Fire-Sale Spillovers and Systemic Risk

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First version: October 2013
This version: February 2015

Abstract

We construct a new systemic risk measure that quantifies vulnerability to fire-sale spillovers using detailed repo market data for broker-dealers and regulatory balance sheet data for U.S. bank holding companies. For broker-dealers, vulnerabilities in the repo market are driven by flight-to-quality episodes, when liquidity and leverage can change rapidly. We estimate that an exogenous 1 percent decline in the price of all assets financed with repos leads to losses due to fire sale spillovers of 8 percent of total broker-dealer equity on average and over 12 percent during the financial crisis. For bank holding companies, vulnerabilities to fire-sales are equally sizable but build up slowly over time. Our measure signals build-up of systemic risk starting in the early 2000s, ahead of many other measures. Our measure also predicts low quantiles of macroeconomic outcomes above and beyond other existing measures, especially at longer horizons.

Keywords: Systemic risk, fire-sale externalities, leverage, linkage, concentration, bank holding company, tri-party repo market.

JEL Classification: G01, G10, G18, G20, G21, G23, G28, G32

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1 Introduction

We use data on broker-dealers from the tri-party repo market and on bank holding companies from regulatory filings to construct a systemic risk measure of fire-sale externalities in the U.S. financial system. Our measure builds on the cross-sectional framework of Greenwood, Landier, and Thesmar (2014), extending it to a panel analysis to track vulnerabilities over time. The framework takes as given banks' leverage, asset holdings, asset liquidation behavior and the price impact of liquidating assets in the secondary market. It then considers a hypothetical negative shock, either to assets or equity capital, that leads to an increase in leverage. Banks respond by selling assets and paying off debt to retrace the increase in leverage. These asset fire sales have a price impact that depends on the liquidity of the assets and the amount sold. Any financial institution holding the fire-sold assets, even if not initially shocked, will see the value of its asset holdings decline, a fire-sale spillover. The resulting systemic risk measure, called aggregate vulnerability (AV), is the sum of all the second-round spillover losses – as opposed to the initial direct losses – as a share of the total equity capital in the system.

Fire sale spillovers are an important dimension of overall systemic risk. The mechanisms, systemic implications and welfare costs of fire sales have been abundantly studied in the theoretical literature.[1] Complementary empirical research has documented the existence and severity of fire sale externalities in financial markets.[2] The last crisis, in particular, demonstrated that repo markets can prove systemic when runs and subsequent fire sales materialize.[3] Indeed, many narratives consider repo ground zero for the crisis and regard fire sales as one of the most important sources of systemic risk.[4] Repo borrowing today accounts for 60 percent of all broker-dealer liabilities and it is still potentially vulnerable to fire sales.[5] Because of the central role that repo markets played during the crisis and continue to play today, and because of the importance of fire sale externalities and systemic risk, we believe it is useful to have a measure that quantifies the systemicness of repo. To our knowledge, our measure is the first one to do so.

The crisis also emphasized that fire sale spillovers are crucially important for commercial

[1] Diamond and Rajan (2011); Gromb and Vayanos (2010); Brunnermeier and Pedersen (2009); Acharya et al. (2009); Mitchell et al. (2007); Allen and Gale (1994); Shleifer and Vishny (1992).

[2] Merrill et al. (2012); Feldhütter (2012); Mitchell and Pulvino (2012); Ellul et al. (2011); Coval and Stafford (2007); Mitchell et al. (2007).

[3] Krishnamurthy et al. (2014); Adrian et al. (2014); Gorton and Metrick (2012); Copeland et al. (2014); Krishnamurthy (2010).

[4] Ellul et al. (2014); Hanson et al. (2011); Shleifer and Vishny (2011); Caballero (2010); Duffie (2010); Acharya et al. (2009); Brunnermeier (2009).

[5] Stein (2013, 2012); Korinek (2011); Duffie (2010); Borio (2009).

banks, who have to liquidate assets in the face of deteriorating equity capital positions.[6] The reduction in financial intermediation due to fire sales feeds directly into the macroeconomy, hurting firms and consumers alike, which is ultimately why we find it important to also apply AV to the broader banking system and not solely broker-dealers.[7]

Our main results are as follows. For the broker-dealers, from July 2008 to March 2014, an exogenous 1 percent decline in the price of all assets financed with repos leads to an average AV – the losses solely due to fire sale spillovers – of 8 percent of total system capital. To put this number in perspective, we can compare it to the direct (non-spillover) losses produced by the exogenous shock which equal 35 percent of system equity. It follows that for every dollar lost due to exogenous declines in asset prices, broker-dealers suffer on average an additional 23 cents of fire sale spillover losses.

There is substantial time variation in broker-dealer AV, broadly split into two phases. The crisis phase, from the beginning of the sample in July 2008 until mid-2009, has the largest AV estimates, reaching a peak of 12.6 percent in November 2008. By combining existing liquidity estimates in the literature with data on repo haircuts, we show that AV was high because of sudden reductions in liquidity, especially in mortgage-backed securities (MBS). Between mid-2009 and 2014, the repo market experienced a period of relative calm, with AV hovering around 8.5 percent. In this phase, changes in AV occur during flight-to-quality episodes when the portfolios of broker-dealers shift to safer assets. Such shifts have two opposing effects on fire-sale vulnerability. On the one hand, safer assets are typically more liquid which makes the system less vulnerable. On the other hand, because safer assets command a lower haircut, leverage in the system increases which makes the system more vulnerable. Neither effect always dominates the other: We show that AV declined during the European crisis in mid-2011, making the liquidity effect dominant, but increased in December 2012 during debt-ceiling negotiations in the U.S. Congress as the leverage effect prevailed.

When looking at quarterly regulatory balance sheet information of bank holding companies (BHCs), we can take advantage of a much longer sample period going back to 1996. We find that AV for BHCs is roughly constant from 1996 to 2000 at 16 percent, and then grows continuously from 2001 until the fourth quarter of 2007, when it peaks at 28 percent just before the crisis. Large capital injections in 2009 reduce AV to around 15 percent before it slowly declines to 9 percent by 2014. Unlike the repo market, in which fast changes in liquidity and flight-to-quality episodes are crucial, AV for BHCs is driven mostly by slow-moving changes in size, leverage and the degree of commonality in asset holdings across BHCs. The

[6] Bernanke (2009).

[7] Guerrieri and Shimer (2012); Lou and Wang (2012); Davila (2011); Shleifer and Vishny (2010); Acharya et al. (2009); Lorenzoni (2008) and many of the citations in previous footnotes.

majority of the buildup before the crisis can be attributed to the broad-based increase in the amount of residential real estate loans held by BHCs, which not only boosted the overall size of the system but also made banks' asset profiles more similar to each other. Increases in leverage also played a role before the crisis, especially in 2006 and 2007.

In addition to being the first measure of systemic risk specific to fire-sale spillovers and the first one applied to repo markets, AV has other unique features that complement and improve upon other existing systemic risk measures. First, AV is constructed from the bottom up using detailed balance sheet information of individual asset classes at each financial institution. In contrast, the predominant strategy in the literature relies on market prices or macroeconomic aggregates to build top-down indicators. Bisias et al. (2012) and Mitra et al. (2011) provide excellent surveys of systemic risk measures. The more than 30 measures considered there all use market prices or macroeconomic aggregates as key inputs. The three measures that also use balance sheet information rely on book equity, total assets and total liabilities only; none use holdings disaggregated by asset class.[8] Although there are many advantages of using market prices, one important disadvantage is that volatilities and risk premia are usually compressed the most just prior to a crisis, pushing models based on market prices towards low values of systemic risk despite the underlying buildup in vulnerability. In contrast, AV signals increased systemic risk starting in the early 2000s, ahead of many other measures. We also more formally show that AV adds to the predictability of low quantiles of macroeconomic outcomes – above and beyond existing measures – especially as the predictive horizon increases.

Extending the framework of Greenwood et al. (2014), we produce a new decomposition of AV into multiplicative factors that sheds light on the underlying causes of changes in systemic risk over time. One component of systemic risk not previously analyzed in the literature that emerges naturally from our study is what we call "illiquidity concentration", the degree to which illiquid assets are disproportionally held by large and levered institutions. We show that, as a determinant of AV, illiquidity concentration is as important as the size and leverage of the financial system. Further decompositions allow us to identify the contribution to systemic risk of individual banks and asset classes. In the repo market, we document that Treasuries are the largest contributor to fire-sale vulnerability, followed by MBS and debt

[8]Among these three, Acharya et al. (2012) and Billio et al. (2012) use a combination of asset prices and book equity for each institution examined. Fender and McGuire (2010) use consolidated balance sheet information for European banks aggregated geographically by country. Although not among the surveyed articles, Pierret (2014) uses a combination of market prices and the subset of short-term assets and liabilities from the Federal Reserve's form FR Y-9C, which is the same data source we use for BHCs. However, she does not disaggregate balance sheets by asset class and focuses on the solvency-liquidity nexus of banks and policy design rather than systemic risk due to fire-sale spillovers.

issued by government sponsored enterprises. For BHCs, residential real estate loans, C & I loans and consumer loans are the most "systemic" asset classes. Bank of America, Citigroup, JP Morgan Chase, Wachovia (before its acquisition) and Wells Fargo are, in that order, the largest average contributors to AV, producing more than 50 percent of all spillovers.

Finally, our measure is immediately useful for policymakers and regulators. The designation of systemically important financial institutions (SIFIs) has become an active area in post-crisis regulation. The Dodd-Frank Wall Street Reform and Consumer Protection Act requires, among other standards, that a financial firm be designated a SIFI when it "holds assets that, if liquidated quickly, would cause a fall in asset prices and thereby [...] cause significant losses [...] for other firms with similar holdings," a description that almost exactly matches the exercise in this paper.[9] Bank stress testing has become another standard tool, yet current implementations mainly consider initial individual losses at large financial institutions, and all but ignore the second-round losses that can create systemic risk.[10] Our analysis can be interpreted as a stylized macro-prudential stress test in which the regulator provides a scenario (the exogenous shock) and the framework computes spillover losses for the system as a whole. Additionally, our framework can easily produce counterfactuals that can be used to evaluate past policies or proposals for future reform. For example, Duarte and Eisenbach (2014) evaluate the Troubled Asset Relief Program (TARP) and find that, given the size of the intervention, it reduced vulnerability to fire sale spillovers almost as much as the framework's optimal policy. Tri-party repo reform is another item high on the list of academics and regulators.[11] Our framework can be used to evaluate the many current proposals – risk-based capital requirements, liquidity requirements, leverage ratios, capital surcharges, universal margin requirements – quantifying by how much the could reduce systemicness and through which channels.

Related literature. Our paper is most closely related to Greenwood et al. (2014). They theoretically develop AV and then estimate it for the cross-section of banks that participated in the European Banking Authority's stress test in the third quarter of 2011. In contrast, we adapt the framework to a panel setting and estimate it using two new data sources. In addition to finding detailed balance sheet information for the relevant financial firms, another key challenge of a panel setting is to estimate the time-varying liquidity of different assets.

[9]Final rule and interpretive guidance to Section 113 of the Dodd-Frank Wall Street Reform and Consumer Protection Act.

[10]Current stress tests do consider macroeconomic shocks that could exogenously embed the second-round shocks. However, they are assumed rather than derived. Greenlaw et al. (2012) argue that in their current form, stress tests are more micro- than macro-prudential.

[11]See "Tri-Party Repo Reform" at http://www.newyorkfed.org/banking/tpr_infr_reform.html.

We use information embedded in repo haircuts to gauge changes in asset-specific liquidity and flow-of-funds data to measure aggregate liquidity. We can then track AV over time, allowing us to construct a coherent account of its determinants and dynamics. Having a time dimension is also necessary to use it as a systemic risk measure and evaluate its merits as a leading indicator. Our factor decomposition yields a new component of AV, "illiquidity concentration", that is more suitable for a time-series setting than the "connectedness" measure in Greenwood et al. (2014). While Greenwood et al. (2014) discuss the theoretical similarities and differences between AV and other leading systemic risk measures, we further contribute by implementing this comparison empirically.

The nature of AV places it squarely in the growing literature on networks. There are several theoretical papers that are closely related to our work, even though they do not empirically estimate systemic risk. Capponi and Larsson (2014) explicitly translate the framework we use to the language of networks and further contribute by adding a non-financial sector and market clearing. Allen, Babus, and Carletti (2012) develop a model where asset commonality plays an essential role in systemic risk. Unlike us, they do not assume leverage targeting behavior by financial firms but instead explicitly model liabilities. Cifuentes, Ferrucci, and Shin (2005) propose a model where financial institutions are subject to solvency constraints and can affect unrelated third parties through balance sheet effects when they sell assets. Wagner (2010) studies the trade-off between contagion and diversification in asset holdings. Chan-Lau, Espinosa, and Sole (2009) consider a "credit-and-funding-shock" model, where fire sales are triggered by a loss of funding. Kapadia, Drehmann, Elliott, and Sterne (2013) focus on liquidity crises but incorporate fire sales triggered by the need of banks to satisfy cash-flow constraints. On the empirical side, the network literature does not focus on the asset side of the balance sheet and spillovers through prices, focusing instead on counterparty risk, runs, information externalities, network formation and other mechanisms. Glasserman and Young (2014) show that for a general network, direct exposures and pure counterparty "domino" effects are unlikely to be as quantitatively important as fire sales or other mechanisms that involve contagion through assets.

2 Framework

2.1 Setup

To calculate potential spillovers from fire sales, we build on the "vulnerable banks" framework of Greenwood et al. (2014). The framework quantifies each step in the following sequence of events of a fire sale:

1. **Initial shock:** An initial exogenous shock hits the banking system. This can be a shock to one or several asset classes, or to equity capital.

2. **Direct losses:** Banks holding the shocked assets suffer direct losses which lead to an increase in their leverage.

3. **Asset sales:** In response to the losses, banks sell assets and pay off debt.

4. **Price impact:** The asset sales have a price impact that depends on each asset's liquidity and the amount sold.

5. **Spillover losses:** Banks holding the fire-sold assets suffer spillover losses. These spillover losses – as opposed to the direct losses in Step 2 – are our measure of interest.

Banks are indexed by $i = 1, \ldots, N$ and assets (or asset classes) are indexed by $k = 1, \ldots, K$. Bank i has total assets a_i with portfolio weight m_{ik} on asset k such that $\sum_k m_{ik} = 1$. On the liabilities side, bank i has debt d_i and equity capital e_i, resulting in leverage $b_i = d_i/e_i$. For the whole banking system we have an $N \times N$ diagonal matrix of assets A with $A_{ii} = a_i$, an $N \times K$ matrix of portfolio weights M with $M_{ik} = m_{ik}$ and an $N \times N$ diagonal matrix of leverage ratios B with $B_{ii} = b_i$. We let $a = \sum_i a_i$ denote the total assets of the system, $e = \sum_i e_i$ system equity capital, $d = \sum_i d_i$ system debt, and $b = d/e$ system leverage. Other than differentiating between debt and equity, we are making no further assumptions on banks' liabilities.

2.2 Spillover measures

We derive the final expression for the spillover losses in which we are interested by following the steps above. For ease of exposition, we defer the discussion of specific assumptions to Section 2.3. We start with an initial shock to assets (Step 1) given by a vector of asset returns $F = [f_1, \ldots, f_K]$. This leads to direct losses (Step 2) given by:

$$\begin{aligned} a_i \textstyle\sum_k m_{ik} f_k \quad & \text{for bank } i \\ AMF \quad & \text{for the system } (I \times 1) \end{aligned}$$

where $(I \times 1)$ denotes the dimension of the matrix AMF. For the asset sales of Step 3 we make two assumptions. First, banks sell assets and reduce debt to return to their initial leverage. To determine the shortfall a bank has to cover to get back to target leverage we multiply the loss by leverage b_i:[12]

$$
\begin{aligned}
b_i a_i \textstyle\sum_k m_{ik} f_k \quad & \text{for bank } i \\
BAMF \quad & \text{for the system } (I \times 1)
\end{aligned}
$$

The second assumption for Step 3 is that banks raise this shortfall by selling assets proportionally to their weights m_{ik} which leads to asset sales given by:

$$
\begin{aligned}
\textstyle\sum_i m_{ik'} b_i a_i \sum_k m_{ik} f_k \quad & \text{for asset } k' \\
M' BAMF \quad & \text{for the system } (K \times 1)
\end{aligned}
$$

These asset sales have price impacts (Step 4) that depend on each asset's illiquidity ℓ_k. In the original framework of Greenwood et al. (2014), the illiquidity ℓ_k is measured in units of percentage points of price change per dollar amount sold which is standard in the empirical literature. However, as noted in Acharya and Pedersen (2005), liquidity expressed in this way is inappropriate when working with longer periods where the relevant markets grow over time.[13] We therefore decompose $\ell_k = \ell_k^* / w$ where w is the wealth of potential buyers of fire-sold assets – in the spirit of Shleifer and Vishny (1992) – and ℓ_k^* is a stationary measure of liquidity for asset k expressed in percentage points of price change per dollar amount sold relative to dollar wealth available to purchase. Placing these illiquidity measures into a diagonal matrix L, the fire-sale price impacts are given by:

$$
\begin{aligned}
\frac{\ell_{k'}^*}{w} \textstyle\sum_i m_{ik'} b_i a_i \sum_k m_{ik} f_k \quad & \text{for asset } k' \\
LM' BAMF \quad & \text{for the system } (K \times 1)
\end{aligned}
$$

Finally, price impacts of Step 4 cause spillover losses to all banks holding the assets that were fire-sold (Step 5) which we can calculate analogously to Step 1 as follows:

$$
\begin{aligned}
a_{i'} \textstyle\sum_{k'} m_{i'k'} \frac{\ell_{k'}^*}{w} \sum_i m_{ik'} b_i a_i \sum_k m_{ik} f_k \quad & \text{for bank } i' \\
AMLM' BAMF \quad & \text{for the system } (I \times 1)
\end{aligned}
$$

[12] For sufficiently large shocks, some banks may not be able to get back to target leverage even when selling all their assets. We take this into account in our empirical implementation by using the element-wise $\max\{1, BAMF\}$ as the shortfalls.

[13] See also Comerton-Forde et al. (2010); Hameed et al. (2010).

Summing the losses over all banks i', we arrive at the total spillover losses $\mathcal{L}$ suffered by the system $\{A, M, B, L\}$ for a given initial shock F:

$$\begin{aligned}\mathcal{L} &= \textstyle\sum_{i'} a_{i'} \sum_{k'} m_{i'k'} \dfrac{\ell^*_{k'}}{w} \sum_i m_{ik'} b_i a_i \sum_k m_{ik} f_k \\ &= 1' AMLM'BAMF\end{aligned} \tag{1}$$

where 1 is a column vector of ones.

It is important to note that $\mathcal{L}$ captures only on the *indirect* losses due to spillovers. It specifically does not include the *direct* losses due to the initial shock which are given by:

$$1'AMF = \textstyle\sum_i a_i \sum_k m_{ik} f_k$$

This makes our analysis different but complementary to the typical stress-test analysis which focuses on the direct losses for a given shock.

We want to distinguish between the effects stemming from aggregate characteristics of the banking system and effects that arise due to the distribution of assets across banks. To do so, we denote by $\alpha_i = a_i/a$ bank i's assets as a share of system assets and by $\beta_i = b_i/b$ bank i's leverage relative to system leverage. For the portfolio weights we denote by $m_k = \sum_i m_{ik} a_i/a$ the system portfolio weight for asset k and by $\mu_{ik} = m_{ik}/m_k$ bank i's portfolio weight for asset k relative to the system portfolio weight. The expression for total spillover losses $\mathcal{L}$ in (1) can then be simplified as:[14]

$$\mathcal{L} = \frac{a^2 b}{w} \textstyle\sum_{k'} \left[m^2_{k'}\, \ell^*_{k'} \sum_i \left(\mu_{ik'} \beta_i \alpha_i \sum_k m_{ik} f_k \right) \right]$$

Based on the total spillover losses $\mathcal{L}$ we define the following three measures of systemic risk.

Aggregate vulnerability: The fraction of system equity capital lost due to spillovers, $\mathcal{L}/e$, captures the aggregate vulnerability of the system to fire-sale spillovers:

$$\text{AV} = \underbrace{\frac{a}{w}}_{\text{rel. size}} \times \underbrace{(b+1)\, b}_{\text{leverage}} \times \underbrace{\textstyle\sum_{k'} \left[m^2_{k'}\, \ell^*_{k'} \sum_i \left(\mu_{ik'} \alpha_i \beta_i \sum_k m_{ik} f_k \right) \right]}_{\text{illiquidity concentration}} \tag{2}$$

We see that AV contains three factors.[15] The first factor is the size of the system relative to the wealth of outside buyers; if the banking system grows faster than outside wealth

[14]Note that the sum over i' drops out since $\sum_{i'} \alpha_{i'} \mu_{i'k} = 1$.
[15]Note that our decomposition differs from the one in Greenwood et al. (2014).

then aggregate liquidity is lower and fire sales are more severe. The second factor is system leverage which enters quadratically; higher leverage implies larger fire sales for given asset shocks *and* larger spillover losses relative to equity capital for given fire sales. The third factor "illiquidity concentration" is a modified Herfindahl index for asset classes; the effect of asset class k' is large if it is (i) widely held with a high aggregate share $m_{k'}$, (ii) illiquid with a high $\ell^*_{k'}$, and (iii) concentrated in banks that are large, levered, and exposed to the initial shock.

Systemicness of bank i: The contribution to aggregate vulnerability by bank i is obtained by dropping the summation over i in the expression for aggregate vulnerability (2) which combines all banks' individual asset sales into one total. It can also be interpreted as the aggregate vulnerability resulting from a shock only to bank i. Highlighting the terms that are specific to bank i we have:

$$\mathrm{SB}_i = \underbrace{\frac{a}{w}(b+1)\,b}_{\text{aggregate}} \times \underbrace{\alpha_i}_{\text{size}} \times \underbrace{\beta_i}_{\text{lever.}} \times \underbrace{\textstyle\sum_{k'} m_{k'}^2 \ell^*_{k'} \mu_{ik'}}_{\text{illiquidity linkage}} \times \underbrace{\textstyle\sum_k m_{ik} f_k}_{\text{exposure}} \tag{3}$$

The first term contains only aggregate factors so it does not vary across banks. The next factors are specific to bank i and imply high systemicness if the bank (i) is large with a high α_i, (ii) is levered with a high β_i, (iii) has high "illiquidity linkage" by holding large and illiquid asset classes, and (iv) is significantly exposed to the initial shock.

Systemicness of asset k: The contribution to aggregate vulnerability by asset k is obtained by dropping the summation over k in equation (2) which combines all assets' direct losses into one total. Similarly to the measure for individual banks, this measure can also be interpreted as the aggregate vulnerability resulting from a shock only to asset k. Highlighting the terms that are specific to asset k we have:

$$\mathrm{SA}_k = \underbrace{\frac{a}{w}(b+1)\,b}_{\text{aggregate}} \times \underbrace{\textstyle\sum_{k'}\left[m_{k'}^2\,\ell^*_{k'}\sum_i\left(\mu_{ik'}\alpha_i\beta_i\mu_{ik}\right)\right]}_{\text{held by systemic banks}} \times \underbrace{m_k}_{\text{size}} \times \underbrace{f_k}_{\text{exposure}} \tag{4}$$

Again, the first factors are aggregate and don't vary across assets. The following factors show that a specific asset class k is systemic if it is large in aggregate and if it is held by systemic banks.

2.3 Discussion of assumptions

In deriving our measures and decompositions we have made several assumptions. The first key assumption is that after a negative shock banks must return to their initial (pre-shock) leverage. This assumption is supported by Adrian and Shin (2010b, 2011), who show that broker-dealers and commercial banks engage in leverage targeting. While in our framework banks do not explicitly optimize an objective function, the rule that banks must return to target leverage can be considered a reduced form for the outcome of an optimization or simply a constraint (see Section 4.3.2). We pick initial leverage as banks' ultimate target but any target can be easily accommodated by using a single scaling factor, as all of our measures scale proportionally with the leverage matrix B. Empirically, banks target book leverage and not market leverage. Hence, we use book leverage for our analysis. Consequently, we must use the book value of assets in our analysis. However, the exogenous shock that triggers fire sales affects the *market* value of assets. In our framework and in our analysis of the repo market, the distinction between book and market values is irrelevant, since all assets are marked-to-market. For BHCs, we show in Appendix A.6 that despite a significant reduction in levels, the patterns in AV remain the same as in the benchmark case when illiquid assets are not marked-to-market.[16]

The second assumption in the framework is that banks retrace the increase in leverage by selling assets and not by raising any equity. We are interested in systemic risk which is usually accompanied by a general deterioration in equity capital positions, broad distress in capital markets and weak macroeconomic conditions. In such a scenario, raising equity can be difficult or undesirable for economic, signaling or other reasons (Shleifer and Vishny, 1992). Alternatively, the selling of assets in our framework can be viewed as the residual adjustment after banks raise some equity. By the linearity of the framework, raising equity is isomorphic to scaling down all initial shocks to capital, where the scaling factor is the same across all banks.[17]

The third assumption is that banks sell assets proportionally to their initial holdings. This assumption is important for our results and we show in Section 4.3.2 and Appendix A.2 how results change under different asset liquidation rules. We picked proportional liquidation of assets as our benchmark specification not only for simplicity (it keeps the framework linear) but also to be agnostic about the relative importance of several opposing forces. Selling the most liquid assets first has the important advantage of minimizing the price impact of fire

[16]For further discussion, see Ellul et al. (2014); Allen and Carletti (2008); Sapra (2008).

[17]If selling assets and raising equity contribute to a constant fraction of delevering at the margin, then the same result applies for shocks to *assets*, see Greenwood et al. (2014). Alternatively, a bank-specific scaling of asset shocks can capture more general forms of issuance of equity.

sales which reduces total losses. In addition, some illiquid assets may simply be impossible to sell.

However, there are several good reasons for selling illiquid assets first. For example, in the summer of 2008, Lehman Brothers sold some of its less liquid assets including commercial MBS, commercial mortgage inventory, leveraged loans and LBO-related debt while keeping a relatively constant liquidity buffer (Valukas, 2010). More generally, if banks expect that markets will become more illiquid in the future, the liquidity premium should be smaller today than tomorrow, creating an incentive to hold on to liquidity until it is more valuable.[18] Regulatory requirements on risk-weighted assets create an incentive to sell assets with high risk-weights first, which tend to be more illiquid.[19] Other regulations such as Basel III's liquidity coverage ratio (LCR) and the net stable funding ratio (NSFR) create further pressure to dispose of illiquid assets first.

Empirically, Coval and Stafford (2007) show that mutual funds are not very selective when fire selling, disposing of liquid and illiquid stocks alike. Manconi et al. (2012) provide evidence that mutual funds retained illiquid securitized bonds and sold corporate bonds during the beginning of the last crisis. Jotikasthira et al. (2012) additionally point out that global funds with different amounts of cash holdings behave indistinguishably when fire selling assets. Finally, fire sales that are approximately proportional to initial holdings do occur in practice: In crises, fire sales frequently involve the sale of entire firms, which by definition implies selling proportionally to holdings (Granja et al., 2014).

The fourth assumption is that the price impact of selling assets is proportional to the amount sold. This is the predominant assumption in the empirical literature and seems to fit the patterns of the data well.[20] In the theoretical literature, the first-round price impact is almost always proportional to the amount sold, with multipliers arising in subsequent liquidation rounds. In addition, we only consider diagonal matrices for the liquidity matrix L, i.e. there are no cross-asset liquidation price impacts. For example, we are assuming that liquidating \$10 billion of agency MBS has no direct impact on the price of corporate bonds – and that the same is true for every pair of distinct assets. The asset classes we consider are sufficiently different that the first-order effects should be consistent with no cross-asset price impacts. In any case, the off-diagonal entries are difficult to estimate, but likely to be positive which would only exacerbate fire sale spillovers.[21]

[18] Scholes (2000); Krishnamurthy (2010); Acharya and Pedersen (2005); Brown et al. (2009).

[19] In Section 4.3.2, we explicitly solve for this case. See also Merrill et al. (2012); Cifuentes et al. (2005); Hameed et al. (2010)

[20] Almost all papers cited in footnote 2 have linear pricing.

[21] Greenwood (2005) shows that in a model of limited arbitrage, similar assets in integrated markets can produce positive off-diagonal values. He uses Japanese stocks as an example.

The fifth assumption is that banks stop selling assets after the initial spell of fire sales. One can imagine that the first spillover losses constitute a new (now endogenous) negative shock which induces firms to restart the delevering sequence. The process can then be repeated until convergence.[22] There are several difficulties in implementing this multi-round approach. First, we need to account for fire-sold assets leaving the system in each current round before proceeding to the next round. This requires using a different asset matrix A in each round which complicates the analysis. One can also imagine that liquidity is not constant across rounds, so simply iterating the linear framework may not produce realistic outcomes. If the price of an asset drops low enough, the price impact of additional sales could be zero as deep-pocketed investors outside the system are enticed to step in.[23] In brief, our baseline assumptions seem less plausible as the number of rounds increases. Nevertheless, in Section 3.3.3, we verify that our main results for the repo market are virtually unchanged in a multi-round setup, and that the first round captures almost all of the total multi-round spillovers. For BHCs, Section 4.3.3 shows that the first five rounds capture essentially all multi-round spillovers, with the first round accounting for about one third of them.

The sixth assumption is that the framework is static. Banks do not make any explicit intertemporal decisions. All considerations regarding tradeoffs between now and the future are implicitly embedded in the choice of the initial shock, liquidation rules, liquidities, target leverage and so on. Accordingly, the framework does not explicitly state a liquidation horizon or timeline. For example, a scenario in which asset sales have a small price impact can also reflect the results of a scenario in which asset sales have a large price impact but liquidation of assets takes place over a longer time span. The values in the liquidity matrix L are therefore one of the main inputs that implicitly reflect the relevant liquidation horizon. In our benchmark, the framework's single period can be interpreted as whatever amount of time it takes for banks to return to target leverage.[24]

[22] Our linear framework can converge to zero if size, leverage or illiquidity concentration are large enough (Capponi and Larsson, 2014). Tepper and Borowiecki (2014) develop a systemic risk measure based on how close the banking system is to being explosive due to high leverage and asset concentration. Interestingly, the spectral density of $LM'BAM$, which is the matrix repeatedly applied during multi-round fire sales, has a correlation with AV of over 90 percent.

[23] During the crisis, sovereign wealth funds, large asset managers like Berkshire Hathaway and eventually the government assumed this role.

[24] Coval and Stafford (2007) estimate price impacts of fire sales that last over eighteen months; Ellul et al. (2011) of over twelve months; Jotikasthira et al. (2012) of at least twenty six weeks.

3 Broker-dealers

3.1 Data and its mapping to the model

We apply the framework described in the previous section to data on the U.S. tri-party repo market which is the key wholesale funding market for broker-dealer banks.

A repurchase agreement (repo) is a form of collateralized lending, usually overnight, structured as a sale and then a repurchase of the collateral. At the beginning of the loan, the borrower sells the collateral to the lender, exchanging collateral for cash. At the end of the loan, the borrower repurchases the collateral from the lender, exchanging cash for collateral. The difference between the sale and repurchase price constitutes the interest on the loan; the difference between the sale price and the market value of the collateral constitutes the "haircut", the over-collateralization of the loan. The third party in a tri-party repo is a clearing bank that provides clearing and settlement services to the borrower and lender which greatly enhances the efficiency of the market.[25] The borrowers in the tri-party repo market are securities broker-dealers. The lenders in the tri-party repo market include money market funds which account for between a quarter and a third of volume and securities lenders which account for about a quarter.[26]

We use data collected daily by the Federal Reserve Bank of New York since July 1, 2008. It is available in real time, allowing day-by-day monitoring of the market. For our analysis we use a sample from July 1, 2008 to March 31, 2014. The data includes, by dealer, all borrowing in the tri-party repo market, aggregated into several asset classes and with information on haircuts. An observation consists of the name of the dealer, the amount borrowed, the type of asset used as collateral and the value of the collateral. For example, a hypothetical observation would be that on July 1, 2008, dealer X borrowed \$98 billion providing as collateral \$100 billion of Treasuries, which implies a haircut of 2 percent. This data allows us to construct the balance sheet financed in the tri-party repo market for each dealer on a daily basis. The total value of the collateral posted by dealer i equals total assets a_i. The share of collateral in asset class k gives the portfolio weight m_{ik}. A dealer's equity capital e_i is based on haircuts, i.e. using the difference between collateral value and loan size:

$$e_i = \sum_k (\text{collateral}_{ik} - \text{loan}_{ik})$$

The balance sheet we construct for a particular dealer is only part of the dealer's overall

[25] For a detailed description of the market, see Copeland et al. (2014).

[26] See Pozsar (2011) for a discussion of large cash investors.

balance sheet. However, based on the Financial Accounts of the U.S. (formerly Flow of Funds), repo borrowing accounts for 59.9 percent of broker-dealer liabilities (on average \$2.1 trillion out of \$3.5 trillion, 2008q3 to 2013q1).[27] Since collateralized borrowing is the main driver of fire sales, we consider our data to capture the key part of a dealer's balance sheet relevant for the model's framework.

To smooth out end-of-month effects, we conduct the analysis at a monthly frequency using monthly averages for all variables. We restrict our sample to the top 25 dealers by asset size every month. This group accounts for 98.5 percent of total assets. We group the data into the nine asset classes listed in Table 1. From this data we construct for each dealer a monthly average balance sheet and then form the matrices A, M and B.[28]

A key input into the model is the liquidity of asset classes $\ell_k = \ell_k^*/w$. To measure the wealth w of potential buyers of fire-sold assets, we use the value of total financial sector assets net of the assets of the dealers in our sample.[29] To capture differences in the liquidity of individual asset classes, we take advantage of the information about asset liquidity embedded in haircuts as proposed in Brunnermeier et al. (2012) and Bai, Krishnamurthy, and Weymuller (2013). As Figure 3 shows, there is both cross-sectional and time-series variation in the haircuts of different asset classes. To map haircuts $h_{k,t}$ into liquidity $\ell_{k,t} = \ell_{k,t}^*/w_t$, we proceed in two steps. In the first step, we anchor the liquidity of corporate bonds in August 2011 to 10^{-13}, i.e. $\ell_{\text{CB,Aug11}} = 10^{-13}$, which corresponds to 10 basis points price change per \$10 billion of trading imbalances. We use this number to match Greenwood et al. (2014) who use the same value in their analysis of a cross-section of European bank balance sheet data released in the summer of 2011.[30]

In the second step, we make liquidity a quadratic function of haircuts, i.e. if asset class k has twice the haircut of asset class k' then k is four times as illiquid as k'. This matches the cross-sectional profile of measures of liquidity in the repo market provided by market participants and the New York Fed's Market staff as reported in Begalle et al. (2013).[31]

[27] The Financial Accounts series for broker-dealer repo borrowing and total liabilities are Z1/FL662150003.Q and Z1/FL664190005.Q, respectively.

[28] We apply a leverage cap of $b_i \leq 100$ which is binding for 3.6 percent of observations.

[29] The Financial Accounts series for total assets of the financial sector is Z1/FL792000095.Q. We interpolate linearly to convert the quarterly series to a monthly frequency.

[30] Ellul et al. (2011) find a median price impact of 7.5 basis points per \$10 billion for corporate bonds, with several basis points of variation depending on bond quality and other factors. Other empirical studies of the price impact of fire sales are Coval and Stafford (2007) for individual stocks, Jotikasthira et al. (2012) for emerging market stock indices and Merrill et al. (2012) for non-agency residential MBS. They find price impact estimates that are significantly higher than those for corporate bonds. However, the assets they study do not specifically fit our asset classes as well as corporate bonds (equities in tri-party repo are predominantly large caps and American or European indices).

[31] Their measure of liquidity is the dollar amount that can be liquidated in one day without an adverse

The two steps just outlined can be expressed by

$$\ell_{k,t} = \frac{\bar{\ell} \times h_{k,t}^2}{w_t} \quad \text{with} \quad \bar{\ell} = \frac{10^{-13} \times w_{\text{Aug11}}}{h_{\text{CB,Aug11}}^2},$$

where w_t are non-dealer financial sector assets and the constant $\bar{\ell}$ is picked to make the liquidity of corporate bonds in August 2011 equal to 10^{-13}.

One concern in using haircuts to indicate relative asset liquidity is that equities have the highest haircuts (8.1 percent on average) although we consider them more liquid than several of the other asset classes. Haircuts can be high because an asset is illiquid or because its price is volatile (or other secondary reasons). For all of our asset classes except for equities, liquidity is the determining factor for haircuts. For haircuts on equities, however, price volatility is more important so we have to adjust them accordingly. We therefore rescale haircuts on equities so that their average across the sample is 4 percent.[32] This makes them less liquid than Treasuries with an average haircut of 1.8 percent, agency debt with 1.9 percent and agency MBS with 2.1 percent but more liquid than all the other asset classes. Our liquidity ordering implied by haircuts aligns closely with measures of liquidity for tri-party repo in Begalle et al. (2013) mentioned above (see Appendix A.5).

The last input we need is the exogenous shock F. We pick a uniform 1 percent decline in the price of all assets as a means to produce a generalized stress in the system. This shock is quite sizable, corresponding to average direct losses equal to 35 percent of total system equity. In assuming this shock, we are not trying to calibrate a realistic shock or a shock that occurs with a certain probability. For example, a shock of 1 percent may be rare for Treasuries but much more frequent for equities. We view a uniform 1 percent shock as a reference point that illustrates well the overall vulnerabilities of the system. Since the framework is linear, and we show asset-specific systemicness below, computing AV for any other shock is immediate. Alternatively, we scale shocks by the volatility of different asset classes' returns and find almost identical results (Section 3.3.2).[33]

Table 1 gives the summary statistics for our panel of balance sheet data. The average dealer size is \$69.9 billion, with considerable variation between the 10th percentile of \$4.3 billion and the 90th percentile of \$160.5 billion and large skew with a median of \$41.4 billion. Leverage also has considerable variation around the mean of 41.8. In terms of portfolio shares, Agencies and Treasuries are dominant, with average portfolio shares of 38.4 percent and 34.3

impact on market prices. See Appendix A.5 for a detailed comparison to our estimates.

[32] Appendix A.5 shows a robustness check for this assumption.

[33] In Appendix A.1, we also consider shocks to equity capital that do not require asset-specific assumptions and show the dynamics of AV are essentially the same.

Table 1: Summary statistics for broker-dealers

	System	p10	Med.	Mean	p90
Assets ($ billions)	1,724.3	4.3	41.4	69.9	160.5
Leverage	35.2	26.4	39.2	41.8	57.6
Portfolio shares (percent):					
Agency MBS	41.4	2.0	39.9	38.4	65.3
U.S. Treasuries	32.3	5.7	32.0	34.3	64.4
Agency debt	8.6	0.3	7.4	8.8	17.6
Corporate bonds	5.3	0.0	3.8	5.4	11.5
Equities	5.1	0.0	0.3	6.8	11.5
ABS & non-agency MBS	4.6	0.0	2.3	4.2	10.4
Money market instruments	1.5	0.0	0.0	0.9	2.8
Municipal bonds	0.8	0.0	0.0	0.9	2.3
Residual securities	0.5	0.0	0.0	0.4	1.5

Note: System statistics are time-series means. All other statistics are over the entire panel.

percent, respectively. However, there is substantial heterogeneity in the dealers' portfolios.

Figure 1 illustrates how system size and leverage vary over the sample period. We see that – except for the first year of the sample – there is considerable comovement between system assets and system leverage which is in line with the general evidence on procyclical leverage of broker-dealers (Adrian and Shin, 2010b, 2011).

Going into the underlying details reveals what happened during the first year of the sample which covers the financial crisis. System assets are at their peak in August 2008 at $2.42 trillion and then decline precipitously during the rest of 2008 and the beginning of 2009 – the worst phase of the financial crisis. Figure 2 shows that the drop in size is accompanied by a dramatic shift in the aggregate portfolio: the share of safe assets – Treasuries but also agency MBS – is increasing while the share of risky assets – corporate bonds as well as ABS and non-agency MBS – is decreasing. Leverage initially drops until October 2008 as the haircuts on risky asset classes increase more quickly than their portfolio shares decrease (see Figure 3). Once the spike in these haircuts recedes in late 2008 while the shift to safe asset classes continues, leverage increases since safer asset classes have lower haircuts, i.e. are held with higher leverage. By the time markets have stabilized in the second quarter of 2009, system assets are down by more than 30 percent and the aggregate portfolio share of Treasuries has increased by more than half while the share of ABS and non-agency MBS has dropped by more than half.

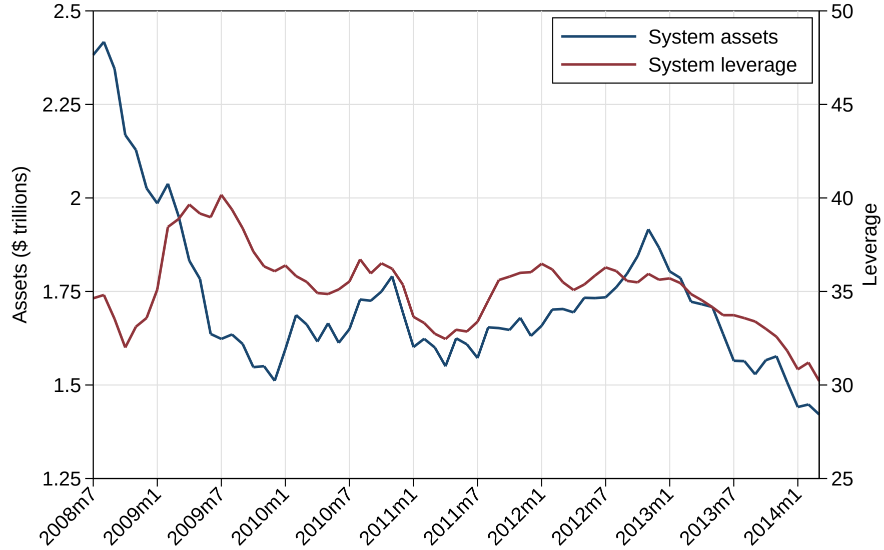

Figure 1: System assets and system leverage for broker-dealers.

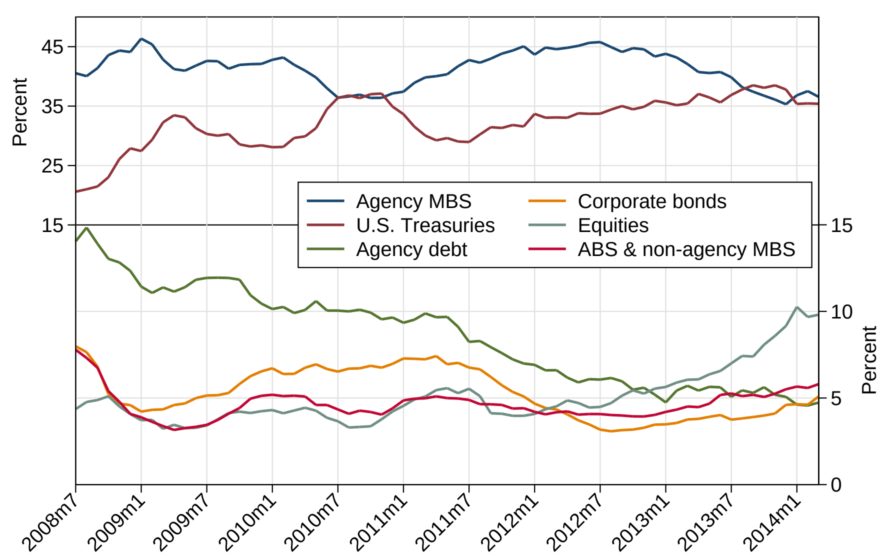

Figure 2: System-wide portfolio shares of main asset classes (broker-dealers).

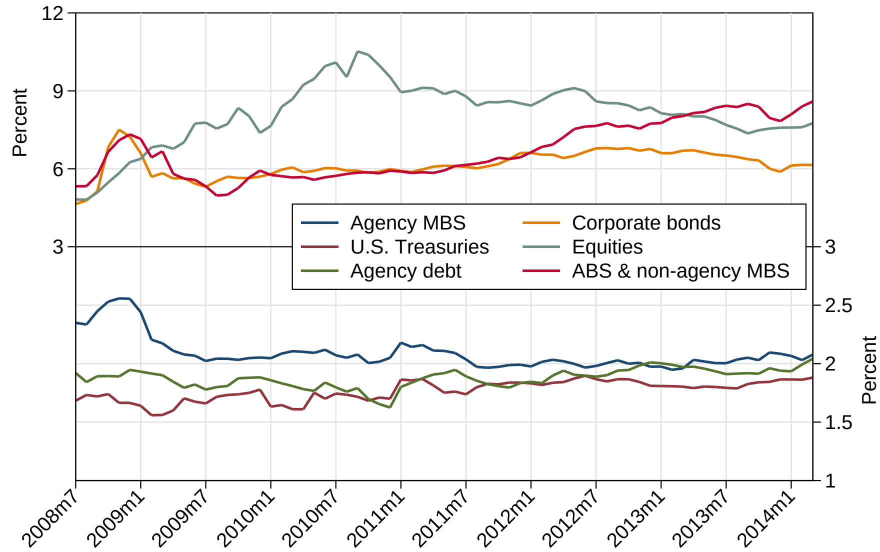

Figure 3: Value-weighted average haircuts for main asset classes (broker-dealers).

Over the rest of the sample, the development in individual asset classes are more idiosyncratic. Of note is the portfolio share of Treasuries which coincides well with flight-to-safety episodes: After increasing during the worst part of the crisis, the share of Treasuries decreases as conditions normalize until late 2009. With resurgent volatility and widening credit spreads over the course of 2010, the share of Treasuries increases, only to decrease again as conditions normalize by early 2011. Finally, a third rise in Treasuries corresponds to the development of the Euro crisis in 2011 and concerns about stagnant growth in developed economies.

3.2 Results and analysis

Figure 4 shows the time series of aggregate vulnerability (AV) for the broker-dealer sector measured as the percentage of aggregate broker-dealer capital that would be lost due to the fire-sale spillover effects after a 1 percent shock to all assets. The calculation is done separately for each month using balance sheet information for that month only – a series of repeated cross-sectional computations. This does not mean that we expect all the fire sales to occur within a single month. The AV numbers represent total losses over whatever horizon it takes for them to be realized, as explained in Section 2.3.

The vulnerability is highest at the beginning of the sample, starting at a level of 12.0 percent in July 2008. It stays high throughout the worst part of the crisis, peaking at 12.6 percent in November 2008. Once the worst of the crisis is over, AV falls by almost 40 percent over the course of 2009. Between the end of 2009 and the end of 2012, the measure fluctuates

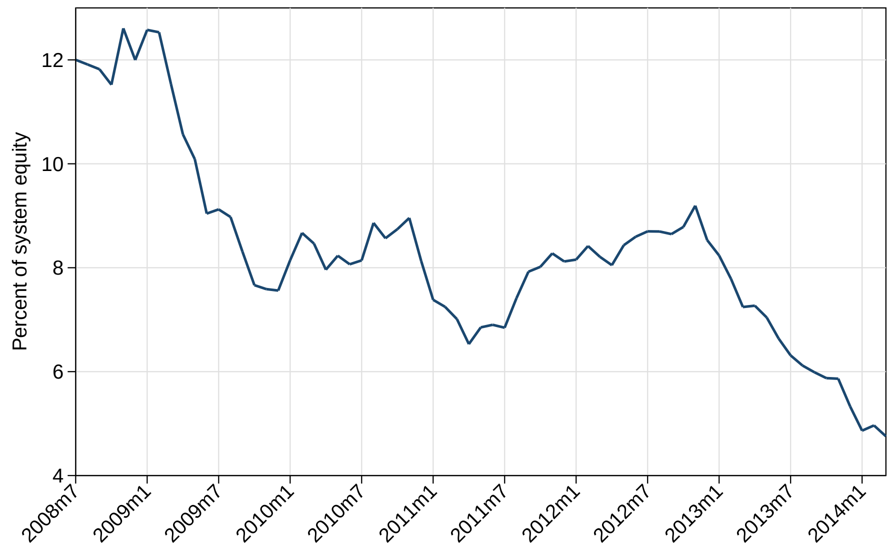

Figure 4: Benchmark aggregate vulnerability (broker-dealers); percentage points of system equity capital lost due to fire-sales per percentage points of initial shock.

around 8.5 percent with a temporary dip to 6.4 percent during 2011 and a maximum of over 9 percent during debt ceiling negotiations in the U.S. Congress at the end of 2012. Finally, AV falls by over 30 percent during 2013, ending the sample period at 4.8 percent in March 2014.

To better understand what is driving the changes in AV over time, Figure 5 shows the evolution of AV together with its components from equation (2). We normalize all series to 100 at the beginning of the sample to illustrate the contribution of each component. For most of the sample, AV is strongly correlated with relative system size which is actually very similar to absolute system size (see Figure 1). It shows that the broker-dealer sector fluctuates significantly in size relative to the rest of the financial sector implying larger variations in the vulnerability to fire-sale spillovers as the potential volume of sales varies relative to the capacity to absorb them.

However, the comovement between AV and relative size is not perfect and the interaction of the other two factors, leverage and illiquidity concentration, plays an important role. Overall, these two latter factors are strongly negatively correlated with each other since data on haircuts enters both but in opposite ways. Interesting effects on AV therefore occur wherever the negative correlation is imperfect so the two measures don't cancel each other. During the worst part of the crisis, from September 2008 until January 2009, illiquidity concentration first increases *faster* than leverage decreases and then – in the reversal –

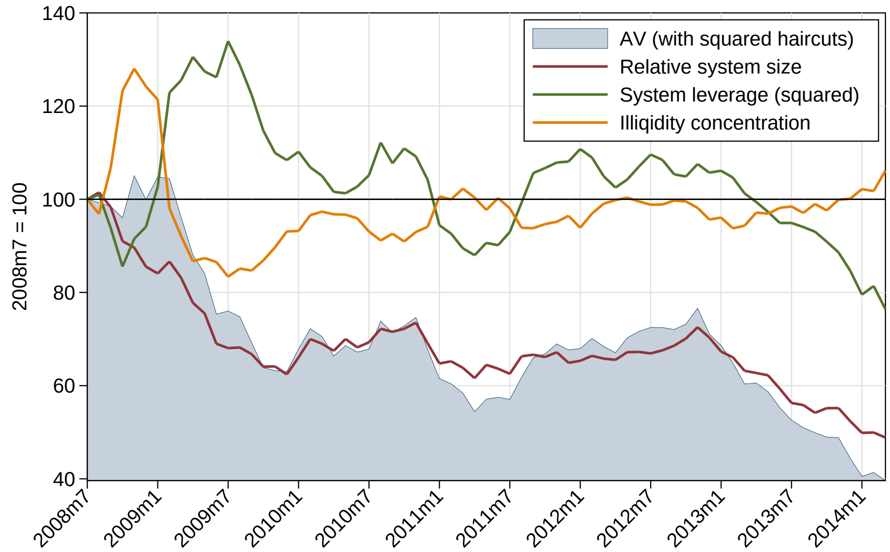

Figure 5: Decomposition of aggregate vulnerability into factors (broker-dealers).

decreases *slower* than leverage increases. The overall effect is for AV to remain high and even increase, although the relative size of the dealer sector shrinks by almost 20 percent.

Figure 6 breaks down the contributions to fire-sale externality by dealer size. We see that at the height of the crisis in late 2008, the five largest dealers by size are responsible for up to 70 percent of aggregate vulnerability and the top 10 for over 90 percent. Over time, this distribution becomes less extreme and by the end of the sample, the share of the top 5 is reduced to 40 percent and the dealers ranked 16–25 account for about 14 percent.

Figure 7 shows the systemicness measure SA_k, i.e. the contribution to aggregate vulnerability of asset class k, for the most systemic asset classes. Comparing to Figure 2, we see that the aggregate portfolio share of an asset class is a key driver of its systemicness as the largest asset classes – agency MBS and Treasuries – are also at the top in terms of systemicness. However, other factors like the relative size of the whole system as well as the changes in the liquidity of an asset class also play a role. For example, the systemicness of Treasuries declines steadily from late 2012 as the system shrinks even though the portfolio share remains roughly constant. Equities, on the other hand increase their portfolio share more than two-fold starting in early 2012 without a large increase in their systemicness.

Since the data on broker-dealers is confidential, we cannot show any analysis of individual dealers' systemicness. We can, however, study how the components of institution systemicness – factored in equation (3) – behave in the cross-section.

Figure 8 shows the cross-sectional rank correlation of size, leverage and illiquidity linkage for each month of our sample. Size and leverage show strong negative correlation over most

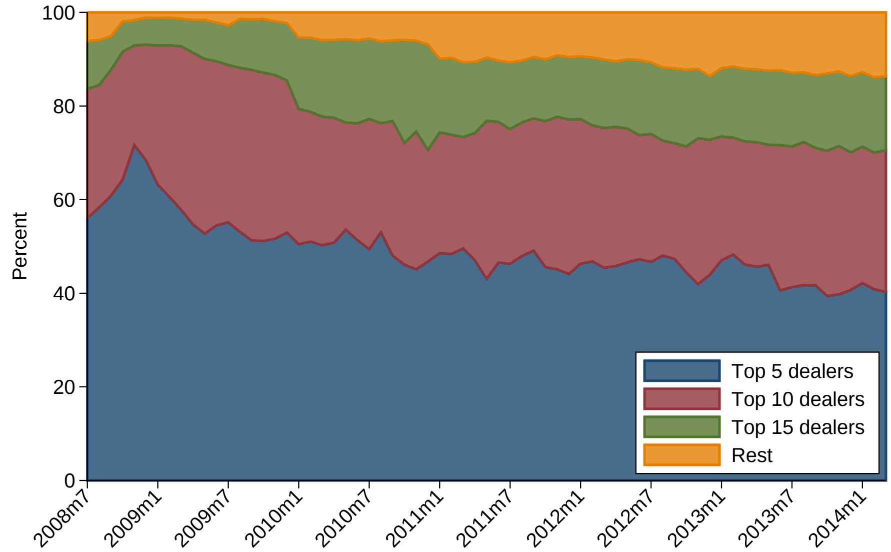

Figure 6: Contributions to fire-sale externality by dealer size (broker-dealers).

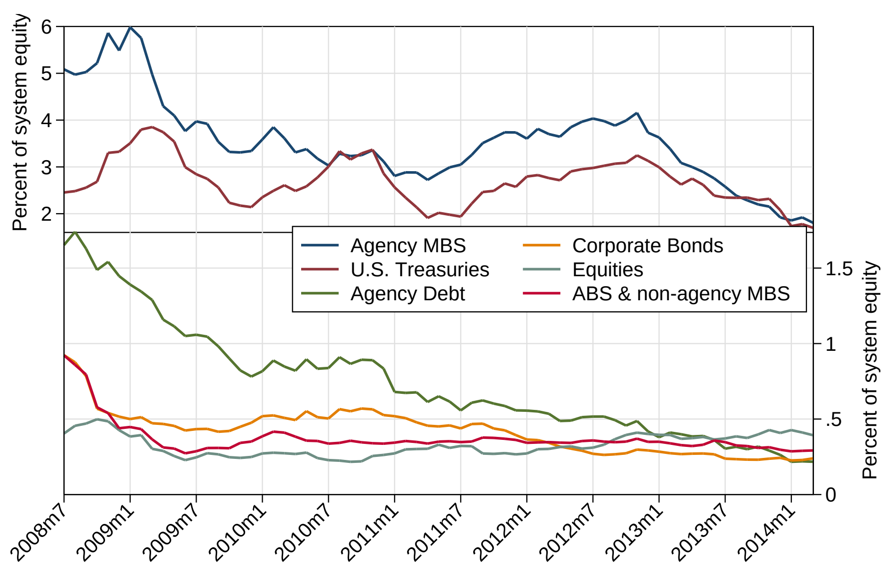

Figure 7: Fire-sale externality of most systemic asset classes (broker-dealers).

Figure 8: Cross-sectional rank correlations of bank size, leverage and illiquidity linkage (broker-dealers).

of the sample, indicating that most of the illiquid assets with high haircuts are held by the larger dealers. Only during the crisis, when the large dealers shift towards safer assets does the correlation briefly spike. Linkage and leverage don't show a clear correlation except during the crisis when the initial positive correlation moves in the opposite direction to the correlation between size and leverage. Finally, the correlation between size and illiquidity linkage is mostly positive, indicating that the large dealers' portfolios are more invested in assets with high potential for fire-sale spillovers.

3.3 Main robustness checks

We consider three key robustness checks for the broker-dealer analysis, specifically on the special nature of U.S. Treasury securities, on shocks scaled by volatility of asset classes and on multiple rounds of fire sales. Further robustness checks are relegated to the appendix.

3.3.1 Liquidity of Treasuries and flight to quality

The asset holdings of broker-dealers are dominated by agency MBS and Treasuries (Figure 2), the latter of which is a somewhat special asset class with different liquidity characteristics and safe-haven properties. Our benchmark specification above is agnostic about this and treats Treasuries the same as the other asset classes, in particular assuming that they exogenously decline by 1 percent with all other assets and assuming they suffer a price impact when sold.

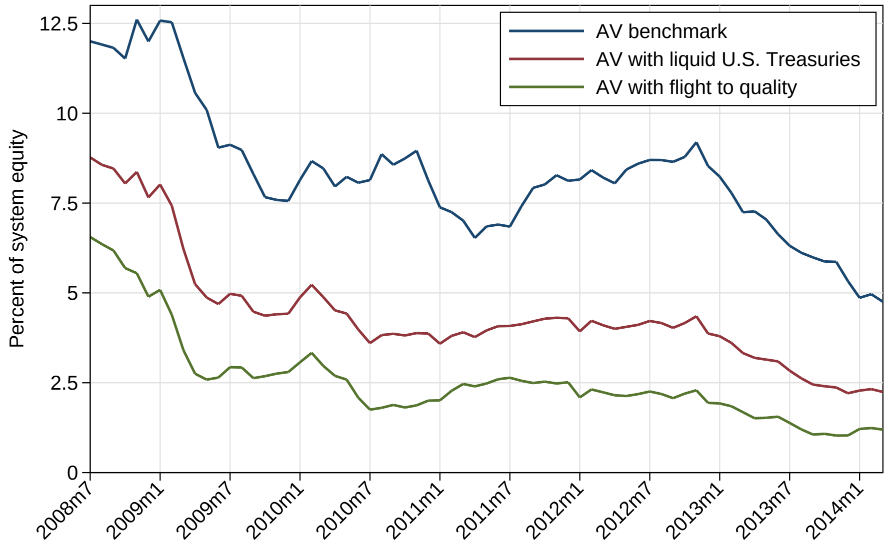

Figure 9: Accounting for the special features of Treasuries

Figure 9 shows the effects of relaxing these assumptions in two steps. In the first step, we assume that Treasuries are equivalent to cash, i.e. they do not receive an exogenous shock and they can be sold without price impact (red line in Figure 9). These modifications have two main effects: First, the overall level of AV is lower, as would be expected. Second, the relative magnitude of the changes in AV during the early part of the sample compared to the rest of the sample is affected. While AV is still highest during the heat of the financial crisis in 2008 and drops significantly as stress recedes in early 2009, the movements from 2010 to 2014 appear much more muted than in the benchmark specification.

We go even further in the second step, assuming not only that Treasuries are perfectly liquid but also that they *increase* in value as all other asset classes receive negative shocks. Specifically, we assume that our stress scenario features "flight to quality" by shocking Treasuries with +1 percent and all other asset classes with −1 percent (green line in Figure 9). While this modification further reduces the overall level of AV, the magnitude of changes over time is not significantly altered compared to the previous case. In summary, we can therefore conclude that while the special liquidity characteristics of Treasuries can change the level of AV, they do not materially affect the use of AV as a systemic risk measure.

3.3.2 Asset shocks scaled by volatility

In our benchmark, the exogenous shock F is a uniform 1 percent decline in the price of all assets. As mentioned above, this shock is designed to trigger generic stress for broker-dealers and is not meant to capture any specific scenario. Figure 10 shows that if each asset is instead

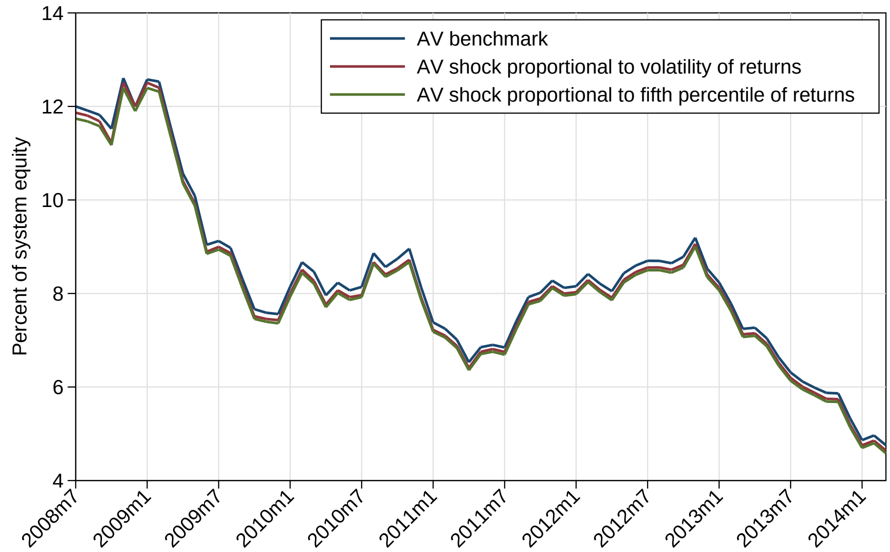

Figure 10: Asset shocks scaled by volatility or low quantiles of asset returns.

shocked proportionally to its volatility we get almost identical AV estimates. The new shock is

$$F_{\text{vol}} = \bar{f} \times [\sigma_1, \ldots, \sigma_K], \tag{5}$$

where σ_k is the volatility of monthly returns for asset k and the constant $\bar{f}$ is chosen so that the initial total direct losses produced by the new shock are identical to those produced by the benchmark shock, i.e. $1'AMF_{\text{vol}} = 1'AMF$. Figure 10 also confirms that AV remains virtually unchanged if we make the shock proportional to left-tail outcomes, in this case the fifth percentile of returns for each asset class. Appendix D reports the time-series of returns we use for each asset class and the estimates for their volatilities and fifth percentiles.

3.3.3 Multiple rounds of fire sales

We now study how AV changes when we iterate the one-shot fire-sale mechanism that we used in our main specification. We think of the spillover losses that arise due to the initial exogenous shock F as a new endogenous "shock" that triggers a second round of fire-sales. The spillover losses of this new round serve as a shock for the next round, and so on. The multi-round AV is the sum of spillover losses in all rounds as a fraction of initial system equity.

When computing several rounds of fire-sales we need to account for fire-sold assets leaving the system in the current round before we can proceed to the next. Total assets inside the system thus decrease in each round of fire-sales. Once we explicitly allow initial and final

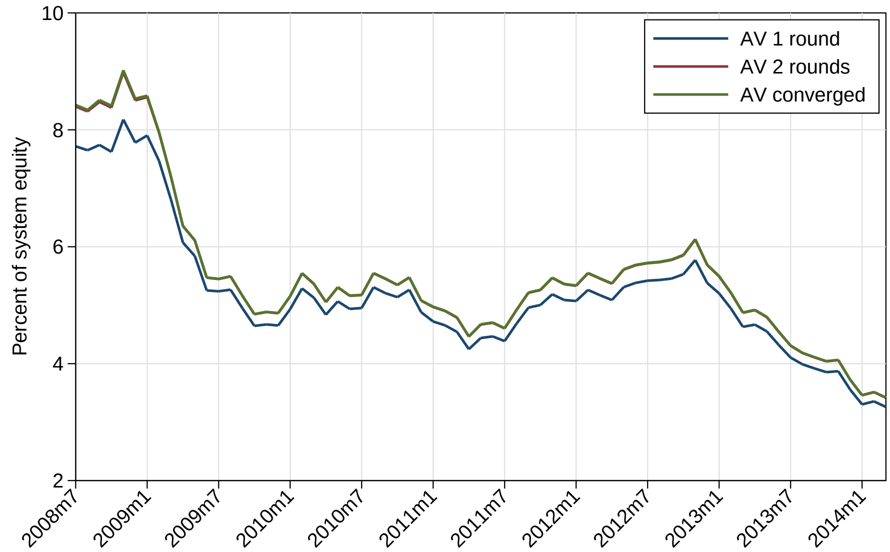

Figure 11: Multiple rounds of fire sales.

assets to differ, the first-round fire-sale spillovers are:

$$\text{AV}_1 = \frac{1}{e}1' A_2 M L M' B A_1 M F_1. \tag{6}$$

The only difference between equation (6) and benchmark AV based on equation (1) is that we distinguish initial assets A_1 from final assets A_2. Our assumption that all fire-sold assets exit the system implies that A_2 is given by the following relation:[34]

$$A_2 1 = A_1 1 - B A_1 M F_1,$$

Using A_2 as initial assets for the second round and the first-round fire-sale effects $F_2 = L M' B A_1 M F_1$ as the new shock, we find second-round spillover losses:

$$\text{AV}_2 = \text{AV}_1 + \frac{1}{e}1' A_3 M L M' B A_2 M F_2.$$

We can iterate this process indefinitely with resulting fire-sale spillovers given by

$$\text{AV}_\infty = \text{AV}_1 + \text{AV}_2 + \text{AV}_3 + \dots.$$

Figure 11 shows how one, two and multiple rounds of fire-sales affect AV for broker-

[34]We multiply the diagonal matrices A_1 and A_2 by a vector of ones to make them conformable with the vector BA_1MF of dollar amounts that each bank must sell to return to target leverage. Since banks sell assets proportionally to their holdings, their portfolio shares M remain unchanged across rounds.

dealers. We see that convergence is achieved by the second round and the shape of AV is preserved while the magnitude changes only marginally. The one-round benchmark therefore captures the vast majority of spillovers.

4 Bank holding companies

4.1 Data and its mapping to the model

In this section, we use data from financial firms that file regulatory form FR Y-9C with the Federal Reserve. Form FR Y-9C provides consolidated balance sheet information for bank holding companies, savings and loans associations and securities holding companies. For convenience, we refer to all of them as bank holding companies (BHCs). The information in the form is publicly available and is generally used by regulators to assess and monitor the condition of the financial sector.[35] BHCs with total assets over \$150 million before March 2006 and over \$500 million thereafter are required to file.

We restrict our study to the largest 100 BHCs by assets in each quarter because they have the most complete and uniform data. We exclude Goldman Sachs and Morgan Stanley which became bank holding companies and started filing Form Y-9C in 2009q1 because they are economically essentially broker-dealers.[36] We drop firms owned by foreign entities because regulation requires that they are well-capitalized on the basis of the foreign entity's capital as a whole, and not necessarily on the basis of equity capital held in the U.S. subsidiary, which is the only one reported in form FR Y-9C. The type and detail of disclosure in the form have changed over time with recent forms providing a more granular view of banks' balance sheets. While the data is available since 1986, the level of detail changes over time. We begin our study in the first quarter of 1996 to strike a balance between a long enough time span for meaningful analysis and substantial granularity in asset classes.

The matrix of total assets A comes directly from the balance sheet data. We group assets into the eighteen categories listed in Table 2 to construct the matrix of portfolio weights M.[37] This is the finest subdivision we can construct while reasonably maintaining the assumption of no cross-asset price impacts of fire sales.

The leverage ratios of firms, defined as the ratio of debt to equity capital, are collected in the diagonal matrix B. We use tier 1 capital as our measure of equity, and subtract equity

[35] A template for the current form and additional information can be found at http://www.federalreserve.gov/apps/reportforms/.

[36] In Appendix A.6, we provide robustness checks to this and the data selection choices that follow.

[37] Appendix E contains the mapping between these asset classes and entries in form FR Y-9C.

from total assets to get our measure of debt. In addition, we drop all banks with negative leverage and cap leverage at 30 whenever it exceeds this threshold.[38]

For the entries $\ell_k = \ell_k^*/w$ of the liquidity matrix L, we follow a strategy similar to the one we followed in in the previous Section. To measure the wealth w of potential buyers of fire-sold assets, we again use the value of total financial sector assets but now net of the assets of the BHCs in our sample. Unlike in the repo market where we can use haircut data, there are no readily available estimates for the liquidity of most assets considered in this section. However, while cross-sectional variation in asset liquidity is important for the analysis of broker-dealer, the same turns out not to be true for the analysis of BHCs.[39]

We therefore first anchor the liquidity of *all* assets in 2011q3 to 10^{-13}, i.e. $\ell_{k,2011\text{q}3} = 10^{-13}$ for all k – except for cash which we always treat as perfectly liquid. This liquidity corresponds to a price impact of 10 basis points per \$10 billion of assets sold and closely matches empirical estimates for the liquidity of corporate bonds. Our strategy makes our estimates comparable to Greenwood et al. (2014), who apply the same liquidity number to all the assets of banks that underwent the stress test conducted by the European Banking Authority in 2011q3. After determining the values for 2011q3, the liquidities of all assets then change over time in proportion to the non-bank financial sector assets:

$$\ell_{k,t} = \frac{\bar{\ell}}{w_t} \quad \text{with} \quad \bar{\ell} = 10^{-13} \times w_{2011\text{q}3} \tag{7}$$

The final input needed, the vector of exogenous asset shocks F, is a uniform 1 percent decline in the price of all assets. This shock produces average direct losses equivalent to 13.9 percent of total system equity.

Table 2 shows summary statistics for our panel of bank balance sheets. System-wide leverage is 13.6 on average. The distribution of leverage is relatively tight around the mean of 12.1; most firms have leverage relatively close to this average with the 10th and 90th percentiles at 8.5 and 15.4, respectively. The table also shows the portfolio shares of the different asset classes. At 15.2 percent aggregate share, loans secured by residential real estate are the largest asset class and have the second highest average portfolio share across banks at 17.6 percent. Commercial real estate loans comprise 7.6 percent of aggregate assets, although the mean portfolio share across banks is the largest of all asset classes at 18.8 percent. The difference between aggregate and average portfolio shares shows that the distribution of commercial real estate loans is skewed, with smaller banks holding a larger proportion of

[38] Winsorizing leverage at 30 only affects 0.3 percent of observations.

[39] In Section 4.3.1, we show that allowing for differences in liquidities across asset classes does not materially change our conclusions for BHCs.

Table 2: Summary statistics for BHCs.

	System	p10	Med.	Mean	p90
Assets ($ billions)	8,054.4	5.7	12.3	80.5	140.7
Leverage	13.6	8.5	11.7	12.1	15.4
Portfolio shares (percent):					
Residential real estate loans	15.2	4.3	17.0	17.6	29.9
C & I loans	11.6	2.3	11.4	12.2	21.7
Consumer loans	9.0	0.4	5.7	7.3	14.4
Agency MBS	8.1	1.8	10.1	11.9	22.9
Commercial real estate loans	7.6	2.9	17.3	18.8	35.2
Repo & fed funds loans	6.9	0.0	0.3	1.8	4.5
ABS & other debt securities	5.8	0.0	0.5	1.9	4.9
Cash	5.7	1.6	3.5	5.1	9.6
U.S. Treasuries	2.0	0.0	0.3	1.7	4.7
Residual loans	4.1	0.2	1.9	2.7	5.7
Lease financings	1.8	0.0	0.6	1.5	4.0
Residual securities	4.8	0.0	0.0	0.7	1.3
Non-agency MBS	1.7	0.0	0.2	1.5	4.0
Agency securities	1.7	0.0	2.0	3.9	10.1
Residual assets	10.6	3.3	6.5	7.8	12.3
Equities & other securities	1.2	0.0	0.3	0.8	1.5
Municipal securities	1.2	0.1	1.1	2.0	4.7
Other real estate loans	1.0	0.0	0.3	1.0	2.0

Note: System statistics are time-series means. All other statistics are over the entire panel.

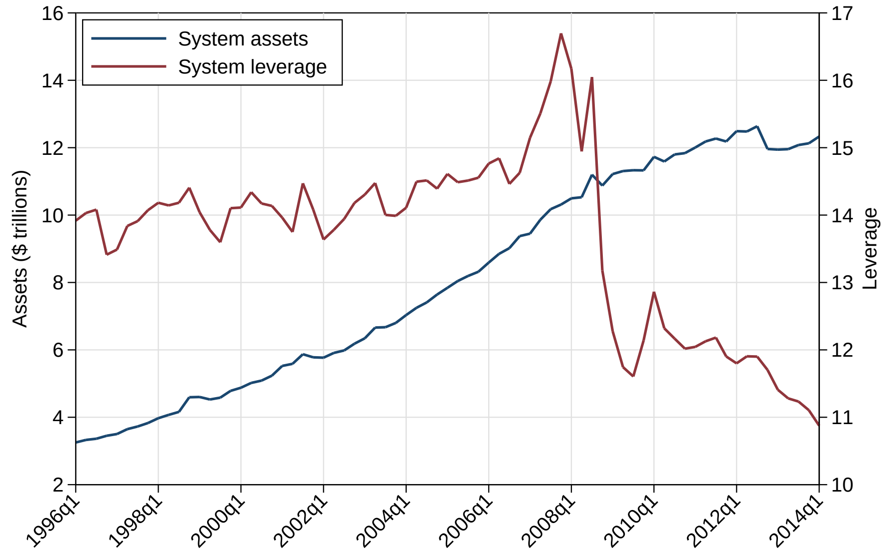

Figure 12: System assets and system leverage for BHCs.

their balance sheet in commercial real estate.

Figure 12 shows the evolution of total assets and system-wide leverage for each quarter of the sample. Assets increase steadily between 1996 and 2014, with an annual growth rate of almost 8 percent. The downward jump in 2012q4 is mainly due to banks preparing to comply with new Basel III regulations. System-wide leverage, also plotted in Figure 12, shows no trend from 1996 to 2004. Then it is slightly increasing until 2007 when the crisis unfolds and banks suffer capital losses. Although the financial sector as a whole was levering up significantly in the run-up to the crisis, most of the increase was in the shadow banking sector and off-balance sheet vehicles, not in commercial banking (Adrian and Shin, 2010a). System leverage peaks in 2007q4 and declines rapidly in 2008 and 2009 as banks are recapitalized and delever. After a brief recovery in 2010, the delevering process continues mostly due to regulatory changes and changes in business plans after the crisis.

Figure 13 plots the aggregate portfolio shares of the largest asset classes over time. Residential real estate loans as well as commercial and industrial (C & I) loans are the largest categories throughout the sample, with aggregate holdings sometimes exceeding 15 percent of total system assets. The evolution of these two asset classes will be key to understanding AV. Both loan categories remain relatively stable through 2001q1, when a bifurcation starts to occur. At that time, the economy was undergoing an "investment-led" recession. In 2001, real nonresidential business fixed investment fell for the first time in 9 years and plummeted 7.5 percent. The economy was subsequently hit by the 9/11 terrorist attacks, a string of corporate governance and accounting scandals, and geopolitical uncertainty due to the Iraq

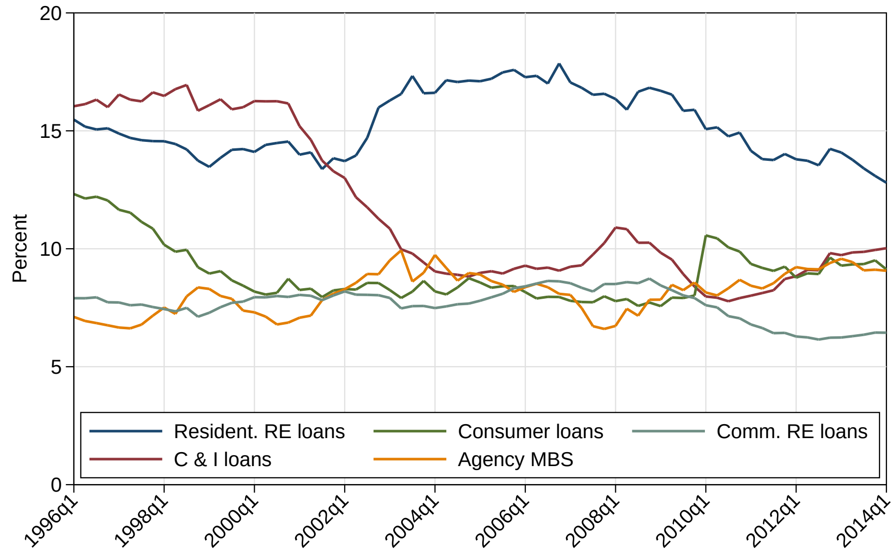

Figure 13: System-wide portfolio shares of asset classes in percent (BHCs).

war. Banks became more risk averse and tightened corporate lending standards. Additionally, with low stock market valuations, increasing oil prices and the "capital overhang" that resulted from hefty investments in the late 1990s, C & I loans dropped noticeably.

In an effort to stimulate the economy, the Federal Reserve lowered the effective federal funds rate from 6 percent in 2001 to 1 percent in 2003. Long rates dropped in lockstep – reinforced by a global "savings glut" – which incentivized corporations to substitute commercial paper and C & I loans with long-term bonds. In brief, supply and demand of C & I loans substantially declined in this period. The low interest rates, however, fueled the residential housing market by lowering mortgage rates, aided by new developments in mortgage finance and other factors. From 2001 to 2003, the S&P/Case-Shiller National Price Index increased almost 28 percent and real private residential fixed investment increased more than 20 percent. A wave of purchasing, refinancing and home equity loans noticeably increased in 2002. The Mortgage Bankers Association (MBA) index of mortgage applications increased by 30 percent in 2002 and, according to the Federal Home Loan Mortgage Corporation (Freddie Mac), holders of conforming mortgages took out $59 billion in equity in the first three quarters of 2002. These numbers reflect the magnitude of the housing boom and explain the increase in residential real estate loans in our data.

4.2 Results and analysis

Figure 14 shows aggregate vulnerability (AV), the percentage of aggregate BHC equity that would be lost due to fire-sale spillovers if all assets exogenously decreased in value by 1

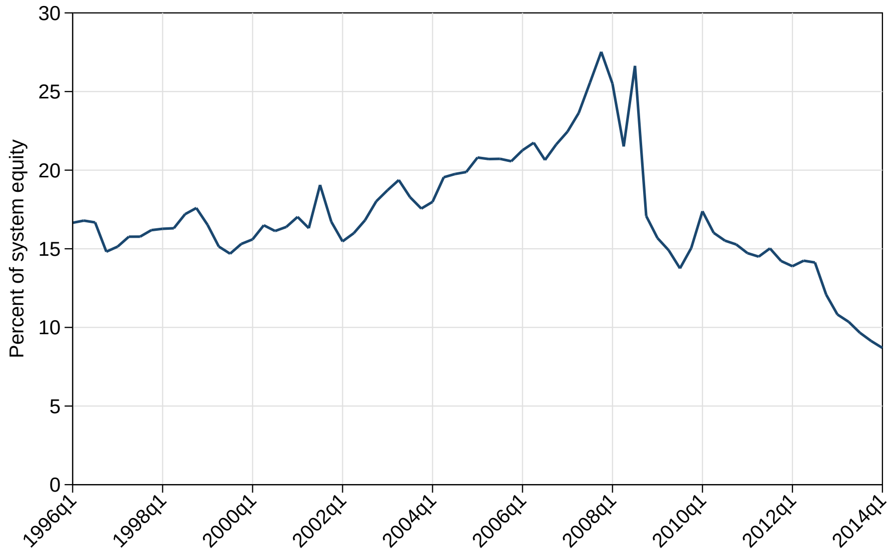

Figure 14: Benchmark aggregate vulnerability (BHCs); percentage points of system equity capital lost due to fire-sales per percentage points of initial shock.

percent. Analogous to the broker-dealer analysis, the AV calculation in a particular quarter uses balance sheet information for that quarter only. The average AV over the sample is 17.1 percent of system equity, although there is substantial time-variation. The measure shows no clear trend between 1996 and 2001. Since then, it builds up steadily from around 17 percent in 2001 until the financial crisis, peaking in 2007q4 at 27.5 percent. If available at the time, our measure would have been useful as an early indicator of vulnerabilities building up; we explore this issue further in Section 5. The measure spikes again in 2008q3 just prior to the height of the crisis. It then decreases more than 10 percentage points in the following four quarters, mostly due to bank recapitalizations (Duarte and Eisenbach, 2014). The 2010–2012 period was characterized by a slow but steady decline in AV in an environment of improving macroeconomic conditions. Since 2012, the decline in AV accelerated as banks became more robust due to new regulations and a continued, if weak, macroeconomic recovery.

We now examine different dimensions and decompositions of AV to understand its behavior in more detail. Fire-sale externalities are caused predominantly by large banks. The five largest by assets account for 40 to 70 percent of AV throughout the sample, as Figure 15 demonstrates. The fifty largest firms produce essentially all externalities, confirming how concentrated systemicness is. The contribution of the largest firms increases before and during the crisis, and stays relatively flat since then.

Figure 16 reports the systemicness measure SB_i from equation (3) for the firms imposing

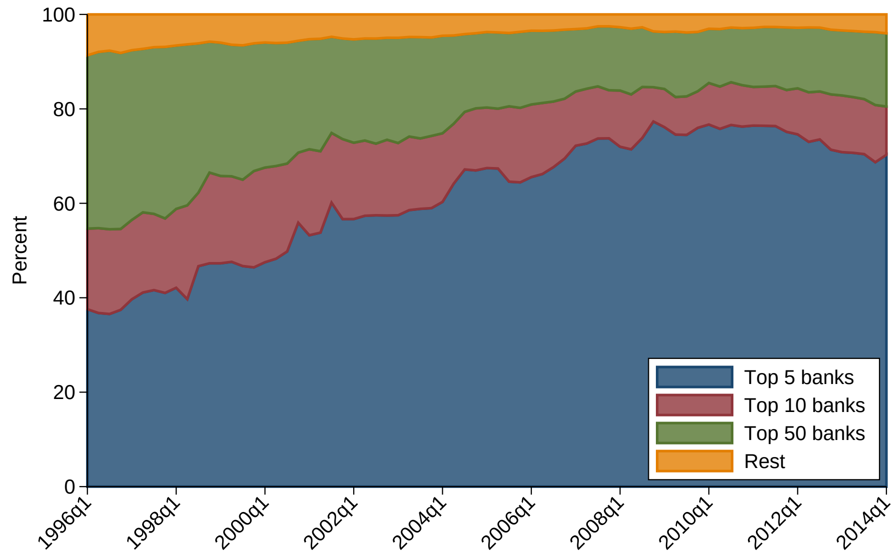

Figure 15: Contribution to aggregate vulnerability by bank size in percent (BHCs).

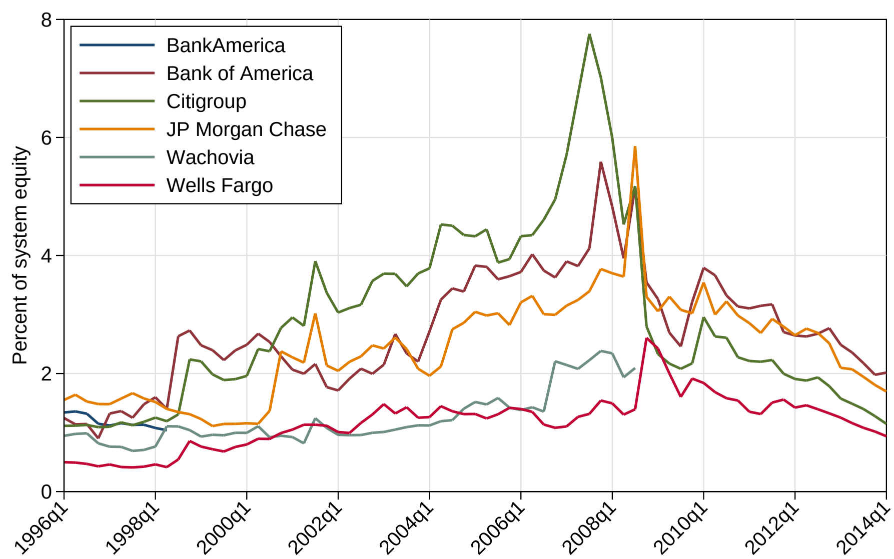

Figure 16: Fire-sale externality of most systemic banks in percent (BHCs).

the highest average externalities on the system. Citigroup leads for most of the sample, with an average systemicness of 2.9 percent of system equity and a peak of 7.8 percent in 2007q3. On average, Citigroup thus accounts for 16 percent of AV. Because the framework is linear, we can interpret Citigroup's systemicness as the fraction of system equity that would be lost due to fire sales if only Citigroup's assets declined in value by 1 percent. Bank of America and JP Morgan Chase follow closely behind, accounting on average for 16 and 14 percent of AV, respectively. The large jumps in bank systemicness before 2006 mostly reflect mergers and acquisitions. For example, Bank of America merged with BankAmerica in 1998, and in 2004 acquired the seventh largest commercial bank in the U.S. at the time, FleetBoston. Note that mergers and acquisitions do not necessarily increase overall AV; whether combining two banks into one makes externalities larger depends on the characteristics of the system. The jumps in 2010q1 are due to a temporary surge in leverage, a significant increase in consumer loans, and a reduction in loss provisions for residential real estate loans. Except for these jumps, the broad trends of Figure 16 can be divided into three segments. Pre-crisis, while Citigroup, Bank of America and Wachovia increased leverage, JP Morgan Chase and Wells Fargo reduced it. Bank of America, Citigroup, JP Morgan Chase and especially Wachovia saw their illiquidity linkage increase. On the other hand, Wells Fargo increased it until 2005 and then significantly reduced it. During the crisis, systemicness of all banks peak due to high leverage induced predominantly by capital losses. After the crisis, illiquidity linkage and leverage decreases for all the banks in Figure 16. Bank of America, Citigroup and JP Morgan Chase shrink in size, while the rest grow. Decomposing bank systemicness according to equation (3) therefore reveals a heterogeneous picture across banks despite their overall systemicness measures being highly correlated.

Figure 17 uses asset systemicness, SA_k from equation (4), to show that the most systemic assets since mid-2001 are residential real estate loans. They are responsible for potential losses of 4.9 percent of system equity at the height of the crisis, corresponding to almost 20 percent of total AV. Residential real estate loans are systemic because they comprise a large fraction of total assets, as Figure 13 shows, and because they are held in large amounts by the most systemic firms. They are also a key determinant of illiquidity concentration: Since 2002 and until 2007, a large proportion of banks increased their portfolio share of residential real estate loans, making balance sheets across the system more similar. The next most systemic asset, C & I loans, are as systemic as residential real estate loans until 2001 when the bifurcation in their aggregate portfolio shares occurs.

Figure 18 shows the evolution of AV together with its components from equation (2), which we normalize to 100 at the beginning of the sample. The changing size of the banking

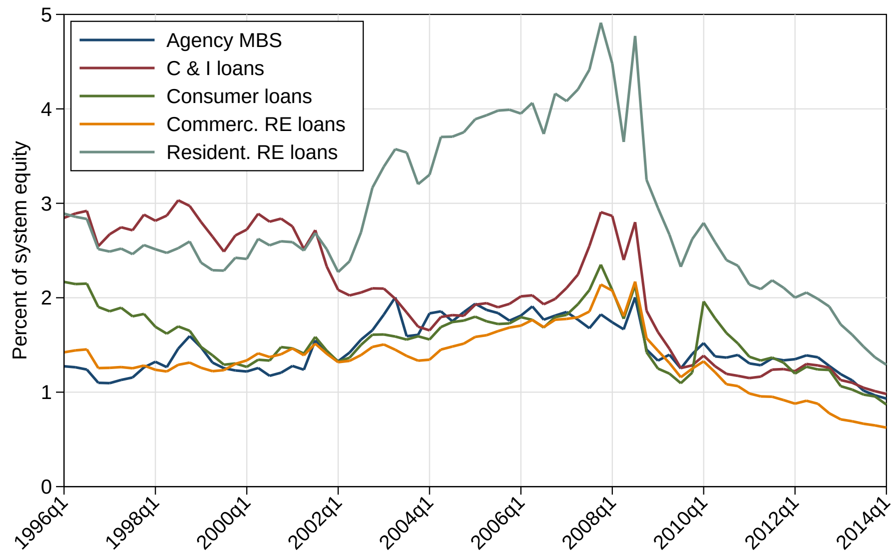

Figure 17: Fire-sale externality of most systemic asset classes in percent (BHCs).

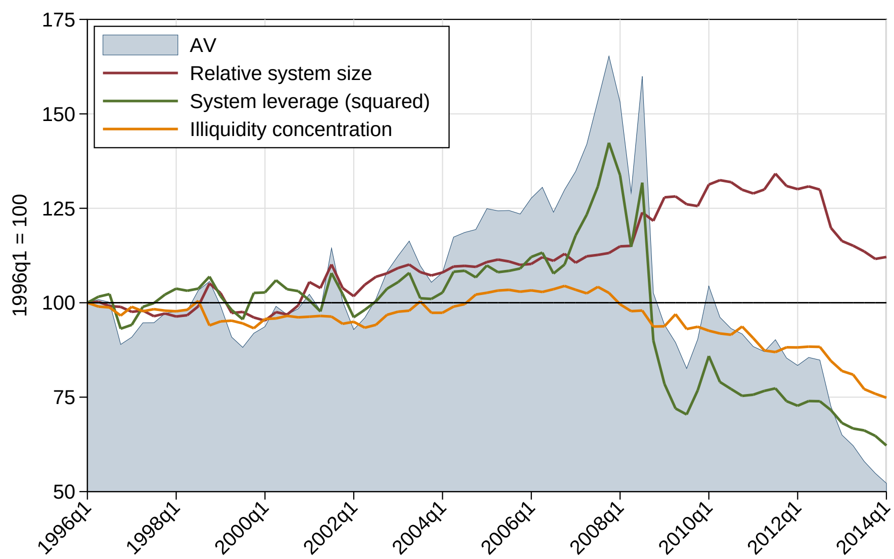

Figure 18: Decomposition of aggregate vulnerability into factors (BHCs).

system relative to the rest of the financial sector is one of the main causes for the increase in AV until the crisis and a mitigant of its decline until 2012. Between 2008 and 2009 firms drastically changed their asset composition. The growth before the crisis is predominantly in real estate loans, repo loans, MBS and other assets. After the crisis, growth is concentrated in cash, government and agency securities, municipal securities, consumer loans and MBS. After 2012, banks started to shrink in the face of subdued loan growth, low net interest margins, and regulatory pressure through stress tests and new Basel III requirements. In terms of individual firms, the largest ten were responsible for the bulk of the growth.

System leverage, the second component, contributes to the growth of AV about as much as system size before 2006. It spikes during the crisis, driving AV upwards with it. After the extremely abrupt delevering of 2009, leverage contributed to a decline in AV. Leverage is also the driving force in quarter-to-quarter changes in AV, while the other components tend to operate at lower frequencies.

Illiquidity concentration has a subdued influence, slowly declining at the beginning of the sample, then increasing with the other two components in the years leading up to the crisis and declining again after 2008. With the initial shock and liquidity being uniform across assets, equation (2) states that illiquidity concentration increases if the aggregate portfolio becomes more concentrated, or if relatively large and levered banks increase the relative holdings of assets that have high concentration in the system. Both on average and for the largest banks, the asset classes showing the highest growth before the crisis also have the largest portfolio weights. The aggregate portfolio becomes more concentrated and illiquidity concentration increases. After the crisis, concentration declines because the large holdings of assets related to real estate decline, disproportionally so in the largest banks.

Another way to understand the components of AV is to look at how they behave in the cross-section of firms. Within each quarter, the size distribution of banks is fat-tailed and well approximated by a power law distribution: a few banks hold almost all assets. Leverage is more evenly distributed, with a cross-sectional mean between 9.7 and 13.0 and a cross-sectional standard deviation between 2.4 and 4.2. Figure 19 shows the cross-sectional rank correlation of size, leverage and illiquidity linkage for each quarter of our sample. Size and leverage show strong positive correlation except during the crisis, when the largest banks delevered the most. Linkage and leverage don't show a strong correlation except just before the crisis, when more levered banks also became more linked. Interestingly, illiquidity linkage and size had a declining correlation leading into the crisis. Unlike the size-leverage and linkage-leverage interactions, the pattern for size and linkage is a moderator of AV.

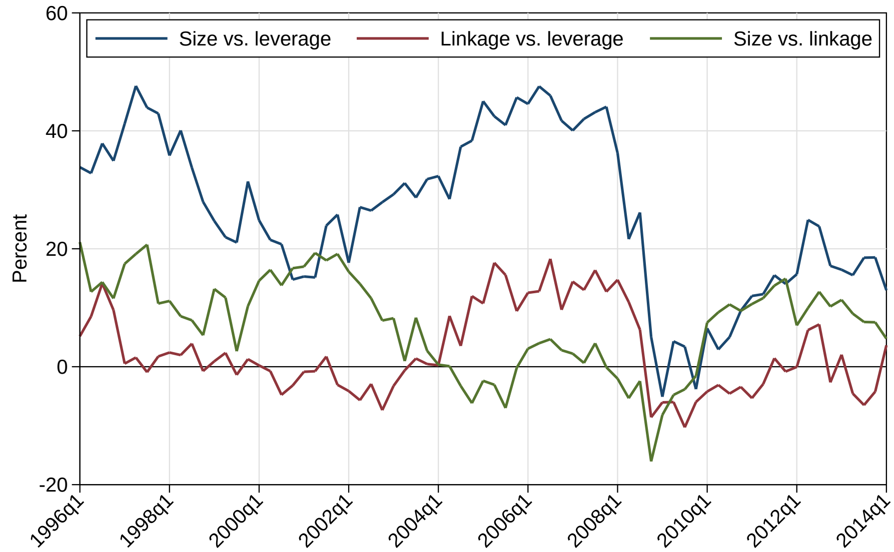

Figure 19: Cross-sectional rank correlations of bank size, leverage and illiquidity linkage (BHCs).

4.3 Main robustness checks

Similar to the broker-dealer analysis, we consider three key robustness checks for BHCs, specifically on the liquidity of asset classes, on risk-based capital constraints and on multiple rounds of fire sales. Further robustness checks are relegated to the appendix.

4.3.1 Liquidity of asset classes

For BHCs, the benchmark specification has identical liquidity for all assets (except cash) since we lack good liquidity estimates for many of the asset classes. We now consider the effects of relaxing this strong assumption and introducing heterogeneity in the liquidity of asset classes using the information contained in two elements of the Basel III regulatory framework, the Liquidity Coverage Ratio (LCR) an the Net Stable Funding Ratio (NSFR). Both ratios involve applying haircuts to different asset classes to account for differences in liquidity. The LCR considers liquidity over a short horizon of 30 days while the NSFR considers liquidity over a longer horizon of one year.[40]

Table 3 illustrates the price impacts resulting from the different liquidity specifications; the values displayed are those for 2011q3, i.e. $\ell_{k,2011q3}$, and the values for other periods are

[40]Appendix G shows in detail how we impute liquidity values for different assets using the LCR and NSFR guidelines. As in the broker-dealer analysis, we respect the empirically supported liquidity for corporate bonds used in the benchmark of 10 basis points of price impact per $10 billion sold.

Table 3: Price impacts used in the heterogeneous liquidity scenarios.

Asset class	Benchmark	LCR	NSFR
Cash	0.0	0.0	0.0
U.S. Treasuries	10.0	0.0	1.4
Repo & fed funds loans	10.0	1.4	2.9
Agency MBS	10.0	4.3	4.3
Agency securities	10.0	4.3	4.3
ABS & other debt securities	10.0	10.0	10.0
Equities & other securities	10.0	14.3	15.7
Municipal securities	10.0	28.6	17.1
Residential real estate loans	10.0	28.6	17.1
Non-agency MBS	10.0	28.6	18.6
C & I loans	10.0	28.6	21.4
Commercial real estate loans	10.0	28.6	21.4
Consumer loans	10.0	28.6	21.4
Lease financings	10.0	28.6	21.4
Other real estate loans	10.0	28.6	21.4
Residual loans	10.0	28.6	21.4
Residual assets	10.0	28.6	28.6
Residual securities	10.0	28.6	28.6

Note: All values are in basis points of price change per $10 billion asset sales.

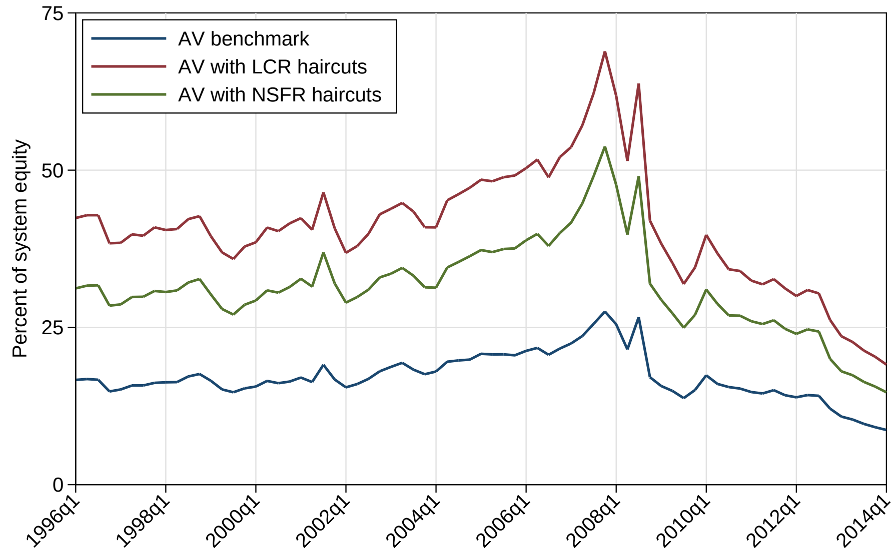

Figure 20: Effect of heterogeneous liquidity across asset classes based on LCR and NSFR haircuts.

given by

$$\ell_{k,t} = \frac{\bar{\ell}_k}{w_t} \quad \text{with} \quad \bar{\ell}_k = \ell_{k,2011\text{q}3} \times w_{2011\text{q}3}.$$

Figure 20 compares aggregate vulnerability for the three liquidity scenarios. Using heterogeneous liquidity increases AV relative to the benchmark specification. This is natural since the benchmark assumes all asset classes (other than cash) to be as liquid as corporate bonds although, in reality, most assets on BCHs' balance sheets are less liquid. Among the two alternative scenarios, using the liquidities based on the LCR yields higher AV than using liquidities based on the NSFR. This is natural as the LCR is a stricter criterion based on a shorter liquidation horizon than the NSFR. Importantly, the heterogeneous liquidity only scales AV up while leaving unchanged the profile of vulnerability over time.

4.3.2 Risk-based capital requirements

Most of the banks we analyze are subject to risk-based capital requirements. In fact, some of these constraints play an important role in forcing financial institutions to delever in response to shocks which is one of the key assumptions of our analysis. Confronted with the need to sell assets while satisfying a capital requirement, banks have an incentive to sell assets with high risk-weights (Merrill et al., 2012). At the same time, however, assets with high risk weights tend to be more illiquid. This creates a tension between selling assets that have high risk-weights but are less liquid – which eases the capital requirement but imposes

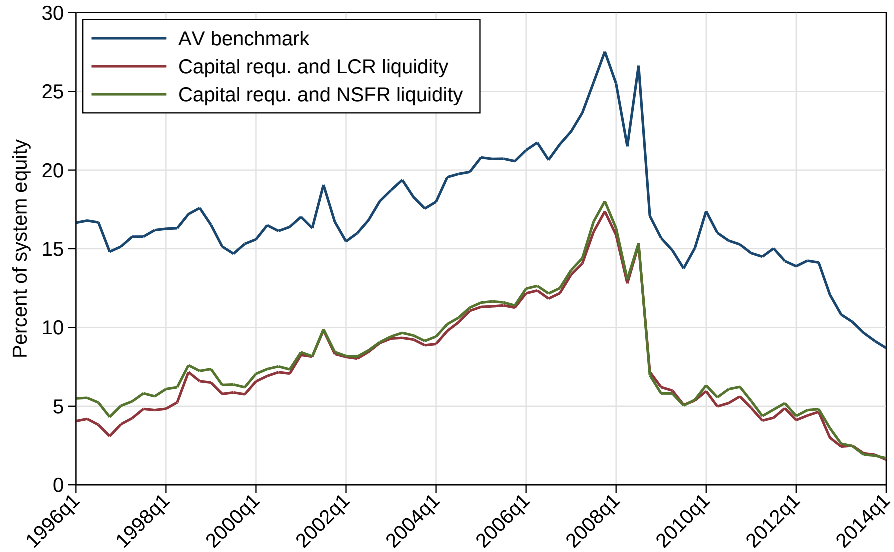

Figure 21: Effect of optimizing behavior with risk-based capital requirements.

higher liquidation costs – or selling assets that have low risk-weights but are more liquid. We therefore study how AV behaves when banks minimize the price impact of their fire-sales subject to a risk-based capital requirement. For risk weights, we use the Basel III regulations while for asset liquidity we use the haircuts of LCR and NSFR as in the previous section. The details of the analysis are in Appendix B.

Figure 21 shows the effect of optimizing subject to capital requirements and heterogeneous liquidity in the two different liquidity scenarios, LCR and NSFR. Compared to the case of selling assets proportionally to initial holdings (Figure 20), AV is now an order of magnitude smaller, both for LCR and NSFR liquidity. In fact, AV now looks quite similar to benchmark AV. However, while the level of AV changes relative to the benchmark specification, the profile of vulnerability over time retains its shape.

4.3.3 Multiple rounds of fire sales

As in the broker-dealer analysis, we study the effect of iterating the one-shot fire-sale mechanism of the main specification. The first-round fire-sale losses then act as the second shock to asset values, again triggering fire-sales and so on until convergence.

Figure 22 shows how one, two and more rounds of fire-sales affect AV for banks. As in the case of broker-dealers, we see that the shape of AV is unaffected by multiple rounds although the magnitude now changes and convergence is achieved only after five rounds. Overall, however, the one-round benchmark of our main analysis appears to be a valid proxy for the changing vulnerability over time.

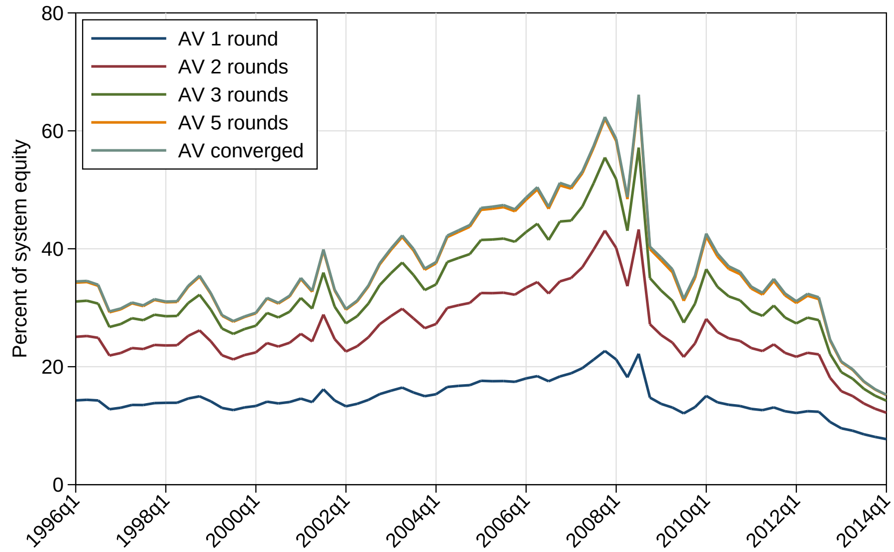

Figure 22: Multiple rounds of fire sales.

5 Comparison with other systemic risk measures

Systemic risk in the financial system has welfare implications through its impact on the real economy. Giglio, Kelly, and Pruitt (2013) assess which of the many risk measures proposed in the literature give a more accurate forecast of adverse tail macroeconomic outcomes. They conclude that none of the measures do particularly well on their own, although using a combination of them significantly increases predictability. In this section, using the same methodology, we compare the 20 measures in their analysis to our aggregate vulnerability measures.[41]

5.1 Relationship between systemic risk measures

The first column of Table 4 shows the correlation between aggregate vulnerability for broker-dealers and the other measures we consider. The second column displays the p-values of the null hypothesis that AV does not Granger-cause each of the other measures (individually, one at a time). The third column is analogous but tests whether the other systemic risk measures do not Granger-cause AV.

At 86 percent, AV is most highly correlated to "GZ", a credit spread index constructed by Gilchrist and Zakrajsek (2012) from prices of individual corporate bonds that can be interpreted as a gauge of disruptions in the financial system. Gilchrist and Zakrajsek (2012)

[41] We thank Stefano Giglio, Bryan Kelly and Seth Pruitt for generously sharing with us their data on systemic risk measures. See Appendix C for the sources of the different systemic risk measures.

Table 4: Comparison of AV for broker-dealers to other measures.

	Correlation	AV Granger-causes	Granger-causes AV
GZ	0.860	0.000***	0.099*
Default Spread	0.843	0.000***	0.013**
MES (SRISK)	0.835	0.000***	0.447
Book Leverage	0.808	0.019**	0.158
Realized Volatility	0.806	0.058*	0.124
TED Spread	0.760	0.193	0.001***
Market Leverage	0.735	0.026**	0.694
Turbulence	0.649	0.006***	0.009***
Amihud Illiqidity	0.632	0.177	0.031**
CoVaR	0.538	0.004***	0.087*
MES (APPR)	0.499	0.006***	0.031**
Δ CoVaR	0.446	0.010**	0.105
Market Herfindahl	0.356	0.024**	0.949
Absorbtion(2)	0.310	0.591	0.838
Δ Absorbtion(1)	0.288	0.732	0.440
Absorbtion(1)	0.288	0.701	0.738
Δ Absorbtion(2)	0.238	0.836	0.209
Dyn. Caus. Ind.	0.221	0.504	0.111
Intl. Spillover	−0.247	0.491	0.860
Term Spread	−0.255	0.083*	0.873

Note: AV is calculated using squared haircuts. For most systemic risk measure, we use monthly data between July 2008 and December 2012, giving 54 observations. However, some series end before December 2012, and thus use fewer observations to compute correlations and Granger Causalities. Book Leverage and Market Leverage only extend to September 2012. The Default Spread, Term Spread, and TED spread all only extend up to December 2011. And Intl. Spillover only extends to April 2010. We report p-values for pair-wise Granger-causality tests after performing VAR with two lags (reduces sample by two observatiosn). One, two and three stars indicate significance at the 10%, 5%, and 1% level, respectively.

argue that the risk-bearing capacity of broker-dealers – which play a key role in the market for corporate bonds – is tightly associated with changes in the GZ index, reductions in the supply of credit and subsequent declines in economic activity. This interpretation is consistent with the high correlation between GZ and AV, since AV captures dislocations in the repo market, the main source of wholesale funding for broker-dealers and one of the first steps in the intermediation chain. By this account, we would expect AV to signal risk somewhat earlier than GZ which is supported by the fact that AV Granger-causes GZ at the 1 percent level.

AV for broker-dealers is similarly highly correlated with other market-based signals of financial distress, such as the default spread, the TED spread and realized volatility. Aggregate market and book leverage for the largest 20 financial institutions are also correlated with AV, since broker-dealer leverage is one of the factors behind AV. Looking at the entire list, AV Granger-causes 12 and 6 other measures at the 10 and 1 percent levels, respectively, while it is Granger-caused by 7 and 2 other measures at those same significance levels. Based on this simple metric, AV for broker-dealers performs relatively well as a leading indicator.

Table 5 is analogous to Table 4, but considers AV for BHCs instead of for broker-dealers. We convert all systemic risk measures to quarterly frequency by taking their average over the three months in the quarter so that observations are at the same frequency as AV for BHCs.[42] There is a wide range of magnitudes for the correlations between AV and the other measures; about half are actually negative. AV is most highly correlated with aggregate book leverage of the 20 largest U.S. financial institutions. As for broker-dealers, this is unsurprising, given that leverage is one of the three factors of AV. The TED spread, again, correlates fairly well with AV. In contrast, GZ, which was highly correlated with AV for broker-dealers is now essentially uncorrelated with AV for BHCs. One possible interpretation is that banks do not play as crucial a role as broker-dealers do in corporate credit markets. Most of the measures that correlate negatively with AV for BHCs are price-based measures that tend to signal low risk during the 2002-2006 period, when AV was increasing. As discussed more below, this lack of predictive power for the financial crisis is the main point of criticism of the market-based measures. Overall, there is also no clear lead-lag relation between AV for BHCs and the other measures: The second and third columns of the table show that, at the 10 percent level, AV Granger-causes 12 and is Granger-caused by 13 of the other measures.

[42] Using the value of the previous quarter for each month in the current quarter gives very similar results.

Table 5: Comparison of AV for BHCs to other measures.

	Correlation	AV Granger-causes	Granger-causes AV
Book Leverage	0.605	0.020**	0.112
TED Spread	0.398	0.001***	0.000***
Turbulence	0.282	0.002***	0.000***
Δ Absorbtion(2)	0.278	0.113	0.702
Δ Absorbtion(1)	0.205	0.108	0.942
Market Herfindahl	0.061	0.357	0.107
Market Leverage	0.050	0.000***	0.013**
GZ	0.002	0.001***	0.023**
Default Spread	−0.022	0.000***	0.045*
Amihud Illiqidity	−0.053	0.419	0.781
Realized Volatility	−0.083	0.015**	0.000***
MES (SRISK)	−0.085	0.001***	0.000***
Dyn. Caus. Ind.	−0.102	0.001***	0.005**
Intl. Spillover	−0.173	0.084	0.639
Absorbtion(2)	−0.188	0.450	0.009**
Absorbtion(1)	−0.198	0.581	0.002***
Term Spread	−0.291	0.218	0.076
Δ CoVaR	−0.326	0.023**	0.018**
CoVaR	−0.331	0.011**	0.022**
MES (APPR)	−0.368	0.003***	0.015**

Note: To achieve a balanced sample, we limit our entire sample to between 1996-Q1 and 2010-Q1 and use quarterly data. Correlations are thus computed using 57 observations. We report p-values for pair-wise Granger-causality tests after performing VAR with two lags on each variable (reduces sample to 55 observations). One, two and three stars indicate significance at the 10%, 5%, and 1% level, respectively.

5.2 Predictive power for macro outcomes

We now study the performance of the different systemic risk measures when trying to predict the 20th percentile of shocks to growth in industrial production. We briefly describe the setup and refer the reader to Giglio, Kelly, and Pruitt (2013) for more details. First, we run the k-period ahead forecasting quantile regression

$$\mathbb{Q}_\tau(y_{t+k} \mid \mathcal{I}_t) = \alpha_\tau + \beta_\tau x_t, \tag{8}$$

where y_{t+k} are innovations to growth of industrial production obtained from an auto-regression; $\mathcal{I}_t$ is the information set at time t; $\mathbb{Q}_\tau(y_{t+k} \mid \mathcal{I}_t)$ is the conditional τth quantile of y_{t+k}; x_t is one of the systemic risk measures; and α_τ, β_τ are quantile regression coefficients. We then evaluate the accuracy of prediction by

$$R^2 = 1 - \frac{\frac{1}{T}\sum_t \rho_\tau\big(y_{t+k} - \hat{\alpha}_\tau + \hat{\beta}_\tau x_t\big)}{\frac{1}{T}\sum_t \rho_\tau(y_{t+k} - \hat{q}_\tau)}, \tag{9}$$

where $\rho_\tau(\cdot)$ is the quantile loss function and $\hat{q}_\tau$ is the unconditional τth quantile of y_t. We consider the 20th quantile ($\tau = 0.2$) to balance the trade-off between the desire to capture extreme events with the limited number of tail observations. The sample of AV for broker-dealers contains only the end of the crisis and is too short to perform a meaningful predictive exercise; we thus focus on AV for BHCs. To avoid discarding potentially useful predictability information in the monthly time-series of the other systemic risk measures, we run all quantile regressions at the monthly frequency. We convert AV from quarterly to monthly frequency by linearly interpolating between the two adjacent quarters.[43] When running the quantile predictive regressions, we lag all systemic risk measures by two months to take into account that some data may not be available in real time, although this has practically no effect on the estimates.

The sample consists of a balanced panel of 172 observations from 1996q1 to 2014q1.

[43] In the previous section, we conducted Granger causality tests using quarterly data by first converting all monthly systemic risk time-series to quarterly frequency. In contrast, in this section we convert AV from quarterly to monthly and keep all other systemic risk measures at their original monthly frequency. The different treatment in the two sections is called for by the different nature of the tasks. For Granger causality tests, using monthly data obtained by interpolating (or repeating) quarterly AV values would produce spurious monthly auto-correlations that can severely bias Granger causality tests. For quantile predictive regressions, on the other hand, we do not want to throw away any of the monthly information in the other time series so as to not artificially decrease their predictability compared to AV. We are thus being more conservative in the relative predictive power of AV. In addition, using monthly data preserves comparability with Giglio, Kelly, and Pruitt (2013), who rightly argue that, especially in shorter samples, quantile regressions are more meaningful with more observations.

Table 6: Individual predictive power for 20th quantile of macro outcomes.

	1y ahead	6m ahead	3m ahead
TED Spread	9.889***	12.680***	12.551***
Intl. Spillover	7.437***	7.884***	1.849
Aggregate Vulnerability	6.944**	6.921**	3.138
Term Spread	3.675**	2.008**	0.248
Default Spread	2.325*	0.216	5.292**
MES (APPR)	2.212	0.108	2.485**
ΔCoVaR	2.066	1.105*	1.161
MES (SRISK)	1.528*	0.060	1.907
Amihud Illiq.	1.450	0.336	0.058
CoVaR	1.261	0.308	4.579***
Market Herfin.	0.964	0.366	0.803
Turbulence	0.862*	7.912***	11.249***
Market Leverage	0.710	1.947	5.398***
Book Leverage	0.677	6.995***	13.354***
Dyn. Caus. Ind.	0.633	0.123	0.834
ΔAbsorbtion(1)	0.335	0.514	0.148
Absorbtion(2)	0.301	8.028***	11.624***
GZ	0.221	10.290***	18.185***
ΔAbsorbtion(2)	0.165	0.048	0.226
Absorbtion(1)	0.107	4.146**	6.347**
Realized Vol.	0.038	5.535***	10.825***
Observations	172	172	172

Notes: We report R-squared values in percent for each in-sample quantile regression. Significance levels are reported by one star, two stars, and three stars indicating significance at the 10%, 5%, and 1% level, respectively. A balanced sample is achieved by using measures between January 1996 and April 2010. AV is linearly interpolated to achieve monthly data. Because of this interpolation, we lag by one quarter plus the stated gap.

This period contains one severe macroeconomic outcome, the last crisis, and a few episodes of financial stress – LTCM, the tech bubble burst and the Eurozone crisis is a possible subjective list – that did not translate into deep downturns, which may be useful to detect false positives. Nevertheless, it is important to keep in mind the limitations of the exercise. We deem the ability to predict the 2008 crisis with enough anticipation as a necessary condition for good forecastability, but by no means a sufficient one. Even under this important yet relatively weak metric, not all measures achieve the same level of success.

When we consider one-year-ahead forecasts, Table 6 shows that AV is the third best measure with an R^2 of 7 percent and a quantile regression coefficient significant at the 5 percent level. The table also shows that AV's relative strength is predictability at longer

Table 7: Composite predictive power for 20th quantile of macro outcomes.

	1y ahead	6m ahead	3m ahead
PCQR1	1.441	2.441***	8.951***
PCQR1 with AV	1.578	2.027***	8.662***
PCQR2	2.491	9.343***	13.122***
PCQR2 with AV	4.595***	11.210***	14.559***
PQR	4.390***	11.336***	12.713***
PQR with AV	4.444***	11.343***	12.714***
Multiple QR	29.532***	39.050***	40.950***
Multiple QR with AV	31.194*	40.198	40.960
Observations	172	172	172

Notes: We report R-squared values in percent for each in-sample quantile regression. The specifications by default do not include AV unless explicity indicated. Significance levels are then reported using one star to report significance at 10%, two stars to indicate significance at 5%, and three stars to indicate significance at 1%. For Multiple QR with AV and with AV and connectedness, the p-value on AV is used to report significance, not an overall F-test, as is done for the benchmark specification. A balanced sample is achieved by using measures between January 1996 and April 2010. AV is linearly interpolated to achieve monthly data. Because of this interpolation, we lag by one quarter plus the stated gap.

horizons, as it ranks only seventh and eleventh at the six-month and three-month-ahead horizons, respectively, with R^2 values of 7 and 3 percent, respectively. This behavior may stem from the inherently sluggish adjustment of balance sheets and the delayed reaction of the real economy to changes in BHCs' behavior.

In Table 7, we study how adding AV to composite systemic risk measures affects predictability. We first perform principal components quantile regressions with one or two principal components (PCQR1 and PCQR2), a partial quantile regression (PQR) and a multivariate quantile regression (Multiple QR) without including AV in their construction. We then include AV and analyze how the R^2 changes. Table 7 shows that AV does not contribute much to one-month-ahead predictability, but does increase the performance of the composite measures as we move to longer prediction horizons, especially one year ahead. The change is most dramatic for the principal components quantile regression with two principal components, for which R^2 increases from 2.5 percent to 4.6 percent. AV thus contains important information about future low realizations of industrial production shocks that is not contained in the other measures.

6 Conclusion

Using a simple model and detailed balance sheet data for broker-dealers and U.S. bank holding companies (BHCs), we find that spillover losses from fire sales have the potential to be economically important. This is true even during normal times, when markets are relatively deep. If the value of assets for one of the largest five BHCs declined by 1 percent by the end of our sample, in the first quarter of 2014, we estimate spillover losses to be between 1 and 2 percent of total equity capital in the system. Similarly, if the value of Treasuries or agency MBS declined by 1 percent, our estimates for March 2014 imply spillover losses for broker-dealers in the repo market of 2 percent of system equity. While these numbers are sizable, they are some of the smallest in our sample. Just before and during the last financial crisis, vulnerabilities were between two and three times larger. Fire-sale externalities are therefore a key component of the overall systemic risk in the financial system. And while spillovers are exacerbated by the size and leverage of financial firms, we show that a new measure of connectedness in the system, "illiquidity concentration", is also a major contributor.

The framework we use has the advantage of being quite simple, enabling straightforward implementation and leading to results that are transparent. However, some of the the stylized assumptions we use may appear unrealistic to some readers. We address this reservation by conducting a battery of robustness tests – in the main text and appendices – that reveal which assumptions are central to our results. For broker-dealers, we find that including otherwise absent "safe-haven" properties for Treasuries can meaningfully reduce fire-sale spillovers. For BHCs, introducing capital requirements and optimizing behavior, or allowing banks to not mark-to-market a large enough share of their illiquid assets, can also decrease vulnerabilities. Modifying the liquidation rule so that banks dispose of liquid assets first, before selling any illiquid ones, can also mitigate spillover losses. In contrast, shocking equity capital instead of assets, calibrating shocks to match observed tail events, multi-round fire-sales, different ways to measure aggregate and asset-specific liquidity, and various cuts of the data, lead to relatively small changes in AV.

For all of these scenarios, whether estimates remain close to the simple benchmark specification or not, the changes are primarily in the level of AV, and not in its dynamics, preserving its appeal as a systemic risk indicator. In other words, thinking of AV as an index – by normalizing it to 100 at the beginning of the sample – makes it considerably more robust to reasonable changes in the assumptions of the framework, at the cost of losing the information about the absolute severity of spillovers is lost. The predictive properties and underlying factors behind movements in AV are also preserved for essentially all the different specifications we consider, providing further confidence in the measure.

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Appendix

A More alternative scenarios and robustness

A.1 Shocks to equity capital

Instead of considering a shock to the value of assets, we now consider a shock that exogenously reduces the equity capital of banks. Conceptually, an equity shock is an appealing way to model idiosyncratic financial distress at a particular firm or set of firms, while asset shocks seem a better way to model market-wide distress, or disruptions in specific asset classes. Modeling capital losses large enough to put firms close to insolvency could be useful when trying to evaluate whether firms should be designated as systemically important financial institutions (SIFIs). For example, the Dodd-Frank act requires, among other standards, that a firm be designated as a SIFI if, whenever it experiences "material financial distress or failure", it "holds assets that, if liquidated quickly, would cause a fall in asset prices and thereby significantly disrupt trading or funding in key markets or cause significant losses or funding problems for other firms with similar holdings."[44] Our framework with equity shocks embodies the spirit of this so-called "asset liquidation channel" quite well if we interpret material financial distress as a severe depletion of equity capital. Note that the law starts with the presumption of material finance distress or failure and does not require reasons or probabilities for that event. Modeling equity shocks as exogenous is therefore very much in accordance with the law.

While for each single bank there is a one-to-one correspondence between asset shocks and equity shocks, it is not possible to construct a uniform system-wide equity shock (with the same shock magnitude for all banks) that exactly reproduces the outcome of a uniform system-wide asset shock. This is because leverage is not constant across firms. For a given asset shock, a more levered firm experiences higher initial capital losses than a less levered firm. Hence, a uniform shock to equity capital with the same initial aggregate losses causes larger capital declines in *less* levered firms. We calibrate the equity shock to have the same average initial direct losses as our benchmark of a one percent uniform asset shock. To do so, we first compute the size $g_{i,t}$ of the equity shock needed so that each bank i has the same direct losses in each time period t as when hit by a one percent asset shock:

$$g_{i,t} = \frac{0.01 \times a_{i,t}}{e_{i,t}}.$$

[44] Final rule and interpretive guidance to Section 113 of the Dodd-Frank Wall Street Reform and Consumer Protection Act.

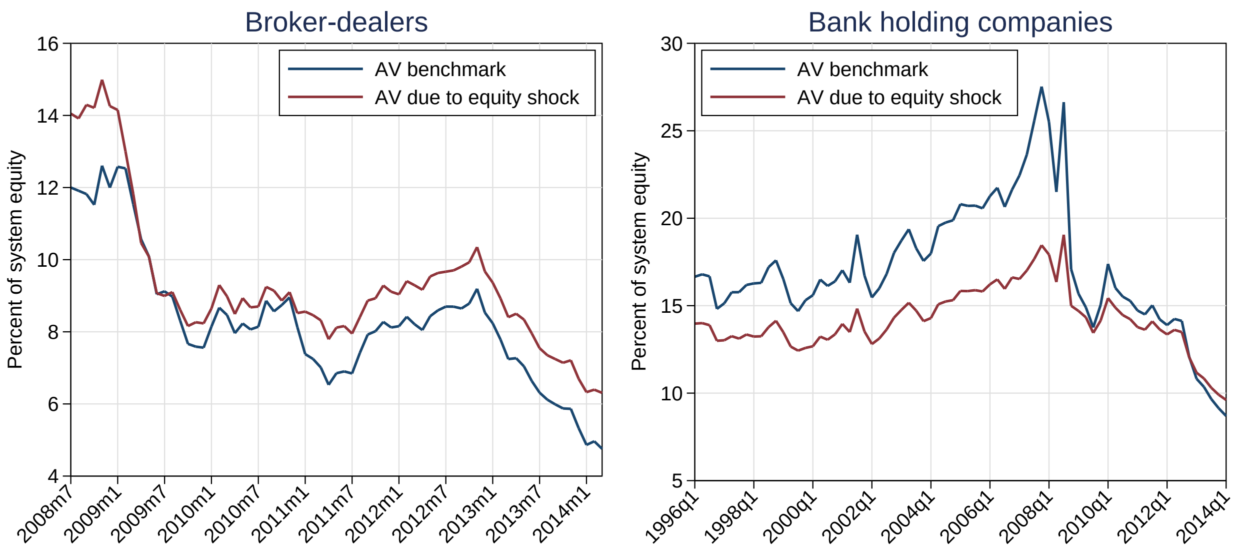


Figure 23: Comparison of AV under asset shocks (the benchmark) and equity shocks.

Then, we take the average of $g_{i,t}$ across all banks i and all time periods t to arrive at a uniform equity shock g. The linearity of the framework is still preserved, so shocking each bank's equity capital separately and then adding the resulting fire-sale spillovers is equivalent to shocking the equity capital of all banks simultaneously.

For broker-dealers, the left panel of Figure 23 shows that AV is very similar under both types of shocks, although equity shocks always produce higher AV than asset shocks. The difference arises because, as mentioned above, less levered dealers sustain larger initial capital losses when hit by an equity rather than an asset shock. Among broker-dealers, leverage is mainly determined by the asset portfolio with more liquid assets being held with higher leverage than less liquid assets. The equity shock therefore affects dealers with more illiquid assets relatively more, leading to higher spillover losses than in the case of asset shocks. The difference between the two is largest during the fall of 2008, when equity shocks produce levels of AV that are about 2 percentage points higher than those produced by asset shocks. The difference disappears during the first half of 2009, when the cross-sectional correlations betweek dealer size, leverage and illiquidity linkage are close to 0 (Figure 8).

For BHCs, the right panel of Figure 23 shows that, for the most part, equity shocks produce *lower* AV than asset shocks. This is due to the fact that less levered banks also tend to be smaller and have lower illiquidity linkage (Figure 19), therefore amplifying and transmitting less externalities. The gap between AV produced by equity and asset shocks starts at around 2 percentage points at the beginning of the sample and progressively widens,

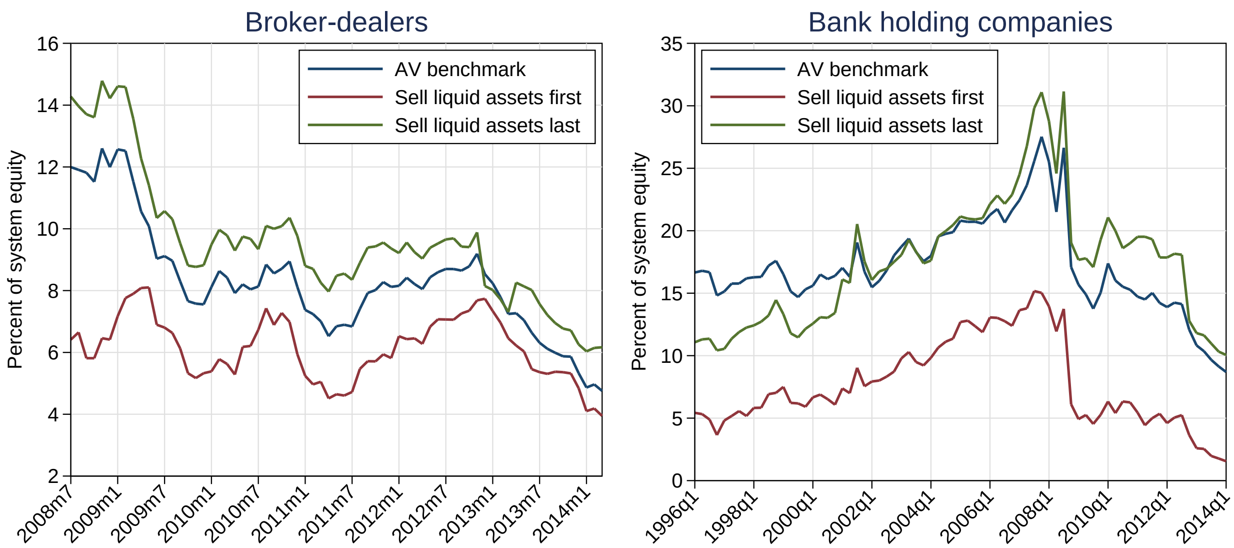


Figure 24: AV under alternative liquidation rules

reaching almost 10 percentage points during the crisis. The increase in the gap occurs because the cross-sectional correlations of leverage with size and illiquidity linkage increase before and during the crisis. Since then and until the end of the sample, the distribution of leverage becomes less dispersed and the cross-sectional correlation between leverage and illiquidity linkage decreases, making AV with equity and asset shocks be essentially equal.

A.2 Alternate liquidation rules

In the benchmark model, banks sell assets proportionally to their balance sheet holdings. We now show how AV changes when banks follow other liquidation rules.

Sell liquid assets first. This liquidation strategy is a "waterfall" strategy, whereby banks sell assets in decreasing order of liquidity until they achieve their desired leverage. For broker-dealers, the selling order is naturally determined by the liquidity order implied by haircuts. For BHCs, we use the liquidity rankings implied by the NSFR in Table 3 to determine the order in which to sell assets, but maintain the benchmark assumption that price impacts for all assets (except cash) are identical and given by equation (7).[45]

The results are in Figure 24. Selling liquid assets first, AV for broker-dealers is reduced by 10 percentage points during the crisis and by 2 to 2.5 percentage points after 2009. The

[45]Note that the NSFR ranks more of the asset classes than the LCR and the two agree on the classes both differentiate. If two or more assets have the same NSFR liquidity, we assume that they are sold simultaneously and proportionally to their initial holdings.

drastic reduction during 2008 and 2009 eliminates any sign of a crisis and is primarily due to broker-dealers selling Treasuries instead of the less liquid agency MBS. After the crisis, haircuts for those two assets become much more similar, so the effect of selling Treasuries instead of agency MBS is not as important.

For BHCs selling liquid assets first, the level of AV is reduced by more than half throughout the sample, although the steady increase in vulnerability from the beginning of the sample until 2008 remains. The reduction in levels comes from the fact that assets with higher NSFR liquidity tend to not be held in a concentrated fashion, especially by large and levered banks. Another change in AV is that not selling the illiquid assets eliminates the large spike before and during the crisis because illiquidity concentration, particularly at the most levered banks, decreases considerably.

Sell liquid assets last. This strategy is the opposite of the previous one so assets are now sold in *increasing* order of liquidity. Broker-dealers quickly exhaust their most illiquid assets since they comprise a relatively small fraction of their balance sheet and end up also selling a considerable fraction of agency debt, agency MBS and Treasuries. The liquidation of the most illiquid assets increase the overall level of AV, but the correlation with benchmark AV remains high.

For BHCs, AV is almost 5 percentage points lower at the beginning of the sample and around 2 to 3 percentage points higher towards the end of the sample, but otherwise very similar to benchmark AV. For most banks, the marginal assets sold are loans, so the differences in AV compared to the benchmark are mostly caused by the shifting composition of loans with different liquidities in the aggregate portfolio. It is worth noting that if we assigned even a moderately larger price impact to the disposition of assets with low NSFR liquidity, AV would certainly be higher than the benchmark in every period.

A.3 Aggregate liquidity over time

In our main specifications for broker-dealers and bank holding companies, we proxy for the wealth w of potential buyers of fire-sold assets using total financial sector assets net of broker-dealers or banks, respectively. We now explore two alternatives. First, we can assume that the entire economy has the capacity to absorb assets when they are fire-sold, instead of just the financial sector. For this first scenario, we replace w_t by nominal GDP in all periods t for both the broker-dealer and BHC analysis.

Second, we can assume that aggregate liquidity is constant across time periods. The price impact, expressed in units of basis points per dollar sold, is therefore independent of the total

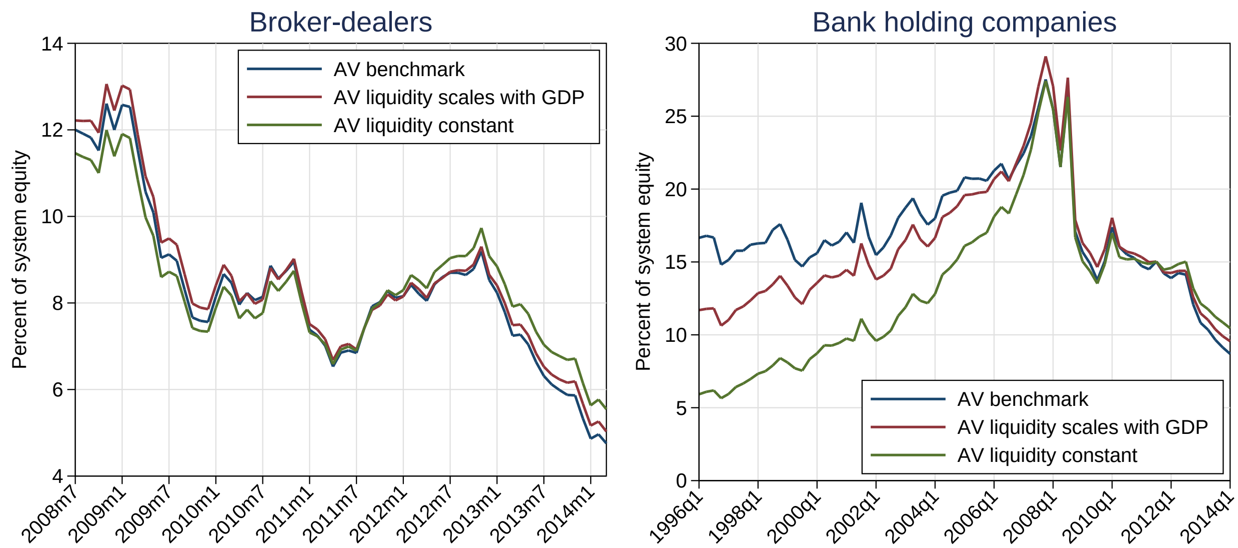


Figure 25: Different adjustments of aggregate liquidity over time.

size of financial markets or the economy. This is an extreme case and implies that wealth of potential buyers remains constant, even in nominal terms. Therefore, this choice could make AV non-stationary, as the total assets of the banks we consider are presumably co-integrated with total assets in the financial system or the economy. For this scenario, we set $w_t = \text{const.}$ in all periods t.

Figure 25 shows the implications of the two scenarios for broker-dealers and BHCs; note that by construction, AV under all three scenarios is the same in August 2011 and 2011q3, respectively. For broker-dealers, we see that the adjustment of aggregate liquidity has no notable impact since neither financial sector assets nor GDP have a strong trend during the sample period. For banks, there is a notable difference in the pre-crisis period, where the growth in AV is faster in both scenarios than in the benchmark. This is due to the fact that over the period from 1996 to 2007, financial sector assets grew significantly faster than GDP. When taking the entire economy as a reference for potential buyers of fire-sold assets, the potential spillovers therefore grow faster as financial sector growth outpaces the rest of the economy.

A.4 Analysis with balanced panels of institutions

In our main analysis, we consider the top 25 broker-dealers and top 100 bank holding companies every period which may be different sets in each period. Our motivation is that many banks either appear, disappear or re-appear in different subperiods of our sample, e.g. due to mergers and acquisitions, bankruptcies and the conversion of non-bank financial institu-

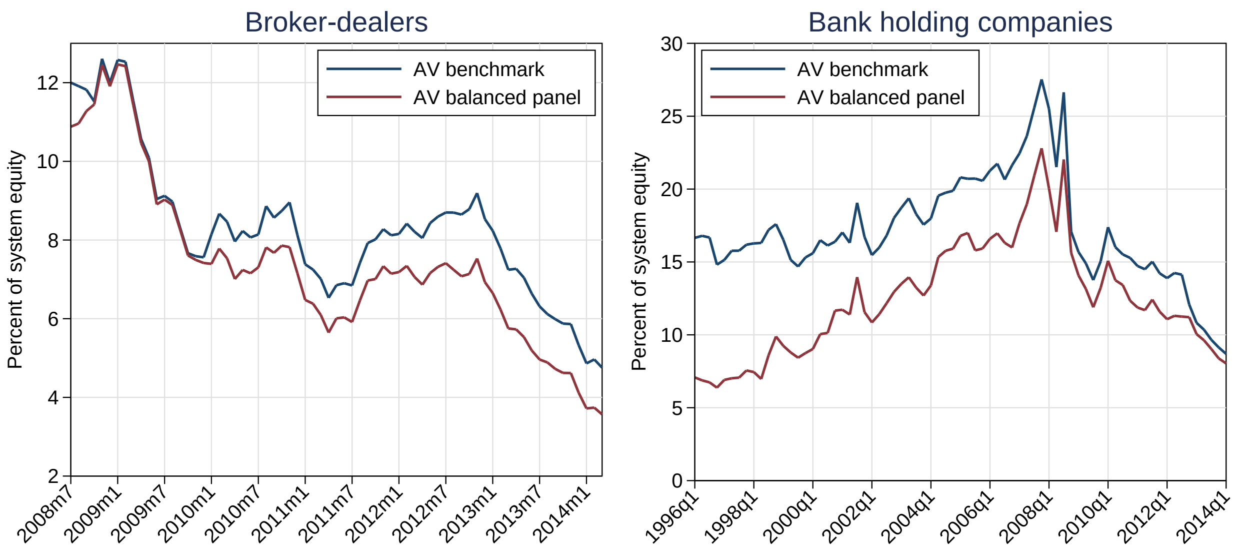


Figure 26: Benchmark AV and AV using balanced panels of institutions.

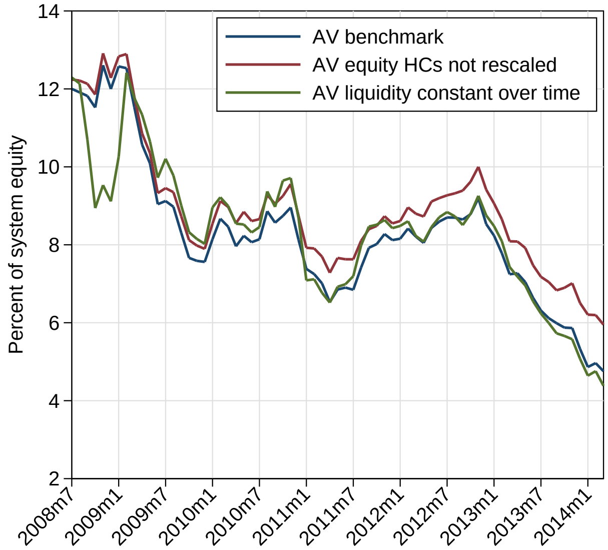
tions into bank holding companies and vice-versa. Restricting analysis to a balanced panel of institutions that are present for the entire sample period may therefore miss important trends. To study how results are affected by some of these changes, Figure 26 displays AV when we only keep firms that have been present throughout the entire sample.

For broker-dealers, the analysis of the balanced panel is very similar to that of the unbalanced panel. Notably, the balanced panel shows a lower level of vulnerability during July through September of 2008, as it excludes dealers such as Lehman Brothers that failed during the crisis. For BHCs, because some large, levered and linked institutions are dropped from the sample, aggregate vulnerability decreases. The qualitative behavior of the measure remains the same, with the curve essentially shifting downwards for all time periods and the run up to the crisis becoming more pronounced.

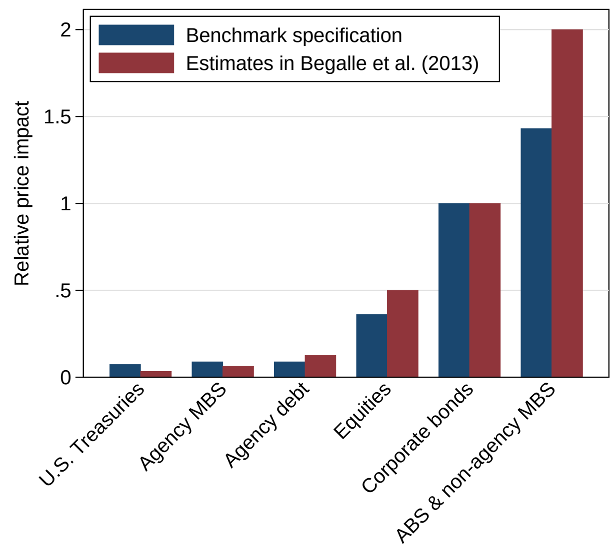
A.5 Robustness specific to broker-dealers

Not adjusting equity haircuts. In our benchmark, we manually rescale the haircuts on equities since we consider them more liquid than implied by the high average haircuts. Figure 27a shows that if we don't rescale equity haircuts, this has a negligible effect on AV.

Keeping liquidity constant over time. The benchmark for broker-dealers has variation in liquidity not only across asset classes but also across time. Figure 27a shows that this only plays a role for AV during late 2008. Strikingly, AV is much lower in late 2008 if we don't take into account the time variation in liquidity that occurs for several asset classes during



(a) Effect of robustness checks on AV.



(b) Comparison of liquidity estimates.

Figure 27: Robustness checks for broker-dealers.

this period (see Figure 3).

Comparison of liquidity estimates. Begalle et al. (2013) discuss the policy concerns associated with potential fire-sales in the tri-party repo market. They report estimates – provided by market participants and the New York Fed's Markets staff – on the liquidity of different asset measured as the dollar amount "that can be liquidated each day without having a material and adverse impact on the market pricing." To compare their estimates to the liquidity used in our benchmark specification, we normalize both to a price impact relative to that for corporate bonds. Figure 27b shows that the two liquidity measures line up closely for all asset classes considered by Begalle et al. (2013).[46]

A.6 Robustness specific to BHCs

Use top 500 instead of top 100 BHCs. Instead of using the largest 100 firms by assets in every quarter, we expand the population to the largest 500 firms. Even though there are now more assets in the system and the total dollar amount of fire-sale spillovers must increase, the percentage of equity capital lost may go down if the newly added firms have

[46]The only notable difference is the liquidity of ABS & non-agency MBS which may be due to the fact that the estimate in Begalle et al. (2013) is for ABS only while our data doesn't allow us to distinguish between ABS and non-agency MBS.

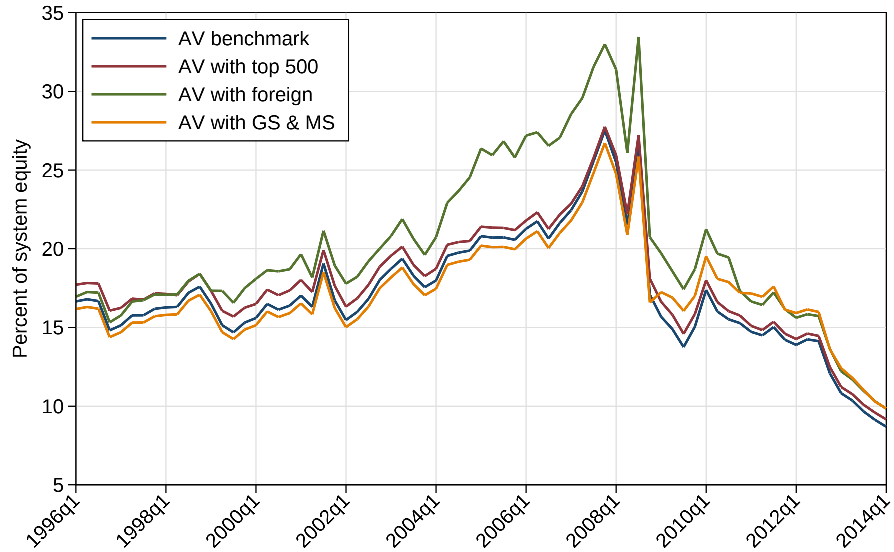


Figure 28: Benchmark AV and AV for various robustness checks.

more capital relative to the additional fire-sale spillovers that they create. Figure 28 shows that this is not the case. Aggregate vulnerability shifts up almost in parallel by 1 percentage point, confirming the message of Figure 15 that large banks are the principal culprit of fire-sale externalities.

Do not exclude foreign firms. In our benchmark, we remove firms owned by foreign banking organizations because regulation requires that they are well-capitalized on the basis of the foreign bank's capital as a whole, and not necessarily on the basis of capital held domestically. Form FR Y-9C contains data of capital held in domestic holding companies only, which could under-represent the true economic strength of the domestic firm. However, some of the largest and most linked firms owned by foreign banking organizations are major players in many US markets and are therefore potentially important contributors to fire-sale externalities. Figure 28 shows – keeping the aforementioned caveats in mind – that when firms owned by foreign organizations are included in the sample, aggregate vulnerability increases markedly, especially around the financial crisis. The major new contributors are Barclays Group, which has the fourth largest average systemicness, and Taunus Corporation, the U.S. bank holding company of Deutsche Bank.

Do not exclude Goldman Sachs and Morgan Stanley. In 2009-Q1, Goldman Sachs and Morgan Stanley started filing form Y-9C after converting to bank holding companies during 2008-Q4. We exclude them from our main specification because they are quite different from other BHC and only have a few quarters of data. However, they are large and levered institutions that have some assets in common with other banks; they may be important for AV. Figure 28 shows that this is indeed the case. Their addition increases AV by about two percentage points after their appearance in the sample. Note that we normalize aggregate liquidity in each period by total financial assets outside the BHCs we consider in 2011q3 (equation (7)). Since Goldman Sachs and Morgan Stanley are part of the BHCs in that quarter, the normalization changes, affecting AV estimates in all quarters.

Some assets not marked-to-market. Unlike broker-dealers, commercial banks don't mark-to-market every asset on their balance sheet. A portion of their balance sheet can be "held-to-maturity," allowing interim unrealized losses to go unrecognized. Other assets are held at fair-value but priced using models that allow for a certain degree of freedom in the assumptions used. For example, residential real estate loans are usually booked at fair-value as "Level 3" assets, which means that some of the inputs to the valuation model are unobservable by definition. In such cases, when confronted with a negative shock, banks may not recognize the full extent of the economic losses on their balance sheets, or may only recognize them slowly. While the economic pressure to sell assets is still present, a more benign accounting-based leverage may relax the need to fire-sell assets, at least in the short run.

We examine two new cases – admittedly stylized – to understand how not marking-to-market some assets affects AV. In the first case, banks simply do not mark down their most illiquid assets when hit by a negative shock. We assume banks do not mark-to-market any loans, residual securities, or residual assets (and mark-to-market the rest of their balance sheet). One interpretation is that these assets are held-to-maturity, and that the shock is transitory and expected to mean-revert before maturity. An alternative interpretation is that the bank has decided to accept a permanently higher level of economic leverage while keeping the same target for book leverage. Of course, this may create different systemic risk concerns, but would reduce immediate fire sales. In the second new case, we assume that banks recognize half of all economic losses for their most illiquid assets, and thus reduce the book value of loans, residual securities and residual assets by half of the amount of the shock.

Figure 29 displays the results. When banks do not mark down illiquid assets at all, AV is cut by two thirds, since book losses are substantially diminished. In the second case, recognizing only half of the losses for the most illiquid assets makes AV about half as large as benchmark AV. For both cases, in terms of the decomposition of AV in equation (2), aggregate size and leverage remain unchanged while illiquidity concentration is reduced significantly

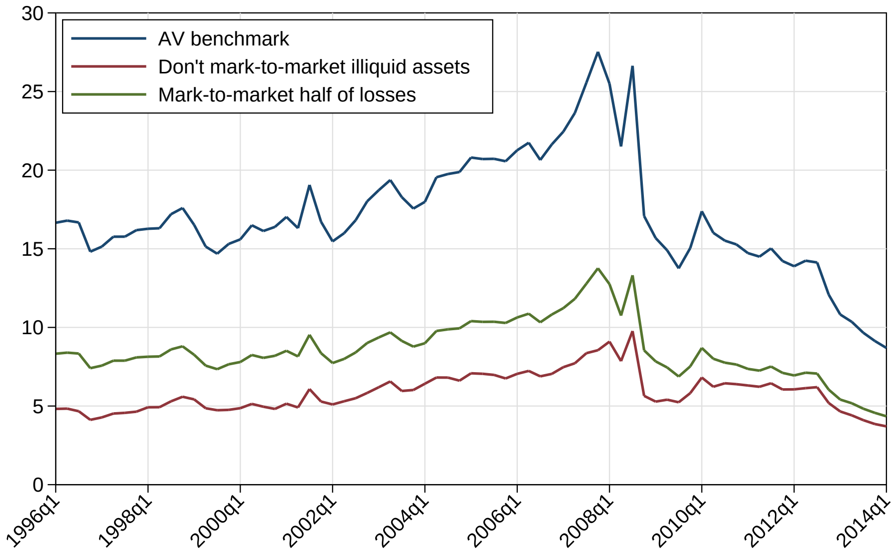


Figure 29: Effect of not marking-to-market some assets.

because the "exposure" term $\sum_k m_{ik} f_k$ is now much smaller. Despite the change in levels, the low frequency patterns in AV remain similar to the benchmark case: flat until 2001, an almost twofold increase from 2001 to 2008, and a return to low levels after 2008.

B Details on risk-based capital requirements

We capture the tradeoff between risk weights and price impact in a simple model. Define risk-weighted assets of bank i for regulatory purposes as

$$a_i^w = \sum_{k=1}^{K} w_k m_{ik} a_i, \tag{10}$$

where $w_k \in [0, \infty)$ is the risk weight of asset k. A risk weight of zero means that the bank does not need to hold any equity against the asset, while a high risk weight makes the regulatory constraint tighter. Bank i's equity capital must exceed a fixed percentage of its risk-weighted assets

$$e_i \geq \kappa a_i^w, \tag{11}$$

where κ is a fixed number picked by the regulator.

In response to a negative shock, each bank must raise an amount c_i by selling assets. In our framework $c_i = b_i a_i \sum_k m_{ik} f_k$ is the dollar amount bank i must raise to return to target leverage b_i after receiving shocks f_k. In this section, we can therefore take c_i as given. Further, each bank wants to minimize the total price discount they suffer when selling assets but still satisfy the capital requirement (equation (11)) and the budget constraint (that it has to raise c_i). We allow neither short-selling nor purchases of assets – only sales of assets on the balance sheet are permitted. The price impact for bank i of selling a share $\rho_{ik} \in [0, 1]$ of its holdings in asset k is $\ell_k \rho_{ik} m_{ik} a_i$ basis points, since $\rho_{ik} m_{ik} a_i$ is the dollar amount sold (before any price impact) and ℓ_k is the liquidity of the asset in units of basis points per dollar. Hence, the loss to the bank due to the price impact is $\ell_k \left(\rho_{ik} m_{ik} a_i\right)^2$ dollars. The amount of asset k remaining on the balance sheet is $\left(1 - \rho_{ik}\right) m_{ik} a_i$ dollars. The bank's optimization problem is then

$$\min_{\rho_{ik}} \sum_{k=1}^{K} \ell_k \left(\rho_{ik} m_{ik} a_i\right)^2 \tag{12}$$

$$\text{s.t.} \quad e_i \geq \kappa \sum_{k=1}^{K} w_k \left(1 - \rho_{ik}\right) m_{ik} a_i,$$

$$c_i = \sum_{k=1}^{K} \rho_{ik} m_{ik} a_i - \sum_{k=1}^{K} \ell_k \left(\rho_{ik} m_{ik} a_i\right)^2 \tag{13}$$

$$0 \leq \rho_{ik} \leq 1 \tag{14}$$

We calibrate risk weights w_k by using the "standardized approach" of capital requirements in Basel III.[47] For the tightness of the risk-based capital requirement we pick $\kappa = 0.06$, which means banks must hold at least six percent of risk-weighted assets in equity. This number corresponds to the minimum Tier 1 capital requirement from Basel III.

[47] Appendix F shows the details. Most large banks use the "advanced approach" instead of the "standardized approach", which usually produces lower overall risk-weights. We use the standardized approach because implementing the advanced approach would require a much finer partition of asset classes in our data.

C Systemic risk measures

Table 8: Systemic risk measures used in Section 5.

Measures	Sources
GZ	Gilchrist and Zakrajsek (2012)
Absorption, ΔAbsorption	Kritzman et al. (2011)
Amihud Illiq.	Amihud (2002)
CoVaR, ΔCoVaR	Adrian and Brunnermeier (2011)
MES (APPR), SysRisk	Acharya et al. (2010)
MES (SRISK)	Brownlees and Engle (2012)
Dyn. Caus. Ind.	Billio et al. (2012)
Intl. Spillover	Diebold and Yilmaz (2009)
Turbulence	Kritzman and Li (2010)

Table 8 lists the sources for the various systemic risk measures we use. See Giglio et al. (2013) for details.

D Return series for assets in tri-party repo

Asset	Return series	Volatility	Mean	5h pctl.	Sample	Obs.
Agency MBS	Barclays U.S. MBS: Agency Fixed-Rate MBS (Bloomberg ticker: LD10TRUU)	0.0644	0.0785	−0.2060	Jan1976–Nov2014	467
U.S. Treasuries	Barclays U.S. Aggregate Total Values Unhedged USD (Bloomberg ticker: LUATTRUU)	0.0526	0.0747	−0.2078	Jan1973–Nov2014	503
Agency debt	Morningstar U.S. Agency Total Returns (Bloomberg ticker: MSBIUATR)	0.0454	0.0500	−0.2077	Nov2000–Nov2014	169
Corporate bonds	Bank of America Merrill Lynch U.S. Corporate Master Total Returns Index (FRED series BAMLCC0A0CMTRIV)	0.0657	0.0803	−0.2702	Jan1973–Oct2014	502
Equities	S&P 500 Index	0.1451	0.0844	−0.7447	Jan1950–Oct2014	778
ABS & non-agency MBS	Barclays U.S. ABS Index Total Returns, values unhedged (Bloomberg ticker: LUABTRUU)	0.0336	0.0516	−0.1055	Dec1992–Nov2014	276
Money market instruments	Federal Reserve H.15: Financial Commercial Paper Interest Rate	0.4673	0.3170	−1.2632	Sept1997–Sept2014	205
Municipal bonds	Federal Reserve H.15: State and Local Bonds	0.1231	0.0125	−0.7457	Jan1973–Sept2014	501

E Mapping between asset classes and form FR Y-9C

Category	Codes on FR Y-9C	
Total assets	Entire sample	bhck2170
Equity	Starting 2014q1	bhck8274 or bhca8274

Category	Codes on FR Y-9C	
	Up to 2013q4	bhck8274
Cash	Entire sample	bhck0081 + bhck0395 + bhck0397
U.S. Treasuries	Starting 2008q1	bhck0211 + bhck1287 + bhcm3531
	Up to 2007q4	bhck0211 + bhck1287 + bhck3531
Agency securities	Starting 2008q1	bhck1289 + bhck1294 + bhck1293 + bhck1298 + bhcm3532
	Up to 2007q4	bhck1289 + bhck1294 + bhck1293 + bhck1298 + bhck3532
Municipal securities	Starting 2008q1	bhck8496 + bhck8499 + bhcm3533
	2001q1 to 2007q4	bhck8496 + bhck8499 + bhck3533
	Up to 2000q4	bhck8531 + bhck8535 + bhck8534 + bhck8538
Agency MBS	Starting 2011q1	bhckg300 + bhckg304 + bhckg312 + bhckg316 + bhckk142 + bhckk150 + bhckg303 + bhckg307 + bhckg315 + bhckg319 + bhckk145 + bhckk153 + bhckg379 + bhckg380 + bhckk197
	2009q2 to 2010q4	bhckg300 + bhckg304 + bhckg312 + bhckg316 + bhckg303 + bhckg307 + bhckg315 + bhckg319 + bhckg379 + bhckg380 + (bhckg324 + bhckg328 + bhckg327 + bhckg331 + bhckg382)/2
	2008q1 to 2009q1	bhck1698 + bhck1703 + bhck1714 + bhck1718 + bhck1702 + bhck1707 + bhck1717 + bhck1732 + bhcm3534 + bhcm3535
	Up to 2007q4	bhck1698 + bhck1703 + bhck1714 + bhck1718 + bhck1702 + bhck1707 + bhck1717 + bhck1732 + bhck3534 + bhck3535
Non-agency MBS	Starting 2011q1	bhckg308 + bhckg320 + bhckk146 + bhckk154 + bhckg311 + bhckg323 + bhckk149 + bhckk157 + bhckg381 + bhckk198
	2009q2 to 2010q4	bhckg308 + bhckg320 + bhckg311 + bhckg323 + bhckg381 + (bhckg324 + bhckg328 + bhckg327 + bhckg331 + bhckg382)/2
	2008q1 to 2009q1	bhck1709 + bhck1733 + bhck1713 + bhck1736 + bhcm3536
	Up to 2007q4	bhck1709 + bhck1733 + bhck1713 + bhck1736 + bhck3536

Category	Codes on FR Y-9C	
ABS & other debt securities	Starting 2009q2	bhckc026 + bhckg336 + bhckg340 + bhckg344 + bhck1737 + bhck1742 + bhckc027 + bhckg339 + bhckg343 + bhckg347 + bhck1741 + bhck1746 + bhckg383 + bhckg384 + bhckg385 + bhckg386
	2008q1 to 2009q1	bhckc026 + bhckg336 + bhckg340 + bhckg344 + bhck1737 + bhck1742 + bhckc027 + bhckg339 + bhckg343 + bhckg347 + bhck1741 + bhck1746 + bhcm3537
	2006q1 to 2007q4	bhckc026 + bhckg336 + bhckg340 + bhckg344 + bhck1737 + bhck1742 + bhckc027 + bhckg339 + bhckg343 + bhckg347 + bhck1741 + bhck1746 + bhck3537
	2001q1 to 2005q4	bhckb838 + bhckb842 + bhckb846 + bhckb850 + bhckb854 + bhckb858 + bhck1737 + bhck1742 + bhckb841 + bhckb845 + bhckb849 + bhckb853 + bhckb857 + bhckb861 + bhck1741 + bhck1746 + bhck3537
	Up to 2000q4	bhck1754 + bhck1773 − (bhck0211 + bhck1287 + bhck3531 + bhck1289 + bhck1294 + bhck1293 + bhck1298 + bhck3532 + bhck8531 + bhck8535 + bhck8534 + bhck8538 + bhck1698 + bhck1703 + bhck1714 + bhck1718 + bhck1702 + bhck1707 + bhck1717 + bhck1732 + bhck1709 + bhck1733 + bhck1713 + bhck1736 + bhck8544 + bhck8550) + bhck3537
Equities & other securities	Starting 2001q1	bhcka511 + bhcm3541
	Up to 2000q4	bhck8544 + bhck8550
Residual securities	Entire sample	bhck1754 + bhck1773 + bhck3545 − all securities above
Repo and fed funds loans	Starting 2002q1	bhdmb987 + bhckb989
	1997q1 to 2001q4	bhck1350
	Up to 1996q4	bhck0276 + bhck0277
Residential real estate loans	Entire sample	bhdm1797 + bhdm5367 + bhdm5368 + bhdmf606 + bhdmf607 + bhdmf611
Commercial real estate loans	Starting 2007q1	bhckf158 + bhckf159 + bhdm1460 + bhckf160 + bhckf161 + bhdmf604 + bhdmf612 + bhdmf613
	Up to 2006q4	bhdm1415 + bhdm1460 + bhdm1480 + bhdmf604 + bhdmf612 + bhdmf613

Category	Codes on FR Y-9C	
Other real estate loans	Starting 2007q1	bhck1410 − (bhdm1797 + bhdm5367 + bhdm5368 + bhckf158 + bhckf159 + bhdm1460 + bhckf160 + bhckf161) + bhckf610 − (bhdmf606 + bhdmf607 + bhdmf611 + bhdmf604 + bhdmf612 + bhdmf613)
	Up to 2006q4	bhck1410 − (bhdm1797 + bhdm5367 + bhdm5368 + bhdm1415 + bhdm1460 + bhdm1480) + bhckf610 − (bhdmf606 + bhdmf607 + bhdmf611 + bhdmf604 + bhdmf612 + bhdmf613)
C & I loans	Entire sample	bhck1763 + bhck1764 + bhckf614
Consumer loans	Starting 2011q1	bhckb538 + bhckb539 + bhckk137 + bhckk207 + bhckf615 + bhckf616 + bhckk199 + bhckk210
	2001q1 to 2010q4	bhckb538 + bhckb539 + bhck2011 + bhckf615 + bhckf616 + bhckf617
	Up to 2000q4	bhck2008 + bhck2011
Lease financings	Starting 2007q1	bhckf162 + bhckf163
	Up to 2006q4	bhck2182 + bhck2183
Residual loans	Entire sample	bhck2122 + bhckf618 − all loans above
Residual assets	Entire sample	bhck2170 − all assets above

Note: We combine all categories under trading assets with the corresponding categories under securities and loans. We use amortized cost for all securities reported as held-to-maturity and fair value for all securities reported as available-for-sale. We use loans and trading assets on a consolidated basis where available. From 2009q2 to 2010q4 commercial MBS are not broken out into agency MBS and non-agency MBS; we allocate them 50:50. Up to 2000q4 municipal securities include small amounts of MBS which are also included in agency MBS and non-agency MBS; we replace negative values of ABS and other debt securities with 0. In the calculation of total assets, loans are adjusted by unearned income but the loan breakdown is unadjusted; we replace negative values of residual loans with 0.

F Basel III capital risk weights

We base our risk weights on the "International Convergence of Capital Measurement and Capital Standards," issued in June 2006 by the Basel Committee on Banking Supervision. When the Basel standards are very different from the U.S. implementation, or too general, we use the Federal Register, Vol. 77, No. 169, August 30, 2012, Part III and the Federal Register, Vol. 78, No. 198, October 11, 2013. When possible, we use the standardized approach. Of course, there is substantial judgment in assigning risk-weights and the advanced approaches could lead to very different risk weights.[48] In addition, some of our asset categories contain assets with heterogeneous risk-weights, whose relative magnitudes are not possible to determine using Y-9C data. Nevertheless, we believe the weights are broadly representative and are sufficiently reasonable to illustrate the effect of capital requirements. We determine the weights as follows:

Asset class	Risk weight	Notes
Cash	0%	Has no credit risk.
U.S. Treasuries	0%	The U.S. has an ECA risk score of 0 to 1, thus receives zero risk weight on its sovereign debt. See Annex 11, Section I.A, paragraph 2 of Basel Committee, 2006.
Repo & fed funds loans	0%	By virtue of Part II, Section 2.D, paragraphs 170 and 171, and since virtually all the collateral in our data are U.S. Treasuries and Agency MBS, we assign a risk-weight of zero.
Agency MBS	20%	Treated as claims on banks and securities firms according to Annex 11, Section I.B, paragraph 7. Based on Annex 11, Section I.C, paragraph 8, we assign a 20% risk weight.
Agency securities	20%	Identical treatment as agency MBS.
ABS & other debt securities	100%	Other assets with 100% risk weight (Annex 11, Section I.J, paragraph 23).
Equities & other securities	100%	Other assets with 100% risk weight (Annex 11, Section I.J, paragraph 23).
Municipal securities	10%	Treated the same as agency securities according to Annex 11, Section I.B, paragraph 7 and thus generically receive a risk weight of 20%. However, the characteristics detailed in footnote 260 are satisfied by a large number of municipal securities, which should then receive a 0% risk weight.

[48] See, for example, Basel II: International Convergence of Capital Measurement and Capital Standards: a Revised Framework and Le Leslé and Avramova (2012).

Asset class	Risk weight	Notes
Residential real estate loans	65%	Annex 11, Section I.F, paragraph 15 proposes 35%. The risk weight could be higher if local regulator deems appropriate (Annex 11, Section I.F, paragraph 16). In the U.S., the implementation of the standardized approach has significantly higher risk-weights, ranging from 50% to 100% depending on the characteristics of the loan (Federal Register, Vol. 78, No. 198, October 11, 2013).
Non-agency MBS	35%	See Annex 11, Section I.F, paragraph 15.
C & I loans	100%	A heterogeneous group of asset types with risk weights ranging from 75% to 150%. See Annex 11, Section I.D-I.I.
Commercial real estate loans	100%	See Annex 11, Section I.G, paragraph 17.
Consumer loans	75%	See Annex 11, Section I.E, paragraphs 12-13. Risk-weight of 75% assumes orientation, product and granularity criteria are met, could be higher if not met. In the U.S., consumer loans get 100% risk-weight under the standardized approach (Federal Register, Vol. 77, No. 169, August 30, 2012, Part III).
Lease financings	100%	Other assets with 100% risk weight (Annex 11, Section I.J, paragraph 23).
Other real estate loans	100%	Mostly collateralized by farmland, treated as commercial real estate loans.
Residual loans	100%	Other assets with 100% risk weight (Annex 11, Section I.J, paragraph 23).
Residual assets	100%	Other assets with 100% risk weight (Annex 11, Section I.J, paragraph 23).
Residual securities	100%	Other assets with 100% risk weight (Annex 11, Section I.J, paragraph 23).

G LCR and NSFR weights

We use liquidity weights based on the weights laid out under the Liquidity Coverage Ratio (LCR) and the Net Stable Funding Ratio (NSFR). The LCR is fully described in "Liquidity Coverage Ratio: Liquidity Risk Measurement Standards," and was finalized by the United States Federal Reserve Board, the Federal Deposit Insurance Corporation, and the Office of the Comptroller of the Currency in September 2014. This finalized rule is based on "Basel III: The Liquidity Coverage Ratio and liquidity risk monitoring tools," issued in January 2013 by the Basel Committee on Banking Supervision. The NSFR is fully described in "Basel III: The Net Stable Funding Ratio," issued in January 2014 by the Basel Committee on Banking Supervision. When necessary, we refer to risk-weights assigned in "International Convergence of Capital Measurement and Capital Standards," issued in June 2006 by the Basel Committee on Banking Supervision. Of course, some level of judgment is used in assigning these weights, as our asset classes do not align perfectly with those described by the documentation on the LCR and NSFR. In addition, some of our asset categories contain assets with heterogeneous liquidity weights, whose relative magnitudes are not possible to determine using Y-9C data. Nevertheless, we believe the weights are broadly representative and are sufficiently reasonable to illustrate the effect of heterogeneous liquidity.

G.1 LCR weights

The weights we assign to assets are equivalent to $100 - w_{\mathrm{LCR}}$, where w_{LCR} is the liquidity weight assigned in "Liquidity Coverage Ratio: Liquidity Risk Measurement Standards." Further, we assign a weight of 100 percent to all assets that are not described as high quality liquid assets (HQLA), as these assets are not further differentiated under the LCR. We determine liquidity weights based on the LCR as follows:

Asset class	LCR haircut	Notes
Cash	0%	Perfectly liquid.
U.S. Treasuries	0%	Level 1 liquid asset. See Subpart C, Section 20, paragraph a.2.
Repo & fed funds loans	5%	We take the collateral underlying reverse repurchase agreements as the relevant assets in determining liquidity weights (Part II, Section B.4, paragraph a on pg. 113). The collateral for most repos is U.S. Treasuries (0% liquidity weight), followed by agency MBS (15% liquidity weight).
Agency MBS	15%	Level 2A liquid asset. See Subpart C, Section 20, paragraph b.1.
Agency securities	15%	Identical treatment as agency MBS.

Asset class	LCR haircut	Notes
ABS & other debt securities	35%	A heterogeneous group of asset types with liquidity weights ranging from 0% to 100%. We judge that portfolio weights are slanted towards more liquid assets. See Subpart C for a full description of HQLA requirements.
Equities & other securities	50%	Level 2B liquid asset. See Subpart C, Section 20, paragraph c.2.
Municipal securities	100%	Not described as HQLA in Subpart C.
Residential real estate loans	100%	Not described as HQLA in Subpart C.
Non-agency MBS	100%	Not described as HQLA in Subpart C.
C & I loans	100%	Not described as HQLA in Subpart C.
Commercial real estate loans	100%	Not described as HQLA in Subpart C.
Consumer loans	100%	Not described as HQLA in Subpart C.
Lease financings	100%	Not described as HQLA in Subpart C.
Other real estate loans	100%	Not described as HQLA in Subpart C.
Residual loans	100%	Not described as HQLA in Subpart C.
Residual assets	100%	Not described as HQLA in Subpart C.
Residual securities	100%	Not described as HQLA in Subpart C.

G.2 NSFR weights

We determine liquidity weights based on the NSFR as follows:

Asset class	NSFR haircut	Notes
Cash	0%	Perfectly liquid. See section II.B, paragraph 29.a.
U.S. Treasuries	5%	See section II.B, paragraph 30.

Asset class	NSFR haircut	Notes
Repo & fed funds loans	10%	We take the collateral underlying reverse repurchase agreements as the relevant assets in determining liquidity weights (see section II.B, paragraph 28 for details). The collateral for most repos is U.S. Treasuries (5% liquidity weight), followed by agency MBS (15% liquidity weight).
Agency MBS	15%	See section II.B, paragraph 31.
Agency securities	15%	Identical treatment to agency MBS.
ABS & other debt securities	35%	A heterogeneous group of asset types with liquidity weights ranging from 5% to 100%. We judge that portfolio weights are slanted towards more liquid assets and thus assign a liquidity weight of 35%. See section II.B, paragraphs 30-34.
Equities & other securities	55%	Non-financial, exchange-traded common equity shares receive a liquidity weight of 50%, while all other equity received a liquidity weight of 100%. See section II.B, paragraphs 32 and 35.
Municipal securities	60%	NSFR Liquidity weights depend on the duration of the residual maturity as well as the assigned risk weight according to "International Convergence of Capital Measurement and Capital Standards." Weights range from 50% to 65%. See section II.B, paragraphs 32-33.
Residential real estate loans	60%	NSFR liquidity weights for residential real estate loans depend on the residual maturity of the loan as well as the assigned risk weight according to "International Convergence of Capital Measurement and Capital Standards." Weights range from 50% to 65%. See section II.B, paragraphs 32-33.
Non-agency MBS	65%	NSFR Liquidity weights depend on the duration of the residual maturity as well as the assigned risk weight according to "International Convergence of Capital Measurement and Capital Standards." Weights range from 50% to 85%. See section II.B, paragraphs 32-34.
C & I loans	75%	NSFR liquidity weights for commercial real estate loans depend on the residual maturity of the loan as well as the assigned risk weight according to "International Convergence of Capital Measurement and Capital Standards." Weights range from 50% to 85%. See section II.B, paragraphs 32-34.
Commercial real estate loans	75%	Identical treatment as C & I loans
Consumer loans	75%	Identical treatment as C & I loans
Lease financings	75%	Identical treatment as C & I loans

Asset class	NSFR haircut	Notes
Other real estate loans	75%	Identical treatment as C & I loans
Residual loans	75%	Identical treatment as C & I loans
Residual assets	100%	See section II.B, paragraph 35.
Residual securities	100%	See section II.B, paragraph 35.