The network origins of aggregate fluctuations

D. Acemoglu, V. M. Carvalho, A. Ozdaglar, A. Tahbaz-Salehi
(Econometrica, 2012)

Chris Ackerman & Antonio Martner
Presentation for Econ 241A, UCLA.
December 7th, 2021

Motivation (1)

Question:
Do microeconomic sector specific shocks lead to aggregate fluctuations in presence of heterogenous intersectoral input–output linkages?

What this paper do:

- Develops a multisector model that captures input–output linkages.
- Propose three 3 key theorems to describe how idiosyncratic shocks propagate and average out.
- Provide an evidence based application of the theory developed.

Motivation (2)

Why is this important:
Independent shocks to specific industries do not vanish as quickly as the previous literature proposed, generating more persistent effects that initially thought.

Key inside:
Microeconomic shocks effects may not remain confined to where they originate.
$\Longrightarrow$ Microeconomic shocks may propagate throughout the economy, affect the output of other sectors, and generate sizable aggregate effects.

Main contribution:
Provide a mathematical framework for the analysis of shocks propagations and to characterize that their role in aggregate fluctuations depend on the structure of interactions between different sectors.

Previous argument

Idiosyncratic shocks generate that aggregate output concentrates around its mean at a very rapid rate.

$\Longrightarrow$ In an economy consisting of n sectors hit by independent shocks, aggregate fluctuations would have a magnitude proportional to $1/\sqrt{n}$

$\Longrightarrow$ Negligible effect at high levels of disaggregation.

This argument ignores the presence of interconnections between different firms and sectors, functioning as a potential propagation mechanism of idiosyncratic shocks throughout the economy.

Real life statement

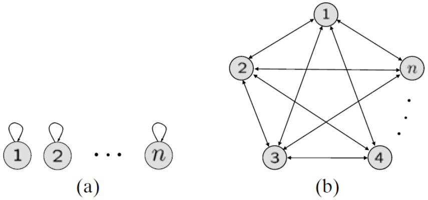
Ford's CEO requested emergency government support for General Motors and Chrysler in nov 2008 (Why in the world he will do that?)

He argued that, given the significant overlap in the suppliers and dealers of the three automakers, the collapse of either GM or Chrysler would have a ripple effect across the industry, leading to severe disruption of Ford's production operations within days, if not hours.

Graph examples: Previous argument works

As n increases and the economy becomes more disaggregated, the diversification argument based on the LLN implies that independent sectoral shocks average out rapidly at the rate $\sqrt{n}$.

Symmetric economies

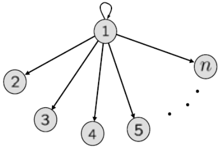


The symmetric structure of this economy ensures that aggregate output is a symmetric function of the shocks to each sector, implying that the diversification argument remains applicable.

Graph examples: Previous argument NOT works

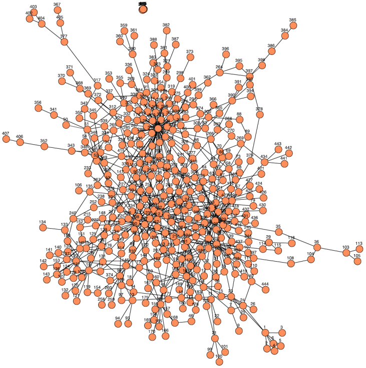
Consider an economy with small number of sectors playing a disproportionately important role as input suppliers to others. Consequently, the interplay of sectoral shocks and the intersectoral network structure may generate sizable aggregate fluctuations.

One sector is the only supplier of all other sectors



How real graphs look

Network corresponding to the U.S. input–output matrix in 1997



$\Longrightarrow$ Small number of sectors playing a disproportionately important role as input suppliers to others

Road map

Investigate whether aggregate volatility, defined as the standard deviation of log output, vanishes as $n \to \infty$.

- In certain cases, such as the star network, the LLN fails and aggregate output does not concentrate around a constant value.
- The main focus, however, is on the more interesting cases in which the law of large numbers holds, yet the structure of the intersectoral network still has a defining effect on aggregate fluctuations.
- Sectoral interconnections may imply that aggregate output concentrates around its mean at a rate significantly slower than $\sqrt{n}$.

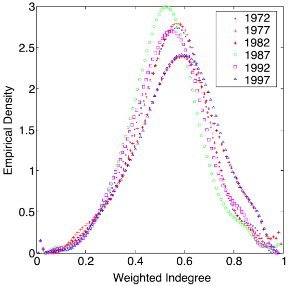
Model

Theorems

Application: Setup

Data: Detailed benchmark input–output accounts spanning the 1972–2002 period, compiled every five years by the Bureau of Economic Analysis.

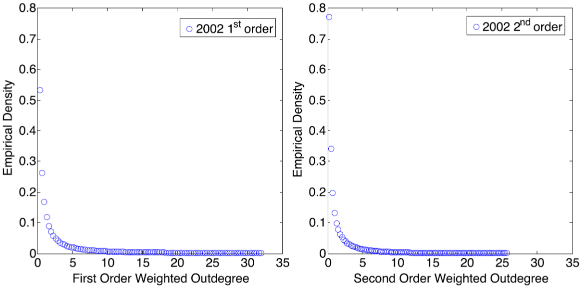
Intermediate input intensity shares:



$\Longrightarrow$ Most sectors are concentrated around the mean (0.55).: on average, 71% of the sectors are within one standard deviation of the mean input share.

First- and second-order OUT-degrees densities

Intermediate input intensity shares:



Heavy right tails, meaning that some commodities are (1) General purpose inputs used by many other sectors. and (2) major suppliers to sectors that produce the general purpose inputs.

$\Longrightarrow$ The tail of the distributions is well-approximated by a power law distribution (Pareto distribution).

Distribution parameters estimation (1)

OLS regression of the empirical log-CCDF on the log-outdegree sequence are downward biased in small samples (Gabaix and Ibragimov, 2011). Thus implement the modified log rank– log size regression. Take the tail of 1 minus the empirical cumulative distribution functions to correspond to the top 20% largest sectors in terms of in an out degrees.

$$CDF_{\text{Pareto}} = 1 - \left(\frac{x_m}{x}\right)^{\alpha}$$

Where x_m is the scale parameter and α is the shape parameter.

Distribution parameters estimation (2)

$\hat{\beta}$ and $\hat{\zeta}$ are the shape parameters for the first and second-order degree distribution. (As higher is the shape parameter, more skewed is the distribution.)

OLS ESTIMATES OF β AND ζ[a]

	1972	1977	1982	1987	1992	1997	2002
$\widehat{\beta}$	1.38 (0.20; 97)	1.38 (0.19; 105)	1.35 (0.18; 106)	1.37 (0.19; 102)	1.32 (0.19; 95)	1.43 (0.21; 95)	1.46 (0.23; 83)
$\widehat{\zeta}$	1.14 (0.16; 97)	1.15 (0.16; 105)	1.10 (0.15; 106)	1.14 (0.16; 102)	1.15 (0.17; 95)	1.27 (0.18; 95)	1.30 (0.20; 83)
n	483	524	529	510	476	474	417

[a]The numbers in parentheses denote the associated standard errors (using Gabaix and Ibragimov (2011) correction) and the number of observations used in the estimation of the shape parameter (corresponding to the top 20% of sectors). The last row shows the total number of sectors for that year.

High degree of asymmetry in the U.S. economy in terms of the roles that different sectors play as direct or indirect suppliers to others.

$\Longrightarrow$ The interplay of sectoral shocks and network effects leads to sizable aggregate fluctuations

Quantitative extent of the network effects (1)

Aggregate effects of sectoral shocks: Compute $||\nu_n||_2$ for the U.S. input–output matrix at different levels of aggregation and for different years.

ESTIMATES FOR $\|v_n\|_2$[a]

	1972	1977	1982	1987	1992	1997	2002
$\|v_{n_d}\|_2$	0.098 ($n_d = 483$)	0.091 ($n_d = 524$)	0.088 ($n_d = 529$)	0.088 ($n_d = 510$)	0.093 ($n_d = 476$)	0.090 ($n_d = 474$)	0.094 ($n_d = 417$)
$\|v_{n_s}\|_2$	0.139 ($n_s = 84$)	0.137 ($n_s = 84$)	0.149 ($n_s = 80$)	0.133 ($n_s = 89$)	0.137 ($n_s = 89$)	0.115 ($n_s = 127$)	0.119 ($n_s = 128$)
$\frac{\|v_{n_d}\|_2}{\|v_{n_s}\|_2}$	0.705	0.664	0.591	0.662	0.679	0.783	0.790
$\frac{1/\sqrt{n_d}}{1/\sqrt{n_s}}$	0.417	0.400	0.399	0.418	0.432	0.518	0.554

[a] $\|v_{n_d}\|_2$ denotes estimates obtained from the detailed level input–output BEA data. $\|v_{n_s}\|_2$ denotes estimates obtained from the summary input–output BEA data. The numbers in parentheses denote the total number of sectors implied by each level of disaggregation.

$||\nu_{n_d}||_2$ at different years are roughly twice as large as $1/\sqrt{n}$ (First row).
$\Longrightarrow$ intersectoral linkages increase the impact of sectoral shocks by at least 2 times.

The third row captures the change in the aggregate effect of sectoral shocks from more to less aggregated data.
$\Longrightarrow$ Taking intersectoral linkages into account simply doubles the impact of sectoral shocks at all levels of disaggregation.

Quantitative extent of the network effects (3)

If indeed taking intersectoral linkages into account simply doubles the impact of sectoral shocks at all levels of disaggregation the reatio will be $\frac{1/\sqrt{n_d}}{1/\sqrt{n_s}}$.

If, on the other hand, network effects are more important at higher levels of disaggregation, then we would expect that:

$$\frac{||\nu_{n_d}||_2}{||\nu_{n_s}||_2} > \frac{1/\sqrt{n_d}}{1/\sqrt{n_s}}$$

Quantitative extent of the network effects (4)

The table early shows that the latter is indeed the case for all years. For example, in 1972, as we move from the more aggregated measurement at the level of 84 sectors (at two-digit SIC) to an economy comprising 483 sectors (roughly at four-digit SIC), the standard diversification argument would imply a decline of 58% in the role of sectoral shocks, whereas the actual decline observed in the data (measured by $\frac{||\nu_{n_d}||_2}{||\nu_{n_s}||_2}$is about 29%.

Back-of-the-envelope calculation (1)

Using TFP estimations across 459 four-digit (SIC) manufacturing industries from the NBER productivity database between 1958 and 2005, compute its average standard deviation to be 0.058.

Average of the U.S. GDP accounted for by manufacturing is around 20% for the same time frame.

Assuming that the manufacturing industries correspond to one-fifth of the GDP, the economy comprises 5459 = 2295 sectors. With a sector volatility of 0.06, if aggregate volatility decayed at the rate $\sqrt{n}$, it expects it to be $0.058/\sqrt{2295} = 0.001$.

Back-of-the-envelope calculation (2)

The shape parameter for the second order degrees $\hat{\zeta} = 1.18$ implies that aggregate volatility decays no faster than $n^{(\zeta-1)/\zeta} = n^{0.15}$.

Using the second-order degree distribution, aggregate volatility decays at the rate $n^{0.15}$, the same number would be $0.058/2295^{0.15} = 0.018$. This corresponds to sizable aggregate fluctuations, in the ballpark of the approximately 2% standard deviation of the U.S. GDP.