Systemic Risk Assessment
Stress Testing the French Banking System*

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Abstract

This paper presents a valuation model adapted to systemic stress testing exercises. The model allows to assess the impact of stress scenarios on a banking system within a top-down approach. A modular and sequential specification is used to capture: (i) the direct impact of a severe shock on the individual bank balance sheets, and (ii) the resulting dynamic process over an arbitrary horizon. The direct impact is assessed on portfolios exposed to market, credit and liquidity risks. Accordingly, new solvency and liquidity ratios are established. Based on these ratios, the dynamic process includes: (iii) individual bank reactions to the shock, (iv) the shock transmission across banks, through interbank networks and financial markets channels, (v) second-round effects, and (vi) public response functions represented by the central bank and the Treasury. The model is estimated and simulated quarterly for the French banking system. The results show a high vulnerability of the trading portfolios compared to other banking activities. Second-round effects seem to be relatively limited except in the presence of a severe stress shock. Public responses turned to be crucial, given that scenarios in which this has been omitted result in a failure of a significant share of the banking sector after only two quarters of simulation.

Key words: Systemic risk, stress testing, valuation models, financial crises, risk management.

JEL classification: C15, G01, G17, G21, G32.

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1 Introduction

The subprime crisis stemming from the US in the 2007 summer suddenly converted into a financial global crisis of serious consequences on the real economic activity. These unexpected effects, both in quantitative and qualitative terms, have urged financial regulators and policy makers towards a better understanding of the financial system functioning. These efforts are expected to allow preventing such events or at least to be able to manage them when they occur. Several analytical tools have been proposed to identify financial systems' vulnerabilities, to assess their expected impact on financial systems and the real activity, and to identify appropriate methods to prevent and/or manage financial crises.

Macro or systemic stress tests are part of this management set. These exercises are designed to *assess the potential impact of severe but plausible scenarios* on the financial and/or economic stability of one or more systems (countries or regions). By doing so, they are assumed to capture the transmission channels of the supposed scenario and the evolution of the corresponding impact over a given horizon. On a conceptual level, stress tests respond exactly to what regulators and policy are asking for. They then have been under the guidance of the main national and international regulations. However, the excitement generated by their introduction was moderated by the limits identified in the first performed exercises. These limits are especially reflected by: (i) failures in identifying sources of systemic vulnerability (the systemic risk factors), (ii) drawbacks of the performed models used to capture the transmission channels of these factors to the financial system and the real economy (the systemic risk), and (iii) the lack of credibility in the considered stress scenarios. These aspects have often led to hasty conclusions and to an illusion of strength of the stressed systems. As an example, one can hold up the case of all the tests conducted within the FSAPs programs between 2005 and 2007 i.e. just before the outbreak of the crisis. More recently, Irish banks have been liquidated a few months after having successfully passed the 2010 stress tests to which they were submitted.

The economic, social and political costs of these errors have reinforced the need for a better control of stress tests. This paper provides an answer to the second limit introduced above. I propose a stress testing model that assesses the systemic risk carried by a banking system. The model is based on a modular and sequential specification of the transmission channels of a (severe) movement in risk factors to the considered system. Combined to a *risk model* that specifies the joint process of the systemic risk factors, the proposed *valuation model* measures the systemic risk based on: (i) the direct impact of a risk factors' movement (hereinafter the shock) on individual bank balance sheets, and (ii) the dynamics of this impact on a given time horizon. The direct impact is measured in terms of changes in the value of balance sheet items exposed to market, credit and liquidity risks. Depending on the direct impact, the model dynamics may include one or more of the following aspects: (iii) private reactions to the shock, (iv) externalities including the shock transmission across banks of the same system, through interbank networks and financial markets channels (v) second-round effects, and (vi) public reaction represented by the central bank and the Treasury. The model is carried out within a top-down approach and applied to balance sheets of the six major French commercial banks.

The specification of the various modules is quite simple and often extensible. Reduced-form equations and rules of thumb are mainly considered here. This choice allows to capture, in an operationally fashion, the evolution of the shock impact and the contribution of the different modules in the final result. A detailed analysis and a straightforward interpretation of the results are also strengthened within this approach. Besides providing an assessment of the potential systemic risk, the proposed model can also be regarded as a quantitative tool allowing a broad assessment of the stress tests conducted by private institutions and regulators.

The rest of the paper is presented as follows. Section 2 reviews the main approaches carried out in the literature to specify the systemic risk and systemic risk factors. A particular focus will be made on stress testing models. Section 3 presents the general framework of the proposed model and details its different modules. The dataset under review and the estimation results are given in section 4. The next section put forward the practical implications of the approach through a set of simulation and ad hoc stress testing exercises. Section 6 summarizes and concludes.

2 Systemic risk modelling

Until the mid-2000s, systemic risk management in the financial system was mainly performed within micro-prudential frameworks. In contrast, macro-prudential or financial stability models have been less stylized and for the most reduced to qualitative specifications. Those aspects significantly reduced the practical usefulness of these models for risk management purposes, unlike monetary policy models for example (see Borio *et al*. 2012). Criticism against the (earlier) macro-prudential models have been about their inability to – accurately – assess the potential impact of systemic risk factors on the financial system, i.e. the inability to quantify systemic risk. This has produced awful consequences in recent times. On the one hand, prudential management measures taken before the crisis proved to be suboptimal, which produced unexpected losses and many bankruptcies. On the other hand, when the crisis erupted, public and private decision makers were often confused about the reactions to adopt. This uncertainty was mainly due to a poor understanding of the financial system, and in particular, the risk transmission channels and the impacts of private equity management and public policy responses to the crisis. These factors explain the sub-optimality of the undertaken measures, often inappropriate in qualitative, quantitative terms and/ or in terms of timing.

More generally, a macro-prudential model is based on three elements: (i) the definition of systemic risk, (ii) and related risk factors, and (iii) the specification of the valuation model, which captures the transmission channels through which the risk factors are translated to the system, i.e. the concretization of the risk factors. A reliable assessment of systemic risk requires an appropriate choice of the three elements. In practice however, this approach faces several theoretical and practical challenges.

2.1 Systemic risk and systemic risk factors

The financial literature does not provide conventional definition of systemic risk which remains an elusive notion. In some papers, this definition is quite broad and often inaccurate. Systemic risk is for instance assimilated to: *distortions caused by financial frictions with respect to a critical threshold* (Haldane, 2004 – In Borio and Drehmann 2009), *circumstances threatening the stability or confidence in the financial system* (Billio *et al*., 2012), financial turmoil *large enough to impact economic growth and welfare* (ECB, 2009), etc. A second body of literature restricts the concept of systemic risk to some of its specific aspects. These include: common exposures to exogenous risk factors (Acharya et al 2010) Stock market bubbles (Rosengren, 2010), contagion (Moussa, 2011), endogeneity (Caballero, 2010), feedback effects (Kapadia *et al*. 2013), information frictions (Mishkin, 2007), the impact on the real economy (G10, 2001), etc. Broad definitions are often useless for operational purposes, while narrower definitions may shrink the scope of analysis and mix up the risk and risk factors notions.

To circumvent these issues, I adopt in this paper a definition of systemic risk based on the underlying risk factors. Accordingly, three main categories systemic risk (factors) are considered: (i) the external risk, (ii) the internal risk and (iii) the risk of contagion. External risk stems from external risk factors to the banking sector. It impacts banks and financial markets in a direct fashion (e.g. macroeconomic, financial, (geo-) political factors, etc.). Internal risk is generated by the accumulation of imbalances and/or dysfunctions within the banking sector. These factors include, among others, common positions (on securities and/or collaterals, with regard to the yield curve, etc.) and informational frictions (mimicry, moral hazard due to the presence of a deposit-insurance system and/or the presence of a LLR, etc.).

Contagion risk refers to the transmission of external and internal risks across the different actors of the banking sector. This transmission is carried by two main channels: the interbank settlements system and financial markets. Thus, contagion risk factors often depend on the channel considered. Contagion generated by the settlement network can be initiated by the concretization of a counterparty risk factor (e.g. Freixas and Parigi, 1998; Allen and Gale, 2000; Freixas *et al*., 2000; Kahn *et al*., 2003; Leitner, 2005; Brusco and Castiglioesi, 2007; Liedrop *et al*., 2010; ECB, 2010; Duffie and Zhu, 2011; Ratnovski and Huang, 2011). It can also stems from liquidity risk factors. In this case, the concretization often takes the form of a bank run (e.g. Chen, 1999; Diamond and Rajan, 2005; Acharya and Yorulmazer, 2007) or uncertainty concerning future liquidity needs (Eisenschmidt and Tapking, 2009). Contagion coming from financial markets channel is often due to fire sales (Cifuentes *et al*., 2005), liquidity spirals (Brunnermeier and Pedersen, 2009), currency crises, etc. (see Upper, 2011 for a detailed review of the related literature).

Stemming from outside the banking system or the financial markets, the internal and external risk factors affect symmetrically banks of similar exposures. The impact of contagion risk factors may however differ with respect to bank idiosyncratic risk factors. Whatever the nature of the considered factor, its impact (i.e. the corresponding systemic risk) is measured on the exposures hold by the individual bank balance sheets. Exposure to market, credit and liquidity risk are considered. The final challenge of macro-prudential models lies in the implementation of structural, specifications able to connect – In a unified framework – the items in the banks' balance sheets to the relevant risk factors. These are the so-called systemic risk valuation or assessment models.

2.2 Systemic stress testing valuation models

The literature identifies three main approaches to assess systemic risk. The first, measures systemic risk within a general equilibrium framework (Goodhart *et al*., 2004, 2006a,b). Deeply stylized, these models present several practical challenges, particularly related to estimation issues (due to a lack of parsimony) and to result interpretation. Reduced versions of these models also exist. These consist in restricting the number of agents, states and time periods used in the model and/or setting some or all of its parameters values (Saade *et al*., 2007). The resulting specifications often lack accuracy, which reduces their usefulness for management purposes. To address this drawback, portfolio managers and policy makers have switched to a more operational approach. This consists in assessing systemic risk through a set of quantitative tools such as the so-called Financial Soundness Indicators or FSIs. While the later are fairly straightforward to implement and to interpret compared to the former approach, it stills much more incomplete. Indeed, since different tools are designed to alternatives purposes, they cannot be combined in a unified framework. Moreover, their construction is often based on simple reduced-form equations, which makes them unsuitable for economic story telling. Unlike structural approaches, these instruments do not allow to capture endogenous phenomena necessary in a systemic risk analysis (e.g. risk transmission channels of risks, the impact of private and public responses, etc.). Systemic stress testing models lie between the former two approaches.

Conceptually speaking, these models are based on a sequential specification, which combines three main blocks. The first, said *risk model*, defines the joint process (i.e. distribution and dynamics) of the exogenous risk factors. The second block is *called valuation* model. It captures the potential impact of a shock in these risk factors on bank balance sheets. This model defines the individual and systemic risk profiles. The last block allow to draw operational risk measures from the evaluated balance sheets. Tools such as VaR or FSIs can be used for this purpose.

Among the previous three blocks, the first two are of particular importance. In particular, the valuation model is fundamental in systemic stress testing. Its specification is assumed to be based on a set of complementary modules. These allow to capture: the direct impact of the shock on balance sheet items, the private and public response functions to the shock, the shock transmission channels – before and after reaction – to the rest of the system (i.e. the risk of contagion) and to the real economy (feedback effects), the dynamics of the shock impact – with and without new shocks – in the medium and long term (second-round effects), etc. However, in practice, most of the carried out models neglect one or more of these aspects. This results in unrealistic specifications and uninformative – and always confusing – conclusions. In most cases, the lack of flexibility in the considered valuation models is motivated by a lack of data, estimation issues, model's implementation and management costs, concerns about the internal and external communication issues related to the model and its outcomes, etc. Even though the main issues are well identified, the existing stress testing models are still limited, which made them one of the most active research areas in the recent period.

Elsinger *et al*. (2006a,b) proposed a one-period quarterly model, adopted by the Austrian Central Bank (OeNB) to test the robustness of the domestic banking sector. This model captures the direct impact of exogenous risk factors on balance sheet items exposed to market, credit, interest rate and counterparty risks. Contagion is captured through the financial markets channel and second-round effects are recorded at the end of the period. Boss *et al*. (2006a,b, 2008) have extended this model –now called SRM – to twelve periods (i.e. three years). They introduced a private response function which admits a profits redistribution at the end of each period. Drehmann *et al*. (2008) and *Wong et al*. (2008) presented a model designed to evaluate balance sheet exposures to credit and interest rate risk, and tested the impact of alternative response functions on the results of each period. Alessandri *et al*. (2009) extended the model of Elsinger *et al*. (2006a) by adding an interest rate risk evaluation module *à la* Drehmann *et al*. (2008), a second contagion channel represented by counterparty credit risk and a response function consisting on reinvesting any profits at the end of each period. This model, called RAMSI is officially adopted by the Bank of England. Aikman *et al*. (2009) extended most of the RAMSI modules and introduced a third contagion channel through funding liquidity – allowing to capture the liquidity spiral in a simplified fashion (see. Brunnermeier and Pedersen, 2009, Gauthier *et al*., 2012). To date, SRM and RAMSI models are the most successful specifications.

Van den End (2010, 2012) presented, for the Bank of the Netherlands (DNB), a stress testing model mainly focused on liquidity risk. However, compared to previous models, this framework also includes an idiosyncratic reputation risk of individual banks and a response function from the central bank.

All previous models still work-in-progress. Remaining common issues are related to: an arbitrary risk factors selection, an absence of critical risk classes (e.g. off-balance sheet exposures, feedback effects on the economy), and a simplicity in the specification of the modules and/or the general dynamics – often linear – of the model as a whole. This review shows that the potential of systemic stress testing methods remains lightly exploited. This justifies the recorded errors in the recent period and partly explains the expressed distrust towards these exercises.

This paper extends the existing literature in several ways. First, it introduces new first-round risk classes; namely market liquidity and reputation risks. Second, it explicitly considers public policy response functions represented by the central bank and the Treasury. Third, the model specification is based on the recent Basel III regulations on solvency and liquidity requirements, expected to be the core risk management standards in the upcoming years. Finally, it proposes a theoretical and empirical framework to systemic risk, including stress testing, of the French banking sector. Since no models are published in this respect, this paper aims to represent a step forward in this direction.

3 The model

3.1 Overview

The risk carried by a banking system is modeled using a top-down dynamic model, based on a modular specification that allows to capture the risk factors' movements and their impact on the considered system. The model is estimated quarterly. Its flexibility allows its use in forecasting and simulation exercises for an arbitrary horizon. These properties will be retained in this paper to conduct systemic stress testing. This section presents the general framework of the model and develops its various modules. The following two sections report the estimation and the stress testing results, respectively.

For a typical period of one quarter, Figure 1 summarizes the role of each module and the sequence of events in the model. A risk model (3.2) defines the (exogenous) risk factors' values at the beginning of the period. From these values, four direct effects on individual bank balance sheets are modeled: gains/losses on the trading portfolio, credit losses, net interest income and liquidity buffers (3.3). After recording these direct effects, the profitability of each bank is evaluated. Two situations can arise: all banks are profitable, or one or more banks making losses. In the first case, the balance sheets are readjusted according to four rules of thumb known to reflect a common banks' behavior (3.4). This readjustment marks the end of the period and the transition to the next period.

When one or more banks making losses, their solvency and liquidity positions are assessed. Regulatory ratios defined by the Basel III standards are used for this purpose. Two situations can arise: the solvency and liquidity ratios are still above regulatory minimums for all non-profitable banks, or at least one of the two thresholds is violated for at least one of these banks. In the first case, a loss of reputation cost is applied to non-profitable banks. This cost is manifested by tightening their access to refinancing, i.e. an increase in the interest rate on new loans – the impact of which on net interest income will be assessed at the next period. This marks the end of the current period and the move to the next one, after readjusting the balance sheets of profitable banks and rebalancing those of non-profitable banks to account for losses.

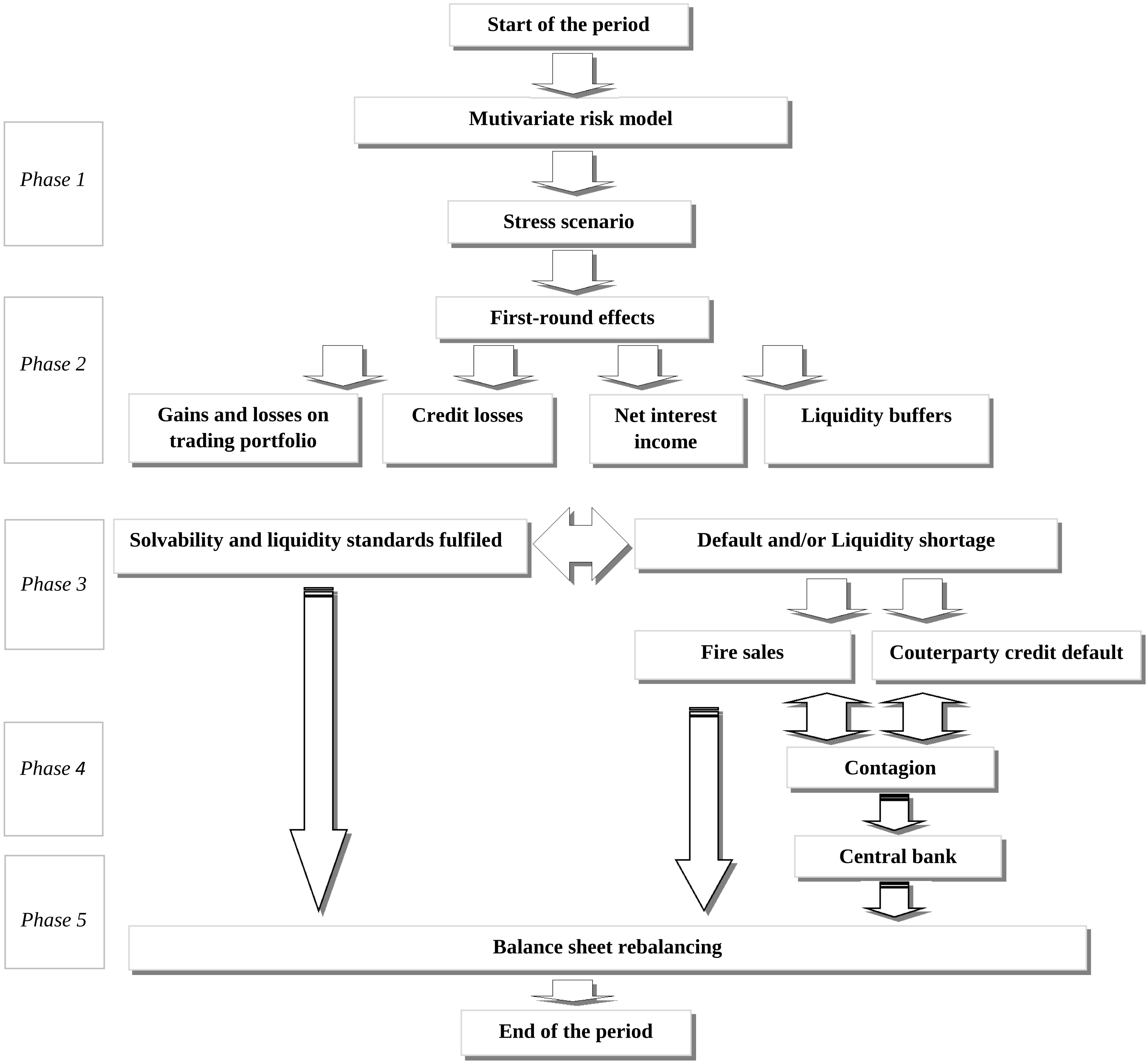

Figure 1. Framework and event sequence of the systemic stress testing model

When a non-profitable bank recorded a solvency and/or a liquidity ratio which is below the regulatory threshold, it is assumed to default. It follows a complex process defined in several stages (3.5). First, the assets of the bank in question will lose part of their face value corresponding to the so-called bankruptcy cost. To fulfil the bank's commitments, the remaining assets are then sold on financial markets. This action affects other banks trough three complementary channels (second-round effects). First, the massive assets' sale creates a supply shock in the relevant market, leading to lower prices and devaluate marked-to-market assets. The trading book of all banks is then impacted (market liquidity channel). Second, revenues from the defaulting bank(s) assets' sales may be insufficient to pay their full debt. Thus, creditor banks will suffer an additional loss related to their counterparty credit risk (interbank network channel). Finally, the failure of one or more banks undermines market confidence towards the entire banking system. Sound banks now face tighter refinancing conditions making that their future borrowings are augmented by an additional risk premium (funding liquidity channel). The sum of the three second-round effects on sound banks is recorded. Their profitability, solvency and liquidity is then reassessed as before. If more failures occur, the procedure is repeated and the three channels described above become contagion channels. This continues until no new failure is recorded or – less likely – until the whole system goes bankrupt.

When the contagion chain ends, and before readjusting the balance sheets of the remaining banks, a last module allows introducing public response. Indeed, to make more realistic the model structure, we considered two central bank and one Treasury reaction functions. The central bank response consist on restoring asset prices in financial markets and interbank market rates to their start-of-the-period levels. For the remaining banks, this allows to absorb losses due to the first and third contagion channels. Treasury reaction consist on reducing the bankruptcy costs stemming from a bank failure. The period is ended by rebalancing the balance sheets to account for the period's gains and losses.

3.2 The risk model

In a previous work, I introduced a multivariate risk model adapted to daily financial time series. This has been used to design micro stress testing scenarios. However, given the depth and the data frequency as well as the number of variables (risk factors) included in this paper, the application of such a framework could be a source of parsimony issues. Accordingly, a less sophisticated Bayesian VAR (BVAR) model is carried out here.

Given the parameter estimates, the model is conducted to simulate the future paths of the exogenous risk factors. These simulations can be carried out with (stress test) or without (forecast) an initial shock (i.e. a pre-specified variation in the model variables). At each period of the forecast or stress horizon, the marginal and the joint distributions of the risk factors are estimated.

The $\{y_t\}_{t=1}^{T}$process of the $(N \times 1)$ vector of exogenous risk factors is defined by a vector autoregressive model of order p, denoted VAR(p), and given by

$$A(L)y_t = \mu + \varepsilon_t, \tag{1}$$

where, $A(L)$ IS a polynomial delay matrix, $\varepsilon_t \sim \mathcal{N}_\mathrm{N}(0, \Sigma)$ a of normal standardized residuals process, $\mathcal{N}_\mathrm{N}$ the N −dimensional Normal distribution and Σ the related covariance matrix.

3.3 First-round effects

The impact of risk factors on bank balance sheets is captured using a series of *balance sheet models*. Unlike *asset pricing models*, this approach allows to take into account a wide range of risks and provides a more detailed analysis of the transmission channels. Moreover, balance sheet models offer a clear understanding of the model's structure and results, making them attractive to regulators in their systemic risk and financial stability analyses. In the more cases however, the use of these models is limited to credit risk (Alessandri *et al*., 2009).

In this section, I consider four direct effects of the exogenous risk factors on individual bank balance sheets. Namely: trading book gains/losses, credit losses, net interest income and liquidity buffers. To capture these effects, I have broken down the balances into fourteen classes, seven asset classes for each of asset and liabilities side (see Table 1). The first class of each side captures gains/losses of the trading portfolio. The second class captures interbank exposures. The following four asset classes are exposed to credit risk, carried by households, administrations, large non-financial companies and other financial institutions, respectively. The remaining classes are only exposed to interest rate risk. To measure the net interest income, we split non-interbank credits (asset classes 3 to 6) and liabilities (classes 3 to 6) into four groups, depending on their maturity: from zero to three month, from three to twelve months, from one to five years and more than five years. The other classes are aggregated and analyzed separately. The second and third columns of Table 1 summarize the considered methods to assess first-round effects. These are detailed below.

3.3.1 Gains/losses from the trading book

The detailed data on the banks' trading portfolios composition is confidential. The model is then based on aggregate amounts of trading assets and liabilities hold by each bank. I assume that the value of these assets changes proportionally to stock market return and the exchange rate, and inversely with changes in interest rates and commodity prices. This specification takes into account the main sources of market risk for each bank. To avoid any uncontrolled impact on the model results stemming from high fluctuations in the stock and commodity returns' volatilities, these two variables are demeaned with respect to their respective historical averages. The trading book return, measured by the change in net value (trading assets - trading liabilities) and denoted VN is thus given by as follows

$$\Delta VN_t = \alpha_0 + \alpha_1(\Delta CAC_t - \Delta\overline{\mathrm{CAC}}) + \alpha_2(\Delta Brent_t - \Delta\overline{Brent}) + \alpha_3 \Delta TC_t + \alpha_4 \Delta TL_t + \alpha_5 \Delta EX_t + \varepsilon_t, \quad (2)$$

where, $\Delta\overline{\mathrm{CAC}}$ and $\Delta\overline{Brent}$ denote historical quarterly return averages of the stock and commodity (crude oil) markets, respectively. $\Delta CAC_t, \Delta Brent_t, \Delta TC_t, \Delta TL_t$ and ΔEX_t are the quarterly changes in stock market, oil prices, interest rates and exchange rate returns, respectively, recorded at time t. $\varepsilon_t \sim \mathcal{N}(0,1)$ is a Gaussian white noise.

3.3.2 Credit losses

The expected losses associated with loans granted by banks to the economy is calculated by multiplying three factors: the probability of default (PD) of the borrower, the loss given default (LGD) and the exposition at default (EAD) of the loan. In addition to credit institutions – analyzed in Section 3.5 – we distinguish four main categories of banks' borrowers: households, administrations, large non-financial companies and other financial institutions. The more the bank has information about its counterparts, the better it can estimate – and manage – the related credit risk. These information – where they exist – are still confidential. To estimate credit losses for French banks, I have considered a model based on public information alongside with some of hypotheses.

I have assumed null the probability of default of the administrations. From the exogenous risk factors, I have defined the probability of default of the other counterparts using a logit model. Since the PDs are not observable in practice, I have considered the historical default rates of each category of borrowers as a proxy. Considering the real economic growth, equity and real estate indices and the real interest rate as exogenous variables, the default rates are modelled using the following model

$$\begin{aligned} L_t &= \ln\left(\frac{TD_t}{1-TD_t}\right) \\ &= \beta_0 + \beta_1 \Delta PIB_{t-1} + \beta_2 \Delta IPLA_{t-1} + \beta_3 \Delta CAC_{t-1} + \beta_4 TCR_{t-1} + \eta_t, \end{aligned} \tag{3}$$

where L_t denotes the log-odds transform of the quarterly rates of default TD_t. $\Delta PIB_{t-1}, \Delta ILPA_{t-1}$ and ΔCAC_{t-1} are the quarterly changes in real GDP, real estate and the stock indices, respectively, TCR_{t-1} is the real short-term interest rate, and $\eta_t \sim \mathcal{N}(0,1)$ a Gaussian white noise.

Therefore, the expected PD for date $t+h$ $(h > 0)$ is given by the following formula

$$\mathbb{E}(PD_{t+h}) = \mathbb{E}\left(\frac{e^{L_{t+h}}}{1+e^{L_{t+h}}}\right), h > 0. \tag{4}$$

As is usual in the literature, I have assumes constant the LGDs rates. These are fixed at 50% for households, 80% for non-financial companies and 10% for other financial institutions. Finally, in order to define the EADs amounts of each category, I have replicated the last observed balance sheet decomposition for each bank. This decomposition structure is carried for the entire simulation horizon (see Section 5).

Credit losses in $t+1$, are defined by multiplying the estimated PDs for $t+1$, the constant LGDs and the EADs of end of t period. By combining these losses to other possible losses due to second-round or contagion effects (Section 3.5), the amount of credits allowed by each bank at the end of date $t+1$ is defined. These credits are allocated as in the last observed balance sheet decomposition, to define the EADs of date $t+1$. These EADs are multiplied by the LGDs and the estimated PDs for $t+2$ to obtain the credit losses of period $t+2$, and so on.

3.3.3 Net interest income

In order to estimate the net interest income, non-interbank loans and liabilities have been split into four maturity buckets: zero to three months, three to twelve months, one to five years and more than five years. The other classes are grouped separately and undergo interest income (for assets) and charge (for liabilities) according to an ad hoc rate defined in Table 1. For classes of credit and liabilities classes, I have considered the risk-neutral valuation model first introduced by Drehmann *et al*. (2008) to determine paid (for debts) and received (for credits) coupon at each period.

Let A be an asset issued at date 0 with a T maturity. The value of the coupon C paid by this asset for each period t $(0 < t \leq T)$ is defined at time 0. A "fair" value of Censures equality between the face value A_0 and the economic value V of the asset A. More formally said

$$A_0 = V = \sum_{t=1}^{T} D_t C A_0 + D_T A_0 \quad (5)$$

where, D_t is a discount factor defined by

$$D_t = \prod_{l=1}^{t} \left(1 + R_{l-1,l}\right)^{-1}$$

with

$$R_{l-1,l} = \frac{r_{l-1,l} + PD_{l-1,l} \cdot LGD}{1 - PD_{l-1,l} \cdot LGD},$$

where, $r_{l-1,l}$ and $PD_{l-1,l}$ denote the expected values of the risk-free rate and the probability of default between dates $l-1$ and l. The yield curve is constructed using a linear interpolation of short and long interest rates. This curve provides the risk-free rate at each period of the simulation horizon. Default probabilities are obtained by model (3) as described in the previous paragraph.

From equation (4) the coupon C is obtained by

$$C = (1 - D_T)/\sum_{t=1}^{T} D_T \quad (6)$$

This coupon takes into account both the interest rate and the credit risk associated to the asset A. Mismatch maturities in the asset and liability sides as well as the probability of unanticipated shocks on interest rates and/or PDs are the main sources of interest rate risk. This is especially true for assets of (very) long maturity. Indeed, the fundamental value of the latters may worsen significantly depending on shocks on rate and/or PDs while their book value remains unchanged – since the coupon is set at the beginning of the period and is in effect until maturity.

3.4 Private responses and reinvestment functions

"The question of the inclusion of institutional responses [...] involves two opposing elements: the comparability of results and the "realistic" aspect of the exercise [...]. Indeed, the hypothesis of "dynamic" bank balance sheets can integrate restructuring plans [...] already underway in certain institutions and which are likely to change their risk profiles. In contrast, assume static balance sheets, that is to say the structure of the balance sheet is frozen for the duration of the stress [...] guarantees a high level of standardization and comparability of results between participating institutions. Moreover, the inability to respond to stress may be the worst possible scenario." (ACPR, 2013, p. 6)

This awareness on the part of the French prudential supervision authority underlines the importance of private response functions in stress testing models. It is, however, the shade created by the last sentence, which leads in most cases to omit these reactions in the conducted tests – Including by the ACP itself. However, a stress test is not limited to the design of more severe scenarios, but the most plausible as well. It is in this context that, in the definition of plausibility one should include shock and post-shock stress. If the initial shock is plausible, but the after-shock is less (assuming no reaction, for example), the resulting scenario become is implausible.

The lack of regular and filtered information about banks' reactions to risk factors' movements preclude the use of econometric methods similar to those carried out for the other parts of the model. In this section, I define the response of private banks (as opposed to the public reaction studied in Section 3.6) using a coherent set of the so-called rules of thumb. These are demonstrated by several empirical studies to reflect the common behavior of banking institutions (cf. e.g. Adrian and Shin, 2008). The nature of these reactions is defined by the position of the banks after recording the first-round effects (gain, loss, bankruptcy, etc.). Hence, before presenting the reaction functions considered in this paper, I discuss the different potential outcomes after recording the first-round effects.

3.4.1 Default rules

For each bank, the combination of models (2)-(6) yields the result for the period following the first-round effects. This is achieved by the sum of trading portfolio and net interest incomes minus credit losses. If a bank recorded a positive result, it is called profitable. To reinvest this profit, the bank in question makes a readjustment of its balance sheet (see Section 3.4.1). If the result of a bank is negative, we use a double solvability-liquidity criterion for determining whether or not it is in default. Two regulatory standards are used for this purpose: the Common Equity Tier 1 capital ratio (CET1) and the Liquidity Coverage Ratio (LCR). The first is obtained by dividing equity by risk-weighted assets; the second, by dividing the short-term liquid resources (typically 1 month) by short-term needs of liquidity. Risk and liquidity weights are calibrated based on the Basel III standard approach (Table 1). The choice of these two ratios has been imposed by the high level of aggregation in the available balance sheet data. Nevertheless, the flexibility of the method allows to replace, modify and/or adapt the criteria and/or default thresholds depending on the accuracy of the information. Other solvency (e.g. Tier 1) and/or liquidity (e.g. NSFR) ratios can therefore be considered.

Basel III standards require minimum thresholds for CET1 and LCR ratios. These are set to 4.5 % and 100 %, respectively. I rely on these criteria to distinguish: non-profitable banks, recording a negative result but meeting both of regulatory requirements, and (ii) failing banks, for which at least one of the two thresholds is violated. Non-profitable banks rebalance their balance sheet to reflect losses (see Section 3.4.2). Failed banks liquidate their remaining assets to deal with their creditors.

Before being placed on the market, these assets are subject to a discount in their face value. This phenomenon, known as bankruptcy cost, is sufficiently documented in the literature (see e.g. James, 1991; Bris *et al.*, 2006). It is rooted in legal costs incurred in the judicial process of liquidation, loss of human capital and loss of reputation, among others. In practice, it is quite tricky to estimate the discount rate since, in addition these determinants, one has also to take into account the tax system and other structural constraints. However, it is common in the literature to set the bankruptcy cost to 10% (see Alessandri *et al.*, 2009). In this work, we include this parameter among the tools of public reaction – In this case, the Treasury. We study its impact on the results, considering different levels of the discount rate.

The failure of one or more banks can drain those of other banks, through second-round effects or contagion (see Section 3.5). For more consistency in the used notation, we will retain the sound banks concept for banks that survived to first-round effects, and the rescued banks concept for those of them who survived to second-round or contagion effects. Furthermore, we call fundamental default a default due to first-round effects, and contagion default a default produced by second-round or contagion the effects. Before developing these processes, I close this section with a detailed presentation of the potential private response functions stemming from the first-round effects.

3.4.2 Private response functions

After recording the direct effects of the period, profitable banks readjust their balance sheets. To do so, they reinvest the generated positive income of the period targeting the following objectives

(i) Maintaining leverage effect: in response to their capital increase, profitable banks subscribe to new debts in order to restore a predefined equity to debts ratio;
(ii) Maintaining the liquidity ratio: by selecting the amounts of short-term and long-term debts to subscribe to, profitable banks aim to restore their respective predefined liquidity (LCR) ratio;
(iii) Maintaining the solvency ratio: by investing in new flows (the positive result of the period and the new debts), profitable banks seek to restore their predefined solvency (CET1) ratio; and
(iv) Maintaining the business model: to meet criteria (ii)-(iii), debt increase and reinvestment are made in the same proportions as in the balance sheet of reference.

Non-profitable banks do not operate these adjustments following first-round effects. Indeed, it is more intuitive to assume that these banks are more concerned to react to losses than enrolling in a long- term target for leverage, solvency and liquidity ratios. Given the difficulty of raising new equities in a too limited time as well as this of liquidating assets at favorable prices given their situation, these banks will only subscribe to new debts at the level of the recorded losses. This operation can therefore be considered as a simple rebalancing of the related balance sheets.

Unlike a readjusted balance sheet, the first-round effects are reported in the following periods in a rebalanced balance sheet. Thus, non-profitable banks accumulate losses over the periods and see their situation even trickier, with serious risks of going bankrupt in case of new losses. In other words, a readjusted balance sheet is a positive multiple of a reference balance sheet (the multiplier is the rate income growth rate for the period) while a rebalanced balance sheet has an identical size but a different structure (the leverage, solvency and liquidity ratios are now less advantageous).

The failure of one or more banks impact – at least through the market liquidity channel – the readjusted/rebalanced balance sheets of sound banks. After second round or contagion effects, rescued banks rebalance their balance sheets for the next simulation period. We then assume that, given the short time allocated and the market stress generated by these effects, even profitable banks are unable to readjust their balance sheets. They shall, in this case, simply rebalancing their balance sheets in the same fashion as non-profitable banks. Thus, when a failure occurs during a period, the related results are reported to the following period. After the first-round effects of the latter, profitable banks will again be able to readjust their balance sheets, which means a better visibility of their own, one quarter later. This assumption seems quite reasonable, given the recent developments in financial markets.

After recording the first-round effects and defined private responses, the simulation ends for the considered period, if any default case is recorded. If the first-round effects have led to one or more failures, these will create *second-round effects*. These can move on *contagion effects* if they also lead to further default cases. Whether it comes from first or second-round effects, a bank failure is transmitted to the rest of the system through several channels. The considered ones are described in the next section.

3.5 Second-round and contagion effects

The transmission of a bank failure to the rest of the system can operate through three basic channels: financial markets, the interbank network and the money market. These three channels impact the trading and the credit portfolios and the net interest income, respectively. The first and last channels are commonly called market liquidity and funding liquidity channels, respectively. The three concepts will be presented separately, before defining a unified framework to take into account the interaction and dynamics of their joint effects. To the best of our knowledge, this work is the first to introduce this level of flexibility.

3.5.1 Financial market channel

After recording the first-round effects and applied the bankruptcy cost, the remaining trading assets of failed banks are sold on the financial market. Given the aggregate nature (one class) of the available data on these assets, a one-market model in considered here i.e. the financial market in general terms. Setting massive sale of assets generates a supply shock on the market, leading to lower prices. The degree of this decrease depends on the amount of sold assets. I have chosen to specify this relationship within a framework similar to Cifuentes (2005).

Let p be the financial market price and x the ratio of bank assets to be sold on the market size. The relation between these two variables is given by

$$p = e^{-\theta x}, \qquad x > 0 \tag{7}$$

where, $\theta > 0$ is the price elasticity with regard to of the amount been traded. The reference price $\overline{p} = 1$ prevails when no default is recorded (i.e. if $x = 0$).

The decline in asset prices depreciate the trading book of sound banks, whose value is indexed to the financial market price or marked-to-market. This is the first second-round effect. The latter is likely to reduce the result of sound banks and deteriorate their solvency and/or liquidity ratios. Taken separately or combined with the effects arising from the other two channels, this effect can therefore generate new failures. Financial market channel then becomes a contagion channel (see below).

3.5.2 Interbank network

Using the income from the sale of its trading assets and loan portfolio, the failed bank repays its creditors – among of which the sound banks. If sales revenue is greater than or equal to total liabilities (excluding shareholders) of the bank, its creditors are repaid at par and the excess returned to shareholders. However, if the sales income is insufficient to cover all liabilities (excluding shareholders), creditors of the bank suffer a total loss corresponding to the missing assets. This loss is shared out to creditors according to their respective seniority levels. First senior debts are paid off. If the balance remains positive, it will be used to pay off the claims of lower priority, and so on, down to the least rated debt. In practice however, information on the precise classification of bank loans is not available. In such a situation, one-class seniority is assumed. The total loss is then distributed over creditors in proportion to the amount of their respective contributions. This is the second second-round effect.

The whole or partial loss of the interbank lending of a sound bank reduce its result worsen its solvency and/or liquidity ratios. Taken separately or combined with the effects of the other two channels, this can cause a failure of this bank and the emergence of new losses and/or failures on its creditors. In turn, the interbank network channel becomes contagion channel (see below).

3.5.3 The money market channel

The failure of one or more banks and the activation of the two previous channels, create a climate of uncertainty, distrust and/or loss of market confidence towards the entire banking sector. This situation results in a degradation of sound banks' refinancing conditions: higher borrowing rates, limitation and/or denied access to credit lines and/or to revolving credit, bank runs, etc. This multitude of reactions form the third second-round effect. In this paper is focused on the rise in money market interest rates, since it is the most observed in practice. This upward movement is applied to all new loans contracted after one or more bank failures are observed. For simplicity, the same rate change is applied regardless of the number of defaults of the period. This assumption seems fairly reasonable, given the market confusion in such circumstances, i.e. a limited discernibility about the effective proportion of the banking sector actually affected by these failures.

Unlike the previous two effects, the impact on sound banks of money market channel is recorded in the following period. Indeed, the accounting in the balance sheet of debt charges issued during one period appears on the balance sheet (or net interest income) of the next period. If, during the latter period, new failures appear, the rates levels will be maintained. Otherwise, the rate returns to its initial level. A short memory (one quarter) of the money market is then assumed, given the central bank intervention (see Section 3.6).

3.5.4 The contagion process

When at least one of the three second-round effects give rise to a new failure, a contagion process is initiated. The three channels described above are then called contagion channels. This section present an iterative algorithm through which, over the same period, bank failures are transmitted to the rest of the system. At each iteration, interaction and joint dynamics of the three channels are considered.

At the end of second round effects, sound banks positions are assessed. If no failure is recorded, the algorithm terminates at the first iteration. If one or more failures appear, a bankruptcy cost is applied to the banks in question – which further reduces the value of their assets. The remaining trading assets are put on the financial market. The amount is added to the asset placed on the market following the first-round effects. The combined effect of two supply shocks produces a decrease in prices measured by model (7). All trading portfolios are then revalued on the basis of the new prices. Given this new value, the next step is to determine the ability of each bank to honor its commitments outside shareholders, i.e. comparing for each bank, total assets to total liabilities except equity. This task cannot be done analytically, since the payment of a bank defines – In part – the assets of other banks (through the 2nd balance sheet class) and *vice versa*. Indeed, the inability of a bank to repay its loans reduces the revenue of its creditor banks. For some of them, the new total of assets can become insufficient to repay the loans.

This generates losses for its creditors, which include the first failing bank. It therefore undergoes a further loss that affects the rest of the system, and so on.

The resolution of this iterative process is carried out using the so-called clearing models. The algorithms presented by Eisenberg and Noe (2001) and Furfine (2003) are the most popular among researchers and practitioners. They are used to define the vector of interbank payments and the number of failures in each iteration – allowing in particular to distinguish the fundamental failures from contagion failures. To take into account the flexibility introduced into the developed model, I have introduced two main extensions to the Eisengerg and Noe algorithm, namely: (i) the default rule defined in Section 3.4.1, and (ii) the interaction financial markets and interbank contagion channels.

After setting interbank payments in the second iteration, one evaluates the position of each bank. If no new failures is recorded, balance sheets are set for the period after being rebalanced. If new failures occur, the procedure described in the last two paragraphs is reiterated. The algorithm terminates, at the latest, after n iterations, where n is the number of banks in the system.

When the chain of contagion ends, and to increase the realism of the model, a series of public response functions have been introduced over the different parts of the model. These functions allow to mitigate the effects of risk factors on the banking system.

3.6 Public response functions

Even more than the functions of private reactions, public reaction functions are neglected by most of the existing models. Yet their introduction allows to increase the plausibility of the scenarios, augment the model results and ensure better – public and private – prevention and/or management decisions. This section introduces a series of unconventional measures, issued by the central bank and the public Treasury. These measures frequently observed in recent years, are defined as follows

(i) Where a fundamental failure is recorded, the central bank reduces the default rule described in Section 3.4.1. Thus, to avoid – or at least limit –contagion failures, a – sound – bank is declared bankrupt only if the amount of its liabilities exceeds that of its assets;

(ii) When a failure is recorded , the Treasury supports a part of the cost of bankruptcy;

(iii) For non-profitable banks suffering a loss of reputation, the establishment of a bilateral relationship allowing them to access central bank refinancing. This measure allows banks to overcome the rising refinancing rates generated by the first-round effects. However, this public response is only introduced during periods marked by one or more failures; and

(iv) At the end of each period, the central bank, through OMO and the interest rate tools resets the financial and monetary markets prices to their respective start-of-the-period levels. The location of this module is motivated by two main reasons. On one hand, given the model estimation frequency and the delay of the central bank response relative to the shock occurrence, considering an intervention at beginning of period – or somewhere before the first losses and/or failures are recorded – seems implausible. On the other hand, designing a reaction at the end of the period avoids potential moral hazard biases due to an announced presence of a lender of last resort.

To assess the importance of these functions, their separate and joint impact on the results of each period is analyzed. Different intensity levels of each function is also tested robustness purposes.

4 Data and estimation results

The estimation of the previous model is based on two datasets: macro-financial data to estimate the risk model, and balance sheet data to estimate the valuation model. The modules are assessed separately on a quarterly basis.

Eight indicators are used to characterize the exogenous risk factors in the French banking sector: real gross domestic product (GDP), the consumer price index – excluding energy (CPI), the price index of old houses in Paris (HPI), the French CAC 40 index (CAC), the interbank overnight rate (SR), the rate of 30 years government bonds (LR), the nominal exchange rate euro/dollar (EX) and the crude oil price (Brent). Data are collected at the end of each quarter, over the period 1992:Q1-2012:Q4 (84 observations). The series of GDP, CPI and HPI, adjusted for seasonality variations, are from the INSEE website. The exchange rate series are provided by Bank of England. The rest of the series are from the historical database of Datastream. Description and preliminary data transform are presented in Table 2.

These risk factors are used to obtain the yield curve and PDs of the considered exposures (i.e. households, administrations, large non-financial companies and other financial institutions) yield by the French banks. For simplicity, and in line with the existing literature, we approximated the yield curve by linear interpolation of short-term and long-term interest rates. These are obtained by simulating the risk model for a given time horizon.

The balance sheet data consist of balance sheets of the major six French banking groups with net banking income is more than 10 billion euros at the end of 2012. The following groups are considered: BNP Paribas (BNPP), Société Générale (SG), Crédit Agricole (GCA), Banque Populaires Caisses d'Epargne (BPCE), Crédit Mutuel-CIC (CMG) and La Banque Postale (LBP). The aggregate net banking income of the six groups accounted for 94 % of the total French banking assets. Five of the six groups are the result of mergers and acquisitions, carried out between 1990 and 2008 in order to consolidate the French banks' positions in a European and international environments. To circumvent the complexity of these arrangements and the lack of (detailed) data for the former entities, I opted for an estimate of the valuation model from the balance sheet data of the SG group. This is in fact the only one not to have suffered significant operations mergers and acquisitions in the considered period. The data used in the estimation cover the 2000:Q1-2012:Q4 period. They are mainly obtained from quarterly reports published by the bank. The estimated parameters are used to simulation stress testing exercises. These are conducted on all banks on the basis of hypothetical scenarios applied to the 2012:Q4 balance sheets.

The optimal lag order selection in model (1) is based on conventional information criteria. These indicate an optimal lag of $p = 1$. Model (2) is estimated for the period 2004:Q4-2012:Q4, for an aggregate portfolio composed by BNPP, SG and GCA assets – representing 70% of the total assets of the considered banking system. Model (3) is estimated over the period 2006:Q4-2012:Q4 for non-financial companies. In France, it is indeed the only category of economic agents for which data on default rates are public. Although the hypothesis may seem strong enough, I have used estimates of PDs obtained for non-financial firms for the other two categories of borrowers. The results must then be treated with caution. Finally, a fixed 0.8 value is set to the parameter θ in model (7). The estimation results of these models are summarized in Table 3. Due to space limitations and given the main focus of the paper, these will not be commented here. The next section reports and comments the simulation results.

5 Simulation Results

This section presents the main results of three (3) stochastic scenarios conducted on the introduced model. The reported outcomes are in no case exhaustive. These are selected due to space limitation while further results are still available from the author upon request.

For each scenario, and given risk factors' data up to 2012:Q4, 1 000 000 Monte Carlo simulations are carried out on model (1). The impact of the scenarios on bank balance sheets is assessed for a three year horizon, over the period 2013:Q1-2015:Q4. The first two scenarios consist on forecasts-in-density of bank balance sheets, respectively, with and without constraining the trading portfolio's gains/losses. The third exercise is a hypothetical stress testing scenario, which assesses the impact of a macroeconomic and financial (multivariate) extreme shock. The shock is derived from a simulation of model (1) at the beginning of the horizon period. Its impact on the bank balance sheets is measured during all the simulation horizon. For each scenario, first-round and second-round effects as well as the impact of the central bank intervention are captured. Aggregate results on the whole banking system are reported considered.

5.1 Simulations results

In the first scenario (hereinafter the baseline scenario), a constant net trading value is assumed on the trading book. This is equivalent to set fixed parameter values in model (2). Namely, $\alpha_0 = 1$ while all other parameters are set to zero. Figure 2 examines the evolution of total assets and equity over the simulation horizon. Aggregated results for the six banks are reported. On the right graph, one see the positive changes in the size of balance sheets over the entire simulation period. This ongoing profitability is due to the specification of modules 3.3 and 3.4, assuming by construction, a net interest rate income higher – on average – than credit losses. This result shows that the negative results observed in practice on commercial banks, is primarily due to losses on trading portfolios (not included in this scenario) and to their second-round effects, as we shall see later . The left panel shows that the balance sheet expansion does not lead to additional risk taking, the regulatory capital ratio remains around the target set at the beginning of the period.

Figure 3 details the previous results, presenting for each risk class, the results distribution in the last simulation quarter. On the upper two panels, one can note significant changes in net interest income and credit losses. This is unrelated to the leptokurtic shape of the considered risk factors' marginal distributions used in model (1). The distribution of net interest income also has a negative skewness, given the module specification. Indeed, this requires a lower boundary (at zero) for the nominal interest rate, without admitting any top border. Therefore, for realizations where interest rate is close to zero, bank incomes are reduced, since they cannot charge negative interest rates on deposits. This shape of the net interest income distribution is transmitted to the net result distribution of the period (lower left panel), since the distribution of credit losses is almost normal. This confirms the results of previous works having selected, as in our framework, a simple specification for credit losses. Other studies that have used a more complex specification (non-linearity, endogeneity of PDs and LGDs, etc.) led to an asymmetric shape of the credit losses distribution (see Alessandri *et al*., 2009). As mentioned above, the two graphs show that the central hypothesis of zero losses on the trading book implies that no loss is recorded through interbank the network (or the non-reported financial markets) contagion.

In the second scenario, the previous assumption is relaxed by introducing trading book volatility in the result analysis. Figure 4 reports the distributions of gains/losses in the last period. The new model leads to greater volatility in the aggregate result (lower left panel). This is particularly due to the weight of market operations in the French banks activity. This variation reflects the equity volatility (lower right panel), following the adjustments made to meet the regulatory solvency and liquidity criteria. In some realizations, the net result is negative, containing potential default cases. Their transmission to the rest of the system through contagion channels generates additional losses (central panel right).

Before studying these channels, the effects of the first two scenarios are compared in terms of the asset distributions in the last period. Figure 5 shows, for the first scenario, a centered and symmetric distribution, and for the second, a more flat and asymmetric and even bimodal distribution with a second lower peak on the lower tail. This bi-modality is mainly due to contagion effects and/or bankruptcy costs. These, indeed, making a downward spiral in case of a bank failure. This generates larger loss volumes and/or frequency which explains the concentration on the lower left tail. Figure 6 confirms this phenomenon on the returns distribution, averaged over the twelve simulation quarters.

Figure 7 compares on the lower tail of the assets distribution, the respective effects of two contagion channels, namely financial market and interbank network channels. The result shows a non- correlation effects. However, it seems difficult to classify the two channels according to their respective impacts. The considered simulations showed that their combined effects increase by at least one case, the number of failures generated by first-round. Considered separately, the two channels of effects amplify the first round, but in two thirds of cases, the amplification results do not draw new business. This result shows the importance of model framework that takes into account several contagion channels as well as their mutual interactions.

5.2 Stress test results

To show the flexibility of the developed model and the weight of each module in the final result, a hypothetical stress testing scenario is carried out. This is done by introducing a set of ad hoc assumptions on model (2) variables. Given the purpose of this paper, these assumptions are limited to some risk factors only. Thus, the considered scenario is inspired by the systemic stress testing exercises regularly conducted by regulatory authorities (cf. e.g. CEBS, 2009, 2010; SCAP, 2009, 2011; Alessandri *et al.*, 2008). The scenario, applied – only – in the first quarter include : (i) a decrease of ten points (1%) on French GDP , (ii) a 10% increase of the HPI , (iii) a 15% decrease on real CAC 40 value , (iv) an increase of 50 basis points on the interbank lending rate, (v) an increase of 30% in the PDs of households and non-financial companies sectors, and (vi) a draw in market liquidity corresponding to a change the value of parameter θ in model (7), now set to 0.9. The plausibility of this scenario can be justified by the prior occurrence of similar events during the financial crisis of 2007-09 and/or earlier on the period used in the sample data. However, its level of severity can be assessed differently, given that only one initial shock is assumed and due to the absence of other risk factors in model (1).

Figure 8 compares the asset distributions, resulting from the baseline and the stress scenarios. Under the latter, the distribution has a lower average (a net left shift), a higher variance and a greater persistence of low values (highest peak on the lower tail). The first two observations are explained by the relative severity of the stress scenario – even when compared to the most extreme realizations of the baseline scenario. The last remark confirms the results of the second scenario, where bankruptcy costs and contagion spiral lead to largest volumes and/or frequencies of asset losses. These losses are greater under the stress scenario, where more failures are recorded (here, three case in the worst realizations).

The sequential structure of the model allows to study the impact of different components on the final result, discarding one or more modules. This analysis can be performed for different configurations of the model, as a management tool to identify risk profiles of the sector, the shock transmission channels and patterns of appropriate preventive and/or management post-shock actions (in terms of timing and amplitude) . To illustrate this advantage, I have isolated the impact of the central bank intervention, aiming to restore financial asset prices, following a stress scenario that generated massive sales. Securities purchases is here considered as a mode of intervention by the central bank (i.e. refinancing operations are excluded).

The impact of the intervention is assessed by comparing, at the end of the first simulation period, the liquidity ratios (LCR) obtained with and without intervention, respectively. Table 4 shows that on average, the action of the central bank improves by 4% the aggregate liquidity ratio of the sector. This advantage reaches 10% for extreme realizations, which correspond to stress scenarios that generated significant second-round effects. In this case, the lower price decrease is more pronounced, and so is the central bank reaction. By simulating the model without allowing central bank to react (i.e. lower prices at the end of a period is carried over to the beginning of the next period, and so on), in 10% of the realizations, no bank remains solvent at the end of the second quarter. This result explains the reaction of central banks, due to liquidity issues caused by the recent financial crisis. From this observation, two main ways of extending the model could be considered. On one hand, consider even more (non-conventional) central bank responses. In the other hand, increase the frequency of the model, using weekly data (or proxies) for instance, allowing to identify the precise vulnerability/resilience time of the individual banks and the whole sector.

6 Conclusion

This paper presented a sequential model allowing to estimate, by mean of stochastic simulations, the vulnerability of the French banking system to a set of systemic risk factors. The model is specified by a sequence of modules to capture risk factors, their direct and indirect impact on bank balance sheets, as well as the nature and the size of private and public response functions following the concretization of these risks.

The first main result of the conducted simulation and stress testing exercises shows a high vulnerability of the (aggregate) trading portfolio compared to other banking activities. The relative volatility of the portfolio and the choice of exogenous risk factors are the main explanations. Under the simulation exercises, the second-round effects have been relatively limited, despite cumulating the results over three years of simulation. However, the introduction of hypothetical stress scenario has led to an important shift (to the left) of the distribution of results. The latter has also a bimodal form, due to the concentration of the negative result stemming from contagion spirals corresponding to the most extreme shocks.

The second main result of the stress test is the important – and even vital – part of the central bank intervention to counteract the negative spiral of asset prices. Indeed, the scenarios in which this non-conventional intervention has been omitted result in a failure of an important share of the sector after only two quarters of simulation. This result clearly justifies the reaction of most of central banks in the wake of the first episodes of the recent financial crisis. An even more extensive modeling of public response functions will be considered in a future research. This allows to reduce the reaction time and to optimize its contents.

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Tables and Figures

Assets			
Class	Gains/losses modelling	Cash flows modelling	Risk weighting (%)
Trading assets[1]	Trading book model	Risk-free rate + 15 basis points (bps)	50
Interbank assets	Interbank network matrix	Risk-free rate + 15 bps	
Households[2]	Credit risk model	Coupon given by the net interest income model + 50 pdb	75
Administrations	Credit risk model	Risk-free rate	0
Non-financial companies	Credit risk model	Coupon given by the net interest income model + 50 pdb	100
Other financial institutions	Credit risk model	Risk-free rate + 15 bps	40
Other assets		Risk-free rate	0
Liabilities			
Trading liabilities[3]	Trading book model	Risk-free rate + 15 bps	
Interbank debts	Interbank network matrix	Risk-free rate + 15 bps	
Household	Credit risk model	Risk-free rate	
Administrations	Funding liquidity risk (reputation cost)	Risk-free rate	
Non-financial companies	Funding liquidity risk (reputation cost)	Risk-free rate	
Other financial institutions	Funding liquidity risk (reputation cost)	Risk-free rate + 15 bps	
Other liabilities		Risk-free rate + 15 bps	

Table 1. Balance sheet items' classification and related valuation models

[1] Includes financial instruments in their fair market value, financial assets available for sale and derivatives.
[2] Including mortgage loans.
[3] Includes financial instruments in their fair market value, debts represented by a securities and derivatives.

Indicator	Description	Source (Code)	Transformation	Data time period	Number of Observations
GDP	Nominal GDP (base 2005)	INSEE (001615898)	$\ln\left(\frac{\mathrm{GDP}}{\mathrm{CPI}}\right)$	1992:Q1–2012:Q4	84
CPI	Consumption price index – energy omitted (base 1998)	INSEE (000641193)	$\ln(\mathrm{CPI})$	1992:Q1–2012:Q4	84
IPH	Price index of old homes in Paris (base 2010)	INSEE (001587636)	$\ln(\mathrm{IPH})$	1992:Q1–2012:Q4	84
CAC	The CAC 40 index value	Datastream (FRCAC40)	$\ln\left(\frac{\mathrm{CAC}}{\mathrm{CPI}}\right)$	1992:Q1–2012:Q4	84
SR	Interbank overnight rate (EONIA, TMP before 01/01/1999)	Banque de France (QS.D.IEUEONIA)	$\ln\left(\frac{1+\mathrm{SR}}{100}\right)\cdot 0.25$	1992:Q1–2012:Q4	84
LR	French government 30 years bonds	Banque de France (QS.D.IFRPHF30)	$\ln\left(\frac{1+\mathrm{LR}}{100}\right)\cdot 0.25$	1992:Q1–2012:Q4	84
EX	Nominal exchange rate euro/USD	Datastream (XUDLERD)	$\ln(\mathrm{EX})$	1992:Q1–2012:Q4	84
Brent	Price of a barrel of Brent crude	Datastream (OILBREN)	$\ln\left(\frac{\mathrm{Brent}}{\mathrm{CPI}}\right)$	1992:Q1–2012:Q4	84

Table 2. Data description

The risk model

	GDP	CPI	IPH	CAC	SR	LR	EX	Brent
GDP_l1	0.86*** (0.04)	0.09*** (0.02)	0.12 (0.14)	1.30 (0.88)	0.06*** (0.02)	0.01** (0.01)	-0.79* (0.40)	-0.16 (1.46)
CPI_l1	0.09 (0.06)	0.88*** (0.04)	-0.26 (0.21)	-2.67** (1.34)	-0.17*** (0.03)	-0.04*** (0.01)	1.24** (0.61)	-0.83 (2.22)
IPH_l1	0.00 (0.01)	0.00 (0.00)	1.00*** (0.02)	-0.24* (0.14)	0.01*** (0.00)	0.00** (0.00)	-0.16** (0.06)	0.82*** (0.23)
CAC_l1	0.02*** (0.00)	-0.01** (0.00)	0.02 (0.01)	0.79*** (0.08)	0.00 (0.00)	0.00 (0.00)	0.05 (0.04)	0.27* (0.14)
SR_l1	-0.36* (0.20)	-0.15 (0.12)	-0.51 (0.71)	-4.13 (4.32)	0.11 (0.10)	-0.12*** (0.04)	6.78*** (1.97)	-13.45* (7.19)
LR_l1	-0.00 (0.42)	-011 (0.25)	-3.77** (1.46)	- 29.76*** (8.86)	0.49** (0.22)	0.81*** (0.07)	-9.12** (4.06)	10.79 (14.79)
EX_l1	0.00 (0.01)	0.00 (0.00)	0.00 (0.02)	-0.17 (0.13)	-0.00 (0.00)	-0.00* (0.00)	0.87*** (0.06)	-0.39* (0.22)
Brent_l1	0.00 (0.00)	-000 (0.00)	0.01 (0.01)	0.12* (0.06)	0.00 (0.00)	-0.00 (0.00)	0.05* (0.03)	0.46*** (0.11)
Constant	0.71*** (0.18)	-011 (0.11)	0.19 (0.62)	4.00 (3.79)	0.21** (0.09)	0.07** (0.03)	1.21 (1.73)	0.23 (6.30)
Observations	83							
R^2	0.99	0.99	0.99	0.99	0.95	0.99	0.97	0.98
Adjusted R^2	0.99	0.99	0.99	0.99	0.95	0.99	0.96	0.98
LLH	2077.88							

The trading book model

	$\hat{\alpha}_0$	$\hat{\alpha}_1$	$\hat{\alpha}_2$	$\hat{\alpha}_3$	$\hat{\alpha}_4$
	3.07*** (0.88)	4.64 (3.22)	-1.12* (0.60)	-0.88 (0.48)	0.01 (0.01)
Observations	12				
R^2	0.43				
Adjusted R^2	0.14				

The credit risk model

	$\boldsymbol{\hat{\beta}_0}$	$\boldsymbol{\hat{\beta}_1}$	$\boldsymbol{\beta_2}$	$\boldsymbol{\hat{\beta}_3}$	$\boldsymbol{\hat{\beta}_4}$
	10.68 (24.10)	-10.29 (27.13)	-5.68 (4.56)	-0.02 (0.59)	-9.65 (4.39)
Observations	25				
Adjusted R^2	-0.25				

Table 3. Estimation results for models (1)-(3)

(in %)	After first-round effects	After individual private responses	After second-round effects	After central bank response
Mean variation	-15.6	-10.1	-47.1	-45.0
95% quantile	-26.1	-12.3	-62.2	-56.4
99% quantile	-26.9	-12.8	-64.0	-57.8

Table. 4 Impact of the central bank intervention on the aggregate LCR ratio

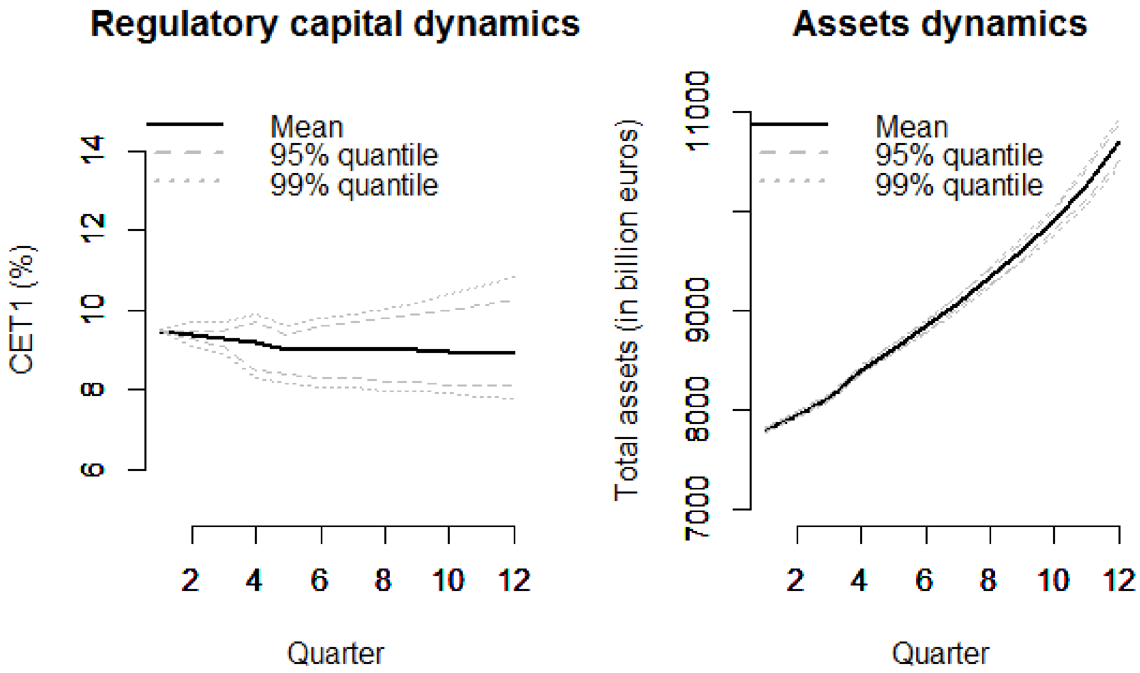

Figure 2. Aggregate balance sheet dynamics over the simulation horizon (Trading book omitted)

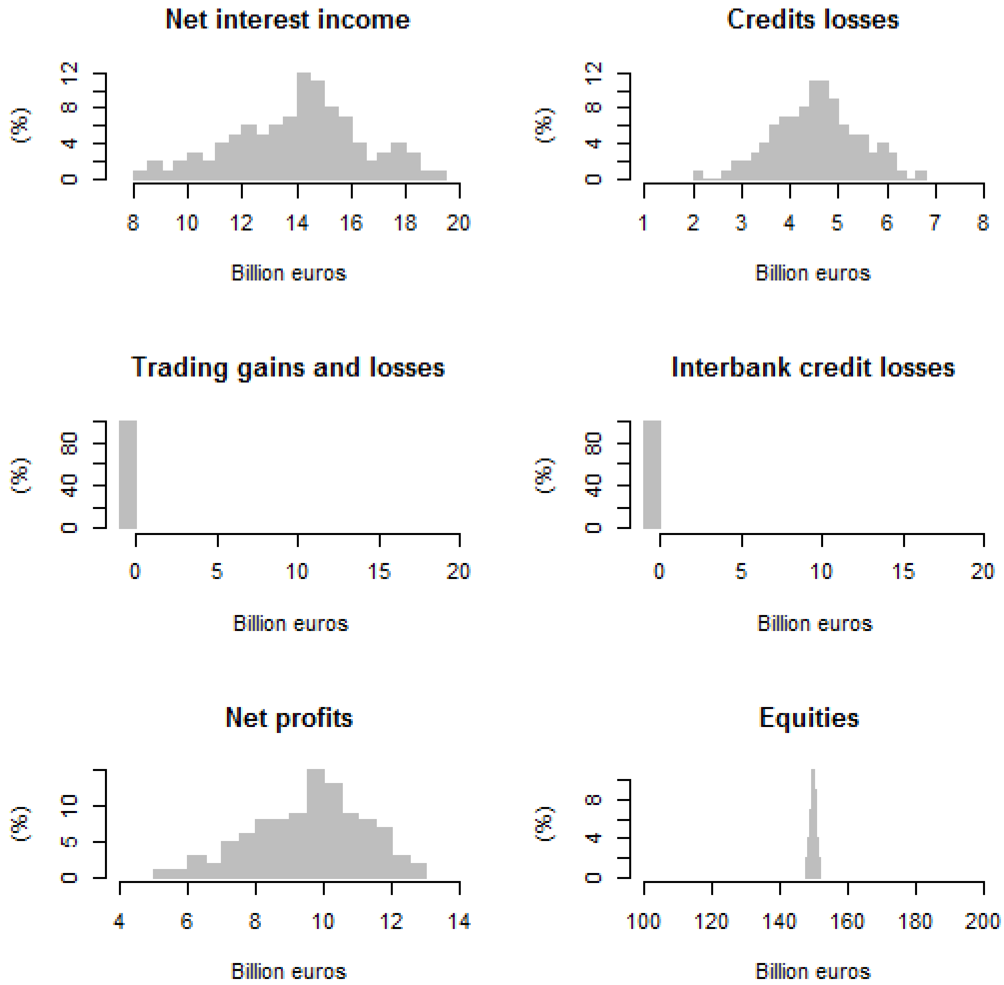

Figure 3. Aggregate results within the baseline scenario: trading book omitted (Last simulation quarter)

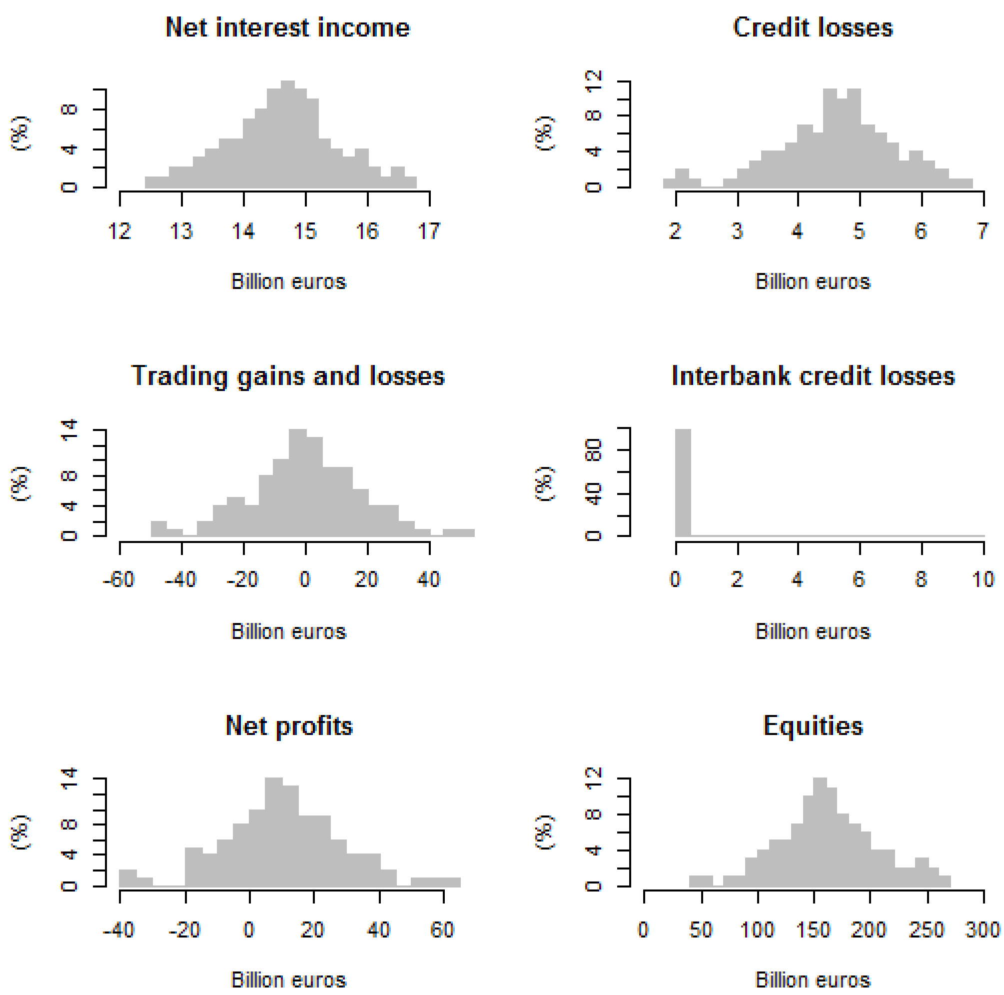

Figure 4. Aggregate results within the second scenario: trading book involved (Last simulation quarter)

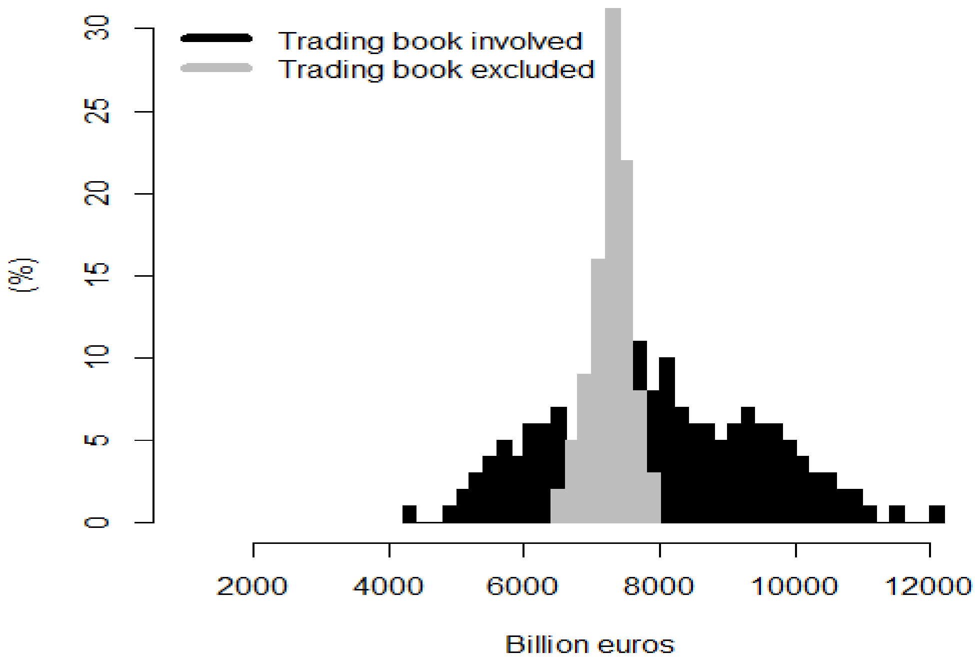

Figure 5. Trading book weight in the banking sector total assets (Last simulation quarter)

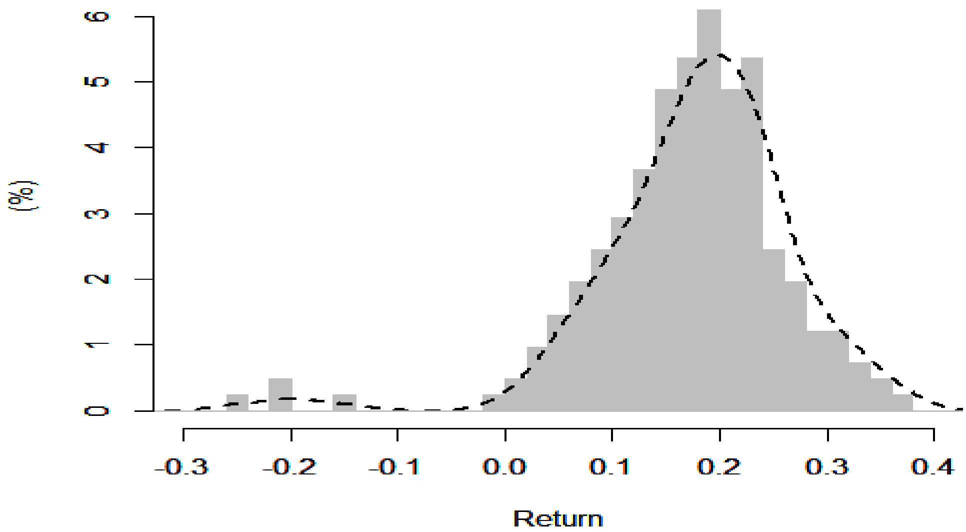

Figure 6. Aggregate ROA distribution (Cumulated over the twelve simulation quarters)

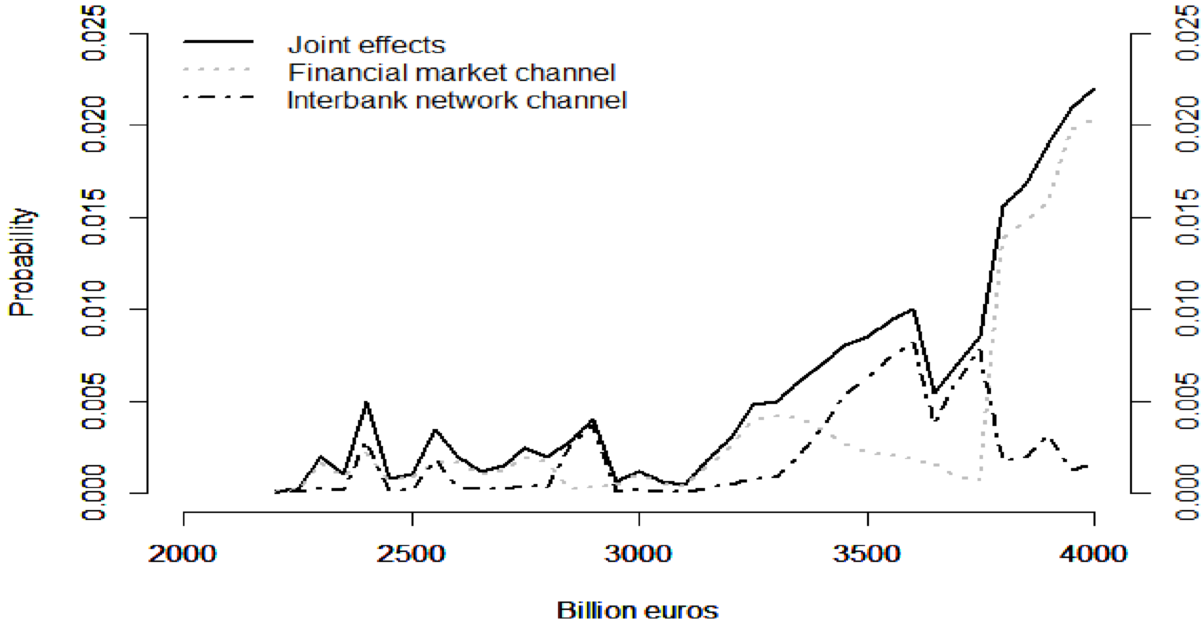

Figure 7. Impact of contagion channels on the aggregate asset distribution (Last simulation quarter)

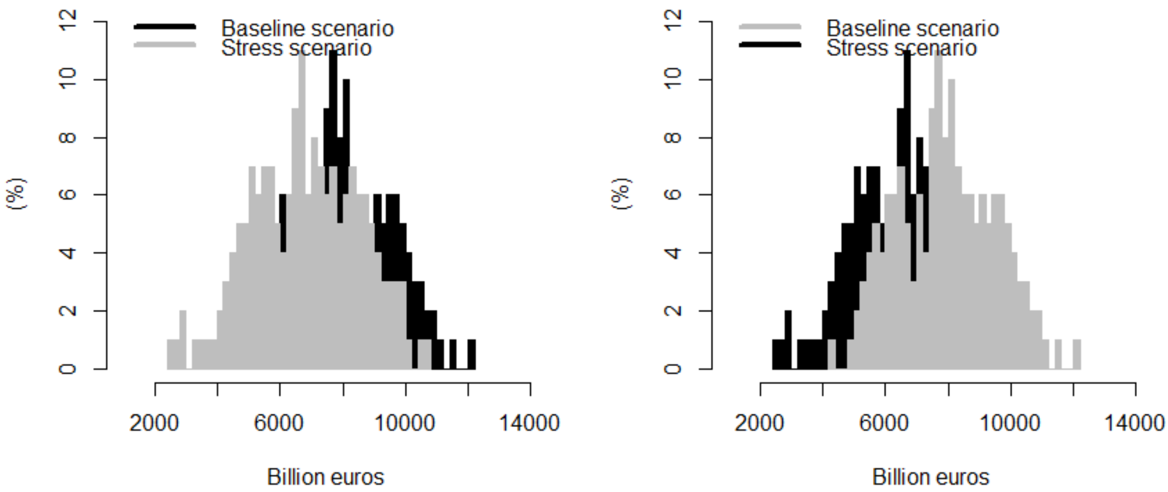

Figure 8. Stress scenario impact on the aggregate asset distribution (Last simulation quarter)