Measuring the Capital Shortfall of Large U.S. Banks

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Abstract

We develop a new methodology to measure the capital shortfall of commercial banks during a market downturn. The measure, which we call stressed expected loss (SEL), adopts the structure of the individual bank's balance sheet. SEL is defined as the difference between the market value of assets in the stress scenario and the book value of the deposits and short-term debt of the bank. We estimate the probability of default and the SEL of the 31 largest commercial banks in the U.S. between 1996 and 2016. The probability of default in a downturn was as high as 25%, on average, between 2008 and 2012. It is now much lower and close to 5%, on average. The SEL was very high (between $250 and $350 billion) during the subprime crisis. In the recent period, it has been close to $150 billion.

Keywords: Systemic Risk, Capital Shortfall, Multi-factor Model.

JEL Classification: C32, G01, G21, G28, G32.

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1 Introduction

Since the recent financial crisis, stress testing large commercial banks has become an imperative task for central banks and financial stability authorities to protect depositors, taxpayers, and economies in general. A typical stress test consists in defining a scenario with a stress event (e.g., a historical event or hypothetical scenario), linking the macroeconomic scenario to the bank's balance sheet, assessing the impact of the shocks on the quality of the balance sheet and, finally, evaluating the potential capital shortfall in such an event. Designing a stress test model is subject to several issues, which include the types of risks that can be stressed by the test, the data needed to measure the capital shortfall, and the definition of the stress scenario, among others. Moreover, there is a trade-off between the ability of a model to assess different types of risks and its complexity.

We propose a simple framework to assess the vulnerability of commercial banks and the amount of capital they need to survive in a market downturn. The flexibility of our framework allows us to identify channels through which a bank could become fragile and evaluate the bank's ability to survive under various market conditions. The main idea is that the market value of a bank's assets may change over time in response to certain stresses to its balance sheet imposed by financial markets. In severe market conditions, such changes can force the bank to sell its assets on short notice or even cause it to default. Unlike conventional stress test models, which require a very detailed accounting classification of the assets, we only use balance sheet information and classify assets by type of borrower and collateral. In particular, we recognize three borrowers, namely government, households, and corporates, and further consider real estate borrowing as a fourth asset class. One advantage of this classification is that a market exists for securities related to each of these asset classes. This classification allows us to evaluate the response of the bank's balance sheet to changes in the creditworthiness of borrowers. We do so by assuming that a change in the creditworthiness of a given type of borrower can be measured by the change in the performance of the representative market factor. We calculate the market value of assets for the next period by simulating stress scenarios affecting financial markets. Finally, we evaluate the capital shortfall that a bank may face by comparing the market value of its assets with the face value of its liabilities. We precisely define capital shortfall as the stressed expected loss (hereinafter, SEL), which corresponds to a commercial bank lacking equity during a financial downturn.

Our contribution to the literature is threefold. First, we describe a bank's balance sheet by classifying assets into a limited number of relevant groups that can be easily related to market stress. This classification frees the results from biases due to differences in accounting standards across countries and to regulatory arbitrage based on the use of risk weights. Moreover, all data that we use throughout the paper are publicly available. Second, our econometric methodology allows us to assess and forecast the vulnerability of commercial banks to alternative market scenarios, for instance by considering shocks of different magnitudes. Third, instead of relying on equity prices, we exploit information in credit markets to measure the potential loss faced by financial institutions. Indeed, recent studies have shown that in the case of financial firms, option prices and credit default swap prices are contaminated by government guarantees, which is consistent with an implicit too-big-to-fail guarantee (Gandhi et al., 2016). That is, while such a government guarantee is intended to protect debt holders at the expense of equity holders, instead, equity investors can benefit from guarantees alongside debt holders. This evidence makes regulators reluctant to rely on stock-based risk measures (Kelly et al., 2016).

Our sample covers the 31 largest commercial banks over the period 1996–2016. This list of banks broadly corresponds to the criterion adopted by the Dodd-Frank Wall Street Reform and Consumer Protection Act and used for the Dodd-Frank Act supervisory stress tests, from which we retain firms whose business is predominantly commercial banking. We define four categories of risky assets that can be subject to a market downturn, i.e., government, real estate, corporate, and household loans or securities. We construct market factor indexes that measure the performance of a well-diversified portfolio for each of these categories. We estimate the joint dynamics of the four representative market factor returns using a dynamic conditional correlation model, in which innovations are modeled using a t copula to capture the possible occurrence of joint extreme events. We use rolling windows of five years to update the estimate of the model's parameters in real time.

We measure the SEL by simulating a large number of market scenarios and identifying those that satisfy our criterion for a market downturn. In such cases, we compute a bank's expected asset losses due to the market downturn. Ultimately, by averaging over all scenarios, we obtain the probability of default and the capital shortfall of a given bank in a given quarter. This approach allows us to analyze the capital shortfalls of large commercial banks over time, possibly under alternative stress scenarios.

We consider as our baseline scenario a three-standard-deviation downturn of real estate, corporate, or household securities markets. We find that the probability of default of commercial banks in such a market downturn was, on average, close to 10% during the dot.com crisis and close to 25% during the subprime crisis. In the recent period (after 2013), the average probability of default has been approximately 5%. The aggregate SEL estimate reveals that the capital shortfall of commercial banks in a market downturn is below \$100 billion until the end of 2007 and then increases to a range between \$250 and \$350 billion during the subprime crisis. In the recent period, the aggregate SEL is close to \$150 billion, on average. On average, 75% of the aggregate SEL is due to the top-4 commercial banks. Finally, on average, the SEL measure is relatively close to the SRISK measure promoted by Acharya et al. (2012b) and Brownlees and Engle (2017). However, the timing of these measures displays some interesting differences. In particular, SEL increases before the start of the subprime crisis, whereas SRISK is close to 0 until 2007. In contrast, SEL increases less than SRISK in the period 2008–2009. In the recent period, the two measures are relatively close to each other.

Relevant Literature. This paper is mainly related to the strand of literature seeking to empirically evaluate the capital shortfall of financial institutions.[1] Our paper differs from most of the papers in this literature in that our measure of capital shortfall has a sensible economic interpretation and therefore can be used for policy analysis. We follow the notion of SEL introduced recently by Jondeau and Khalilzadeh (2017). In a general equilibrium framework, they explicitly describe capital shortfall as the expected loss on the deposits of commercial banks during stressed periods. This definition is close to that of Acharya et al. (2012b), in which the externality that generates systemic risk is a financial institution's propensity to be undercapitalized in a crisis, i.e., when the financial system as a whole is undercapitalized. We compare our result with the SRISK measure of Brownlees and Engle (2017), who provide an empirical evaluation of this notion. Other papers relying on the SRISK measure are Acharya et al. (2012a), Acharya et al. (2014), and Engle et al. (2015).

An important feature of the SEL measure is that it is driven by the difference between the market valuation of the assets and the book valuation of the liabilities. A similar point is made by Adrian and Shin (2010, 2014). In particular, Adrian and Shin (2014) show that the procyclicality of the leverage of investment banks is mainly explained by the difference in valuation approaches. In a market downturn, the loss on a bank's assets forces it to reduce its debt, which results in deleveraging. In contrast, the contracyclicality of the leverage of commercial banks is explained by He and Krishnamurthy (2014) with a different line of argument: in a market downturn, the bank cannot compensate for the loss on its assets by a reduction in household deposits. Therefore, equity decreases and leverage increases. A default occurs if the bank cannot find additional financing to satisfy its capital requirement. Jondeau and Khalilzadeh (2017) combine both mechanisms in a general equilibrium model and show how macroeconomic shocks generate commercial capital shortfalls for commercial banks through the collateralization process and the transmission of losses from investment banks.

[1] See Bisias et al. (2012) for an exhaustive survey of systemic risk analytics.

Our paper is also related to Begenau et al. (2015), who study banks' risk exposure to interest-rate and credit risks through factor portfolios. We share with their paper the assumption that the sensitivity of the assets of a bank to market shocks is well captured by representative market factor indexes. However, we do not restrict our risk factors to interest-rate and credit risks alone. Instead, we identify the channels through which risks related to different types of borrowers can impact the bank's balance sheet.

Another related field is stress testing. Several economies, including the U.S. and the euro area, impose regular stress tests to large financial institutions. Surveys presenting stress-testing methodology before and after the subprime crisis are Sorge (2004), Drehmann (2009), and more recently, Kapinos et al. (2015). Our approach can be viewed as a more compact tool to evaluate the sensitivity of commercial banks to a stress scenario.

SEL measures what the cost of a bank failure would be for the government, assuming that deposits are guaranteed by an insurance mechanism, such as the FDIC. The fraction of deposits that could not be repaid by the defaulting bank should be repaid by the authorities and, therefore, ultimately by taxpayers. Clearly, this approach does not encompass all potential costs that may have to be covered by the government. Some papers investigate the potential costs to the government from bank failures. These costs can arise from (explicit or implicit) guarantees, which may be necessary to limit contagion effects. In particular, Arslanalp and Liao (2015) define a banking sector contingent liability index, which measures the cost of the implicit guarantee from the government under an adverse scenario.

The rest of the paper is organized as follows. In Section 2, we describe the theoretical aspects and methodology of our approach to construct the SEL. In Section 3, we provide details about the data that we use to estimate SEL. In Section 4, we present and comment our empirical results. Section 5 concludes.

2 Methodology

The objective of the paper is to propose a measure of the capital shortfall of commercial banks in a crisis with the following properties: (1) it has theoretical grounds and precisely follows the logic of a stress test; (2) it is easy to compute and update with publicly available data; and (3) it can be used to investigate various stress scenarios.

The logic of this approach is to follow the strategy of the Fed's stress tests, using available data only. In essence, we measure what the impact of a crisis would be on the balance sheets of large commercial banks in the next period. The crisis scenario consists of shocks to the main market factors that are likely to affect banks' balance sheets.[2]

2.1 Measuring Capital Shortfall

A market downturn can generate capital shortfalls because the value of the assets of a financial institution in the next period varies with financial market conditions, whereas the value of its liabilities is known in advance. As deposits and debt (liabilities, in short) have to be repaid at their face (or accounting) value plus interest, it is possible that the value of the assets decreases to such an extent that the bank cannot repay its liabilities and defaults. Following the logic of a stress test, we assume that financial markets are hit by a set of shocks (of possibly different magnitudes). Some asset classes, such as cash or fixed assets, are insensitive to these shocks, but other categories of assets, which we call market-sensitive assets, are directly affected by market shocks.

The structure of the balance sheet of bank i in quarter t is presented in Schema 1 below. The numbers in parentheses indicate the interest rates or rates of return of the various assets and liabilities. By assumption, only the returns on market-sensitive assets and equity are determined at the end of the period. We use the notation $R_{a,t}$ to denote the simple return of item a and $r_{a,t}$ to denote the log-return, which we will use for the econometric model.

[2] We do not relate these scenarios to a complete macro-finance scenario, but this could be done in a relatively straightforward way.

Schema 1: Simplified balance sheet of a commercial bank

	Assets	Liabilities	
$(R_{F,t})$	Cash: $Cash_t^{(i)}$	Deposits: $Dep_t^{(i)}$	$(R_{Dep,t})$
$(R_{MA,t+1})$	Market-sensitive Assets: $MA_t^{(i)}$		
$(R_{G,t+1})$	- Government: $G_t^{(i)}$	Debt: $D_t^{(i)}$	$(R_{D,t})$
$(R_{R,t+1})$	- Real estate: $R_t^{(i)}$	- Short-term debt: $SD_t^{(i)}$	$(R_{SD,t})$
$(R_{C,t+1})$	- Corporates: $C_t^{(i)}$	- Long-term debt: $LD_t^{(i)}$	$(R_{LD,t})$
$(R_{H,t+1})$	- Households: $H_t^{(i)}$		
$(R_{O,t})$	Other Assets: $O_t^{(i)}$	Equity: $N_t^{(i)}$	$(R_{N,t+1})$

In the balance sheet above, $Cash_t^{(i)}$ refers to any asset with maturity less than one quarter. Market-sensitive assets ($MA_t^{(i)}$) are the assets of the bank that are subject to market risks and could be affected by substantial changes in their prices. We define four categories of market-sensitive assets according to the borrower: government securities, real estate loans and securities, corporate loans and securities, and household loans and securities.[3] We have done our best to classify all assets within the four market-sensitive asset categories where possible. When this was not possible, we kept them as other assets. Essentially, the other assets category includes fixed and intangible assets. Overall, they represent less than 4% of total assets. We assume that the return on other assets is independent of the market returns.[4]

The structure of the balance sheet imposes that at the end of quarter t, the following equality holds:[5]

$$(1 + R_{F,t}^{(i)})Cash_t^{(i)} + (1 + R_{MA,t+1}^{(i)})MA_t^{(i)} + (1 + R_{O,t}^{(i)})O_t^{(i)} \\ = (1 + R_{Dep,t}^{(i)})Dep_t^{(i)} + (1 + R_{D,t}^{(i)})D_t^{(i)} + (1 + R_{N,t+1}^{(i)})N_t^{(i)}. \tag{1}$$

Publicly available bank data cannot be used to measure the sensitivity of the assets to market shocks for two reasons. First, bank data are available at a quarterly frequency,

[3] Chakraborty et al. (2016) define three categories of assets for a bank: real estate exposure (measured by MBS, unsecuritized non-commercial real estate loans, and commercial mortgages), consumer loans (including all loans to individuals not secured by real estate), and commercial and industrial loans. We also include government securities as market-sensitive assets because they are also affected by interest-rate risk (see Begenau et al., 2015).

[4] Details on the construction of the various items are provided in Appendix A.2.

[5] We neglect taxation in this analysis, although it is an important issue, because we are precisely considering situations in which the bank is incurring losses and therefore is unlikely to pay taxes.

whereas market shocks can take place at any time during the quarter. Estimating the sensitivity at a quarterly frequency would produce very noisy numbers. Second, following the logic of stress tests, we need to measure the change in the market value of the asset classes due to changes in prices only, independent of the rebalancing of the portfolio by the bank. However, in balance sheet data, the change in the value of the assets from one quarter to the next combines changes in prices (due to market shocks) and in changes in quantities (due to rebalancing). Consequently, using bank data to measure the direct effect of the shock would result in biased sensitivity measures. To avoid this pitfall, we rely on market factor indexes that capture the price impact only. Specifically, we assume that the price change in a given category of a bank's market-sensitive assets corresponds to the price change in the market index: $R_{a,t}^{(i)} = R_{a,t}^{(m)}$.[6] The definition of the market factor indexes is discussed in Section 3.2.

The market value of the market-sensitive assets at the end of quarter t (excluding portfolio rebalancing) is measured as $(1 + R_{MA,t+1}^{(i)})MA_t^{(i)}$, where we define the market-sensitive asset return as

$$\begin{aligned} R_{MA,t+1}^{(i)} &= \frac{1}{MA_t^{(i)}}\left[G_t^{(i)}\ R_{G,t+1}^{(m)} + R_t^{(i)}\ R_{R,t+1}^{(m)} + C_t^{(i)}\ R_{C,t+1}^{(m)} + H_t^{(i)}\ R_{H,t+1}^{(m)}\right] \\ &= w_{G,t}^{(i)}\ R_{G,t+1}^{(m)} + w_{R,t}^{(i)}\ R_{R,t+1}^{(m)} + w_{C,t}^{(i)}\ R_{C,t+1}^{(m)} + w_{H,t}^{(i)}\ R_{H,t+1}^{(m)}, \end{aligned} \tag{2}$$

with $w_{a,t}^{(i)}$ being the weight of asset category a in total market-sensitive assets at the beginning of the period. The market value of total assets at the end of quarter $t+1$ is

$$A_{t+1}^{(i)MV} = (1 + R_{F,t}^{(i)})Cash_t^{(i)} + (1 + R_{MA,t+1}^{(i)})MA_t^{(i)} + (1 + R_{O,t}^{(i)})O_t^{(i)}.$$

This relationship quantifies the impact of a shock to market factors on the assets of the bank at the end of the period.

The one-quarter-ahead capital shortfall of a bank i is the expectation at time t of the lack of capital if the bank defaults in a market downturn between t and $t+1$. The default

[6] Assuming a unit sensitivity between the market factor return and the price change in the corresponding bank's market-sensitive asset is also justified by the fact that we consider large commercial banks, which presumably hold well-diversified portfolios. We follow the approach adopted by Begenau et al. (2015), who proxy the return on asset classes by the return on representative market factor indexes.

trigger is defined as

$$[A_{t+1}^{(i)MV} \mid \text{Market downturn}_{t:t+1}] \leq L_{t+1}^{(i)BV}, \tag{3}$$

where $L_{t+1}^{(i)BV}$ denotes the face value of deposits, short-term debt, and long-term debt, including interest payments:

$$L_{t+1}^{(i)BV} = (1 + R_{Dep,t}^{(i)})Dep_t^{(i)} + (1 + R_{SD,t}^{(i)})SD_t^{(i)} + (1 + R_{LD,t}^{(i)})LD_t^{(i)}. \tag{4}$$

We condition on the occurrence of a market downturn because a bank defaulting in normal market conditions is very unlikely. A default in normal market conditions would probably be an idiosyncratic event, and the financial system as a whole would not be substantially affected by this default.

Finally, SEL is the additional amount of equity that the bank would need to cover its short-term liabilities in a market downturn:

$$\begin{aligned} SEL_{t:t+1}^{(i)} &= (1 + R_{Dep,t}^{(i)})Dep_t^{(i)} + (1 + R_{SD,t}^{(i)})SD_t^{(i)} \\ &\quad - E_t[A_{t+1}^{(i)MV} \mid A_{t+1}^{(i)MV} \leq L_{t+1}^{(i)BV} \text{ in a Market downturn}_{t:t+1}]. \end{aligned} \tag{5}$$

Two remarks are in order regarding Equation (5): First, the regulator should be concerned by losses incurred by depositors but also by losses on short-term debt. The reason is that most short-term debt is interbank debt. Therefore, losses on short-term debt during a default could result in a cascade of defaults of other banks. By including short-term debt, the SEL partly takes the interconnectedness of the banking system into account.

Second, our approach is different from SRISK, introduced by Brownlees and Engle (2017). In SRISK, the impact of a crisis on a bank is estimated through the change in the latter's market capitalization, assuming that equity markets are able to fully measure the effect of the crisis on the assets of the bank. In our approach, we rely on the composition of the assets of the bank and their sensitivity to credit market shocks. This approach has three main advantages. First, it measures more precisely the relationship between the bank's assets and the fixed income and credit markets. Second, it allows us to consider different crisis scenarios, which may have different impacts on the bank's assets. Third, SRISK measures capital shortfall during a crisis but does not identify banks that would potentially default during such a crisis. Our approach also estimates the probability of default of each bank during a crisis.

2.2 Model for Market Risk Factors

The main question is now how to determine the market value of the market-sensitive assets during a financial downturn. To address this question, we design a model that describes the joint dynamics of daily market factor returns. Specifically, the model captures two important properties of the data: (1) the time dependence of market factor returns, which describes how a stress scenario can develop over time, and (2) the contemporaneous dependence between the market factor returns, which has to allow for joint crashes. To do so, the model has the following properties: time dependence is described by a dynamic conditional correlation (DCC) model; contemporaneous dependence is described by a copula model, which allows for joint crashes. A similar approach is adopted by Brownlees and Engle (2017) and Engle et al. (2015).

The model is the following: we define the vector of market factor log-returns on day $d+1$, $r_{d+1}^{(m)} = \left(r_{G,d+1}^{(m)}, r_{R,d+1}^{(m)}, r_{C,d+1}^{(m)}, r_{H,d+1}^{(m)}\right)'$. To describe the time dependence of the system, we define a vector that includes two consecutive daily log-returns: $X_{d+1} = (r_{d+1}^{(m)}, r_d^{(m)})'$. Conditional on the information set on day $d-1$, the return process at $d+1$ has mean $E_{d-1}[X_{d+1}] = 0$ and covariance matrix $V_{d-1}[X_{d+1}] = H_{d+1}$. The conditional covariance matrix H_{d+1} is estimated using a DCC model (Engle and Sheppard, 2001; Engle, 2001):

$$
\begin{aligned}
H_{d+1} &= D_{d+1}^{-1/2} \Gamma_{d+1} D_{d+1}^{-1/2}, \\
\Gamma_{d+1} &= \left(\mathrm{diag}\left(Q_{d+1}\right)\right)^{-1/2} Q_{d+1} \left(\mathrm{diag}\left(Q_{d+1}\right)\right)^{-1/2}, \\
Q_{d+1} &= (1-\delta_1-\delta_2)\bar{Q} + \delta_1 Q_d + \delta_2 \, D_{d-1}^{-1/2} X_{d-1} X_{d-1}' D_{d-1}^{-1/2},
\end{aligned}
$$

where $\mathrm{diag}(Q_{d+1})$ denotes a matrix with zeros, except for the diagonal, which contains the diagonal of Q_{d+1}, and D_{d+1} is the diagonal matrix with the variances of X_{d+1} (conditional on $d-1$) on its diagonal and zero elsewhere. Parameters δ_1 and δ_2 are restricted to ensure that the conditional correlation matrix, Γ_{d+1}, is positive definite ($\delta_1 + \delta_2 < 1$).

Using the dynamic covariance matrix H_{d+1} estimated with the DCC model, we then estimate a dynamic conditional beta (DCB) model, which describes the dynamics of the market factor returns (see Engle, 2016). We have investigated several specifications of this model. Time dependence is captured by allowing each market factor return to depend on its own lag. In addition, the government factor return, which reflects interest-rate risk, is allowed to affect all other asset classes contemporaneously. Finally, the real estate factor return is contemporaneously affected by household and corporate market factor returns.[7] The model can be written as follows:

$$\begin{aligned}
r^{(m)}_{G,d+1} &= \beta^{(GL)}_{G,d+1}\, r^{(m)}_{G,d} + \varepsilon_{G,d+1} \\
r^{(m)}_{R,d+1} &= \beta^{(RL)}_{R,d+1}\, r^{(m)}_{R,d} + \beta^{(G)}_{R,d+1}\, r^{(m)}_{G,d+1} + \beta^{(C)}_{R,d+1}\, r^{(m)}_{C,d+1} + \beta^{(H)}_{R,d+1}\, r^{(m)}_{H,t} + \varepsilon_{R,d+1} \\
r^{(m)}_{C,d+1} &= \beta^{(CL)}_{C,d+1}\, r^{(m)}_{C,d} + \beta^{(G)}_{C,d+1}\, r^{(m)}_{G,d+1} + \varepsilon_{C,d+1} \\
r^{(m)}_{H,d+1} &= \beta^{(HL)}_{H,d+1}\, r^{(m)}_{H,d} + \beta^{(G)}_{H,d+1}\, r^{(m)}_{G,d+1} + \varepsilon_{H,d+1}.
\end{aligned} \tag{6}$$

We use the notations $H_{[A,B],d+1} = Cov[r^{(m)}_{A,d+1}, r^{(m)}_{B,d+1}]$ and $H_{[A,b],d+1} = Cov[r^{(m)}_{A,d+1}, r^{(m)}_{B,t}]$, where the upper case means that the return is dated $d+1$ and the lower case means that the return is dated d. With these notations, we define dynamic beta parameters as follows:

$$\beta_{G,d+1} = \beta^{(GL)}_{G,d+1} = H^{-1}_{[g,g],d+1} H_{[G,g],d+1},$$

for the government factor,

$$\begin{aligned}
\beta_{R,d+1} &= (\beta^{(RL)}_{R,d+1}, \beta^{(G)}_{R,d+1}, \beta^{(C)}_{R,d+1}, \beta^{(H)}_{R,d+1}) \\
&= \begin{pmatrix} H_{[r,r],d+1} & H_{[r,G],d+1} & H_{[r,C],d+1} & H_{[r,H],d+1} \\ H_{[G,r],d+1} & H_{[G,G],d+1} & H_{[G,C],d+1} & H_{[G,H],d+1} \\ H_{[C,r],d+1} & H_{[C,G],d+1} & H_{[C,C],d+1} & H_{[C,H],d+1} \\ H_{[H,r],d+1} & H_{[H,G],d+1} & H_{[H,C],d+1} & H_{[H,H],d+1} \end{pmatrix}^{-1} \begin{pmatrix} H_{[R,r],d+1} \\ H_{[R,G],d+1} \\ H_{[R,C],d+1} \\ H_{[R,H],d+1} \end{pmatrix},
\end{aligned}$$

[7] Given the restrictions on the elements of the covariance matrix, in principle, six contemporaneous beta parameters can be identified. Our model therefore imposes one restriction, which is that there is no contemporaneous interaction between corporate and household factor returns. As we show in Section 3.2.2, the correlation between the innovations of these two factors is close to 0, suggesting that this restriction is supported by the data. We also discuss the empirical performance of this model.

for the real estate factor and

$$\beta_{A,d+1} = (\beta^{(AL)}_{A,d+1}, \beta^{(G)}_{A,d+1}) = \begin{pmatrix} H_{[a,a],d+1} & H_{[a,G],d+1} \\ H_{[G,a],d+1} & H_{[G,G],d+1} \end{pmatrix}^{-1} \begin{pmatrix} H_{[A,a],d+1} \\ H_{[A,G],d+1} \end{pmatrix},$$

for the corporate and household factors, with $A = C, H$.

As conditional information is defined two periods earlier, the error term $\varepsilon_{d+1} = \{\varepsilon_{G,d+1}, \varepsilon_{R,d+1}, \varepsilon_{C,d+1}, \varepsilon_{H,d+1}\}$ has potentially a moving average MA(1) structure. It may also be non-linearly dependent both in the time series (due to heteroskedasticity) and in the cross-section (due to tail dependence). To address heteroskedasticity, we assume a univariate asymmetric GARCH model (Glosten et al., 1993), where, as before, the volatility is conditional on the information set at date $d-1$:

$$\varepsilon_{a,d+1} = \sigma_{a,d+1}\ (z_{a,d+1} + \xi_a\ z_{a,d}), \tag{7}$$

where ξ_a denotes the MA(1) parameter and

$$\sigma^2_{a,d+1} = \omega_a + \alpha_a \varepsilon^2_{a,d-1} + \beta_a \sigma^2_{a,d} + \gamma_a \varepsilon^2_{a,d-1} 1_{(\varepsilon_{a,d-1} \leq 0)}, \tag{8}$$

for $a \in \{G, R, C, H\}$.

The standardized error term $z_{a,d+1} = \varepsilon_{a,d+1}/\sigma_{a,d+1}$ is described as skewed t random variable $z_{a,d+1} \sim f(z_{a,d+1}; \nu_a, \lambda_a)$, where f denotes the pdf of the skewed t distribution, with ν_a being the degree of freedom and λ_a the asymmetry parameter. We define $u_{d+1} = \{u_{G,d+1}, u_{R,d+1}, u_{C,d+1}, u_{H,d+1}\}$ as the value of the marginal distribution evaluated at the observed z_{d+1}. Thus, $u_{a,d+1} = F(z_{a,d+1}; \nu_a, \lambda_a)$, where F is the cumulative distribution function (cdf) of the skewed t distribution. Then, we describe the dependence structure of u_{d+1} with a t copula. The t copula has been found to capture the dependence structure of the data very well (Engle et al., 2015). It accommodates tail dependence, and its elliptical structure provides a convenient way to cope with large-dimensional systems. The cdf of the t copula is defined as:

$$C_{\Gamma,\bar{\nu}}(u_{G,d+1}, ..., u_{H,d+1}) = t_{\Gamma,\bar{\nu}}(t^{-1}_{\bar{\nu}}(u_{G,d+1}), ..., t^{-1}_{\bar{\nu}}(u_{H,d+1})), \tag{9}$$

where $t_{\bar{\nu}}$ is the cdf of the univariate t distribution with degree of freedom $\bar{\nu}$ and $t_{\Gamma,\bar{\nu}}$ is the cdf of the multivariate t distribution with correlation matrix Γ and degree of freedom $\bar{\nu}$. The contemporaneous dependence between the innovation terms is captured by the matrix Γ. It is worth noting that, in simulation, this model will be able to generate joint crashes, which would not be the case with a standard DCB model with Gaussian innovations. In addition, as some model parameters, such as the degree of freedom and the dependence matrix, are likely to vary over time, we use a rolling window approach to accommodate changes in these parameters. See Section 3.2.2 for additional details on the estimation.

2.3 Forecasting Strategy

Consistent with the definition of SEL (Equation (5)), we now forecast the market value of the bank's assets when assuming market stress in the next quarter. For this purpose, we simulate a large number of draws of the factor model described in Section 2.2 for the next $D = 60$ days following the estimation period. We select the draws that satisfy the predefined stress scenario. Then, using Equation (2), we forecast the market value of the market-sensitive assets under these stress scenarios. Specifically, we proceed as follows:

Step 1: Initialization.

At the end of quarter t (day d), we observe the various items on the balance sheet of the bank for quarter t.[8] We determine the weights $w_{a,t}^{(i)}$ for the four categories of market-sensitive assets. We estimate the factor model using daily data over the last five years.

We define a stress scenario as a set of thresholds $\theta_t = (\theta_{G,t}, \theta_{R,t}, \theta_{C,t}, \theta_{H,t})'$ based on the information available at the end of quarter t. If the market factor return at the end of quarter $t+1$ is such that $R_{a,t+1}^{(m)} \leq \theta_{a,t}$, then we will consider market a to be under stress in quarter $t+1$. Section 3.2.3 describes how we define and compute the thresholds.

Step 2: Simulation of market factor returns.

Using the factor model, we simulate a sequence of D daily market factor returns, from day $d+1$ to day $d+D$ corresponding to quarter $t+1$. We select the samples corresponding to

[8] In fact, the balance sheet of quarter t is known with some lag. To avoid using unavailable information, we systematically use the balance sheet from the previous previous quarter $t-1$ at the end of quarter t.

the definition of market stress. In our baseline scenario, we consider that overall market stress in quarter $t+1$ in simulated sample s exists when any of the three risky markets is under stress, i.e., $R^{(m)s}_{R,t+1} \leq \theta_{R,t}$, $R^{(m)s}_{C,t+1} \leq \theta_{C,t}$ or $R^{(m)s}_{H,t+1} \leq \theta_{H,t}$. We denote by $S_{C,t+1}$ the number of simulated samples that satisfy this condition in quarter $t+1$.

We also denote by $r^{(m)s}_{a,d+1}$ the log-return of market factor a on day $d+1$ and by $R^{(m)s}_{a,t+1} = \exp\left(\sum_{k=d+1}^{d+D} r^{(m)s}_{a,k}\right) - 1$ the cumulative simple return of the market factor in quarter $t+1$, for simulated sample $s = 1, \cdots, S_{C,d+1}$.

Step 3: Simulation of the bank's balance sheet.

As bank i does not rebalance its portfolio during the quarter, for a given sample s with a market downturn, we forecast the market-sensitive asset returns at the end of quarter $t+1$ as

$$R^{(i)s}_{MA,t+1} = w^{(i)}_{G,t}\ R^{(m)s}_{G,t+1} + w^{(i)}_{R,t}\ R^{(m)s}_{R,t+1} + w^{(i)}_{C,t}\ R^{(m)s}_{C,t+1} + w^{(i)}_{H,t}\ R^{(m)s}_{H,t+1}.$$

We deduce the market value of the assets at the end of quarter $t+1$ as $A^{(i)s}_{t+1} = (1 + R^{(i)}_{F,t})Cash^{(i)}_t + (1 + R^{(i)s}_{MA,t+1})MA^{(i)s}_t + (1 + R^{(i)}_{O,t})O^{(i)}_t$.[9]

The bank is expected to default in a given sample s with a market downturn if, at the end of quarter $t+1$, the market value of its assets is below the accounting value of the liabilities:

$$A^{(i)s}_{t+1} \leq L^{(i)}_{t+1} = (1 + R^{(i)}_{Dep,t})Dep^{(i)}_t + (1 + R^{(i)}_{SD,t})SD^{(i)}_t + (1 + R^{(i)}_{LD,t})LD^{(i)}_t.$$

We iterate Steps 2 and 3 for each sample s with a market downturn, for $s = 1, \cdots, S_{C,t+1}$.

Step 4: Summary.

As we simulate a large number of samples ($S = 100,000$), we estimate the probability of a market downturn in quarter $t+1$ as

$$\Pi_{C,t+1} = \Pr[\text{Market downturn}_{t+1}] = \frac{S_{C,t+1}}{S}.$$

[9]We note that the value of cash $Cash^{(i)}_{t+1}$ that we will observe on the actual balance sheet of bank i in quarter $t+1$ does not correspond to our measure $(1 + R^{(i)}_{F,t})Cash^{(i)}_t$. The reason is that we do not allow the bank to rebalance its asset portfolio during the quarter, consistent with the stress test methodology.

The probability of default of bank i in quarter $t+1$ is the proportion of simulated samples in which the bank defaults:

$$\Pi^{(i)}_{D,t+1} = \Pr[\text{Bank } i\text{'s default} \mid \text{Market downturn}_{t+1}] = \frac{1}{S_{C,t+1}} \sum_{s=1}^{S_{C,t+1}} 1_{\{A^{(i)s}_{t+1} \leq L^{(i)}_{t+1}\}}.$$

The estimate of SEL is obtained as follows:

$$SEL^{(i)}_{t+1} = [(1+R^{(i)}_{Dep,t})Dep^{(i)}_t + (1+R^{(i)}_{SD,t})SD^{(i)}_t] - \frac{1}{S_{C,t+1}} \sum_{s=1}^{S_{C,t+1}} A^{(i)s}_{t+1}\, 1_{\{A^{(i)s}_{t+1} \leq L^{(i)}_{t+1}\}}.$$

We note that the value of SEL is conditional on a market downturn. The unconditional SEL would be $SEL^{(i)}_{t+1} \times \Pr[\text{Market downturn}_{t+1}] = SEL^{(i)}_{t+1} \times \frac{S_{C,t+1}}{S}$.

3 Data and Preliminary Analysis

In this section, we provide details on our selection of large commercial banks. We present the structure and the temporal evolution of the aggregate balance sheet. We describe the construction of the market factor indexes and present the estimate of the model used to describe the market factor dynamics.

3.1 Commercial Banks

3.1.1 Sample of Commercial Banks

While our approach is applicable to any financial institution whose source of funding is predominantly deposits, we focus on large depository institutions. To define our sample of commercial banks, we start with the sample of 34 large financial institutions with \$50 billion or greater in total consolidated assets considered by the Federal Reserve Board in its 2017 stress test.[10] The list consists of 28 banks, 4 specialty lenders, and 2 global investment banks. All of these large firms have as subsidiaries one or more commercial

[10] The Dodd-Frank Wall Street Reform and Consumer Protection Act, passed by the Congress in 2010, requires the Board of Governors of the Federal Reserve System to conduct an annual supervisory stress test of large financial institutions with \$50 billion or greater in total consolidated assets. The assessment, which has a quantitative and forward-looking stance, is conducted through the Dodd-Frank Act supervisory stress testing and evaluates the health of large financial institutions under stressful economic and financial market conditions.

banks. Given our interest in the commercial banking activity of these firms, we further check whether the business of the firms is predominantly commercial banking. For instance, Bank of America Corporation has several nested bank holding companies (BHCs), with two commercial banks owned by the last nested BHC. Our criteria for the inclusion of each commercial bank are that (1) it sufficiently represents the top-tier BHC and (2) the deposits of the bank represent most of the liabilities of the top-tier BHC. Thirty-one commercial banks, listed in Table 1, pass these criteria.[11] Balance sheet data come from Call Report forms FFIEC 031 and 041.[12] All such data are available at a quarterly frequency and collected from the SNL platform. Our final sample is 31 commercial banks over the period 1996–2016, that is, 2,604 bank-quarter observations, representing more than 70% of the total assets of all commercial banks.

Table 1 reveals that the top-4 banks in our sample (JPMorgan Chase Bank, Wells Fargo Bank, Bank of America, and Citibank) represent more than 60% of total assets and total deposits and slightly less than 60% of total equity. In addition, on average, the book leverage (equity over total assets) is equal to 12%, with a minimum of 7.3% and a maximum of 16.7%.

Table 2 presents summary statistics of some important ratios for the commercial banks in our sample. The assets of the commercial banks represent the main assets of their ultimate parent: on average, they represent 88% of the assets of the ultimate parent, with a minimum of 60%. Furthermore, on average, deposits represent 87% of the liabilities (deposits plus debt) of these commercial banks. Finally, on average, deposits in

[11]The remaining three institutions are American Express Company, Goldman Sachs Group, and Morgan Stanley. American Express Company is a specialty lender with a BHC. The BHC includes a commercial bank and a savings and loan association, which together represent 54% of the total assets of the firm and hold deposits that represent only 42% of total liabilities of the firm. Goldman Sachs Group and Morgan Stanley also have commercial bank subsidiaries but they represent only 18% and 16% of the total assets of the ultimate parents, respectively, and they hold deposits that represent only 15% of total liabilities of the ultimate parents in both cases. As deposits represent less than half of the liabilities, we drop these three firms from the sample.

[12]FFIEC 031 is the consolidated report of condition and income for a bank with domestic and foreign offices, and FFIEC 041 is the same form filed by banks with only domestic offices. This form is different from that completed on a quarterly basis by the top-tier BHC (FR Y-9C) and from that of the parent company itself (FR Y-9LP), if the institution holds at least $500 million in total assets. Thus, although the commercial banks in our sample are subsidiaries of a larger BHC, which itself might be owned by a top-tier BHC, we do not need to examine these two latter forms. The balance sheet of commercial bank subsidiaries contains more detailed information such as the maturities of loans and securities. However, other important information such as the market capitalization and the credit rating are usually available for the top-tier BHC only.

the commercial banks represent 77% of the liabilities of their ultimate parent. Santander Holdings USA has the minimum deposit holdings (52%) within its commercial bank, Santander Bank.

[Insert Tables 1 and 2 here]

3.1.2 Structure and Evolution of the Balance Sheet

Schema 2 provides a summary of the aggregate balance sheet of the largest commercial banks. Cash refers to any asset with maturity less than one quarter. As we are interested in the expected loss of the bank in the next quarter, we treat assets maturing within a quarter as safe assets, such that the risk-free rate is set at the beginning of each quarter. Cash represents 13.3% of total assets. Market-sensitive assets are the assets of the bank that are subject to fixed income and credit risks and could be affected by substantial changes in their value. They represent, on average, 80.3% of total assets. The remaining assets correspond to derivatives (3.8%) and the other assets that are not present in our classification above (3.6%).

Banks report as derivatives with a positive (negative) fair value, the amount of revaluation gains (losses) from the marking to market of interest rate, foreign exchange rate, commodity, equity, and credit derivative contracts held for trading purposes. In our sample, the magnitude of this item is, on average, 3.8% on the asset side and 3.5% on the liability side. We assume that the gains and losses of the trading derivatives cancel one another out, and the net is on average 0.3% of total assets. The risk taken on most of derivatives is interest-rate risk and, therefore, similar to government securities. As our stress scenarios consider shocks to the risky asset classes, we do not expect any material impact on our calculation of SEL.[13]

[13] These derivatives are for trading purposes. Derivatives used for hedging are reported in the other assets category. Recent papers by Rampini and Viswanathan (2017) and Vuillemey et al. (2017) show that the magnitude of hedging through derivatives is fairly small and that most banks cut their hedging in bad times.

Schema 2: Simplified aggregate balance sheet of commercial banks (average, as a % of total assets)

Assets		**Liabilities**	
Cash:	13.3	Deposits:	66.7
Market-sensitive Assets:	80.3		
- Government:	6.0	Debt:	20.9
- Real Estate:	36.2	- Short-term debt:	19.0
- Corporate:	25.6	- Long-term debt:	1.9
- Household:	12.7		
Derivatives:	3.8	Derivatives:	3.5
Other Assets:	3.6	Equity:	9.0

Figure 1 shows the temporal evolution of the four categories of assets. We note that the weight of the asset classes is relatively stable over time. The weight of the main category, market-sensitive assets, ranges from 75% to 85%, with a value equal to 80% at the end of the sample. Cash has slightly increased, whereas derivatives and other assets have decreased. These levels and trends suggest that our decomposition of the assets and our focus on risky assets as the main source of stress affecting the bank's balance sheet are likely to provide relevant results.

We define four categories of market-sensitive assets: (1) government securities (6% of total assets) include U.S. Treasury securities (44%), government agency securities, government sponsored agency securities (22%), and securities issued by state and political agencies (34%). (2) Real estate loans and securities (36.2% of total assets) are assets related to real estate of any kind. They are either real estate loans directly lent by the banks (68%) or securities backed by real estate loans (MBS) (32%). We consider real estate independently from other household and corporate loans and securities because both residential real estate borrowing by households and commercial real estate borrowing by firms share the same underlying risk, i.e., real estate risk. (3) Corporate loans and securities (25.6% of total assets) include loans with commercial and industrial purposes (C&I) (92%), which can be secured (but not by real estate) or unsecured, and securities backed by these loans (8%). (4) Household loans and securities (12.7% of total assets) are either consumer loans directly lent by the bank (89%) or securities backed by consumer loans or other asset-backed securities (ABS) (11%). In both cases, the underlying assets are loans such as automobile loans and credit card loans.

The evolution of the various categories of market-sensitive assets is plotted in Figure 2. Real estate assets are the largest category and are followed by corporate and household securities. The figure also reveals important changes in the composition of the portfolio of commercial banks over the sample period. At the onset of the dot-com crisis, at the beginning of the sample, banks reduced their holdings of corporate and government securities and invested more in real estate loans and securities. However, after the subprime crisis, banks lightened their real estate portfolios and increased their holdings of government securities.

Total liabilities consist of 66.7% of deposits, 20.9% of debt (19% of short-term debt and 1.9% of long-term debt), 3.5% of derivatives, and 9% of equity capital. Figure 3 displays the evolution of the liability classes over time. It clearly shows that long-term debt represents a negligible part of commercial banks' financing. We also observe that after the subprime crisis, commercial banks increased their financing through deposits (from 65% of total liabilities before the crisis to 75% after the crisis) and reduced the use of short-term debt (from 20% to 10%, respectively). Finally, the figure reveals that the strengthening of bank capital regulation resulted in an increase in equity financing after the subprime crisis (from 9% to 11%).

[Insert Figures 1 to 3 here]

3.2 Market Factors and Thresholds

3.2.1 Construction of Market Factors

In this section, we provide details on the market factors that we use to measure the performance of the market-sensitive asset classes. As each of these categories contains different types of loans and debt securities, we did our best to select market-wide indexes reflecting the performance of these components. Specifically, we use total return indexes provided by Bank of America Merrill Lynch (BofA).[14] The list of these indexes is displayed

[14] In Appendix B, we provide details on the constituents and characteristics of each index and describe our approach for constructing the market factors based on the above-mentioned BofA indexes.

in Table 3. They track the performance of the market-sensitive asset classes that financial institutions hold in their portfolios.

Indexes are available at a daily frequency from January 1991 onward. Table 4 reports summary statistics on market factor returns based on the 1996–2016 sample, which corresponds to the availability of bank accounting data. The annualized return of the household factor is lower than that of the government factor because its average duration is much lower. The correlation matrix reveals that in normal times, the factors are highly correlated, in particular the government, real estate, and household factors. When the 2008–2009 period is included in the sample, these correlations are substantially reduced because of the temporary disconnection of the government factor from the other, riskier factors.

Figure 4 displays the evolution of the four factor indexes in level and return over the sample period. We observe that large price changes are very limited for government securities. The other market factors have been very volatile over some periods of time, in particular 2007–2010. Corporate securities also exhibit large drawdowns in 2001, 2002, and 2015. Real estate securities experienced large price changes in 2011 and 2013.

[Insert Tables 3 and 4 and Figure 4 here]

3.2.2 Estimation of the Market Factor Model

Table 5 reports parameter estimates of the market factor model when the complete sample (1996–2016) is used for the estimation. In the construction of the SEL measure, we use five-year rolling windows to allow the parameters to be updated in real time.

The moving-average parameter ξ_a in the innovation process is positive and highly significant for all market factors except the government factor. Most of the parameters driving the dynamics of the volatility process are standard. However, we find that the asymmetry parameter γ_a is negative but insignificant, except for corporate market index returns, for which it is large and positive. Regarding the univariate skewed t distribution, the degree of freedom parameter ν_a is particularly low for the real estate and household factors, reflecting the large excess kurtosis observed for these factors. The asymmetry parameter λ_a is negative and highly significant for all factors. These estimates reveal that the univariate distribution has fat tails and a negative asymmetry for all innovation processes.

The degree of freedom $\bar{\nu}$ of the copula is also low, close to 6. This value suggests that the dependence between the market factor returns is large in the extremes. Finally, the copula correlation matrix Γ indicates that, after capturing the linear dependence through the DCB model, the dependence between the innovations of market factors is low. In particular, the correlation between corporate and household innovations is equal to 0.065, which suggests that our restriction of no interaction between these innovations is supported by the data.

Finally, the table reports the adequacy test proposed by Diebold et al. (1983) for the null hypothesis that the model accurately describes the data. The univariate model cannot be rejected for the market factors. For the real estate factor, the p-value is equal to only 3%.

[Insert Table 5 here]

Figure 5 displays the dynamics of the conditional betas implied by the model, which reflect the time dependence between factor returns. Some patterns emerge. First, own lagged factor return usually has a limited impact. The only exception is the lagged corporate factor return, which has a large positive impact on the current corporate factor return. Second, the sensitivity to the government factor return is always positive, typically between 0.2 and 0.6, reflecting the sensitivity of credit markets to interest rate risk shocks. We note that the contemporaneous effect of the government factor tends to decrease in the recent period. Third, the real estate factor return is, in general, more sensitive to the household factor than to the corporate factor, reflecting the fact that most real estate loans and securities held by banks are issued by households. However, there was a switch during the subprime crisis, with a stronger sensitivity to the corporate factor and a weaker sensitivity to the household factor.

Even if balance sheet data are available at a quarterly frequency only, we estimate the probability of default and SEL at a monthly frequency. Therefore, for months in the same quarter, we use the same balance sheet data but update the market factors and thresholds. Every month, we consider a market downturn in the next three months.

We use a five-year rolling window to estimate the model parameters every month, as this is the typical estimation window used by banks. Figure 6 displays the evolution of the copula parameters over time. In Panel A, we observe that the degree of freedom $\bar{\nu}$ increased substantially between 2001 and 2007, from 5.5 to 9.5, indicating that market factors were relatively less affected by joint extreme events. However, $\bar{\nu}$ severely decreased during the subprime crisis to levels close 6, suggesting a stronger dependence between market factors.

We also find that the dependence between market factor returns implied by the copula model slightly varies over time. The dynamics of the correlation matrix Γ are presented in Panels B and C. On the one hand (Panel B), the dependence between the government factor and the other factors varies between -10% and 10% over time. The correlation between the government and real estate factors is the only correlation to be affected by a large change, which occurred in 2009, with a decrease from 0 to -25%. On the other hand (Panel C), the other dependence parameters vary in a similar range between -10% and 10%. The correlation between corporate and household factors is the only correlation to vary more substantially. It is as high as 40% at the beginning of the sample, and it again reaches 30% in 2014.

[Insert Figures 5 and 6 here]

3.2.3 Thresholds

In principle, any downturn in the government, real estate, corporate, or household factors is a potential stress to the banks' assets. Therefore, stress scenarios can be defined as a combination of markets hit by a shock. The main results we report in Section 4 are based on a scenario in which one of the three credit markets (excluding Treasuries) suffers from a downturn. More precisely, we count as a downturn any simulated quarterly return $R_{a,t+1}^{(m)s}$ below the given threshold $\theta_{a,t}$ in one of the three markets $a = R, C, H$.[15]

Regarding the size of the downturn, we define a monthly threshold $\theta_{a,t}$ in real time using the performance of each market in the recent past. We considered three approaches: (1) the standard deviation of three-month returns estimated with an expo-

[15] One can also impose simultaneous downturns in the three markets, which is a more restrictive scenario. Other stress scenarios could include a downturn in the Treasury market.

nentially weighted moving average (EWMA); (2) the standard deviation of three-month returns estimated over the previous five years; and (3) the standard deviation of three-month returns estimated over an increasing window.

The results in the main text correspond to an EWMA standard deviation with memory parameter $\phi = 0.99$.[16] The main advantage of the EWMA approach is that it produces crash thresholds that are consistent with the recent conditions of the market. This is a realistic assumption, as the creditworthiness of the bank's borrowers, either set by external rating agencies or by internal evaluation, differs across borrower types and over time.

Using this strategy, we compute the thresholds that define a market downturn for each asset class. In Figure 7, we display the thresholds based on EWMA standard deviations of three-month returns. The thresholds vary substantially over time, with large differences before and after the financial crisis. The real estate market threshold ($\theta_{R,t}$) has an average equal to -4.2%, -11.6%, and -10.4% for the pre-crisis (1996–2007), crisis (2008–2013), and post-crisis (2014–2016) periods, respectively. The corporate securities threshold ($\theta_{C,t}$) has an average equal to -7.5%, -13.7%, and -12.7%, respectively. Finally, the average of the household securities threshold ($\theta_{H,t}$) is -3.6%, -5.2%, and -4.6%, respectively.

[Insert Figure 7 here]

4 Analysis of Banks' Capital Shortfall

In this section, we follow the forecasting steps explained in Section 2.3 to compute the probability of default and the SEL for the selected commercial banks.

4.1 Probability of Crash, Probability of Default, and SEL

Figure 8 displays the temporal evolution of the probability of a market downturn in the next three months based on $S = 100,000$ simulated samples. We observe that the

[16] The EWMA standard deviation of three-month returns is computed as follows: every month, we predict the next month's variance as $\sigma^2_{a,t+1} = \phi\sigma^2_{a,t} + (1-\phi)R^{(m)2}_{a,t}$, where $R^{(m)}_{a,t}$ denotes the cumulative return on month t. Then, we define the prediction of next three-month standard deviation as $\sqrt{3}\sigma_{a,t}$. In Section 4.4.1, we report results based on the other approaches. We find that the probability of a crash and the probability of a default are affected by the value of the thresholds. However, the SEL is nearly unaltered by changes in the thresholds because it is conditional on both a crash and a default.

probability increases substantially in 1998 just before the dot-com crisis, reflecting notably the decrease in the degree of freedom of the t copula. It is close to 13% at the end of 1998 and remains close to 10% until 2005. The probability of a market downturn decreases substantially from 2005 to the beginning of 2007 to approximately 2.5%. This evolution reflects the low volatility in financial markets and the high degree of freedom of the copula, which implies a low probability of large joint events. The probability of a market downturn substantially increases in the second semester of 2007, from 2.5% to 10%, and again in the second semester of 2008, from 10% to 25%. We observe in the model that the real estate factor return becomes less dependent on the government return and more dependent on the corporate return. In parallel, the degree of freedom of the copula substantially decreases. This higher probability of a crash is obtained before the crisis started to affect the balance sheets of commercial banks. Interestingly, the probability of a downturn decreases after 2009, to levels lower than 5%.

The figure also displays the average probability of default by commercial banks. It should be noted that this probability is conditional on a market downturn and does not correspond to the probability of default in normal times. The probability of default is usually below 15% before 2008. During the dot.com bubble and crisis, the probability increases to approximately 15%. Afterwards, it remains at a relatively low level (typically between 5% and 10%) until the beginning of the subprime crisis. At the end of 2008, the probability of default jumps to 35%. This period is exceptional because it combines a high probability of a crash and a high probability of default conditional on a crash. The unconditional probability of default is equal, on average, to 8.5% (which corresponds to 2 to 3 banks out of 31). The conditional probability of default remains close to 20% until 2011. After 2011, the probability of default during a market downturn decreases to low levels, between 5 and 10%. There are two complementary reasons for this result. First, the magnitude of the downturn is lower because credit markets are much less volatile. Second, commercial banks have restructured their balance sheets in a safer way: they increased their capital ratios and therefore financed their investment with less short-term debt. In addition, they substantially increased their cash holdings, which also contributes to a less fragile balance sheet.

The bottom part of the figure displays the temporal evolution of the SEL measure in levels and as a percentage of total assets, deposits, and equity. Before 2007, the capital shortfall of commercial banks was relatively small, i.e., below \$100 billion with a maximum in 2001–2002. In 2007, it increases to \$200 billion and jumps to approximately \$300 billion at the end of 2008. This level approximately corresponds to 4% of total assets, 6% of deposits, and 45% of equity. This last number reflects the high leverage of commercial banks at the beginning of the subprime crisis and the substantial lack of equity. Between 2008 and 2014, the SEL is consistently between \$250 and \$350 billion. In the last three years, it has decreased to levels close to \$150 billion, reflecting the improvement in banks' conditions. Given the increase in the size of the banks' balance sheets, the SEL represents approximately 1.5% of assets, 2% of deposits, and 15% of equity. These numbers are historically low values, which reflects the reduction in the systemic risk of U.S. banks in the recent period.

In Figure 9, we illustrate the relative contribution of the top-4 banks and other banks to the average probability of default and the aggregate SEL. Top-4 banks account for most of the aggregate SEL. Before 2000, the SEL of both groups of banks is below \$25 billion. Between 2001 and 2007, the aggregate SEL of the top-4 banks is approximately \$60 billion, whereas the remaining banks only account for less than \$20 billion. In 2008–2013, both groups contribute to the increase in the SEL. Top-4 banks have an aggregate SEL close to \$200 billion. The contribution of the other banks is lower and close to \$100. At the end of 2016, top-4 banks account for 60% of total assets but 75% of the capital shortfall of commercial banks.

[Insert Figures 8 to 9 here]

4.2 Comparison with SRISK

It is worth comparing SEL with the SRISK measure proposed by Acharya et al. (2012b) and Brownlees and Engle (2017). Both measures provide an estimate of banks' capital shortfall during a market downturn, but the methodology is different. SRISK relies on market capitalization to evaluate the impact of an equity market decline (by 40%). SEL relies on fixed income and credit markets to evaluate the impact of a combination of market downturn (equal to 3 standard deviations). We denote by $W_t^{(i)}$ the market capitalization of firm i in quarter t and $L_t^{(i)} = A_t^{(i)}/W_t^{(i)}$ the quasi-leverage of the bank. SRISK in quarter $t+1$ is defined as

$$SRISK_{t+1}^{(i)} = \left\{ \vartheta(L_t^{(i)} - 1) - (1-\vartheta) E_t \left[1 - LRMES_{t+1}^{(i)} \right] \right\} W_t^{(i)}, \tag{10}$$

where $LRMES_{t+1}^{(i)} = -E_t \left[W_{t+1}^{(i)}/W_t^{(i)} - 1 \mid \text{Market downturn}_{t+1} \right]$ denotes the long-run marginal expected shortfall of the firm's return in the event of a financial crisis and ϑ is a regulatory capital ratio. It is defined as

$$LRMES_{t+1}^{(i)} = -E_t \left[R_{t+1}^{(i)} \mid R_{t+1}^{(M)} \leq \theta_{M,t} \right], \tag{11}$$

where $\theta_{M,t}$ is the threshold for a downturn in the equity market.

In Brownlees and Engle (2017), the market downturn corresponds to a $\theta_{M,t} = -40\%$ decline in the stock market index. One advantage of SRISK is that it only requires an estimate of how much a bank's market capitalization would be affected in a market downturn. In contrast, SEL requires measuring the sensitivity of the asset classes to a downturn in the various market factors and taking the dependence between the market factors into account. However, SRISK implicitly assumes that the shock to market capitalization correctly reflects the impact of the market downturn on the asset classes, an assumption that may not always be true. In addition, it does not allow for alternative market stress scenarios.

We compute SRISK by aggregating the individual measures provided by the Volatility Laboratory on its website.[17] Figure 10 reveals that the two series have similar dynamics, although they exhibit some noticeable differences. First, the SEL measure is substantially higher than SRISK before the subprime crisis (close to \$100 billion vs. \$25 billion). At the beginning of 2007, the estimated values are equal to \$175 billion for SEL and \$80 billion for SRISK. As argued by Acharya et al. (2009), the risk of the crisis was already

[17]The website is available at https://vlab.stern.nyu.edu/. As some of the 31 banks on our list are not covered by VLab, we aggregate the SRISK of all of the available banks. Furthermore, SRISK is computed at the BHC level because it relies on their market capitalization. Therefore, there is a difference between the two measures due to their different scopes. As BHCs also include firms that are not commercial banks (such as securities brokers and dealers or insurance companies), the SRISK estimates are likely to be larger than SEL estimates.

visible by mid-2006 with the downturn in the real estate market and the increase in credit instrument spreads. These events are at least partly captured by the credit market factors and are incorporated into the SEL. In contrast, as the equity market did not react as quickly to these events, SRISK is not affected in 2006–2007 until the downturn in the equity market.

Second, the SEL increases less than SRISK after the start of the crisis. In 2009, SRISK is almost twice as large as SEL ($560 billion vs. $300 billion). The difference can be explained by some specific events that affected large BHCs. Citigroup was in trouble as early as 2007 because of its investment in the real estate market. Its SRISK jumped from 0 to $111 billion in 2008, whereas Citibank's SEL did not vary proportionately (from $18 to $53 billion). In addition, in 2008, JPMorgan Chase Bank and Bank of America acquired investment banks that were in trouble (Bear Stearns and Merrill Lynch, respectively). These events were perceived as risky by equity markets, meaning that SRISK of these institutions increased significantly in 2008 (from $47 to $138 billion for JPMorgan Chase Bank and from $25 to $125 billion for Bank of America in 2008, respectively). However, their commercial banks were not directly affected by these deals, meaning that their contribution to SEL is limited. The increase in the SEL is only from $35 to $61 for JP Morgan Chase Bank and from $39 to $81 for Bank of America in 2008.

Thereafter, the two measures have a similar temporal evolution. At the end of 2016, SEL and SRISK are equal to $175 billion and $130 billion, respectively. These estimates suggest that the risk borne by commercial banks is relatively stable in the recent period and that the equity market correctly assesses the risk borne by commercial banks in the fixed income and credit markets.

[Insert Figure 10 here]

4.3 Individual Probability of Default and SEL

We now present results for individual banks. Table 6 reports our estimates of the individual probability of default and SEL for all banks, averaged before, during, and after the subprime crisis. Banks are sorted according to their total assets as of the end of 2016. As expected, the probability of default jumps for most of the banks during the subprime crisis. For instance, for the four largest banks, the probability of default during a downturn increased from an average of 10% before the crisis to an average of 20% during the period 2008–2013. After 2013, the probability decreases substantially, to levels usually below 10%.

We also observe that the SEL is rather low before 2008. Only two banks (JPMorgan Chase Bank and Citibank) suffer from an estimated SEL larger than $10 billion. During the financial crisis, the SEL exceeds $25 billion, on average, for the four top banks with an aggregate SEL of $178 billion. In the recent period (2014–2016), the SEL has decreased for all banks with the exception of Citibank. The aggregate SEL for the Top-4 banks is close to $126 billion on average.

[Insert Table 6 here]

4.4 Robustness Analysis

This section summarizes additional analyses that we have performed to evaluate the robustness of our main results.

4.4.1 Alternative Thresholds

An important aspect of the stress scenario is the way the thresholds are determined. In the main results, the thresholds are based on the EWMA estimation of the standard deviation of the market factor returns. As alternative approaches, we examined two other cases: (1) the standard deviations are estimated with a five-year rolling window, or (2) the standard deviations are estimated with an increasing window.

Figure 11 displays the alternative thresholds obtained from these approaches. The levels are relatively similar before the subprime crisis. However, the impact of the crisis is much stronger (almost twice as large) with the five-year window than with the expanding window. After the crisis, the thresholds implied by the five-year window go back to pre-crisis levels, while those implied by the expanding window remain at low levels.

Figures 12 and 13 show that these approaches have the opposite impacts on the probability of a market downturn and the average probability of default. In the case of five-year rolling windows, the probability of crash is reduced compared to our baseline case in the five years following the subprime crisis. The reason is that observations in the crisis matter more in computing the thresholds, such that the thresholds are lower and a crash is less likely. However, if a downturn occurs, a default by a bank is more likely. In contrast, in the case of an expanding window, the probability of a downturn is increased compared to our baseline case after the subprime crisis. In contrast, the probability of default is significantly reduced. These results clearly indicate that the probabilities of downturn and default depend on the magnitude of the shocks that we consider.

Interestingly, the figures also indicate that the estimate of the SEL is essentially the same in the three cases that we consider. The reason is that it is computed conditional on both a market downturn and a default. This result is important because it clearly shows that the way the thresholds are defined has limited impact on the SEL value.

[Insert Figures 11 to 13 here]

4.4.2 Change in Sensitivity to Shocks

We now evaluate the sensitivity of our results to some of the parameters that we calibrate to compute the SEL. We first consider the case where, in the event of default, the liquidation of the market-sensitive assets results in a price impact on the value of these assets. Several papers discuss the importance of price impacts in a fire sale process, which results in a further decrease in market prices (Coval and Stafford, 2007, Shleifer and Vishny, 2011, Duarte and Eisenbach, 2013, and Caballero and Simsek, 2013). We denote by φ the average price impact on the market value of market-sensitive assets ($\varphi \in [0,1]$). The estimate of SEL is obtained as follows:

$$SEL_{t+1}^{(i)} = [(1+R_{Dep,t}^{(i)})Dep_t^{(i)} + (1+R_{SD,t}^{(i)})SD_t^{(i)}] - \frac{1}{S_{C,t+1}} \sum_{s=1}^{S_{C,t+1}} A_{t+1}^{(i)s}\, 1_{\{A_{t+1}^{(i)s} \leq L_{t+1}^{(i)}\}},$$

where $A_{t+1}^{(i)s} = (1+R_{F,t}^{(i)})Cash_t^{(i)} + (1-\varphi)(1+R_{MA,t+1}^{(i)s})MA_t^{(i)s} + (1+R_{O,t}^{(i)})O_t^{(i)}$.

We assume a relatively low value of the price impact, equal to $\varphi = 2.5\%$. As Figure 14 reveals, even in this conservative case, the effect of the price impact during a liquidation on SEL is substantial. After the subprime crisis, the increase in SEL that would result from a 2.5% price impact ranges between \$150 and \$200 billion. At the end of our sample, SEL would be close to \$350 billion instead of \$175 billion when $\varphi = 0$, which means that SEL would be almost twice as large as in the case with no price impact.

In our main results, we assume that the reclassified other assets have the same sensitivity to the market factors as the market-sensitive assets. In fact, it is not clear if the sensitivity should be lower or higher. Other assets include, for instance, foreign bonds, which would probably be less sensitive to the market shocks that we consider. In contrast, equity securities are likely to be more sensitive to the market shocks. To evaluate the impact of this assumption, we proceed as follows: consider the case of assets related to corporates. Thus far, we have assumed that the sensitivity of corporate loans and securities (denoted by $C_t^{(i)}$) and the sensitivity of the other assets reclassified as corporate loans and securities (denoted by $\tilde{C}_t^{(i)}$) are equal to 1. Therefore, the contribution of corporate-related assets to the market-sensitive asset return in Equation (2) was equal to $(C_t^{(i)} + \tilde{C}_t^{(i)})R_{C,t+1}^{(m)}$. We now allow the relative sensitivity of the other assets to be equal to γ, i.e., the contribution is now $(C_t^{(i)} + \gamma\tilde{C}_t^{(i)})R_{C,t+1}^{(m)}$. We consider two values of γ, 0.5 and 1.5. Figure 15 indicates that the sensitivity of the SEL to γ is limited over most of our sample. The impact is substantial only in the very recent period (2015–2016): a higher sensitivity ($\gamma = 1.5$) would result in an increase in the SEL from \$175 and \$225 billion.

[Insert Figure 14 here]

5 Conclusion

In this paper, we develop a new methodology to measure the capital shortfall of commercial banks during a market downturn. The measure, which we call stressed expected loss (SEL), takes the structure of an individual bank's balance sheet. The capital shortfall is defined as the lack of bank equity in the event of a market downturn. We first identify how the various asset categories are related to market factors capturing the temporal evolution of government, real estate, corporate, and household securities. Then, we define a market downturn scenario as a decline in some of the market factor indexes. SEL is then the difference between the market value of assets in the stress scenario and the book value of the deposits and short-term debt of the bank.

We estimate the evolution of the probability of default and the SEL of the 31 largest commercial banks between 1996 and 2016. The probability of default during a downturn has been as high as 35%, on average, in 2008 and close to 20% between 2009 and 2012. It is now much smaller and close to 5%, on average. The SEL was very high (between $250 and $350 billion) during the subprime crisis. In the recent period, it is close to $150 billion, which represents approximately 1.5% of total assets or 15% of equity.

Our approach has two main advantages. First, it is easy to implement because it relies only on publicly available data (individual bank's accounting data and market factor indexes). In particular, the bank does not need to be listed, as we use the accounting value of the assets and not of the equity. Second, our approach can be used to investigate alternative scenarios of a market downturn. For instance, a market downturn may specifically come from corporates or from the real estate market.

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Table 1: List of the 31 commercial banks in our sample

Ultimate Parent	Commercial Bank	Assets	Deposits	Equity
JPMorgan Chase & Co.	JPMorgan Chase Bank, National Assoc.	2,083	1,480	205
Wells Fargo & Co.	Wells Fargo Bank, National Assoc.	1,727	1,339	155
Bank of America Corporation	Bank of America, National Assoc.	1,677	1,334	206
Citigroup Inc.	Citibank, National Assoc.	1,350	946	144
U.S. Bancorp	U.S. Bank, National Assoc.	441	343	45
PNC Financial Services Group, Inc.	PNC Bank, National Assoc.	356	262	38
Capital One Financial Corp.	Capital One, National Assoc.	286	217	35
TD Group US Holdings LLC	TD Bank, National Assoc.	269	229	35
Bank of New York Mellon Corp.	Bank of New York Mellon	258	213	24
State Street Corp.	State Street Bank and Trust Co.	239	192	22
BB&T Corp.	Branch Banking and Trust Co.	214	168	28
SunTrust Banks, Inc.	SunTrust Bank	201	162	23
HSBC North America Holdings Inc.	HSBC Bank USA, National Assoc.	197	147	24
Fifth Third Bancorp	Fifth Third Bank	140	107	17
KeyCorp	KeyBank, National Assoc.	134	107	15
Regions Financial Corp.	Regions Bank	125	100	16
Northern Trust Corp.	Northern Trust Co.	124	102	9
Ally Financial Inc.	Ally Bank	124	79	18
M&T Bank Corp.	Manufacturers and Traders Trust Co.	123	97	15
Citizens Financial Group, Inc.	Citizens Bank, National Assoc.	117	83	16
MUFG Americas Holdings Corp.	MUFG Union Bank, National Assoc.	116	89	16
BMO Financial Corp.	BMO Harris Bank, National Assoc.	106	80	15
Huntington Bancshares Incorp.	Huntington National Bank	100	78	11
Discover Financial Services	Discover Bank	91	54	10
BancWest Corp.	Bank of the West	84	62	12
BBVA Compass Bancshares, Inc.	Compass Bank	84	68	12
Santander Holdings USA, Inc.	Santander Bank, National Assoc.	83	60	13
Comerica Inc.	Comerica Bank	73	60	7
Zions Bancorporation	ZB, National Assoc.	63	54	8
Deutsche Bank Trust Corp.	Deutsche Bank Trust Co. Americas	54	42	9
CIT Group Inc.	CIT Bank, National Assoc.	42	32	5

Note: This table presents the list of the 31 commercial banks in our sample sorted by their total assets. It reports the names of the bank, the name of its ultimate parent, and the value of the total assets, deposits, and equity of the commercial bank for 2016:Q4 (in $ billion).

Table 2: Summary Statistics on Commercial Banks and their Ultimate Parent

	$\frac{\text{Commercial Bank Assets}}{\text{Ultimate Parent Assets}}$	$\frac{\text{Commercial Bank Deposits}}{\text{Commercial Bank Liabilities}}$	$\frac{\text{Commercial Bank Deposits}}{\text{Ultimate Parent Liabilities}}$
Mean	0.88	0.87	0.77
Median	0.96	0.88	0.77
Std dev.	0.12	0.06	0.13
Minimum	0.60	0.67	0.52
Maximum	0.998	0.98	0.97

Note: This table presents summary statistics on the commercial banks in our sample and their ultimate parent. Numbers are based on balance sheet of the 31 commercial banks and their ultimate parent as of 2016:Q4.

Table 3: Selected Market Factor Indexes

Selected Index	Ticker	#Bonds	Rating	Effective Duration
Government				
US Treasury Master	G0Q0	259	AAA	6.0
US Agencies Composite Master	UAGY	447	AA-AAA	3.9
National Select Municipal Securities	UAMA	7897	AA-AAA	7.9
Real Estate				
US GNMA MBS	MGNM	116	AAA	5.4
US Fixed Rate Commercial MBS	CMA0	2146	A-AAA	4.7
US Fixed Rate Commercial MBS	CB45	372	BBB	4.7
US Fixed Rate Home Equity Loan ABS	R0H1	1	AAA	1.6
US Fixed Rate Home Equity Loan ABS	R0H2	5	BBB-AA	6.2
Corporate				
US Non-Financial Corporate	CF0X	5619	BBB-AAA	7.8
US High Yield Corporate	H0A4	1576	B-BB	4.1
US High Yield Corporate	H0A3	312	D-CCC	3.1
Household				
US Fixed Rate Automobile ABS	R0U1	616	AAA	1.2
US Fixed Rate Automobile ABS	R0U2	481	BBB-AA	1.8
US Fixed Rate Credit Card ABS	R0C1	90	AAA	1.9
US Fixed Rate Credit Card ABS	R0C2	19	BBB-AA	1.5

Note: This table presents details on the market factor indexes selected for our empirical analysis. The first column shows the selected total return indexes separated by the asset classes defined earlier. The second column shows their ticker identified by Bank of America Merrill Lynch (BofA). The third column shows the number of constituent bonds in each index. Rating is the average of Moody's, S&P, and Fitch ratings. The last column presents the effective duration of each index provided by BofA as of end of 2016.

Table 4: Descriptive Statistics of Daily Market Factor Returns

Market index	Annual. mean (in %)	Annual. std dev. (in %)	Skewness	Kurtosis	Minimum (in %)	Maximum (in %)	AR(1)
Panel A: Univariate statistics							
Government	4.778	3.566	-0.368	5.449	-1.568	1.231	0.094
Real estate	4.672	4.774	-2.087	159.5	-6.959	7.335	0.100
Corporate	6.512	4.234	-1.513	23.19	-4.149	2.196	0.376
Household	4.757	2.222	-1.270	42.83	-2.312	1.883	0.048
Panel B: Correlation matrix							
	Full sample			**Excluding 2008–2009**			
	Govern.	Real est.	Corp.	Govern.	Real est.	Corp.	
Real estate	0.537	–	–	0.768	–	–	
Corporate	0.427	0.382	–	0.496	0.522	–	
Household	0.632	0.482	0.332	0.785	0.704	0.391	

Note: This table presents summary statistics of returns of constructed market indexes. Mean, Standard deviation, Minimum, and Maximum are in percentage. Mean and Standard deviation are annualized. The correlation matrix is computed over the full sample and over the period excluding 2008–2009. Numbers are based on daily data from January 1996 to December 2016 (5,409 observations).

Table 5: Parameter Estimates (Based on the 1996–2016 Sample)

	Government	Real estate	Corporate	Household
Univariate parameters				
ξ_a	-0.0127	0.0352	0.0501	0.0290
	(0.019)	(0.011)	(0.011)	(0.011)
ω_a ($\times 10^6$)	0.0495	0.0188	0.0231	0.0052
	(0.014)	(0.003)	(0.005)	(0.001)
α_a	0.0452	0.0912	0.0956	0.1200
	(0.009)	(0.011)	(0.012)	(0.025)
γ_a	-0.0051	-0.0165	0.0749	-0.0370
	(0.011)	(0.009)	(0.017)	(0.023)
β_a	0.9483	0.9160	0.8659	0.8975
	(0.007)	(0.009)	(0.014)	(0.014)
Skewed t distribution				
ν_a	6.9827	2.8330	5.0914	3.3429
	(0.669)	(0.104)	(0.322)	(0.165)
λ_a	-0.0887	-0.0612	-0.0998	0.0238
	(0.017)	(0.013)	(0.017)	(0.015)
Multivariate parameters				
δ_1		0.0141 (0.0004)		
δ_2		0.9843 (0.0004)		
Copula degree of freedom				
$\bar{\nu}$		6.3018 (0.2990)		
Copula correlation matrix Γ				
	$R_{G,t}$	$R_{R,t}$	$R_{C,t}$	
$R_{R,t}$	-0.0122	–	–	
$R_{C,t}$	0.1097	-0.0475	–	
$R_{H,t}$	0.0196	0.0480	0.0605	
DGT adequacy test				
	119.51	127.24	106.60	94.40
	(0.079)	(0.030)	(0.283)	(0.612)

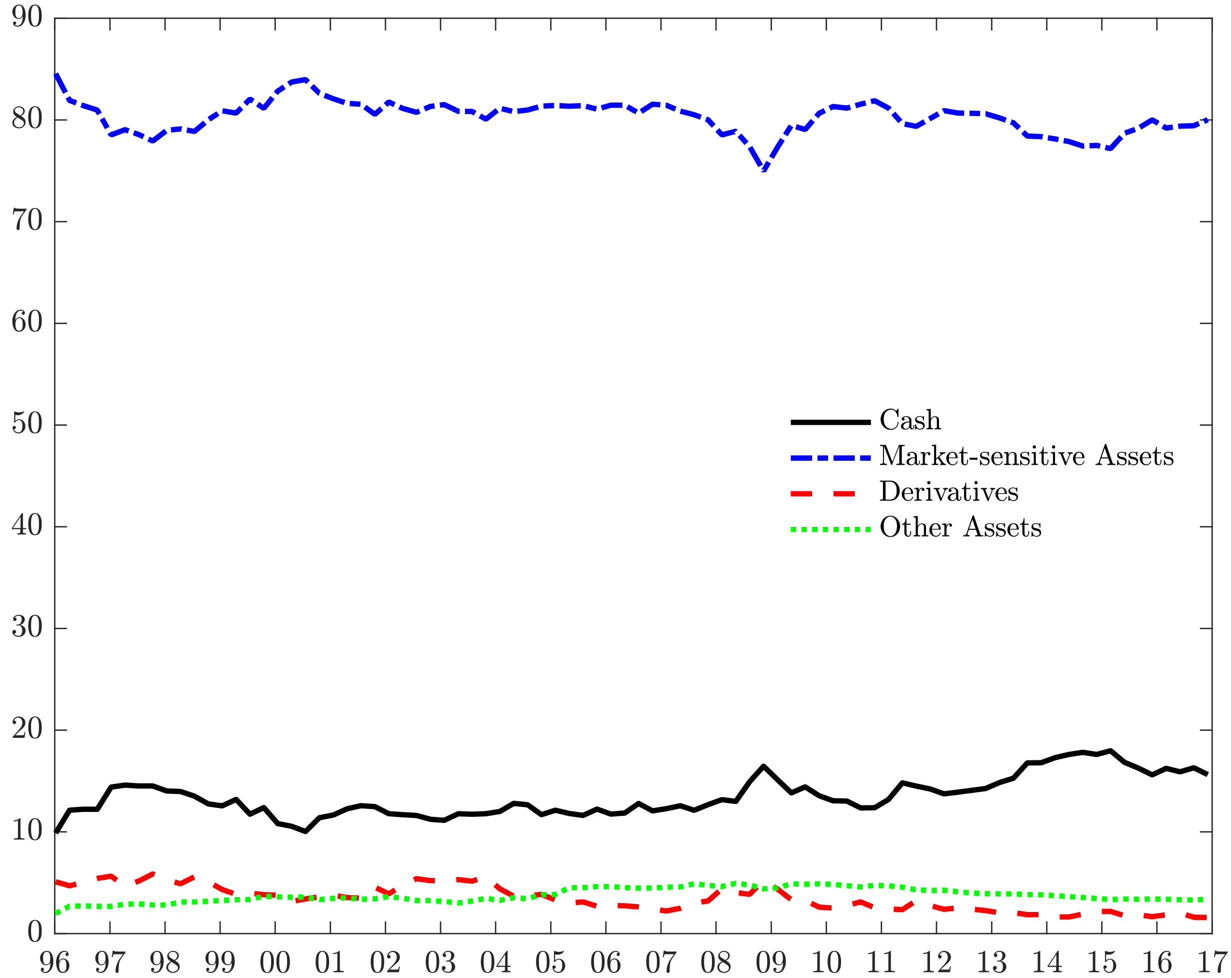
Note: This table presents parameter estimates of the DCB model with t copula innovations. Estimates are based on the sample 1996–2016. Volatility dynamics are for the return series. Estimated parameters of the Skewed t distribution are for the individual innovations. the degree of freedom $\bar{\nu}$ and the correlation matrix Γ correspond to the t copula of the innovation margins. DGT test is the Diebold et al. (1983) adequacy test.

Table 6: Probability of Default and SEL for Commercial Banks in our Sample

Commercial Bank	Pre-crisis 1996–2007 Π_D	Pre-crisis 1996–2007 SEL	Crisis 2008–2013 Π_D	Crisis 2008–2013 SEL	Post-crisis 2014–2016 Π_D	Post-crisis 2014–2016 SEL
JPMorgan Chase Bank	14.4	10.3	29.9	52.8	8.0	48.8
Wells Fargo Bank	3.1	6.6	19.7	36.9	6.0	19.9
Bank of America	7.5	15.4	14.3	62.0	3.5	25.3
Citibank	15.1	8.8	14.4	25.8	9.1	31.7
U.S. Bank	5.5	0.6	22.3	10.0	7.2	5.4
PNC Bank	8.9	0.5	18.3	8.7	7.3	1.0
Capital One	4.6	0.3	2.8	6.9	0.5	3.5
TD Bank	7.3	0.5	4.1	5.9	1.1	5.5
Bank of New York Mellon	6.8	2.7	9.3	5.0	5.1	4.4
State Street Bank and Trust	1.8	1.2	9.1	4.1	2.4	2.5
Branch Banking and Trust	6.3	0.0	22.6	4.1	2.6	0.6
SunTrust Bank	5.9	0.3	15.6	6.3	6.9	3.9
HSBC Bank USA	7.2	1.4	18.1	5.6	8.3	5.9
Fifth Third Bank	8.2	0.1	13.8	3.2	8.6	0.2
KeyBank	14.0	0.2	26.2	3.3	13.7	0.5
Regions Bank	7.1	1.2	17.3	6.0	5.0	2.4
Northern Trust	7.3	0.1	10.4	1.1	12.7	0.9
Ally Bank	0.4	0.0	7.8	0.0	8.5	0.0
Manufacturers and Traders Trust	5.6	0.3	16.2	3.9	3.5	0.5
Citizens Bank	0.1	0.4	7.9	6.3	2.5	1.2
MUFG Union Bank	7.7	1.5	20.9	2.5	5.5	0.8
BMO Harris Bank	10.1	0.6	7.9	2.7	2.6	2.3
Huntington National Bank	20.0	0.0	43.4	1.3	14.6	0.1
Discover Bank	0.3	1.3	2.2	1.8	0.4	0.6
Bank of the West	1.6	0.3	4.5	0.8	0.4	1.3
Compass Bank	9.3	0.1	4.1	3.0	3.2	0.3
Santander Bank	25.6	2.2	18.9	3.4	3.4	0.1
Comerica Bank	13.6	0.8	34.4	3.2	26.3	3.3
ZB	17.6	0.2	32.3	0.9	6.8	0.8
Deutsche Bank Trust Americas	6.0	1.3	0.4	0.5	0.0	0.0
CIT Bank	0.0	0.0	11.6	0.8	7.3	0.3

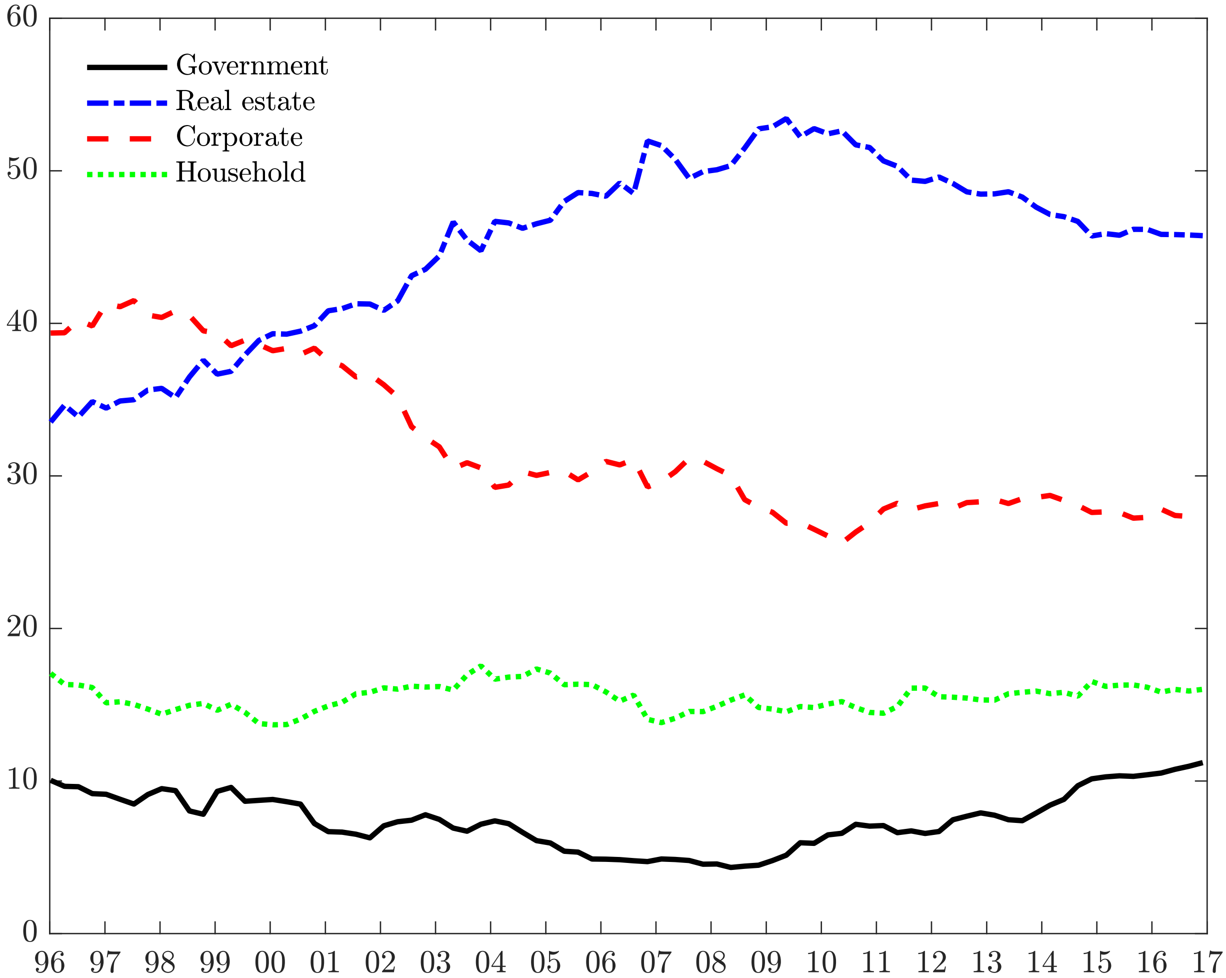
Note: This table reports estimates of the probability of default and SEL for all banks, averaged before, during, and after the great financial crisis. Banks are sorted according to their total assets as of 2016:Q4. The probability of default Π_D is in percentage. SEL is in \$ billion.

Figure 1: Evolution of the Main Categories of Assets



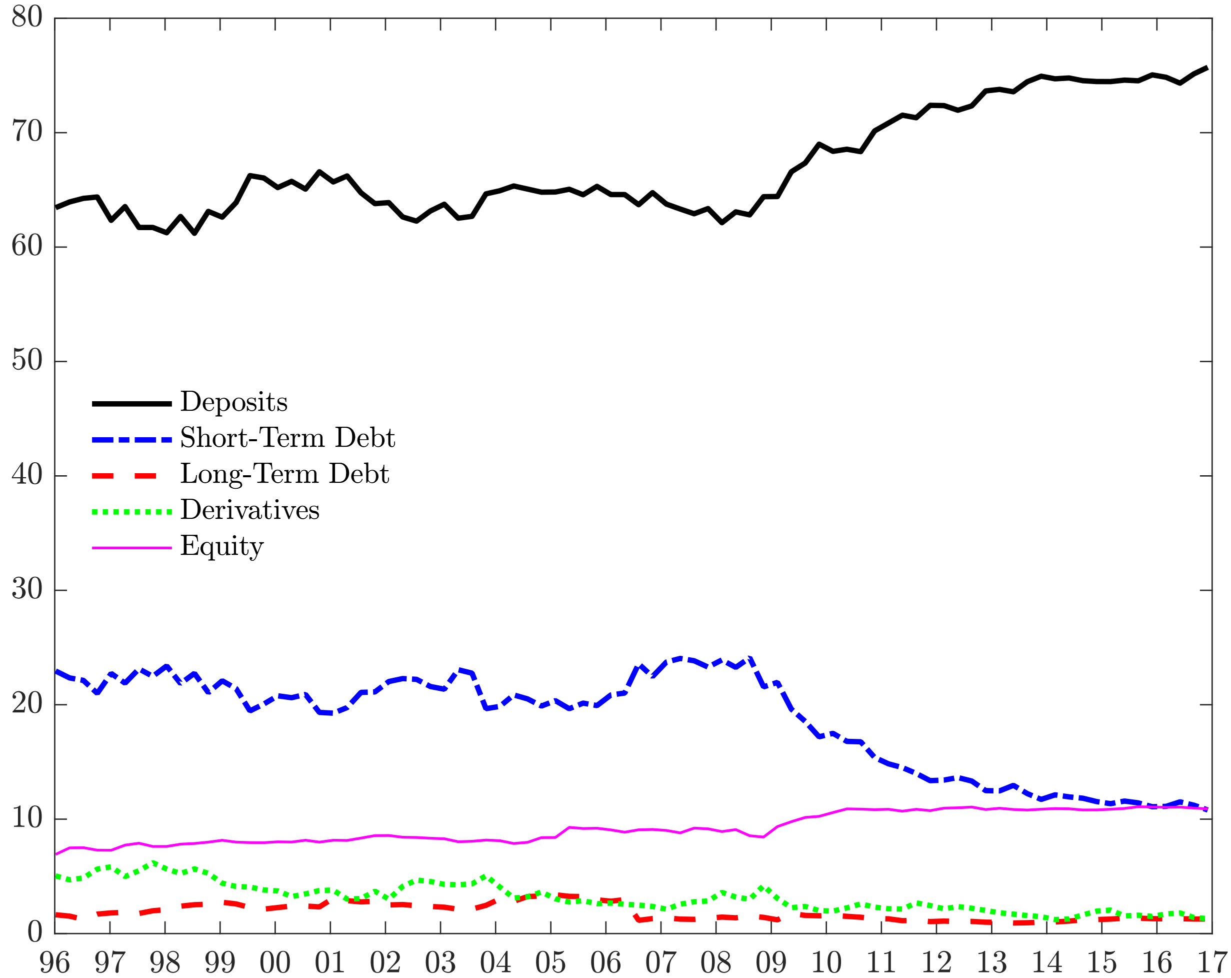
Note: This figure displays the four main types of assets as a fraction of total assets. Data are quarterly and obtained from Call Reports. Averages are taken across banks and are weighted by total assets of each bank.

Figure 2: Evolution of the Main Categories of Market-sensitive Assets



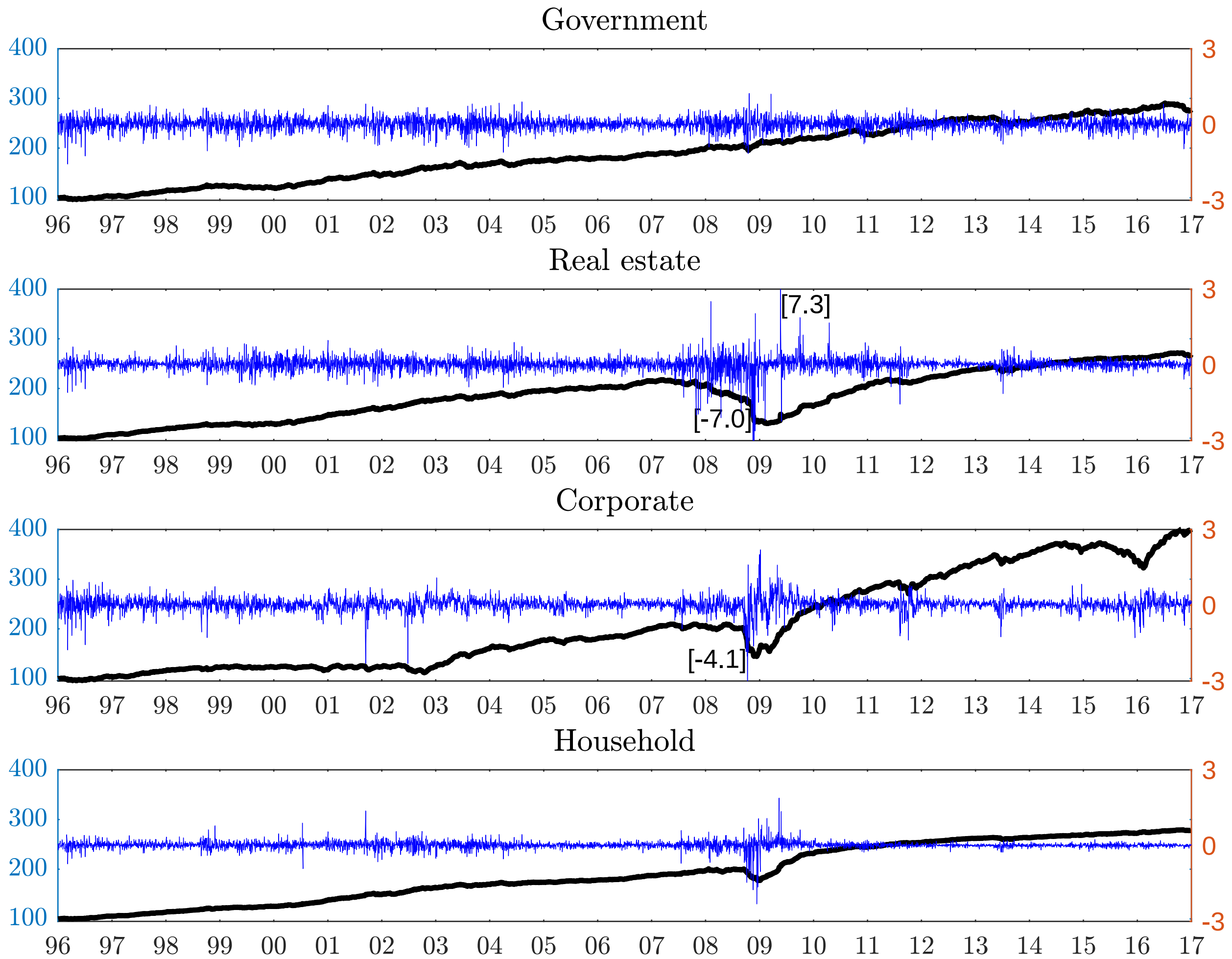
Note: This figure displays the four main types of market-sensitive assets as a fraction of total market-sensitive assets. Data are quarterly and obtained from Call Reports. Averages are taken across banks and are weighted by total assets of each bank.

Figure 3: Evolution of the Main Categories of Liabilities and Equity



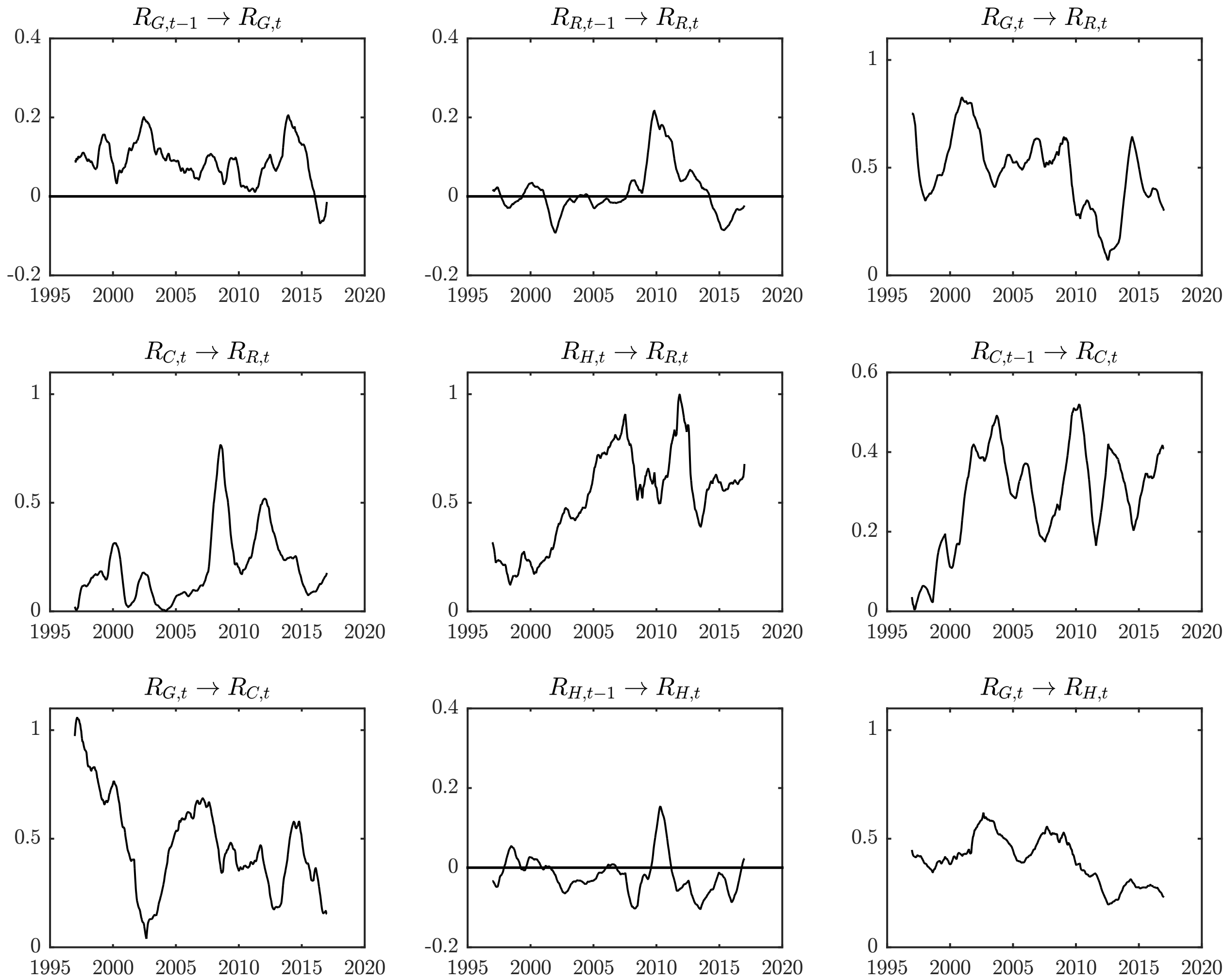
Note: This figure displays the composition of debt of the bank as a fraction of total debt. Data are quarterly and obtained from Call Reports. Averages are taken across banks and are weighted by total assets of each bank.

Figure 4: Evolution of the Market Factors Prices and Returns



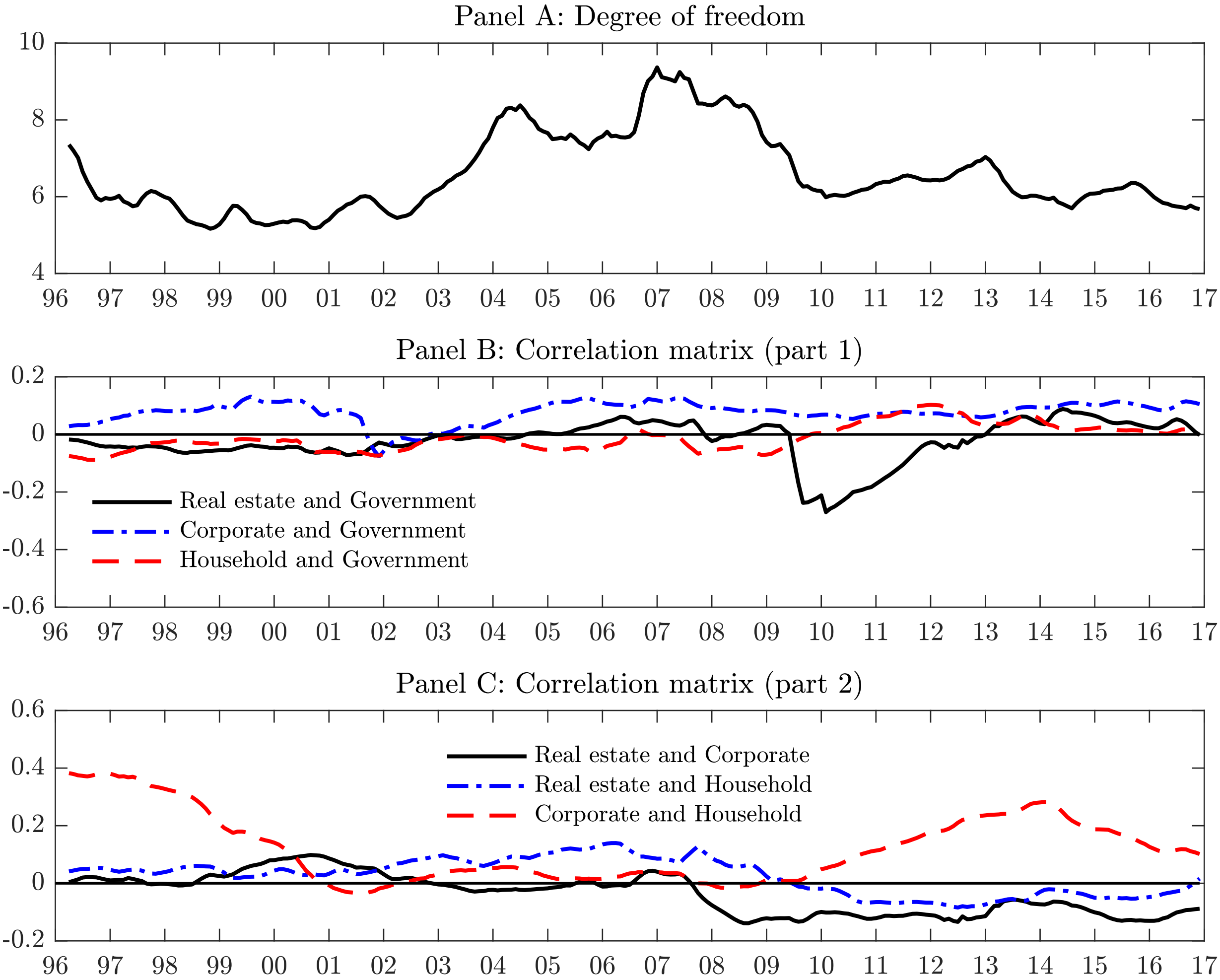
Note: This figure displays the levels of the constructed market factors on the left axis and their returns on the right axis for the period from January 1996 to December 2016.

Figure 5: Estimates of Conditional Dynamic Betas



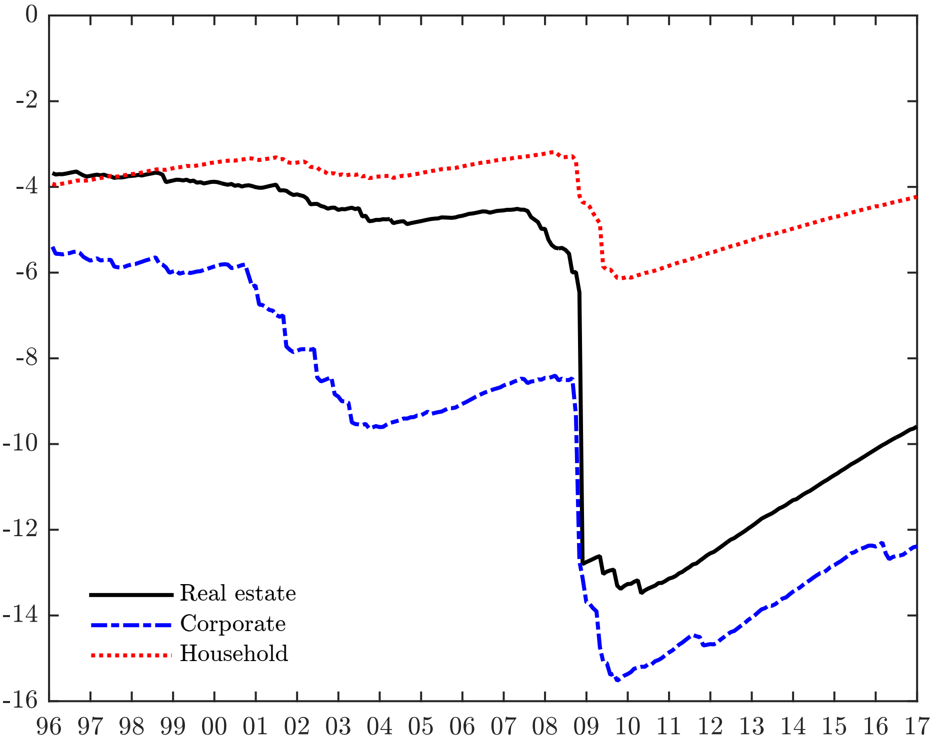
Note: This figure displays the temporal evolution of the conditional beta estimates. The model is estimated using full sample.

Figure 6: Temporal Evolution of Copula Parameter Estimates



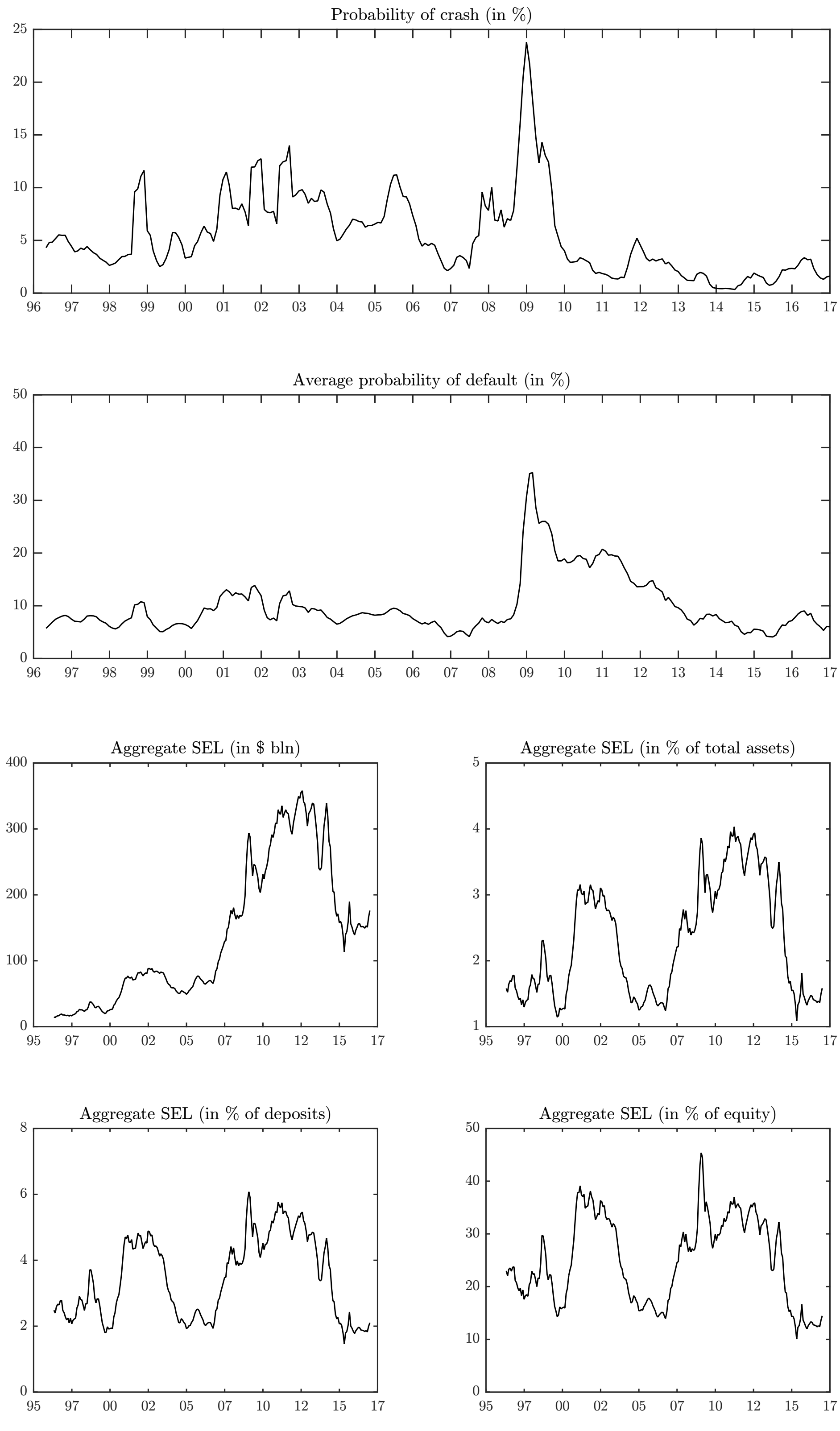
Note: This figure displays the temporal evolution of the estimates of the copula degree of freedom $\bar{\nu}$ and correlation matrix Γ. The model is estimated using rolling windows of five years.

Figure 7: Thresholds Based on EWMA Standard Deviation (in %)



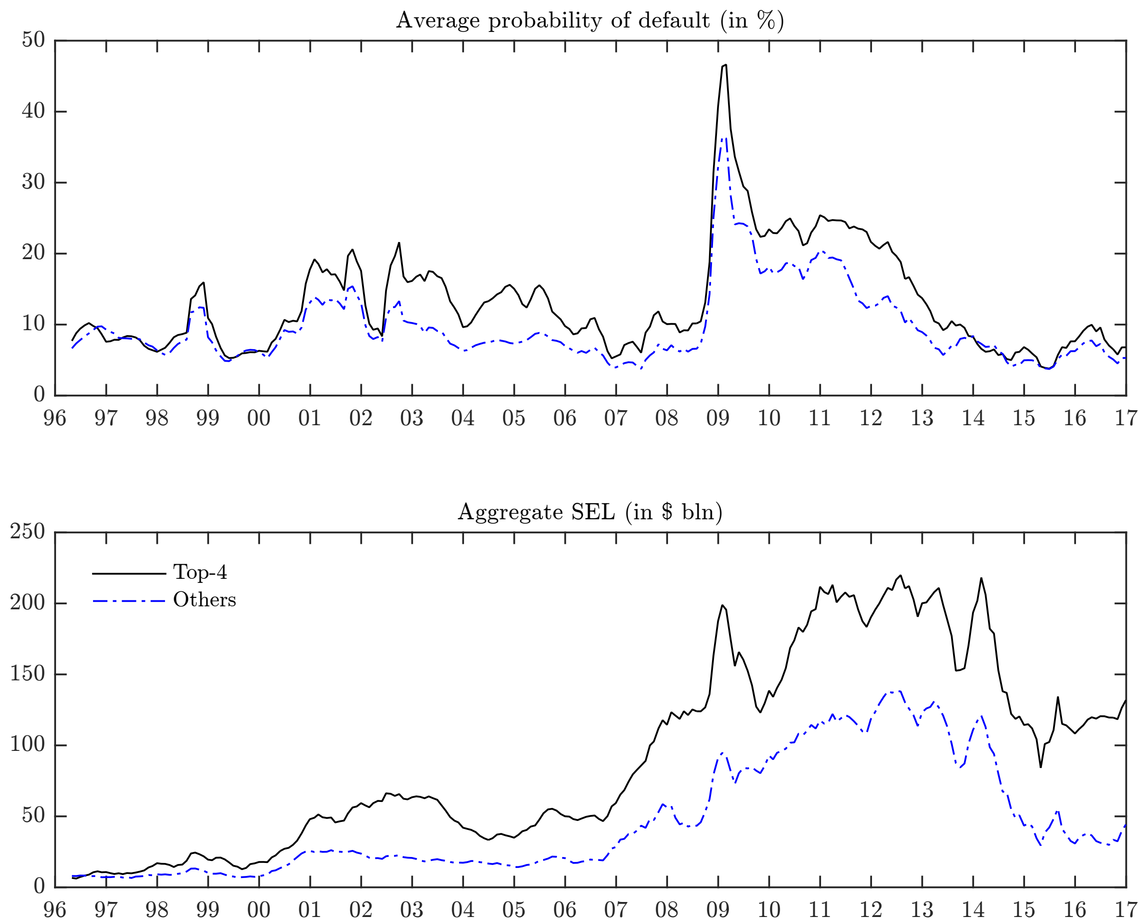
Note: This figure displays the temporal evolution of the thresholds used for the selection of market downturns. Thresholds are computed using an EWMA standard deviation with memory parameter $\phi = 0.99$.

Figure 8: Probability of Crash, Probability of Default, and Aggregate SEL



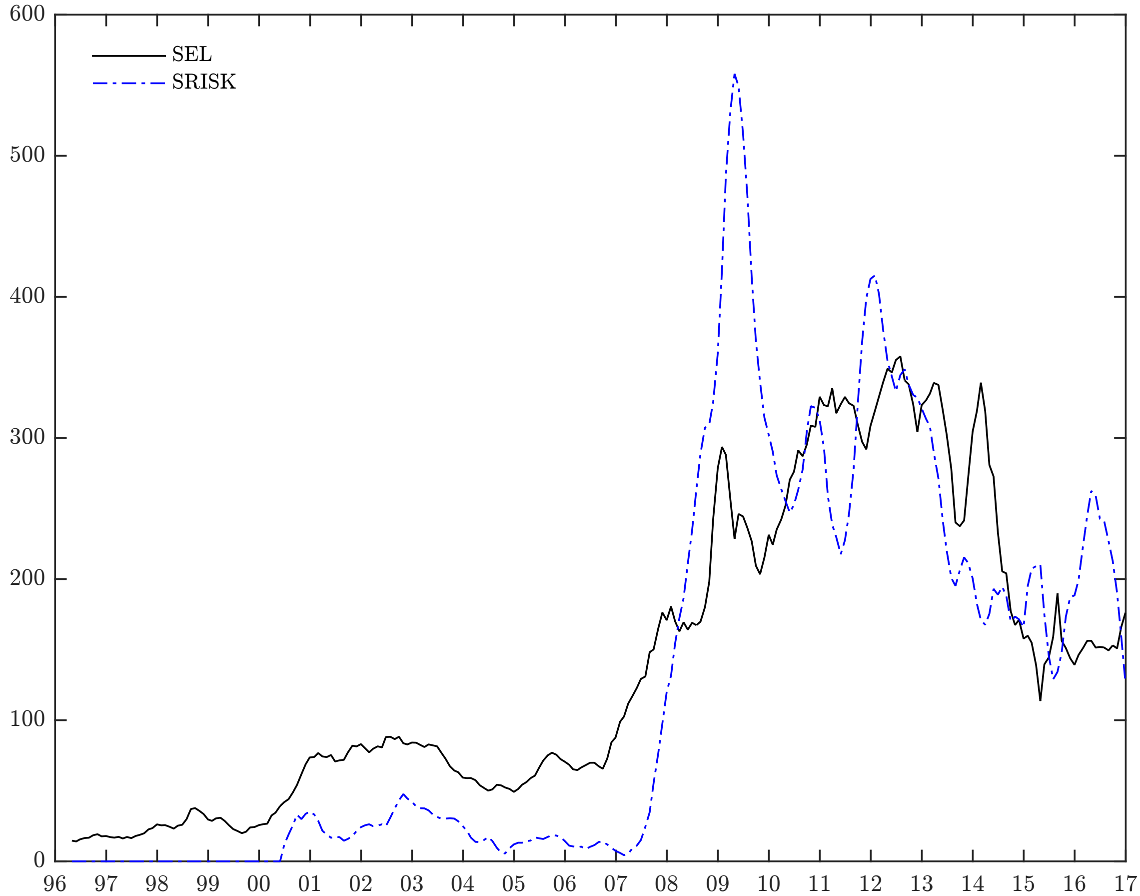
Note: Panel A displays the probability of crash, measured in percentage. Panel B displays the average probability of default, measured in percentage. Panel C displays the aggregate SEL, measured in $ billion.

Figure 9: Probability of Default and Aggregate SEL for Top-4 and Others



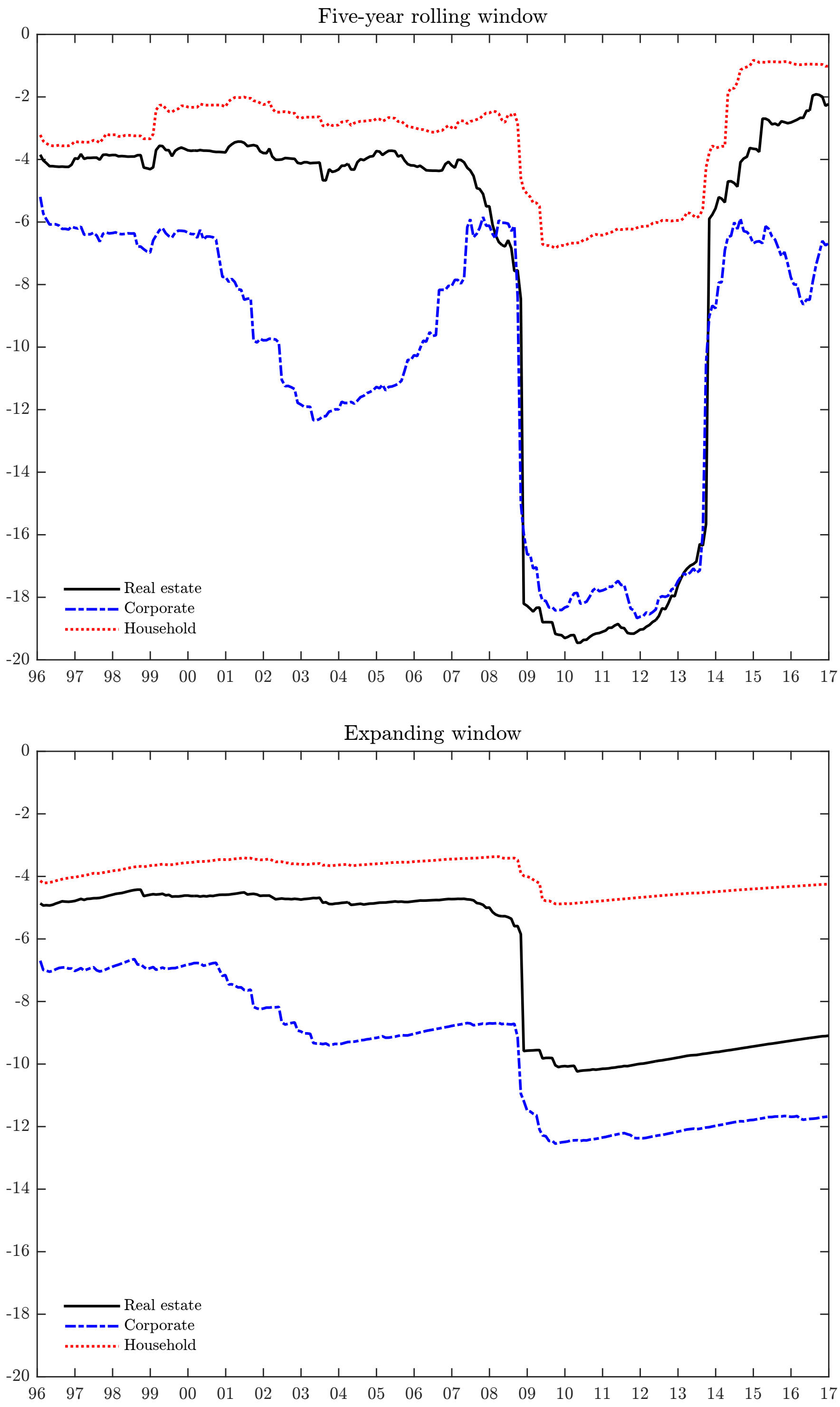
Note: This figure displays the aggregate probability of default and SEL for the Top-4 commercial banks and the group of the other banks. The probability of default is measured in percentage and SEL is measured in $ billion.

Figure 10: SEL and SRISK



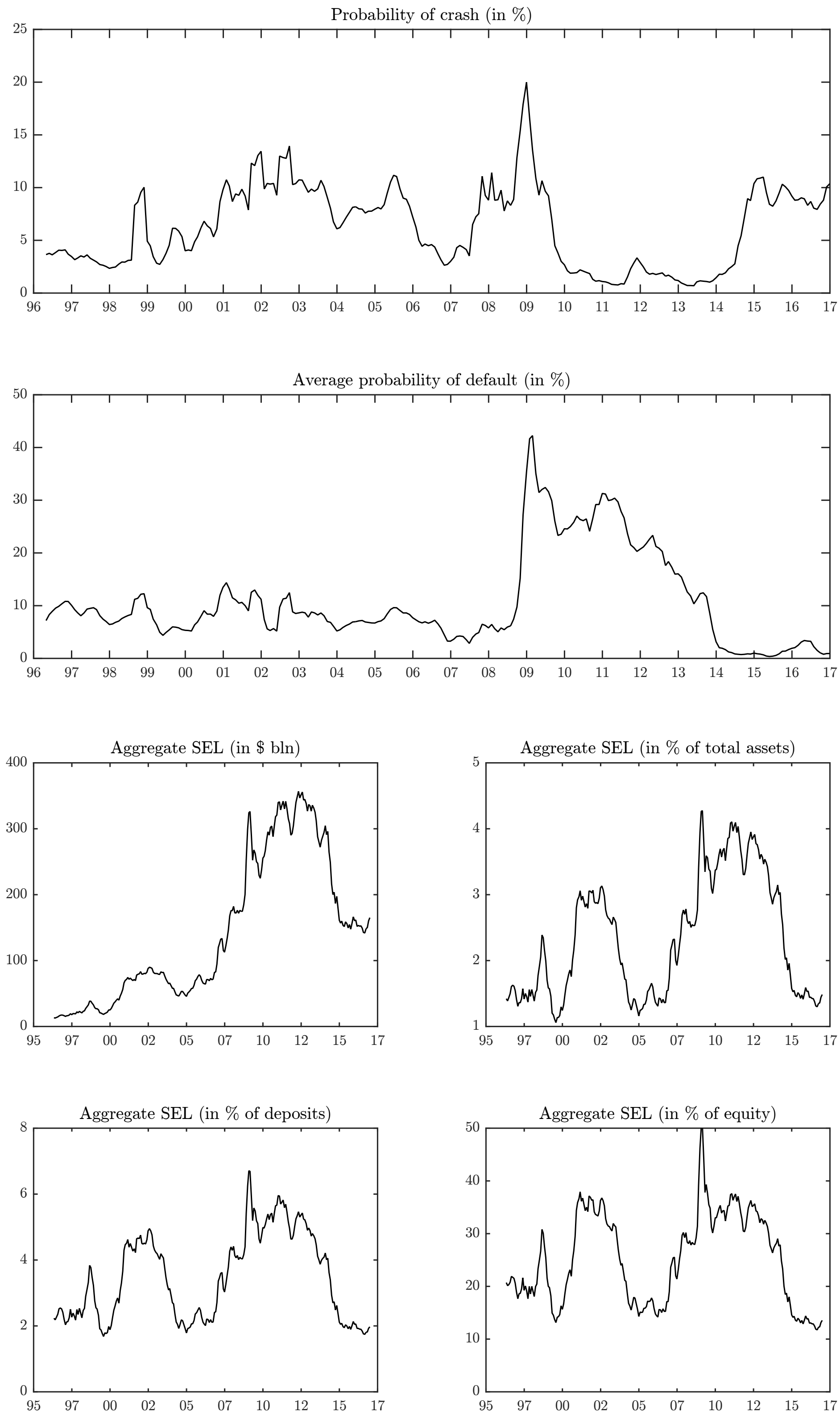
Note: This figure display the SEL and the SRISK measures for the banks for which the SRISK measure is available on the Volatility Laboratory website. The SEL and SRISK are measured in $ billion.

Figure 11: Alternative Threshold Estimates



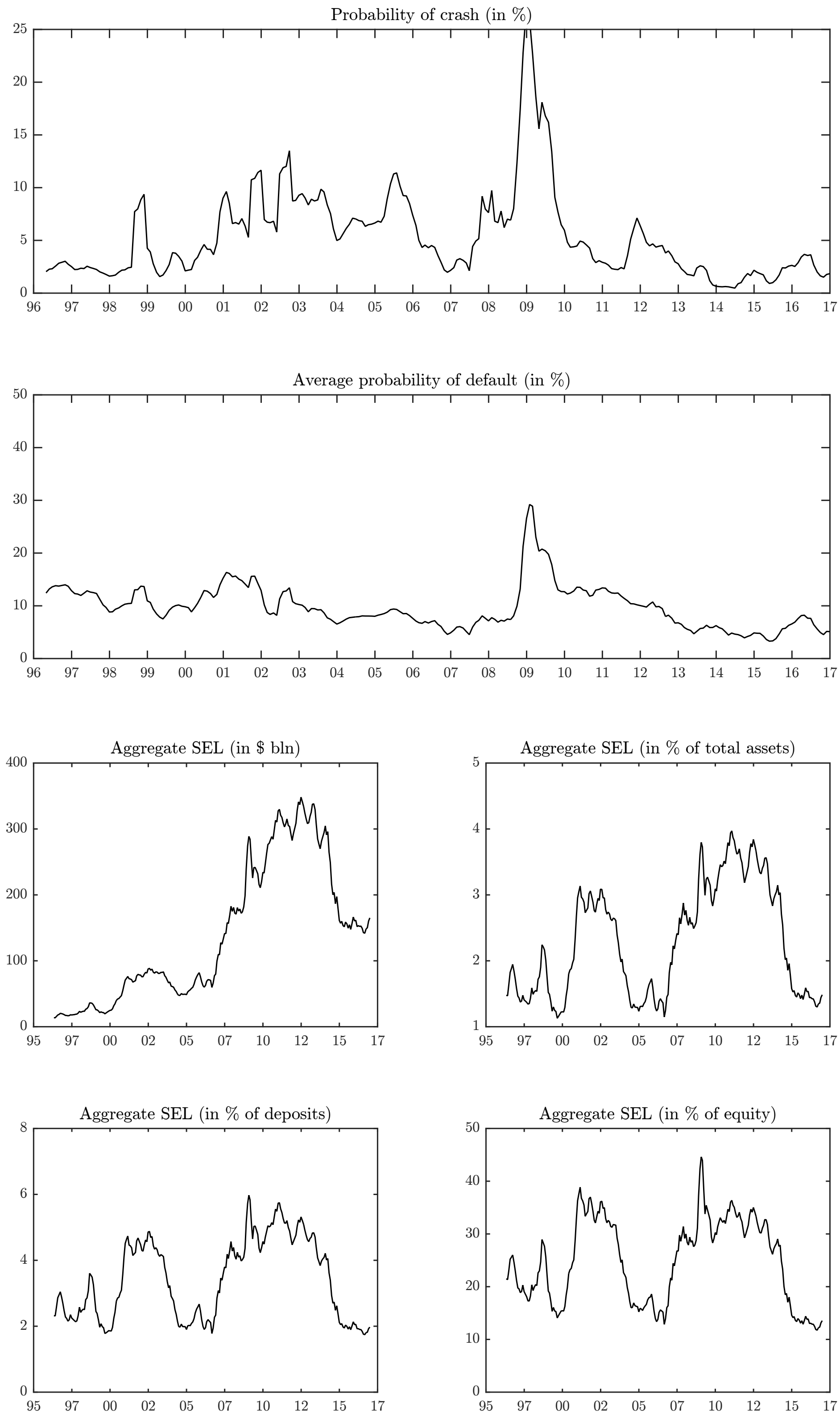
Note: This figure display the thresholds implied by two alternative approaches: (1) standard deviation are estimated over five-year rolling windows, or (2) standard deviations are estimated over an increasing window.

Figure 12: SEL with Five-Year Rolling Window Threshold



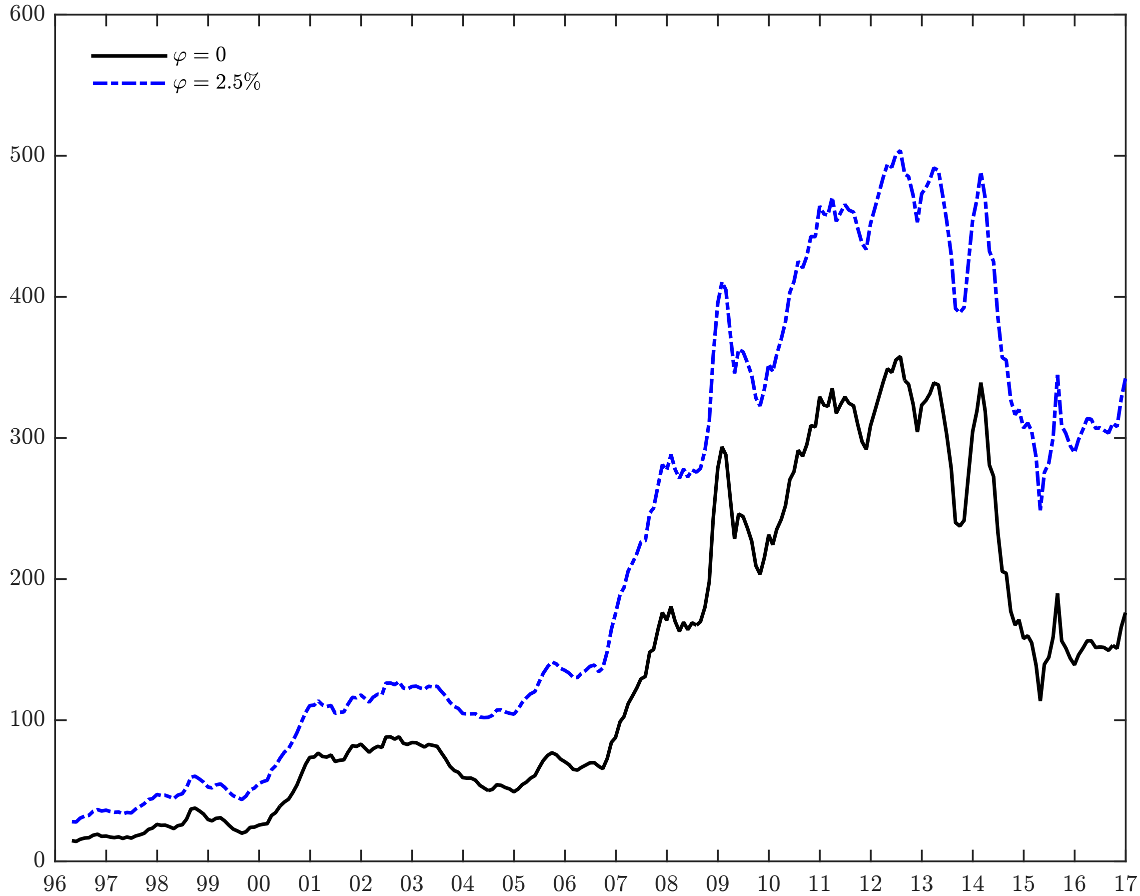
Note: Panel A displays the probability of crash, measured in percentage. Panel B displays the average probability of default, measured in percentage. Panel C displays the aggregate SEL, measured in $ billion.

Figure 13: SEL with Expanding Rolling Window Threshold



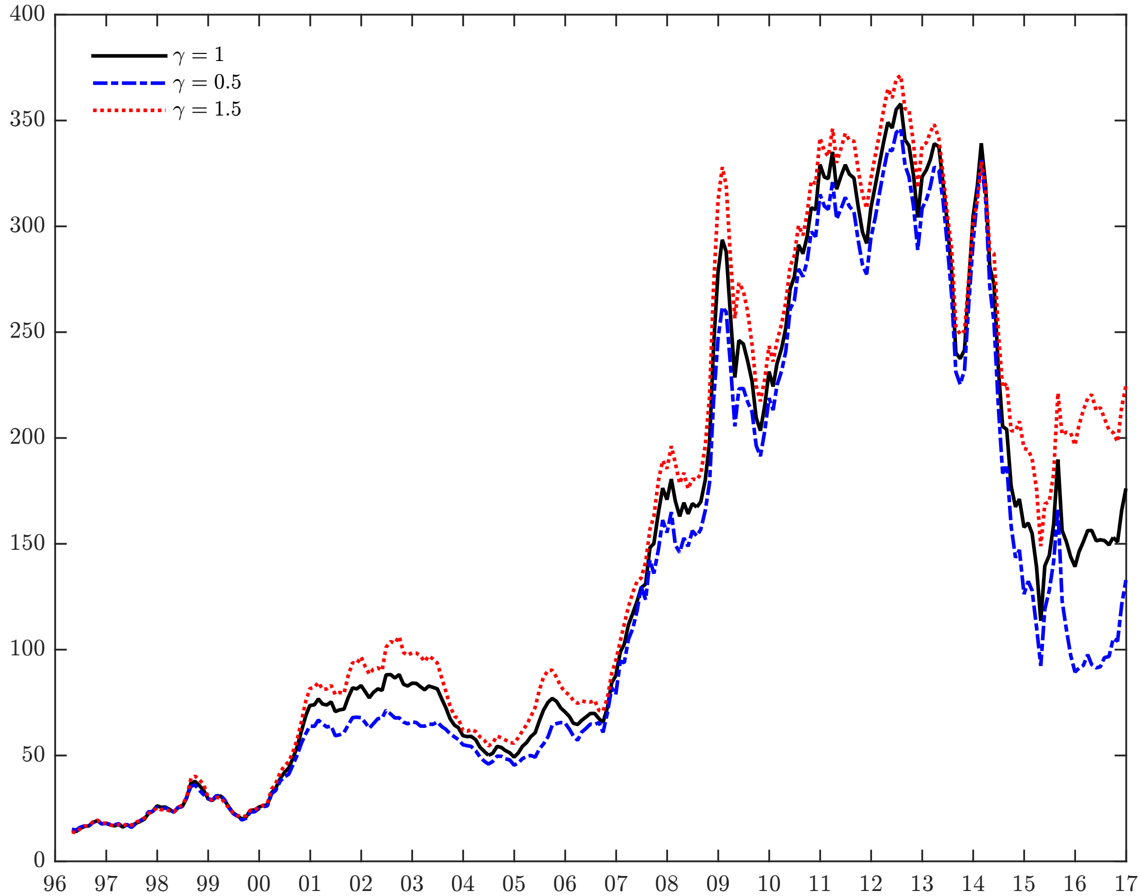
Note: Panel A displays the probability of crash, measured in percentage. Panel B displays the average probability of default, measured in percentage. Panel C displays the aggregate SEL, measured in $ billion.

Figure 14: SEL with Price Impact



Note: This figure displays the SEL when a price impact of $\varphi = 2.5\%$ is assumed on the value of the market-sensitive assets. The aggregate SEL is measured in $ billion.

Figure 15: SEL with Different Sensitivity of Reclassified Other Assets



Note: This figure displays the SEL when the sensitivity of the reclassified other assets to the market factors is changed from $\gamma = 0.5$ to $\gamma = 1.5$. The aggregate SEL is measured in \$ billion.

Appendices

A Banks' Balance Sheet

In this appendix, we start with the balance sheet of commercial banks and provide details on the main categories of assets. Banks in general hold loans and securities. Loans are issued and usually held until they mature, whereas, securities might be sold before they mature.[18] Banks classify loans they issue based on the borrower's purposes or collateral for secured loans. For instance, they separate loans to borrowers who wish to buy a residential real estate property with the property being as the collateral from loans to corporate firms for commercial and industrial purposes. Securities, on the other hand, can be standard securities, such as Treasury bills, or structured securities, such as mortgage backed securities (MBS).

In Section A.1, we provide a description of loans and securities that banks hold. In Section A.2 we explain how each of such assets fit our definition of asset classes, and how we relate the asset classes to their market factors.

A.1 Asset Categories

A.1.1 Loans

In this section, we briefly explain different loan types that banks hold in their balance sheet. We use terms similar to the ones used in the balance sheet and focus only on the three main loan types, i.e., real estate loans, commercial and industrial loans, and consumer loans, which differentiate the business of the commercial banks from that of other financial institutions. Finally, we use the term other loans to describe loans other than these three types.

Real Estate Loans. Banks report a loan as real estate loan when it is secured by a real property. Formally, a loan secured by real estate is a loan that, at origination, is secured wholly or substantially by a lien or liens on real property. To be considered wholly or

[18] Banks also hold a small fraction of loans in their trading portfolio.

substantially secured by a lien or liens on real property, the estimated value of the real estate collateral at origination (after deducting any more senior liens) must be greater than 50 percent of the principal amount of the loan at origination. For our purpose of categorization as well as reporting by the bank, the purpose of the borrower does not matter.

Here is an example that illuminates these issues. A bank grants a $\$25,000$ line of credit and a $\$125,000$ term loan to a commercial borrower for working capital purposes on the same date. The loans will be cross-collateralized by equipment with an estimated value of $\$40,000$ and a third lien on the borrower's residence, which has an estimated value of $\$140,000$ and first and second liens with unpaid balances payable to other lenders totaling $\$126,000$. The two loans should be considered together to determine whether they are secured by real estate. Because the estimated equity in the real estate collateral available to the subsidiary is $\$140,000-\$126,000 = \$14,000$, the two cross-collateralized loans for $\$150,000$ should not be reported as loans secured by real estate. Instead, the loans should be reported as commercial and industrial loans.

Commercial and Industrial Loans. These are loans originated by the banks to borrowers as long as it is for commercial and industrial purposes. Examples of borrowers are individuals, partnerships, corporations, and other business enterprises. The loan can be secured or unsecured, single-payment, or installment. Example of collateral can be production payments of a company. These loans may take the form of direct or purchased loans. Banker's acceptances are also reported as commercial and industrial loans only when the counterparty is a commercial or industrial enterprise. What matters for the bank to report a loan as commercial and industrial loan is the purpose of the borrower and not the borrower itself. For instance, a loan to a commercial entity for investment or personal expenditure would not be reported as such loans, whereas, a loan to an individual for the purpose of financing capital expenditures and current operations would be reported in this category. We note that this is unlike the previous category, real estate loans, where the collateral (the real estate) matters for the bank. So in the previous example, a loan to an individual for the purpose of financing capital expenditures and current operations would be reported as real estate loan if it is secured by real estate property.

Consumer Loans. Banks report loans to individuals for household, family, and other personal expenditures as consumer loans. Loan types can vary from extension of credit to credit cards to auto-loans. Purpose of the loan also can vary from purchases of household appliances or a boat, educational or medical expenses to personal taxes or vacations. All such loans must not meet the definition of a loan secured by real estate, and excludes loans to individuals for the purpose of purchasing or carrying securities. So in the case of consumer loans, borrower's type, purpose of the borrower and collateral, if any, all matter for the bank when they report the loan in their balance sheet. For instance, credit extended to individuals through credit cards or loan to an individual for buying an automobile would not be counted as consumer loan if it is substantially secured by a real estate property. The three types of loans described above are mainly in the loan portfolio of the bank. However, all such loans can also exist in the trading portfolio of the bank.

Other Loans. Banks also owe loans other than those explained above. These include loans to finance agricultural production and other loans to farmers. Examples are loans for purpose of financing agricultural production, for purchases of farm machinery, equipment, and implements, or purposes associated with the maintenance or operations of the farm. Also loans to depository institutions and acceptances of other banks, and loans to nondepository financial institutions. Example of the latter are loan to real estate investment trusts and to mortgage companies that specialize in mortgage loan originations and warehousing or in mortgage loan servicing, or to insurance companies and investment banks, or even to federally-sponsored lending agencies. Finally are loans to foreign governments and official institutions, and lease financing receivables. All these other loans are classified as corporate loans.

A.1.2 Standard Debt Securities

Treasury, Agency, State, and Politically Related Securities. Treasuries are all types of fixed income instruments issued by the U.S. government. In government agency securities, debt obligations are fully and explicitly guaranteed by the U.S. government. The difference between government agencies and government-sponsored agencies is that in the latter case the debt obligations are not explicitly guaranteed by the full faith and credit of the U.S. government. As an example, Ginnie Mae is a government agency, whereas Freddie Mac is a government-sponsored agency. Last, states and political subdivisions also issue debt obligations. We merge these three groups into one class of assets, i.e., Government securities.

A.1.3 Structured Debt Securities

Structured assets are those backed by a pool of other assets originated by the bank itself or other financial institutions. Another type of structured assets are collateralized debt obligations, which are pools of risky tranches from other structured assets further tranched and formed into a new security. In all cases of such assets, what matters for the purpose of our classification are the final holding institution of the asset (the bank) and the underlying assets.

Mortgage Backed Securities. Bank holding of MBS consists of Residential MBS and Commercial MBS.[19] In either case, the mortgages are in the form of pass-through and non-pass-through mortgages.[20] Both pass-through and non-pass-through mortgages (RMBS and CMBS) can be issued and/or guaranteed by GSEs and non-GSEs.[21] So, in total one can think of eight different possible combinations. For instance, banks hold pass-through RMBS, which are issued by GSEs, or pass-through CMBS, which are issued

[19] In the case of an RMBS, the underlying property is a 1-4 family residential property, whereas for CMBS, the securitization is done on commercial properties. As opposed to an RMBS, commercial mortgages are often set for a fixed term and therefore are less exposed to prepayment risk.

[20] Non-pass-through mortgages include all classes of collateralized mortgage obligations (CMO), real estate mortgage investment conduit (REMIC) and stripped MBS.

[21] Main GSEs are the Government National Mortgage Association (GNMA, Ginnie Mae), the Federal National Mortgage Association (FNMA, Fannie Mae), and the Federal Home Loan Mortgage Corporation (FHLMC, Freddie Mac). Non-GSEs are non-U.S. government issuers such as depository institutions, insurance companies, state and local housing authorities.

by non-GSEs. It can also happen that the issuers are different for a CMO. For instance, a CMO is issued by a non-GSE but the collateral is an MBS, which is issued by a GSE.

We note that the underlying securities in this class are residential or commercial real estate properties. Information on the weights of RMBS and CMBS are not available in Call Reports prior to 2009. Since then, the majority of pass-through RMBS are issued and guaranteed by GSEs. Other RMBS, such as CMO and REMIC, are mainly due to GSEs. However, it is likely that the order has been reverse prior to 2009, that is, banks tended to hold private labeled RMBS.

Asset Backed Securities. Although both MBSs and ABSs are structured products in a broad sense, banks report them as different items. As a rule of thumb, banks report assets either directly or indirectly related to a real property as a separate item. For instance, a commercial paper backed by loans secured by 1-4 family residential properties is reported under the MBS category, whereas, asset-backed commercial papers are reported as ABS and other debt securities. ABSs exist in both trading and non-trading accounts of the banks.

Structured Financial Products. Structured financial products generally convert a pool of assets (such as whole loans, securitized assets, and bonds) and other exposures (such as derivatives) into products that are tradable capital market debt instruments. Some of the more complex financial product structures mix asset classes in order to create investment products that diversify risk. One of the more common structured financial products is referred to as a collateralized debt obligation (CDO). Other products include synthetic structured financial products (such as synthetic CDOs) that use credit derivatives and a reference pool of assets, hybrid structured products that mix cash and synthetic instruments, collateralized bond obligations (CBOs), resecuritizations such as CDOs squared or cubed (which are CDOs backed primarily by the tranches of other CDOs), and other similar structured financial products. These strands of assets exist in both trading and non-trading accounts of the banks.

A.2 Market-Sensitive and Quasi Market-Sensitive Assets

In this section, we classify assets of the bank into groups that are sensitive to interest-rate and credit risks, such that assets within the same group are sensitive to the same risk factor. Such classification however is not straightforward as information about some assets cannot be found in details in the Call Report. In such cases, we group those assets as quasi market-sensitive assets. Market risk factors are defined in Section B.

A.2.1 Market-Sensitive Assets

Our perspective in classifying assets is twofold as we take stand of both borrowers' type and reference asset of loans or securities. Borrowers of the loans issued by the banks are households and firms. For instance, households are usually recipients of consumer loans, whereas firms usually receive commercial and industrial loans. But borrowers' type alone is not enough to account for all loans because it is likely that a loan issued to a firm is backed by some real estate property. In such cases, we take the view of loans' reference asset. For instance, when the loan meets the criteria of being a real estate loan, issued to either households or firms, we take them as real estate assets due to the important role of the real estate value in the dynamics of the economy. Similarly, for securities our stand is both borrowers' type and securities' reference asset. For instance, for Treasuries the borrower is the government, whereas for the MBS we rely on the type of the underlying asset to decide about the asset class of the MBS.

More specifically, the government class of market-sensitive assets consists of all trading and non-trading securities that are related to government, namely, Treasuries, government agency and government sponsored agency securities and state and political subdivisions securities. There exist also loans to states and political subdivisions, which we allocate in this class.

The real estate class of market-sensitive assets is predominately real estate loans, which are secured by real estate. We allocate all MBSs and commercial MBSs into this class as the reference assets are all real estate assets. Real estate loans, MBSs, and CMBSs are reported by banks as loans and securities. Banks also report *other debt securities*, which consists of structured debt securities (see A.1.3 for more details). In some case, they report the collateral for these securities and, when available and applicable, we use such information in order to assign them to the real estate class of market-sensitive assets.

Similar to the previous class, the corporate class of market-sensitive assets consists of assets from the loan portfolio as well as securities of the bank. Loans belong to the commercial and industrial loans, which can also be in the trading account when held for trading, or in the securities portfolio when backing asset backed securities.

Finally, the household class of market-sensitive assets consists of consumer loans both in the loan portfolio and trading account, and asset backed securities backed by such loans.

A.2.2 Quasi Market-Sensitive Assets

The task of assigning "other" assets into market-sensitive asset classes is not always straightforward. Given the significant size of such assets (approximately 20% of total assets), it is important to have a clear strategy account for them. In most cases, reclassifying these assets to the four market-sensitive asset classes is relatively easy.

However, there are instances where the information about an asset, its collateral or the borrower is not detailed enough. Different situations that we face and our decision criteria for each are as follow. When the asset cannot be clearly identified (e.g., when the collateral of an asset backed security is not known), we assign it equally to the real estate, corporate and household classes. Another instance is when the assets are known but cannot be disaggregated. As an example, *other debt securities* (see A.1.3 for details) in the trading account contains government securities and corporate bonds without any further information about the proportion of each item. We assign this category equally to government and corporate securities. The third situation occurs when an asset cannot be clearly linked to one of the four asset classes. For instance, we treat equity securities as corporate securities. In most cases, the value of the quasi market-sensitive assets that are hard to reclassify is low and may not have an impact on our evaluation of the capital shortfall of the bank.

In our empirical analysis, we assume that the sensitivity of the reclassified other assets to market factor indexes is the same as the sensitivity of the market-sensitive assets. One reason for this assumption is that some quasi market-sensitive assets may be more sensitive (for instance, equity securities) and some others may be less sensitive (for instance, foreign bonds). In the robustness analysis (Section 4.4.2), we consider alternative sensitive values for quasi market-sensitive assets, from low sensitivity, $\gamma = 0.5$, to high sensitivity, $\gamma = 1.5$. Our evaluation suggests that the impact on SEL is limited.

A.3 Other Assets

Table A1 summarizes information about other assets, which are not explicitly classified as cash or market-sensitive or quasi-market-sensitive assets. These assets, which are mainly fixed and intangible assets, represent on average 3.6% of total assets of commercial banks.

Table A1: Composition of Other Assets

Description	Amount ($ billion)	% of total
Investment in Unconsolidated Subsidiaries	1.2	5.7
Premises and Fixed Assets	4.0	18.4
Intangible Assets	16.4	75.8
Total	22	100

Note: This table displays the other assets, which are not part of risky assets. Numbers in the second column are asset weighted averages across banks from 1996 to 2016.

B BofA indices and Construction of Market Factors

BofA provides extensive coverage of global fixed income markets through 4'500 standard indexes tracking more than $66 trillion in fixed income securities. These indexes are available across different market segmentations such as sector, rating, maturity, and combinations of them. Information about criteria for selecting constituent securities and weighting and rebalancing strategies are available in the BofA website and by third party data vendors. Information about the indexes is summarized in Table 3 in the main text.

B.1 Government Related Indexes

As we explained in Section A of this appendix, government related assets are the sum of Treasuries, agency, state, and politically related assets. Thus, among the universe of BofA indexes, we select those whose performance best explains the performance of such assets. The selected indexes are the U.S. Treasury Master total return index, the U.S. Agencies Composite Master total return index, and the National Select Municipal Securities total return index. Treasury Master index contains 259 sovereign bonds across all maturities, with effective duration of about 6 years. Bonds with effective duration of up to 5 years represent around 60% of the total value of the index and bonds with effective duration of 10 years and more represent approximately 17%. Except few government guaranteed bonds in the Agencies Composite Master index, the other 95.5% of 447 bonds are agency securities. The effective duration is approximately 4 years. The third index contains U.S. Tax-Exempt Municipals, which contains $7,897$ bonds including Revenue bonds (54%), General Obligation bonds (45%), and Refunded bonds (1%). The effective duration is approximately 8 years.

The first index is available as early as 1990, the other two exist on a daily basis since 1996 and 2001, respectively, making them absent in our construction of the government index for the periods before.

To construct the final index, we calculate the weights of each of the three categories, that is, Treasuries, agency, and municipal securities over time using aggregate data (Flow of Funds) of the banking sector. On average, close to half of the government related assets are Treasuries and the other half is split between agency (20%) and municipal (30%) bonds. We construct a weighted average index using the weights of Treasuries, agency and municipal securities. Table 4 in the main text presents the summary statistics for the constructed indexes.

B.2 Real Estate Related Indexes

For real estate securities, we choose three types of indexes. First, Government National Mortgage Association (GNMA) represents the agency guaranteed mortgage backed securities. It consists of 116 bonds and has an effective duration of 5.4 years. Second, two indexes based on commercial mortgage backed securities and composed of $2'518$ bonds together are used to represent investment grade rating, with an average duration of 4.7 years. Finally, there are two indexes based on six home equity loan asset backed securities, with durations equal to from 1.6 and 6.2, respectively.

Similar to the government index, to construct the real estate risk factor, we approximate the contribution of various real estate securities in the banking sector using the Flow of Funds data. On average, 60% of the real estate assets are residential loans and securities and the rest are 32% commercial mortgages backed securities and finally 8% of home equity loans. We use these weights to construct the final real estate index. The selected indexes contribute to the final index only when they are available. For instance, the CMBS with BBB rating is only available since 2006, so we use the same index with bonds maturing 0-10 years only, which is available since 1998.

B.3 Corporate Related Indexes

The index representing corporate assets (commercial and industrial loans issued by the bank) is based on three indexes. The first index tracks the performance of $5'619$ non-financial investment grade corporate bonds, with an average duration of 7.8 years. The other two indexes represent sum of $1,888$ high yield corporate bonds. The majority of the bonds in these indexes belong to the industrial sector, so that the financial sector only represents 6% of the total number of bonds. The duration of the high yield indexes is half the duration of the high grade index.

As information about the weights of the various categories of corporate loans and securities in banks' balance sheet is not available in Flow of Funds data, we use an equal weighting for the three subindexes.

B.4 Household Related Indexes

We select an index such that it represents the non-residential household assets of the banks. Most of the household assets of banks are consumer loans, which are non-securitized. However, since the credit quality of the underlying affects the claims on the asset, we assume that the performance of the securitized assets is a good proxy for the performance of the underlying. Consumer loans are mostly composed of credit card loans and automobile loans. Thus we select four indexes that track the performance of credit card and automobile asset-backed securities across. These indexes together include 1206 securities with duration ranging from 1.2 to 1.9 years and correspond to different ratings of the ABS.

We construct the final risk factor using the weighted average of individual indexes where we infer the weights from the Flow of Funds data. On average consumer loans consist of 45% automobile loans, 55% credit card loans.

C Interest Rates

The cost of deposits ($R^{(i)}_{Dep,t}$) is obtained for each bank by dividing *Interest Expenses on Deposits* to *Average Interest Bearing Deposits*, where the latter is the average of interest bearing deposits of current and previous calendar quarters. The cost of borrowing ($R^{(i)}_{D,t}$) is computed as *Interest Expenses on Borrowing* divided by *Average Borrowing*. Average Borrowing is defined as *Average Interest Bearing Liabilities* minus *Average Interest Bearing Deposits*. For the interest rate on cash ($R^{(i)}_{F,t}$), we use the Federal Fund rate for all banks. Last, for other (unclassified) assets, which are mostly fixed assets, we assume that the return is $R^{(i)}_{O,t} = 0$.

Comparing these rates obtained from the information in the balance sheet and Federal Fund rate, we find that $R_{F,t} < R^{(i)}_{Dep,t} < R^{(i)}_{D,t}$ (with average values: $1.8\% < 1.9\% < 3.5\%$).[22]

[22]These rates required some cleaning. Missing values were replaced by the value from previous quarter. For the cases where the first quarter was missing, we used the rate of the same quarter from next firms in the size ranking. Rates higher than 20% were replaced by the median of the sample for the same quarter.