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

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Abstract

Relatively small sectoral productivity shocks could lead to sizable macroeconomic variability. Whereas most contributions in the literature analyze the issue of aggregate sensitivity using simple general equilibrium models, a novel approach is proposed in this paper, based on stochastic simulations with a global CGE model. We estimate the statistical distribution of the real GDP in 109 countries, assuming that the productivities of the industrial value added composites are identically and independently distributed random variables. We subsequently undertake a series of regressions in which the standard error of the GDP is expressed as a function of variables measuring the "granularity" of the economy, the distribution of input-output trade flows, and the degree of foreign trade openness.

We find that the variability of the GDP, induced by sectoral shocks, is basically determined by the degree of industrial concentration as counted

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by the Herfindhal index of industrial value added. The degree of centrality in inter-industrial connectivity, measured by the standard deviation of second order degrees, is mildly significant, but it is also correlated with the industrial concentration index. After controlling for the correlation effect, we find that connectivity turns out to be statistically significant, although less so than granularity.

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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 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. In a recent paper, Johnson (2014) follows a similar approach, although the research question we address here is somewhat different. The model we use is the standard GTAP Computable General Equilibrium model (Hertel, 1997). We consider 109 countries[1] 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 (57) 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

[1]This is the maximum level of regional disaggregation allowed in the GTAP Social Accounting Matrix data base.

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, discussing why our findings may differ from those obtained in theoretical models. 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 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:

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

Notice that national GDP is just the sum of sectoral values added. If the v_i are regarded as independent random variables, then y would also be 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 intermediate 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 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. In other words, to the extent that most intermediate factors are imported, the propagation of shocks between domestic industries would be quite limited.

The magnitude of this spill-over effect depends, in a model, on the assumptions about the trade balance, which affect the relative prices of domestic and imported products. In a partial equilibrium formulation, for instance, the price of imports may be taken as fixed. In a general equilibrium model, like the one used in this exercise, the prices of imports are endogenously determined. If prices of domestic and imported goods moves to the same direction, relative prices would not change much, and the substitutability between production factors of different origin would be rather curbed. On the contrary, when prices diverge, it would be easier to substitute imported factors with domestically produced ones, or vice versa. The role of the trade balance constraint will be discussed in more detail in Section 4.4.2.

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.[2] 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.[3]

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 that distribution. A fat-tailed distribution of degrees would mean that there are some 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

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

[3] 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.

vector can be computed by solving the following linear system:

$$\underset{(n\times1)}{\mathbb{B}} = \underset{(n\times1)}{\mathbb{F}} + (1-\alpha)\underset{(n\times n)}{\mathbb{A}}\underset{(n\times1)}{\mathbb{B}} \tag{4}$$

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 significant.

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 Computable General Equilibrium (CGE) models, 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[4], 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.

[4] 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.

- 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 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 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.[5] 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.[6]

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

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

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

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 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, for a subset of 25 countries out of 109 in our dataset. Oman is the country with the highest GDP variability, followed by Russia. More precisely, Oman is the country which displays the highest sensitivity of national income to domestic productivity shocks, under the assumption that sectoral shocks are independently and identically distributed, and they affect all primary factors (value added composite) in a uniform way[7]. 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:

[7] The productivity shock can be seen as a multidimensional random variable. In our experiment, we are assuming that its covariance matrix is diagonal with all values equal. In a more general setting, the structure of the covariance matrix can be arbitrary, and results may greatly differ. For example, a country may have an economy dominated by a large sector which, nonetheless, may be characterized by a rather limited variability in productivity, and co-variability with other sectors. In this case, that country would not be particularly sensitive to domestic productivity shocks.

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%

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 therefore 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[8], in the distribution of first order degrees in the input-output network;
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 in the third class 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.

We also consider a control variable, namely 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.

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

Table 2: Explanatory variables considered

Variable	Acronym	Min	Max	Mean
HHI index on industry sales	HHIs	0.039	0.172	0.068
HHI index on industrial value added	HHIva	0.041	0.319	0.094
Sum of squared Domar weights	Domar	0.134	0.978	0.295
(X+M)/GDP index of trade openness	XM	0.201	2.593	0.854
Share of imported intermediate factors	VIFM	0.087	0.673	0.303
Standard deviation first order degrees (total flows)	sdFO	0.920	3.155	1.403
Standard deviation second order degrees (total flows)	sdSO	1.087	2.275	1.563
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	0.015	0.059	0.027
Standard deviation of share value added in total cost	sdINCva	0.147	0.482	0.232
Standard deviation first order degrees (domestic flows)	sdFOdom	0.974	3.814	1.683
Standard deviation second order degrees (domestic flows)	sdSOdom	0.330	2.800	1.838
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	0.019	0.068	0.031

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 the 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.[9]

Among the granularity factors, we have hardly found any significance for Domar weights. Herfindhal indices, on the other hand, are statistically very significant. 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*. This suggests that the impact of trade openness on GDP variability operates directly through its incidence on the purchases of intermediate production factors. Usually, this variable displays the expected negative sign, but it is weakly significant or not significant.

Table 3: Regression results #1

Variable (log)	coeff.	s.e.	t	R^2
constant	-1.297	0.038	-34.05	0.9506
HHIva	0.488	0.012	40.19	
VIFM	-0.002	0.010	-0.19	
sdSOdom	0.038	0.024	1.57	

To detect the effect of input-output linkages on GDP variability, best results are obtained when factors referring only to the matrix of domestic trade flows are employed, and the variables are the coefficients of variation in the distribution of first or second order degrees. On the other hand, the additional control variable (standard deviation in the distribution of value added shares) has never found to be statistically relevant.

We consider all possible combinations of explanatory variables in the three

[9] Further details are available on request.

classes (3x2x10) and we evaluate the regression results on the basis of both the R^2 index of fitness and the sign of estimated parameters. 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 not significant. The standard deviation of the second order degrees, computed on the matrix of domestic input-output flows, has the correct sign and it is weakly significant.

Therefore, our results seem to suggest that, once real world data are taken into account, granularity (industrial concentration) matters, whereas inter-industrial linkages do not matter very much. Notice that, if there would be no purchases of intermediate factors in the economy (that is, if the input-output matrix would be empty), then HHIva would fully explain the variability of the (nominal) GDP.

However, sdSOdom and HHIva are positively correlated[10], meaning that larger industries in terms of value added tend to be the same industries which are also main suppliers of intermediate factors in the economy. Because of this, the estimated coefficient for sdSOdom in Table 3 captures the connectivity effect *net of its correlation with the industry size distribution*: the high significance of the granularity variable may actually mask the relevance of the input-output structure.

To control for this correlation effect, we first run a regression of HHIva on sdSOdom:

$$\text{HHIva} = \alpha + \beta\,\text{sdSOdom} + \epsilon \tag{6}$$

then we build an instrumental variable HHIva* $= \text{HHIva} - \beta\,\text{sdSOdom}$, netting out HHIva from its correlation with sdSOdom.

On Table 4 we report results for an alternative specification, in which HHIva* replaces HHIva. Results are remarkably similar to those of Table 3, but this time sdSOdom is much more statistically significant.

4.4 Interpreting the findings

Any divergence between our empirical results and those of other studies can be traced back to fundamental differences in the structure of the models used in

[10]The correlation index is 0.26, and 0.38 when the variables are expressed in logarithms.

Table 4: Regression results #2

Variable (log)	coeff.	s.e.	t	R^2
constant	-1.297	0.038	-34.05	0.9506
HHIva*	0.488	0.012	40.19	
VIFM	-0.002	0.010	-0.19	
sdSOdom	0.409	0.023	17.92	

the analysis. In the following, two specific differences are discussed: functional forms and the open/close nature of the economy.

4.4.1 Different functional forms

Almost all theoretical and applied models based on Long and Plosser (1983) use linear logarithmic (Cobb-Douglas) production and utility functions, which are necessary to derive closed form analytical solutions. By contrast, in a simulation model like GTAP, a complex nested CES production function is assumed, 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.

To understand the role played by the chosen functional forms it may be useful to think of the propagation of productivity shocks as equivalent to the effect of factor cost variations on total production costs. For example, consider the impact of a cost variation for a certain production factor inside a Leontief and a Cobb-Douglas production / cost function. If the cost (or productivity) of a given factor is seen as a random variable and the parameters for both functions have been calibrated using the same data set, then the average cost in the Leontief case would higher that in the Cobb-Douglas function, but its variance would be *smaller*[11]. This means that the aggregate sensitivity to factor cost shocks is higher when the elasticity of substitution is larger.

[11] Parameters for production functions in computable models are typically estimated by assuming that baseline prices, and aggregate costs, are set to one (trough the appropriate choice of quantity units of measure). Suppose that the cost share of a given parameter, with a unit cost w, is 1/2. The Leontief cost function would then be specified as $C(w) = 0.5w + 0.5$, whereas the Cobb-Douglas equivalent would be $C(w) = w^{0.5}$. Using these cost functions, it is easy to check that the variability in $C(w)$ (measured as standard deviation, variance, etc.) is larger in the Cobb-Douglas formulation. More generally, it would be larger with a higher elasticity of substitution.

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 of the value added aggregate in one specific industry. Any change in productivity would directly affect the GDP, because GDP is just the sum of industrial values added. This is the granularity effect, which of course depends on the size of the industry. The shock then propagates to other industries, through the price of the output good, used as an intermediate factor. The lower variability of production costs and prices under the Leontief specification makes this effect smaller than in the typical theoretical model. On the other hand, the high elasticity in the CES nesting between imported and domestic goods amplifies the transmission of the shock[12], again in comparison with the linear logarithmic benchmark. The two impacts tend to cancel each other. Therefore, the empirical lower relevance of input-output linkages in explaining GDP variability can hardly be attributed to a different choice of production functions.

4.4.2 Foreign trade and international capital flows

A second major difference between the model used in this study and others in the literature is its open economy nature. When some production factors are imported, the propagation of productivity or cost shocks from one domestic sector to another domestic sector could be smaller than in the case of closed economy. To assess the role of trade openness on our results, it is essential to ascertain how prices of foreign goods would move in response to a domestic productivity shock. In a general equilibrium model, this is determined by the closure rule adopted for the foreign trade balance or, equivalently, to the way regional investments are allocated.

In this respect, the GTAP model is characterized by a peculiar treatment of international capital flows. Domestic savings and investments do not equal in the model. Savings (a constant share of national income) are pooled by a virtual world bank and regionally redistributed according to the relative returns on capital, on the basis of an elasticity parameter (called RORFLEX in the model). A low value for this parameter makes international investments more mobile, which can be interpreted as a stronger integration of international financial markets. Because of the accounting identity between net savings and foreign

[12] The more so if, as discussed in Section 4.4.2, lower domestic prices are associated with higher prices of imported products.

trade balance, any capital inflow implies a trade deficit, with the value of imports exceeding the value of exports.

Other general equilibrium models, in particular single country CGE models, often adopt the alternative assumption of no changes in the trade balance, following any variation in variables or parameters of the model. Under this alternative closure rule, a positive (negative) productivity shock entails a deterioration (improvement) in the terms of trade, that is a real devaluation (revaluation) of the national currency[13]. Therefore, imported goods would become more (less) expensive, thereby amplifying the substitution with domestic products, whose prices move to the opposite direction.

We have undertaken a robustness check of our results under different foreign trade closure rules. We have generated two new sets of estimates for the standard deviation of the real GDP variable under (a) a value of the RORFLEX elasticity reduced by 50%, and (b) the imposition of a trade balance invariance constraint.

Let us consider the case of a low RORFLEX parameter first. Lower values would make the inflow of foreign investment, in response to increases in the marginal productivity of capital, larger. Since aggregate investments are one component of the GDP, this may suggest that domestic GDP should display a higher variability when international capital flows are more mobile (low RORFLEX). However, we found that this it is not always the case: the standard deviation of the real GDP increases when RORFLEX is reduced in just 85% of all countries in our data set[14].

When the regressions illustrated in Section 4.3 are repeated using new data for the dependent variable, we found that the explanatory power of all regression models is dramatically reduced. This can be related to the overlapping of a demand side shock (additional investment demand) to the primary shock on productivity, making the overall impact on GDP blurred. Also, we consistently found lower significance and wrong sign for the trade openness variables (XM, VIFM). This is due to the fact that, with a low RORFLEX, most positive (negative) productivity shocks would trigger more (less) investments and

[13] A positive productivity shock for primary inputs is equivalent to an increase in the endowment of primary resources. Resources get more abundant and cheaper, and the same occurs for domestic goods, which are produced using these resources.

[14] The opposite result may emerge, for example, when the relatively "large" industries are not capital intensive, because positive shocks on those industries could offset negative shocks on small, capital intensive industries, which ultimately brings about net gains in national income associated with lower demand and returns on capital.

a foreign trade deficit (surplus). Therefore, domestic and foreign prices could actually move to the same direction, possibly reversing the intermediate factors substitution mechanism discussed in Section 2.3.

Secondly, we imposed a trade balance constraint for all countries[15]. Again, we repeated all our regression experiments with the new estimates for the dependent variable "standard deviation of the GDP". Overall, results turn out to be quite similar to the ones obtained by our first set of regressions, indicating that the international mobility of capital in the baseline model, with the assigned value for RORFLEX, is already rather limited. Table 5, corresponding to Table 3, shows the results for the best fitting regression. Notice that the statistical significance of the VIFM variable has increased, as expected, although it remains rather limited.

Table 5: Regression results #1 with trade balance constraint

Variable (log)	coeff.	s.e.	t	R^2
constant	-1.269	0.039	-32.40	0.9494
HHIva	0.499	0.012	40.01	
VIFM	-0.004	0.011	-0.38	
sdSOdom	0.023	0.025	0.91	

5 Conclusion

Most papers dealing with the propagation of productivity shocks use general equilibrium models, which consider a single, closed economy. Simple functional forms for production processes and the utility of the representative consumer are usually adopted. These studies reveal that there are two main determinants for the sensitivity of aggregate income to sectoral productivity shocks: (1) the size distribution of industries, and (2) the input-output structure of the economy.

A novel approach has been proposed in this paper, based on stochastic simulations with a global CGE model. CGE models are widely used tools in applied economic analysis, and have been utilized in many different fields. However, they have never been employed (to the best of our knowledge) to investigate the

[15]This is easily obtained by swapping some endogenous and exogenous variables in the model.

relationship between economic structure and aggregate sensitivity to sectoral productivity shocks.

We made use of a popular CGE model (GTAP) to estimate the statistical distribution of the real GDP in 109 countries, assuming that the productivities of the industrial value added composites are identically and independently distributed random variables. Our estimates highlight that significant differences exist among countries in terms of standard deviation of the real GDP distribution, meaning that the sensitivity to sectoral shocks is remarkably dissimilar.

In order to understand what originates these diverse characteristics, we undertook a series of regressions in which the standard error of the GDP is expressed as a function of variables measuring the "granularity" of the economy, the distribution of input-output trade flows, and the degree of foreign trade openness. Many formulations have been tested, using alternative variables and indices proposed in the literature.

We found that the variability of the GDP, induced by sectoral shocks, is basically determined by the degree of industrial concentration as counted by the Herfindhal index of industrial value added. The degree of centrality in inter-industrial connectivity, measured by the standard deviation of second order degrees, is mildly significant, but it is also correlated with the industrial concentration index. After controlling for the correlation effect, we found that connectivity turns out to be statistically significant, although less so than granularity.

The degree of openness to international trade, in this case calculated as the share of imported intermediate factors, is not statistically significant. However, we ascertain that the impact of trade openness variables critically depends on the assumptions adopted in the model, and in particular on the existence of a trade balance constraint.

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