\gamma > 2$, which corresponds, as noted earlier, to less-asymmetric sectors.

The input-output system's recursive nature and the introduction of graph theory, which will be elaborated further in the subsequent section, shed light on the contribution of the system to the formation of aggregate volatility. Indeed, the matrix L can be written as follows[7]: $L = I + L \cdot A$. This implies that the v_i are linked to each other by[8]:

$$v_i = 1 + \sum_{j=1}^{N} a_{ji} v_j \tag{14}$$

This representation coincides with the Bonacich centrality measure (see next section for details). This measure reflects the idea that a sector is central in an economic network if it sells inputs to other sectors of the same importance (i.e. they are also central).

[6] Corresponding to the fact that all sectors have the same weight of Domar $\lambda_i = \lambda$ because in this case $y_i = y_j = y/N$.

[7] Indeed, given that $\mathrm{L} = (\mathrm{I} - \mathrm{A})^{-1}$, then $\mathrm{L} \cdot (\mathrm{I} - \mathrm{A}) = \mathrm{I}$, and $\mathrm{L} \cdot \mathrm{I} - \mathrm{L} \cdot \mathrm{A} = \mathrm{I}$, establishing at the end the relationship $\mathrm{L} = \mathrm{I} + \mathrm{L} \cdot \mathrm{A}$.

[8] By multiplying the above equation by $\mathbb{1}$' transposes the unit vector as follows: $\mathbb{1}'L = \mathbb{1}'I + \mathbb{1}'L \cdot A$. This leads to : $v' = \mathbb{1}' + v'A$, hence the result given.

Thus, according to equation 13, microeconomic or industry-level shocks can generate more significant macroeconomic fluctuations when sectors are heterogeneous in terms of centrality. Economies characterized by more or less homogeneous centrality (e.g. complete or circular economies) of their activities would, therefore, be less volatile compared to economies where a few sectors are much more central than others. Carvalho and Tahbaz-Salehi (2019) derived a significant finding from these interpretations, namely, that economies with lower levels of interconnectedness exhibit greater volatility and demonstrate reduced co-movement between their respective sectors. This phenomenon can be elucidated by invoking the concept of diversification, wherein the density of inter-sectoral connections enhances the potential for mitigating sector-specific shocks.

Acemoglu *et al*. (2012) provided nuance to this formulation by distinguishing between connections based on their order and timing. It should be noted at this point that Bonacich centrality, as it measures the overall supply power of a sector, reflects all connections regardless of their order (after the impact process has converged).

Formally, the volatility of GDP is bounded (when N is large) by :

$$\sigma_{agg} > \frac{1}{\sqrt{N}} + \frac{1 + CV(C^{Out})}{\sqrt{N}} + \frac{\sqrt{S_2}}{N} \tag{15}$$

Here, C^{Out} is the measure of first-order output centrality (outdegree centrality to be more precise), defined by $C^{Out} = A \cdot \mathbb{1}$ where A is the matrix of technical coefficients a_{ij}, CV is the coefficient of variation, and S_2 is the sum of second-order output centralities. The latter reflects a sector's ability to link with sectors that have significant supply capacity. This conception can be generalized to higher-order connections without altering the intuition of its result.

The intuition behind this inequality (15) is that if the supply capacities of sectors (centralities) are sufficiently heterogeneous, which means a higher coefficient of variation, aggregate volatility tends to be higher. Central sectors influence the rest of the economy and ultimately impact GDP volatility.

The second-order characteristic of centrality can be meaningfully understood by examining its distribution. Increased volatility aligns with heavy-tailed distributions, where high values are more frequent compared to a normal (Gaussian) distribution. An analytical approach to studying this transmission of volatility is through the use of power-law distributions: as long as its parameter is empirically small, so long as the sectoral variance ($CV\left(C^{Out}\right)$ or $var(v)$) is large, and vice versa.

Recall the definition of the power-law distribution (see more details in Clauset *et al*., 2009). A variable C follows this distribution if :

$$F_C(x) = P(C > x) = ax^{-\xi} \quad pour \quad x > a^{1/\xi} \tag{16}$$

With ξ the shape *parameter*. Note that this formulation can also be rewritten, with minor transformations, in the form of density, i.e. $P_C(x) = P(C = x) = \gamma x^{-\alpha}$. In this case, α is the *power* parameter and is related to ξ via the following relationship: $\alpha = \xi + 1$. Acemoglu *et al* (2012) showed that sectoral volatility σ decreases at the aggregation when $1 < \xi < 2$ at a rate of $N^{1-1/\xi}$, which is lower than that resulting from the diversification assumption ($N^{1/2}$). The aforementioned assertion holds for both first and second-order connections, as stated by the same author.

3.3. Production Network and Input-Output Framework

Network theory, an important part of discrete mathematics, plays a key role in the economics of production networks (Newman, 2018). A network, or graph, is a set of elements linked together by relationships. The production system of an economy, as described by inter-industry trade, can be represented as a directed and weighted network. In this sense, the elements of the graph, called the production *network*, are the industries of the economy, and the connections are the transactions (in intermediate inputs) between them.

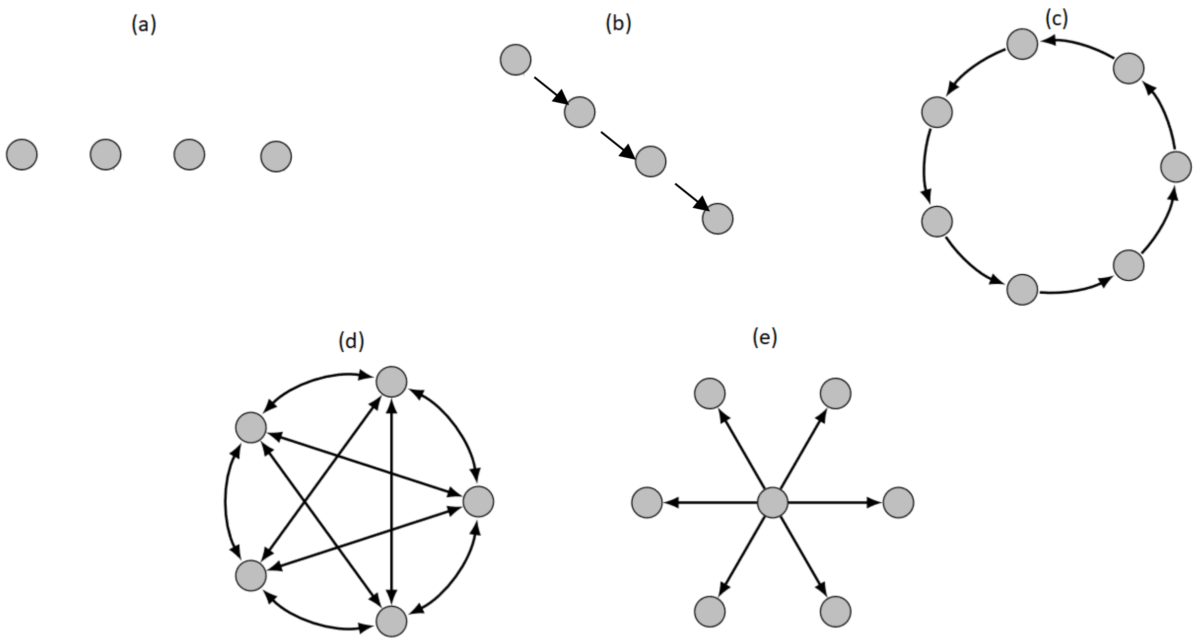
As discussed previously, the graph is not just another, more-effective representation of the input-output system. It is considered superior in representing and comprehending the production network and its complexity holistically. While input-output analysis tools offer individual analyses and measurements by industry, the network-theory framework enables a holistic description of a production network.

The application of network theory provides valuable insights into the analysis of input-output systems about shock propagation. To enhance comprehension in this area, Figure 1 illustrates specific and stylized networks in an economic context. These didactic cases, though extreme and designed for academic purposes, serve to enhance understanding of actual networks and their characteristics (Acemoglu *et al*., 2012; Carvalho and Tahbaz-Salehi, 2019; Grassi and Sauvagnat, 2019). Moreover, these cases prove valuable because real-world networks typically exhibit a combination of these depicted scenarios. Notably, the following examples can be cited in this regard:

- *Horizontal* economy: This economy is composed of independent industries, each with intermediate self-consumption. These industries are not interconnected, as shown by an empty graph (Figure 1.a). Consequently, shocks affecting one sector do not propagate to the others. There is a case of an absence of a propagation process within a network.
- *Vertical* economy: This economy is characterized by a hierarchical relationship among its industries. Each industry supplies another without the possibility of direct or indirect feedback, thereby forming an open chain (Figure 1.b). One sector is positioned upstream in the chain, producing primary products requiring further transformation, while another sector is located downstream, providing directly to the consumer. Between these two extreme sectors, all intermediate industries act as connectors. This vertical pattern reflects the stages of industrial transformation from the primary product to the final product. All sectors in this arrangement have equal influence (Bigio and La'O, 2016).
- *Circular* economy: In this economy, each sector is linked to *two* others (a supplier sector and a customer sector). Ultimately, all sectors are indirectly linked to each other, forming a closed chain (Figure 1.c). All industries serve as connectors and have an equal impact on the network. This configuration forms a symmetric network, which mitigates the internal propagation mechanism (Carvalho and Tahbaz-Salehi, 2019).

- *Complete* economy: Each sector is linked to all other sectors of this economy (Figure 1.d). The argument of diversification, which posits that shocks offset each other when the number of industries is sufficiently large, applies to this balanced network (Acemoglu *et al.*, 2012). The latter is relatively uninformative. With sectors exhibiting homogeneous centrality, this type of network presents a weak system for propagating industry-level shocks (as indicated by zero variance in centrality, as shown in equation 13 above).
- *Star* economy: It is distinguished by the presence of a central sector within the network that communicates (in one direction or another) with all other sectors (Figure 1.e). This network exhibits extreme inequality. An idiosyncratic shock affecting this central sector has a significant impact on the rest of the economy. Furthermore, this type of economy reveals a centers-periphery structure: dominant sectors (centers) and peripheral industries with low influence.

Figure 1: Schematic Network of Stylized Economies



In the real world, observed production networks are more complex. Hence, application of network theory tools is valuable to identify their internal patterns. Beyond their pedagogical value, these simple cases also contribute to a better understanding of more complicated networks, as observed empirically. To do that, several measures are used in the analysis of production networks. The first one is density, which indicates the degree of internal connectivity. This density, noted D, is calculated by dividing the number of existing connections in the network, noted C, by the number of potential connections (N^2): $D = C/N^2$.

The centrality of an industry in the production network is important for our purpose because it sheds light on the main 'actors'. The main centrality measures related to the shock's propagation concern are those based on primal connections and Bonacich's centrality. The former are equal, for a given industry, to the weighted aggregation of its links with the other industries of the network. These define the direct importance of a sector. However, a sector may also have indirect effects, which are summarized by Bonacich's centrality. This is calculated by[9]:

$$C^B = \beta(I - \alpha A)^{-1}\mathbb{1} \tag{17}$$

This centrality measure is also the most compatible with the economics of production networks as developed in the theoretical section (Acemoglu *et al.*, 2012; Carvalho, 2014; Carvalho and Tahbaz-Salehi, 2019). This allows us to gauge, for an industry, its supply's power to the rest of the economy.

4. PRODUCTION NETWORK AND SECTORAL SHOCK: PROPAGATION OR RESILIENCE FACTOR?

4.1. Data Used

The data used comes from various sources. The core data are the Moroccan Supply and Use Tables (SUT) for the three available base years (2014, 2007, and 1998) published by the High Commission for Planning (Haut Commissariat au Plan, 2022a, 2022b, 2022c). These SUTs have been transformed into Input-Output Tables (IOT) in several stages. The first consists of eliminating all foreign transactions and all margins, taxes, and subsidies, leaving only transactions between internal agents expressed at the basic price. The second is to construct an industry-industry flow matrix, following the fixed product sales structure assumption. Two industry classifications are used in these SUTs (ISIC 3 and ISIC 4), which make it necessary to adopt a common classification for comparison purposes. For additional comparison, we complete the data with the latest edition of the international input-output tables published by the OECD (OECD, 2021). This database covers 66 economies, including Morocco (see the appendix for details).

4.2. Power-law Fitting

As shown earlier, the heterogeneity between industries can lead to the propagation of a sectoral shock to the aggregate economy. The key question remains whether the sector's asymmetry is significant enough to give rise to idiosyncratic sectoral-shock propagation mechanisms. This is the question that we will try to answer in this section. After the statistical distributional analysis of centralities, we will attempt to measure empirically the propagation mechanisms specific to the Moroccan production network. The robustness of our results is tested in the last paragraphs.

Figure 2 presents the distributions of measures of both outdegree and indegree centrality. At first glance, the distribution of indegree centrality is more symmetrical than the others (Figure 2.b). The extreme values of indegree (the lowest and highest) are relatively rarer than for the two other centralities. Although not symmetrical, there is significant concentration around its central tendencies (less so in 1998). In other words, this centrality is nothing but the rate of intermediate

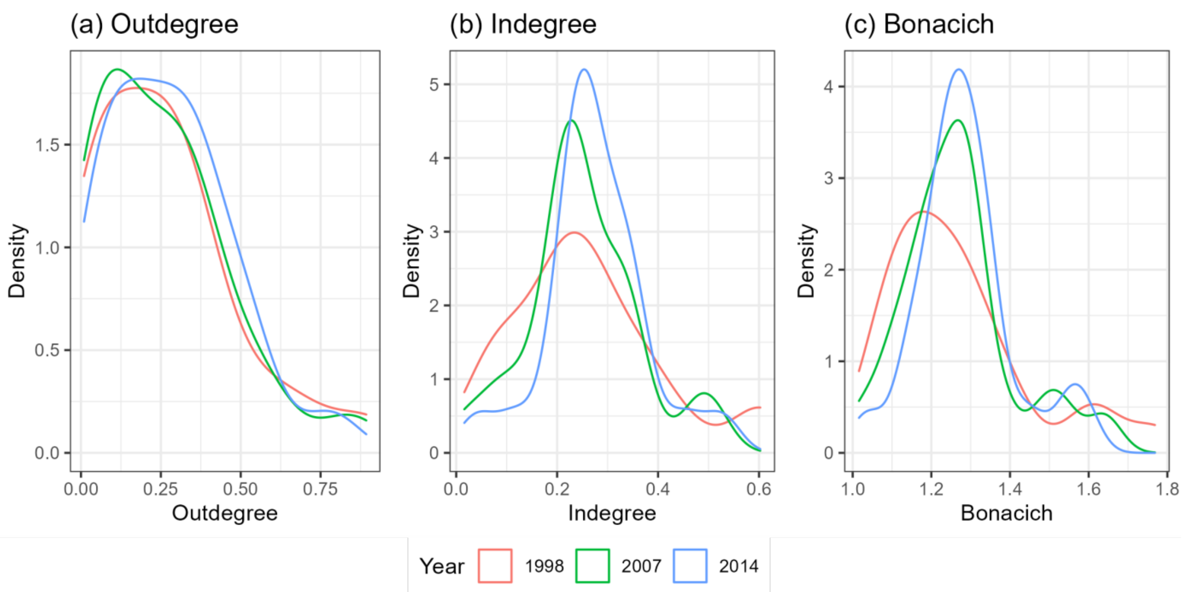
[9] α and β are positive constants (they are generally chosen as follows $\beta = \alpha = 1$). β is the minimum centrality affected to the sectors. The parameter α reflects the trade-off between the endogenous factors and exogenous factors (minimum centrality) . When α converges to 0 then C^B converges to the β vector.

consumption. In this sense, this distributional form is not unique to Morocco, as it has also been observed in several other countries.

Regarding outdegree centrality, it is noticeable that the offers of production input are much less symmetrical than the demands of input (indegree) (Figure 2.a). The average outdegree oscillates between 0.25 and 0.28 depending on the year. Their medians are slightly lower (between 0.23 and 0.25) while the modal values are between 0.10 and 0.18. This hierarchy of central tendencies is corroborated by a higher skewness coefficient (0.7 in 2014 and 1.1 in 1998) than in the case of indegree (0.2 in 2014 and 0.7 in 1998). This positive asymmetry (the right tail is longer than the left) is symptomatic of the presence of basic products that are general-purpose inputs used by many other sectors. As mentioned in the previous section, the services provided by the research and development industry, and services provided to businesses (MN0), transportation (H00), trade (G00), as well as agriculture (A00), can be considered as part of these basic inputs that are furthermore diffused widely throughout the Moroccan production network.

The overall strength of supply, measured by the Bonacich centrality, presents a distribution at the crossroads of the two previous centralities (Figure 2.c). It is relatively shifted to the left compared to indegree but displays less frequent minimal values compared to outdegree. This observation may shed light on the links existing between indegree and outdegree centralities on the one hand, and Bonacich on the other hand. The average Bonacich centrality is 1.27, while its median is only slightly lower (1.26). The maximum centrality reaches 1.52 (sector of construction). The distribution for 1998 was relatively different from the two other years. The skewness coefficient was 1.13 compared to 0.6 in 2014. The most extreme scores (i.e. the central industries) were more frequent during that year.

Figure 2: Distribution of the Centralities



Note: This figure plots, for 2014, 2007, and 1998, the densities of the three centrality measures: outdegree centrality in graph (a); indegree centrality in graph (b); Bonacich centrality in graph (c).

Source: TRE of 2014, 2007, and 1998, HCP. Authors' calculations.

The outdegree and Bonacich distributions exhibit more visible right tails, particularly for 1998. However, this configuration does not necessarily imply the existence of important industries that could influence the aggregate volatility of the economy. To address this issue, we conform to the literature and adjust the outdegree centrality to the power-law distribution. These adjustments are based on the method developed by Clauset *et al*., (2009).

Table 2 presents the estimation results. These estimates lead to a power parameter ranging from 3.3 to 4.8 for the outdegree centrality, depending on the classification system and the year considered. Furthermore, this parameter has increased since 1998. This reflects a rebalancing of the Moroccan production network, whereby activities have become more homogeneous over the years. This is consistent with the differences observed between the outdegree distributions (especially in 1998, which is the least centralized) and the developments described in the previous section that the Moroccan production network has undergone. In particular, the quantitative densification of the network over the years has made it more balanced, resulting in fewer central industries.

Table 2: Power-Law Fitting

Years	2014	2014	2007	1998
Classification used	27 industries	23 industries		
Power parameters	**4,80**	**4,81**	**4,04**	**3,32**
Number of industries (observations)	27	23	23	23
Number of observations in the fitting	10	9	8	11

Note: The table provides, for each year and classification system considered, the power parameter (α) of the adjustment of outdegree centralities to power law distributions using the method developed by Clauset *et al*., (2009), and the number of observations retained (greater than the minimum threshold). These estimates were carried out for the three base years (2014, 2007 and 1998). For 2014, adjustments were made for both classification systems (27 and 23 industries respectively). To make comparisons between the three years, we have adopted the 23-industries classification proposed by Elguellab and Ezzahid (2022).

Source: TRE of 2014, 2007 and 1998, HCP. Calculations by the authors.

Finally, the power parameter is empirically higher than the threshold of 3 (shape parameter higher than 2 respectively, see equation 16 above), below which the sectoral volatility spreads to the others and ultimately influences the volatility of GDP[10]. The parameters of the Moroccan economy are, in this sense, different from what is documented in the literature. Thus, the Moroccan production network is probably not of the *scale-free* type and is thus not likely to channel industry-level shocks to the rest of the economy. On the contrary, it has a sectoral structure in which these shocks tend to offset rather than amplify each other

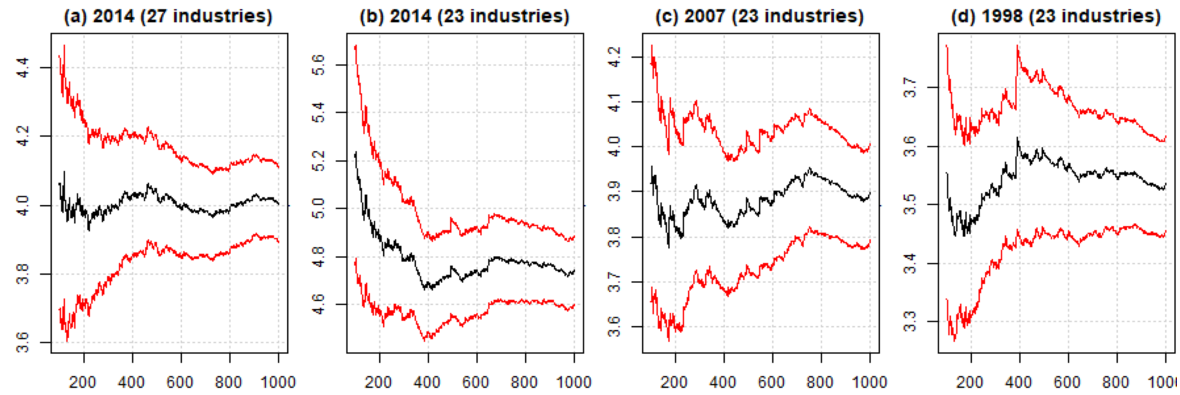
4.3. Robustness check

The various estimates in the previous paragraph seem to lead to the same conclusion: the absence of an industry that can significantly influence aggregate volatility. And this is true whatever the year and the desegregation adopted. This indirectly constitutes a first indication of the robustness of the aforementioned conclusion. To verify this conclusion differently, simulation exercises were

[10] We have limited ourselves to the first-order connections as the empirical values of the power parameters are above the threshold of 3.

carried out. They show the stability of estimates around the first results (Figure 3). The 1,000 draws carried out led to similar and robust estimates. Despite this, the fact remains that the small number of observations used in the adjustments to the power distributions is not sufficient to definitively assure the robustness of our initial results. As shown in Table 2 and visually in Figure 4, these estimates will be sensitive to changes in the base data.

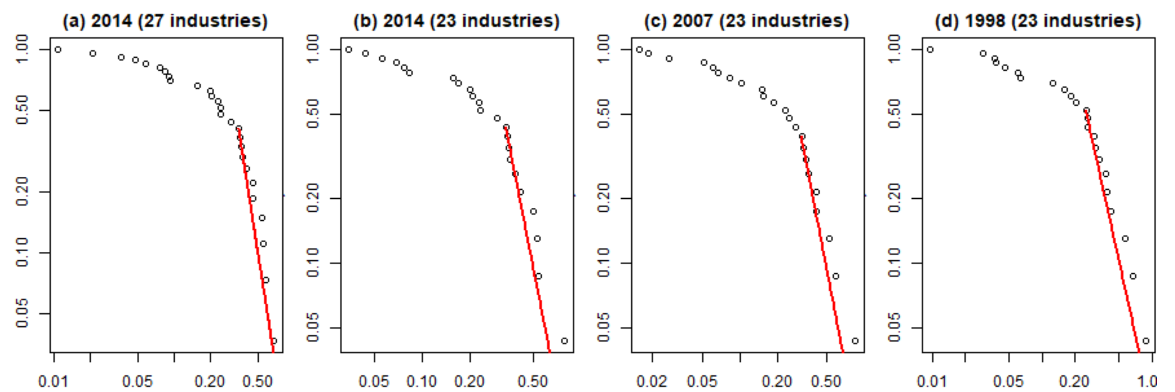
Figure 3: Bootstrap Simulation of Power Parameters



Note: These graphs visualize, for each year and classification, the evolution and convergence (black lines) of the power parameters over 1000 draws using the Bootstrap method. See details in (Gillespie, 2020, 2015). The red curves indicate the 95% confidence intervals. For 2014, adjustments were made for both classification systems (27 and 23 industries respectively). To make comparisons between the three years, we adopted the 23-industries classification proposed by Elguellab and Ezzahid, (2022).

Source: TRE of 2014, 2007 and 1998, HCP. Calculations by the authors.

Figure 4: Zipf's Plot and Power-Law Fitting



Note: These plots show visually, for each year and classification, the quality of the power-law fitting. The red lines correspond to the estimated models, and the points correspond to outdegree centrality scores. The fitting lines cover points beyond the minimum threshold according to the approach of Clauset *et al.*, (2009). For 2014, adjustments were made for both classification systems (27 and 23 industries respectively). To make comparisons between the three years, we have adopted the 23-industries classification proposed by Elguellab and Ezzahid (2022).

Source: TRE of 2014, 2007 and 1998, HCP. Calculations by the authors.

In this context, and to further validate the robustness of these empirical results, we repeat the estimation of power distributions, but with the OECD Input-Output Tables. The results obtained from these new estimates corroborate our initial conclusions (see Table 3). On the one hand, the power parameter remains high. On the other hand, the balancing of the generation network is also visible from these second estimates, since the power parameter also increased between 1998 and 2014. The only exception, compared to the estimates based on HCP data, is that the generation network in 1998 can be considered, with OECD data, as scale-free (shape coefficient less than 2).

Table 3: Power-Law Fitting (OECD Tables)

Years	2014	2007	1998
Power parameter	**3,23**	**3,26**	**2,80**
Number of industries (observations)	44	44	44
Number of observations in the fitting	11	9	20

Note: The table gives, for each year, the power parameter (α) of the fitting of outdegree centralities to power distributions according to Clauset et al., (2009), and the number of observations retained (above the minimum threshold). These estimations were carried out for three years (2014, 2007, and 1998) to make the results more comparable with those in Table 2. The OECD nomenclature consists of 45 industries.

Source: OECD IO tables. Authors' calculations.

We adopt a simulation-based approach for our final robustness check but in a different way. This exercise consists of building a large number of theoretical networks according to *a priori* chosen characteristics, which will be considered as a benchmark for the Moroccan production network. We simulate two types of theoretical networks, calibrating them according to the characteristics of the Moroccan network (the number of industries and connections).

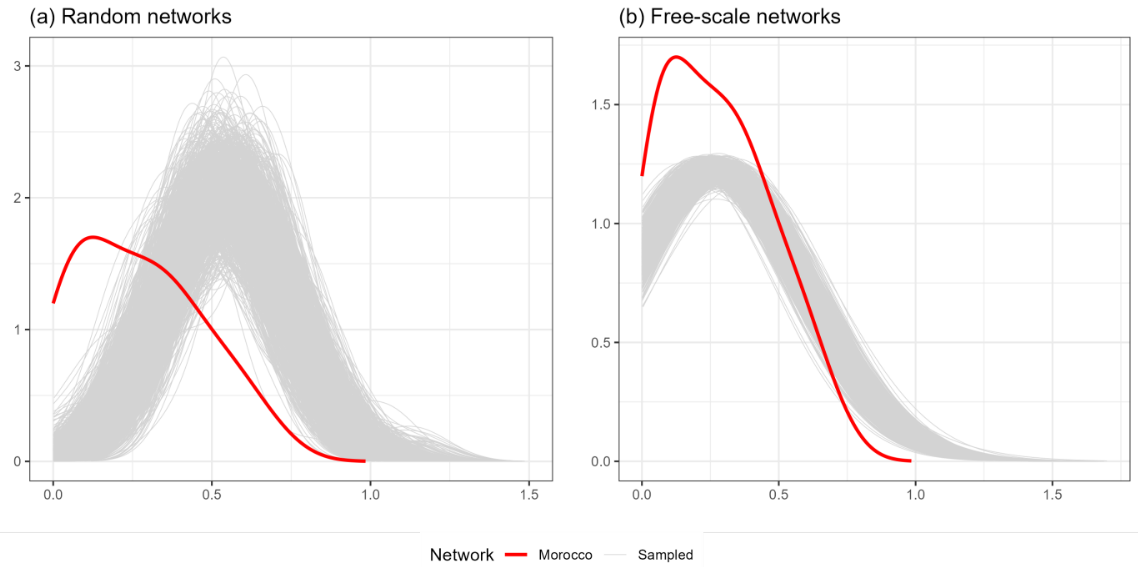
The first simulated type consists of a network whose weights a_{ij} are distributed according to a normal distribution, whose mean and standard deviation are those of the 2014 Moroccan network. As a result, the simulated network is sufficiently balanced so that sectoral shocks cancel each other out, and do not ultimately impact aggregate volatility. The connections in this network are generated by the Erdos-Renyi method (Erdos, 1959; Tamás, 2022).

The second simulated network is of the scale-free type, i.e. whose outdegree centralities follow a power-law distribution (Coscia, 2021; Newman, 2018). The shape parameter is chosen uniformly between 1 and 2, meaning that the simulated network contains sectors that are all the more central as they would influence overall volatility. The method used to generate connections for this second type of network is that developed by Cho *et al.*, (2009) and Tamás (2022). As this approach only produces unweighted networks, we have added weights following the same scheme as above (simulated according to a normal distribution).

We generated 1,000 random networks of each type. Figure 5 summarizes the results of these simulations. At first glance, the Moroccan production network is far from being a balanced network, as a normal distribution might suggest (Figure 5.a). Indeed, industries with low centrality are more present in the real network than in the networks simulated by a normal distribution. Over and above this asymmetry, a shift in mean values is visible between the Moroccan network and these theoretical networks. This distance between the Moroccan network and these theoretical networks is all the more intuitive and expected, given that uniform networks are rarely observed in reality.

The Moroccan network seems closer to a scale-free network than to a uniform network. Indeed, as shown in Figure 5.b, the Moroccan network has an average closer to the theoretical networks of the second type. However, an important difference remains. The outdegree tails of the Moroccan network are thinner than those of the scale-free networks. This means that industries with high outdegree centrality are rarer in the Moroccan case than in the power networks. This comparison corroborates previous power-law estimates, insofar as the empirical value of the power parameter exceeds the threshold of 3, above which the diversification argument is more plausible.

Figure 5: Moroccan Production Network vs. Random Networks



Note: These graphs compare the distribution of the outdegree centrality of the 2014 Moroccan production network (red curve) with the 1000 simulated theoretical networks (grey curves). In graph (a), the theoretical network is one in which the connections are generated using the Erdos-Renyi method. In graph (b), the connections of the theoretical network are generated using the method of Cho *et al* (2009) and Tamás (2022). In both cases, the weights a_{ij} of the connections are simulated according to a normal distribution, with the mean and standard deviation borrowed from the 2014 Moroccan network.

Source: TRE of 2014, HCP. Calculations and elaboration by the authors.

5. DISCUSSION

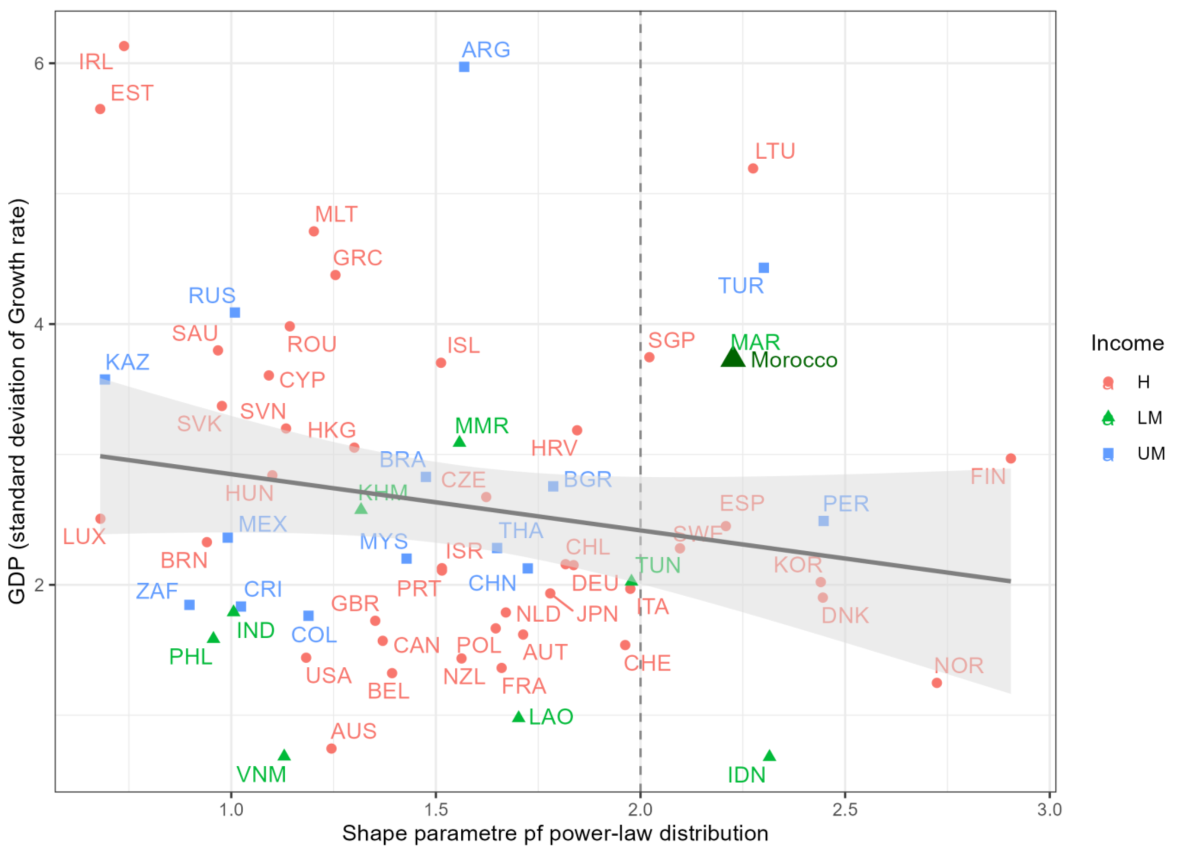
Our estimations indicate that the Moroccan production network cannot be classified as scale-free, particularly in recent years (since 2007). The empirical power parameter exceeds the threshold of 3 (a shape parameter greater than 2, respectively), unlike the majority of countries in our benchmark (refer to Figure 6 below). The robustness of these empirical findings has been further validated using alternative data sources (such as OECD data) or simulations.

Ultimately, the empirical values of the power (shape) parameters surpass the threshold below which sectoral volatility spreads to other sectors and ultimately influences the aggregate volatility in Morocco. In this regard, the Moroccan economy deviates from the prevailing patterns documented in the literature (see second section). Consequently, it appears that the Moroccan production network cannot work as a propagation mechanism of industry-level shocks to the broader economy.

In Morocco, the low polarization among sectors, particularly in more recent periods, implies that sectoral shocks tend to offset one another instead of mutually amplifying. This ultimately results in less aggregate volatility. Figure 6 illustrates a negative correlation between the value of the power-law parameter and aggregate volatility. As long as this parameter remains high (or low), GDP fluctuations exhibit lower (or higher) volatility. This relationship has also been highlighted in the existing literature. For instance, Pinto (2021) demonstrated that countries with more diversified production networks experience lower GDP volatility. Additionally, Pinto noted that service-oriented countries, like Morocco, exhibit lower volatility because of the greater diversification of suppliers within the service industries.

In light of the aforementioned points, the contribution of sectors to aggregate fluctuations is more closely tied to sectoral volatility, particularly in the agricultural sector, rather than the production network as a propagation mechanism. This leads us to question the underlying model, which is constructed based on an assumed universe comprising uniform sectoral shocks. More specifically, the assumption that sectoral shocks possess identical volatility (i.e. $\sigma_i = \sigma \; \forall \; i = 1, \dots, N$) is less realistic in the case of the Moroccan economy.

Figure 6: Shape Parameter and Aggregate Volatility



Note: This figure visualizes the estimated values of power law shape parameters as a function of economic volatility. The latter is calculated by the standard deviation of the GDP growth rate. The countries considered are represented according to their income bracket (H = High-income countries, LM = Lower-middle-income countries, UM = Upper-middle-income countries) and represented by their code (iso3c). These codes are given in the annex 2. The graph also shows the regression line (in dark grey) with its 95% confidence interval (in light grey). We removed Latvia from this graph due to its atypical nature.

Source: Data from (OECD, 2021) for the year 2014. Calculations by the authors.

6. CONCLUSION

The present study has focused primarily on examining the role of sectoral structure in driving economic fluctuations within the Moroccan economy. This investigation is undertaken in the context of an emerging literature that combines a general equilibrium economic approach with the tools of network theory. This literature generally posits that production networks have the potential to propagate sectoral shocks, ultimately impacting aggregate volatility.

However, the empirical inquiry conducted in this paper reveals that the production network in Morocco diverges in terms of shock propagation. Specifically, we have demonstrated that the Moroccan production network exhibits relatively low density and lacks significant polarization. This low asymmetry across various industries, in terms of centrality, implies that the production network in Morocco maintains a state of relative balance, limiting the impact of sectoral shocks on aggregate volatility.

Several avenues exist for improvement of this paper. First, the rigidity inherent in the Cobb-Douglas technology utilized in the model may warrant consideration. While its purpose is to elucidate the mechanism of propagation, introducing variable substitutability between labor and inputs could yield additional noteworthy insights. Endogenizing intermediate consumption represents another promising direction for future enhancements.

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Annex 1: Industry classification adopted (2014, 27 industries, HCP)

Industries			Aggregated industries	
#	Heading	Code	Heading	Code
1	Agriculture, forestry and fishing	A00	Agriculture, forestry and fishing	A00
2	Extractive industries	B00	Extractive industries	B00
3	Food and beverage manufacturing	CA0	Manufacturing and other industries	CDE
4	Manufacture of textiles, wearing apparel, leather and leather products	CB0		
5	Manufacture of wood and paper products; printing and reproduction of media	CC0		
6	Coking and manufacture of refined petroleum products	CD0		
7	Manufacture of chemicals	CE0		
8	Manufacture of basic pharmaceutical products and pharmaceutical preparations	CF0		
9	Manufacture of rubber and plastic products and other non-metallic mineral products	CG0		
10	Manufacture of basic metals and fabricated metal products, except machinery and equipment	CH0		
11	Manufacture of computers, electronic and optical goods	CI0		
12	Manufacture of electrical equipment	CJ0		
13	Manufacture of machinery and equipment	CK0		
14	Manufacture of transport equipment	CL0		
15	Other manufacturing, repair and installation	CM0		
16	Electricity and gas supply, water supply, sewage system, waste treatment	DE0		
17	Construction	F00	Construction	F00
18	Wholesale and retail trade; repair of motor vehicles and motorbikes	G00	Mainly market services	ServMarch
19	Accommodation and catering activities	I00		
20	Transport and storage	H00		
21	Information and communication	J00		
22	Financial and insurance activities	K00		
23	Real estate activities	L68		
24	Research and development and business services	MN0		
25	Public administration and compulsory social security	O84	Mainly non-market services	OPQ
26	Education, human health and social work activities	PQ8		
27	Other services	RS0	Mainly market services	ServMarch

Source: (Haut Commissariat au Plan, 2022d) et INSEE.

Annex 2: OECD Database Countries and Country Development Classification

#	Country	Code (iso3c)	Group's Income	Stage of development	#	Country	Code (iso3c)	Group's Income	Stage of development
1	Australia	AUS	H	ID	34	Sweden	SWE	H	ID
2	Austria	AUT	H	ID	35	Switzerland	CHE	H	ID
3	Belgium	BEL	H	ID	36	Turkey	TUR	UM	EDtoI
4	Canada	CAN	H	ID	37	United Kingdom	GBR	H	ID
5	Chile	CHL	H	EDtoI	38	United States	USA	H	ID
6	Colombia	COL	UM	ED	39	Argentina	ARG	UM	EDtoI
7	Costa Rica	CRI	UM	ED	40	Brazil	BRA	UM	EDtoI
8	Czech Republic	CZE	H	ID	41	Brunei	BRN	H	FDtoE
9	Denmark	DNK	H	ID	42	Bulgaria	BGR	UM	ED
10	Estonia	EAST	H	EDtoI	43	Cambodia	KHM	LM	FD
11	Finland	END	H	ID	44	China	CHN	UM	ED
12	France	FRA	H	ID	45	Croatia	HRV	H	EDtoI
13	Germany	DEU	H	ID	46	Cyprus	CYP	H	ID
14	Greece	GRC	H	ID	47	India	IND	LM	FD
15	Hungary	HUN	H	EDtoI	48	Indonesia	IDN	LM	ED
16	Iceland	ISL	H	ID	49	Hong Kong	HKG	H	FD
17	Ireland	IRL	H	ID	50	Kazakhstan	KAZ	UM	EDtoI
18	Israel	SRI	H	ID	51	Laos	LAO	LM	
19	Italy	ITA	H	ID	52	Malaysia	MYS	UM	EDtoI
20	Japan	JPN	H	ID	53	Malta	MLT	H	ID
21	South Korea	KOR	H	ID	54	Morocco	MAR	LM	ED
22	Latvia	LVA	H	EDtoI	55	Myanmar	MMR	LM	
23	Lithuania	LTU	H	EDtoI	56	Peru	PER	UM	ED
24	Luxembourg	LUX	H	ID	57	Philippines	PHL	LM	FDtoE
25	Mexico	MEX	UM	EDtoI	58	Romania	ROU	H	ED
26	Netherlands	NLD	H	ID	59	Russia	RUS	UM	EDtoI
27	New Zealand	NZL	H	ID	60	Saudi Arabia	UAA	H	FDtoE
28	Norway	NOR	H	ID	61	Singapore	SGP	H	ID
29	Poland	POL	H	EDtoI	62	South Africa	ZAF	UM	ED
30	Portugal	PRT	H	ID	63	Taiwan	TWN	H	ID
31	Slovakia	SVK	H	ID	64	Thailand	THA	UM	ED
32	Slovenia	SVN	H	ID	65	Tunisia	TUN	LM	
33	Spain	ESP	H	ID	66	Viet Nam	VNM	LM	FD

Note: Countries are ranked by World Bank in groups (2021 ranking): H = High-income countries, LM = Lower middle-income countries, UM = Upper middle-income countries. The stage of development, derived from the World Economic Forum Schwab (Schwab et al., 2012, pp. 2012-2013) classifies countries according to the 5 stages: Factor-driven (FD), Factor-driven to Efficiency (FDtoE), Efficiency-driven (ED), Efficiency-driven to innovation (EDtoI) and Innovation-driven (ID).

Source: World Bank, OECD, World Economic Forum.

About the Authors

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