The Impact of Final Demand and Technology Shocks in the French Economy

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Abstract

The emergence and nature of cascading effects and avalanches has not been fully explored in the economic literature. We investigate the diffusion mechanisms of shocks on final demand and technology creating avalanches in the economy. To undertake this investigation we represent the economy as a network and apply three diffusion models. The first model considers the spread of a shock on final demand based on the Input-output model. The second is an adaptation of a network diffusion model to study the impact of changes in the technological relationships between sectors by decreasing the flow of inputs. The third model is an extension of the second, were we introduce an additional step: after a sector gets hit by a shock, the flow of inputs decreases and each sector updates its production level to these new conditions. Results for the French economy show that the first model brought about large and homogeneous avalanche sizes across sectors. On the other hand, the second and third models shows heterogeneous and predominantly large avalanche sizes. The sectors that triggered the largest avalanches applying the network diffusion models are similar and have high global centrality in the French input-output network. In particular, we highlight the capacity of the financial sector to trigger one of the largest avalanches in the economy when using the network diffusion model.

Key words: input-output analysis, intersectoral dependencies, diffusion, avalanches
JEL Classification: C67, C63, D57, O52

Introduction

The structure of intersectoral relationships in the economic system shapes the diffusion mechanisms through which shocks may diffuse from one sector to another in the form of avalanches. Evidence of this contagion process was the crisis observed in 2008-2009. Its aftermath shows the importance of analyzing the mechanisms of contagion in order to react properly and prevent its consequences in the productive sphere. In this paper we investigate the spread of shocks in the form of avalanches or cascades throughout the input-output network of an economy.

Input-output analysis provides the tools to analyze the intersectoral dependencies and the impact of a sector on the economy. The tools researchers use in this approach are linkage measures and others such as structural decomposition analysis (Miller and Blair 2009). Backward and forward linkages are used to study the impact of a sector and to identify the key sectors that can be object of selective promotion in a development strategy (Dietzenbacher 1992, McGilvray 1977, Jones 1975, Chenery and Watanabe 1958, Hirschman 1958, Rasmussen 1956). Despite the fact that input-output analysis has studied the connections and interdependencies between sectors, it has not explored the emergence and nature of cascading effects and avalanches from one sector to another explicitly. This investigation complements the analysis with network diffusion models which allow going beyond standard impact analysis.

The investigation is part of a multidisciplinary approach were input-output data is used to analyze the economy as a network. This allows one to compute network measures used to study the structural properties of the economic system. Examples include Slater (1978), Blöchl et al. (2011), Xu et al. (2011), Duan (2012), and McNerney et al. (2012) which study the properties of the national economies using network analysis; and Acemoglu et al. (2012; 2013) which incorporated a centrality measure to capture intersectoral linkages in a multisectoral macroeconomic model to measure the impact of sectoral idiosyncratic shocks on aggregate volatility.

Diffusion models in networks have been applied to study the spreading mechanisms of information, innovations, infectious diseases, and failures throughout a network. These models, originally used to analyze social and physical networks, have been used to study the spreading mechanisms in economic networks such as the spread of crisis in the international trade network (Lee et al. 2011, Garas et al. 2010), and the spread of shocks or crisis within the network embedded in the financial sector (Kücük et al. 2012, Toivanen 2013, Karimi and Raddant 2013). In this paper we investigated the diffusion of shocks from one sector to others in the form of steps following production chains. This is a progressive process where once a sector has been hit by a shock it cannot get hit again.[1] Using network diffusion models to analyze the diffusion of shocks among sectors has the advantage of taking into account the entire structure of intersectoral relationships in the economy, which in turn allows one to capture local and global effects. It also presents an opportunity to explore different settings beyond the linear and fixed relationships established in the Input-output model through the inclusion of technology shocks that change the flows of inputs.

We use the 2007 French input-output table provided by Institut National de la Statistique et des Etudes Economiques (INSEE) to construct the French input-output network. This network provides the structure through which a sectoral shock diffuses throughout the economy. We investigate the spread of two types of shocks using three diffusion models. The first model is based on the Input-output model and studies the effects of a change in final demand. The second and third diffusion models are an adaptation of the models used in Kinney et al. (2005) and Lee et al. (2011), applied to study the impact of changes in the technological relationships between sectors. The spreading process is specified using two parameters: the decrease in the supply and demand of inputs when a sector gets hit by a shock, and a production level threshold above which the shock spreads to other sectors. The third diffusion model has an additional step. First a sector gets hit by a shock and its input supply and demand decrease by a fraction f. Following, production level gets updated according to the input-output model. Finally, the shock spreads to other sectors if the total decrease in input supply and demand exceeds the new capacity threshold. Main results for the French economy showed that the impact of changes in final demand translate into all sectors triggering homogeneous and

[1] A non-progressive process would imply that a sector may be hit repetitively number of times, as a person catching a disease, recovers and is, thus, susceptible of contagion again, instead of becoming immune (Kleinberg 2007). For examples of progressive and non-progressive diffusion models see Garas et al. (2010) and Kücük et al. (2012).

very large avalanche sizes. On the other hand, the second and third models showed heterogeneous and predominantly large avalanche sizes. The sectors that triggered the largest avalanches in model two and three are similar but different from the ones observed with model one. Network diffusion models highlighted the capacity of the most globally central sectors to trigger large avalanches. In particular, the financial sector is able to spread a shock to most of the sectors in the economy.

The paper is organized as follows. Section two covers materials and methods, where we detailed the database we use and the diffusion models applied for the evaluation of avalanches in the economy. Section tree presents the results for the French economy. On section four we make a discussion about the different results according to the models and conclude.

Data and Methods

Data

We use the intermediate demand table for France for 2007 provided by the Institut National de la Statistique et des Etudes Economiques (INSEE). This table classifies the economy into 118 sectors according to the French classification and gives information on the intermediate demands for each sector as economic transactions made by buying and supplying inputs. We take the 116 sectors with positive interactions with the rest of the economy. We use the intermediate demand table to compute the technical coefficients matrix following Leontief (1936) Input-Output model, and to construct the input-output network.

Input-Output Network

The structure of intersectoral dependencies, represented in the intermediate demand table, gives rise to a weighted directed graph with self loops. This graph is the network representation of the economy where a node represents a sector and a weighted directed edge represents an economic transaction conducted between sectors to buy or sell inputs (Blind and Murphy 1974, Blöchl et al. 2011, Amaral et al. 2007) (see figure 1). Self loops capture the idea of a sector using its own product as input, and will be of importance when analysing the concentration of additional resources flowing through the network. The weighted adjacency matrix has entries:

$$w_{ij} = z_{ij} > 0 \tag{1}$$

when sector i conducts a transaction with sector j. z_{ij} is the ij-th element of the intermediate demand matrix which is equivalent to be the ij-th element of the weights matrix defined above, which will be positive if there is an input-output relationship between sector i and sector j. When $w_{ii} > 0$ it means that sector i has a self loop of magnitude w_{ii}. Since the network is directed, we have $w_{ij} \neq w_{ji}$.

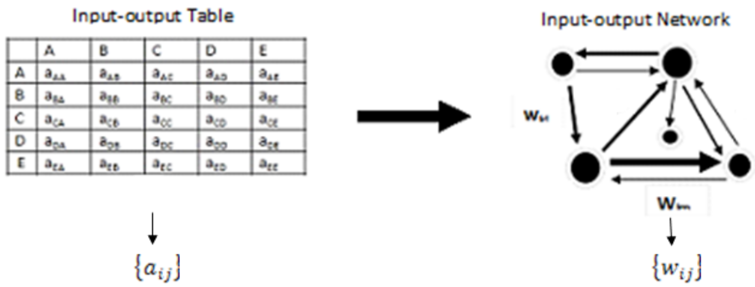

Figure 1: Construction of the input-output network

Model 1. The Input-Output Model

In the Input-Output Model, total output of a sector, x_i is expressed as a function of the demand for the different commodities produced in the economy. Production is defined in vector form as:

$$\mathbf{x} = \mathbf{z1} + \mathbf{D} \tag{2}$$

where x is the $n \times 1$ column vector of output, z is the intersectoral flow or intermediate demand matrix, and D is the $n \times 1$ column vector of final demand. An element of the intermediate demand matrix, z_{ij}, gives the flow of inputs from sector i to sector j used by j to produce.

Equation 2 can be equivalently written as follows:

$$\mathbf{x} = \mathbf{xA} + \mathbf{D} \tag{3}$$

where x is the $n \times 1$ column vector of output, and $A = [a_{ij}] = z_{ij}/x_j$ is the $n \times n$ matrix of technical coefficients,

Solving for x yields:

$$\mathbf{x} = (\mathbf{I} - \mathbf{A})^{-\mathbf{1}}\mathbf{D} = \mathbf{LD} \tag{4}$$

where x is the $n \times 1$ column vector of output, and $L = (I - A)^{-1} = [l_{ij}]$ is an $n \times n$ matrix known as the Leontief inverse or the total requirements matrix.

We can compute total output of all individual sectors as a function of final demand once we know the magnitudes of the technical coefficients. The impact of sector i on aggregate production is defined as the change in production of sectors needed to compensate a change in final demand of sector i. The final demand of the exogenous sector is constituted by household consumption, government consumption, exports, and capital formation. The effect of a shock on final demand is computed as follows:

$$\mathbf{\Delta x} = \mathbf{x^1} - \mathbf{x^0} = \mathbf{L}(\mathbf{D^1} - \mathbf{D^0}) \tag{5}$$

Equivalently,

$$\mathbf{L\Delta D} = \mathbf{L} * \mathbf{f}, \tag{6}$$

where $\mathbf{f}$ is a column vector with entries assuming sector i receives a shock:

$$\mathbf{f} = \begin{pmatrix} 0 \\ \vdots \\ f_i \\ \vdots \\ 0 \end{pmatrix}$$

The number of sectors with $\Delta x \neq 0$ defined in equation 5, gives the avalanche size triggered after introducing a shock on final demand. To compare the impact across sectors, we normalized the effect of the shock by the size of the shock, which implies that the aggregate impact is determined by the column sum of the Leontief matrix, $\mathbf{L}$, as if the shock was equal to 1 for all sectors (a unit increase on final demand). The origin or nature of the shock on final demand is beyond the scope of this paper where we do not distinguish between the different components of the final demand of the exogenous sector.

Model 2. Diffusion of a Shock on Technology

In this section we present a network diffusion model to analyze the spread of sectoral shocks on technology throughout the input-output network. The shocks we consider are shocks that change the flow of inputs. The spreading mechanism is a progressive process where once a node has been hit by a shock it cannot longer get hit again. This is a discrete process in which the shock spreads step by step as following production chains. We assume that the initial shock is triggered by an external cause, which is not in the scope of this investigation. This external shock is such that it affects a sector as a whole. An example of such a shock could be a natural disaster that hits a geographical area where firms of the same sector are localized such as the nuclear power plants in northern Japan that were severely damaged by the 2009 tsunami, which also affected other sectors like the automobile industry that needed the electrical power to run the plants, and the fishing and agricultural activities which were also affected by the nuclear pollution. Another example is droughts in northern Mexico where water scarcity has a major impact on the agricultural activities that take place there, which, in turn, impacts the supply of inputs for the food industry and restaurants, affecting household consumption and tourism.

The spreading model we use is based on the model used in Kinney et al. (2005) which evaluates the avalanche mechanism of failures in power grids and used by Lee et al. (2011) to measure the impact of the collapse of one country on the rest of the world trade network. In this chapter the spread of shocks takes place in the input-output network where nodes are sectors and weighted directed edges are the economic transactions between them. Each node has an attribute defined as its capacity or production (x_i). Similarly, each edge has an attribute defining the weight of the link between two sectors, (w_{ij}), equal to the magnitude of the economic transaction. As opposed to the standard impact analysis conducted using the Input-output model in this case final demand is fixed. Production levels are kept fixed during the diffusion process, and we assume that a shock arrives at one sector modifying the economic transactions taking place by supplying and buying inputs. This is a symmetric model where both the supply and demand of inputs changes, thus total strength of a sector is evaluated in the condition to spread a shock (see equation 15).

Suppose a shock hits sector i. As a result, the supply and demand of inputs of sector i decrease by a fraction f. New weights of the connections of i with its input suppliers and buyers are defined as follows:

$$w^*_{ij} = (1-f)w_{ij}, 0 < f < 1 \tag{7}$$

for the links between i and i's input buyers, and

$$w^*_{ji} = (1-f)w_{ji}, 0 < f < 1 \tag{8}$$

for the links between i and i's input suppliers. If the total decrease of either the incoming or outgoing link weights of any sector j connected to the shocked sector i exceeds a threshold c of its node capacity x_j, then the first shock propagates hitting the sectors that transact with sector i. If i received the original shock, for j in the set of suppliers and buyers (neighborhood) of i, the shock will propagate to j if:

$$\left(\sum_{k\in N(j)} w_{jk} - \sum_{k\in N(j)} w^*_{jk}\right) + \left(\sum_{k\in N(j)} w_{kj} - \sum_{k\in N(j)} w^*_{kj}\right) > c * x_j, 0 < c < 1 \tag{9}$$

where $k \in N(j)$ refers to some sector k in the set of input suppliers and buyers of j or $j's$ neighborhood.

If the previous condition holds, sector j gets hit by the shock and its supply and demand of inputs decreases according to the following expressions:

$$w^*_{jk} = (1-f)w_{jk}, 0 < f < 1 \tag{10}$$

and

$$w^*_{kj} = (1-f)w_{kj}, 0 < f < 1 \tag{11}$$

for $k \in N(j)$. After the shock, supply and demand of inputs decrease, which has an impact over sector j's neighbors $N(j)$. Substituting w^*_{jk} and w^*_{kj} by their definitions given by equation 10 and equation 11, then equation 9 can be written, from sector j's perspective, as follows:

$$(\sum_{k\in N(j)} w_{jk} - \sum_{k\in N(j)} (1-f)w_{jk}) + (\sum_{k\in N(j)} w_{kj} - \sum_{k\in N(j)} (1-f)w_{kj}) > c * x_j \tag{12}$$

Equivalently,

$$\sum_{k\in N(j)} fw_{jk} + \sum_{k\in N(j)} fw_{kj} > c * x_j \tag{13}$$

Equation 13 yields the following condition for a shock to spread from one sector to other sectors:

$$\sum_{k\in N(j)} (w_{jk} + w_{kj}) > (c/f) * x_j \tag{14}$$

First term on the left hand side of equation 14 is the outstrengh of node j and the second term on the is instrength of node j. Therefore, equation 14 can be further expressed in terms of node j's total strength as follows:

$$s_j^{out} + s_j^{in} > (c/f) * x_j \tag{15}$$

Equation 15 expresses that if the sector is strongly connected and node size is not enough to absorb the shock, then the shock propagates to its neighbors.

The shock on sector j decreases its weight links by a fraction f and initiates an avalanche of shocks. This, in turn, can cause the shock to propagate even further to their neighbors, and the avalanche proceeds until there are no more sectors that have not received a shock. The f and c parameters are the same for all the sectors in the economy and are values between zero and one. Is important to highlight that the determinant of the spreading mechanism is not each parameter alone but the ratio of the two: c/f. This ratio gives information on the total resilience of the system, both of links and nodes. Note that although f and c are the same for all countries, the effect of a shock and the capacity threshold depend on each country's characteristics; therefore they do vary across countries. The key quantities in the resulting dynamics are: 1) number of subsequently collapsed sectors starting from a given sector's collapse (avalanche size A); and 2) avalanche size distribution for each country.

Model 3. Diffusion of a Shock on Technology with Updating in Production

Model 2 is a first approximation to the spreading mechanism of shocks in the economy. However, in reality one may think that each sector adjusts to the new conditions after they are hit by a shock. Model 3 incorporates this idea by introducing a second step in the diffusion process. First, a sector gets hit by a shock and the magnitude of the economic transactions that this sector conducts with its neighbors decreases by f. This translates into changes in the i-th row and i-th column of the input-output matrix, which in turn changes the technical coefficients matrix. Second, production is updated. A sector that is hit by a shock has fewer inputs to produce after the shock and supplies less inputs to other sectors. Final demand remains fixed, and the condition for the shock to spread to other sectors is the same as in the previous model. At stage t of the diffusion process, the weights of the links between sectors, as well as the other variables such as production, are indexed by t, for example: $z_{ij}(t)$. The flow of inputs decrease according to the following equations:

$$z_{ij}(t+1) = z_{ij}(t) * (1-f), 0 < f < 1 \tag{16}$$

for sector i's input buyers, where $z_{ij}(t+1)$ is the new magnitude of the supply and

$$z_{ji}(t+1) = z_{ji}(t) * (1-f), 0 < f < 1 \tag{17}$$

for sector i's input suppliers, where $z_{ji}(t+1)$ is the new magnitude of the demand for inputs of i. This decrease in the flows of inputs further changes the technological coefficients, a_{ij}, as follows:

$$a_{ij}(t+1) = z_{ij}(t+1)/x_j(t) \tag{18}$$

and

$$a_{ji}(t+1) = z_{ji}(t+1)/x_i(t) \tag{19}$$

Then, the new production level is calculated as follows:

$$\mathbf{x(t+1)} = (\mathbf{1} - \mathbf{A(t+1)})^{-\mathbf{1}}\mathbf{d} = \mathbf{L(t+1)d} \tag{20}$$

where $\mathbf{x(t+1)}$ is the new production vector, $\mathbf{A}(t+1) = z_{ij}(t+1)/x_j(t)$ is the new technological coefficients matrix, $\mathbf{L(t+1)}$ is the new Leontief inverse, and $\mathbf{d}$ is the final demand vector, which remained fixed. This mechanism can be viewed as a process where feedbacks arise and effects are reinforced. In this process each update is incorporating previous updates.

After production has been updated, sectors evaluate the same condition as before but with the new production value $\mathbf{x(t+1)}$. If i received the original shock, for j in the neighborhood of i, the shock will propagate to j if:

$$\sum_{k \in N(j)} (w_{jk}(t) - w_{jk}(t+1)) + \sum_{k \in N(j)} (w_{kj}(t) - w_{kj}(t+1)) > c * x_j(t+1) \tag{21}$$

After substituting the definitions of $w_{jk}(t+1)$ and $w_{jk}(t+1)$ in equation 20 and rearranging we obtain:

$$\sum_{k\in N(j)} (w_{jk}(t) + w_{kj}(t)) > (c/f) * x_j(t+1) \tag{22}$$

where the evaluation is made taking into account the new production value $x_j(t+1)$.

Results

Model 1

The diffusion of the effect of a shock on final demand according to the Input-output model is heterogeneous in magnitudes, but homogeneous in terms of the number of sectors affected by the shock (black squares line in figure 2). This means that the avalanche size is the same for every sector and is around 107 sectors out of 116. To break with this homogeneity, and taking advantage of the highly positive skewed distribution of the magnitudes of the effects, we can establish a threshold above which we count an effect as part of an avalanche. Therefore, if the effect on sector j of a propagating shock originally triggered by sector i is larger than some threshold, then sector j is part of an avalanche triggered by sector i. In figure 2 we show the distribution of avalanches according to different thresholds as percentage of the aggregate effect.

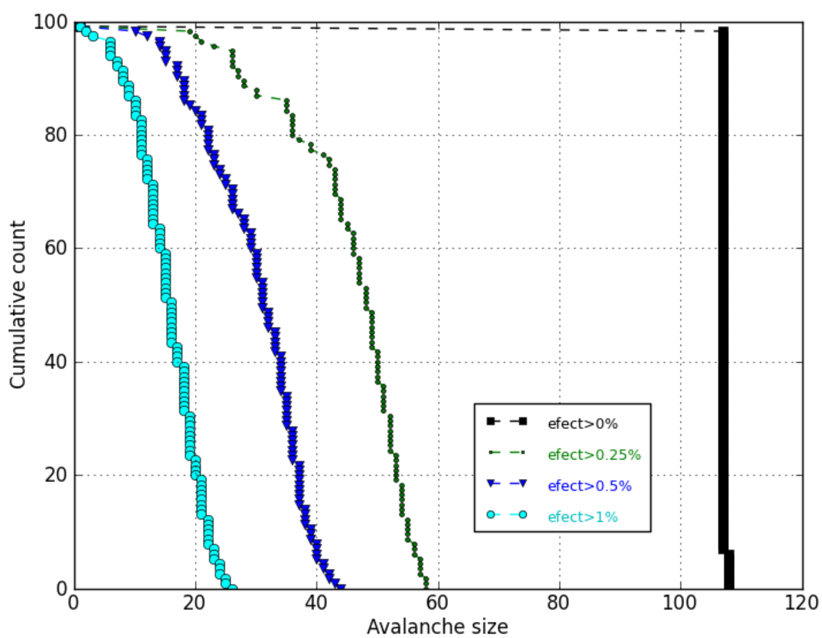

Figure 2: Avalanche size distributions for different effect thresholds as percentage of aggregate effect.

We can observe from the distributions in figure 2 that, as the threshold becomes larger, the distributions become more positively skewed, to the point of having mainly small avalanche sizes. Since most of the magnitudes of the effects are very small, we only require a small threshold to observe heterogeneity. As soon as we disregard effects smaller than 0.25 percent of the aggregate effect, the concentration of avalanche sizes falls in a wider range, mainly from 25 to 40 but the maximum number of sectors that can be part of an avalanche decrease from 116 to 58. When the threshold is 0.5 percent, the avalanche size distribution becomes normal-like. However, when we increase the size of the threshold even more, we lose this normal-like shape again towards a positively skewed distribution. In most cases, the sectors that triggered the smallest avalanche size are: domestic services and road, rail, and waterways network sanitation.

On the other hand, the sectors that triggered the largest avalanche sizes are not constant. When the threshold is large artificial fibbers and mechanic equipment and fabrication of machinery triggered the largest avalanches. But when the threshold became smaller, the sectors home appliances, weapons and ammunition, and automobile equipment triggered the largest avalanches.

The homogeneous avalanche size distribution is a direct result from using the input-output model, were the linear and fixed intersectoral relationships bring about the same diffusion of a shock, spread throughout the structure of linkages which is determined by the fixed requirements matrix. To overcome this limitation, we explore the diffusion of a shock using network diffusion models, were we can introduce threshold effects causing non linearities in the diffusion process and allow breaking with the fixed technological relationships between sectors without losing information.

Model 2

In this section we report the results for the spreading of a shock according to model two. A shock in technology is such that it changes the magnitudes of the supply and demand of inputs between sectors. The key parameter in this model is the ratio between the size of the shock and the capacity threshold: f/c. For an f much smaller than c, the French economy experienced no avalanches ($A = 0$). Therefore we focus on results for $f/c > 1$. Results of this diffusion model to the French economy showed that the diffusion of a shock on technology brings about different avalanche size distributions according to the sector that triggered the avalanche.

The avalanche size distributions according to all parameter specifications are skewed highlighting the heterogeneity in the spreading of shocks (figure 3). In all cases the largest avalanche size is above 100 sectors. When the ratio was the largest (f/c=7), the largest avalanche size was 108, whereas when the ratio was the smallest (f/c=1.5), the largest avalanche size was 105 (see table 1). The frequency of avalanches above 105 sectors is the highest for the largest ratios. As the ratio decreases, the frequency of avalanches of size zero, one, or two sectors increases. For the most pessimistic scenario where the shock is the highest and the capacity threshold is the lowest (f/c=7), the sector that triggered the largest avalanche was financial intermediaries and in second place we find real-estate and other services (see first row in table 1).

As the parameters ratio became smaller (lower f and higher c), the financial intermediaries and real-estate sectors lost their place as triggers of the largest avalanches and security, cleaning and other services, computer and related, hotels and restaurants, and telecommunications were left

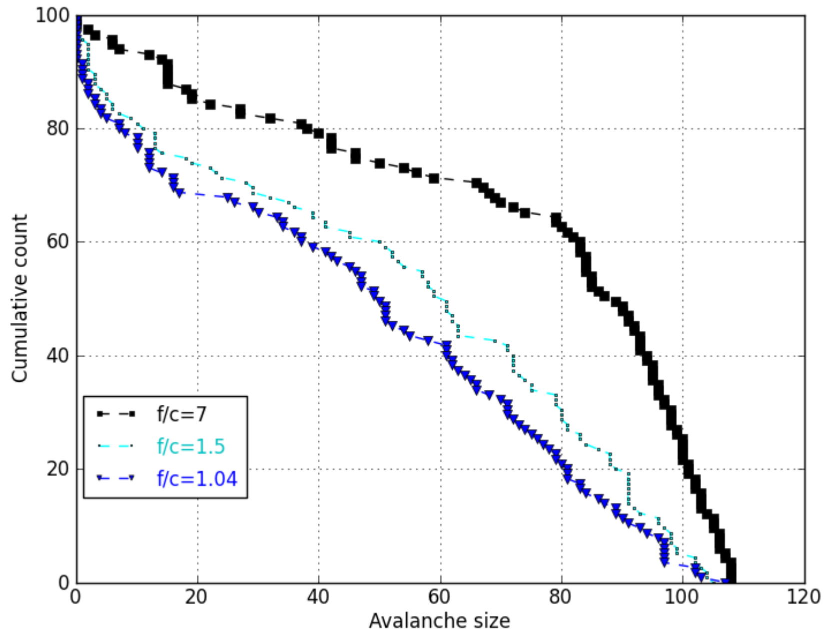

Figure 3: Avalanche size distributions for different c/f.

as the triggers of the largest avalanches (see table 1). This result emphasizes the capacity of the financial sector to spread a large shock throughout the economic system when the economy is weak and vulnerable. But when the shock is smaller and the economy is more resilient, the financial sector has a smaller impact, although it still triggers large avalanches.

On the contrary, the sectors that most of the cases brought about the smallest avalanche size were: tobacco and domestic services. As the parameters ratio became smaller, the group of sectors that triggered the smallest avalanche size grew to include other sectors like photographic and optic materials and weapons and ammunition. The higher frequency of very small avalanche sizes gives evidence that as the f parameter gets smaller and the c parameter gets larger it is more difficult to trigger large avalanches, which increases the number of sectors that spread small avalanches.

Table 1: Sectors that triggered the largest and smallest avalanches in the European Union, Model 2

	Largest Avalanche		**Smallest Avalanche**	
f/c	Triggering sector	Size	Triggering sector	Size
7	Financial intermediaries, Real-estate, computer and related, security cleaning and other services, and hotels and restaurants	108	Domestic services and tobacco,	0, 2
1.5	Security cleaning and other services, Telecommunications and post office, computer and related, hotels and restaurants, and diverse food industry	105-103	Tobacco, weapons and ammunition, domestic services, and photographic and optic materials	0, 1
1.04	Computer and related activities, Professional services, Security, cleaning and other services, Hotels and restaurants	107, 103, 102	Fishing, tobacco industry, photographic and optic materials, weapons and ammunition, domestic services, forestry, leather, and jewellery	0, 1

Model 3

Results of the third diffusion model showed that when the economy can adjust to the shock it experiences larger avalanche sizes increasing the frequency of medium and large avalanches. Moreover, the size of the largest avalanche was larger than with model two. Large sizes are reinforced as a result of feedback effects, where the economy becomes more fragile and supplies fewer inputs to other sectors after a shock, which in turn makes other sectors vulnerable. Therefore, the shock spreads easier creating larger avalanches.

In figure 4 we show the distributions for the simulation results using different parameters' ratios. We use the same ratios as with model two to be able to compare results. As before, the distributions show heterogeneity in the avalanche sizes and are skewed. In particular, we observe that the probability to find an avalanche larger than half of the economy increased, although the larger change was found for the avalanche sizes larger than 80 sectors. Larger the parameters ratio bring about larger avalanches and more frequent very large avalanches.

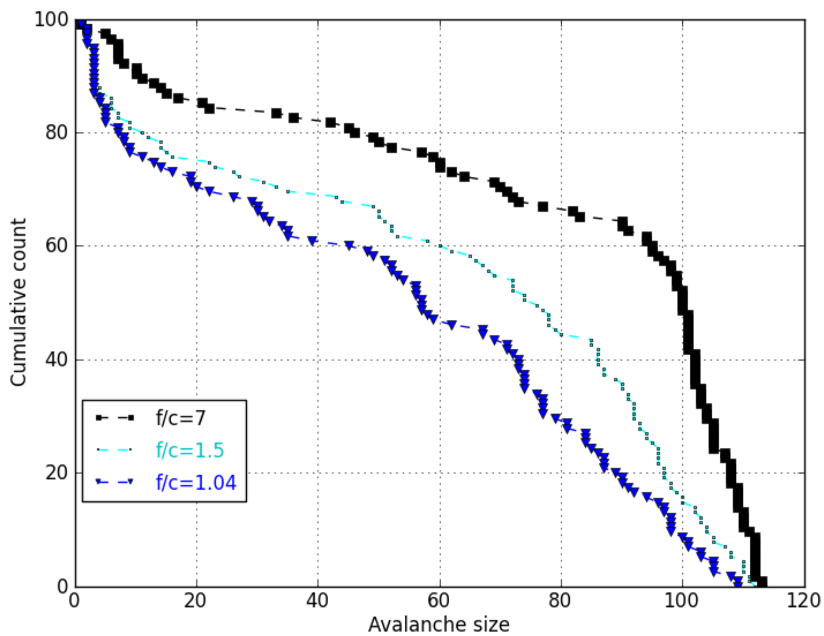

Figure 4: Avalanche size distribution with updating in production for different c/f.

The differences with respect to the results from model 2 can be seen as larger avalanche sizes and a higher frequency of medium and large avalanches. In particular, the smallest avalanche sizes are larger. Therefore updating in production reinforced the behavior found previously with model 2.

The sectors that triggered the largest and smallest avalanches are similar to those found applying model 2. Examples include security, cleaning and other services, construction, and telecommunications for the triggers of the largest avalanches, and domestic services for the trigger of the smallest avalanche.

To explore the characteristics of the triggers of the largest avalanches applying the network diffusion models we compute the global centralities of sectors according to their role as input suppliers and buyers. Authority and hub scores give a ranking of sectors according to their global centralities taking into account positive feedbacks in the diffusion process of a shock. The scores are based on a mutually reinforcing relationship, where a good authority is pointed by a good hub. These scores were originally applied to analyze web pages through the HIT (Hypertext Induced Topic Selection) algorithm. This algorithm assigns a hub score y_i and an authority score x_i to each node or web page, where the authorities are the most prominent sources of primary content, and hubs assemble high-quality guides and resource lists directing the users of web pages to recommended authorities (Kleinberg 1999). In the input-output context, a good authority is a sector that buys inputs from equally important hubs or input suppliers thus is highly connected, directly or indirectly, to other sectors through different production chains. Connections between sectors are appropriately weighted to take into account that the supply of inputs from a highly ranked sector is more important than that of a low ranked one. A shock hitting a good authority, or hub, will trigger a chain of effects along the down and upstream linkages through this connections, where effects on good authorities feedback to good hubs, and the effects on good hubs feedback again to good authorities and so on.

The key sectors according to their authority scores are: oil refining, security, cleaning and other services, hydrocarbon extraction, agriculture and hunting, steel industry and steel first transformation, organic chemistry industry, non-ferrous metals production, metallic products fabrication, financial intermediaries, and advertising and market studies. On the other hand, the top ten sectors with the highest hub scores are: metallic minerals extraction, oil refining, organic chemistry industry, meat industry, milk industry, fuel production and distribution, food industry, steel industry and steel transformation, reception devices fabrication, and motorcycle materials.

The triggers of the largest avalanches in the French economy have high global centrality or are connected to sectors that have high global centrality. Examples include security cleaning and other services, which is the second best authority; financial intermediaries, which is the ninth best authority; and hotels and restaurants, which is connected to the meat and milk industries, and to agriculture, all of which have high global centralities. Nevertheless, these sectors do not necessarily have strong direct or local connections.

Discussion

In this paper we evaluated different diffusion mechanisms through which a shock spreads throughout the economy creating cascade effects and avalanches. The complex architecture of the French input-output network makes the economy vulnerable to a wide spread of shocks. A high interconnected economy, where the financial sector plays a central role, could be object of contagion and cascades such as the one observed in the financial crisis of 2008-2009.

To investigate the emergence and nature of avalanches of sectoral shocks in the economy we applied three diffusion models. First we used the Input-output Model to simulate the diffusion of the effect of a shock on final demand. With this model, the diffusion of the shock is homogeneous and very large. To capture the heterogeneity in the avalanche sizes we must impose a threshold above which we count an effect of a shock as part of an avalanche. Results showed that when this threshold increases we observe highly positively skewed distributions. On the contrary, when the threshold is low, most of the avalanche sizes are large. However, by imposing a threshold to count an effect as part of an avalanche we lose information. As the size of the threshold increases, the maximum number of sectors that are part of an avalanche decrease considerably since most of the effects are small.

On the other hand, when we evaluated the avalanche size distributions applying a network diffusion model, were the spread of a shock is determined by the capacity of each sector and its connectivity, the avalanche size distributions were heterogeneous and concentrated on large sizes. Applying the network diffusion model we identified the sectors that trigger the largest avalanches in the economy. These sectors are predominantly services activities like financial intermediaries, real-estate, security cleaning and other services, and hotels and restaurants. On the other hand, the sector that triggers the smallest avalanches, concentrating the effects on itself, is domestic services.

The third diffusion model that allowed the economy to adjust to the new conditions after a shock brought about heterogeneous and larger avalanches than with model two. As a result, the frequency of large avalanches increased. When the systems adjusts, as it happens in the real economy, the effects of a shock on one sector are reinforced and create feedback effects that turn other sectors vulnerable, facilitating the propagation of shocks throughout the economy. The triggers of the largest avalanche sizes were similar to the ones found previously with model two, but with model three they trigger larger avalanches.

Results showed that the Input-output model does not allow disentangling the different diffusion mechanisms and the wide range of impacts of sectoral shocks. According to their role and importance in the economy, different sectors impact the economy in different magnitudes and through different channels. An example is the financial sector, which triggered the largest avalanche size applying the network diffusion models when the shock is large and the economies are fragile. This result points out the limitations of using linear and fixed relationships between sectors to model the spread of shock. Results also highlight the advantages of applying network diffusion models to evaluate the impact of sectoral shocks in the macroeconomy, incorporating non linear effects.

Extensions of the present investigation include analyzing other diffusion mechanisms and making a cross-country analysis.

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