Fire-Sale Spillovers and Systemic Risk

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Abstract

We construct a new systemic risk measure that quantifies vulnerability to fire-sale spillovers using detailed regulatory balance sheet data for U.S. commercial banks and repo market data for broker-dealers. Even for moderate shocks in normal times, fire-sale externalities can be substantial. For commercial banks, a 1 percent exogenous shock to assets in 2013-Q1 produces fire sale externalities equal to 19 percent of system capital. For broker-dealers, a 1 percent shock to assets in August 2013 generates spillover losses equivalent to almost 23 percent of system capital. Externalities during the last financial crisis are between two and three times larger. Our systemic risk measure reaches a peak in the fall of 2007 but shows a notable increase starting in 2004, ahead of many other systemic risk indicators. Although the largest banks and broker-dealers produce – and are victims of – most of the externalities, leverage and linkages of financial institutions also play important roles.

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 commercial banks from regulatory filings and on broker-dealers from the tri-party repo market to construct a measure of fire-sale externalities in the U.S. financial system, a particular yet important dimension of overall systemic risk. Our measure is an empirical implementation of the framework in Greenwood, Landier, and Thesmar (2012). The framework takes as given a simple adjustment rule banks use when hit by adverse shocks, their leverage, asset holdings, and the price impact of liquidating assets in the secondary market. It then considers a hypothetical shock, either to asset returns or bank capital, that leads to an increase in banks' leverage. Banks respond by selling some assets and paying off debt to retrace the increase in leverage. These asset sales have a price impact that depend on the liquidity of the assets and the amount sold. Banks holding the fire-sold assets consequently suffer spillover losses. The main systemic risk measure of interest is aggregate vulnerability (AV) defined as the sum of all second-round spillover losses – as opposed to the initial direct losses – as a share of the total equity capital in the system.

The key challenge in implementing this framework is the availability of detailed balance sheet data of financial institutions. Greenwood, Landier, and Thesmar (2012) implement the framework for one cross-section of European banks released as part of the 2011 stress tests. In contrast, we implement the framework using U.S. panel data – quarterly from 2001 to 2013 for commercial banks and monthly from July 2008 to August 2013 for broker-dealers. This allows us to construct time series of aggregate vulnerability, understand the dependence on individual components and evaluate its merit as a leading indicator for systemic risk.

When looking at quarterly regulatory balance sheet information of bank holding companies, we find that AV builds up steadily from 2001 until it peaks during the financial crisis of 2007–2008. Our benchmark specification estimates that in the fourth quarter of 2007, a 1 percent exogenous reduction in the value of all assets in the financial system would have produced fire sale externalities equal to 41 percent of total equity capital held in the financial system. Measured by their contribution to fire-sale spillovers, the ten largest financial institutions are the most systemic, accounting for over 80 percent of AV. However, we show that to explain the upward trend in AV before the crisis, the increase in "illiquidity concentration" in the banking system is as important as its increase in size and only a moderate increase in leverage. After the peak during the crisis, AV drops sharply as banks become significantly less levered and less linked, even though they keep increasing their size.

For the tri-party repo market, our benchmark specification estimates average spillover losses of 73 percent of total system capital for a 1 percent decline in the price of all assets. The time variation in AV is driven by two overlapping effects. First, AV increases during flight-to-quality episodes. The portfolios of broker-dealers shift to safer assets, especially Treasuries. Because safer assets command a lower haircut, equity capital in the system decreases and the resulting increase in leverage makes the system more vulnerable. Second, however, safer assets are typically more liquid which should counteract the first effect. We therefore use data on haircuts to proxy for the liquidity of different assets. AV then increases significantly in the fall of 2008 when the liquidity of most assets deteriorates. Concentration in the repo market plays a similar role to when we use regulatory balance sheet data. In late 2008, the top five dealers account for 70 percent of AV and even by the end of our sample in August 2013 they still account for 40 percent.

While many systemic risk measures have been proposed,[1] ours has unique features that complement the existing literature well and make it appealing to policymakers. First, given the prominence of repos in many narratives of the crisis and their propensity for fire sales and runs, we believe it is important to have an indicator of systemic risk in this market, something not yet developed in the literature.[2] Repo borrowing accounts for about 56 percent of all broker-dealer liabilities and almost all of this borrowing happens in the tri-party repo market. In addition, the existence of real-time daily data makes AV ideally suited for timely monitoring. Second, our quarterly systemic risk measure that uses regulatory data is the first to use detailed balance sheet information for U.S. financial institutions. The fine granularity allows for a detailed view of the evolution, composition and major causes of vulnerability to fire-sales in commercial banking. Third, our methods satisfy several current policy needs of regulators. Stress testing has become a standard tool in the hands of regulators, yet current implementations only consider initial individual losses at large financial institutions, and all but ignore the second-round losses arising from systemic risk.[3] Although many systemic risk measures could be used for this purpose, the framework we implement is simple and transparent, and can be readily adjoined to existing stress tests in their present form just by taking as inputs

[1]Good surveys are De Bandt and Hartmann (2000); IMF (2011); Acharya, Pedersen, Philippon, and Richardson (2012); Bisias, Flood, Lo, and Valavanis (2012).

[2]For discussions of the repo market and its role in the crisis, see Copeland, Martin, and Walker (2011); Gorton and Metrick (2012); Krishnamurthy, Nagel, and Orlov (2013).

[3]Current stress tests do consider macroeconomic shocks that could exogenously embed the second-round shocks. However, they are assumed rather than derived.

the shocks that are already assumed in the different scenarios that regulators posit. The designation of systemically important financial institutions (SIFIs) is another active area in post-crisis regulation. The Dodd-Frank act requires, among other standards, that a financial firm is designated as a SIFI if it "holds assets that, if liquidated quickly, would cause a fall in asset prices and thereby [...] cause significant losses or funding problems for other firms with similar holdings," a description that closely resembles the contents of this paper.[4] Fourth, our measures Granger-cause several popular and widely used systemic risk measures, confirming it has value as a leading indicator of systemic stress.

2 Framework

2.1 Setup

To calculate potential spillovers from fire sales, we build on the "vulnerable banks" framework of Greenwood et al. (2012). The framework quantifies each step in the following sequence of events of a fire sale:

1. **Initial shock:** An initial 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.

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

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

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.

2.2 Spillover measures

We derive the final expression for the spillover losses in which we are interested by following the steps above. Several of the assumptions of the framework are strong but could be relaxed if desired. However, we consider the stylized nature of the framework a virtue, as it provides a transparent benchmark against which to evaluate alternative specifications. We start with the 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.[5] To determine the shortfall a bank has to cover to get back to target leverage we multiply the loss by b_i:

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

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:[6]

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

These asset sales have price impacts (Step 4) that depend on each asset's illiquidity ℓ_k (cf. Amihud, 2002). Combining these illiquidity measures into a diagonal matrix L, the

[5] Leverage targeting has been established empirically for broker-dealers as well as commercial banks by Adrian and Shin (2010b, 2011).

[6] See Coval and Stafford (2007) for evidence on asset sales by mutual funds in response to shocks.

fire-sale price impacts are given by:[7]

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

Finally, price impacts 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:[8]

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

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:

$$\begin{aligned} \mathcal{L} &= \textstyle\sum_{i'} a_{i'} \sum_{k'} m_{i'k'} \ell_{k'} \sum_i m_{ik'} b_i a_i \sum_k m_{ik} f_k \\ &= 1' AMLM'BAMF \end{aligned}$$

where 1 is a column vector of ones. If instead of an initial shock to assets we consider a shock to equity capital, we simply replace MF in Step 1 by the corresponding percentage of capital lost due to the shock. Based on the total spillover losses $\mathcal{L}$ we define three different measures:

1. **Aggregate vulnerability:** The fraction of system equity capital lost due to spillovers:

$$\text{AV} = \frac{1}{e} \textstyle\sum_{i'} a_{i'} \sum_{k'} m_{i'k'} \ell_{k'} \sum_i m_{ik'} b_i a_i \sum_k m_{ik} f_k \tag{1}$$

2. **Systemicness of bank i:** The contribution to aggregate vulnerability by bank i:

$$\text{SB}_i = \frac{1}{e} \textstyle\sum_{i'} a_{i'} \sum_{k'} m_{i'k'} \ell_{k'} m_{ik'} b_i a_i \sum_k m_{ik} f_k \tag{2}$$

This measure is obtained by dropping the summation over i in equation (1) which

[7] For evidence on fire-sale effects in equities see Coval and Stafford (2007), in corporate bonds Ellul, Jotikasthira, and Lundblad (2011) and in bank loans Drucker and Puri (2009). More generally, there could be cross-asset price impacts in a fire sale. This can be accommodated by letting L be a matrix where the off-diagonal element $\ell_{kk'}$ represents the impact sales of asset k' have on the price of asset k.

[8] Note that this calculation implicitly assumes that the asset matrix A is unchanged and is therefore valid only as an approximation for sufficiently small shocks f_k.

combined 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.

3. **Systemicness of asset k:** The contribution to aggregate vulnerability by asset k:

$$\mathrm{SA}_k = \frac{1}{e}\textstyle\sum_{i'} a_{i'} \sum_{k'} m_{i'k'} \ell_{k'} \sum_i m_{ik'} b_i a_i m_{ik} f_k \tag{3}$$

   This measure is obtained by dropping the summation over k in equation (1) which combined all assets' direct losses into one total. Similar to the measure for individual banks, this measure can also be interpreted as the aggregate vulnerability resulting from a shock only to asset k.

It is important to note that these measures focus only on the indirect losses due to spillovers. They specifically do not include the direct losses due to the initial shock which are given by:[9]

$$\textstyle\sum_i a_i \sum_k m_{ik} f_k$$

This means that our analysis is very different but complementary to the typical stress-test analysis which focuses on the direct losses for a given shock. In addition, the framework and all of our results are conditional on the exogenous initial shock F having occurred, and we do not assess the probability of such a shock occurring.

2.3 Factor decomposition

To understand the driving forces causing spillover losses and their variation over time, we decompose AV into several factors. We want to distinguish between the effects of the aggregate characteristics of the banking system and the effects of the composition of the banking system. 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.

[9] The measures also do not include additional indirect losses due to subsequent rounds of spillovers. Due to the linearity of the framework, iterating further rounds of spillovers doesn't guarantee convergence to a state with non-zero system equity capital. The framework could be adapted straightforwardly by assuming price impacts decreasing in the number of rounds to ensure such convergence.

Using this notation, we can rewrite aggregate vulnerability from equation (1) as:[10]

$$\mathrm{AV} = \underbrace{a}_{\text{size}} \times \underbrace{(b+1)\,b}_{\text{leverage}} \times \underbrace{\textstyle\sum_{k'} \left[m_{k'}^2 \, \ell_{k'} \sum_i \left(\mu_{ik'} \alpha_i \beta_i \sum_k m_{ik} f_k \right) \right]}_{\text{illiquidity concentration}} \tag{4}$$

We see that AV is made up of three factors. The first factor is system size which plays a role since asset liquidity doesn't scale with system size so a larger system suffers larger price impacts.[11] The second factor is system leverage which enters quadratically since 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.

Analogous to the decomposition of aggregate vulnerability, we can decompose the systemicness of an individual bank from equation (2). Highlighting the terms that are specific to bank i we have:

$$\mathrm{SB}_i = \underbrace{a\,(b+1)\,b}_{\text{aggregate}} \times \underbrace{\alpha_i}_{\text{size}} \times \underbrace{\beta_i}_{\text{lever.}} \times \underbrace{\textstyle\sum_{k'} m_{k'}^2 \ell_{k'} \mu_{ik'}}_{\text{illiquidity linkage}} \times \underbrace{\textstyle\sum_k m_{ik} f_k}_{\text{exposure}} \tag{5}$$

The first factors are aggregate and don't 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 exposed to the initial shock.

Finally, the systemicness of an individual asset from equation (3) can be factored as well. Highlighting the terms that are specific to asset k we have:

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

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, i.e. that are large and levered and, in turn, hold other large and illiquid asset classes. Finally, an asset is naturally more systemic if it has higher exposure in terms

[10] Note that our decomposition differs from the one in Greenwood et al. (2012).

[11] We relax this assumption in the robustness analysis in Appendix A.

of the initial shock.

2.4 Spillover elasticities

In most of the analysis we assume a constant shock of to all asset classes, $f_k = f$ for all k. In that case all the spillover measures are linear in the size of the shock so scaling f by a constant changes all the measures proportionally. Similarly, adding up the spillovers from shocking each asset independently or each firm independently gives the same result as shocking all of them together. In addition, we can divide all measures by f and turn them into elasticity measures. Slightly abusing notation, we have:

$$\begin{aligned} \mathrm{AV} &= a\,(b+1)\,b\sum_{k'}\left[m_{k'}^2\,\ell_{k'}\sum_i\left(\mu_{ik'}\alpha_i\beta_i\right)\right] \\ \mathrm{SB}_i &= a\,(b+1)\,b\sum_{k'}\left[m_{k'}^2\ell_{k'}\mu_{ik'}\right]\alpha_i\beta_i \\ \mathrm{SA}_k &= a\,(b+1)\,b\sum_{k'}\left[m_{k'}^2\,\ell_{k'}\sum_i\left(\mu_{ik'}\alpha_i\beta_i\mu_{ik}\right)\right]m_k \end{aligned}$$

AV now tells us the percentage points of system equity capital lost due to fire-sale spillovers per percentage points of initial shock to assets and similarly for the systemicness of firm i and asset k. Assuming a shock of 1 percent, $f = 0.01$ would give equivalent results.

3 Commercial banks

3.1 Data and its mapping to the model

We apply the framework described in the last section to firms that file regulatory form FR Y-9C to the Federal Reserve Board. Form FR Y-9C provides consolidated balance sheet information for bank holding companies (BHCs). The information in the form is used to assess and monitor the condition of the financial sector and is public.[12] Firms file the form at the end of each quarter and the information is typically available two and a half months later, although minor revisions are sometimes incorporated for several additional months. Firms with total assets over \$150 million before March 2006 and over \$500 million since then are required to file. We restrict our study to the largest 100 firms by assets each quarter because they have the most complete and uniform data. [13] We drop firms owned

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

[13] We also show that using the 500 largest firms gives results that are nearly identical to our benchmark case, since fire sale spillovers are predominantly caused by larger firms, see Appendix A.

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.[14] The type and detail of disclosure in the form have changed over time with recent forms providing a more granular view of firms' balance sheets. While the data is available since 1986, we begin our study in the first quarter of 2001 to strike a balance between having a long enough time span for meaningful analysis and substantial granularity in asset classes.

We group assets into the 13 categories listed in Table 1 to construct the matrix of portfolio weights M. We only deviate from the classification on form FR Y-9C by combining all items listed under "trading assets" with the corresponding items listed under "securities" and "loans". This means we don't distinguish between, e.g. Treasuries held in the trading book and those held in the banking book. We choose to group assets into these 13 categories because it is the finest subdivision we can construct such that it is reasonable to assume that there are no cross-asset price impacts of fire sales. For example, we are assuming that selling \$10 billion of loans secured by real estate has no direct impact on the price of mortgage backed securities – and that the same is true for every pair of distinct assets. This assumption makes the matrix L diagonal, simplifying the analysis. The main challenge of a non-diagonal L matrix would be the empirical estimation of its non-diagonal elements.[15]

For the liquidity matrix L, given the lack of empirical estimates, we follow Greenwood et al. (2012) and assume all diagonal elements are equal to 10^{-13} except for cash, which is perfectly liquid. This liquidity value corresponds to a price impact of 10 basis points per \$10 billion of assets sold. Amihud (2002) shows that this is close to the liquidity of a broad spectrum of stocks. Given that most of the assets we consider are less liquid than stocks, we are likely producing a lower bound for the size of fire sale externalities. We also report results under a few alternative liquidity scenarios, where Treasuries are more liquid and other assets are less liquid than in our main specification. In all of these scenarios, fire-sale externalities increase and sometimes substantially so.

[14] New rules that implement section 165 of the Dodd-Frank act state that starting in 2015, foreign banking organizations with a significant presence in the U.S. will be required to organize all of its US subsidiaries into a single Intermediate Holding Company (IHC). The IHCs will then be regulated essentially as if they were a domestically-owned bank holding company, with similar capital, liquidity and other prudential standards. Including firms with foreign ownership only increases the size of fire-sale spillovers, see Appendix A.

[15] How we partition assets matters, even if L is diagonal. As a robustness check, we show that when we collapse the eighteen categories described above into eleven, results are qualitatively similar but give substantially higher estimates of fire-sale externalities, see Appendix A.

Table 1: Summary statistics for BHCs in 2013-Q1.

	System	p10	Med.	Mean	p90
Assets ($ billions)	13,692.9	7.1	14.9	136.9	259.1
Leverage	11.6	7.0	10.0	11.1	13.3
PF shares (percent):					
Real-estate loans	18.5	6.7	37.3	35.4	53.0
Repo & FF loans	11.1	0.0	0.0	1.6	3.2
MBS	10.5	3.0	12.9	13.9	25.2
C & I loans	9.0	3.7	10.9	12.6	23.0
Cash	8.8	1.5	4.7	6.5	12.7
Consumer loans	8.2	0.2	2.9	6.1	11.4
ABS & debt sec.	7.3	0.0	0.8	2.5	7.1
U.S. Treasuries	2.4	0.0	0.0	1.1	3.9
Municipal sec.	1.4	0.0	1.6	2.7	7.8
Agency sec.	1.0	0.0	0.8	2.6	8.4
Residual loans	6.3	0.8	3.2	4.7	9.9
Residual sec.	5.6	0.0	0.3	1.3	2.0
Residual assets	9.9	3.7	8.5	9.1	12.8

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 from total assets to get a measure of debt. In addition, we drop all banks with negative leverage and cap leverage at 30 whenever it exceeds this threshold.[16]

Table 1 shows summary statistics for the distribution of assets across banks in 2013-Q1. The largest firm is JP Morgan Chase (JPMC), with $2.4 trillion of total assets, while the smallest firm is Chemical Financial Corp. with $6 billion. The average amount of total assets across firms is $137 billion with a standard deviation of $407 billion. The second row of the table shows that the average leverage is 11.1, and that most firms have leverage relatively close to this average, with the 10th and 90th percentile at 7.0 and 13.3, respectively. Figure 1 shows the evolution of total assets and system-wide leverage for each quarter of the sample. Assets increase steadily between 2001 and late 2008, with an annual growth rate of almost 9 percent. The small increase between 2008-Q2 and 2008-Q3 is due to JPMC acquiring Bear Stearns and Washington Mutual, Bank of America acquiring Countrywide, and Bank of NY Mellon and State Street receiving significant amounts of TARP funds. The large jump between 2008-Q4 and 2009-Q1 is due to Bank

[16]Winsorizing leverage at 30 only affects 0.4 percent of observations.

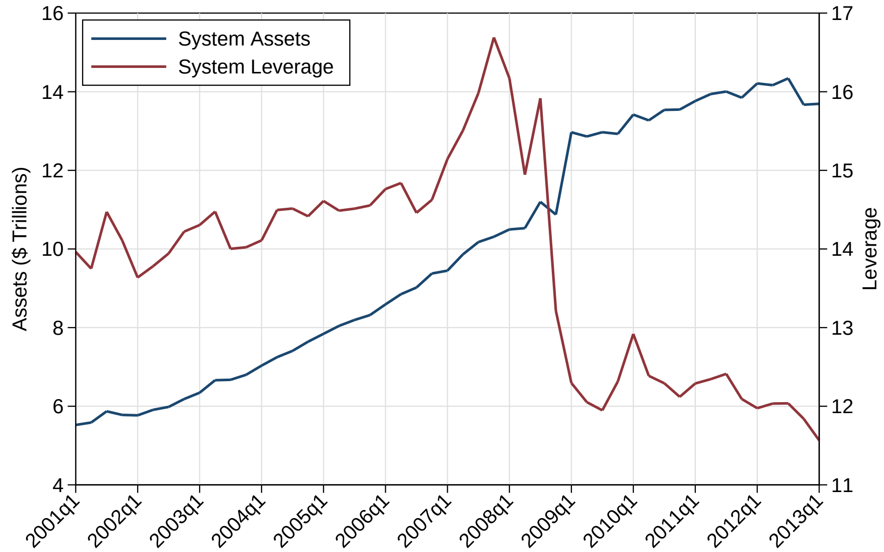

Figure 1: System assets and system leverage for BHCs.

of America acquiring Merrill Lynch and receiving TARP funds, as well as Goldman Sachs, Morgan Stanley and GMAC (now Ally Financial) converting to bank holding companies and being consequently required to file form FR Y-9C.[17] Since early 2009, assets grow at 1.4 percent per year and in a more uneven fashion than before the crisis.

Leverage, also plotted in Figure 1, shows a slightly increasing trend until late 2006 then increases significantly as the crisis unfolds and banks suffer capital losses. It peaks in 2007-Q4 due to capital losses and declines rapidly as banks are recapitalized and delever. 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). One of the motivations of this paper is to show that despite the relatively small increase in book and regulatory leverage, vulnerabilities were building up even when looking at the traditional banking sector as a closed system.

Table 1 also shows summary statistics on the portfolio shares of the different asset classes. At 18.5 percent aggregate share, loans secured by real estate are by far the largest asset class in aggregate and also have the highest average portfolio share across banks at 35.4 percent. The big difference between aggregate and average portfolio share shows the skewed distribution of some asset classes, e.g. repo and fed funds loans are concentrated

[17]Fire-sale spillovers are reduced by about three to five percentage points every quarter if we constrain our sample to firms who are present throughout the whole sample. We give more details of this case in Appendix A.

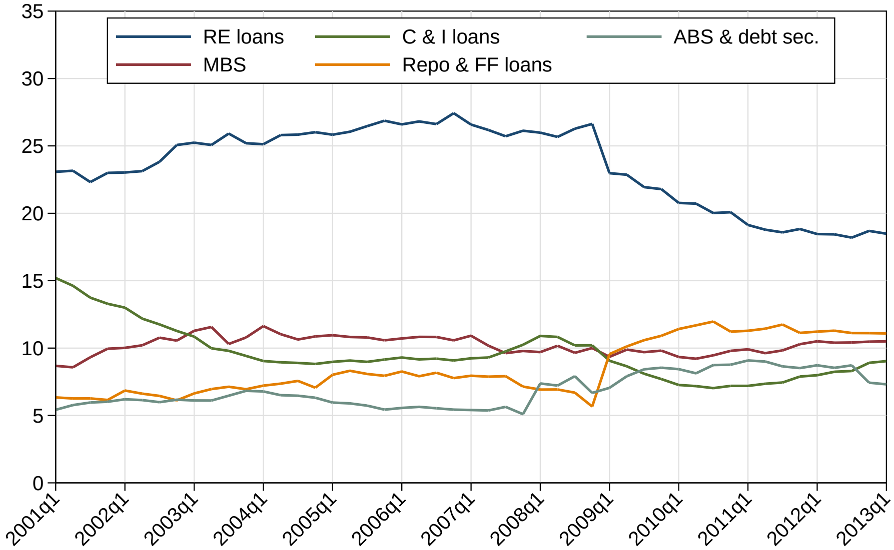

Figure 2: System-wide portfolio shares of asset classes (BHCs).

among the largest banks. Figure 2 plots the aggregate portfolio shares of the largest asset classes over time. Real estate loans is the largest category throughout the sample, with holdings increasing slightly before the crisis and then decreasing to slightly below 20 percent of total assets.

3.2 Results and analysis

Figure 3 shows aggregate vulnerability (AV), the percentage of system equity capital that would be lost due to fire-sale spillovers if all assets exogenously decreased in value by 1 percent. The estimates in a particular quarter use balance sheet information for that quarter only; the exercise is a series of repeated cross-sectional computations. This does not mean that we expect all the fire sales to occur within the quarter. The AV numbers represent total losses over whatever horizon it takes for them to be realized. The notion of horizon is implicitly captured by the liquidity assumptions we make: higher liquidity can mean that markets absorb assets with less of a price impact in a fixed window of time or that liquidation is taking place over a longer span of time. The average AV over the sample is 23.7 percent of system equity capital, although there is substantial time-variation. The measure builds up steadily from around 14 percent at the beginning of the sample until the financial crisis, peaking in 2007-Q4 at 40.7 percent. After that, the measure spikes again in 2008-Q3 before decreasing to around 23 percent where it remains until decreasing slightly toward the end of the sample. The estimate tells a story of a steady increase in

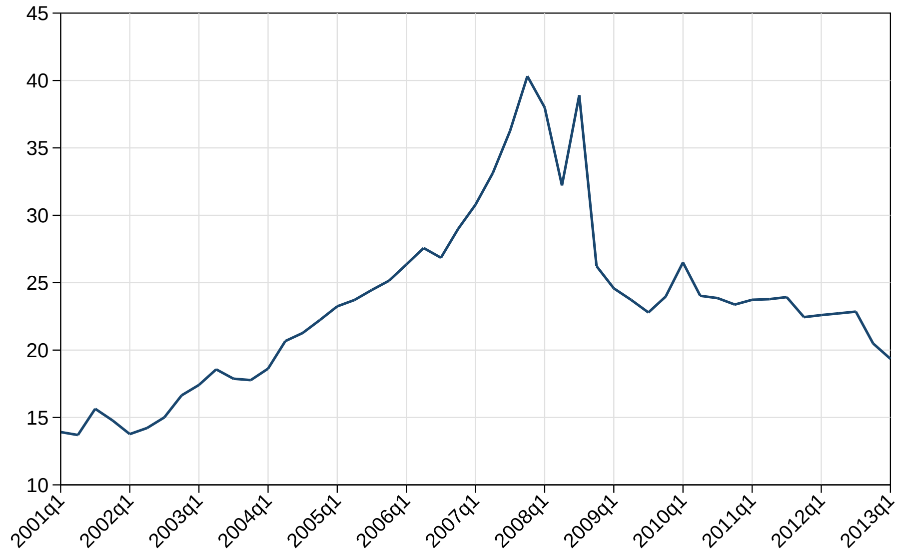

Figure 3: Benchmark aggregate vulnerability (BHCs); percentage points of system equity capital lost due to fire-sales per percentage points of initial shock.

vulnerability in the financial sector well before the crisis started. It tripled between 2001-Q1 and 2007-Q4, with half of that increase occurring between 2001-Q1 and 2006-Q1. If available in real time, our estimate may have been useful as an early indicator of the crisis. We explore this issue in Section 5.

Fire-sale externalities are caused predominantly by large banks. The five largest firms by assets account for 50 to 70 percent of AV throughout the sample, as Figure 4 demonstrates. The ten largest firms produce between 70 and 80 percent of all potential externalities, confirming how concentrated systemicness is. The contribution of the largest firms increases before and during the crisis, and stays relatively flat since then. The pre-crisis trend is due to all components of AV: the largest banks become larger, more levered and more linked during this period. Figure 5 reports the five firms that impose the highest externalities on the system as of 2013-Q1, using the systemicness of banks SB_i in equation (2). Bank of America leads the group, contributing 3.6 of the 19.4 percentage points in aggregate vulnerability in 2013-Q1. Because the framework is linear, we can interpret Bank of America's 3.6 percent number as the fraction of system equity capital that would be lost due to fire-sales if only Bank of America's assets declined in value by 1 percent.

Figure 6 uses SA_k from equation (3) to show that the most systemic asset class is real estate loans for all periods of our sample. It is responsible for potential losses of 11.1

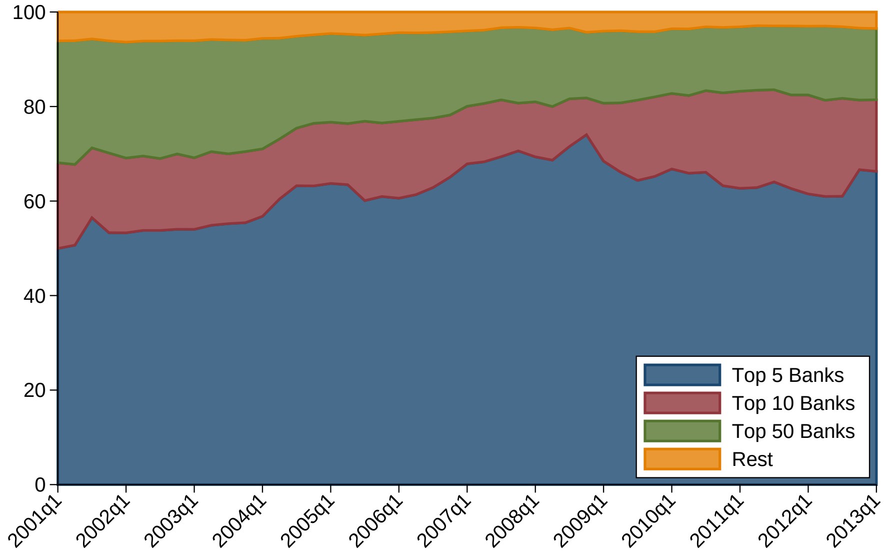

Figure 4: Contribution to aggregate vulnerability by bank size (BHCs).

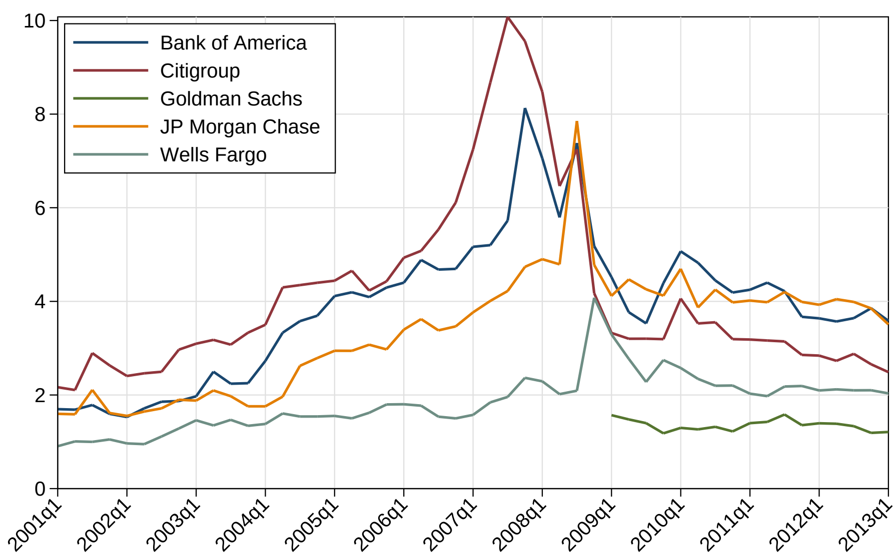

Figure 5: Fire-sale externality of most systemic banks (BHCs).

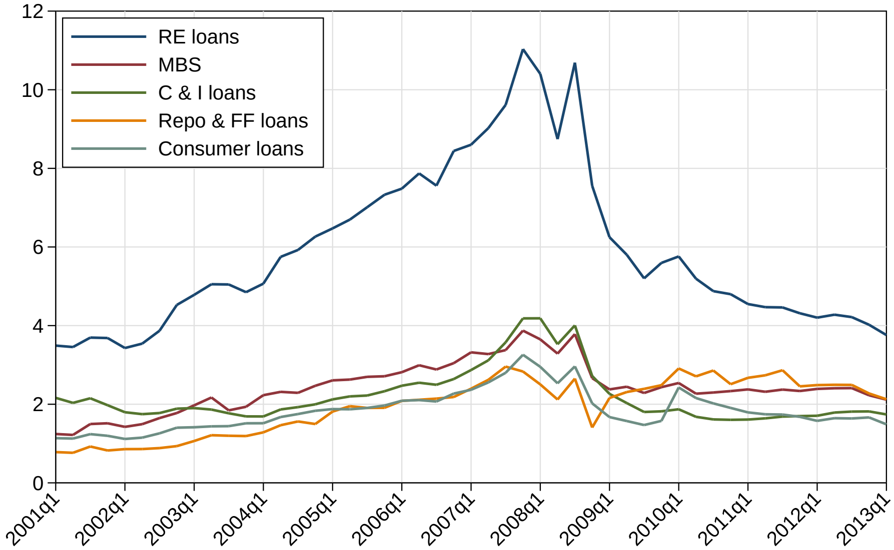

Figure 6: Fire-sale externality of most systemic asset classes (BHCs).

percent of system equity capital at the height of the crisis, corresponding to almost a quarter of total AV. Just as was the case for individual banks, the contribution of real estate loans to aggregate vulnerability can be interpreted as the losses that would occur due to a fire sale if this particular asset class were the only one that suffered a shock. Even in 2013-Q1, after a substantial reduction in systemicness, a 1 percent price decline in real estate loans would lead to a 3.8 percent loss of system equity capital. Another notable feature of real estate loans is how similar their systemicness profile is to the profile of aggregate vulnerability in Figure 3, reaffirming that they are a main driver of fire-sale spillovers. Real estate loans are systemic because they comprise a large fraction of total assets, as Figure 2 shows, and because they are held in large amounts by the biggest firms. The next four most systemic assets, also shown in Figure 6 are MBS, C & I loans, repo & fed funds loans and consumer loans.

To explain the causes behind the dynamics of AV, we use the four components given in Section 2.3: System size, leverage and illiquidity concentration. Figure 7 shows the evolution of these components, which we normalize to 100 in 2007-Q1. The expanding size of firms is one of the main causes for the increase in AV pre-crisis and a mitigant of its decline post-crisis.[18] Between 2008 and 2009 firms drastically changed their risk profile. The asset 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

[18] As explained previously, the large increase in 2009-Q1 is due mainly to investment banks joining the sample because they converted into bank holding companies.

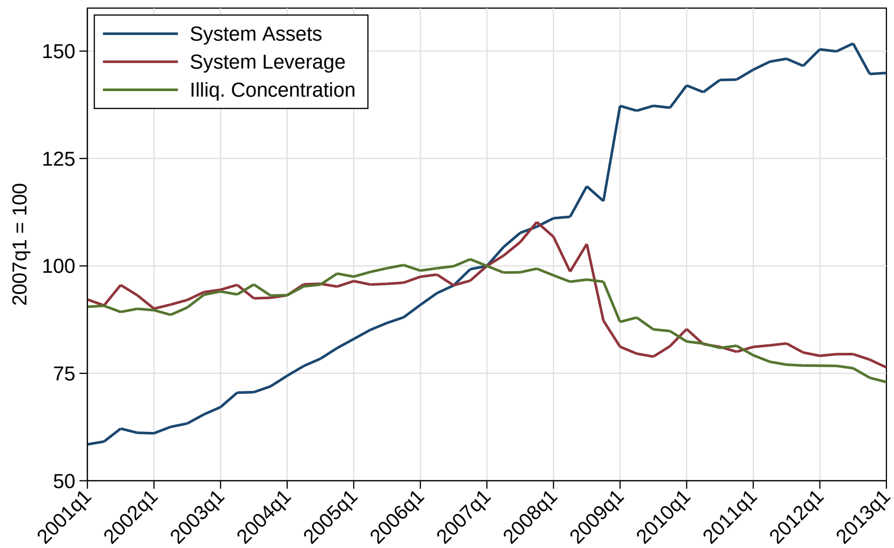

Figure 7: Decomposition of aggregate vulnerability into factors (BHCs).

securities, municipal securities, consumer loans and MBS, which is the only asset class that shows consistent high growth throughout the sample. In terms of individual firms, the largest ten firms were responsible for the bulk of the growth.

System leverage, the second component, increases slowly before the crisis then faster during the crisis before decreasing sharply and then staying flat until the end of the sample. It therefore contributes somewhat to the buildup of AV into the crisis and its reduction afterwards. Between its peak and 2013-Q1, leverage for the system as a whole and for the largest ten banks decreased by more than 30 percent, helping reduce AV.

Illiquidity concentration has a more subdued influence on AV, increasing from the beginning of the sample until early 2007 and then receding until the end of the sample. Equation (4) states that concentration increases if the aggregate portfolio becomes more concentrated and more illiquid. In our benchmark, since liquidity of all non-cash assets is identical, what matters most for concentration is what happens to the assets with the largest portfolio weights like real estate loans.[19] Both on average and for the largest banks, the asset classes that show the highest growth before the crisis also have the largest portfolio weights. Therefore, illiquidity concentration rises because the aggregate portfolio becomes more concentrated in assets related to real estate lending. After the crisis, concentration declines because the large holdings of assets related to real estate and trading assets decline or stay flat while overall assets continue to grow.

[19] When we consider different liquidity scenarios in the following section, the assets with the largest portfolio weights will also turn out to be among the most illiquid.

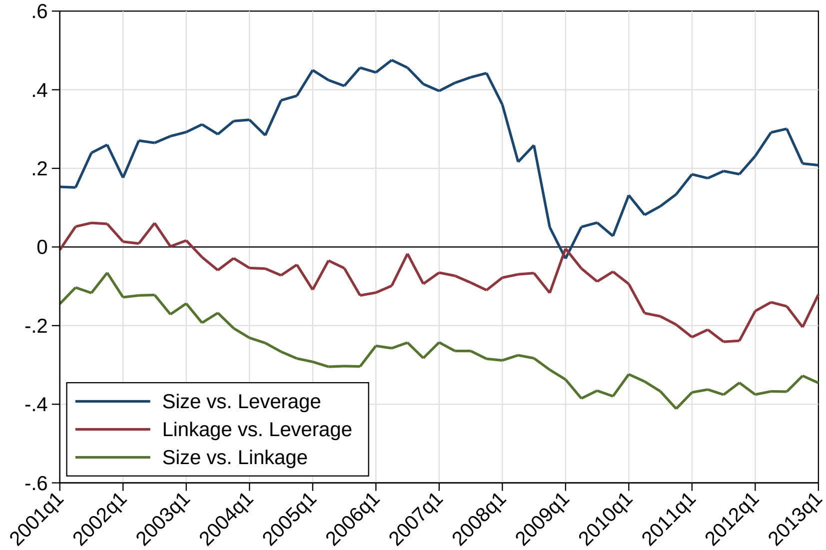

Figure 8: Cross-sectional rank correlations of bank size, leverage and illiquidity linkage (BHCs).

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 very 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 10 and 13 and a cross-sectional standard deviation between 2.5 and 4, depending on the quarter. Illiquidity linkage doesn't show a large dispersion across-banks either, with its cross-sectional standard deviation fairly constant until early 2009 and then decreasing. Figure 8 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, where the largest banks seem to have delevered the most. Linkage and leverage don't show a strong correlation except towards the end of the sample where the more levered banks have lower linkage. Interestingly, illiquidity linkage and size are clearly negatively correlated and trending downwards: smaller firms tend to be more linked and this effect has become more pronounced over time. This pattern is an important moderator of AV. The largest firms are below the median in illiquidity linkage, and sometimes even around the 80th percentile, as illustrated in Figure 9. A notable exception is Wells Fargo, which goes up from rank 60 to 20 between 2001 and 2004, only to return to rank 60 by 2009.[20] Since the crisis, Bank of America shows an increase in linkage compared to other

[20]The main cause of this swing is that Wells Fargo first increases and subsequently decreases its holdings of domestic real estate loans. Even after the reduction in holdings of real estate loans, Wells Fargo has

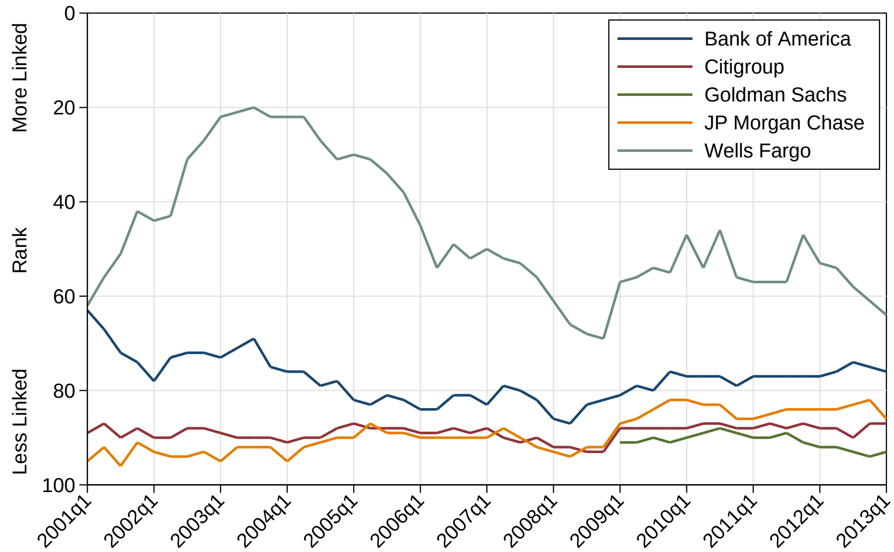

Figure 9: Rank of illiquidity linkage for the most systemic banks (BHCs).

firms, a potentially important pattern for the future evolution of fire-sale externalities.

Another way to study the effect of bank heterogeneity is to construct a counterfactual system where all banks are the same and compare the resulting vulnerability measures. To construct such counterfactual measures we assume that all banks are equally sized, have the same leverage and hold the same asset portfolio, effectively creating a representative bank. This requires setting $\alpha_i = 1/N$, $\beta_i = 1$ and $\mu_{ik} = 1$ for all i, k in the expressions for aggregate vulnerability and asset systemicness.[21] Taking the ratio of actual aggregate vulnerability with heterogeneous banks to hypothetical vulnerability with homogeneous banks, yields an average of 1.027. Aggregate spillovers are therefore 2.7 percent higher due to the fact that banks are heterogeneous in their size, leverage and asset holdings.

Turning to the effect of heterogeneity on asset systemicness, Figure 10 plots the ratio of actual to hypothetical asset systemicness for the nine asset classes (excluding cash) over time. We see some interesting differences across asset classes in size and direction of the effect of bank heterogeneity. While heterogeneity reduces the systemicness of Agencies by 3.3 percent on average it increases the systemicness of real estate loans by 8.8 percent on average.

the largest exposure to this asset class among the ten largest firms.

[21]Note that bank systemicness in this counterfactual analysis is the same for all banks and equal to AV$/N$.

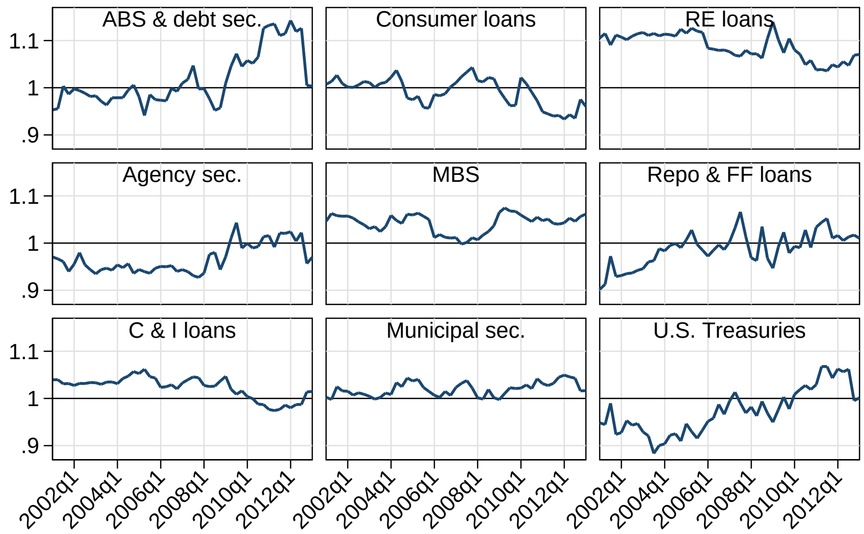

Figure 10: Effect of bank heterogeneity on asset systemicness (BHCs). Ratio of actual systemicness to hypothetical systemicness with homogeneous banks.

Shocks to equity capital. Our benchmark case considers an exogenous decline in the price of assets. Another trigger for fire-sales is an exogenous decline in the equity capital of firms. Conceptually, a capital shock may be a more appropriate way to model financial distress at a particular firm, while asset shocks may be a better way to model market-wide distress. 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 in "material financial distress or failure" is designated as a SIFIs whenever 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."[22] The framework that we use embodies the spirit of this so-called "asset liquidation channel" quite well.

We consider a shock that reduces the equity capital of all firms by 1 percent. While for each single firm there is a one-to-one correspondence between asset shocks and capital shocks, it is not possible to construct a uniform system-wide asset shock that exactly reproduces the outcome of a common capital shock across firms. This is because leverage is not constant across firms. A more levered firm experiences higher capital losses for

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

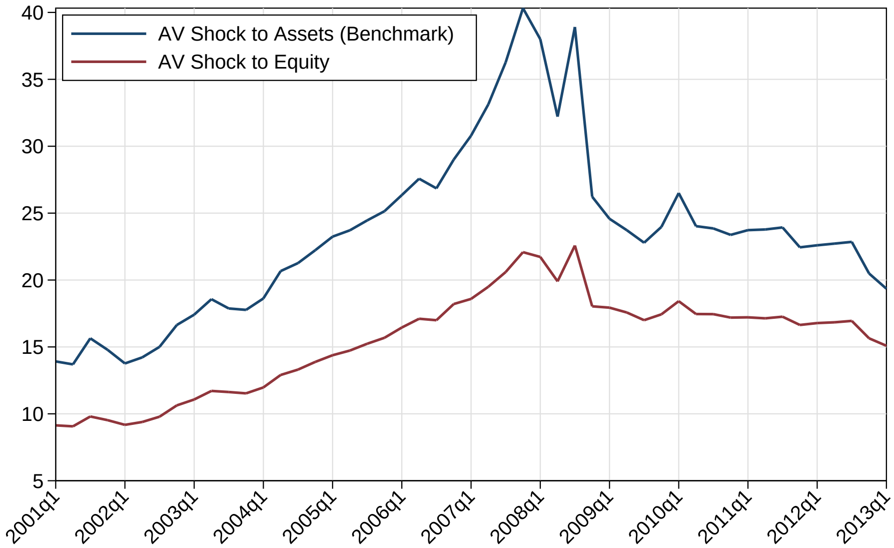

Figure 11: Aggregate vulnerability to a 1 percent asset shock (the benchmark) and a 1 percent shock to equity capital (BHCs).

a given asset shock than a less levered firm. Hence, compared to a common 1 percent asset shock to all firms, a common 1 percent shock to equity capital causes larger initial losses in less levered firms. Whether aggregate vulnerability increases in this case depends on whether more levered firms are also bigger and more linked. Figure 11 shows that, on average, a capital shock produces smaller aggregate vulnerability than an asset shock, although the two converge towards the end of the sample. The banking system is therefore more vulnerable to direct price shocks than to solvency shocks, at least until 2012.

Different liquidity conditions. Although there are no readily available empirical estimates for the price-impact of liquidating large quantities of assets for many of the asset classes we consider, it is reasonable to assume that different asset classes have different price impacts when fire-sold. In addition, liquidity conditions are likely linked to the state of financial markets and the macroeconomy. In our benchmark, we use the conservative assumption that all assets are roughly as liquid as equities. We now explore how different assumptions about the liquidity matrix L change our results.

Table 2 shows the liquidity scenarios we analyze. In the two new scenarios, we make Treasuries and agency securities perfectly liquid, i.e. there is no price impact when they get fire-sold. Other asset classes become less liquid. Figure 12 shows the results. In the two liquidity scenarios we consider, AV is increased substantially. The main reason is that many of the most illiquid assets, including real estate loans, are also among the most

Table 2: Price impacts in the different liquidity scenarios.

Asset class	Bench-mark	Liquid	Less liquid	Asset class	Bench-mark	Liquid	Less liquid
Cash	0	0	0	Residual sec.	10	20	20
U.S. Treasuries	10	0	0	C & I loans	10	30	30
Agency sec.	10	0	0	Cons. loans	10	30	30
Municipal sec.	10	10	10	RE loans	10	30	40
Repo&FF loans	10	10	10	Residual loans	10	30	40
MBS	10	10	20	Residual assets	10	30	40
ABS & debt sec.	10	10	20				

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

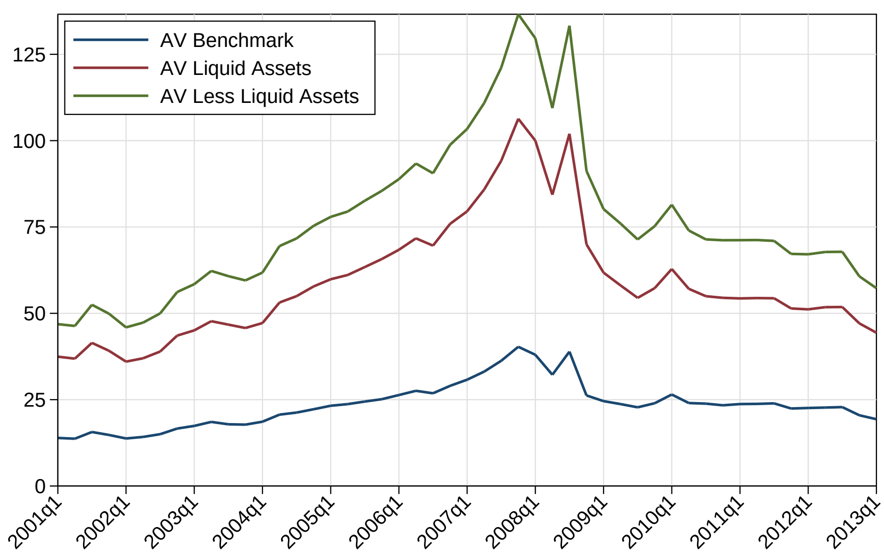

Figure 12: Aggregate vulnerability where every asset is as liquid as equities (benchmark) and with liquidity conditions of Table 2 (BHCs).

systemic (see Figure 6). While the ascent and descent of AV before and after the crisis become more pronounced as illiquidity increases, the general profile of AV remains very similar.

4 Broker-dealers

4.1 Data and its mapping to the model

The data used in the previous section mainly covers the commercial banking sector but not the broker-dealer sector. In this section we use data on the U.S. tri-party repo market, the key wholesale funding market for broker-dealer banks.

A repurchase agreement (repo) is a form of collateralized lending 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 and 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.[23] The borrowers in the tri-party repo market are securities broker-dealers. Among the main lenders in the tri-party repo market, money market funds account for between a quarter and a third of volume and securities lenders for about a quarter.[24]

We use data collected daily by the Federal Reserve Bank of New York since 1 July 2008; it is available in real time, allowing day-by-day monitoring of the market. For our analysis we use a sample from 1 July 2008 to 31 August 2013. 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, one observation is that on 1 July 2008, dealer X borrowed \$100 billion providing \$105 billion of Treasuries as collateral, which implies a haircut of 5 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

[23] For a detailed description of the market, see Copeland et al. (2011).
[24] See Pozsar (2011) for a discussion of large cash investors.

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:

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

Of course, the balance sheet we construct for a particular dealer is only a part of the dealer's overall balance sheet. However, based on the U.S. Flow of Funds, repo borrowing accounts for 56 percent of broker-dealer liabilities (on average \$2.1 trillion out of \$3.7 trillion, 2008-Q3 to 2013-Q1).[25] 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.

We restrict our analysis to the top 25 dealers by average asset size every month. This group accounts for 99.3 percent of total assets. We group the data into the 10 asset classes listed in Table 3. From this data we construct for each dealer a monthly average balance sheet and then form the matrices A, M and B.[26] As in the analysis of Section 3, we initially set liquidity and shocks to be the same across assets. For the market liquidity of assets, we initially set $\ell_k = 10^{-13}$ for all k but subsequently study scenarios with heterogeneous liquidity across assets.

Table 3 gives the summary statistics for the cross section of our balance sheet data for the month of August 2013. The average dealer size is \$62.6 billion, with considerable variation between the 10th percentile of \$9.7 billion and the 90th percentile of \$139.5 billion and large skew with a median of \$41.5 billion. Leverage also has considerable variation around the mean of 36.3. In terms of portfolio shares, Agencies and Treasuries are dominant, with average portfolio shares of 39.4 percent and 39.6 percent, respectively. However, there is substantial heterogeneity in the dealer's portfolios.

Figure 13 illustrates how system size and leverage vary over the sample period. System assets are at their peak in August 2008 at \$2.42 trillion and then decline with the contraction of dealer balance sheets to the sample low-point of \$1.51 trillion by December 2009, a drop of 38 percent. System assets then go through two cycles, first increasing by 19 percent to \$1.79 trillion in November 2010 and shrinking again to \$1.57 trillion in April 2011, then increasing by 24 percent to \$1.95 trillion in November 2012 and shrinking again to \$1.59 trillion in August 2013. Looking at leverage, we see that except for the first

[25]Note that total liabilities in the main Flow of Funds table for broker-dealers only average to \$2.0 trillion between 2008-Q3 and 2013-Q1. This is due to the netting of repos (liabilities) and reverse repos (assets). The correct comparison for our analysis is based on gross repo liabilities (Series FL662150003).

[26]We apply a leverage cap of $b_i \leq 100$ which is binding in less than 2 percent of observations.

Table 3: Summary statistics for broker-dealers in August 2013.

	System	p10	Median	Mean	p90
Assets ($ billions)	1,564.4	9.7	41.5	62.6	139.5
Leverage	33.6	27.2	35.4	36.3	45.6
PF shares (percent):					
Agency MBS & CMO	38.2	13.1	37.3	37.8	64.8
U.S. Treasuries	37.8	11.5	37.7	38.0	63.7
Equities	7.4	0.0	5.0	9.4	17.0
Agency debt	5.4	1.0	5.8	5.0	9.3
Corporate bonds	3.8	0.2	3.3	4.1	8.1
ABS	2.6	0.0	1.6	2.2	5.3
Private label CMO	2.5	0.0	1.0	2.0	5.3
Money market	0.9	0.0	0.0	0.6	1.8
Municipal bonds	0.9	0.0	0.0	0.6	2.8
Residual securities	0.4	0.0	0.1	0.3	0.6

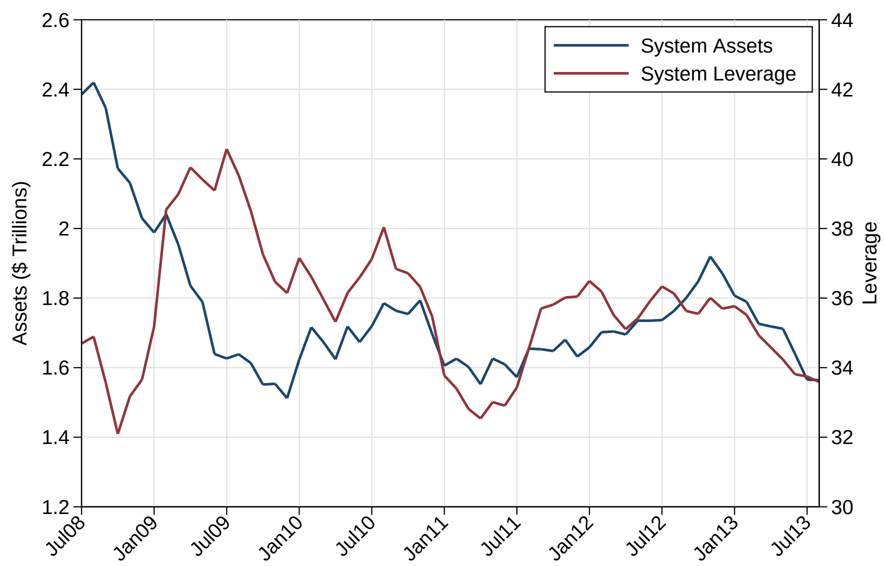

Figure 13: System assets and system leverage for broker-dealers.

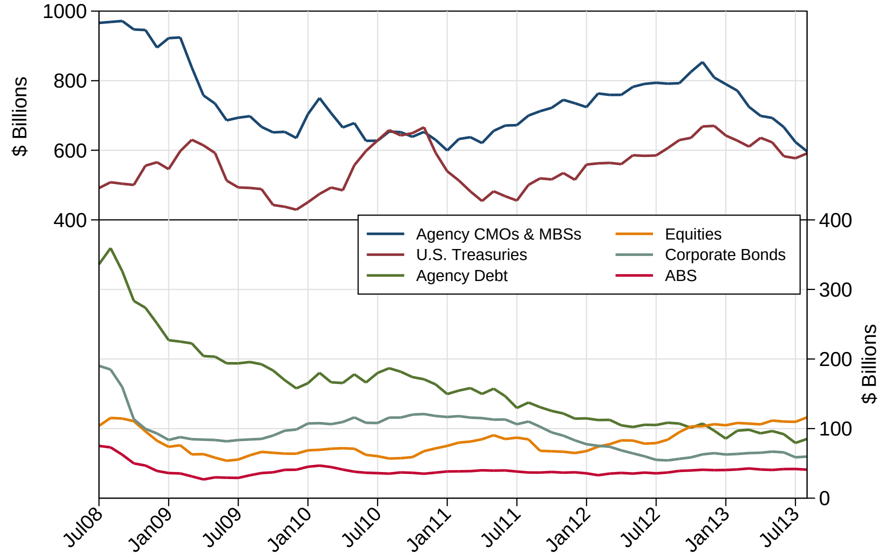

Figure 14: Sizes of main asset classes (broker-dealers).

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).

To provide some details on what happened to different asset classes, Figure 14 shows the sizes of the main asset classes and Figure 15 shows average haircuts by asset class. In the fall of 2008, we see the financial crisis unfolding with the size of risky fixed-income assets (corporate bonds and ABS) collapsing at the same time as their haircuts spike. While corporate bonds make a temporary comeback in terms of size by January 2011, these categories of risky assets end the sample at much smaller size and higher haircuts than they initially had. The size of Treasuries corresponds well with flight-to-safety episodes. It increases during the worst part of the crisis until the beginning of 2009, then decreases as conditions normalize until late 2009. With resurgent volatility and widening credit spreads over the course of 2010 Treasuries increase, 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.

4.2 Results and analysis

Figure 16 shows the aggregate vulnerability of the broker-dealer sector in our benchmark specification that has a homogeneous liquidity matrix L with $\ell_k = 10^{-13}$ for all asset classes. The measure displays considerable variation around its mean of 73 with three

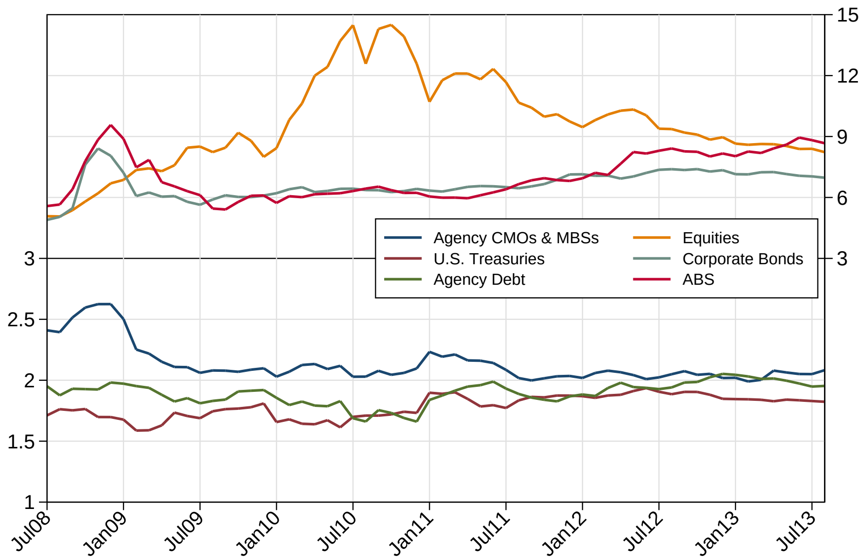

Figure 15: Value-weighted average haircuts for main asset classes (broker-dealers).

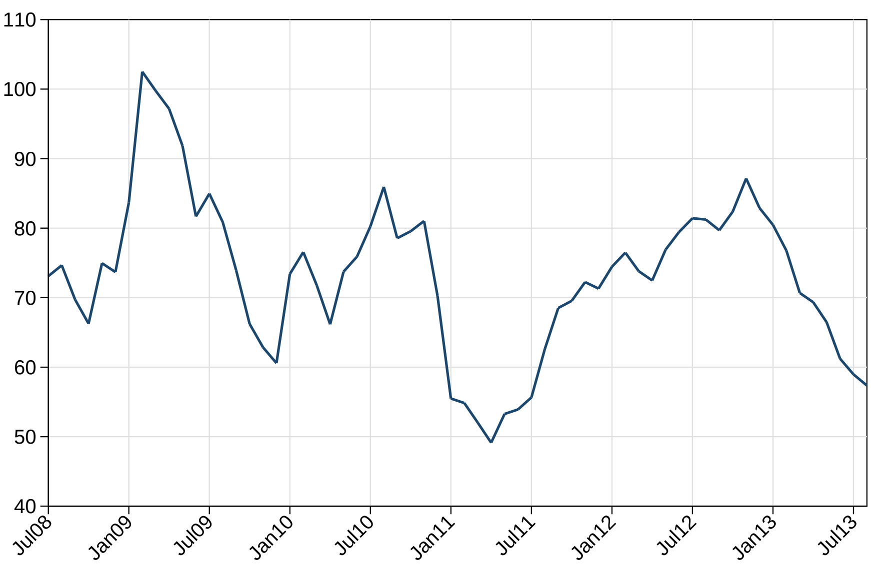

Figure 16: Benchmark aggregate vulnerability (broker-dealers); percentage points of system equity capital lost due to fire-sales per percentage points of initial shock.

peaks, in early 2009, mid 2010 and late 2012. However, most of the movement is due to the behavior of system leverage (Figure 13). Looking at the asset classes in Figure 14 makes clear that leverage, and therefore aggregate vulnerability, is closely associated with the amount of Treasuries in the system. This follows directly from our construction of dealer leverage from haircuts and the assumption of homogeneous liquidity across asset classes. Intuitively, a system-wide shift towards safer assets should have two effects on systemic risk: First, since haircuts on safe assets are lower, dealers can lever up more against them and system leverage increases. This effect is captured by the benchmark case and explains most of the movements of AV in Figure 16. Second, however, we would expect safe assets to be more liquid and produce less fire-sale externalities. This effect should go against the first effect but is ruled out by the assumption of homogeneous liquidity.

To address this issue we have to introduce differences in liquidity across asset categories. We can 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 15 shows, there is both cross-sectional as well as time-series variation in the haircuts of different asset classes. One concern in using haircuts to indicate relative asset liquidity is that equities have the highest haircuts (9.6 percent on average) although we consider them more liquid than several of the other asset categories. Haircuts can be high because an asset is illiquid or because its price is volatile. For most of our asset classes, liquidity is the determining factor and the implied ordering in terms of liquidity aligns well with our intuition. For haircuts on equities, however, price volatility is more important so we have to adjust them accordingly. We therefore first rescale haircuts on equities so that their average across the sample is 3 percent. This makes them less liquid than Treasuries at 1.8 percent, agency debt at 1.9 percent and agency CMOs & MBSs at 2.1 percent but more liquid than all the other asset classes, e.g. corporate bonds at 6.6 percent. Then we run three scenarios differing in how we scale the cross-sectional variation:

1. Liquidity proportional to haircuts: $\ell_{k,t} \propto h_{k,t}$
2. Liquidity proportional to squared haircuts: $\ell_{k,t} \propto h_{k,t}^2$
3. Liquidity proportional to cubed haircuts: $\ell_{k,t} \propto h_{k,t}^3$

Finally, we normalize each scenario so that the average liquidity of equities is equal to 10^{-13}, which corresponds to 10 basis points price change per \$10 billion asset sales. This

Table 4: Average price impacts used in the heterogeneous liquidity scenarios.

Asset class	$\propto h$	$\propto h^2$	$\propto h^3$	Asset class	$\propto h$	$\propto h^2$	$\propto h^3$
U.S. Treasuries	5.9	3.4	1.8	Other	16.6	28.1	49.1
Agency Debt	6.3	3.8	2.2	Municipal Bonds	19.0	35.7	67.0
Agency CMOs & MBSs	7.1	4.8	3.1	Corporate Bonds	22.1	46.8	95.1
Equities	10.0	10.0	10.0	Asset Backed Securities	23.5	53.5	118.7
Money Market	13.1	16.3	19.4	Private Label CMOs	23.7	55.1	126.0

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

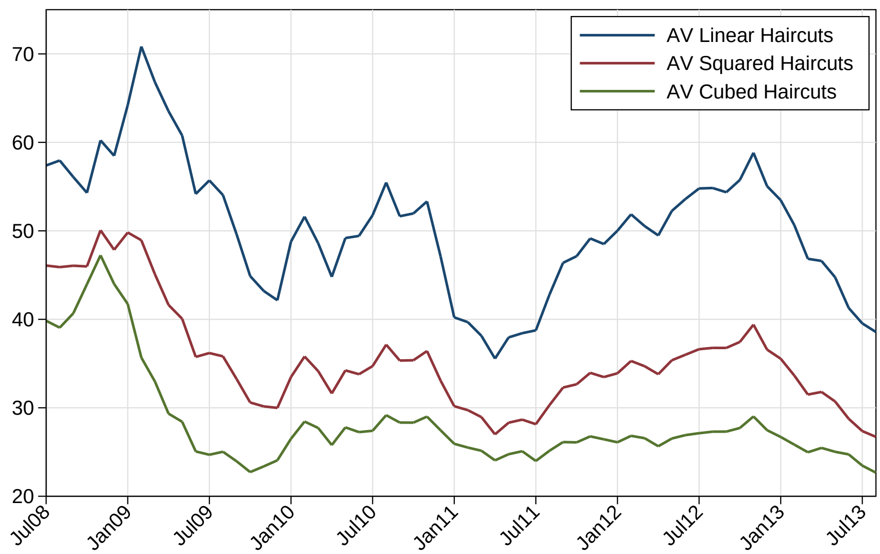

Figure 17: Aggregate vulnerability measures for the heterogeneous liquidity scenarios in Table 4 (broker-dealers).

is the same level of liquidity that we assumed for equities in Section 3 when we used regulatory balance sheet data, and corresponds to estimates by Amihud (2002). Table 4 lists the averages of the resulting price impact measures across asset classes for the three scenarios.

Figure 17 illustrates the aggregate vulnerability measures resulting from the three scenarios. Amplifying the cross-sectional variation in haircuts has three effects. First, overall aggregate vulnerability decreases since the largest asset classes Treasuries, Agencies and agency debt become more and more liquid. Compared to the average AV of 73 in the benchmark, linear haircuts lead to an average AV of 50, squared haircuts to 35 and cubed haircuts to 28. Second, the variation in aggregate vulnerability increases over the first part of the sample but decreases afterwards. Third, the peak in aggregate vulnerability moves from February 2009 to October 2008. The latter two effects highlight the importance of

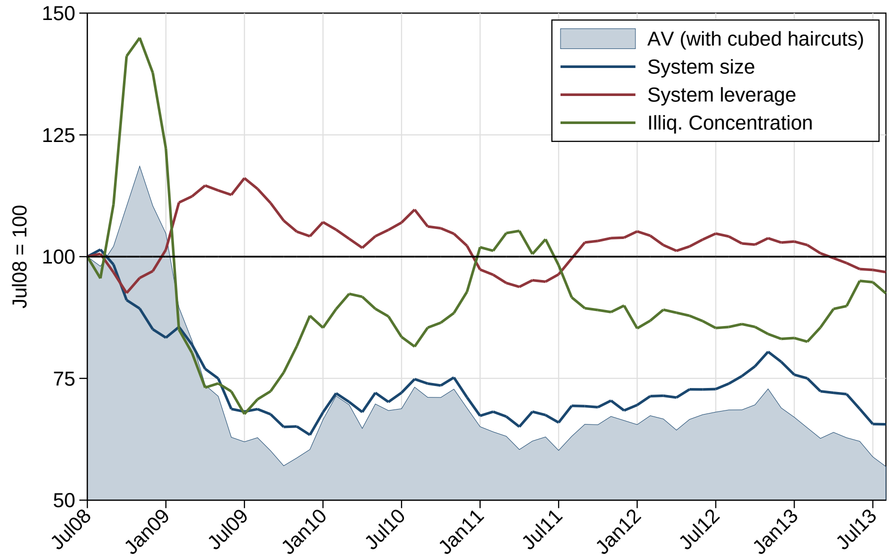

Figure 18: Decomposition of aggregate vulnerability into factors (broker-dealers).

the change in asset composition over the sample period with the fraction of risky assets going down dramatically. In the following, we focus on the third scenario based on cubed haircuts.

Figure 18 shows the decomposition of our preferred measure of AV into the three factors system size, system leverage and illiquidity concentration. We see that no longer does one of the three factors on its own explain most of the behavior of AV. While in the latter part of the sample fluctuations in system size and leverage are the drivers of AV, the crisis period at the beginning of the sample looks different. Initially, although the system is shrinking and deleveraging, AV is pushed to its peak by the dramatic increase in illiquidity concentration. Towards the end of 2008 and the beginning of 2009, AV falls sharply since illiquidity concentration falls dramatically and system size continues contracting even though leverage is increasing again.

Figure 19 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 15 percent.

Figure 20 shows the systemicness measures SA_k of the main asset classes, i.e. the

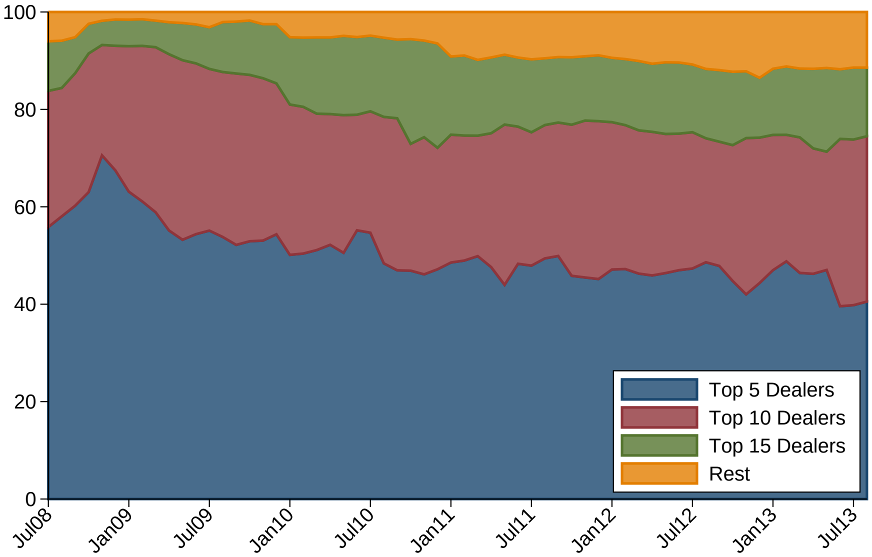

Figure 19: Contributions to fire-sale externality by dealer size (broker-dealers).

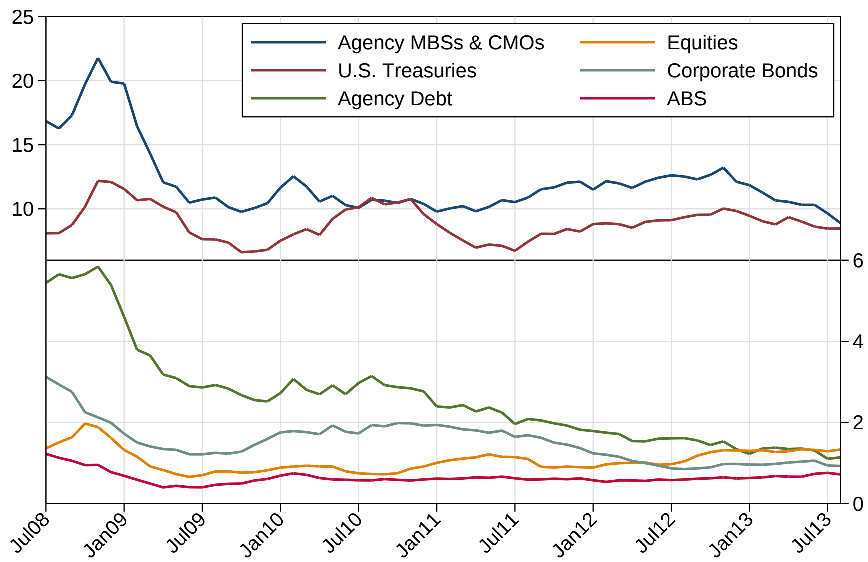

Figure 20: Fire-sale externality of most systemic asset classes (broker-dealers).

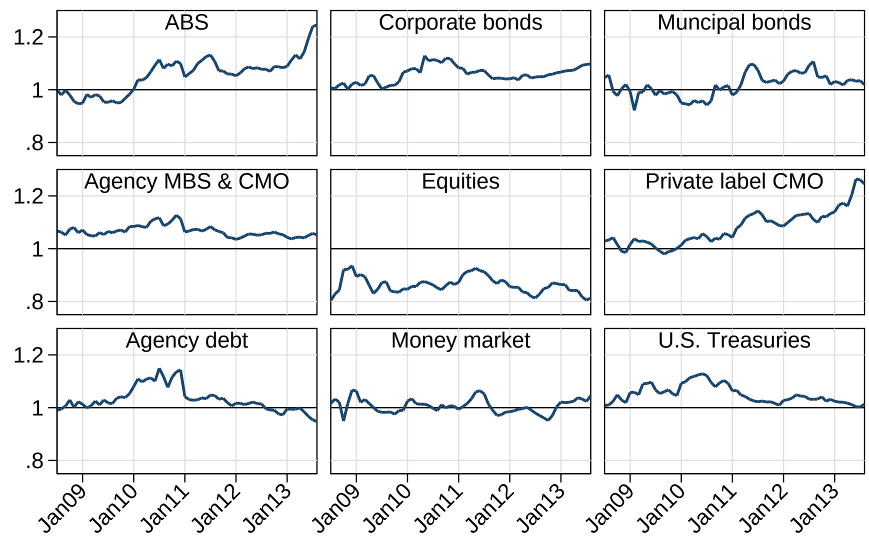

Figure 21: Effect of bank heterogeneity on asset systemicness (broker-dealers). Ratio of actual systemicness to hypothetical systemicness with homogeneous banks.

contribution to aggregate vulnerability of asset class k. Note that this measure can also be interpreted as the total AV for an initial shock only to asset class k. Comparing to Figure (14), we see that the size of an asset class is a key driver of its systemicness as the larges asset classes Agencies and Treasuries are also at the top in terms of systemicness. However, size doesn't explain everything as can be seen from the increase in Agencies' systemicness in the fall of 2008 even though their size was declining. Here, the decrease in Agencies' liquidity as indicated by the increase in their haircuts played a role in driving up systemicness.

Turning to the effect of dealer heterogeneity on the vulnerability measures, we again compare the actual measures to hypothetical measures in a system with homogeneous dealers of equal size, leverage and asset portfolios ($\alpha_i = 1/N$, $\beta_i = 1$ and $\mu_{ik} = 1$ for all i, k). Taking the ratio of actual aggregate vulnerability with heterogeneous dealers to hypothetical vulnerability with homogeneous dealers, yields an average of 1.048. Aggregate spillovers are therefore 4.8 percent higher due to the fact that dealers are heterogeneous in their size, leverage and asset holdings; this is almost twice the size compared to the effect of heterogeneity in the analysis of commercial banks.

Turning to the effect of heterogeneity on asset systemicness, Figure 21 plots the ratio of actual to hypothetical asset systemicness for the nine asset classes over time. As in the analysis of commercial banks, there are interesting differences across asset classes. The largest positive effect on asset systemicness is 8.0 percent on average for private label CMOs while the largest negative effect is –13.7 percent for equities. In addition, there are apparent trends, e.g. for ABS and private label CMOs for which dealer heterogeneity increases systemicness by more than 20 percent toward the end of the sample.

5 Comparison with other systemic risk measures

When it comes to measures of systemic risk, we have what Bisias et al. (2012) call an "embarrassment of riches". Since the financial crisis made apparent the need to understand systemic risk, more than thirty different ways to measure it have been proposed.[27] To our knowledge, there are no systemic risk measure that use repo data prior to ours. For balance sheet data, the papers most related to the framework of Greenwood et al. (2012) that we use are Chan-Lau et al. (2009, Chapter 2) and Fender and McGuire (2010). They both use balance sheet data to map the network structure of financial institutions. Unlike our study, they use balance sheet data that considers broad asset classes and is aggregated across countries or geographic regions. The advantage of their approach is that they can use consistent data for many countries, while we focus on the U.S. only. However, we provide a more detailed view of the network structure because we can track assets at a finer granularity on a firm-by-firm basis. Another difference is we estimate fire-sale externalities while their research has mainly focused on the international transmission of funding shocks.

Giglio, Kelly, and Pruitt (2013) assess which of the many risk measures 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 "quantile principal component" of them significantly increases predictability. We compare the twenty measures they consider to our aggregate vulnerability measures.[28] If necessary, and to aid interpretation, we adjust the sign of the systemic risk measures so that a higher value always denotes higher systemic risk. The risk measures from Giglio et al. (2013) are given at a monthly frequency, while our measure for commercial banks is only quarterly. To make the frequencies consistent, we convert high frequency data to low frequency by taking the average within the corresponding period.[29] For example, we take the average of the values

[27] See De Bandt and Hartmann (2000); IMF (2011); Acharya et al. (2012); Bisias et al. (2012).

[28] We thank Stefano Giglio for generously sharing with us the data of systemic risk measures.

[29] Taking the last observation of the period gives similar results.

Table 5: Comparison of AV for commercial banks to other measures.

	Correlation	AV Granger-causes	Granger-causes AV
Absorption(1)	0.108	0.586	0.015**
Absorption(2)	0.146	0.301	0.033**
Amihud Illiq.	–0.452	0.160	0.932
CoVaR	–0.116	0.078*	0.015**
ΔCoVaR	–0.026	0.152	0.042**
MES (APPR)	0.011	0.010**	0.019**
MES (SRISK)	0.279	0.007***	0.000***
SysRisk	0.465	0.000***	0.002***
Book Leverage	0.181	0.004***	0.917
Dyn. Caus. Ind.	0.438	0.006***	0.167
Default Spread	–0.318	0.011**	0.000***
ΔAbsorption(1)	0.013	0.795	0.333
ΔAbsorption(2)	–0.011	0.845	0.398
Intl. Spillover	–0.076	0.767	0.003***
Market Herfin.	0.749	0.160	0.008***
Market Leverage	0.453	0.000***	0.049**
Realized Vol.	0.228	0.006***	0.000***
TED Spread	0.699	0.002***	0.000***
Term Spread	–0.430	0.671	0.005***
Turbulence	0.443	0.000***	0.000***

Notes: We report p-values for pair-wise Granger-causality tests. One, two and three stars indicate significance at the 10%, 5% and 1% level.

for January, February and March to get estimates for the first quarter of a year.[30]

The first column of Table 5 shows the correlation between systemic risk measures and the aggregate vulnerability measure for commercial banks that we construct using balance sheet data from the FR Y-9C form. There is a wide range of magnitudes for these correlations. Our measure is most highly correlated with the Herfindahl index of the size distribution of financial firms. This is consistent with how important size is for aggregate vulnerability (Figure 7) and how highly concentrated externalities are in the largest firms (Figure 4). Aggregate vulnerability is only mildly correlated with book leverage, also confirming the intuition of figure 7 that size and illiquidity concentration are important components of AV. *Market* leverage, however, correlates fairly well to aggregate vulnerability as do other price-based indicators such as the TED spread and the SysRisk measure of Acharya et al. (2012). The second and third columns show the p-values of Granger (1969) causality tests. The middle column tests the hypothesis that aggregate vulnerabil-

[30]See Appendix B for the sources of the different systemic risk measures.

Table 6: Comparison of AV for broker-dealers to other measures.

	Correlation	AV Granger-causes	Granger-causes AV
Absorption(1)	0.119	0.968	0.940
Absorption(2)	0.116	0.900	0.944
Amihud Illiq.	0.696	0.402	0.338
CoVaR	0.258	0.017**	0.177
ΔCoVaR	0.142	0.041**	0.121
MES (APPR)	0.160	0.045**	0.148
MES (SRISK)	0.703	0.003***	0.099*
SysRisk	0.613	0.000***	0.631
Book Leverage	0.366	0.001***	0.524
Dyn. Caus. Ind.	–0.074	0.437	0.297
Default Spread	0.504	0.002***	0.002***
ΔAbsorption(1)	0.249	0.496	0.616
ΔAbsorption(2)	0.293	0.718	0.338
Intl. Spillover	–0.223	0.022**	0.012**
Market Herfin.	–0.080	0.818	0.463
Market Leverage	0.558	0.000***	0.430
Realized Vol.	0.813	0.001***	0.856
TED Spread	0.845	0.106	0.002***
Term Spread	–0.556	0.224	0.266
Turbulence	0.723	0.000***	0.049**

Notes: AV is calculated using cubed haircuts. We report p-values for pair-wise Granger-causality tests. One, two and three stars indicate significance at the 10%, 5% and 1% level.

ity Granger-causes the other measure, while the last column tests that the other measure Granger-causes aggregate vulnerability. At the 99 percent confidence level, aggregate vulnerability Granger-causes eight of the other measures, while nine of the other measures Granger-cause aggregate vulnerability. Based on this simple metric, aggregate vulnerability derived from balance sheet data seems to be on par with other systemic risk measures as a leading indicator. System size, leverage and illiquidity concentration, when taken one at a time, Granger-cause a much smaller number of systemic risk measures, highlighting the usefulness of combining them into the single AV measure. Table 6 repeats the same exercise for the aggregate vulnerability measure for broker-dealers derived from tri-party repo data. Similarly to the balance sheet measure, aggregate vulnerability of the broker-dealer sector correlates well with market leverage, SysRisk and the TED spread. In addition, it is correlated with realized volatility and the MES measure of Acharya et al. (2012). Interestingly, however, it does not correlate well to the market Herfindahl, showing that the two measures convey somewhat different information. Broker-dealer AV Granger-causes seven measures at the 99 percent confidence level: MES (SRISK), SysRisk, book leverage, default spread, market leverage and turbulence, but is Granger caused by only two measures, default spread and TED spread. Correlations and Granger causality tests for this case should be interpreted with caution, though, since they are computed using a small number of observations.

6 Conclusion

Using a simple model and detailed balance sheet data for U.S. bank holding companies (BHCs) and broker-dealers, we find that spillover losses from fire-sales have the potential to be economically large. This is true even for moderate shocks during "normal" times, when markets are relatively deep. For example, if the value of assets for one of the largest five BHCs declined by 1 percent in 2013-Q1, we estimate spillover losses equivalent to 21 percent of total equity capital held in the commercial banking sector. For broker-dealers, a 1 percent decline in the price of all assets financed in the tri-party repo market would lead to spillovers amounting to almost 60 percent of system equity capital for the same time period. While these numbers are sizable, they are between one half and one fourth of the spillovers we find during various scenarios of market stress, when illiquidity is more severe.

One direct implication is that fire-sale externalities are a key component of overall systemic risk for the financial system. While they are mostly caused by large firms, we show that high leverage and the "illiquidity linkage" of firms also contribute to fire-sale spillovers. We also identify the particular assets that serve as the main transmission mechanism for fire-sales. For BHCs, real estate loans pose the highest threat, while for broker-dealers Treasuries and agency MBS are the most systemic assets. Our hope is that having identified the main causes, institutions and asset classes that contribute to fire-sale externalities is informative for policymakers seeking to tackle systemic risk. In addition, our framework allows policymakers to straightforwardly consider counterfactual exercises to understand what would happen if certain shocks materialized or if certain policies were enacted. While for BHCs our estimates are only available quarterly, our tri-party repo data is available daily and in real time, providing valuable information for regulators monitoring market risk.

There are several limitations in our study. First, there are few empirical estimates of the price impact of selling assets, especially when thinking about how the liquidation of one asset class affects the price of a related yet different class of assets. We have dealt with this limitation by considering several distinct scenarios and using repo haircuts as proxies for liquidity. However, more direct estimates would be desirable and would lend higher confidence to our results. Second, we have assumed a mechanical rule for liquidating assets in response to adverse shocks: positions are liquidated proportionally to their initial holdings. It is not clear whether this is a good approximation of reality. Banks and broker-dealers may prefer to sell the most liquid assets first in order to minimize their direct losses. Alternatively, if they anticipate that illiquid assets may become even more illiquid in the near future, they may decide to get rid of those assets first. In brief, the model has no optimizing behavior and the liquidation rule is not contingent on economic conditions. Third, we have looked only at the asset side of the balance sheet, and assumed liabilities adjust accordingly and automatically. The interplay between assets and liabilities within and across banks, and what liabilities are more "runnable", may be important drivers of fire-sale spillovers. Fourth, we have assumed that firms return to target leverage solely by selling assets and not by raising capital. This is a minor limitation, since including capital injections is very easy in our framework; we have left this option out to make the mechanism as transparent as possible. If firms have access to capital outside of the system and are willing to dilute existing shareholders, then fire-sale externalities can be mitigated. On the other hand, the feasibility and willingness of firms to raise private capital during episodes of severe market distress may be limited, as was the experience during the last crisis.

A promising avenue for future research is to empirically estimate multi-round liquidity spirals. In the model, there is a single round of fire-sales, and our assumptions may still hold for second-round liquidations but most likely start to fail when additional rounds are considered. But second and third round losses should be expected, which calls for a non-linear relation between the size of liquidations and their price impact. Another helpful complement to our study would be to estimate the probability of shocks that kick-start the fire-sales. We only consider externalities that occur conditional on the shock having materialized, but policymakers and economic agents may want to weight outcomes by the likelihood with which they happen.

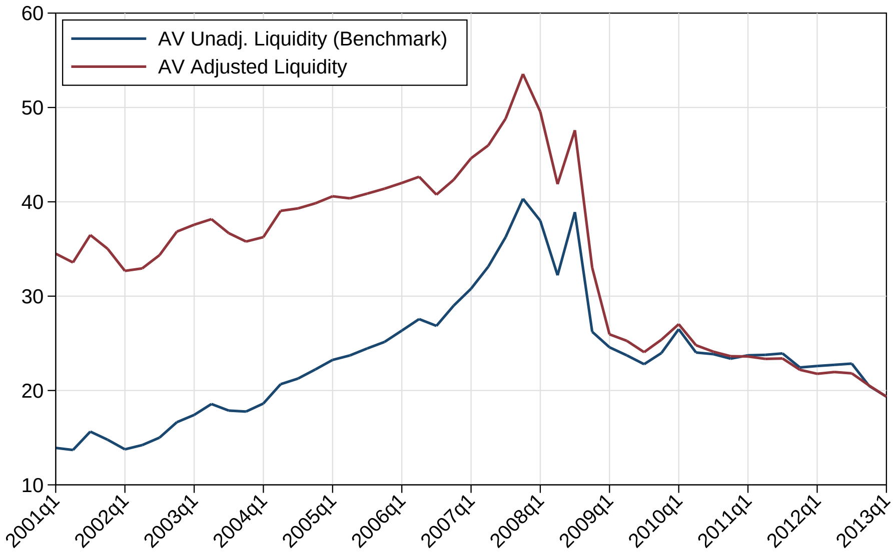

Figure 22: Aggregate vulnerability when liquidity is not time-varying (benchmark) versus liquidity that increases one-for-one with market size (BHCs).

Appendix

A More alternative scenarios and robustness

Liquidity adjusted by size of markets. As is standard in the literature (e.g. see Amihud, 2002), we have expressed liquidity in units of basis points of price impact per dollar amount sold. However, as noted in Acharya and Pedersen (2005), a constant liquidity expressed in those units can be inappropriate for long time series.[31] It is reasonable to assume, for example, that selling \$1 billion in a \$100 billion market creates a larger proportional price impact than selling \$1 billion in a \$500 billion market. If this is the case, because the size of markets has been increasing over time, we must adjust the liquidity matrix L. Figure 22 shows aggregate vulnerability when we make L time-varying by scaling it by the growth rate of assets g_t, i.e. we use $L_t = (g_t/g_0)L$.

Eleven asset classes. For Figure 23, we collapse "other domestic debt securities" and "foreign debt securities" into a single category called "debt securities." We also collapse all loan categories into a single one. This new specification can not be achieved simply by

[31]See also Comerton-Forde, Hendershott, Jones, Moulton, and Seasholes (2010); Hameed, Kang, and Viswanathan (2010).

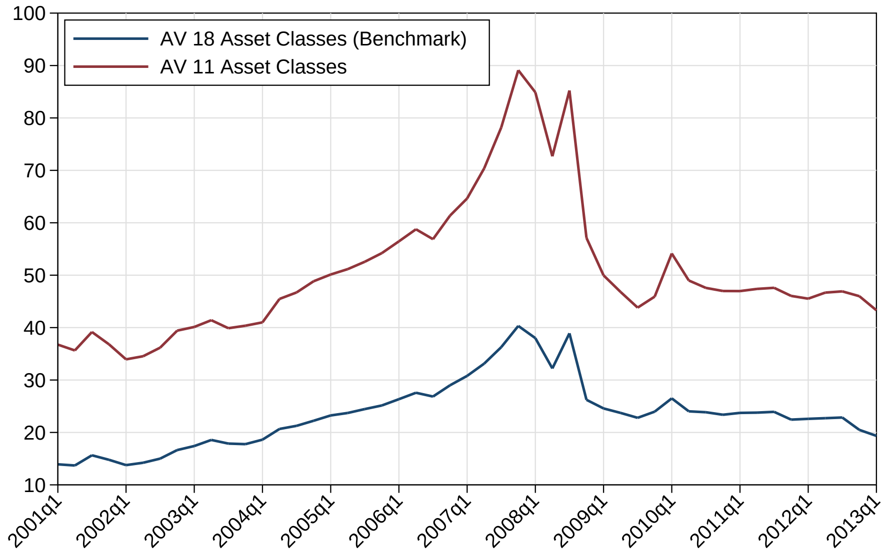

Figure 23: Aggregate vulnerability using eighteen asset classes (benchmark) versus collapsing them to eleven (BHCs).

changing the liquidity matrix L or the portfolio weights matrix M.

Top 500 banks. 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 more capital relative to the additional fire-sale spillovers that they create. Figure 24 shows that this is not the case. Aggregate vulnerability shifts up almost in parallel by 1 percentage point, confirming the message of Figure 4 that large banks are the principal culprit of fire-sale externalities.

Keep foreign banks. 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 25 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

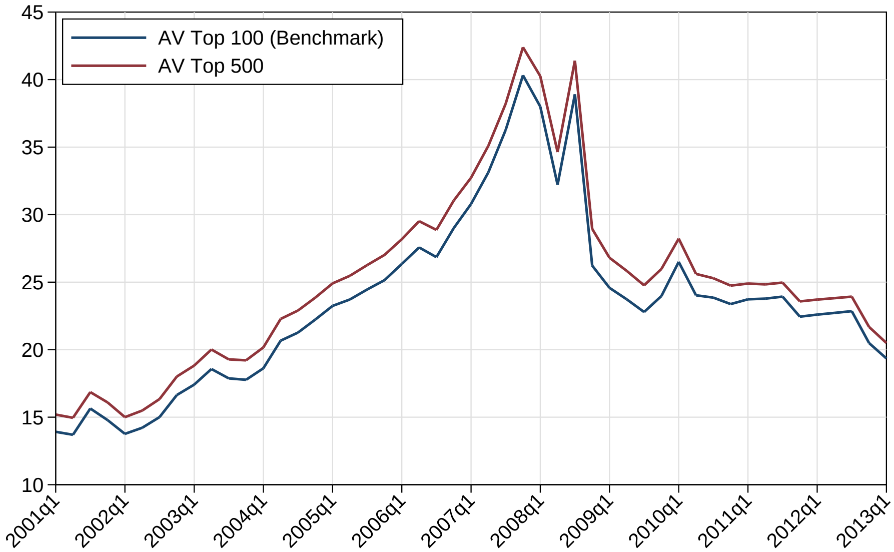

Figure 24: Aggregate vulnerability using the largest 100 banks (benchmark) versus using the largest 500 banks (BHCs).

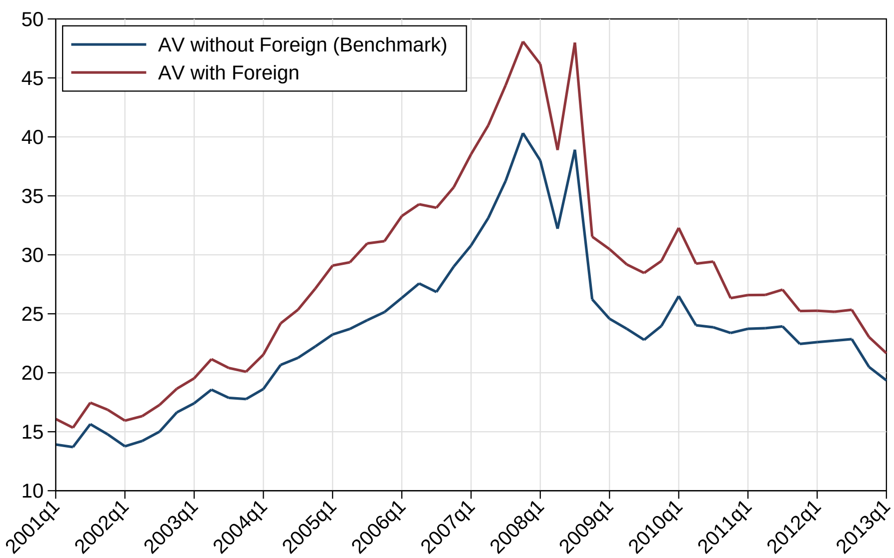

Figure 25: Aggregate vulnerability excluding foreign banks (benchmark) versus including them (BHCs).

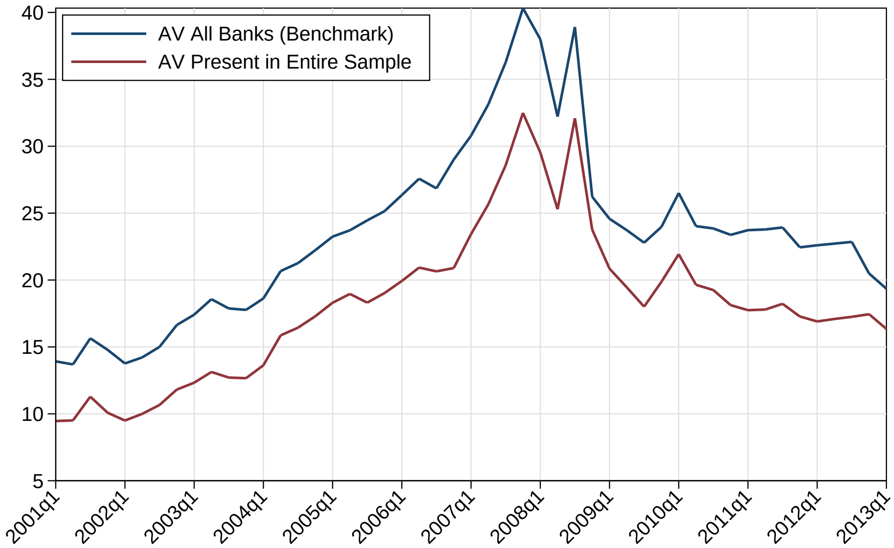

Figure 26: Aggregate vulnerability using the top 100 banks (benchmark) versus using the top 100 banks that have data for every quarter (BHCs).

contributor is Taunus Corporation, the U.S. bank holding company of Deutsche Bank.

Keep firms with data for the entire sample. Many firms either appear, disappear or re-appear in different periods of our sample. This behavior is due to mergers, acquisitions, bankruptcies and the conversion of non-bank financial institutions into bank holding companies and vice versa. Notable examples are mentioned in Section 3.1. To study how results are affected by some of these changes, Figure 26 displays our fire-sale spillover measure when we only keep firms that have been present throughout the entire sample. As expected, 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 by about 5 percentage points.

B Systemic risk measures

Table 7: Systemic risk measures used in Section 5.

Measures	Sources
Absorption, ΔAbsorption	Kritzman et al. (2011)
Amihud Illiq.	Amihud (2002)
CoVaR, ΔCoVaR	Adrian and Brunnermeier (2011)
MES (APPR), SysRisk	Acharya et al. (2012)
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 7 lists the sources for the various systemic risk measures we use. See Giglio et al. (2013) for details.

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