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Domino Effects when Banks Hoard Liquidity: the French network

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Abstract

We investigate the consequences of banks' liquidity hoarding behavior for the stability of the financial system proposing a new model of banking contagion through two channels, bilateral exposures and funding shortage. Inspired by the key role of liquidity hoarding in the 2007-2009 financial crisis, we incorporate banks' hoarding behavior in a standard Iterative Default Cascade algorithm to compute the propagation of a common market shock through a banking system. In addition to potential solvency contagion, a market shock leads to banks' liquidity hoarding that may generate problems of short-term funding for other banks. As an empirical exercise, we apply this model to the French banking system. Relying on data on bank's bilateral exposures collected by the French Prudential Supervisor Authority, the French banking sector appears resilient to the combination of an initial market shock (losses on marked-to-market assets) and of the resulting solvency and liquidity contagion. Gauging the relative weights in the total loss of the various factors, the model sheds light on the complexity of liquidity hoarding effects.

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Domino Effects when Banks Hoard Liquidity: the French network[*†]

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Résumé: Afin d'analyser les effets systémiques de la thésaurisation des banques sur la stabilité d'un réseau financier, cet article propose un nouveau modèle de contagion bancaire. Cette dernière est étudiée suivant deux canaux : les expositions bilatérales directes entre établissements de crédit et les difficultés de financement à court-terme auxquelles les banques peuvent éventuellement faire face si une crise de confiance vient à se matérialiser (comportement préventif de thésaurisation). En s'inspirant du rôle majeur joué par la thésaurisation pendant la crise financière de 2007-2009, le modèle développé dans cet article se distingue du traditionnel algorithme séquentiel de calcul de défauts en cascade largement évoqué et employé dans la littérature sur le risque systémique pour mesurer les effets d'un choc de marché sur l'ensemble d'un systme bancaire, en introduisant le comportement de thésaurisation des banques. Au-delà de la simple contagion via les expositions bilatérales, un tel phénoméne initié par certaines banques peut entraîner des problèmes de financement à court-terme pour d'autres. En s'appuyant sur les données d'expositions bilatérales des banques francaises collectées par l'Autorité de Contrôle Prudentiel, le secteur bancaire francais semble être relativement robuste lorsqu'il est à la fois soumis à un risque de marché (pertes sur les actifs de marché détenus par les banques dans leur portefeuille) et aux effets induits de la contagion par insolvabilité et par difficulté de financement à court-terme. Les résultats obtenus en termes de poids relatifs de chacun des canaux de contagion étudiés sur les pertes totales estimées mettent en exergue le caractère fondamental et complexe des effets de la thésaurisation.

Mots-clés: Thésaurisation, contagion par insolvabilité et par difficulté de financement, réseaux financiers, risque systémique
JEL classification: G01, G21, G28

Abstract: We investigate the consequences of banks' liquidity hoarding behavior for the stability of the financial system proposing a new model of banking contagion through two channels, bilateral exposures and funding shortage. Inspired by the key role of liquidity hoarding in the 2007-2009 financial crisis, we incorporate banks' hoarding behavior in a standard Iterative Default Cascade algorithm to compute the propagation of a common market shock through a banking system. In addition to potential solvency contagion, a market shock leads to banks liquidity hoarding that may generate problems of short-term funding for other banks. As an empirical exercise, we apply this model to the French banking system. Relying on data on banks bilateral exposures collected by the French Prudential Supervisor Authority, the French banking sector appears resilient to the combination of an initial market shock (losses on marked-to-market assets) and of the resulting solvency and liquidity contagion. Gauging the relative weights in the total loss of the various factors, the model sheds light on the complexity of liquidity hoarding effects.

Keywords: Liquidity hoarding, solvency and funding contagion, financial networks, systemic risk
JEL classification: G01, G21, G28

1 Introduction

The recent financial crisis has challenged the traditional view on the characteristics of system financial stability and the channels of propagation of losses. Whereas capital levels were closely monitored, heavy reliance of financial institutions on whole-sale funding was overlooked. And banks that seemed to be safe experienced creditor runs and significant cash outflows, that ultimately led to their bail-outs or defaults. For instance, in September 2008, Lehman Brothers Holding Inc. filed for bankruptcy protection despite the reassuring conclusions of a report affirming its solvency; Dexia faced liquidity shortages leading to a restructuring of the bank in spite of successfully passing the stress-test run by the European Banking Authority in July 2011 with a Tier 1 Capital representing 12.1% of its risk-weighted assets[1].

Liquidity constraints played a key role during the crisis, since the whole interbank market on both sides of the Atlantic froze, requiring central banks to intervene as a lender of last resort. A high level of uncertainty and increased counterparty risk were the main reasons for this sudden decrease in the interbank market activity and for the observed banks' liquidity hoarding behavior. Indeed, being uncertain about the future availability of liquidity and fearing insolvency of their counterparts, banks stopped lending to each other and started withdrawing their short-term positions.[2] The consequences of such a behavior were especially adverse to the extent that many banks were highly leveraged and heavily relying on short-term wholesale funding in the run-up to the crisis.

Whereas the literature on the propagation of losses through bilateral interbank exposures (solvency contagion) is abundant and shows, in general, scarce evidence of contagion, solvency contagion in a joint framework with banks' liquidity hoarding behavior (funding shortage) has been hardly studied. Therefore, our paper aims at filling this gap and proposes a simple model that allows studying how banks' preemptive actions to secure their liquidity needs can affect the system in a framework of a common market shock and potential solvency contagion.

In this paper, we model a banking system as a weighted directed network, explicitly taking into account the bilateral relationships between banks. Since linkages among financial institutions are of a different nature regarding the ease with which the link can be broken, we distinguish between short- and long-term commitments. On the one hand, only short-term links such as overnight loans play a significant role in the liquidity shortage that can materialize within the system as they can be easily reduced in size or even cut in a short

[1]For more details on Dexia situation, see Bank of International Settlements 2013.

[2]See Acharya and Skeie (2011), Brunnermeier (2009) for more evidence on the last financial crisis

period of time. On the other hand, long-term exposures are a channel of solvency contagion. A description of the lending and borrowing activities of Lehman Brothers proposed by the financial industry think tank "Committee on Capital Markets Regulation" (2012) gives an intuitive difference between the two types of exposures and therefore sources of risk: "Lehman was extensively reliant on short-term funding, particularly through repos, and consequently it suffered a liquidity crisis when this short-term funding became unavailable. Had Lehman been more reliant on long-term, unsecured debt, it may have been less likely to fail in the first place, although third-party exposure would have been greater in that event."

Intuitively, the mechanism is as follows. We consider events occurring within a week. Initially, a system is hit by a market shock that impacts many banks at the same time. A market shock weakens the system and makes it vulnerable to contagion. Some banks may default immediately if they are not enough capitalized to absorb the losses due to this market shock. As a result, defaulting banks do not honor their commitments and impose direct losses to their counterparts, thus potentially triggering solvency contagion. At the same time, banks that have to write down losses after the market shock perceive the situation of the entire system as being in distress and may start hoarding liquidity, thus generating cash outflows for their counterparts and exacerbating their funding problems. Eventually, the banks will suffer from a liquidity shortage and file for bankruptcy due to illiquidity[3]. Both channels may subsequently lead to multiple rounds of contagion.

The paper is closely related to the strand of literature that studies solvency contagion using a network approach (to name a few, Furfine, 2003; Mistrulli, 2011; Upper, 2004). All these papers share a common framework: financial institutions are linked through their bilateral exposures, thus forming a financial network, and a shock to one bank can propagate through the system via the existing linkages. Most of the papers on financial networks examine solely the solvency contagion under an idiosyncratic (Mistrulli, 2011) or a market shock (Cont *et al.*, 2010), whereas we model the propagation of losses through both solvency

[3]Officially, a bank files for bankruptcy with no distinction made between defaults due to insolvency or illiquidity. Though in our model, we underline the reason of bankruptcy: lack of capital or lack of liquidity. As evidence that defaults due to the lack of liquid assets took place during the recent crisis, we cite Christopher Cox, the chairman of the Securities and Exchange Commission (SEC), explaining the background and the circumstances of the run on Bear Stearns in March 2008: "The fate of Bear Stearns was the result of a lack of confidence, not a lack of capital. When the tumult began last week, and at all times until its agreement to be acquired by JP Morgan Chase during the weekend, the firm had a capital cushion well above what is required to meet supervisory standards calculated using the Basel II standard. Specifically, even at the time of its sale on Sunday, Bear Stearns' capital, and its broker-dealers' capital, exceeded supervisory standards. Counterparty withdrawals and credit denials, resulting in a loss of liquidity - not inadequate capital - caused Bear's demise." (Letter to the Chairman of the Basel Committee on Banking Supervision, March 20, 2008: www.sec.gov/news/press/2008/2008-48.htm)

and liquidity contagion channels after different adverse events[4].

The paper contributes to the literature in several ways. First, it delivers a theoretical framework to analyze how banks' actions to hoard liquidity may lead to liquidity shortage in the interbank market, and eventually, the defaults of their counterparts. We also derive a measure of losses propagating through this specific channel. Second, we design an operational approach to implement a realistic market shock, either a shock common to all banks or driven by the fall of one specific asset class. Third, the empirical part of the paper is a direct application of the model to the French banking system. It measures the resilience of the French banking system to financial contagion, both solvency and liquidity ones, thus enriching the evidence available for most of the industrialized countries.

From a different point of view, our paper also contributes to the emerging literature on multilayer financial networks. In such a framework, each layer is a network in one particular market, e.g. interbank exposures in a CDS market represent one network, whereas exposures in the interbank money market can represent another network and so on (see Barigozzi *et al.*, 2010). All these layers are interconnected: a shock can affect all the networks at the same time or pass from one layer to another. In our basic model, we consider two networks, namely, the one on long-term interbank exposures and the one on interbank short-term exposures. These two networks propagate different types of contagion. However, a deeper analysis of the possible interactions between these two networks remains out of the scope of this paper.

At the same time, we are aware of the limits of our empirical exercise. First of all, the French banking system is highly integrated in the EU and the world systems, and the banks are not only exposed to other French banks but also to foreign ones, what we can not take into account in our analysis due to data limitations. Second, we analyze the system at one date, on the 31st of December 2011, therefore the results might be very specific to this date, and it would be very interesting to look how the network and the results change over time. Third, we use exogenous recovery rates, though testing the results for a range of recovery rates.

The paper is organized as follows. Section 2 presents the model implemented here which aims at proposing a rationale to explain how solvency defaults and liquidity hoarding can occur in a banking network when the system is affected by a market shock. Section 3 provides an application of our methodology to the French banking system with a comprehensive set of results. Section 4 discusses avenues for future work and concludes.

[4]Gai *et al.* (2010) build up a stylized model to study propagation of a liquidity shock through a banking system. Gauthier *et al.* (2010) take into account both propagation channels, though the authors assume an exogenous probability of creditors run and do not take into account that banks may create liquidity problems in the system by their own actions.

2 The model

In this section, we provide a framework to model liquidity and solvency contagion using the sequential default approach used in the network literature, as well as we propose realistic common market shocks.

We consider a set of N banks that are exposed to each other. We distinguish short-term exposures from long-term exposures. Liquidity contagion only spreads through short-term exposures whereas long-term exposures are a channel of solvency contagion. We denote E^{LT} (resp. E^{ST}) the matrix of long-term (respectively short-term) exposures, where $E^{LT}(i,j)$ (resp. $E^{ST}(i,j)$) represents the gross (resp. netted) exposure of bank i towards bank j (for $(i,j) \in [1;N]^2$). Exposures encompass loans and securities. The asset side of bank i is decomposed into several items: interbank exposures ($E^{LT}(i,j)$ and $E^{ST}(i,j)$ for $j \in [1;N]$), cash $Ca(i)$ and other assets $OA(i)$. We denote the total assets by $TA(i)$. The liability side of bank i consists of equity $C(i)$ (hereafter capital), interbank exposures ($E^{LT}(j,i)$ and $E^{ST}(j,i)$ for $j \in [1;N]$ and $j \neq i$) and all other liabilities gathered in $OL(i)$. The market shocks affect the component OA of banks' balance sheets.

Banks start hoarding liquidity when they consider a situation as a distress, and we use a shock to the banks economic capital as a signal of the distress in the system. We denote the economic capital of bank i as $EC(i)$, and we interpret it as the global level of capital that is considered by the bank as the capital mandatory to optimally run its business in the long run.[5] At the same time, bank's leverage ratio gives a public signal of fragility of a bank. If a bank acts preemptively by withdrawing liquidity, it hoards more from its riskier, more leveraged, counterparts.

Lastly, as we consider an iterative approach with multiple rounds, we have to keep track of the different values taken by the different items of the network at each step of the algorithm. To do so, the variables are indexed by t for the round of contagion and upper-indexed by k for the algorithmic steps.

A schematic balance sheet of bank i is represented in Table 1.

[5]In our application, we used the required capital as a proxy of the economic capital.

	Assets	Liabilities	
Long Term	$E_t^{LT}(i,1)$	$E_t^{LT}(1,i)$	Long Term
Interbank	$\vdots$	$\vdots$	Interbank
Assets	$E_t^{LT}(i,N)$	$E_t^{LT}(N,i)$	Liabilities
Short Term	$E_t^{ST}(i,1)$	$E_t^{ST}(1,i)$	Short Term
Interbank	$\vdots$	$\vdots$	Interbank
Assets	$E_t^{ST}(i,N)$	$E_t^{ST}(N,i)$	Liabilities
Cash	$Ca_t(i)$	$OL_t(i)$	Others
Others	$OA_t(i)$	$Ca_t(i)$	Capital
Total asset	$TA_t(i)$	$TL_t(i)$	Total liability

Table 1: Bank i's stylized balance sheet at date t

As evoked in the literature, contagion usually spreads only through a system that is weakened by a market shock, therefore realistic market shocks are a crucial element to correctly assess the significance of contagion during a distress. We provide the details of the market shocks proposed in the paper, which defer from the shocks so far used in the literature.

These elements are presented in the following subsections. We follow the process of the algorithm step by step: we describe the market shocks that trigger initial losses, then we analyze the contagion mechanisms by disentangling solvency contagion from liquidity contagion, and finally, we introduce the indicators of fragility supposed to reflect the systemic risk inherent to the system. In the last subsection, we illustrate how the model works using a simplified network.

2.1 Market shocks

Before describing the contagion mechanisms, we present the implemented market shocks. To assess the impact of the default of a specific bank on the resilience of a banking system under adverse conditions, we need to define an external event that will affect the system stability and the specific bank in question. As noted in Upper (2011), contagion is likely to occur only when the entire system is under stress.

Papers differ in the types of shocks they consider. The basic setting is to envisage idiosyncratic shocks. For instance, Upper and Worms (2004) for Germany, Mistrulli (2011) for Italy, van Lelyveld and Liedorp (2006) for the Netherlands, Toivanen (2009) for Finland, Furfine (2002) for the USA successively consider the effect of the default of one bank. Though as underlined in Elsinger *et al.* (2006a,b), a large common market shock impacting all the credit institutions of the system at the same time appeared to be a necessary condition to observe contagion propagation. Therefore, several papers, such as Cont *et al.* (2010) and Elsinger *et al.* (2006a,b), analyze the resilience of the system by applying shocks with one systematic component hitting all the banks in the network.

In this paper, we provide an explicit formulation of the common shocks implemented, which affect the category "Other Assets" held in the portfolio of each bank (OA) at the initial date. We define two types of common shocks corresponding to different ways of considering stress episodes. In the first exercise, a general common shock is simulated so that the whole banking sector is in a distress. This general common market shock enables us to assess the resilience of the network from a global perspective. In an other exercise, we consider asset-class specific common market shocks. This asset class specific approach simulates a large range of scenarii in which a sudden and dramatic price drop is observed in a particular financial market. The dotcom bubble and, more recently, the mortgage crises can be an illustration of such asset specific shocks.

We have to emphasized that the shocks differ from usual ones presented in stress-test exercises. Actually, the paper focus on the risk of interbank market freezing that is phenomenon that can appear in only few days. The triggering event has to be very dynamic, unexpected in a sense. Therefore, we consider very short-term shock (occurring within a week[6]) on marked-to-market assets whereas traditional stress-scenario last for several years implying degradation on the banking book. Moreover, this very short-term perspective is compatible with the fact that the initial exposures are taken as given.

2.1.1 Common market shock

Similarly to Elsinger *et al.* (2006a), we define a common market shock as losses on banks' balance sheet component "other assets" (OA) due to a correlated deterioration in asset prices.

The first step is to define and simulate the joint distribution of banks' other assets (OA). We consider that banks' OA is composed of four types of assets: equities, corporate debt, insurance[7] debt and sovereign debt. We do not analyze retail activity, even though retail assets represent a significant part of banks' assets. The main reason is that retail assets are not priced in the same way, and we can not obtain relevant estimation of marked-to-market value of retail assets. On the other hand, retail assets are also less volatile, for instance,

[6]One week span has been chosen for simplicity; considering 3 days or 10 days does not change our results.
[7]Rigorously, this class regroup all financial institutions except banks.

probability of default of real estate assets hardly changed during the crisis. The French real estate market has some specificities. The vast majority of the retail activity corresponds to real estate loans taken by households. Contrary to most countries (especially to the USA and to the UK), French households rarely enter into mortgages. French real estate loans depend on the past income of the household and not on the future expected value of the acquired house. Therefore, the retail activity is barely sensitive to the business cycle and unlikely to suffer from a real estate price collapse. Furthermore, French banks have mitigated their individual retail activity risk with a risk-pooling mechanism for real estate loans. Lastly, the time horizon in the housing market is tremendously larger than a week. For each bank in the scope of the analysis, we identify the weights that each type of assets in the category "others assets" OA represent in the bank's portfolio.

To have an accurate idea of how the asset values jointly evolve in order to properly simulate the shocks that affect banks' balance sheets, we collect time series for these financial variables. We retain four price series for the period from 02/01/2001 to 30/05/2012: Eurostoxx 50 for the equities, JPM Insurance Senior All Index for Insurance, JPM Euro Area Government Bond All Index and JPM Large Corporate Bond Index. Table 2 reports a standard statistical analysis of the daily returns.

	Returns	**Variance**	**Correlation**			
			Equity	**Sovereign**	**Insurance**	**Corporate**
Equity	-0.83%	1.07%	1	-0.28	0.23	0.19
Government Bonds	1.15%	0.04%	-0.28	1	0.43	0.50
Insurance Bonds	1.28%	0.06%	0.23	0.43	1	0.86
Corporate Bonds	1.44%	0.03%	0.19	0.50	0.86	1

Table 2: Statistics of daily returns (02/01/2001-30/05/2011). The average daily return of the Equity is -0.83%, its variance is 1.07% and its correlation with Sovereign daily return is -0.28.

To obtain the joint distribution of the four assets, we estimate a t-Student copula of those four time series using weekly returns between 02/01/2001 and 30/05/2011. The marginal probability distributions are estimated non parametrically with the kernel density method. By aggregating the "other assets" of all the banks, we construct an imaginary consolidated French banking system portfolio. Afterwards, using the correlated returns simulated for each asset type and the weights of these assets in the aggregated portfolio, we compute the profit-and-loss of the imaginary bank. Our ultimate shocks are the left tail of the profit-and-loss distribution for the entire system represented by the aggregated bank.

2.1.2 Asset-class-specific shock

Several crises seem to have been ignited by concerns coming from one particular asset type, thus one might be interested in measuring the resilience of the network after a significant asset price drop. Although one could interpret it as the bursting of a bubble, in this paper we do not pretend that our shocks perfectly represent the way a bubble occurs, we simply consider that one asset class suffers from a sizeable drop in value. We adapt the framework presented for the "common market shock" methodology into this perspective.

We have four asset classes (equities, corporate debt, insurance debt and sovereign debt), thus, we analyze the effect of one asset-class-specific shock at a time. We keep the same data and the same estimation methodology as for the common market shock. But, instead of considering the profit-and-loss of the French banking system, we consider blocks of joint realizations. In each block, we keep the realization in which the considered asset has the lowest values. We obtain, at the same time, the joint distribution of the three other assets conditionally on the specific asset being at its lowest return.

Based on this simulated distribution of the specific asset, we apply the contagion algorithm presented in the following section.

2.2 Mechanism of default contagion

The mechanisms of default contagion combine solvency and liquidity default cascades. We first consider a round of pure solvency contagion occurring during the period ($t = 1$) right after the initial shock at date ($t = 0$). Then, we consider several periods ($t = 2$, $t = 3$...) during which there is room for liquidity hoarding. Liquidity hoarding at period t can end up with new defaults. These defaults might imply new losses due to solvency contagion and a new wave of liquidity hoarding that will take place at time $t + 1$.

The timing of the model is explained in details in Table 3. As for the variables characterizing the nodes of the network, they are updated at the end of each period t.

The whole process is presented schematically on Figure 1, page 9.

2.2.1 Solvency contagion

There exist two strands in the literature that attempt to address the issue of solvency contagion. The first one is often called the "Clearing Vector Approach" based on the seminal paper by Eisenberg and Noe (2001). This approach, extended in Gauthier *et al.* (2010) or

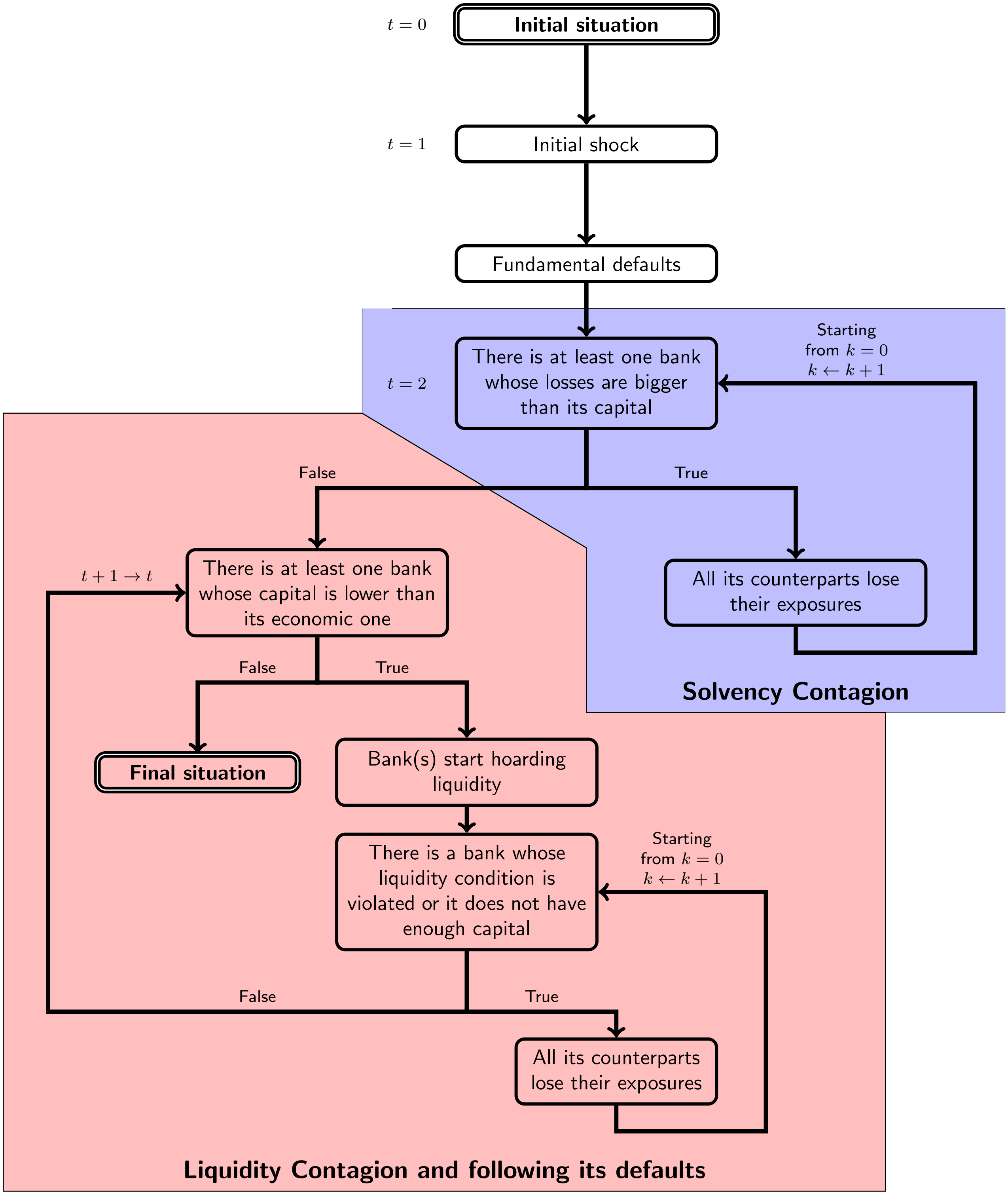


Figure 1: Scheme of Default Contagion.

$t = 0$	– Initial situation
$t = 1$	– An initial shock hits the system. – Banks account for the fundamental losses due to this shock.
$t = 2$	– Solvency defaults propagate through the system until there are no more defaults. – Banks record all the losses due to the solvency default contagion.
$t = 3$	– Solvent banks for which the capital requirement condition is violated start hoarding liquidity from their solvent counterparties. – This generates reallocation of resources and possible liquidity defaults, which in its turn may trigger solvency defaults contagion. – Liquidity contagion cascades stop when there are no more defaults, and banks record all the losses.
$t = 4, \ldots$	– New waves of liquidity contagion may take place if there are banks whose capital is lower than the required one. – And the same process as at $t = 3$ takes place. – All the rounds of $t \geq 4$ stop when liquidity hoarding leads only to reallocation of resources and no defaults because of the violation of liquidity conditions.

Table 3: Timing of the model

in Gouriéroux *et al.* (2012, 2013), establishes the existence and uniqueness of the debt repayment among banks: it provides endogenous recovery rate on interbank assets. The second strand refers to the "Iterative Default Cascade" developed by Furfine (2003). This method proposes an algorithm that mimics domino effects: instead of looking for a joint vector of debt repayment, this algorithm writes down the losses step by step as it may happen during a default cascade. Since we consider events within a week, we argue that the second approach is more realistic to replicate banks' behavior. Intuitively, the algorithm relies on two essential rules. First, we define that a bank is in default when its capital has been wiped out. Second, when a bank failed on its commitments, all its counterparts incur losses equal to their exposure towards that defaulted bank and have to absorb the losses using their capital.[8] We consider an exogenous recovery rate for solvency contagion denoted R^S. We run a case-sensitive analysis for different levels of R^S in order to insure the robustness of our results.

At time $t = 1$, the "other assets" of the N banks are hit by a shock according to the methodology previously described. If the initial losses are higher than the capital of a bank, the latter goes into bankruptcy. We can therefore define the set of all banks defaulting due

[8]One might argue that it takes several months for the official resolution of the bankruptcy, but we rather take a point of view of how the information spreads: as soon as a bank files for bankruptcy, all the agents in the market are aware about it and immediately take the actions.

to a market shock, named "fundamental defaults", as

$$
\begin{aligned}
\mathbf{FD(C)} &= \left\{ i \in \mathbf{N} : C_0(i) + \underbrace{OA_0(i) - OA_1(i)}_{\text{initial shock}} \leq 0 \right\} \\
&= \{ i \in \mathbf{N} : C_1(i) = 0 \},
\end{aligned}
\tag{2.1}
$$

where $C_1(i) = (C_0(i) + OA_0(i) - OA_1(i))^+$ is the capital of bank i just after the initial shock.

From this situation, we can define a *Solvency Default cascade* (in Amini *et al.*'s terminology) as a sequence of capital levels $(C_2^k(i),\ i \in \mathbf{N})_{k \geq 0}$ (where k represents the algorithmic step) occurring at time $t = 2$ and corresponding to the defaults due to insolvency:

$$
\begin{cases}
C_2^0(i) = C_1(i) \\
C_2^k(i) = \max(C_2^0(i) - \sum_{\{j,\, C_2^{k-1}(j)=0\}} (1 - R^S) \times E_0(i,j); 0), \text{ for } k \geq 1.
\end{cases}
\tag{2.2}
$$

The sequence is converging (in at most n steps) since $(C_2^k)_k$ is a component-wise decreasing sequence of positive real numbers. Note that subscripts are used for periods of time and superscripts for rounds of cascades. By "period", we mean the sequential spread of losses through different channels. It does not refer to a time line interpretation: we consider that all the events are jointly occurring within a week.

Comparison of the banks initially in default (that is $\mathbf{FD(C)}$) and the banks in default at the end of $t = 2$ corresponds to the set of institutions that defaulted only due to solvency default contagion. We label this set S_2.

2.2.2 Mechanism of liquidity hoarding

The liquidity contagion has been scarcely studied in the literature on financial networks. However, two main strands of research can be mentioned. The first channel is about asset or market liquidity, and losses in asset value (deterioration of the bank's balance sheet and ultimate insolvency) driven by the massive sales of the asset. The studies interested in this so called fire-sales phenomenon aim to model the adverse effects of massive asset sales initiated by one or several financial institutions to the whole financial network. Banks hit by a shock will attempt to improve their leverage ratio by massively selling their assets. Other banks may hold the same assets in their portfolio, therefore, the large sales will deteriorate the value of these assets and contaminate balance sheet of other banks, which will in turn start selling the same assets, making the whole system enter into a vicious circle. Cifuentes *et al.* (2005) model banks' reaction as a mechanical rule of selling assets in order to improve their solvency ratios. The asset prices are decreasing with the growing volume of assets sold.

The other approach to liquidity contagion tackles the issue of funding liquidity, that is, the issues arising on the liability side. The seminal paper by Allen and Gale (2001) analyzes several types of stylized networks with exogenous probability of funding difficulty. Their study provides interesting insights about the propagation of a liquidity shock through a network, though it remains unapplied due to the simplicity of the networks used. Some interesting exceptions studying propagation of liquidity shocks are the papers by Gai *et al.* (2010) that build up a stylized model to study how banks' hoarding behavior leads to the propagation of a liquidity shock through the system and by Gauthier *et al.* (2010) that disentangle credit and liquidity risks in a game theory framework proposed by Morris and Shin (2010). Our paper is closely related to the second strand of the literature, we as well model the liquidity risk: a bank may experience funding problems when its counterparts start hoarding liquidity during a crisis. And we propose a mechanism that endogenously takes into account funding shortage.

After a round of solvency contagion, some banks are in default while others have enough capital to absorb the losses. These banks will consider themselves in distress if their new level of capital does not satisfy supervisory requirement anymore. As explained by Acharya and Skeie (2011) and Brunnermeier (2009), these banks can fear that their counterparts are also in distress, therefore the perception of counterparty risk increases and the banks, as preemptive defensive actions, start hoarding liquidity[9]. One may argue that banks can borrow from the money market if they experience a liquidity shortage, though during a crisis - and we consider only a stressed time - banks can hardly raise funds from a private investor for many reasons: an investor will request a high quality collateral, high interest rates and haircuts or simply reject the transaction. Therefore, in this simple model, we assume that banks can only stop rolling over existing short-term loans when they need liquidity and increase their cash (or alternatively put the received cash at the central bank deposit facility[10]). The liquidity obtained is used to improve the liquidity position in view of potential future problems on the interbank market and to reimburse their creditors which have started hoarding liquidity too. If a bank fails to satisfy its short-term commitments, it defaults due to illiquidity.

To know how much liquidity a bank hoards in total, and how much it hoards from each counterpart, we make some assumptions. First of all, the total amount of liquidity withdrawn depends on the size of the shock to the bank's capital: the bigger the losses due to the market shock, the more the bank hoards liquidity. The proportion of liquidity

[9]Please note, that in our model, the only reason for hoarding is a precautionary one. Namely, we exclude any predatory behavior.

[10]We exclude Central Banks' policy tools from our analysis in order to study what may happen without any public intervention.

to be hoarded by bank i is $\lambda(i) \in [0;1]$. It is assumed to depend on the gap between the capital $C(i)$ and the economic capital $EC(i)$ of the institution : at time t, we denote $\lambda_t(i) = \phi_{(\theta_1,\theta_2)}\left(\frac{(EC_t(i) - C_t(i))^+}{EC(i)}\right)$, where $\phi_{(\theta_1,\theta_2)}(x)$ is the cumulative density function of a Gaussian law with mean of θ_1 and variance of θ_2.[11] We assume that bank i curtails its positions in the short-term interbank market by stopping rolling over debt for a total amount $\lambda_t(i)E_t^{ST}(i)$ where $E_t^{ST}(i) = \sum_{j\in S_{t-1}} E_{t-1}^{ST}(i,j)$ and S_{t-1} is the set of non-defaulted banks at the end of period $t-1$.

Second, the amount of liquidity the bank hoards from each counterpart depends on the market perception of the counterparty risk, for which the leverage ratio can be used as a proxy. The higher the leverage, riskier is a bank perceived, the more its counterparts will hoard from it. Defining $\mu_t(j)$ as $\mu_t(j) = 1 - C_t(j)/TA_t(j)$, we can decompose the total amount of hoarding liquidity by bank i with respect to the counterparts:

$$\lambda_t(i)E_t^{ST,k-1}(i) = \lambda_t(i)E_t^{ST,k-1}(i) \underbrace{\sum_{j,C_t^{k-1}(j)\geq 0} \frac{\mu_t(j)E_t^{ST,k-1}(i,j)}{\Sigma_h \mu_t(k)E_t^{ST,k-1}(i,h)}}_{=1}. \tag{2.3}$$

When a bank hoards liquidity, it improves its liquidity position, whereas liquidity withdrawn by its counterparts deteriorates it. Therefore, the following liquidity condition simply says if bank i has enough liquid assets, either interbank or non-interbank, to pay its short-term debt:

$$\underbrace{Ca_t(i)}_{\text{cash}} + \underbrace{\lambda_t(i)E_t^{ST,k-1}(i)}_{\text{hoarding inflows}} - \underbrace{\sum_{j,C_t^{k-1}(j)\geq 0} \lambda_t(j)E_t^{ST,k-1}(j)\frac{\mu_t(i)E_t^{ST,k-1}(j,i)}{\Sigma_l \mu_t(l)E_t^{ST,k-1}(j,l)}}_{\text{hoarding outflows}} > 0. \tag{2.4}$$

The above stated rule to model liquidity hoarding and the liquidity condition is a direct extension of usual rules used in the literature. For instance, Gai and Kapadia (2011) assume that a constant exogenous proportion of liquidity is hoarded in case of distress. With our notations, it would be expressed as $\lambda_t(i) = \lambda$. We contribute to the literature by proposing a hoarding rule that accounts for the magnitude of liquidity hoarding (driven by a capital gap) and the distribution of it among the counterparts (driven by the respective individual leverage ratios).

In line with the solvency contagion algorithm, we state that a bank is in default when

[11] In practice, we test a range of parameters value in order to check the robustness of our results.

its capital has been wiped out (solvency condition) or when it can not satisfy its short-term commitments (liquidity condition).

$$\begin{cases} C_t^0(i) = C_{t-1}(i) \\ \text{ for } k \geq 1, \\ \textbf{Solvency condition:} \\ C_t'^k(i) = C_t^0(i) - \sum_{\{j, C_t^{k-1}(j)=0\}} (1 - R^L) E_t^{ST}(i,j) \\ \textbf{Liquidity condition:} \\ C_t''^k(i) = \begin{cases} 0 & \text{if } Ca_t(i) + \lambda_t(i) E_t^{ST,k-1}(i) - \\ & \sum_{h, C_t^{k-1}(h) \geq 0} \lambda_t(h) E_t^{ST,k-1}(h) \frac{\mu_t(i) E_t^{ST,k-1}(h,i)}{\Sigma_l \mu_t(l) E_t^{ST,k-1}(h,l)} < 0 \\ C_t'^j(i) & \text{otherwise} \end{cases} \\ \textbf{Updating equation:} \\ C_t^k(i) = max(C_t'^k(i); C_t''^k(i); 0) \end{cases} \tag{2.5}$$

We denote the recovery rate in the liquidity cascade by R^L. In general, one can distinguish a recovery rate in case of a default due to illiquidity from a recovery rate of a default due to insolvency (R^S). And one might argue that the former recovery rate should be higher, since the asset side of an illiquid bank is not impaired. In the proposed algorithm, all banks that do not satisfy the liquidity condition have their total assets higher than their total debts (that make them solvent). Thus, R^L is to represent bankruptcy cost that do not reflect insolvency but costs associated to the liquidation of an illiquid bank[12].

At the end of period t, the algorithm provides the status of each bank (alive or in default), their capital and their short-term exposures. Some banks may have defaulted during period t, thus some non-defaulted banks have recorded losses on their capital level. If the capital is then lower than their economic one, another round of liquidity hoarding treated in period $t+1$ will take place.

2.3 Indicators

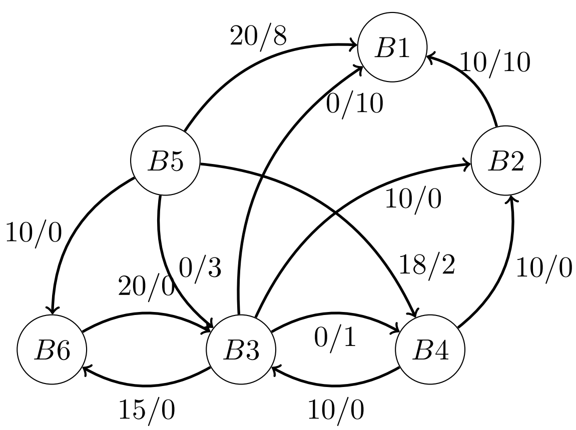
In the paper, we perform several types of shocks (common market shocks and asset class specific shocks). As previously explained, we are interested in tail events, therefore we report the effect distribution trough Value-at-Risk (VaR) and Expected Shortfall (ES). VaR and ES are usually risk measures but they are very informative concerning the tail of a distribution. In our framework, the $VaR(q)$ is defined as the level of total loss in percentage of total capital at quantile q (for instance, "$VaR(1\%) = 0.1\%$" means that the 1% worst

[12]Based on a survey for U.S. banks, James (1991) establishes a bankruptcy cost of 10%.

losses are greater than 0.1% of total capital) while the $ES(q)$ is the average total loss in percentage of total capital over the worst q cases (for instance, "$ES(1\%) = 0.2\%$" means that over the 1% worst cases, the losses represent in average 0.2% of total capital). As we are interested in very adverse situations, we consider only the following levels: 5%, 1%, 0.1% and 0.01% (that corresponds respectively to statistical events occurring respectively once among 5 months, 2 years, 20 years and 200 years).
Since we adopt a pure sequential approach we can easily decompose the indicator in three terms: the effects of the "fundamental shock" (prior to any contagion), the effects of solvency contagion (posterior to shock and prior to liquidity contagion) and the effects of liquidity contagion (posterior to solvency contagion). Comparing the relative weight of each term is very informative of the mechanisms at stake during the stressed situations.

2.4 Illustration of contagion mechanisms for a simple network

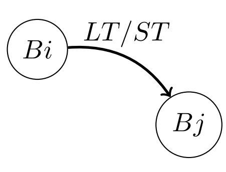
Let us consider a basic network composed of six banks represented in Figure 2. We assume that both recovery rates, R^S and R^L, are set to 0 for simplicity.



Balance-sheet info

Bank	C	EC	$Cash$
$B1$	1	0.5	0.5
$B2$	12	10	1
$B3$	32	30	2
$B4$	22	5	1.5
$B5$	32	4	2
$B6$	22	5	2

Legend



Bank i is exposed to bank j for LT in long term and ST in short term.

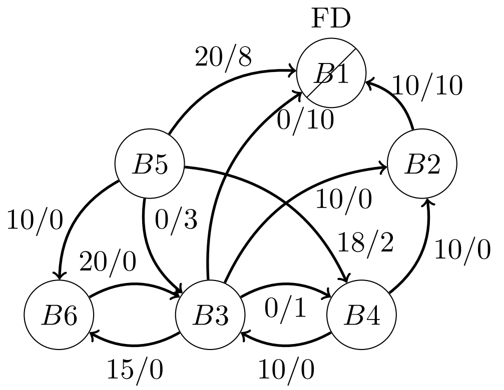
Figure 2: Initial Network

2.4.1 Round of solvency contagion

Let us consider that at $t = 0$ an initial shock erodes the capitals of all banks by a decrease of 2. All banks can absorb this shock except bank $B1$ that goes into bankruptcy. The fundamental default set is reduced to bank 1. The solvency algorithm takes place and its various steps are represented in Figure 3.

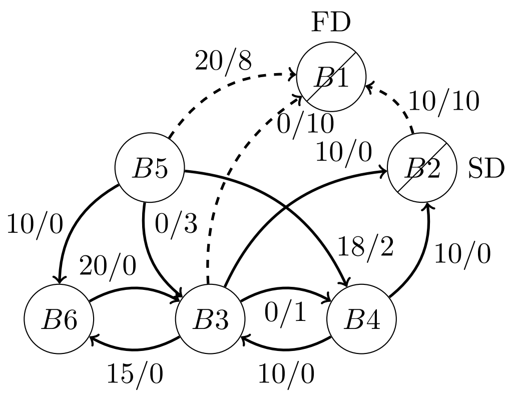
The default of bank $B1$ implies losses for its counterparts: banks $B2$, $B3$ and $B5$. For each bank in question, the losses induced and corresponding to its total exposure towards bank $B1$, are absorbed by its capital. Bank $B2$ has not enough capital to absorb its exposures, so it goes into default. Banks $B3$ and $B5$ are sufficiently capitalized to stay alive. Bank $B2$ default is characterized as a "solvency default".
The default of bank 2 implies losses for banks 3 and 4. This second step of solvency contagion is the last one since all the banks exposed to bank 2 have enough capital to absorb the losses.

The solvency equilibrium (last step of this round of solvency contagion) is represented in Figure 4.



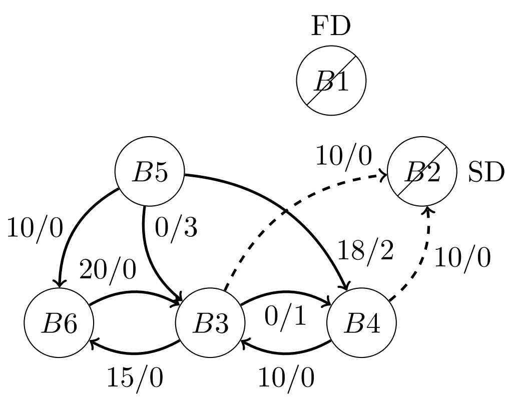
Bank	C	EC	$Cash$
$B1$	$0 = (1-2)^+$	0	0
$B2$	$10 = (12-2)^+$	10	1
$B3$	$30 = (32-2)^+$	30	2
$B4$	$20 = (22-2)^+$	5	1.5
$B5$	$30 = (32-2)^+$	4	2
$B6$	$20 = (22-2)^+$	5	2

(a) Fundamental Default



Bank	C	EC	$Cash$
$B1$	0	0	0
$B2$	$0 = (10-20)^+$	10	1
$B3$	$20 = (30-10)^+$	30	2
$B4$	20	5	1.5
$B5$	$2 = (30-28)^+$	4	2
$B6$	20	5	2

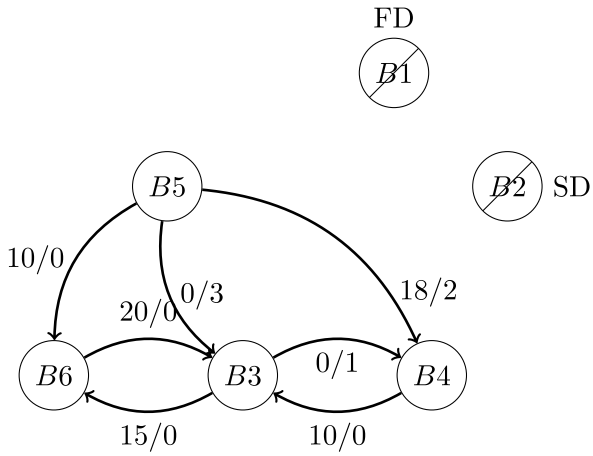
(b) Round of Solvency contagion, First step



Bank	C	EC	$Cash$
$B1$	0	0	0
$B2$	0	0	0
$B3$	$10 = (20-10)^+$	30	2
$B4$	$10 = (20-10)^+$	5	1.5
$B5$	2	4	2
$B6$	20	5	2

(c) Round of Solvency contagion, Second step

Figure 3: Solvency Contagion



Balance-sheet info

Bank	C	EC	$Cash$
$B1$	0	0	0
$B2$	0	0	0
$B3$	10	30	2
$B4$	10	5	1.5
$B5$	2	4	2
$B6$	20	5	2

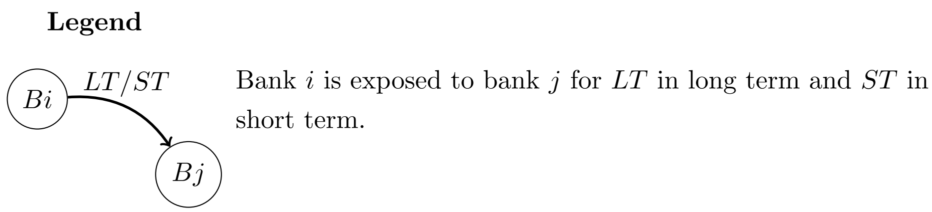


Figure 4: Solvency Round Equilibrium Network

2.4.2 First Liquidity Contagion Round

Since the solvency contagion is closed, banks $B3$, $B4$ and $B5$ are solvent. But, when comparing their capital (in column C) with their economic capital (in column EC), banks $B3$ and $B5$ start hoarding liquidity whereas bank $B4$ does not modify its behavior since its capital is largely above its economic capital.

In this example, we consider simply that $\lambda_i = (EC_i - C_i)^+/EC_i$ and that this proportion of liquidity hoarding is uniformly applied to all short-term exposures (or equivalently, that all banks have the same leverage ratio). Therefore, banks $B3$ and $B5$ diminish their total short-term exposures by respectively 66% ($= (30-10)^+/30$) and 50% ($= (4-2)^+/4$)). Consequently, the cash outflows are:

$$\begin{aligned}
\text{Cash outflow for bank } B3 = \ & 1.5 = \underbrace{0.5 \times 3}_{\text{toward bank } B5} \\
\text{Cash outflow for bank } B4 = \ & 1.66 = \underbrace{0.5 \times 2}_{\text{toward bank } B5} + \underbrace{0.66 \times 1}_{\text{toward bank } B3} \\
\text{Cash outflow for bank } B5 = \ & 0.
\end{aligned}$$

Symmetrically, the cash inflows are:

$$\begin{aligned}
\text{Cash inflow for bank } B3 = \;& 0.66 = \underbrace{0.66 \times 1}_{\text{from bank } B4} \\
\text{Cash inflow for bank } B4 = \;& 0 \\
\text{Cash inflow for bank } B5 = \;& 2.5 = \underbrace{0.5 \times 3}_{\text{from bank } B3} + \underbrace{0.5 \times 2}_{\text{from bank } B4}
\end{aligned}$$

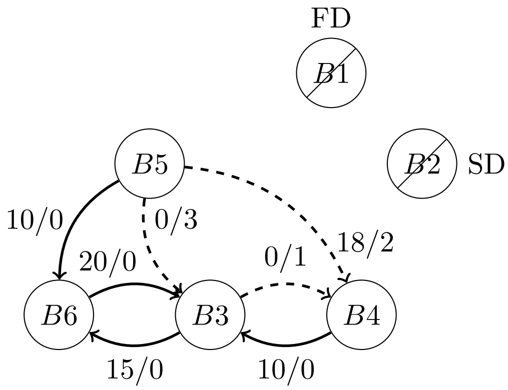
For all the steps of the liquidity hoarding phenomenon, the algorithm will consider that a bank is in default if it does not satisfy one of the two conditions (solvency and liquidity conditions) previously evoked in the theoretical model. A bank remains alive if its capital is above zero (solvency condition) and if its cash position allows it to honor its short-term commitments (liquidity condition). At each step, these two conditions are simultaneously checked for every bank. For the sake of the explanation, we will consider them sequentially and first look at whether each bank satisfies its liquidity condition and then check if each bank is still solvent.

For this first step, as the network is initially in an equilibrium in terms of solvency contagion, only the liquidity condition is checked. Combining the cash inflow, the cash outflow and the cash of each bank, one can check if each bank fulfill its liquidity condition. For bank $B5$, we have a positive value since there is no cash outflow. Although bank $B3$ has a bigger cash outflow (1.5) than its cash inflow (0.66), its cash holding (2) can absorb the difference ($2+0.66 > 1.5$). On the contrary, bank $B4$ is short in terms of liquidity. Actually, its cash outflow (1.66) is higher than its cash inflow (0) and it has not enough liquid assets (1.5) to pay back its creditors. In other terms, banks $B5$ and $B3$'s behaviour that consists in stopping rolling over the short debt issued by bank $B4$ generates a cash outflow for bank $B4$ that cannot cope with it. We consider that bank $B4$ is in default due to illiquidity. Note that is this particular case, the sole action of bank $B5$ or of bank $B3$ would have not led bank $B4$ to be short on liquidity since each component of the cash outflow of bank $B4$ is lower than its cash holdings. The situation after this first step of liquidity hoarding is represented in the top network of Figure 5.

In this new step, the check on whether the liquidity condition for each bank is respected or not, involves only banks $B3$ and $B5$, and is represented in the middle network of Figure 5. One can easily see that bank $B5$ satisfies its liquidity condition in the sense that bank $B5$ is a pure short-term lender. For bank $B3$, the cash inflow is now 0 since $B4$, the only initial short-term debtor of bank $B3$, is in distress and its cash outflow (towards bank $B5$) is 1.5. Since bank $B3$'s cash position is 2, bank $B3$ fulfills its liquidity condition. The situation at the end of the liquidity contagion step (middle network of Figure 5) is not a solvency equilibrium since the losses due to bank $B4$'s default have not been taken into account. Thus, during this second step there is an additional check with respect of the solvency condition in the algorithm of contagion represented in the lowest plot of Figure 5. Bank $B5$ suffers a loss of 20 ($= 18 + 2$) while bank $B3$ suffers a loss of 1 ($= 0 + 1$). Bank $B5$ has not enough capital to absorb this loss while $B3$ has. This fact triggers solvency contagion: bank $B6$ is able to absorb the induced losses corresponding to its exposure towards bank $B5$.

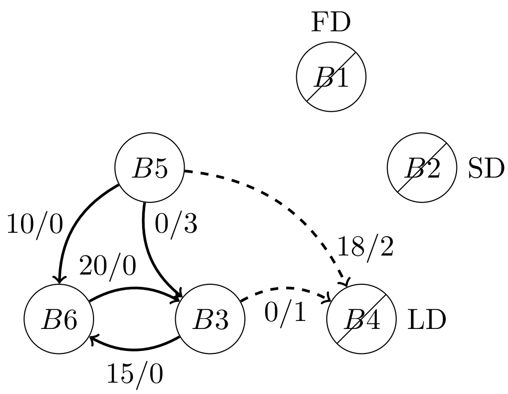
The situation after this first round of solvency contagion and after this first round of liquidity contagion is stable from a solvency point of view (all remaining capitals are strictly positive) and from a liquidity point of view (all cash holding are sufficiently high). Note that the two remaining banks, $B3$ and $B6$, have their capitals lower than their economic capitals; but since their are not short lender, this cannot lead them to stop short term lending. Therefore, we consider that the final situation, represented in Figure 6, is the equilibrium situation reached within a week.

In this example, the equilibrium is reached with only one round of solvency contagion and one round of liquidity contagion. With more complex network, several rounds of liquidity contagion are easily feasible.



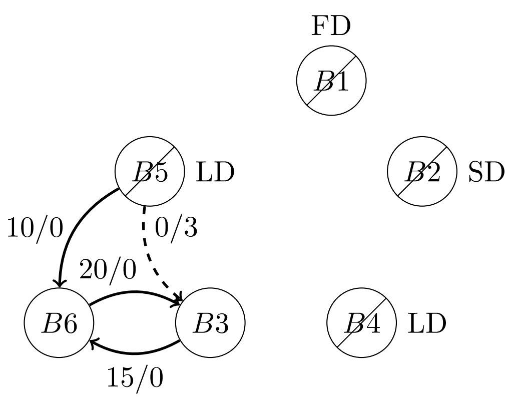
Bank	C	EC	$Cash$
$B1$	0	0	0
$B2$	0	0	0
$B3$	10	30	$2+0.66-1.5>0$
$B4$	10	5	$1.5+0-1.66<0$
$B5$	2	4	$2+2.5-0>0$
$B6$	20	5	2

(a) First Round of Liquidity Contagion, First step



Bank	C	EC	$Cash$
$B1$	0	0	0
$B2$	0	0	0
$B3$	10	30	2
$B4$	10	5	0
$B5$	2	4	2
$B6$	20	5	2

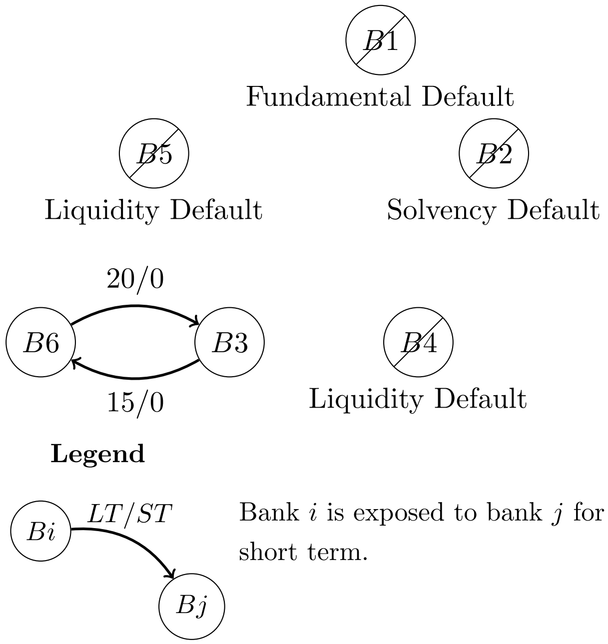
(b) First Round of Liquidity Contagion, Second step, Liquidity condition



Bank	C	EC	$Cash$
$B1$	0	0	0
$B2$	0	0	0
$B3$	$9=(10-1)^+$	30	2
$B4$	0	0	0
$B5$	$0=(2-20)^+$	4	2
$B6$	$10=(20-10)^+$	5	2

(c) First Round of Liquidity Contagion, Second step, Solvency condition

Figure 5: First Round of Liquidity Contagion



Balance-sheet info

Bank	C	EC	$Cash$
$B1$	0	0	0
$B2$	0	0	0
$B3$	9	30	2
$B4$	0	0	0
$B5$	0	0	0
$B6$	10	5	2

Figure 6: Final Equilibrium

3 Application to the French banking system

This section gives us an empirical application of our model to a real network. We first introduce the data used in our framework followed by some descriptive statistics of the French banking system. Lastly the results are presented.

3.1 Data

French credit institutions are required to report to the Autorité de Contrôle Prudentiel (French Prudential Supervisor Authority) a full and detailed description of their balance sheets (FINREP Report, CEBS, 2009a) and all the large bilateral exposures that they can have towards either other credit institutions or even a country or a company (Large Exposure Report, CEBS, 2009b). Such data allow the French Prudential Supervisory Authority to closely and continuously monitor the evolution of the network and banks' counterparty risks. Data on balance sheet are collected on a semi-annual basis whereas information on large exposures is reported quarterly. In the Large Exposure report, each credit institution is compelled to communicate all its exposures that represent an amount higher than 10% of its capital or above 300 millions of Euros. We use this unique data set on bilateral exposures and balance sheet composition to reconstruct the French banking network in December 2011.

Each bilateral exposure corresponds to the gross bilateral sum of both securities and loans[13] that a bank holds in its portfolio with respect to a certain counterpart. Given that there is no information about the assets maturity held by each bank in the Large Exposure reports, we extract the ratio of short term over long term[14] assets from their balance sheet. We then apply this ratio to the amount of bilateral exposure of the corresponding bank reported in the Large Exposure dataset to have an estimation of long-term and short-term bilateral exposures.

The French banking system consists of more than 300 financial institutions at the solo level. Nevertheless, the French banking system is highly clustered with five major banking groups at the consolidated level embodying more than 80% of the total assets of the system. We select the 11 largest banking groups such that our study accounts for an almost complete representation of the French banking sector, both in terms of size and business models. Indeed, it is composed of several major universal banks (either mutual banks or purely commercial banks) but also specialized banks (such as consumer-loan activity). French banks differ also in terms of their degree of cross-border activities: some of them have intensive international activities while others have mainly, not to say only, home activities. At the end, the sample of banks here retained[15] enables us to consider all these heterogeneities (bank size, business model, global/local activity).

While some French banks have a global activity, a national level analysis is still relevant from a macroprudential perspective since the French banks have the major part of their activity in France. Besides, international level analysis (see for instance Alves *et al.*, 2013) are complementary to the national ones. They allow to consider the major role that can play some "hub" banks under stressed situation. Last, while source of funding considerations are central in contagion phenomenon, other contagion channels should not be underestimated (behavioral dynamics, fire-sales, reinvestment decisions...) Indeed, a further project of research is to complement our model by the other sources of funding (such as foreign banks or insurance companies).

Given that we study banks at the group-consolidated level, we do not consider, inside a group, exposures between subsidiaries. Since a group will likely try to avoid any failure of

[13]Amounts are taken before any type of deduction, provision or risk mitigation and without any netting process carried out. We exclude derivatives, off balance sheet exposures and marked-to-market short-long positions. Note that the items that we selected account for almost of all balance-sheet instruments.

[14]Short term is defined as "less than 1 month" while long term is defined as "more than 1 month". Comparing the one-week base for shock with this threshold of one-month maturity of exposure introduces a conservative bias for the effect of liquidity condition.

[15]Société Générale, Groupe Crédit Agricole, BNP Paribas, Banque Populaire-Caisse d'Epargne, La Banque Postale, Groupe Crédit Mutuel, HSBC Frace, PSA Finance, RCI Banque, Oséo, Laser Groupe.

any of its subsidiary, by reallocating the profits and losses between subsidiaries for instance, considering the banking sector at a solo level will considerably bias any contagion analysis by artificially counting defaults that would not occur in reality.

As it is documented in almost all the studies on real financial networks, the latter are usually scale-free, meaning that a few banks are connected to many other banks. This scale-free characteristic commonly observed for financial networks does not hold when we consider a small number of banks: in this sense, the network of the French banking system is rather special, since it is an almost complete one, as one can see in Figure 7[16].

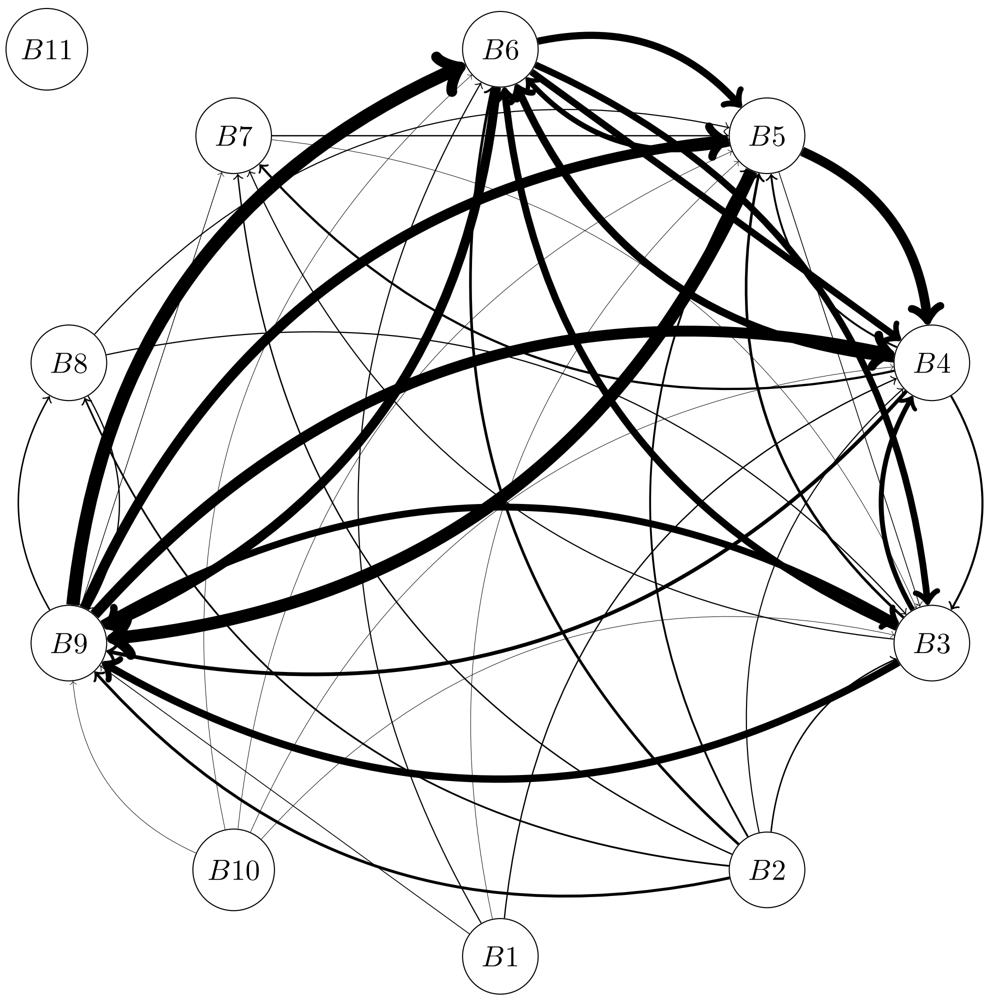


Figure 7: The French Banking Network in December 2011. The nodes correspond to the 11 largest French credit institutions while the edges represent the exposures (loans and securities) between the credit institutions. The widths of edges are proportional to exposures.

[16]There are few banking systems characterized by very limited number of banking groups, another example can be Canada.

3.2 Descriptive statistics

Table 4 reports some descriptive statistics about the French banking system.

Descriptive statistics			
in %	**Mean**	**Standard Deviation**	**Median**
Interbank Exposures / TA	2.2	2.1	1.6
Interbank Exposures / Cap	34.2	28.2	27.9
Net position / Cash	171.1	557.1	0.0

Table 4: Descriptive statistics of the French banking network. "Exposures/TA" corresponds to the sum of all reported exposures by a bank expressed as a percentage of its total assets. "Exposures/Cap" is the sum of all reported exposures by a bank expressed as a percentage of its capital. "Net position/Cash" is the ratio of the difference between all the short-term assets owned by a bank and all its short-term liabilities vis-a-vis its lenders over its cash holding.

The amount of money that the 11 largest French banks lend to each other, corresponding to the sum of the interbank exposures, represents about 2.2% of the total assets. Even if this number may seem minor at first glance, the sum of exposures reaches in average 34.2% of total capital. The exposure distribution is asymmetric with most banks reporting small exposures while a few banks declare larger ones.

The ratio of total asset interbank exposures over total capital can be an indicator of a bank's sensitivity to solvency contagion, the capital representing a safety cushion when losses are recorded. This ratio has a mean of 34.2% with a standard deviation of 28.2%. As the distribution is asymmetric, we may consider the median as a "central" indicator. With a 27.9% median for interbank exposure over capital, a general spread solvency contagion seems unlikely from a very first analysis based on descriptive statistics.

Besides, another indicator that may help to measure a bank's sensitivity to liquidity contagion is its net position (all credit granted minus all loans borrowed) with respect to cash. Depending on its net position, a bank will not only start hoarding liquidity but will also be able to cope with a liquidity shock. A large amount of cash will reduce its probability of becoming illiquid. The range of values observed for this indicator within the sample is ample. This finding can be explained by the fact that this indicator takes into account two characteristics of a bank, its position towards the rest of the network and the amount of cash it holds as expressed in our model. The greater the value, the lower the likelihood that the bank suffers from liquidity hoarding. Comparing a negative mean and a zero median indicates that, generally speaking, the liquidity hoarding would not massively impact the network but that few banks may be sensitive to this phenomenon.

3.3 Results

Since our model relies on several parameters, we have checked the robustness of our results by running simulations for a large set of parameters (see Appendix for details). For simplicity, we report the values for one set of parameters that seems either representative or conservative. First, we present the results for a solvency recovery rate of 40% which is conservative regarding EBA stress-tests.[17] Second, as for a bank becoming illiquid does not necessarily mean that the value of its assets is subject to a large deterioration, the recovery rate faced by banks whose counterparty defaulted due to illiquidity issues is assumed to be equal to 80% corresponding to twice the bankruptcy cost estimated in James (1991). Third, among the various functional forms of lambda we tested, the results displayed correspond to cases in which banks start hoarding liquidity when their capital falls below 120% of their economic one (however, the choice of lambda does not impact the results).

Lastly, the scope of this paper is to assess the emergence of potential contagion phenomena from a macroprudential perspective; we do not focus on bank individual exposures towards specific risk factors (which is related to microprudential concerns). Therefore, we decompose the effect of a shock in three terms: the direct effect of a shock before any contagion mechanism takes place, the incremental effect of solvency contagion and the incremental effect of liquidity contagion.

3.3.1 General and Asset Class Specific Market Shocks

In this subsection, the analysis is based on two different exercises where in the first one the system is hit by a common market shock and in the second one, asset class specific shocks are envisaged.

The first result is that considering either a general shock or an asset class specific shock, there is no bank going into default. This finding is a direct consequence of 2 facts: firstly, in December 2011, French banks are well capitalized and largely above the required capital; secondly, banks' exposures towards the considered asset classes are limited, and negative shocks to the value of any of these assets are not large enough to trigger the default of any of the banks. Extremely large financial market shocks are required to observe the default of at least one bank, though in our exercise we use weekly returns to compute market shocks. The system appears resilient to these shocks. Solvency contagion is then by definition absent. Liquidity contagion can emerge, though it is rather limited. This last result points out to the fact that liquidity contagion appears even when there is no solvency contagion. We could

[17] EBA stress test 2011 exercise report that recovery rates on banks varies between 85% and 55%.

explain such small losses by the state of the banking system at the date of the analysis: as mentioned above, banks' capital is largely above the required one, as well as they have enough liquid assets compared to their interbank funding. Therefore, after all the efforts done by the authorities, it is rather meaningful that banks are resilient to the market shock, and liquidity contagion is limited.

The second result of such stress-test exercises is that the losses recorded are mainly if not only caused by the initial shock, except in the extreme left tail of the distribution (see Table 5). In the extreme case, for VaR(0.01%) of a general shock, there is 0.71% of capital loss due to liquidity hoarding phenomena. This almost 1% loss must nonetheless be compared to a shock of magnitude 39.8%.

We emphasize the fact that we obtain similar and therefore robust results for different recovery rates and for other specifications of the liquidity hoarding rule.

We note also that our results are in line with the past stress-tests of the French banks with respect to the market risk (see e.g. IMF 2012), even though the performed stress-tests are much smaller in scope that our study.

General Market Shock (Capital Loss, % of the Total Capital)						
	VaR(0.01%)	**VaR(0.1)%**	**VaR(1%)**	**VaR(5%)**	**ES(1%)**	**ES(5%)**
Shock (A)	39,8	26,1	14,2	7,6	11,7	32,0
Solvency contagion (B)	0,0	0,0	0,0	0,0	0,0	0,0
Liquidity contagion (C)	0,92	0,0	0,0	0,0	0,36	0,01
Total (=A+B+C)	40,7	26,1	14,2	7,6	12,1	32,0

Table 5: Capital loss in a French banking system (as a % of the total capital of the system) after being hit by a general market shock decomposed by the source of losses: due the general market shock itself, due to solvency and liquidity contagion. Solvency recovery rate is equal 40%; liquidity recovery rate is equal to 80%. λ is so that banks start hoarding liquidity when there capital falls below 120% of required capital. Example, at $VaR(0.01\%)$ the system loss is 40.51% of capital, of which 39.8% is due to the general market shock. Solvency contagion is absent by definition.

3.3.2 Idiosyncratic shocks combined with common market shocks

One may also be interested in a scenario when there is a common market shock and one bank goes into default (for other reasons than a market shock). To deal with this concern, we perform a second set of stress-test exercises, where we forced all the banks to default, one at a time, in the presence of the same market shocks. The figures presented in the following tables are averages over the 11 individual idiosyncratic scenarios.

These complementary exercises give the following results: either general shock or asset class specific shock, combined with one idiosyncratic default leads to no defaults due to solvency contagion, liquidity contagion is present but limited. The absence of the domino effect when even the biggest banks default can be explained by the high capitalization of the banks as well as by the small interbank exposures, in total and, especially, to one concrete counterparty. The size of losses measured as a percentage of the system's capital is totally due to the fact that banks lose their exposures to the defaulted bank. As seen from Table 6, these losses are equal to 1.2% over all the types of shocks and all the quantiles. The number shown is the average over the losses due to defaults of 11 banks, and it is bigger or smaller depending on how strongly the system is exposed to the defaulted bank.

We pinpoint that the effects of the various shocks (common, on equity, on bonds issued by financial institutions...) on the low level of risk (for instance $VaR(5\%)$) worth an explanation. The negative numbers associated to the shock mean that in spite of negative shocks on equity, the banks benefit from capital gains consequent to the positive shocks observed at the same time in the other types of asset classes. Yet, these benefits are undermined by contagion effects.

Results of liquidity hoarding are similar with those of sole market shocks without idiosyncratic shocks.

The effects of solvency contagion and those of liquidity contagion are of the same magnitude, each of them triggering losses accounting for about 1.5% of the total capital under the most adverse scenarios ($VaR(0.1\%)$ and $VaR(0.01\%)$). At the same time, the direct losses due to the initial shock (see Table 6) are 30 times larger than those occurring via each of both channels.

The robustness check exercises (see Appendix for more details) underline the quality and the steadiness of our results with respect to different specifications. When the solvency recovery rate varies from 0% to 100%, the figures keep the same approximate magnitude, but we observe some non-monotonic effects in several cases. For instance, in Table 8 that report capital losses due to liquidity contagion only, the risk measure first increases and then decreases with the solvency recovery rate of the defaulted banks. This feature is explained by the fact that the solvency recovery rate affects the risk measure through the solvency channel and the liquidity channel. Indeed, for the solvency channel, there is a decreasing effect. But for the liquidity channel, a higher solvency recovery rate means in the first round lower losses leading to less liquidity hoarding. Liquidity hoarding has an ambiguous effect since it can lead some weak banks to default but it also consists on a reduction of exposures towards these weak banks. This reduction of exposures lead to diminish the losses in case of default. This example make us grasp that forecasting the effect of liquidity hoarding is not trivial and, therefore, should be carried out with care.

General Market Shock + Idiosyncratic shock (Capital Loss, % of the Total Capital)						
	VaR(0.01%)	**VaR(0.1)%**	**VaR(1%)**	**VaR(5%)**	**ES(1%)**	**ES(5%)**
Shock (A)	45,3	32,9	22,0	15,5	19,8	33,1
Solvency contagion (B)	1,18	1,18	1,18	1,18	1,18	1,18
Liquidity contagion (C)	1,63	1,38	0,47	0,47	0,38	0,53
Total (=A+B+C)	48,1	35,4	23,6	17,2	21,3	34,8

Shock on Equity + Idiosyncratic shock (Capital Loss, % of the Total Capital)						
	VaR(0.01%)	**VaR(0.1)%**	**VaR(1%)**	**VaR(5%)**	**ES(1%)**	**ES(5%)**
Shock (A)	45,3	32,5	20,3	-2,8	15,8	16,0
Solvency contagion (B)	1,18	1,18	1,18	1,18	1,18	1,18
Liquidity contagion (C)	1,6	1,0	0,5	0,5	0,1	0,5
Total (=A+B+C)	48,1	34,6	22,0	-1,2	17,0	17,7

Shock on Financial Institutions Bonds + Idiosyncratic shock (Capital Loss, % of the Total Capital)						
	VaR(0.01%)	**VaR(0.1)%**	**VaR(1%)**	**VaR(5%)**	**ES(1%)**	**ES(5%)**
Shock (A)	45,3	32,3	19,3	-18,2	14,5	17,2
Solvency contagion (B)	1,18	1,18	1,18	1,18	1,18	1,18
Liquidity contagion (C)	1,6	1,4	0,5	0,5	0,3	0,5
Total (=A+B+C)	48,1	34,8	20,9	-16,5	16,0	18,9

Shock on Sovereign Bonds + Idiosyncratic shock (Capital Loss, % of the Total Capital)						
	VaR(0.01%)	**VaR(0.1)%**	**VaR(1%)**	**VaR(5%)**	**ES(1%)**	**ES(5%)**
Shock (A)	45,3	32,3	19,1	-9,2	14,3	13,6
Solvency contagion (B)	1,18	1,18	1,18	1,18	1,18	1,182
Liquidity contagion (C)	1,6	1,4	0,5	0,5	0,4	0,5
Total (=A+B+C)	48,1	34,8	20,7	-7,5	15,9	15,3

Shock on Large Corporate Bonds + Idiosyncratic shock (Capital Loss, % of the Total Capital)						
	VaR(0.01%)	**VaR(0.1)%**	**VaR(1%)**	**VaR(5%)**	**ES(1%)**	**ES(5%)**
Shock (A)	45,3	32,4	19,9	-9,4	15,1	17,8
Solvency contagion (B)	1,18	1,18	1,18	1,18	1,18	1,18
Liquidity contagion (C)	1,6	1,4	0,5	0,5	0,4	0,5
Total (=A+B+C)	48,1	35,0	21,5	-7,7	16,6	19,5

Table 6: Capital loss in a French banking system (as a % of the total capital of the system) after being hit by different market shocks (general market shock and asset specific shocks) and an idiosyncratic shock, decomposed by the source of losses: due the general market shock itself, due to solvency and liquidity contagion. Solvency recovery rate is equal 40%; liquidity recovery rate is equal to 80%. λ is so that banks start hoarding liquidity when there capital falls below 120% of required capital.

Average Number of Defaulted Banks					
VaR(0.01%)	**VaR(0.1)%**	**VaR(1%)**	**VaR(5%)**	**ES(1%)**	**ES(5%)**
0,82	0,55	0,00	0,00	0,40	0,03

Table 7: Number of banks defaulting due to liquidity contagion when the system is hit by a general market and an idiosyncratic shocks.

General Market Shock + Idiosyncratic shock (Capital Loss, % of the Total Capital)										
Recovery Rate	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
VaR(0.01%)	1.10	1.36	1.54	1.63	1.65	1.57	1.42	1.18	0.86	0.46

Table 8: Loss in capital $VaR(0.01\%)$ due to liquidity contagion only for various solvency recovery rate for a shock on equity associated to idiosyncratic shocks.

4 Conclusion

This paper develops a model that allows us to take into account the losses of the system due to solvency and liquidity contagion after an initial correlated shock hitting the system. This is one of the first papers that permits disentangling between the losses caused by different sources of risk. We also propose a toolkit to simulate market shocks in line with liquidity hoarding phenomena. We use this model to evaluate the resilience of the French banking system to systemic market shocks.

The literature on the pure default contagion is much vaster, though the results are rather controversial. In a similar framework, Cont *et al.* (2010) studying Brazilian banking system find evidence of sizeable domino effects after an initial shock. At the same time, Elsinger *et al.* (2006a) who analyze the Austrian banking network record rare occurrences of such effects. Other studies held on network contagion without any initial stress on the whole banking system document rather very limited consequences (Amundsen and Arnt (2005), Upper and Worms (2004)). What seems to be really essential for the existence of the domino effects is not only the initial market shock, but also its magnitude.

Our results, that complete the study of pure solvency default contagion with the liquidity channel, shed light on four points. First, we clearly identify that for the French banking system on the 31st of December 2011, the contagion effects appear to be significantly lower than the initial shock. Second, we find that losses due to solvency and liquidity contagion are of similar magnitude, therefore one would underestimate losses in the system without taking into account distress propagating through funding shortage. Third, we show that liquidity hoarding behavior may lead to defaults even in the absence of solvency defaults due to the market shock. Last, we emphasize that the liquidity hoarding phenomena can have ambiguous effects: intuitively, it may increase the probability of default (due to liquidity shortage), but it also decreases the loss given default (since hoarding implies lower interbank exposures).

The real case analysis shows the high resilience of the French banking system towards market risks as well as contagion effects. The losses due to market shocks lead, under extremely adverse simulations, to very few defaults and imply low capital losses due to contagion. They are much smaller than the ones from to market shocks. Such results suggest that actions undertaken by authorities for the recapitalization of the banks as well as exceptional credit lines offered to them to avoid any liquidity shortage should have had a positive effect on the financial stability of the system.

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6 Appendix: Robustness Check

Running the simulation needs to define 3 mains specifications:

- The solency recovery rate, R^S, is varying from 0.1 (only 10% of exposures it repaid) to 1 (absence of loss). Indeed, the results vary with the solvency recovery rate but keep the same approximate size, as explained in the discussion of the paper.

- The liquidity recovery rate R^L is set to 0.8: in case of default due to liquidity shortage, 20% of exposures are lost. Using another recovery rate do not change our results since the liquidity contagion spread is not overwhelming. As said before, 20% is a conservative setting since it is twice the bankruptcy cost estimated in James (1991).

- The hoarding function $\lambda(.)$ is a more sophisticated figure. We consider the inverse of a Gaussian c.d.f. as baseline shape. We run the simulations with 9 couples for the mean and the variance. The magnitudes of results are stable across specifications. However, the results are more sensitive to the mean than to the variance. In fact, the mean parameter acts as a threshold for triggering hoarding phenomena; therefore, it is logical than an easy triggering threshold leads to a more effective liquidity hoarding phenomenon.

As illustration, Table 9 reports the effect of a general market shock (with and without idiosyncratic shocks) for various solvency recovery rates.

General Market Shock

Recovery	Capital Loss						Number of Defaulted Banks (% of the Total Capital)					
Rate	VaR(0.01%)	VaR(0.1)%	VaR(1%)	VaR(5%)	ES(1%)	ES(5%)	VaR(0.01%)	VaR(0.1)%	VaR(1%)	VaR(5%)	ES(1%)	ES(5%)
0,1	0,98	0,00	0,00	0,00	0,39	0,02	1,00	0,00	0,00	0,00	0,40	0,02
0,2	0,97	0,00	0,00	0,00	0,38	0,02	1,00	0,00	0,00	0,00	0,40	0,02
0,3	0,95	0,00	0,00	0,00	0,37	0,01	1,00	0,00	0,00	0,00	0,40	0,02
0,4	0,92	0,00	0,00	0,00	0,36	0,01	1,00	0,00	0,00	0,00	0,40	0,02
0,5	0,88	0,00	0,00	0,00	0,34	0,01	1,00	0,00	0,00	0,00	0,40	0,02
0,6	0,83	0,00	0,00	0,00	0,33	0,01	1,00	0,00	0,00	0,00	0,40	0,02
0,7	0,78	0,00	0,00	0,00	0,30	0,01	1,00	0,00	0,00	0,00	0,40	0,02
0,8	0,71	0,00	0,00	0,00	0,28	0,01	1,00	0,00	0,00	0,00	0,40	0,02
0,9	0,64	0,00	0,00	0,00	0,25	0,01	1,00	0,00	0,00	0,00	0,40	0,02
1	0,56	0,00	0,00	0,00	0,22	0,01	1,00	0,00	0,00	0,00	0,40	0,02

General Market Shock + Idiosyncratic shock

Recovery	Capital Loss						Number of Defaulted Banks (% of the Total Capital)					
Rate	VaR(0.01%)	VaR(0.1)%	VaR(1%)	VaR(5%)	ES(1%)	ES(5%)	VaR(0.01%)	VaR(0.1)%	VaR(1%)	VaR(5%)	ES(1%)	ES(5%)
0,1	1,10	0,83	0,18	0,18	0,39	0,24	0,82	0,55	0,00	0,00	0,40	0,06
0,2	1,36	1,09	0,31	0,31	0,38	0,38	0,82	0,55	0,00	0,00	0,40	0,05
0,3	1,54	1,27	0,41	0,41	0,37	0,47	0,82	0,55	0,00	0,00	0,40	0,04
0,4	1,63	1,38	0,47	0,47	0,36	0,53	0,82	0,55	0,00	0,00	0,40	0,03
0,5	1,65	1,40	0,49	0,49	0,34	0,54	0,82	0,55	0,00	0,00	0,40	0,03
0,6	1,57	1,34	0,47	0,47	0,33	0,51	0,82	0,55	0,00	0,00	0,40	0,02
0,7	1,42	1,19	0,41	0,41	0,30	0,44	0,82	0,55	0,00	0,00	0,40	0,02
0,8	1,18	0,84	0,31	0,31	0,28	0,33	0,82	0,45	0,00	0,00	0,40	0,02
0,9	0,86	0,36	0,18	0,18	0,25	0,19	0,82	0,18	0,00	0,00	0,40	0,01
1	0,46	0,00	0,00	0,00	0,22	0,01	0,82	0,00	0,00	0,00	0,40	0,01

Table 9: Capital loss in a French banking system (as a % of the total capital of the system and in number of defaulted banks) after being hit by a general market shock with and without an idiosyncratic shock. λ is so that banks start hoarding liquidity when there capital falls below 150% of required capital.

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