Why can sectoral shocks lead to sizable macroeconomic fluctuations? Assessing alternative theories by means of stochastic simulation with a general equilibrium model

Roberto Roson*
Martina Sartori†

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Abstract

We use a global, computable general equilibrium model to estimate how idiosyncratic, independent shocks to sectoral productivity could bring about variations to real income in a country. Some theories have been elaborated to explain why relatively small sectoral shocks could lead to sizable macroeconomic variability. We process the results of our simulation experiments to assess the relative importance of a number of potential explanations, as well as of other factors not accounted for in theoretical models. We find that the variability of the GDP, induced by sectoral shocks, is basically determined by the degree of industrial concentration. We interpret the absence of significant inter-industry propagation effects as a consequence of the fact that, typically, a non-negligible share of intermediate production factors is imported.

*Ca'Foscari University, Venice and IEFE Bocconi University, Milan, Italy. E-mail: roson@unive.it.

†University of Trento and IEFE Bocconi University, Milan, Italy. E-mail: martina.sartori@unive.it.

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1 Introduction

In an economy composed of several independent sub-units, any perturbation affecting a single unit would have little impact on the aggregate. However, if the units are linked, for example by trade relationships, then a shock could propagate though the system, possibly leading to significant aggregate variability.

This argument has been long explored in the real business cycle literature, both theoretically and empirically, mainly after the seminal work by Long and Plosser (1983). More recently, a number of papers have revisited the issue, proposing new approaches and perspectives. For instance, Gabaix (2011) argues that the distribution of sectors or firms in an economy is typically very fat-tailed and, under these circumstances, idiosyncratic shocks to large subunits do affect aggregate outcomes. Acemoglu et al. (2012) consider the set of input-output relationships among industries in terms of network, finding that the propagation of micro shocks at the macro level depends on some specific network characteristics. The common lesson emerging from all these studies is that the structure of an economy is a key determinant in the transmission mechanism.

The large majority of empirical works in this field have focused on a single national economy, studying how rapidly aggregate effects die out when the number of sectors is increased (equivalently, when primary shocks affect smaller business units); in other words, the applicability of the law of large numbers in this context. Much less attention has been given to comparing different economic structures with the same number of sectors, despite the fact that understanding which economies are more vulnerable to micro shocks, and why, would be of obvious practical relevance.

Also, empirical studies typically use time series data to decompose aggregate volatility (e.g., in GDP growth rates) in terms of common (sometimes, policy driven) shocks and industry-specific shocks (Stockman, 1987; Canning et al., 1998), or to trace back the degree of micro-macro correlation to some economic system characteristics (Hornstein and Praschnik, 1997; Carvalho and Gabaix, 2010). One work in the latter class which is related to this paper is Foester, Sarte and Watson (2011), where alternative explanations are tested. Using factor methods, Foester, Sarte and Watson (2011) decompose industrial production into components arising from aggregate and sector-specific shocks, using a multisector growth model to adjust for the effects of input-output linkages. They found that the role of idiosyncratic shocks increased considerably after the mid-1980s. In contrast to Gabaix (2011), sectoral weights appear to play little role in explaining the aggregate variability, suggesting that the "few-large-sectors" explanation should be ruled out, in favor of explanations based on covariability across sectors.

In this paper, rather than relying on historical time series, we "artificially create" a data base of shock distributions through simulations with a multi-regional, global computable general equilibrium model. This model is the standard GTAP model (Hertel, 1997). We consider 25 countries and we perform systematic sensitivity analysis with the RunGTAP software, by varying (i.i.d) the multifactor productivity of the value added aggregate, corresponding to the productivity of an hypothetical single primary factor. This process allow us to get an estimate of the standard error of the real GDP.

We consider the same number of industries in all countries. Furthermore, we adopt the same distribution of productivity shocks for all sectors in all countries. Why then the impact on GDP variability turn out to be different? Any potential explanation should refer to dissimilarities in the economic structure, for example in the distribution of sectors, degree of international trade openness, or configuration of input-output (network) linkages.

We analyze the data produced by our stochastic simulation exercise, to ascertain which factors, among the ones proposed in the literature, appear to be most significant in explaining aggregate variability, on the empirical ground. We also consider a few other elements, which are absent in theoretical models, but could nonetheless play a role in more realistic settings.

The paper is organized as follows. In the next section, a number of alternative theories and explanations for the impact of micro shocks on macroeconomic aggregates are reviewed. In Section 3, our simulation strategy is illustrated, with a brief description of the CGE model and of the stochastic simulation techniques. Section 4 presents the results and analyzes the empirical relevance of a number of explanatory factors. Section 5 provides some concluding remarks.

2 Alternative theories and explanations

2.1 System criticality

A first argument supporting the relevance of micro shocks on aggregate economic quantities relies on catastrophic effects and system criticality.

There may be specific conditions under which social or physical system are highly sensitive to minor perturbations. An example is the model discussed in Bak et al. (1993). This paper illustrates how fluctuations in aggregate economic activity can result from many small, independent shocks to individual sectors. The effects of the small independent shocks fail to cancel in the aggregate due to the presence of two non-standard assumptions: local interaction between productive units (linked by supply relationships), and non-convex technology. The model is formally isomorphic to a sandpile model. More recently, the existence of production chains has been proposed as a possible amplification mechanism (Huang and Liu, 2001; Levine, 2012).

Gabaix (2011) notice that these models are conceptually innovative, but they are hard to work with theoretically and empirically. On one hand, the conditions for the emergence of criticality in the system are quite special, on the other hand the models generate wider fluctuations than those observed in reality. For these reasons, this interpretation will not be taken into account in our empirical exercise.

2.2 Granularity

Gabaix (2011) observes that the distribution of firm sizes is typically very fat-tailed. That fat-tailedness makes the central limit theorem break down, and idiosyncratic shocks to large firms (or, more generally, to large subunits in the economy such as family business groups or sectors) affect aggregate outcomes. This paper illustrates this effect by taking the example of GDP fluctuations. It argues that idiosyncratic shocks to the top 100 firms explain a large fraction (one-third) of aggregate volatility in the United States.

It is shown that, in a simple island economy composed of n sectors, the following relationship links the variance of the GDP (y) to the variance of uncorrelated sectoral shocks:

$$\sigma_y^2 = \sum_{i=1}^{n} \left(\frac{s_i}{y}\right)^2 \sigma_i^2 \tag{1}$$

where s_i are total sales of the i-th sector.

Equation (1) may be contrasted with a similar one, emerging when there are no intermediate inputs, so that gross output, or sales, s_i coincide with net output, or value added, v_i:

$$\sigma_y^2 = \sum_{i=1}^{n} \left(\frac{v_i}{y}\right)^2 \sigma_i^2 \tag{2}$$

Equation (2) can also be derived by noting that GDP is just the sum of sectoral values added. If the v_i are regarded as independent random variables, then y is also a random variable obtained by summation, which implies (2).

Using the theorem provided by Hulten (1978), Gabaix demonstrates that (1) carries over to an economy with a number of competitive firms buying intermediary inputs from one another. Somewhat surprisingly, this would imply that aggregate shocks can be calculated without knowing the input–output matrix: the sufficient statistic for the impact of firm/sector i would be its size, as measured by its sales s_i. However, it is important to stress that Hulten's theorem has been obtained for a closed, perfectly competitive economy, on the basis of the envelope theorem. As a consequence, this proposition does not perfectly fit when the basic conditions are not met, in particular when significant deviations from a baseline equilibrium are considered.

Carvalho and Gabaix (2010) call "fundamental volatility" the variability of the GDP that can be attributed to sectoral shocks on the basis of (1). They find that fundamental volatility accounts for the swings in macroeconomic volatility in the US and other major world economies in the past half century. Furthermore, they interpret the recent rise of macroeconomic volatility as a direct consequence of the increase in the size of the financial sector. A similar result is obtained for the manufacturing sector in Germany by Wagner (2011).

2.3 Trade openness

A vast literature is available on how the degree of openness to international trade affects macroeconomic variables (investments, trade balance, income, etc.)

and their variability over time. It is generally found that relatively more open economies exhibit greater GDP variability (see, e.g., Crucini, 1997; Easterly and Kraay, 2000).

There are two main explanations for this fact. First, an open economy may easily "import" shocks from abroad. This point is not relevant in this context, because we are focusing here on the impact of domestic productivity shocks on domestic GDP. Second, international trade brings about higher industrial specialization, driven by comparative advantages. The recent literature on heterogeneous firms and trade initiated by Melitz (2003) adds, to this phenomenon, a higher intra-industry concentration. In both cases, as noted by Di Giovanni and Levchenko (2012) and Eaton, Kortum and Sotelo (2012), international trade amplifies the "granularity" of an economy, therefore its sensitivity to sectoral shocks.

As we are already considering the effects of granularity as a potential explanation for aggregate variability, it would be worth to investigate the effects of international trade *net* of its impact on concentration and specialization. This is also because most theoretical results are based on models, which consider only closed economies (e.g., Gabaix, 2011; Acemoglu et al., 2012).

From this perspective, one could easily argue that trade openness should imply, ceteris paribus, a *reduction* in the impact of sectoral shocks on aggregate income. This is because part of the shocks would spill over, outside the boundaries of the domestic economy. For example, to the extent that most intermediate factors are imported, the propagation of shocks between domestic industries would be quite limited.

Special attention should be given to the role a trade balance constraint could play in this game. Consider, for instance, the case of an economy in which all intermediate factors are imported. In principle, there should be no comovements in industrial productivity. However, if the trade balance has to remain in equilibrium, any negative productivity shock would bring about a real devaluation. In turn, this would make imported intermediates more costly, which reestablishes a link among industrial productivities, since non-shocked sectors would then experience an increase in production costs and a loss of competitiveness.

2.4 Network connective asymmetry

The real business cycle literature has long recognized that input-output trade linkages among industries can induce positive comovements in sectoral employment and output following changes in relative productivities (Hornstein and Praschnik, 1997). Using a dynamic, stochastic, multisectoral general equilibrium model, derived from Long and Plosser (1983), Horvath (1998) finds that the effects on GDP of idiosyncratic productivity shocks at the sectoral level are dampened, when the number of sectors is increased, at a rate lower than that implied by the law of large numbers. This finding is obtained under the condition that the number of sectors supplying no intermediate inputs to any other sector in the economy grows more than proportionally that the total number of sectors, at higher levels of disaggregation (a condition which is typically met in real economies). This result is confirmed in Horvath (2000), where a numerical DSGE for the US economy is employed.

However, Dupor (1999) provides conditions under which there is an observational equivalence between multi-sector models and some single-sector counterparts. It is also shown that, for a wide class of input-output structures, interdependence is a poor mechanism for turning independent sector shocks into aggregate fluctuations.

The findings by Horvath and Dupor are not necessarily in contradiction. As noted by Acemoglu et al. (2010) and Acemoglu et al. (2012) it is not the mere existence of large input-output flows that amplifies sectoral shocks, but rather the existence of relatively few, "dominant" suppliers of intermediate factors. They propose to interpret the input-output structure as a (weighted) network, where the nodes correspond to the industries and the links to the input-output trade flows.[1] The relative importance of an industry as a supplier for the other industries in the economy is captured by the sum of weights of all outgoing links. In network theory, this is called the "degree" of a node.[2]

Acemoglu et al. (2010) and Acemoglu et al. (2012) focus on the distribution of degrees in the economy and, in particular, on the "fat-tailedness" of the distribution. A fat-tailed distribution of degrees would mean that there are some

[1] The value of the flows is normalized so that the sum of all incoming flows (purchases) is one.

[2] Acemoglu et al. (2010) and Acemoglu et al. (2012) also propose to analyze "second order degrees", considering the weighted sum of degrees of those nodes which are connected to a certain node.

sectors which have several connections to many other sectors. Any shock affecting these "central" sectors would propagate easily to the rest of the economy, and would not be (fully) compensated by shocks in the opposite direction. If the degree distribution is well approximated by a Pareto distribution, a single parameter would determine the "fat-tailedness". They show that the value of this parameter affects how rapidly aggregate variability decays to zero when the number of sectors is increased.

Acemoglu, Ozdaglar and Tahbaz-Salehi (2013) complement the findings above and establish that the effects of the economy's input-output structure and the nature of the idiosyncratic firm-level shocks (that is, the shape of shock distributions) on aggregate output are not separable, in the sense that the likelihood of large economic downturns is determined by the interplay between the two.

The analytical results for the latter papers have been obtained from a simple general equilibrium model, characterized by: (a) log-linear production and utility functions, (b) symmetric taste preferences by the final consumer, (c) existence of a single primary factor, having the same value share in all industries, (d) closed economy. Under these assumptions, it is shown that the following relationship, corresponding to (1) and (2), holds:

$$\sigma_y^2 = \sum_{i=1}^{n} b_i^2 \sigma_i^2 \tag{3}$$

where b_i are the elements of a vector $\mathbb{B}$, termed *influence vector*. The influence vector can be computed by solving the following linear system:

$$\underset{(n\times 1)}{\mathbb{B}} = \underset{(n\times 1)}{\mathbb{F}} + (1-\alpha) \underset{(n\times n)}{\mathbb{A}} \underset{(n\times 1)}{\mathbb{B}} \tag{4}$$

where α is a scalar, expressing the value share of the primary factor in the production processes, $\mathbb{F}$ is a vector, having all values set at α/n (where n is the number of sectors) and $\mathbb{A}$ is an input-output matrix, whose generic element a_{ij} stands for the flow of intermediate factors sold by industry i to industry j. In this setting, the column sums of $\mathbb{A}$ have been normalized to one.

The influence vector is also known in network theory as the Bonacich centrality vector (Bonacich, 1987). As the name suggests, it measures how important the nodes are in terms of interconnections with the rest of the network. Therefore, the meaning of (4) is clear: the variance of the GDP is a weighted sum of the variances of the independent sectoral shocks, where the weights are given by the (square of) Bonacich centrality index. An high centrality means that the sector supplies many inputs to other sectors, therefore its influence on the aggregate is relatively high.

Interestingly, Acemoglu et al. (2012) show that, in their model and in the proximity of the general equilibrium point, the elements of the influence vector coincide with the share of sectoral sales, that is:

$$b_i = \frac{s_i}{\sum_{j=1}^{n} s_j} \tag{5}$$

Taking together equations (3) and (5) one can easily draws a connection between measures of network connectivity and granularity (see (1) and (2)). The same caveats discussed in section 2.2 apply. Furthermore, if the elements of the influence vector $\mathbb{B}$ would always been well approximated by sale shares, then there would be no need to consider the structure of input-output linkages.

3 Methodology

3.1 The GTAP Computable General Equilibrium model

The Global Trade Analysis Project (GTAP) is an international network which builds, updates and distributes a comprehensive and detailed data base of trade transactions among different industries and regions in the world, framed as a Social Accounting Matrix (SAM). The SAM is typically used to calibrate parameters for a Computable General Equilibrium (CGE) model, and the GTAP data base is accompanied by a relatively standard CGE model and a software, that can be used to conduct simulation experiments (RunGTAP). The model structure is quite complex and it is fully described in Hertel (1997). We only summarize here the main relationships in the model:

- Production volumes for all industries in all regions equal intermediate domestic consumption, final demand (private consumption, public consumption, demand for investment goods) and exports to all other regions.
- Endowments of primary factors (e.g., labour, capital) are given and match demand from domestic industries. There is perfect domestic mobility for

labour and capital (single regional price) and imperfect domestic mobility for land (industry-specific price), but no international mobility.

- Representative firms in each regional industry allocate factors on the basis of cost minimization. Production functions are nested CES functions, with calibrated structural parameters and given elasticities of substitution. Intermediate factors and the value added aggregate are not substitutable among themselves (Leontief). Intermediate and final demand is split according to the source of production: first between domestic production and imports[3], subsequently the imports among the various trading partners. The Armington assumption is adopted: goods in the same industry but produced in different places are regarded as imperfect substitutes. Allocation is based on relative market prices, including transportation, distribution, and tax margins. Unit prices for goods and services equals average production costs, including taxes.

- National income equals returns on primary factors owned by domestic agents, and is allocated to private consumption, public consumption and savings (constant, calibrated shares). Savings are virtually pooled by a world bank and redistributed as regional investments, on the basis of expected future returns on capital. Therefore, there is no equality between domestic savings and investment, which implies the absence of a strict trade balance constraint.

- The structure of private consumption is set on the basis of utility maximization under budget constraint. The utility function is a non-homothetic CDE function and goods have different income elasticities.

From a mathematical point of view, the model is a very large non-linear system of equations. Structural parameters are set so that the model replicates national accounts and trade data at a base year. In this paper, we use the GTAP 8.1 model version, calibrated at the year 2007. Numerical simulations entail changing exogenous variables or parameters, to determine of a counterfactual equilibrium.

We analyze here the effects of changes in the multifactor industrial productivity of the value added aggregate, which is a CES composite factor. We take into

[3]Elasticities of substitution between domestic goods and imported composites depend on the industry. They range from a minimum of 1.9 for Services to a maximum of 3.6 for Energy.

consideration a specific country, then we shock the productivity parameters of all industries in that country, as explained in the sub-section below. In each run, GTAP estimates the percentage change for all endogenous variables in the model. Among those variables, we focus on real domestic GDP, to ascertain the impact of variations in domestic industrial productivity on national income.

3.2 Stochastic simulation with the GTAP model

The software that can be used to perform simulation experiments with the GTAP model (RunGTAP) allows to undertake "systematic sensitivity analysis" on key parameters and exogenous variables, using statistical quadrature techniques (Arndt, 1996). One or more parameters are "perturbed" on the basis of ex-ante (subjective) probability distributions.[4] For each realization of the random variables, the model computes a general equilibrium state. Results from a series of runs are subsequently processed to infer the statistical distribution for all endogenous variables.[5]

Like in Valenzuela et al. (2005), we use this methodology to mimic the impact of idiosyncratic shocks in primary factors productivity on the real domestic GDP. We consider one country at a time. For all industries in each country (57), the model generates random realizations of the productivity parameter for the value added CES composite factor. The ex-ante distributions are all equal, independent and rectangular in [0.5, 1.5], therefore with mean 1 and standard error 0.2887. Among the various output variables, we focus on domestic real GDP and, in particular, on the relationship between standard error of the productivity shock and standard error of the GDP.

As expected, the estimates of the GDP standard error differ by country. The next step in our analysis is understanding why they are different and which, among the various explanatory factors proposed in the literature, appear to be most significant in influencing the degree of GDP variability.

[4] At the moment, only two distributions can be adopted to this purpose: rectangular and symmetric triangular.

[5] The software reports the estimated mean and standard error for all endogenous variables.

Table 1: Relative GDP standard deviation, by country

	sdGDP/sdPr
1 Belgium	34%
2 Bolivia	27%
3 China	20%
4 Costa Rica	28%
5 Denmark	33%
6 Egypt	22%
7 Ethiopia	25%
8 Germany	33%
9 Ghana	29%
10 India	24%
11 Israel	31%
12 Italy	33%
13 Japan	30%
14 Madagascar	25%
15 New Zealand	28%
16 Oman	47%
17 Russia	37%
18 Senegal	25%
19 South Africa	28%
20 South Korea	27%
21 Tanzania	24%
22 Tunisia	29%
23 Turkey	27%
24 UAE	28%
25 USA	32%

4 Analysis of simulation results

4.1 Estimates of GDP variability by country

Table 1 shows the estimates for the standard error of the GDP produced by the stochastic simulation exercise, relative to the standard error of the productivity shock. Oman is the country with the highest GDP variability, followed by Russia. More precisely, Oman is the country which is expected to have the highest sensitivity of national income to domestic productivity shocks. On the opposite side, China is the least sensitive country, followed by Egypt.

A quick inspection of the table reveals that there is no obvious correlation between country characteristics and the degree of GDP variability. Therefore, we turn now to a more systematic search for explanations.

4.2 Potential explanatory factors

We consider three classes of possible explanatory factors.

The first class includes different measures of "granularity". We consider:

1. The Herfindhal concentration index applied to industry sales or output (see eq.5);
2. The Herfindhal concentration index applied to industrial value added (see eq.2);
3. The sum of squared Domar weights (see eq.1).

Higher values for all these indices indicate that there are relatively few large sectors in the economy, which should increase the sensitivity of the GDP to internal shocks. A positive correlation sign is thus expected.

The second class includes measures of the degree of trade openness. We consider:

1. A general index of trade openness, namely the ratio of the sum of total export and imports over GDP;
2. A more specific index related to intermediate factors: the share of imported intermediate goods on total intermediate consumption.

On the basis of our discussion in section 2.3, we expect a negative correlation between standard deviation of the GDP and some measure of trade openness, as the indirect effect of international trade on specialization is already captured by the granularity factors.

The third class includes indices of inter-industry connectivity. More precisely, we take into account:

1. The standard deviation, or coefficient of variation[6], in the distribution of first order degrees in the input-output network;

[6]As the sum of weights for all incoming links is normalized to one, the distribution of degrees (sum of outgoing links) has unitary mean.

2. The standard deviation computed on the second order degrees (Acemoglu et al., 2012);
3. The power parameter of the best fitting Pareto distribution approximating the distribution of first order degrees;
4. Same as above, applied to the second order degrees distribution;
5. The sum of squared elements of the incidence vector (see eq.4).

All the variables above have been computed in two different ways: one referring to the matrix of total input-output trade flows, the other one limited to domestic inter-industry flows. Therefore, ten alternative variables have been tested. All are expected to be positively correlated with the GDP variability, with the exception of Pareto parameters, which should be negatively correlated, because lower values indicate fat tails in the distributions.

In addition, we consider a control variable, which is the standard deviation in the distribution of industrial value added shares on total production costs. The reason is that in the original model by Acemoglu et al. (2010) and Acemoglu et al. (2012) it is assumed that the single primary factor has the same (constant) value share in all industries (parameter α in equation 4). The lower this standard deviation, the closer real data are to the theoretical model structure. This extra variable is intended to be used in association with one of the other variables above. Its expected sign is the opposite of the sign of the associated variable, since a higher standard deviation should reduce its explanatory power.

4.3 Assessing the explanatory power of different factors

We have regressed the logarithm of the GDP standard deviation against the logarithm of three candidates explanatory variables, selected in each of the three groups described in the previous section. In some cases, we have also added a fourth control variable. The reason why we have used a logarithmic formulation is because the relationships between variances or standard deviations (e.g., equation 1) are multiplicative. We have run many regressions, to test alternative model formulations, and we report here only a synthesis of our main findings.[7]

Among the granularity factors, we have hardly found any significance for Domar weights. Herfindhal indices, on the other hand, are statistically very significant.

[7] Further details are available on request.

Table 2: Explanatory variables considered

Variable	Acronym	Min	Max	Mean
HHI index on industry sales	HHIs	0.041	0.135	0.062
HHI index on industrial value added	HHIva	0.042	0.220	0.085
Sum of squared Domar weights	Domar	0.152	0.463	0.266
(X+M)/GDP index of trade openness	XM	0.201	1.570	0.684
Share of imported intermediate factors	VIFM	0.110	0.526	0.283
Standard deviation first order degrees (total flows)	sdFO	1.018	2.043	1.376
Standard deviation second order degrees (total flows)	sdSO	1.120	2.237	1.553
Power parameter Pareto distrib. 1st degrees (total flows)	plFO	2.100	3.715	2.542
Power parameter Pareto distrib. 2nd degrees (total flows)	plSO	1.725	3.217	2.276
Sum of squared elements of incidence vector (total flows)	IV2	0.021	0.039	0.027
Standard deviation of share value added in total cost	sdINCva	0.147	0.344	0.230
Standard deviation first order degrees (domestic flows)	sdFOdom	1.072	2.438	1.647
Standard deviation second order degrees (domestic flows)	sdSOdom	1.216	2.794	1.836
Power parameter Pareto distrib. 1st degrees (domestic flows)	plFOdom	1.669	5.391	2.386
Power parameter Pareto distrib. 2nd degrees (domestic flows)	plSOdom	1.542	3.795	2.222
Sum of squared elements of incidence vector (domestic flows)	IV2dom	0.023	0.046	0.031

Table 3: Regression results #1

Variable (log)	coeff.	s.e.	t	R^2
constant	-1.208	0.077	-15.66	0.9477
HHIva	0.525	0.028	18.85	
VIFM	-0.020	0.019	-1.04	
sdFOdom	0.015	0.045	0.33	

The best index is the one built on value added shares. On the basis of (2), this suggests that sectoral productivities are relatively independent variables.

Concerning trade openness, the importance of imported intermediate factors has proved to be consistently higher than the one of the general index *(X+M)/GDP*. Usually, this variable displays the expected negative sign, and it is weakly significant. This result suggests that the impact of trade openness on GDP variability operates directly through its incidence on the purchases of intermediate production factors.

Detecting an effect of input-output linkages on GDP variability has proved to be much more difficult. The potential explanatory variables are typically not significant and sometimes they have the wrong sign. In any case, better results are obtained when factors referring only to the matrix of domestic trade flows are employed, and the best performing variable is the coefficient of variation in the distribution of first order degrees. Furthermore, the additional control variable (standard deviation in the distribution of value added shares) has never found to be relevant.

Table 3 displays a summary of results for what we consider to be the best performing model formulation. Almost all the GDP variability is explained by the Herfindhal index on the value added. The VIFM factor is weakly significant. The standard deviation of first order degrees, computed on the matrix of domestic input-output flows, has the correct sign, but it is not statistically significant.

On Table 4 we report results for an alternative formulation, in which the other Herfindhal index (the one computed on industry sales) replaces HHIva. Overall, this formulation does not score as good as the previous one. However, HHIs is still quite significant, and this time both VIFM and sdFOdom are also significant (although much less so).

Table 4: Regression results #2

Variable (log)	coeff.	s.e.	t	R^2
constant	-0.889	0.172	-5.17	0.8373
HHIs	0.626	0.063	10.00	
VIFM	-0.051	0.035	-1.46	
sdFOdom	0.188	0.080	2.37	

4.4 Interpreting the findings

The key message emerging from our simulation experiments and regressions is that, once real world data are taken into account, granularity (industrial concentration) matters, whereas inter-industrial linkages do not. There are two possible reasons for this irrelevance result. One is clear from our findings: to the extent that a significant share of intermediate factors is imported, the propagation of productivity shocks from one domestic industry to another domestic industry is necessarily limited.

A second, more subtle argument, has to do with the different cost and production functions adopted in the different models. In fact, almost all theoretical and applied models based on Long and Plosser (1983) use linear logarithmic (Cobb-Douglas) production and utility functions. By contrast, a complex nested CES production function is used in GTAP, where the upper nesting is Leontief (for intermediate factors and the value added composite), whereas substitutability between domestic and imported goods is modeled as a CES function with a relatively high elasticity. The reason why the chosen functional form may play a role is because the propagation of productivity shocks is equivalent to the effect of factor cost variations on sectoral cost functions.

For example, consider the impact of a cost variation for a certain production factor inside a Leontief and a Cobb-Douglas production / cost function. Since factor substitution is possible in the Cobb-Douglas, but not in the Leontief, in case of a negative cost shock (higher cost) the increase in total production costs would be lower in the Cobb-Douglas. Vice versa, in case of a positive shock (lower cost), the reduction in the aggregate cost would be larger. If the cost (or productivity) of a given factor is seen as a random variable, the average level for the aggregate cost function in the Leontief case would simply be the total cost computed using the expected value for the factor cost. On the other hand, because of the concavity of the Cobb-Douglas function, the average cost would be *lower*, even if the factor cost distribution is the same. The concavity of the function does not simply affect the mean of the aggregate variable, but also its variance. For instance, it can be shown that the aggregate cost function would have a lower mean but *a higher variance* when the elasticity of substitution is increased.

What does all this imply when the production functions used in GTAP are compared with the ones typically used in the literature? Consider the productivity factor of the value added aggregate in one specific industry. Since the value added composite factor is linked to other intermediate factors by means of a Leontief function in GTAP, the variability of the aggregate multifactor productivity *within the same industry* would be lower than what it could be if the Cobb-Douglas specification had been chosen instead. On the other hand, when the effects are propagated, through trade, from one industry to another, exactly the opposite occurs. The high elasticity in the CES nesting between imported and domestic goods *amplifies the transmission of the shock*, again in comparison with the linear logarithmic benchmark.

Taken together, these two combined effects imply that *the different functional specification in GTAP should make granularity effects less relevant*, since intra-industry variations of productivity would then be smaller than in most theoretical models, *but connectivity effects larger*. Therefore, the empirical irrelevance of input-output linkages in explaining GDP variability cannot be attributed to a different choice of production functions.

5 Conclusion

Most papers dealing with the propagation of productivity shocks use general equilibrium models, which consider a single, closed economy. In this work, instead, we have stochastically simulated the effects of idiosyncratic sectoral shocks by means of a global CGE model, comparing different economies.

We have not found empirical evidence of comovements in industrial multifactor productivities. Therefore, the variability of the GDP, induced by sectoral shocks, is basically determined by the degree of industrial concentration. The latter is sometimes termed in the literature the “granularity” of an economy. We have interpreted the absence of significant inter-industry propagation effects as a consequence of the fact that, in most countries, a non-negligible share of intermediate production factors is imported. Globalization makes the economies more interdependent, but relatively less sensitive to domestic shocks.

We plan to extend the analysis in the future, by considering more countries and simulations. Yet, we do not expect any significant modification in our qualitative results.

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