Structural Contagion and Vulnerability to Unexpected Liquidity Shortfalls

Simone Giansante\textsuperscript{a}, Carl Chiarella\textsuperscript{b}, Serena Sordi\textsuperscript{c}, Alessandro Vercelli\textsuperscript{c}

\textsuperscript{a}School of Management, University of Bath, Claverton Down, Bath, BA2 7AY, UK
\textsuperscript{b}UTS Business School, University of Technology, Sydney P.O. Box 123 Broadway, NSW 2007 Australia
\textsuperscript{c}Dipartimento di Politica Economica, Finanza e Sviluppo (DEPFID), Universitá di Siena, Piazza San Francesco 7, 53100 Siena, Italy

Abstract
This paper assumes that financial fluctuations are the result of the dynamic interaction between liquidity and solvency conditions of individual economic units. The framework is an extension of Sordi and Vercelli (this issue) designed as an heterogeneous agent model which proceeds through discrete time steps within a finite time horizon. The interaction at the micro-level between economic units monitors the spread of contagion and systemic risk, producing interesting complex dynamics. The model is analyzed by means of numerical simulations and systemic risk modelling, where local interaction of units is captured and analysed by the bilateral provision of liquidity among units. The behavior and evolution of economic units are studied for different parameter regimes in order to investigate the relation between units’ expectations, liquidity regimes and contagion. Liquidity policy implications are briefly discussed.

Keywords: Financial fluctuations, Contagion, Systemic risk, Heterogeneous agents, Complex dynamics

1. Introduction
The complex dynamics of financial fluctuations reflects the impact of individual decisions on the macro variables of the economy within the technological, financial and institutional constraints characterizing a given economy.
Among the structural constraints the financial conditions of economic units play a crucial role. In particular, the interaction between the liquidity and solvency conditions of economic units seems to play a crucial role in the emergence of complex financial fluctuations. This interaction is significant at the level of single financial units, under suitable simplifying assumptions, to modelling the typical fluctuations of their financial conditions. The model may be also applied to the economy as a whole providing some general insights on its financial fluctuations and its policy implications (Sordi and Vercelli, this issue, 2006; Vercelli, 2000, 2011; Dieci et al., 2006). However, a crucial feature of real financial fluctuations is missing in this approach: the interaction between the units’ balance sheets that heavily affects their behavior.

A case in point is the so-called “contagion” that has played a crucial role in recent financial crises and has enhanced systemic risk. There is a vast and growing literature on systemic risk and financial contagion, in particular post financial crisis 2007-2008 (see Haldane (2009) for an overview). The origins of systemic risk has been modelled as a “bank run” where the loss in confidence in the banking system pushes depositors to withdraw money from their banks, so triggering a contagion effect (see for example De Bandt and Hartmann (2000) for an overview of different forms of systemic risk). Alternatively, it can occur as a consequence of an exogenous shock (see Kaufman and Scott (2003); Kaufmann (2005) for a qualitative overview).

The other important component of systemic risk modelling is the description of the spread of contagion in the system. Two main approaches have been developed in recent literature. The first one is what it is called the “firesale” approach, in which the propagation of contagion is driven by the losses in asset values due to liquidation of failing banks (Allen and Gale, 2001; Diamond and Rajan, 2005; Freixas et al., 2000). The second one directly models the bilateral flows between units in a financial network as a direct channel of contagion (see Markose et al. (this issue); Krause and Giantsante (this issue); Vivier-Lirimont (2004); Iori et al. (2008); Cohen-Cole et al. (2010) for an extensive literature review).

This work will address the problem of systemic risk by modelling the origins of contagion as a result of an endogenous liquidity shock closely related

\footnote{According to the Bank of International Settlements, systemic risk is defined as “the risk that the failure of a participant to meet its contractual obligations may in turn cause other participants to default with a chain reaction leading to broader financial difficulties” (BIS, 1994)}
to the “bank run” approach, in which the trigger event is driven by the economic business cycle as described in Sordi and Vercelli (this issue) and the central bank liquidity policy. The losses spread along direct connections of liquidity flows between units in the network of liquidity provision.

The interaction between units’ balance sheets is particularly visible during the most serious financial crises but plays a crucial role in all the phases of the cycle as it reflects the interdependence via the financial inflows and outflows of the economic units. Increased outflows of a unit translate in increased inflows of other units and the other way round. In order to study this interaction we adopt an heterogeneous-agent model which proceeds through discrete time steps within a finite time horizon. Economic units decide their liquidity flows on the basis of their liquidity index, solvency index and financial fragility parameters, defined in the next Section. It is also assumed that the units can also borrow money from the Central Bank in order to meet their liquidity needs.

The paper is organized as follows. Section 2 presents the approach explored in this paper by modelling the behavior of financial units and their interactions with other units and the Central Bank. Section 3 presents an exercise of a stylized economy with three units interacting under different liquidity policy regimes. Section 4 extends the previous results by modelling and simulating a larger system. Section 5 concludes.

2. The Model

The model proceeds through discrete time steps. A set of $N$ economic units (each labelled by an index $i = 1, \ldots, N$) interacts at each timestep $t$. Economic units encompass all kinds of private economic units including firms, banks, and households. The private units of a certain economy interact not only among themselves but also with the public economic units. We will consider only one of the public units that plays a crucial role in monetary and financial policy: the Central Bank.

2.1. Current Financial Ratios

Units are heterogeneous in terms of their liquidity positions and exchange strategies.

Let us define an $N \times N$ matrix $X$ of bilateral flows where the element $x_{i,j}$ represents the directed flow between units $i$ and $j$. This flow is an inflow from the point of view of unit $j$ and an outflow from the point of view of
unit $i$. Therefore, the elements of the row $i$ describe the outflows of the unit $i$, while the elements of the column $j$ describes the inflows of the unit $j$.

The sum of the elements of the row $i$ equals the total outflow of unit $i$, while the sum of the elements of the column $j$ equals the total inflow of unit $j$.

\[ y_{j,t} = \sum_i x_{ji}, \quad \text{(1)} \]

and

\[ e_{i,t} = \sum_j x_{ij}. \quad \text{(2)} \]

define the total inflows and outflows respectively.

We measure the liquidity of unit $i$ at time $t$ according to Sordi and Vercelli (this issue) as the surplus of financial inflows $y_{i,t}$ minus financial outflows $e_{i,t}$, all flows being measured at the same time unit. We can then define the liquidity index for unit $i$ at time $t$, $f_{i,t}$, as

\[ f_{i,t} = y_{i,t} - e_{i,t}. \quad \text{(3)} \]

On the other hand, the solvency of the unit is captured by its “net worth”, defined as the discounted value of its expected surpluses and deficits. We define the solvency index for unit $i$ at time $t$, $f^*_i$, as

\[ f^*_i = \sum_{s=0}^{T_i} \frac{E_{t-1}[f_{i,t+s}]}{(1+r)^s}. \quad \text{(4)} \]

where $E_{t-1}[.]$ denotes the conditional expectation operator based upon information available at the end of period $t-1$ and $T_i \geq 1$ is the time horizon of unit $i$. The nominal interest rate $r$ is used as the discount factor.$^3$

2.2. Dynamic interaction between units' solvency and liquidity conditions

Following Sordi and Vercelli (this issue), we obtain a feedback relation between the solvency and liquidity indices under the assumption that units forecast their future liquidity indices for the next $T_i$ periods by using a mix

\[ ^3\text{We do not need to distinguish between nominal and real interest rates as prices are fixed for simplicity.} \]
of heterogenous (extrapolative and regressive) expectations.\textsuperscript{4} In this case, from (4) we arrive at the equation

\[ f_{i,t+1} = \beta_{i,t}^e \beta_{i,t}^r f_{i,t} + (1 - a_i \beta_{i,t}^e \beta_{i,t}^r) f_{i,t}^* \]  

(5)

where \( a_i = \sum_{s=0}^{T_i} \frac{1}{(1 + r)^s} = \frac{r (1 + r)^{T_i}}{(1 + r)^{T_i} - 1} \) and where, indicating by \( \rho_i \) and \( \eta_i \) the coefficients of extrapolative and regressive expectations respectively, and with \( b \) a small positive magnitude, we have:

\[
\beta_{i,t}^e \beta_{i,t}^r = \begin{cases} 
\frac{(1-\rho_i^e)((1+r)^{T_i}-(1-\rho_i^e)^{T_i}+1)}{(1+r)^{T_i}(1+r(1-\rho_i^e))}, & \text{if } |f_{i,t} - a_i \mu_i| > b \\
\frac{(1+\rho_i^e)((1+r)^{T_i}-(1+\rho_i^e)^{T_i}+1)}{(1+r)^{T_i}(1+r(1+\rho_i^e))}, & \text{if } |f_{i,t} - a_i \mu_i| < b 
\end{cases} 
\]  

(6)

In this definition of the parameter \( \beta_{i,t}^e \beta_{i,t}^r \), the crucial role is played by \( \mu \) that represents a safe liquidity margin that units do not want to bridge, i.e. the minimum value of its net worth sufficiently higher than zero, beneath which units do not want to go.

Then, we define here the desired liquidity index \( \widehat{f}_{i,t+1} \) as the liquidity target that unit \( i \) aims to achieve at \( t+1 \). It is described by the dynamic equation

\[ \widehat{f}_{i,t+1} = f_{i,t} - \alpha (f_{i,t}^* - \mu_i). \]  

(7)

Following Sordi and Vercelli (this issue), when a unit at time \( t \) is aware that the value of its solvency index is greater than the safety margin \( \mu_i \), it reacts (in the next period) by reducing outflows relative to inflows and vice versa when the value of its index is less than \( \mu_i \).

The intended contribution of this paper is the description and implementation of the micro-interactions between units that originate from their attempts to meet their individual liquidity targets. As a preliminary step, the latter are described and discussed in the next section.

\[ \textit{2.3. Liquidity targets} \]

At each time step, units compute their liquidity index \( f_{i,t} \) (3) and their solvency index \( f_{i,t}^* \) (4) on the basis of the bilateral matrix flow \( X_t \). Depending on the value of their solvency index, units may decide to increase or decrease

\textsuperscript{4}We emphasize that liquidity indices \( f \) are realized values while the solvencies indices \( f^* \) are expected values.
their current liquidity index by modifying the level of inflows and outflows. One way to do so is to negotiate new monetary flows with other units with opposite liquidity needs. In order to differentiate units by their liquidity needs, we define here the absolute deviation $z$ of the liquidity index $f_{i,t}$ from the next period liquidity target $\widehat{f}_{i,t+1}$ as follows:

$$z_{i,t} = \widehat{f}_{i,t+1} - f_{i,t},$$  \hspace{1cm} (8)

The value of $z$ captures the absolute change of the current liquidity index to meet the outflows targets for the next period (captured by $\widehat{f}$). In other words, the sign of $z$ allows us to differentiate between units with a positive and a negative liquidity gradient (i.e. units that want to increase or decrease their liquidity index respectively).

It is clear that new liquidity negotiation can only occur between units with opposite signs of $z$. The next section presents a matching mechanism of bilateral liquidity flows adjustment according to each liquidity target.

2.4. Matching mechanism

In principle there is an infinite number of ways to adjust $e_{i,t+1}$ and $y_{i,t+1}$ that satisfy $\widehat{f}_{i,t+1}$. In particular, the deviation $z$ is used as a proxy for the gradient of liquidity that the unit aims to achieve. A positive value of $z$ describes an economic unit wishing to increase the liquidity index for the next period, while a negative value of $z$ describes an economic unit wishing to reduce the liquidity index. Both positive and negative changes can be easily achieved by modifying the outflows or inflows according to the rules of the matching mechanism. We model a mechanism that matches units with opposite directional changes$^5$.

We define two new variables $\tau_{i,t}^y$ and $\tau_{i,t}^e$, as percentage change in $y$ and $e$, consistent with $\widehat{f}$ as

---

$^5$The same results may be achieved by decreasing inflows (for negative $z$) or outflows (for positive $z$). However, this second option would require renegotiation procedures between parties about previous deals with penalties to be paid from the party who decides to withdraw from a contract. As we are only interested in the evolution of the indices (not inflow and/or outflows separately), the incremental mechanism is the easiest solution at this stage.
\[
\tau_{i,t}^y = \begin{cases} 
\frac{z_{i,t}}{y_{i,t}} & \text{if } z_{i,t} > 0, \\
0 & \text{otherwise.}
\end{cases}
\] (9)

\[
\tau_{i,t}^e = \begin{cases} 
\frac{|z_{i,t}|}{e_{i,t}} & \text{if } z_{i,t} < 0, \\
0 & \text{otherwise.}
\end{cases}
\] (10)

As we can see in (9) and (10), \(\tau_{i,t}^y\) takes only positive values of \(z_{i,t}\), relative to the amount of inflow of the unit. It represents the percentage change of inflow needed to reach a positive change in liquidity. On the other side, \(\tau_{i,t}^e\) takes only negative values of \(z_{i,t}\) (in absolute terms) relative to the amount of outflows the unit has to increase in order to decrease its liquidity index (as \(z\) is negative). In other words, we use \(\tau^y\) and \(\tau^e\) to split our population of economic units into two groups on the basis of the liquidity gradient. Therefore, the two populations will try to achieve different investment decisions, either by increasing inflows (\(\tau^y\)) or by increasing outflows (\(\tau^e\)).

The evolution of each bilateral flow \(x_{ij}\) is computed according to

\[
x_{ij,t+1} = (1 + \min \left[ \tau_{j,t}^y, \tau_{i,t}^e \right]) x_{ij,t}.
\] (11)

Equation (11) describes a dynamic update of bilateral flows that takes into account the strategies of units \(i\) and \(j\) for next period. Remember that the flow \(x_{ij}\) is an outflow for \(i\) and an inflow for \(j\). In the case of a matching both parties \(i\) and \(j\) agree to increase the flow \(x_{ij}\), which can only accommodate the minimum of the two. Therefore, the \(\min\) function in equation (11) applied to \(\tau_{i,t}^e\) and \(\tau_{j,t}^y\) (representing the percentage increase of the flow \(x_{ij}\) that agents \(i\) and \(j\) would like to achieve for next period respectively), prevents an overincrease of \(x_{ij}\) that would be above the limit of one of the two parties.

2.5. Central bank liquidity policy

Business cycle fluctuations directly affect the success of units in meeting their liquidity needs. However, the intervention of the Central Bank as lender/borrower of last resort can help units to fulfill their liquidity goals by fully or partially offsetting the units’ position not covered by the other units.

We define the central bank intervention \(C_{i,t}\) for unit \(i\) for next time period \(t+1\) as

\[
C_{i,t+1} = \lambda_{i+1}^C \left( \hat{f}_{i,t+1} - f_{i,t+1} \right), \quad 0 \leq \lambda_{i+1}^C \leq 1
\] (12)
where \( \lambda_{t+1}^C \) is the percentage support the central bank is willing to grant at time \( t + 1 \). The higher the percentage, the bigger the support of the central bank to the unit. A positive value of the central bank intervention \( C_{i,t+1} \) identifies a lending operation to the unit, while a negative value identifies a borrowing operation of the central bank from the unit.

We define the maximum liquidity buffer the central bank is willing to grant to units in each time \( t \) as \( L_t \). It describes the maximum net intervention of the central bank in the market at time \( t \). In other words, banks can borrow money from the central bank up to \( L_t \), \( \forall t = 1, \ldots, S \) where \( S \) represents the number of time periods of the entire system. We expect that liquidity needs from the economic units up to \( L_t \) are fully covered by the central bank, while higher needs can only be partially covered up to \( L_t \). A first attempt of liquidity need redistribution we implements here is by describing the dynamics of \( \lambda_{t+1}^C \) as follows

\[
\lambda_{t+1}^C = \begin{cases} 
1 & \text{if } \sum_{i,t+1} \left[ \hat{f}_{i,t+1} - f_{i,t+1} \right] \leq L_{t+1}, \\
\frac{L_{t+1}}{\sum_{i,t+1} \left[ f_{i,t+1} - f_{i,t+1} \right]} & \text{otherwise.}
\end{cases}
\tag{13}
\]

Values of \( L_{t+1} \) in (13) greater than the sum of all liquidity needs from the units (after the matching mechanism) means that the central bank is willing to offer enough liquidity buffer to satisfy the entire system. Therefore, the value of \( \lambda_{t+1}^C \) will be equal to 1, meaning that the central bank will give 100% support to the units in reaching their liquidity targets. However, values of \( L_{t+1} \) below the liquidity need of the market represents a situation in which the central bank does not have enough liquidity to fully support the units. In that case, \( \lambda_{t+1}^C \) will be set up as the ratio between \( L_{t+1} \) and the overall liquidity need, that is the partial support that the central bank is able to provide \((\lambda_{t+1}^C < 1)\).\(^6\)

Finally, we can easily write the equation describing the dynamics of the liquidity index as

\[
f_{i,t+1} = y_{i,t+1} - e_{i,t+1} + C_{i,t+1}. \tag{14}
\]

where, as we know from (12), the value of \( C_{i,t+1} \) also depends on the Central Bank support.

---

\(^6\)Note that the adjustment of \( \lambda_{t+1}^C \) assures a proportional distribution of liquidity to the units relative to the amount requested.
The following example shows a numerical exercise that implements the matching mechanism introduced above.

**Example**

Assume that the bilater matrix $X_0$ of an economic system with three units is given by

$$X_0 = \begin{bmatrix}
0 & 0.5 & 0.3 \\
0.4 & 0 & 0.3 \\
0.5 & 0.4 & 0
\end{bmatrix}$$

from which units computes their outflows $e_0 = [0.8 \ 0.7 \ 0.9]'$ and inflows $y_0 = [0.9 \ 0.9 \ 0.6]$. Assuming no central bank intervention at time $t = 0$, the vector of the liquidity index at this time $f_0$ will be

$$f_0 = y_0 - e_0 + C_0 = \begin{bmatrix}
0.9 \\
0.9 \\
0.6
\end{bmatrix} - \begin{bmatrix}
0.8 \\
0.7 \\
0.9
\end{bmatrix} + \begin{bmatrix}
0 \\
0 \\
0
\end{bmatrix} = \begin{bmatrix}
0.1 \\
0.2 \\
-0.3
\end{bmatrix}$$

According to equation (4)\textsuperscript{7}, the solvency index of next time period will be $f_1^* = [0.16 \ 0.29 \ -0.35]'$ and therefore the desired liquidity index for next period will be $\hat{f}_1 = [0.15 \ 0.25 \ -0.24]'$\textsuperscript{8}.

The matching mechanism will split the units into those willing to either increase $y$ or $e$ by computing the percentage changes $\tau_1^c$ and $\tau_1^y$ on the basis of the directional change $z_1$:

$$z_1 = \begin{bmatrix}
0.052 \\
0.052 \\
0.052
\end{bmatrix} \quad \tau_1^c = \begin{bmatrix}
0 \\
0 \\
0
\end{bmatrix} \quad \tau_1^y = \begin{bmatrix}
0.058 \\
0.058 \\
0.087
\end{bmatrix}$$

The values of $z$ clearly show that all units want to increase their liquidity index as all $z$ entries are positive. Therefore, the only way for the units to increase their inflows is to borrow liquidity from the central bank. If we assume a full support with unlimited liquidity from the central bank, by setting $\lambda_i^c = 1$, $\forall i = 1, 2, 3$, then $C_1 = [0.052 \ 0.052 \ 0.052]'$. Here the public intervention allows units to fulfill their liquidity needs and realize their desired liquidity index, that is $f_1 = \hat{f}_1 = [0.15 \ 0.25 \ -0.24]'$.

\textsuperscript{7}We use $f_0^* = [0.1 \ 0.1 \ 0.1]'$, $\rho = 0.3$, $r = 0.05$, $\mu_i = 0.2 \ \forall i = 1, 2, 3$ and $T = 1$. 

\textsuperscript{8}Values have been rounded to 2 decimal places.
2.6. Bankruptcy

The last component of the model is a criterion for unit bankruptcy. For the purpose of this exercise, we will focus on situations of liquidity deficit that may lead to bankruptcy, meaning an prolonged period of negative liquidity issue that make the unit insolvent. Therefore, an economic unit is declared bankrupt if its liquidity index is negative for more than $b$ consecutive time steps. The number of time steps $b$ is then the length of time window that units have to raise liquidity from the market to avoid bankruptcy. When a unit is declared bankrupt, all flows from and to the bankrupt unit are set to zero.

3. A three units example

This section presents the results of a three unit exercise that is based on the example presented in the previous section. We set $b = 5$, which means that units with negative liquidity indices will have to raise liquidity in not more than 5 time steps to avoid bankruptcy. We set up three different liquidity policy scenarios to underline policy implications of market stability. For simplicity, we will consider a constant liquidity policy over time, that is $L_t = L, \forall t = 1, \ldots, S$. We do not apply any liquidity constraint and bankruptcy criterion in the first 100 time steps to allow the market to converge to a stable business cycle.

3.1. Scenario 1: Complete Central Bank Intervention ($L \to \infty$)

The first scenario we present describes an environment with an liquidity buffer that approaches to infinity held by the central bank at every step. This means that units can always meet their liquidity needs by borrowing money from the central bank if the market cannot provide enough liquidity. As $L$ approaches infinity, $\lambda_t^C$ will converge to $1 \forall t = 1, \ldots, S$ which means that the central bank will always meet the units’ need for liquidity in the case when funds cannot be raised from the market. Figure 1 pictures fluctuations of liquidity and solvency indices for each unit. On the left hand side, we plot the time series of the liquidity index $f_i$ (red) and solvency index $f_i^*$ for each unit $i = 1, 2, 3$, while on the right hand side we show all combination points of liquidity and solvency indices of each unit.

This scenario represents the business cycle base line for comparison with the other two scenarios (Sordi and Vercelli, this issue).
Figure 1: Scenario 1: time series of liquidity (red line) and solvency (blue line) indices for each unit on the left hand side; phase plot of solvency/liquidity indices on the right hand side
3.2. Scenario 2: Contagion and Counterparty Risk ($L = 0.1$)

The second scenario describes an environment with a limited liquidity buffer held by the central bank, which is set at $L_t = 0.1$, $\forall t = 1, \ldots, S$. When the market shows an excess of liquidity demand, the central bank can only supply the market with a maximum amount of $L$. This will produce a lack of liquidity in the system.

Figure 2 shows nine cases with lack of liquidity, meaning that $\lambda^C < 1$ from equation (13). The value $1 - \lambda^C$ can be interpreted as percentage liquidity deficit in the market as a result of the central bank liquidity policy. Note that three major peaks of liquidity lacking greater than 20% at time 109, 123 and 134 respectively can be observed, with an average of 13.6% across all events. The impact of this liquidity policy is pictured in Figure 3, where the 22% liquidity deficit faced by the units at time 134 caused unit 3 to go bankrupt, which occurs at time 139. Unit 3 was the only unit facing a
Figure 3: Scenario 2: time series of liquidity (red line) and solvency (blue line) indices for each unit on the left hand side; phase plot of solvency/liquidity indices on the right hand side.
negative liquidity index at the time of the event (time 134). The default of
unit 3 spreads to the other units as counterparty risk. Unit 2 had a positive
exposure to unit 3, that is outflows to unit 3 greater than inflows from unit
3 $(x_{2,3} > x_{3,2})$; this event triggered a positive jumps in the unit 2 liquidity
index as it faced a net loss in its outflows. Unit 1 had an opposite effect
as it was negatively exposed to unit 3. This bankruptcy event pushed unit
1 to more exposed positions as a result of a negative jump its its liquidity
index. However, unit 1 was able to raise liquidity within 5 time steps and
avoid bankruptcy.

The last scenario, with a more rigid monetary policy, will describe a
different outcome for this unit.

3.3. Scenario 3: Contagion and Systemic Risk ($L = 0.08$)

In the last scenario we reduce further the maximum liquidity buffer $L$ to
0.08.

As shown in Figure 4, the lack of systemic liquidity is more substantial
than in the previous scenario (average loss of 19.2%). The last and biggest
lack in liquidity the units faced at time 131 (32% loss) pushed unit 3 to
bankruptcy at time 135. Consequently, the negative exposure of unit 1 to
unit 3 results in a downward jump of its liquidity index that dictated its
bankruptcy at time 140 (see Figure 5).

With two units bankrupt out of three, the entire market collapses. The
very restrictive liquidity policy tested in this scenario eventually triggers a
domino effect that results in the collapse of the system.

4. Simulation results: endogenous fluctuations and bankruptcy

In this section we extend the three unit example by having a large eco-
nomic system, with number of units $N = 100$. Our aim is to understand the
implications of one aspect of the monetary policy strategies, that is the the
impact of the systemic liquidity constraint $L$, to the spread of contagion and
systemic risk.

The initialization of the parameters related to the units behavior are the
following$^9$: $\mu = 0.2$, $b = 0.02$, $\rho_c = 0.2$, $\rho_r = 0.08$, $\alpha = 0.25$.

$^9$The magnitude of the parameters have been choses according to the simulation ex-
periments presented in Sordi and Vercelli (this issue).
Figure 4: Scenario 3: liquidity deficit (in percentage) of the system as the result of the Central Bank liquidity policy $L$. 
Figure 5: Scenario 3: time series of liquidity (red line) and solvency (blue line) indices for each unit on the left hand side; phase plot of solvency/liquidity indices on the right hand side.
Units are allowed to interact, that is to transfer monetary flows, to any other unit in the market at zero transaction or search costs. Therefore, any economic unit can have up to \( N - 1 \) counterparties in each time step\(^{10}\).

We initialize the matrix \( X \) of bilateral flows in a random fashion and we test the model under different values of \( L, r \) and \( T \).

### 4.1. Determinants of contagion at the system level

First of all, we report the number of bankrupt units under different liquidity policy regimes. To compare the system with a different number of units, we define \( \hat{L} = L/N \) as the average amount of liquidity the central bank is willing to provide for each unit. Note that \( \hat{L} \) varies in the range \([0, 0.1]\), which means that the max liquidity buffer the central bank can use to satisfy unit liquidity needs is \( \hat{L}xN \).

Figure 6 shows the effect of strict liquidity policy regimes to the number of bankrupt units due to systemic risk. Indeed, the lower the level of the liquidity buffer \( L \), the larger the number of bankrupt units, up to the extreme case with zero liquidity buffer and the complete collapse of the system. The direct effect of the liquidity regime on unit behavior is captured by the unit expectation index, representing the percentage number of times the units adopt extrapolative expectation instead of regressive ones. As we can see in Figure 6, larger liquidity buffers drive the units to more exposed positions, by using more extrapolative expectations than regressive ones. However, the transition from lower to higher levels of \( L \) does not necessarily mean a monotonic transition from a lower to a higher expectation index value. What appears to be very interesting is the transition, which is not linear as we would have expected to see. Indeed, by constantly reducing liquidity provision \( L \), the number of defaulting units first increases, then decreases to increase again in the proximity of \( L = 0 \) (the case with \( T = 4 \) in Figure 6).

Sordi and Vercelli (this issue) discussed the effect of higher values of \( T \), that is the discrete time window of units solvency conditions forecast, on the fluctuations of the liquidity index. Indeed, higher values of \( T \) amplify the fluctuations of the individual liquidity index, making the unit more exposed to liquidity distress. This can be observed in Figure 6 with \( T = 4 \). As

\(^{10}\)An interesting extension to the model would be to limit the number of counterparties each unit can have. That would allow us to study the contribution of the specific topology of the network flows among economic units to the spread of contagion. As this analysis is beyond the scope of this paper, we will leave it to future work.
Figure 6: Scatter plots of the number of bankrupt units (blue dots) and the expectation index (green dots) relative to the monetary policy buffer $L$ of the system, under different values of $T$. 

18
units take more exposed positions, they end up using regressive expectations even with high levels of $L$ (no lack of liquidity due to limited amount of $L$) just because of their strategy. In this scenario, units seem to have an altered perception of the liquidity policy in operation by the central bank that causes the adoption of extrapolative expectations even with very tight liquidity regimes. The outcome of this altered behavior is a jump in the number of bankrupt units that were not able to realize in time how exposed their position was. They should have recovered very quickly their loss by using regressive expectations. However, the altered perception of market conditions described above does not allow the units to realise their dangerous situation, so increasing their chances of bankruptcy.

4.2. Determinants of contagion at the individual level

We are confident that the approach suggested above may help us to understand the individual determinants of bankruptcy of economic units. A preliminary step in this direction is to record the level of liquidity and solvency indices of each bankrupt unit at the time they are affected by either a lack of liquidity due to the liquidity regime of the central bank or the default of one or more counterparties.

Figure 7 plots the combinations of liquidity and solvency values of all bankrupt units when they first were affected by the loss in liquidity (either from the central bank or the counterparty). These plots give us information about the fragility of units along the business cycle. Units are particularly vulnerable to contagion when they have a negative liquidity index. However, the majority of the most exposed points in our simulations is concentrated in the area with positive solvency values around the value $\mu$. In other words, the majority of units that went bankrupt because of contagion are the ones that at the time of the contagion had a negative liquidity index and positive solvency index. A tentative interpretation of this prima facie surprising result may be that units with a positive solvency react to a worsening of their liquidity index induced by contagion with insufficient energy being reassured by an insolvency index that they still believe to be fairly safe. However the solvency index depends on expectations that deteriorate very rapidly in a period of financial crisis characterized by contagion. In such a situation a positive net worth may very rapidly become negative determining the insolvency of the economic unit. Finally, another result of our simulations is that higher values of $T$ increase the fluctuations of the liquidity and solvency indices and then amplify the variability of the marginal distribution of the two
Figure 7: Scatter plot of the combination of liquidity and solvency values of bankrupt units at the time of the contagion. The bar plots at the side and below refer to the marginal histograms of the distribution of the liquidity and solvency values respectively.
indices. This result is not surprising since a longer time horizon amplifies more the effects of a change of expectations contributing to the strength of financial fluctuations.

This phenomenon increases their chance of going bankrupt and explains the concentration of the points plotted in Figure 7 around the value of $\mu$. Higher values of $T$ increases the fluctuation of the liquidity and solvency indices and then amplify the variability of the marginal distribution of the two indices.

5. Concluding remarks

This work has aimed at a preliminary investigation of the interaction between liquidity and solvency conditions within systemic risk framework. Previous research by the authors has shown that this interaction contributes to the explanation of financial fluctuations for single economic units or for an agent representative of the entire economy. The aggregate approach of these contributions, however, clouds some crucial features of financial fluctuations, such as contagion, that critically depend on the complementarity between the balance sheets of economic units. This relation brings about a second order interaction between liquidity and solvency conditions at the level of the entire economy that depends on their interaction at the units level. This increases the degree of complexity of the economic dynamics that characterizes a financialized economy. The simulations performed in the second part of the paper suggest preliminary results on how financial contagion is transmitted throughout the economy and clarify under which financial conditions the units are more likely to be affected. The complex dynamics of this model economy increases the financial fragility of the illiquid economic units even if their solvency index looks satisfactory in the light of current expectations.

However, the significance of the results of the current model is limited by a series of simplifying assumptions that we aim to relax in future works. In particular, we refer to the homogeneity of economic units reaction functions which follows from setting, as we have done in basic dynamic equations as (7) and (12), the parameters equal across all units. As for policy implications, a more comprehensive analysis requires the introduction of public expenditure.

References

Settlements.

Cohen-Cole, E., Patacchini, E., Zenou, Y., 2010. Systemic Risk and Net-
Research Paper.

35. ECB.

Journal of Finance 60, 615–647.

Chaos, Solitons & Fractals 29(3), 595–610.

Freixas, X., Parigi, B.M., Rochet, J.C., 2000. Systemic risk, interbank re-
lations, and liquidity provision by the central bank. Journal of Money,
Credit and Banking 32, 611–38.

Student Association. Amsterdam.

Iori, G., De Masi, G., Precup, O.V., Gabbi, G., Caldarelli, G., 2008. A net-
work analysis of the italian overnight money market. Journal of Economic
Dynamics and Control 32, 259–278.

regulators retard or contribute to it? Technical Report 7. Independent
Review.


Krause, A., Giansante, S., this issue. Interbank lending and the spread of
bank failures: A network model of systemic risk. Journal of Economic
Behavior and Organization.

Markose, S., Giansante, S., Gatkowski, M., Shaghaghi, A., this issue. Too
interconnected to fail: Financial contagion and systemic risk in network
model of cds and other credit enhancement obligations of us banks. Journal
of Economic Behavior and Organization.


