Technical Appendix (Online)

This document, not intended for publication, provides supplementary material to the paper "Predicting the Stressed Expected Loss of Large U.S. Banks." We provide additional details on the econometric methodology (Section A), on the data (Sections B, C, D, E, and J), and on the results (Sections F, G, H, and I).

A Dynamic Conditional Beta Parameters

We use the notations $H_{[A,B],d+1} = Cov_{d-1}[r^{(m)}_{A,d+1}, r^{(m)}_{B,d+1}]$ and $H_{[A,b],d+1} = Cov_{d-1}[r^{(m)}_{A,d+1}, r^{(m)}_{B,d}]$, where an upper-case letter for the asset class means that the return is dated $d+1$ and a lower-case letter means that the return is dated d. With these notations, we define dynamic beta parameters as follows: Government factor:

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

Real-estate factor:

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

Corporate factor:

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

Household factor:

$$\beta_{H,d+1} = (\beta^{(HL)}_{H,d+1}, \beta^{(G)}_{H,d+1}) = \begin{pmatrix} H_{[h,h],d+1} & H_{[h,G],d+1} \\ H_{[G,h],d+1} & H_{[G,G],d+1} \end{pmatrix}^{-1} \begin{pmatrix} H_{[H,h],d+1} \\ H_{[H,G],d+1} \end{pmatrix}.$$

B Commercial Banks

B1 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. 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 DFAST stress testing and evaluates the health of large financial institutions under stressful economic and financial market conditions. 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 banks. Given our interest in the commercial banking activity of these firms, we further check whether the business of the institutions is predominantly commercial banking.

Our criteria for the inclusion of a given commercial bank are that (1) total assets of the bank represent at least 50% of the total assets of the parent BHC and (2) the deposits of the bank represent at least 50% of the liabilities of the parent BHC. Thirty-one commercial banks, listed in Table 1 in the main text, pass these criteria.[1] Balance sheet data come from Call Report forms FFIEC 031 and 041.[2] All such data are available at a quarterly frequency and collected from the SNL platform. Our final sample is 31 commercial banks over the

[1]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.

[2]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. These forms are different from the consolidated financial statement completed on a quarterly basis by the top-tier BHC (FR Y-9C) and from that completed by the parent companies only (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. Other important information, such as the market capitalization and the credit rating, is usually available for the top-tier BHC only.

period 1996–2016, that is, 2,604 bank-quarter observations, representing more than 70% of the total assets of all commercial banks.

Table A.1 presents summary statistics of some important ratios for the commercial banks in our sample as of 2016Q4. First, the assets of the commercial banks represent the main assets of their ultimate parent, as they represent on average 88% of the assets of the ultimate parent, with a minimum of 60%. Second, deposits represent on average 87% of the liabilities (deposits plus debt) of these commercial banks. Finally, deposits in the commercial banks represent on average 77% of the liabilities of their ultimate parent. Santander Holdings USA has the minimum deposit holdings (52%) within its commercial bank, Santander Bank.

Table A.1: Summary Statistics on Commercial Banks and Ultimate Parents

	$\frac{\text{Commercial Bank Assets}}{\text{Ultimate Parent Assets}}$	$\frac{\text{Commercial Bank Deposits}}{\text{Commercial Bank Liabilities}}$	$\frac{\text{Commercial Bank Deposits}}{\text{Ultimate Parent Liabilities}}$
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 BHC. Numbers are based on balance sheet of the 31 commercial banks and their ultimate parent as of 2016:Q4.

B2 Structure and Evolution of the Balance Sheet

Table A.2 below provides a summary of the aggregate balance sheet of the large commercial banks in our study (in percentage of total assets). Cash refers to any asset with maturity less than one quarter. It represents 13.7% of total assets. Market-sensitive assets are subject to interest rate and credit risks and could be affected by substantial changes in their value. They represent 80.2% of total assets on average. The remaining assets correspond to derivatives (3.2%) and the other assets that are not present in our classification above (3.7%). Figure A.1 (Panel A) demonstrates that the weights of the four categories of assets are relatively stable over time. In particular, the weight of market-sensitive assets ranges from 75% to 85%, with a value equal to 80% at the end of the sample.

The four categories of market-sensitive assets are composed as follows. (1) Government securities (7.2% of total assets) include U.S. Treasury securities (44%), government agency and government-sponsored agency securities (22%), and securities issued by state and political agencies (34%). (2) Real-estate loans and securities (37.2% of total assets) are assets related to real estate of any kind. They are either real-estate loans directly lent by the banks (58.7%) or mortgage-backed securities (MBS) and other debt securities that are classified in this category (41.3%). 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. Residential real-estate loans represent 74% on average of all real-estate loans.[3] (3) Corporate loans and securities (23.1% of total assets) include loans with commercial and industrial purposes (55%) and securities backed by these loans, corporate bonds, and other debt securities that are classified in this category (45%). (4) Household loans and securities (12.7% of total assets) are either consumer loans directly lent by the bank (59%) and securities backed by consumer loans or other asset-backed securities (ABS) that are relevant to this category (41%).[4]

Table A.2: Simplified aggregate balance sheet of commercial banks

Assets		**Liabilities and Equity**	
Cash:	13.7	Deposits:	68.1
Market-sensitive Assets:	80.2		
- Government:	7.2	Debt:	19.4
- Real estate:	37.2	- Short-term debt:	17.6
- Corporate:	23.1	- Long-term debt:	1.8
- Household:	12.7		
Derivatives:	3.2	Derivatives:	3.0
Other Assets:	3.7	Equity:	9.4

The evolution of the various categories of market-sensitive assets is plotted in Figure A.1 (Panel B). The figure reveals some important changes in the composition of the portfolio

[3]The Financial Accounts of the United States indicate that a common trend exists between the two categories of real-estate loans. The correlation between the annual growth rates of residential and commercial loans is equal to 84% on average between 1996 and 2016.

[4]Details on the classification of the various market-sensitive assets are provided in Online Appendix **??**. As this classification requires further assumptions for some assets, we also demonstrate that the impact on SEL of these assumptions is limited.

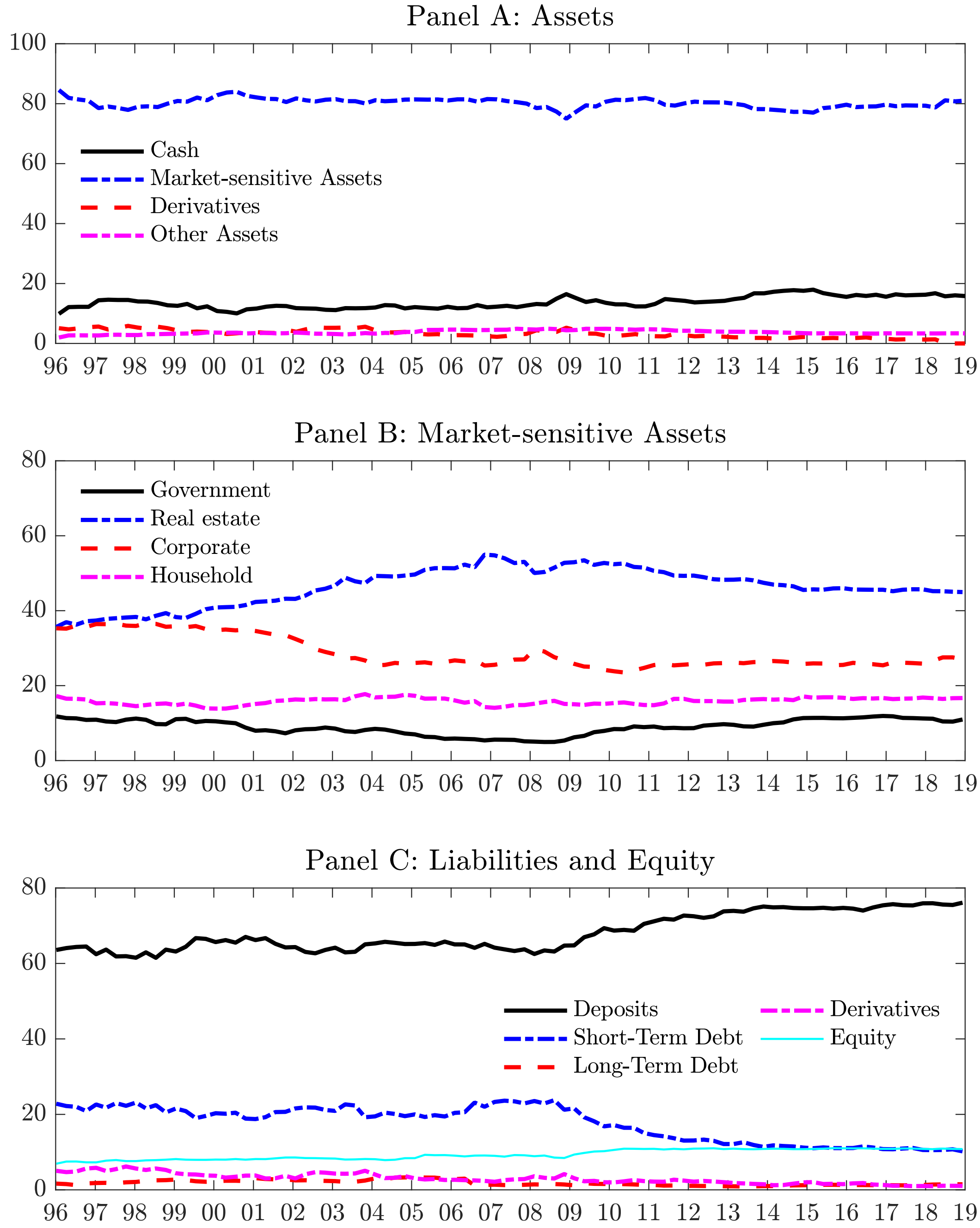
of commercial banks over the sample period. At the onset of the dot.com crisis, at the beginning of the sample, banks reduce their holdings of corporate and government securities and massively invest in real-estate loans and securities (from 34% in 1996 to 54% in 2009). However, after the global financial crisis, banks lighten their real-estate portfolios in favor of government securities.

Banks report the amount of revaluation gains (losses) from the mark-to-market value of interest rate, foreign exchange rate, commodity, equity, and credit derivative contracts held for trading purposes as derivatives with a positive (negative) fair value. We neglect the contribution of derivatives for two reasons. First, in our sample, derivatives represent, on average, 3.2% of the assets and 3% of the liabilities. If we assume that the gains and losses of the trading derivatives cancel one another out, the net is on average equal to 0.2% of total assets only. Second, as the portfolio of derivatives is mainly composed of interest rate swaps, the risk taken on most derivatives is interest rate risk. As our stress scenarios consider shocks to the credit market risk factors, we do not expect any material impact on SEL estimates.[5]

Total liabilities consist of 68.1% deposits, 19.4% debt (17.6% short-term debt and 1.8% long-term debt), 3% derivatives, and 9.4% equity capital. Panel C of Figure A.1 displays the evolution of the liability classes over time. It clearly demonstrates that long-term debt represents a negligible part of commercial banks' financing. We also observe that after the global financial crisis, commercial banks rely more on deposits (from 65% of total liabilities before the crisis to 75% after the crisis) and substantially reduce their use of short-term debt (from 25% before the crisis to 10% after the crisis). Finally, the figure reveals that the strengthening of bank capital regulation results in an increase in equity financing after the crisis (from 9% to 11%).

[5] Recent papers by Rampini and Viswanathan (2019) and Vuillemey et al. (2020) show that the magnitude of hedging through derivatives is fairly small and that most banks cut their hedging in bad times. In addition, Caglio et al. (2016) use transactions in the corporate single-name CDS market and document that, in contrast to the goal of using credit derivatives for hedging, banks are net sellers of credit protection for the firms in their loans and securities portfolios. Begenau et al. (2015) propose an elaborate strategy to measure the sensitivity of derivatives to interest rate and credit risks. They report negligible credit risk exposure of the derivatives book.

Figure A.1: Evolution of the Main Categories of Assets



Note: Panel A displays the four main types of assets as a fraction of total assets. Panel B displays the four main types of market-sensitive assets as a fraction of total market-sensitive assets. Panel C displays the five main types of liabilities of the bank as a fraction of total liabilities and equity. Data are quarterly and obtained from Call Reports. Averages are taken across banks and are weighted by the total assets of each bank.

C Measuring SEL for BHCs

Our main results are based on data at commercial bank level. As discussed in Section 3.1 of the main text, we need to address two important issues to apply our methodology to BHCs. First, BHCs are not requested to provide as much information as commercial banks on the composition of their assets, in particular regarding the issuers of the securities held by the bank. Currently the data provided by BHCs on the composition of their assets is sufficient to construct the SEL measure. However, the historical data for some BHCs are not available or sufficiently detailed, and thus we did some data adjustment. Overall, there are ten BHCs in our sample with missing data for a few years at the beginning of the sample. In seven cases (mostly subsidiaries of foreign financial institutions), we used the data from the commercial bank subsidiary to represent the parent BHC. In three cases (Goldman Sachs Group, Morgan Stanley, and American Express Company), which were operating as an entity other than a BHC before the financial crisis and were not involved in any significant commercial banking activity, we could not compute their SEL before 2009, which is assumed to be equal to 0 until the end of 2008. As a result, before 2009 the estimated SEL for BHCs is only a proxy for the measure we would have constructed if we had full sample data for all BHCs.

Second, if we consider BHCs instead of commercial banks, we need to take into account the implicit guarantee of the BHC long-term debt by the government.[6] Arslanalp and Liao (2015) assumes that the government implicitly guarantees a fraction $(1-\alpha)$ of all BHC liabilities, where α denotes the percent loss per insured liability. We follow a similar approach and proceed as follows: First, we compute the total capital shortfall of a defaulting BHC in an extreme downturn assuming that all liabilities (including long-term debt) are guaranteed by the government:

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

This measure can be viewed as an upper bound for the cost to the government because it assumes that the government would bail out all debt issued by a defaulting BHC.

Second, we measure the implicit cost of the guarantee by the government of all the

[6] Whereas long-term debt only represents 1.9% of commercial bank liabilities on average, it corresponds to 7.9% of BHC liabilities.

deposits and short-term debt and a fraction $(1-\alpha)$ of the long-term debt:

$$\begin{aligned} SEL^{(i)}_{t:t+1} &= (1+R^{(i)}_{Dep,t})Dep^{(i)}_t + (1+R^{(i)}_{SD,t})SD^{(i)}_t + (1-\alpha)(1+R^{(i)}_{LD,t})LD^{(i)}_t \\ &\quad -E_t[A^{(i)MV}_{t+1} \mid A^{(i)MV}_{t+1} \leq L^{(i)BV}_{t+1} \text{ in a Market downturn}_{t:t+1}]. \end{aligned} \tag{A.2}$$

As before, a default occurs when the mark-to-market value of the assets falls below the book value of the liabilities. We consider two values for the implicit cost of the guarantee, $\alpha = 0\%$ and $\alpha = 20\%$, which corresponds to the calibration proposed by Arslanalp and Liao (2015).

In Figure A.2, we display the average probability of default and the aggregate SEL for the 34 BHCs covered by the 2017 stress test performed by the Federal Reserve Board. This list includes the two large investment banks, Goldman Sachs Group, Morgan Stanley, and American Express Company. We do not report the evolution of the probability of crash as it is the same as the one reported in Figure 3. The average probability of default of BHCs is lower than the probability of default estimated for commercial banks. In January 2009, the average probability of default is equal to 40% for commercial banks and 33% for BHCs. Similarly, in December 2018, it is equal to 2% for commercial banks and 2.5% for BHCs. The main reason for this low probability of default is that BHCs rely more on equity financing and therefore suffer slightly less in a market downturn.

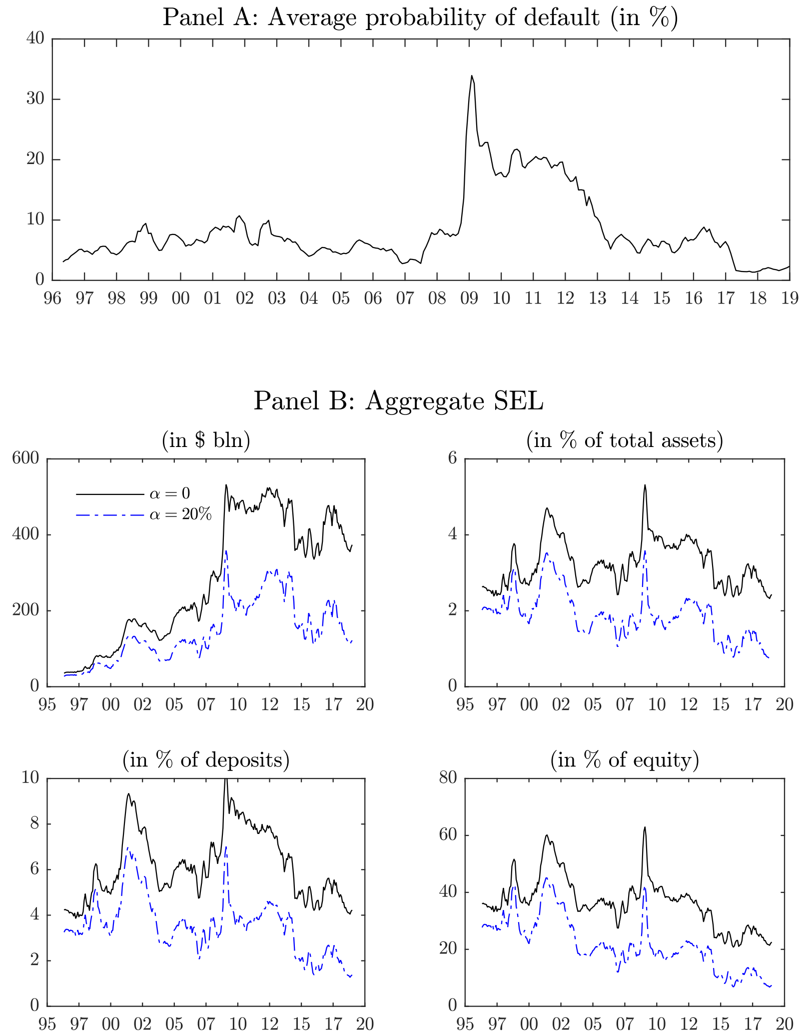
For $\alpha = 0$, the aggregate SEL would be higher than our previous estimate for commercial banks for two reasons. First, we now use all BHCs of the list of the 2017 stress test (including Goldman Sachs Group and Morgan Stanley). Second, we assume that all long-term debt is guaranteed by the government. Numbers before 2009 are probably underestimated because we do not have sufficient details on the assets of Goldman Sachs Group and Morgan Stanley. As Panel C reveals, during the financial crisis, SEL increases to $532 billion. This level corresponds to approximately 5.1% of total assets, 10% of deposits, and 61% of capital equity. This last value reflects the high leverage of banks at the beginning of the subprime crisis and their lack of equity. Between 2009 and 2013, SEL is consistently between $450 and $525 billion. In the last five years of the sample, it decreases to levels close to $400 billion, and is as low as $370 billion at the end of 2018, reflecting the improvement in bank conditions. Given the increase in the size of the banks' balance sheet, SEL reduces to approximately 2.4% of assets, 4.2% of deposits, and 22.6% of equity.

If we now assume that 80% of the long-term debt is guaranteed by the government, SEL is approximately equal to 300 billion between 2009 and 2013 and below 200 billion afterwards.

This estimate is close to the SEL obtained for commercial banks. At the end of the sample, BHC SEL is close to 1% of total assets, 2% of deposits, and 10% of equity.

In Table A.3, we consider the same exercise but now we estimate SEL at the BHC level for all 34 institutions listed in the 2017 stress test (assuming $\alpha = 0\%$). We define SRISK accordingly, which consists in adding Goldman Sachs Group, Morgan Stanley, and American Express Company to the list. As expected, the results improve for SEL because we define the capital shortfall for the same entities as in the stress tests. Panel A corresponds to the government capital injections in the financial crisis. Panel B corresponds to the prediction of the loss of capital projected in the DFAST stress tests. The parameter estimates for SEL are close to 1 and highly significant for all all regressions. The adjusted R^2 values range between 50% and 85%. In general, for SRISK, parameter estimates and adjusted R^2 are substantially lower. Adjusted R^2 values are in a range between 25% and 65%. The reason for this disappointing result is that some banks (such as Wells Fargo, U.S. Bancorp, or PNC Financial Services Group) have SRISK values equal to 0 since 2014, whereas the projected loss of capital is high.

Figure A.2: Probability of Default and Aggregate SEL for BHCs



Note: Panel A displays the probability of default, measured in percentage. Panel B displays the aggregate SEL, measured in $ billion, in % of total assets, in % of deposits, and in % of equity. BHCs correspond to the sample of the 34 largest and most complex BHCs subject to the 2017 stress test carried out by the Federal Reserve Board.

Table A.3: Predicting Government Capital Injections in the Financial Crisis and Loss of Capital Projected in the Severely Adverse Scenario for BHCs

	I	II	III	IV	V	VI
Panel A: Government Capital Injections in the Financial Crisis						
	Regressors as of 2007-12			**Regressors as of 2008-3**		
Constant	-0.375	0.996***	–	-0.420 *	1.105***	–
	(1.580)	(4.772)		(1.725)	(5.012)	
$\log(1+SEL_i)$	0.910***	–	1.024***	0.892***	–	1.026***
	(8.299)		(5.635)	(8.252)		(6.448)
$\log(1+SRISK_i)$	–	0.539***	-0.024	–	0.496***	-0.026
		(3.727)	(0.131)		(2.895)	(0.164)
Adjusted R^2 (in %)	77.238	39.186	77.259	77.036	26.954	77.069
Panel B: Loss of Capital Projected in the Severely Adverse Scenario						
	2014 Stress test			**2015 Stress test**		
Constant	-0.6472 *	0.9590***	–	-0.6142***	0.8330***	–
	(1.943)	(5.424)		(2.498)	(4.482)	
$\log(1+SEL_i)$	0.9657***	–	0.6438***	1.0234***	–	0.8127***
	(6.760)		(3.864)	(9.069)		(5.463)
$\log(1+SRISK_i)$	–	0.6067***	0.3562 **	–	0.6809***	0.1873
		(5.342)	(2.138)		(5.482)	(1.259)
Adjusted R^2 (in %)	57.530	45.491	62.840	71.114	46.816	72.477
	2016 Stress test			**2017 Stress test**		
Constant	-0.0712	0.9589***	–	-0.6180 **	1.1924***	–
	(0.265)	(4.385)		(2.346)	(6.876)	
$\log(1+SEL_i)$	0.9484***	–	0.8235***	0.9560***	–	0.8617***
	(6.908)		(4.530)	(8.763)		(6.604)
$\log(1+SRISK_i)$	–	0.5405***	0.1765	–	0.5607***	0.1383
		(4.244)	(0.971)		(3.951)	(1.060)
Adjusted R^2 (in %)	58.608	34.018	59.793	69.665	30.688	70.694
	2018 Stress test			**All stress tests**		
Constant	-0.8962	1.3088***	–	-0.4850***	1.0582***	–
	(3.150)	(6.445)		(3.836)	(12.442)	
$\log(1+SEL_i)$	1.1596***	–	0.8786***	0.9726***	–	0.7816***
	(9.841)		(7.541)	(17.431)		(11.985)
$\log(1+SRISK_i)$	–	0.6641***	0.1214	–	0.5939***	0.2184***
		(3.997)	(1.042)		(10.166)	(3.349)
Adjusted R^2 (in %)	74.387	31.212	75.227	64.184	37.718	66.425

Note: This table presents cross-section predictive regressions. Panel A predicts the total amount of capital injection by the U.S. government between October 2008 and December 2009 (CPP of the TARP). The endogenous variable is the log total amount of capital injection $\log(CI_{t+1}^{(i)})$. Panel B predicts the loss of capital projected by large financial institutions in the severely adverse scenario of DFAST stress tests. Regressors are $\log(SEL_t^{(i)}+1)$ and $\log(SRISK_t^{(i)}+1)$. Regressors for the stress test for year Y are as of end of December of year $Y-1$. The table reports the parameter estimates, the p-values in parentheses, and the adjusted R^2. ***, **, and * denote significance at the 1%, 5%, and 10% significance level, respectively.

D Classification of Market-Sensitive Assets

In this appendix, we explain how we classify the assets of a bank into groups that are sensitive to interest-rate and credit risks, such that assets within the same category are sensitive to the same risk factor. For some other assets, such classification is not always straightforward because information about these assets cannot be found in details in the Call Reports. In such cases, when relevant, we adopt simple rules to reclassify them as market-sensitive assets and when impossible we keep them as other assets. The Appendix J provides details on the main categories of banks' assets.

D1 Market-Sensitive Assets

Our classification of the market-sensitive assets relies on both the borrowers' type and the reference asset of the loans or securities. More specifically, the government category 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. We also allocate loans to states and political subdivisions to this category.

The real-estate category of market-sensitive assets is predominately composed of real-estate loans, which are secured by a real-estate property. We also allocate all mortgage-backed securities (MBSs) and commercial MBSs to this category, as the reference assets are all real-estate assets. Banks also hold a small amount of securities backed by home equity loans, which we assign to the real-estate asset category.

Similarly, the corporate category of market-sensitive assets consists of commercial and industrial loans (in the loan portfolio or in the trading account when held for trading) and asset-backed securities backed by such loans. Other assets that belong to this category are some structured financial products and "other debt securities" in the trading account that also includes corporate bonds.

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

D2 Reclassification of Other Assets

As the "other assets" category in the banks' balance sheet represents approximately 20% of total assets (before reclassification), it is important to have a clear strategy to account for them. We have adopted relatively simple rules to reclassify an asset when the information about the asset, its collateral, or the borrower is not sufficiently detailed (16.4% of total assets). Different situations that we face and our decision criteria for each are as follow.

- The asset cannot be clearly identified. For instance, when the collateral of an asset-backed security is not known. We assign it proportionately to the real-estate, corporate, and household classes.

- The asset is known but cannot be disaggregated. For instance, the item "other debt securities" in the trading account contains government securities and corporate bonds without any further information about the proportion of each item. We assign this category proportionately to government and corporate securities.

- The asset cannot be clearly linked to any of the four asset classes. For instance, equity securities cannot be classified as loans or debt securities. We assign this category to corporate securities.

The total value of the assets that we could not reclassify with this set of rules is low (approximately 3.6% of total assets). They are mainly intangible assets (75.8%) and premises and fixed assets (18.4%), the rest being essentially investment in unconsolidated subsidiaries. They are unlikely to have any substantial impact on the evaluation of the capital shortfall of the bank.

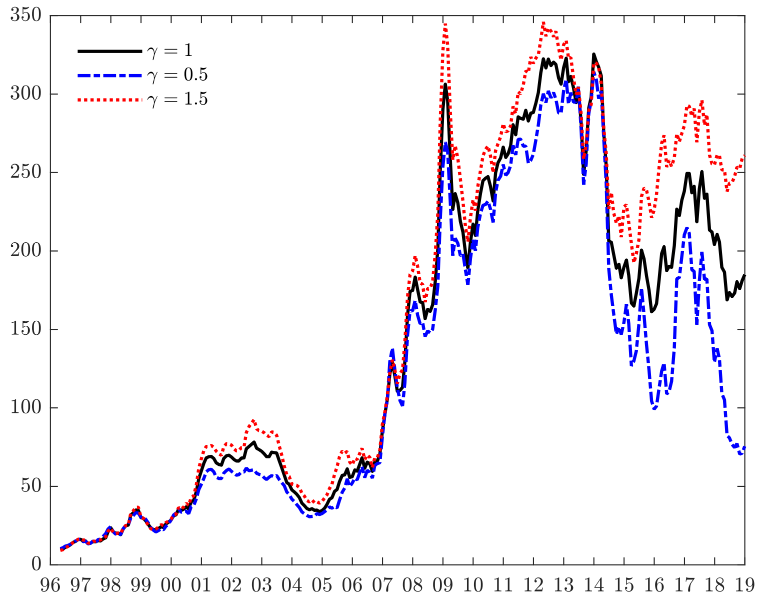
D3 Sensitivity Analysis

In our empirical analysis, we assume that the sensitivity of the reclassified assets to market factor shocks is the same as the sensitivity of the market-sensitive assets. One reason for this assumption is that some reclassified assets may be more sensitive (for instance, equity securities) and some others may be less sensitive (for instance, foreign bonds).

To evaluate the impact of this assumption, we proceed as follows: if we consider the case of assets related to corporate firms, thus far we have assumed that the sensitivity of corporate loans and securities (denoted here 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, which means that 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) for the four categories of market-sensitive assets. Figure A.3 indicates that the sensitivity of SEL to γ is limited over most of our sample. The impact is sizable only in the very recent period (2015–2016). A higher sensitivity ($\gamma = 1.5$) would result in an increase in SEL from \$250 and \$280 billion. This overall limited effect is due to the relatively small weight of reclassified other assets.

Figure A.3: SEL with Different Sensitivity of Reclassified Other Assets



Note: This figure displays 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.

E Construction of Market Risk Factors

Bank of America Merrill Lynch (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 on Bank of America Merrill Lynch website and from third party data vendors. Information about the indexes is summarized in Table A.4.

E1 Government Related Indexes

As explained in Section J of this Online Appendix, government related assets are the sum of Treasuries, agency, state, and politically related assets. Thus, among the universe of 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 period before. To construct the final index, we use 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.

E2 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.[7] 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 a duration equal to from 1.6 and 6.2 years, respectively.

Similar to the government risk factor, 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 mortgage-backed securities and finally 8% of home equity loans. We use these weights to construct the final real-estate risk factor. 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 in 0–10 years only, which is available since 1998.

E3 Corporate Related Indexes

The factor 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 $1,888$ 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 sub-indexes.

[7] This index is very close to the Federal National Mortgage Association (FNMA) and Federal Home Loan Mortgage Corporation (FHLMC) indexes, with correlations equal to 98.1% and 97.9%, respectively, over the sample.

E4 Household Related Indexes

We construct a factor that 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 and automobile loans. Thus we select four indexes that track the performance of credit card and automobile asset-backed securities. These indexes together include $1,206$ 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 and 55% credit card loans.

Table A.4: Selected Market Risk Factor Indexes

Selected Index	I Ticker	II Number of bonds	III Rating	IV 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 risk 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. 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 Bank of America Merrill Lynch as of end of 2016.

F Parameter Estimates

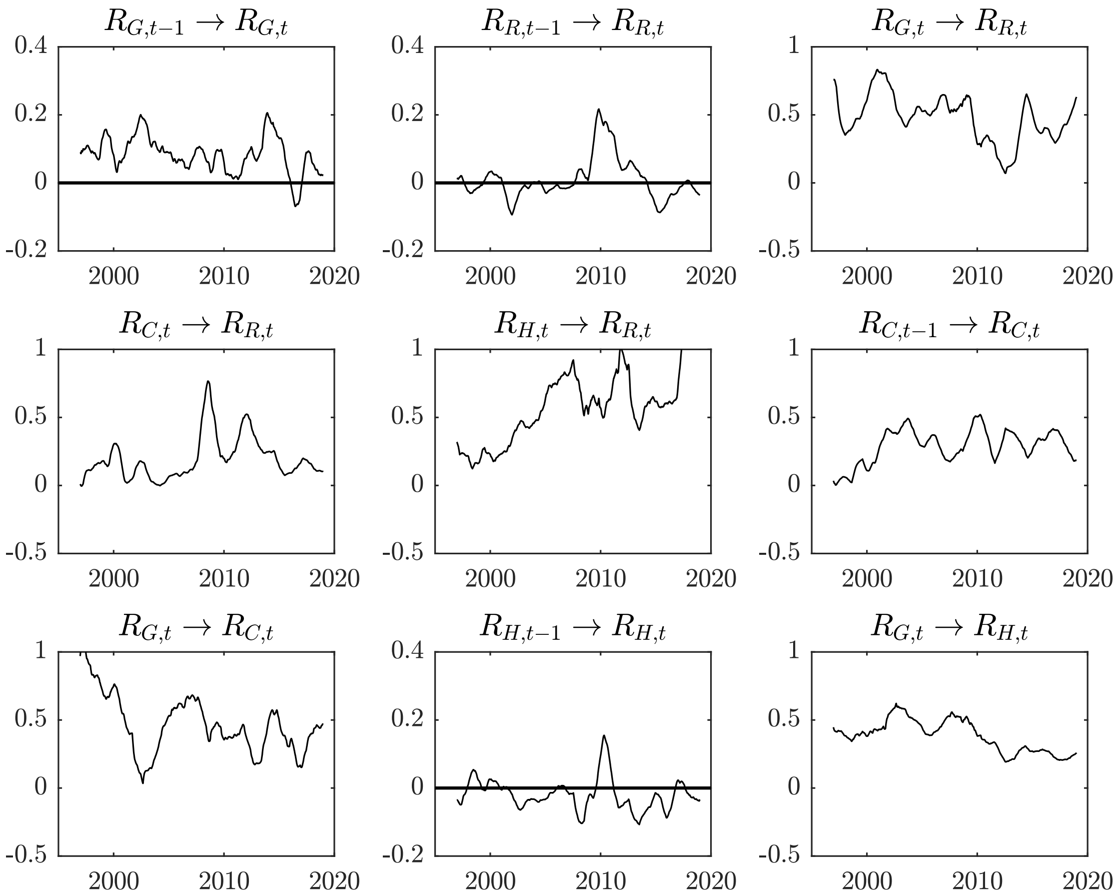
Figure A.4 displays the dynamics of the conditional betas implied by the model (estimated over the complete sample), which reflect the time dependence between factor returns. Some interesting patterns emerge. First, own lagged factor return usually has a limited impact. The only exception is the lagged corporate risk factor return, which has a large positive impact on the current corporate risk factor return. Second, the contemporaneous sensitivity to the government risk factor return is always positive, typically between 0.2 and 0.7, reflecting the sensitivity of credit markets to interest-rate risk shocks. We note that the sensitivity to the government factor tends to decrease in the recent period. Third, the real-estate risk factor return is, in general, more sensitive to the household risk 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 temporary switch during the subprime crisis, with a stronger sensitivity to the corporate factor and a weaker sensitivity to the household factor.

Figures A.5 and A.6 display the evolution of the estimated parameters over time, based on five-year rolling windows. Figure A.5 represents the parameters of the univariate MA(1)-GARCH models and the skewed t distribution. We do not report ω_a to save space. As the figure reveals, the parameters vary substantially over time, which suggests that a rolling window estimation is necessary. The temporal evolution is pronounced for the MA(1) parameter ξ_a (corporate and household risk factors), for the GARCH asymmetric parameter γ_a (corporate risk factor), for the skewed t degree of freedom ν_a (government and corporate risk factors), and for the skewed t asymmetry parameter λ_a (real-estate risk factor).

Figure A.6 displays the evolution of the DCC and copula parameters over time. Parameters δ_1 and δ_2 vary over time and indicate that the correlation matrix is highly persistent. The degree of freedom of the copula $\bar{\nu}$ increases substantially between 2001 and 2007, from 5.5 to 9.5, indicating that market factors are relatively less affected by joint extreme events. Estimates of $\bar{\nu}$ severely decrease during the subprime crisis to levels close 6, suggesting a stronger dependence between market risk factors.

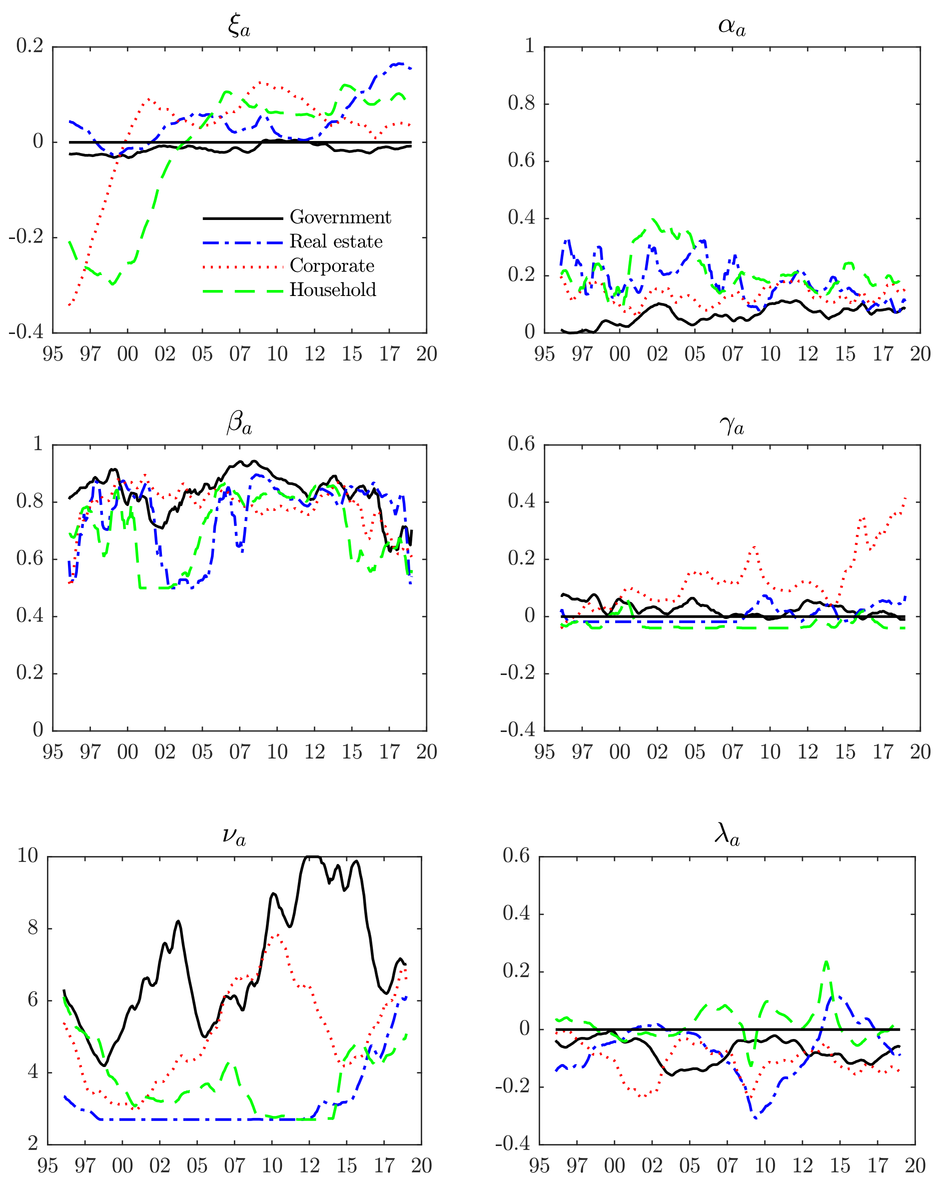
We also find that the dependence between market risk factor returns implied by the copula model slightly varies over time. The dynamics of the correlation matrix Γ are presented in Panels B and C. On the one hand, the dependence between the government risk factor and the other factors is low and varies between -10% and 10% over time. The correlation between the government and real-estate risk factors is the only correlation to be affected by a large change, as it temporarily decreased to −25% in 2009. On the other hand, most of other dependence parameters vary in a similar range between −10% and 10%. The only correlation that varies more substantially is between corporate and household risk factors. Even if it is close to 0 over most of the sample and equal to 6% on average, it experiences some episodes at a relatively high level.

Figure A.4: Estimates of Dynamic Conditional Betas



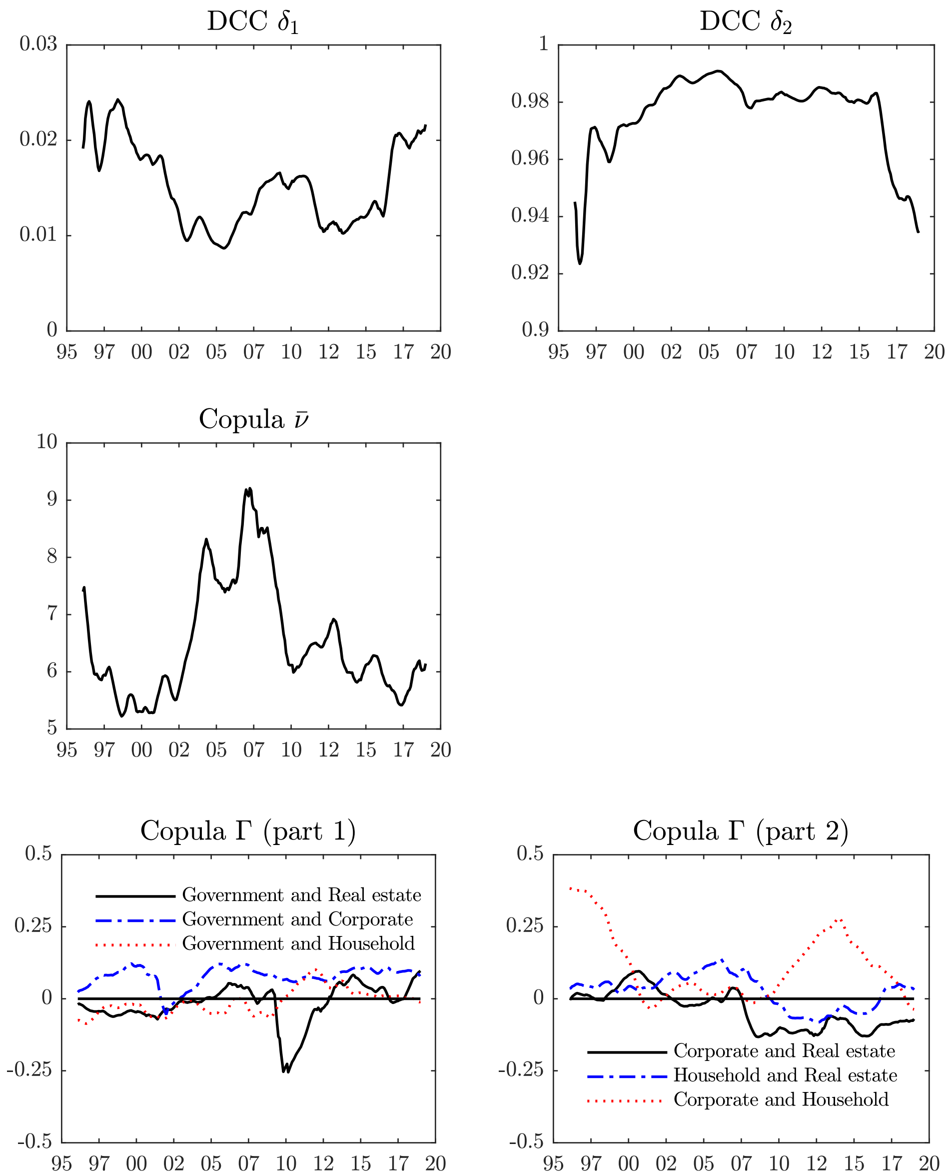
Note: This figure displays the temporal evolution of the conditional beta estimates. The model is estimated using the full sample from January 1996 to December 2018.

Figure A.5: Temporal Evolution of Univariate GARCH Parameter Estimates



Note: This figure displays the temporal evolution of the estimates of the univariate GARCH models: the MA(1) parameter ξ_a; the GARCH parameters α_a, β_a, and γ_a; and the skewed t parameters ν_a and λ_a. The parameters are estimated using rolling windows of five years.

Figure A.6: Temporal Evolution of DCC and Copula Parameter Estimates



Note: This figure displays the temporal evolution of the estimates of the DCC and copula degree of freedom: the DCC parameters δ_1 and δ_2; and the degree of freedom $\bar{\nu}$ and correlation matrix Γ of the copula. The parameters are estimated using rolling windows of five years.

G Alternative Thresholds

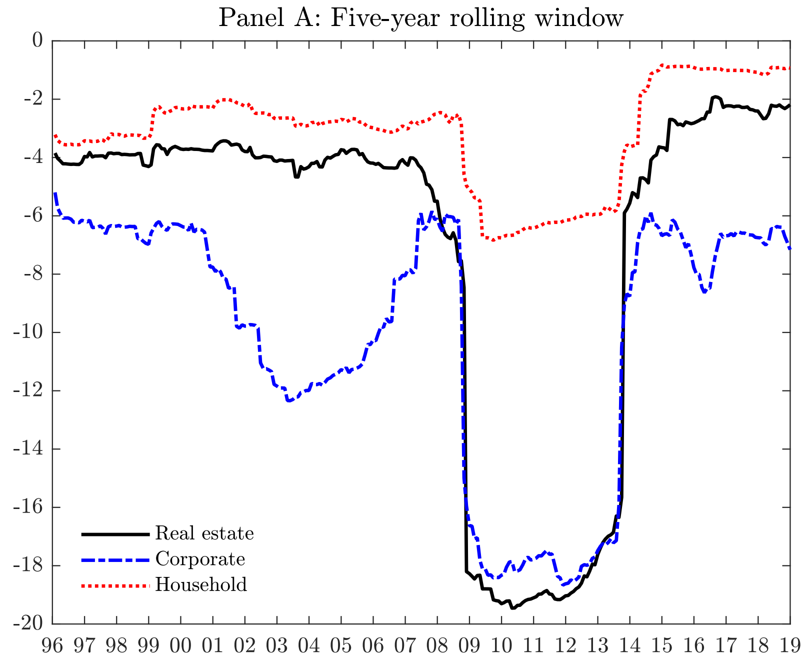
An important aspect of the stress scenario is the way the thresholds are determined. In the main results, the thresholds are based on the EWMA estimation of the standard deviation of the market factor returns. As alternative approaches, we examine two other cases: (1) the standard deviation is estimated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

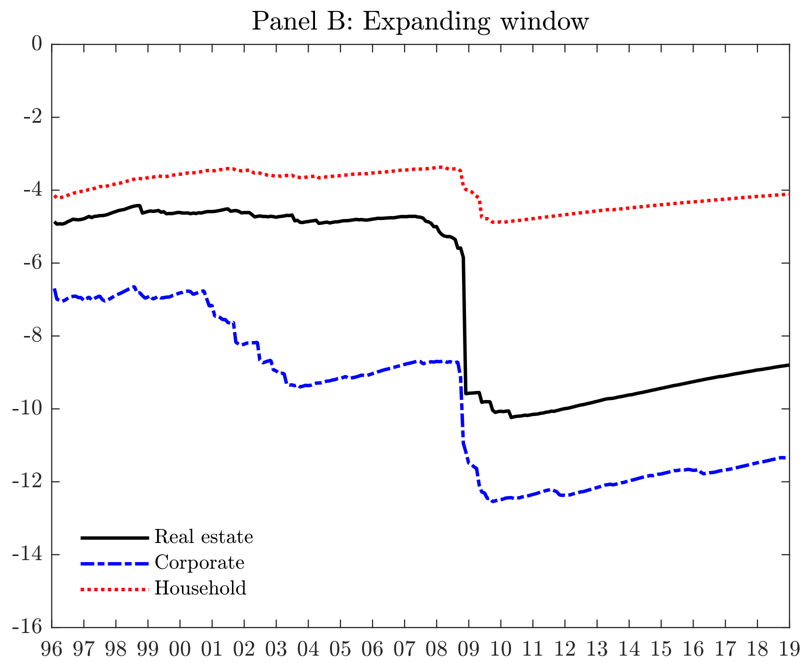
Figure A.7 displays the alternative thresholds obtained from these approaches. The levels are relatively similar before the subprime crisis. However, the impact of the crisis is much stronger (almost twice as large) with the five-year window than with the expanding window. After the crisis, the thresholds implied by the five-year window go back to pre-crisis levels, while those implied by the expanding window remain at relatively low levels. Our baseline case based on EWMA standard deviations can be viewed as an intermediate case.

Figures A.8 and A.9 show that these approaches have an opposite impact on the probability of a credit market downturn and the average probability of default during and after the subprime crisis. With the five-year rolling window, the probability of downturn is reduced compared to the 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 downturn is less likely. However, if a market downturn occurs, a default of a bank is more likely. In the case of an expanding window, the probability of a downturn is increased compared to the baseline case after the subprime crisis. In contrast, the probability of default is significantly reduced. These results clearly indicate that the probabilities of a downturn and a bank's default depend on the magnitude of the shocks that we consider.

Importantly, the figures also indicate that the estimate of 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 bank's default. This result is important because it demonstrates that the precise way the thresholds are defined has limited impact on the SEL value.

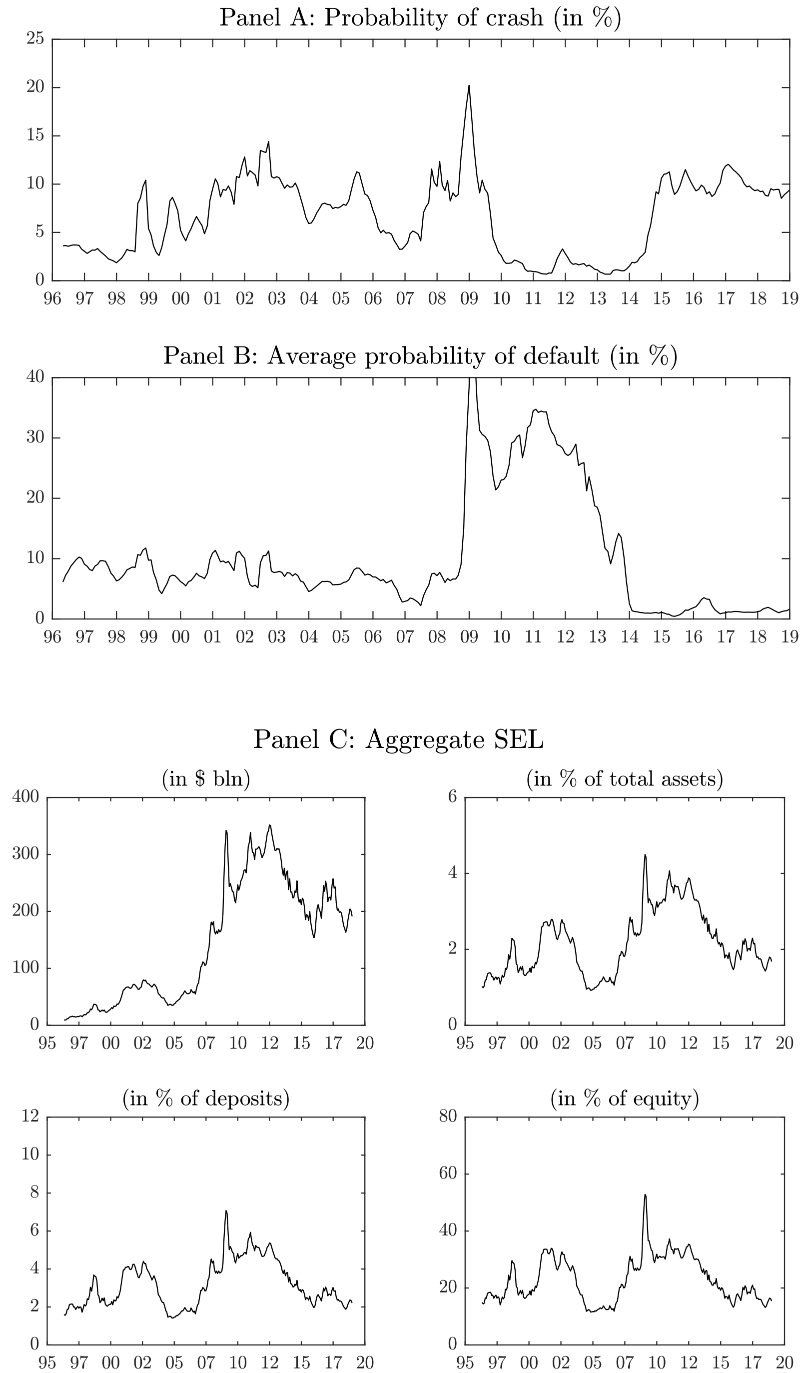
Figure A.7: Alternative Threshold Estimates





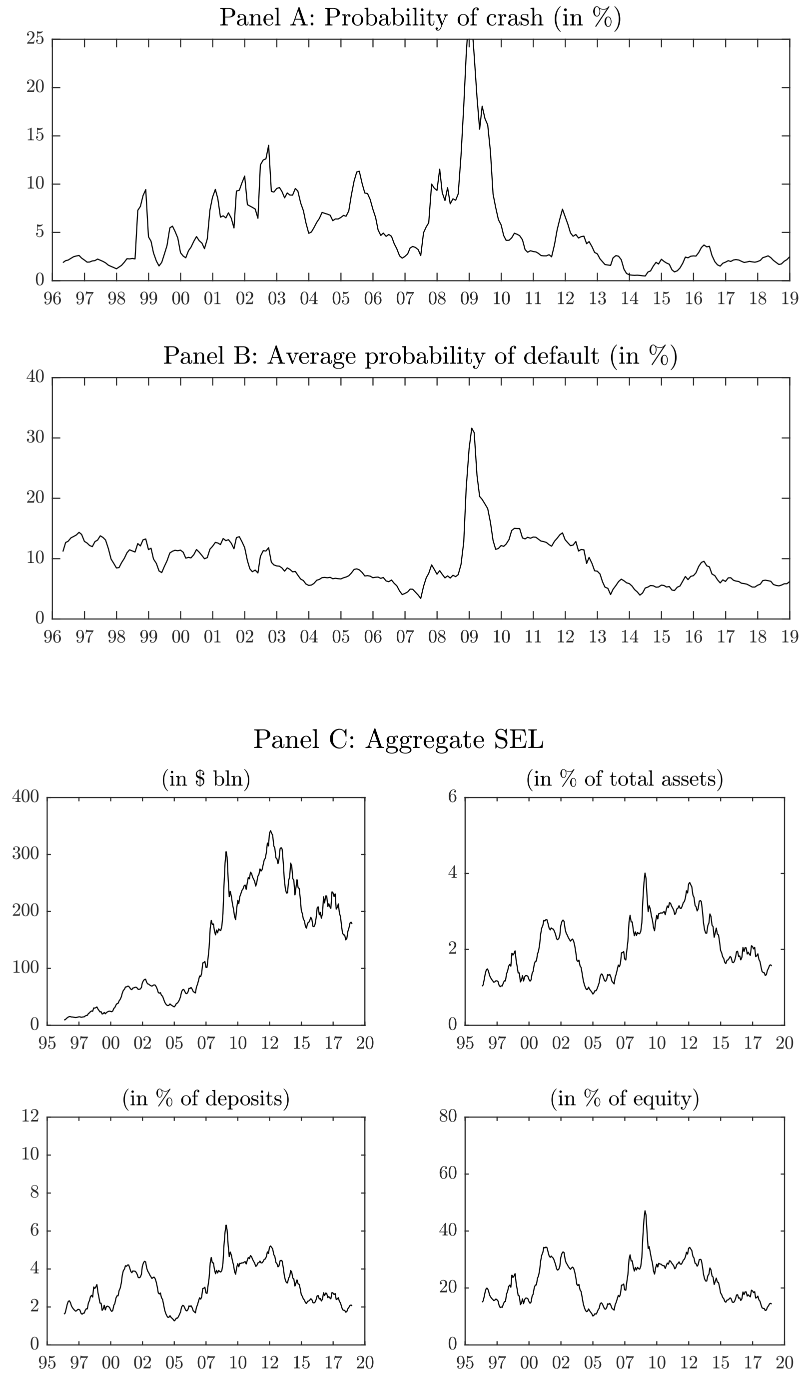
Note: This figure displays the three-month thresholds implied by two alternative approaches: In Panel A, standard deviation are estimated over five-year rolling windows. In Panel B, standard deviations are estimated over an expanding window.

Figure A.8: SEL with Five-Year Rolling Window Thresholds



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, in % of total assets, in % of deposits, and in % of equity.

Figure A.9: SEL with Expanding Window Thresholds



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, in % of total assets, in % of deposits, and in % of equity.

H Price Impact

In this section, we evaluate the sensitivity of our results to the calibration of the price impact. In the main, we assume that, in the event of a default, the liquidation of the market-sensitive assets has no price impact on the value of these assets. Several papers discuss the importance of the price impact 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, among others). We denote by φ the average price impact on the mark-to-market value of market-sensitive assets ($\varphi \in [0,1]$). In the case when the fire sale has a price impact, the estimate of SEL is obtained as follows:

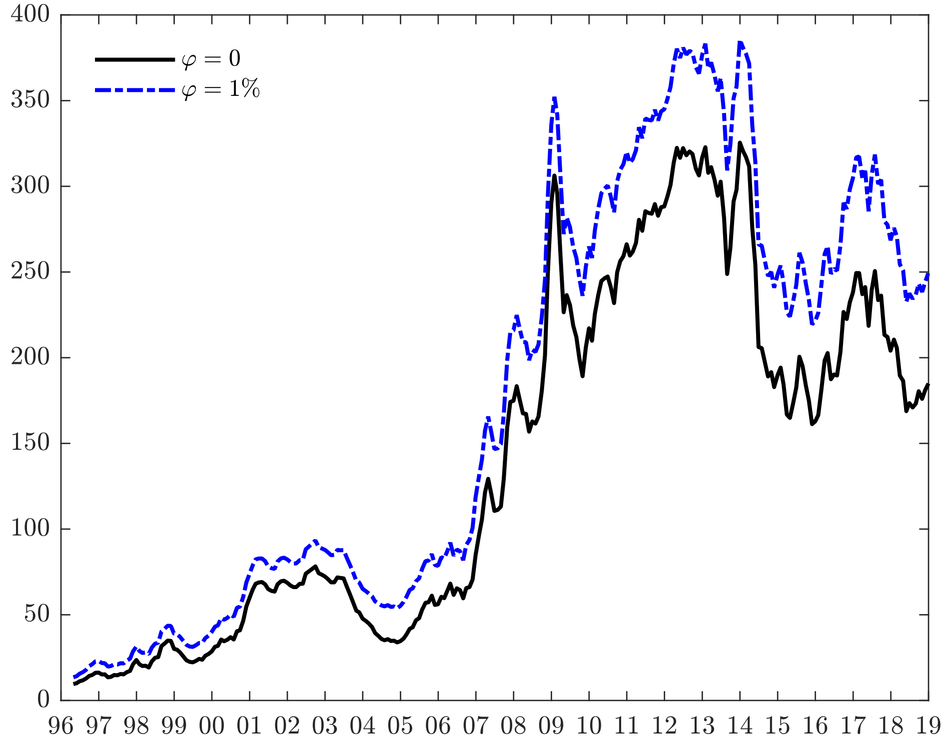
$$SEL^{(i)}_{t:t+1} = [(1+R^{(i)}_{Dep,t})Dep^{(i)}_t + (1+R^{(i)}_{SD,t})SD^{(i)}_t] - \frac{1}{S_{C,t+1}} \sum_{\tilde{s}=1}^{S_{C,t+1}} A^{(i)\tilde{s}}_{t+1} \, 1_{\{A^{(i)\tilde{s}}_{t+1} \leq L^{(i)}_{t+1}\}}$$

where

$$A^{(i)\tilde{s}}_{t+1} = (1+R^{(i)}_{F,t})Cash^{(i)}_t + (1-\varphi)(1+R^{(i)\tilde{s}}_{M,t+1})MA^{(i)\tilde{s}}_t + (1+R^{(i)}_{O,t})OA^{(i)}_t.$$

We assume a relatively modest value of the price impact, equal to $\varphi = 1\%$. As Figure A.10 reveals, even in this conservative case, the effect of the price impact on SEL is substantial. After the subprime crisis, the increase in SEL that would result from a 1% price impact ranges between \$40 and \$70 billion. At the end of the sample, SEL would be close to \$310 billion instead of \$250 billion when $\varphi = 0$, which means that SEL would be almost 25% larger than in the case with no price impact.

Figure A.10: SEL with Price Impact



Note: This figure displays SEL when a price impact of $\varphi = 1\%$ is assumed on the value of the market-sensitive assets. The aggregate SEL is measured in $ billion.

I Predictive Regressions for Alternative Systemic Risk Measures

In this section, we compare the predictive ability of SEL and other two well-established measures of systemic risk: the systemic expected shortfall (SES) of Acharya et al. (2017), and the ΔCoVaR of Adrian and Brunnermeier (2016).

The SES of a bank is the sum of its expected default losses and the expected contribution to a systemic crisis. Acharya et al. (2017) report evidence that SES is mainly driven by the marginal expected shortfall (MES) of the bank and its leverage (Lev). They measure MES as the average return of a bank's stock over the 5% worst days for the market return: $MES_{5\%} = \frac{1}{\#T_{5\%}} \sum_{t \in T_{5\%} R_{i,t}}$, where $\#T_{5\%}$ represents the set of 5% days worst market returns. Leverage is measured as the quasi-market value of assets divided by the market value of equity: $Lev = (\text{book assets} - \text{book equity} + \text{market equity})/(\text{market equity})$. Acharya et al. (2017) find that, in the global financial crisis, individual realized SES was best predicted by the following relation:

$$SES_t = 0.02 - 0.15 MES_t - 0.04 Lev_t,$$

as shown in their Table 4. This relation is multiplied by -1, so that an increase in SES means an increase in systemic risk. See also Berger et al. (2020).

ΔCoVaR is the change in the value at risk of the financial system conditional on an individual institution being under stress relative to its median state. For a given bank i, ΔCoVaR is computed as

$$\Delta\text{CoVaR}_\alpha^{system|i} = \text{CoVaR}_\alpha^{system|r_i = VaR_\alpha^i} - \text{CoVaR}_\alpha^{system|r_i = VaR_{50}^i}$$

which means that ΔCoVaR of the bank is the difference between the VaR of the financial system conditional on this particular bank being in financial distress and the VaR of the financial system conditional on the firm's return being equal to its median level. We compute ΔCoVaR using a quantile regression as in Adrian and Brunnermeier (2016). See their Appendix I.

To compute these measures, we need listed stocks, so the list of banks covered by these measures is different from our sample for SEL. For this reason, we also report results for SEL based on the same sample of firms. For consistency, we use the same log transformation as in the main text, However, the results would be affected in using the SES and ΔCoVaR measures directly.

In Table A.5, we report results of the predictive regressions for the loss of capital projected in the DFAST severely adverse scenario. As we estimate these regressions with a different sample of banks, results for SEL differ slightly from those reported in the main text. In general, SES has a positive and significant parameter (Panel A). However, the adjusted R^2 is in general relatively low, below 20%. For ΔCoVaR, the parameter is negative and usually significant, with a low adjusted R^2.

In Table A.6, we report results of the predictive regressions for macroeconomic variables using aggregate SEL, SES and ΔCoVaR. We find that SEL outperforms SES for most variables and most horizons. For ΔCoVaR, results are mixed. ΔCoVaR outperforms SEL at short horizons for industrial production growth, unemployment rate change, utilization rate change, and the credit spread, although not significantly. For longer horizons (usually 24 and 36 months), SEL dominates ΔCoVaR.

Table A.5: Predicting the Loss of Capital Projected in the DFAST Severely Adverse Scenario

	I	II	III	IV	V	VI	VII	VIII	IX
Panel A: SEL vs. SES									
	2014 Stress test			**2015 Stress test**			**2016 Stress test**		
Constant	-0.0143	-2.1696	–	0.3182	-1.4921	–	0.9560***	-4.0644	–
	(0.043)	(1.084)		(1.543)	(0.592)		(4.883)	(1.597)	
$SEL^{(i)}$	0.8047***	–	0.8165***	0.8997***	–	0.9399***	0.7258***	–	0.8574***
	(5.729)		(5.255)	(8.017)		(7.679)	(6.294)		(5.339)
$SRISK^{(i)}$	–	0.9155*	0.1835	–	0.7894	0.0601	–	1.5649**	0.1426
		(1.901)	(1.181)		(1.205)	(0.491)		(2.296)	(0.888)
Adj. R^2	62.614	12.101	65.303	76.906	2.324	77.212	67.025	18.360	68.410
	2017 Stress test			**2018 Stress test**			**All Stress test**		
Constant	0.5156**	-2.8721	–	1.0565***	-3.0404	–	0.6711***	-1.7876*	–
	(1.990)	(1.433)		(5.038)	(1.058)		(5.931)	(1.849)	
$SEL^{(i)}$	0.6700***	–	0.9015***	0.7737***	–	0.9982***	0.7015***	–	0.9476***
	(5.415)		(4.402)	(6.384)		(6.100)	(12.136)		(10.923)
$SRISK^{(i)}$	–	1.1534**	0.0985	–	1.3318*	0.0018	–	0.8998***	0.0524
		(2.259)	(0.481)		(1.718)	(0.011)		(3.608)	(0.604)
Adj. R^2	59.849	17.752	60.358	67.665	9.319	67.666	59.636	10.826	-0.646
Panel B: SEL vs. ΔCoVaR									
	2014 Stress test			**2015 Stress test**			**2016 Stress test**		
Constant	-0.0143	4.7154	–	0.3182**	8.7783	–	0.9560***	16.2522*	–
	(0.043)	(1.293)		(1.543)	(1.311)		(4.883)	(1.780)	
$SEL^{(i)}$	0.8047***	–	0.9862***	0.8997***	–	0.9779***	0.7258***	–	1.0095***
	(5.729)		(5.574)	(8.017)		(7.699)	(6.294)		(5.738)
$SRISK^{(i)}$	–	-0.8202	0.0138	–	-1.7248	0.0221	–	-3.2903	-0.0095
		(0.856)	(0.078)		(1.085)	(0.174)		(1.589)	(0.054)
Adj. R^2	62.614	-1.426	62.627	76.906	0.921	76.945	67.025	7.426	67.030
	2017 Stress test			**2018 Stress test**			**All Stress tests**		
Constant	0.5156**	6.4085	–	1.0565***	16.9126**	–	0.6711***	3.3814**	–
	(1.990)	(0.714)		(5.038)	(2.202)		(5.931)	(2.039)	
$SEL^{(i)}$	0.6700***	–	1.0145***	0.7737***	–	0.9159***	0.7015***	–	1.0250***
	(5.415)		(5.387)	(6.384)		(5.576)	(12.136)		(12.054)
$SRISK^{(i)}$	–	-1.0755	-0.0145	–	-3.3773**	0.0841	–	-0.4001	-0.0250***
		(0.533)	(0.077)		(1.959)	(0.512)		(1.031)	(0.294)
Adj. R^2	59.849	-3.914	59.862	67.665	12.991	68.130	59.636	0.063	-0.932

Note: This table presents cross-section predictive regressions. Panel A predicts the loss of capital projected by large financial institutions in the severely adverse scenario of DFAST stress tests. Panel B predicts total loan losses projected by large financial institutions in the severely adverse scenario of DFAST stress tests. Regressors are $\log(SEL_t^{(i)}+1)$, $\log(SES_t^{(i)}+1)$, and $\log(\Delta CoVaR_t^{(i)}+1)$. Regressors for the stress test for year Y are as of end of December of year $Y-1$. The table reports the parameter estimates, the p-values in parentheses, and the adjusted R^2.

Table A.6: Out-of-sample Prediction of Macroeconomic Indicators

	I	II	III	IV	V	VI	VII	VIII
Horizon	Without controls		With controls		Without controls		With controls	
(in months)	$\Delta\bar{R}^2_{OOS}$	DM	$\Delta\bar{R}^2_{OOS}$	DM	$\Delta\bar{R}^2_{OOS}$	DM	$\Delta\bar{R}^2_{OOS}$	DM
	SEL vs. SES				**SEL vs. ΔCoVaR**			
Panel A: Industrial production growth								
6	4.39	1.46	7.11	1.84*	-8.74	-1.25	-10.56	-1.36
12	26.20	3.13***	28.05	3.19***	-0.18	-0.01	4.46	0.18
24	1.62	0.28	2.70	0.43	10.14	0.63	10.61	0.68
36	-16.05	-3.76***	-17.60	-3.94***	-4.72	-0.98	-4.66	-0.96
Panel B: Employment growth								
6	3.92	1.18	4.79	1.37	2.10	0.29	5.01	0.68
12	32.68	4.54***	35.07	4.56***	0.56	0.09	0.66	0.10
24	31.88	4.32***	33.48	4.40***	31.93	2.65***	32.86	2.69***
36	-0.12	-0.02	-1.31	-0.37	12.68	2.62***	13.88	2.85***
Panel C: Unemployment rate change								
6	2.33	1.03	4.54	1.56	-10.07	-1.65	-10.66	-1.59
12	23.16	3.67***	25.01	3.78***	-10.20	-1.48	-9.78	-1.21
24	26.09	3.01***	26.61	3.05***	17.48	1.54	18.49	1.60
36	11.97	2.45**	9.41	2.04**	2.72	0.59	3.17	0.65
Panel D Utilization rate change								
6	4.70	1.19	7.90	1.61	-11.68	-1.84*	-12.72	-1.85*
12	29.57	3.28***	31.08	3.27***	-1.86	-0.10	2.09	0.08
24	23.12	1.88*	23.47	1.96**	16.90	0.76	18.13	0.85
36	4.96	0.91	3.13	0.57	6.04	0.81	6.22	0.90
Panel E: Consumer price inflation								
6	16.63	2.85***	12.83	2.44**	10.65	1.17	11.02	0.90
12	15.75	2.84***	18.35	2.80***	9.62	1.36	12.50	2.31**
24	-1.80	-0.37	-0.88	-0.15	13.05	2.00**	15.24	2.20**
36	-4.58	-1.65	-4.59	-1.49	12.16	2.61***	15.07	2.84***
Panel F: Bank credit growth								
6	2.77	1.00	1.51	0.51	6.74	1.40	8.06	1.48
12	8.45	1.88*	11.19	2.15**	6.87	0.66	6.10	0.62
24	11.98	1.70*	11.97	1.59	15.83	1.76*	17.72	1.77*
36	10.58	2.85***	11.06	2.93***	22.93	3.87***	24.11	3.93***
Panel G: Credit spread								
6	2.26	1.14	2.93	1.22	-1.04	-0.22	-3.86	-0.77
12	19.65	2.29**	20.49	2.26**	15.59	0.89	17.84	0.98
24	8.56	1.35	10.49	1.70*	20.68	2.76***	22.26	3.08***
36	9.75	1.83*	10.66	1.32	12.83	2.01**	17.29	1.99**

Note: This table presents predictive regressions of macroeconomic indicators with SEL, SES, and ΔCoVaR. Columns I to IV correspond to the comparison of SEL and SES with and without controls, columns V to VIII correspond to the comparison of SEL and ΔCoVaR. For each case, the first column corresponds to the gain in adjusted out-of-sample R^2 of using SEL instead of the other indicator ($\Delta\bar{R}^2_{OOS}$) and the second column to the Diebold and Mariano (1995) test statistic. ***, **, and * denote significance at the 1%, 5%, and 10% significance level, respectively.

J Banks' Balance Sheet

In this appendix, we provide details on the main categories of assets held by commercial banks. Banks in general hold loans and securities. Loans are issued and usually held until they mature, whereas securities might be sold before they mature.[8] Banks classify loans that they issue based on the borrower's purposes or the 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. On the other hand, securities can be standard securities, such as Treasury bills, or structured securities, such as mortgage-backed securities (MBSs).

J1 Loans

In this section, we briefly explain different types of loans 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 types of loans, 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 substantially secured by a lien on real property, the estimated value of the real-estate collateral at origination (after deducting any more senior liens) must be greater than 50% 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.

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.

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

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 a loan, 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. Such loans can vary from extension of credit to credit cards to auto-loans. The 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 exclude 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, credits extended to individuals through credit cards or loans to an individual for buying an automobile would not be counted as consumer loans if they are substantially secured by a real-estate property.

The three types of loans described above are mainly reported in the loan portfolio of the bank. However, such loans can also exist in the trading portfolio of the bank.

Other Loans. Banks also owe loans other than those described above. They 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. They also include loans to depository institutions and acceptances of other banks, and loans to non-depository financial institutions. Examples of the latter are loans 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, they include loans to foreign governments and official institutions, and lease financing receivables. All these other loans are classified as corporate loans.

J2 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. Last, states and political subdivisions also issue debt obligations. We merge these three groups into one class of assets, i.e., Government securities.

Corporate Bonds. This category includes all bonds, notes, and debentures issued by corporations and held as investments by commercial banks.

J3 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 is 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.[9] In either case, the mortgages are in the form of pass-through and non-pass-through mortgages.[10] Both pass-through and non-pass-through mortgages (RMBS and CMBS) can be issued and/or guaranteed by GSEs and non-GSEs.[11] So, in total one can

[9] 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.

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

[11] Main GSEs are the Federal National Mortgage Association (FNMA, Fannie Mae), and the Federal Home Loan Mortgage Corporation (FHLMC, Freddie Mac). The Government National Mortgage Association (GNMA, Ginnie Mae) is a government agency. Other non-GSEs are non-U.S. government issuers such as

think of eight different possible combinations. For instance, a bank holds a pass-through RMBS, which is issued by a GSE, or a pass-through CMBS, which is issued by a non-GSE. 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 categories are not available in Call Reports prior to 2009. Since then, the majority of pass-through RMBSs are issued and guaranteed by GSEs. Other RMBSs, 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 RMBSs.

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 risks. 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.

depository institutions, insurance companies, state and local housing authorities.

J4 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 the Federal Fund rate, we find that $R_{F,t} < R^{(i)}_{Dep,t} < R^{(i)}_{D,t}$ (with average values: $1.8\% < 1.9\% < 3.5\%$).[12]

[12] 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.

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