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Abstract

We identify and track over time the factors that make the financial system vulnerable to fire sales by constructing an index of aggregate vulnerability. The index starts increasing quickly in 2004, before most other major systemic risk measures, and triples by 2008. The fire-sale-specific factors of delevering speed and concentration of illiquid assets account for the majority of this increase. Individual banks' contributions to aggregate vulnerability predict other firm-specific measures of systemic risk, including SRISK and DCoVaR. The balance sheet-based measures we propose are therefore a useful early indicator of when and where vulnerabilities are building up.

Key words: systemic risk, fire-sale externalities, leverage, linkage, concentration, bank holding company

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1 Introduction

Fire-sale spillovers have long been recognized as a potentially important source of contagion in financial markets and therefore are a systemic risk concern.[1] The mechanisms, systemic implications, and welfare costs of fire sales have been abundantly studied in the theoretical literature.[2] In contrast, the empirical literature is understandably thinner, as it is difficult to conclusively identify fire sales. A few notable papers have documented the existence and severity of fire-sale spillovers for particular episodes or particular asset classes by exploiting one-time changes in the environment or specific institutional peculiarities that allow for credible identification strategies.[3] From an aggregate welfare perspective, however, we are ostensibly more concerned with fire sales that affect a large portion of the financial sector and many different markets simultaneously, especially in states of high marginal utilities — crises being the paradigmatic example. Clean identification in such turbulent times is quixotic at best. Even if possible, it would be too late to do much about them in terms of welfare, save for costly liquidity provision or other kinds of interventions.

A more promising complementary goal is to understand the ex-ante *vulnerability* of the financial system to fire sales, especially to those with aggregate consequences. In addition to circumventing the issue of identification, if detection of vulnerability can be done far enough in advance, then it may be possible for the affected parties and policymakers to intervene before the fire sales materialize. Detecting ex-ante vulnerabilities comes with its own set of challenges. What are the factors that make the financial system vulnerable to fire sales? Can we track them over time? Is it possible to predict not only when vulnerabilities develop, but where in the financial sector they lurk?

In this paper, we address these questions by constructing an index of aggregate vulnerability to fire sales of large bank holding companies. The index decomposes additively into each bank's "systemicness" (its contribution to a fire sale) as well as multiplicatively into aggregate and cross-sectional factors that drive fire-sale vulnerability. We find that the aggregate vulnerability index (AV, for short) starts increasing slowly in 2000 and ac-

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

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

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

celerates in 2004, before many other major systemic risk measures. It then rises steadily, more than doubles by the end of 2006 and peaks at three times its initial level in 2008. After the crisis, AV decreases equally dramatically, before stabilizing in 2015 at roughly 40 percent of its initial level in 1999.

We highlight the fire-sale specific factors of delevering speed and concentration of illiquid assets which jointly account for 60 percent of the growth of AV and 50 percent of its variance between the beginning of our sample in 1999 and the third quarter of 2008, when AV peaks. Using dynamic panel regressions and real-time data to minimize look-ahead bias, we show that individual banks' "systemicness" is an excellent five-year-ahead predictors of five prominent and widely used measures of firm-specific systemic risk (SRISK, ΔCoVaR, MES, SES and Systemic CCA). For example, even after controlling for contemporaneous SRISK and several bank characteristics, an increase in systemicness of 1 percent is associated with an increase in SRISK of 3.24 percent five years later at the 1 percent level of statistical significance. In addition, the exposure of each bank to fire-sale spillovers — which we call "vulnerability" — predicts actual capital shortfalls during the financial crisis as early as the last quarter of 2004. A 1 percent increase in bank vulnerability in the last quarter of 2004 is associated with a 16.5 percent increase in TARP injections. Had they been available at the time, our measures would therefore have been useful early indicators of when and where vulnerabilities were building up.

Our analysis extends the cross-sectional "vulnerable banks" framework of Greenwood, Landier, and Thesmar (2015), adapting it to a panel analysis to track and dissect vulnerabilities over time as well as across banks. The framework takes as given banks' leverage, asset holdings, asset liquidation behavior, and price impact of liquidating assets. It then considers a hypothetical large negative shock that leads to an increase in leverage. Banks respond by selling assets and paying off debt to at least partially 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 bank that happens to hold assets similar to those that were fire-sold, even if not initially shocked, will see the value of these asset holdings decline, a fire-sale spillover. The AV index is the sum of all of these spillover losses — as opposed to the initial direct losses — as a share of the total equity capital in the system.

We offer two methodological contributions relative to the framework of Greenwood et al. (2015) that are instrumental in deriving and interpreting our empirical results. First, we separate the role of aggregate versus cross-sectional drivers of fire-sale vulnerability by decomposing AV into aggregate factors and a cross-sectional measure we call "illiquidity concentration." While it is well known that size and leverage — two of the aggregate factors — are relevant to systemic risk for various reasons, illiquidity concentration is a factor that is specific to *fire-sale spillovers*. Its magnitude, and therefore the vulnerability of the system to fire sales, depends on the cross-sectional distribution of illiquid assets across banks of different size, leverage and propensity to delever.[4]

Second, in Greenwood et al. (2015), a bank's pre-shock leverage is assumed to be its post-shock target leverage, and the bank is assumed to fully and immediately adjust back to its target leverage following a shock. This is a strong assumption for a dynamic application with as long a sample period as ours and would (i) implicitly interpret observed variation over time in a bank's leverage as variation in the bank's leverage target and (ii) rule out variation over time in a bank's speed of adjustment toward target following a shock. We generalize this part of the framework and assume that, in response to shocks, a bank partially adjusts leverage toward a latent target, with time variation both in the target and in the adjustment speed. Importantly, we are able to seamlessly integrate the partial adjustment behavior of banks into the AV framework of Greenwood et al. (2015), providing a new dynamic factor in the decomposition: the adjustment speed to target leverage. Spillover losses and therefore vulnerability to fire sales are increasing in the adjustment speed.

We apply the AV framework to a quarterly panel of U.S. bank holding companies (BHCs) from 1999 to 2016. We focus on BHCs for several reasons: they are a large fraction of the entire U.S. financial sector, including not only commercial banks but also large broker-dealers and other financial institutions;[5] they are a good window into the broader shadow banking system (Cetorelli et al., 2012; Adrian et al., 2015); detailed regulatory data on their balance sheets is publicly available; they were forced to fire-sell assets in the face of deteriorating equity capital during the financial crisis (Bernanke, 2009); and they were the focus of government interventions. Of course, there are other parts of the finan-

[4]That different measures of "portfolio overlap" or "interconnectedness" are important for fire sales has been widely recognized in the literature (Falato, Hortaçsu, Li, and Shin, 2016; Acharya, Shin, and Yorulmazer, 2009; Acharya, Pedersen, Philippon, and Richardson, 2009; Allen and Carletti, 2008; Bernanke, 2009; Cont and Schaanning, 2017; Greenwood, Landier, and Thesmar, 2015).

[5]Throughout the paper we also refer to BHCs as "banks" for simplicity.

cial sector beyond the scope of our analysis that can generate large spillovers, either by themselves or when their linkages with banks are considered. For example, Falato et al. (2016) study the potential for systemic consequences of fire sales among mutual funds.

Looking at the drivers of overall vulnerability, we find that each of the four AV factors contributes differently to the total and that the relative contribution of the factors change over time. Size and leverage — known factors of systemic risk — show the expected trends, increasing in the pre-crisis period and decreasing towards the end of the sample. The two factors that we identify as specific to fire-sale spillovers — leverage adjustment speed and illiquidity concentration — also play important roles in the evolution of AV and in the cross-section of bank systemicness.

Leverage adjustment speed is roughly constant until 2006, before increasing by over 50 percent and causing AV to spike in late 2008. This is notable since, in our estimation, we control for any adjustments via equity issuance. The increase in estimated adjustment speed during the crisis therefore captures greater delevering through balance sheet contraction, consistent with fire sales. At the bank level, adjustment speed is positively related to the level of leverage which adds an interesting asymmetry to the cyclicality of leverage (Adrian and Shin, 2010), since it implies faster delevering from high leverage than vice versa.

Illiquidity concentration, the measure capturing vulnerabilities stemming from the cross-sectional distribution of assets and their liquidities across banks with different size, leverage, and adjustment speed, has a positive trend starting in late 2002 and increases by roughly 25 percent until early 2007. We confirm the importance of illiquidity concentration with two further exercises. First, we do a variance decomposition of AV into the contributions of the variances (and covariances) of the constituent factors; illiquidity concentration, after size, is the second greatest contributor to variation in AV pre-crisis and it is the most stable factor in terms of its contribution across the pre-crisis, crisis, and post-crisis subsamples. Second, we compare actual AV to a hypothetical AV for a counterfactual banking system that has the same aggregate portfolio and leverage, but is composed of homogeneous banks. Over the majority of our sample, AV is over 20 percent higher due to the heterogeneity of banks in the data.

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 bank. In contrast, the predominant strategy in the literature relies on market prices or macroeconomic aggregates to build top-down indicators. The more than 30 measures considered in the survey by Bisias, Flood, Lo, and Valavanis (2012) all use market prices or macroeconomic aggregates as key inputs. The three measures that also use balance sheet information rely only on book equity, total assets, and total liabilities; none use holdings disaggregated by asset class as we do. Although there are many advantages to using market prices, one important disadvantage is that volatilities and risk premia are usually compressed 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 and a consistent buildup at least five years ahead of the crisis. We replicate 35 systemic risk measures from Bisias et al. (2012) and Giglio, Kelly, and Pruitt (2016) and show that only four of them are able to capture the slow and steady buildup of risk that accrued before the crisis, highlighting the usefulness of adding AV to the suite of existing measures. Out of these four measures, three are constructed using different data and methodologies than AV yet are closely related to AV, which we interpret as additional evidence that the mechanism through which systemic risk increased before the crisis is related to the fire-sale channel we consider. Of course, one must be careful when extrapolating past predictability results into the future and take into account the various sources of uncertainty not explicitly modeled or estimated.

Finally, our measure is — and already has been — 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 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.[6] An earlier version of our measure was used in the designation of AIG, Metlife, and other companies as systemically important by the Financial Stability Oversight Council (FSOC), and in the evaluation and dismissal of Fidelity and other asset

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

managers' cases.[7] It has also been adapted to other countries and markets.[8]

Bank stress testing has become another standard regulatory 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. Our analysis can be interpreted as a stylized macro-prudential stress test in which the regulator provides a scenario (the initial exogenous shocks to assets) and the framework computes spillover losses for the system as a whole. Even though the framework is equally easy to implement for any combination of shocks (any scenario), we calculate the time series of AV by applying the same shock every quarter, allowing us to understand in a consistent way if changes in the system from one quarter to the next have affected the vulnerability of the system to fire sales.

Last, our framework can easily produce counterfactuals to evaluate past policies or proposals for future reform. For example, we evaluate how vulnerable the system would have been without the Troubled Asset Relief Program (TARP) and without the post-crisis tightening in capital and liquidity regulation.

The rest of the paper is structured as follows. In Section 2, we present the framework used to calculate fire-sale spillovers. In Section 3, we describe the estimation of leverage targets and adjustment speeds. In Section 4, we present and discuss the results on fire-sale spillovers. In Section 5, we show robustness of our results with respect to a number of assumptions. In Section 6, we document the predictive power of the measures.

2 Framework

To calculate potential spillovers from fire sales, we build on the "vulnerable banks" framework of Greenwood et al. (2015). The framework assumes a simple fire-sale scenario where, after an exogenous shock to assets, banks suffer losses and sell assets to delever. Aggregate fire sales have a price impact, causing the fire-sale spillovers that are the focus of the analysis.

[7] United States Department of the Treasury (2012); Financial Stability Oversight Council (2015); Financial Stability Board (2016); U.S. House of Representatives (2016).

[8] Levy-Carciente et al. (2015); Zhou et al. (2016); Fricke and Fricke (2017); McKeown et al. (2017); Ellul et al. (2018).

Banks are indexed by $i = 1, \ldots, N$ and assets (or asset classes) are indexed by $k = 1, \ldots, K$. In period t, bank i has total assets a_{it} with portfolio weight m_{ikt} on asset k such that $\sum_k m_{ikt} = 1$. On the liabilities side, bank i has debt d_{it} and equity capital e_{it}, resulting in leverage $b_{it} = d_{it}/e_{it}$. We let $a_t = \sum_i a_{it}$ denote the total assets of the system, $e_t = \sum_i e_{it}$ system equity capital, $d_t = \sum_i d_{it}$ system debt, and $b_t = d_t/e_t$ system leverage. Other than differentiating between debt and equity, we are making no further assumptions on banks' liabilities.

2.1 Partial adjustment to target leverage

Greenwood et al. (2015) assume that following a shock s, banks actively adjust leverage to return to their initial (pre-shock) leverage b_{it}. This is a strong assumption, however, especially for a dynamic empirical application with a long sample period like ours: (i) it requires all observed variation in a bank's leverage to be interpreted as variation in the bank's leverage target and (ii) it rules out variation in the adjustment speed over time. We therefore generalize this part of the framework and, motivated by the evidence of Adrian and Shin (2010, 2011), assume that banks' leverage evolves according to the partial adjustment model

$$b_{it+1} = \lambda_{it} b_{it}^{*} + (1 - \lambda_{it})\, b_{it+1}^{p}, \tag{1}$$

where the new level of leverage b_{it+1} is a convex combination of a passive leverage b_{it+1}^{p} and a leverage target b_{it}^{*} with λ_{it} representing the adjustment speed towards the target. For $\lambda_{it} = 1$, the bank fully adjusts to its target in one period, while for $\lambda_{it} = 0$, the bank does not adjust towards its target at all. Passive leverage is defined by

$$b_{it+1}^{p} = \frac{d_{it}}{e_{it} + \Delta e_{it+1}^{s} + \Delta e_{it+1}^{\text{iss}}}, \tag{2}$$

where Δe_{it+1}^{s} is the change in equity due to the shock s and $\Delta e_{it+1}^{\text{iss}}$ is the change in equity due to issuance or dividends. Passive leverage is the leverage that the bank would have if it did not sell any assets. We estimate adjustment speeds λ_{it} and leverage targets b_{it}^{*} for each bank in Section 3. We show how alternative assumptions about leverage adjustment affect the calculation of fire-sale spillovers in Section 5.1.

2.2 Fire-sale spillovers

To quantify vulnerability to fire-sale spillovers, we postulate a hypothetical scenario and trace how banks respond to the scenario using the partial adjustment model. The fire-sale scenario is defined by a vector of given shocks $(f_{1t}, \ldots, f_{Kt})^\top > 0$ across asset classes that hits all banks at the end of period t. The shock f leads to direct losses for bank i, changing its equity by $\Delta e^f_{it+1} = -a_{it}\sum_k m_{ikt} f_{kt} < 0$ and increasing its leverage. We assume that all assets are marked-to-market. We show in Section 5.2 that not marking to market assets that are usually not marked-to-market in practice (such as loans) does not significantly affect our results. During the episodes of systemic risk that we are interested in, which are usually accompanied by distress in capital markets and weak macroeconomic conditions, equity issuance is expected to be limited, difficult, or undesirable for economic, signaling, or other reasons (e.g. Shleifer and Vishny, 1992). We therefore assume $\Delta e^{\text{iss}}_{it+1} = 0$ in our hypothetical fire-sale scenario.

Substituting the expression for Δe^f_{it+1} and $\Delta e^{\text{iss}}_{it+1} = 0$ into equation (2), passive leverage in our scenario is given by

$$b^p_{it+1} = \frac{d_{it}}{e_{it} - a_{it}\sum_k m_{ikt} f_{kt}}. \tag{3}$$

Without equity issuance, leverage can only be reduced by paying down debt so leverage after adjustment is given by

$$b_{it+1} = \frac{d_{it+1}}{e_{it+1}} = \frac{d_{it} + \Delta d_{it+1}}{e_{it} - a_{it}\sum_k m_{ikt} f_{kt}}, \tag{4}$$

with $\Delta d_{it+1} < 0$ determined by the partial adjustment equation (1). Substituting passive leverage (3) and actual leverage (4) into the partial adjustment equation, we can solve for the total amount of cash needed to pay down debt and achieve the desired level of leverage:

$$-\Delta d_{it+1} = \underbrace{\lambda_{it} b^*_{it} a_{it}\sum_k m_{ikt} f_{kt}}_{x^f_{it}} + \underbrace{\lambda_{it}\,\frac{b_{it} - b^*_{it}}{b_{it} + 1}\,a_{it}}_{x^b_{it}}.$$

This expression is made up of two parts. The first part, x^f_{it}, is the adjustment we are interested in, i.e. in response to the shocks f_{kt}. The second part, x^b_{it}, is a baseline adjustment towards target that occurs even in the absence of any shocks f_{kt} and therefore does not depend on our scenario. If leverage is above target, $b_{it} > b^*_{it}$, there are baseline asset sales, $x^b_{it} > 0$, and vice versa for purchases. Empirically, x^b_{it} is much smaller than x^f_{it} and, economically, it is unrelated to fire sales following a shock, so we set it to zero in our fire-sale scenario. For our calculation of fire-sale spillovers, we focus on the asset sales necessary to raise an amount of cash x^f_{it}.

The cash x^f_{it} must be raised by selling some combination of the different types of assets held by the bank. We denote by $\widetilde{m}_{ikt}$ the amount of each asset that the bank sells as a share of total sales, i.e. $x^f_{ikt} = \widetilde{m}_{ikt} x^f_{it}$. We assume for our benchmark that banks sell in proportion to their existing portfolio weights, $\widetilde{m}_{ikt} = m_{ikt}$ (as in Greenwood et al., 2015), to be agnostic about the relative importance of several opposing forces that could lead to more sales of relatively liquid or illiquid assets.[9] We discuss these forces in Section 5.3 together with several alternatives for the liquidation strategy $\widetilde{m}_{ikt}$ and how they affect the results. Summing the sales of asset k across banks implies that aggregate sales of asset k are given by

$$y_{kt} = \textstyle\sum_i \widetilde{m}_{ikt} x^f_{it} = \sum_i m_{ikt} \lambda_{it} b^*_{it} a_{it} \sum_{k'} m_{ik't} f_{k't}. \tag{5}$$

Next, we assume that the asset sales have a price impact that is linear in the volume sold. This is the predominant assumption in the empirical literature and seems to fit the patterns of the data well.[10] In addition, we assume there are no cross-asset price impacts, e.g. selling agency MBS has no direct impact on the price of corporate bonds. The asset classes we construct in our empirical implementation are sufficiently different to have the first-order effects be consistent with no cross-asset price impacts. The price impact of asset k is assumed proportional to its illiquidity ℓ_k and inversely proportional to the wealth w_t of potential buyers of fire-sold assets (motivated by Shleifer and Vishny, 1992). Aggregate

[9] For sufficiently large shocks, some banks may be selling all of their assets. We take this into account in our empirical implementation by using $x^f_{it} = \min\left\{a_{it}, \lambda_{it} b^*_{it} a_{it} \sum_k m_{ikt} f_{kt}\right\}$.

[10] Almost all empirical papers that identify fire sales cited in footnote 3 have linear pricing. In the theoretical literature, the first-round price impact is almost always proportional to the amount sold, sometimes with multipliers arising only in subsequent liquidation rounds (Kyle, 1985; Glosten and Harris, 1988; Bertsimas and Lo, 1998; Obizhaeva and Wang, 2013). Quadratic and non-linear costs have also been used and estimated (Heaton and Lucas, 1996; Hasbrouck and Seppi, 2001; Almgren, 2003; Gârleanu and Pedersen, 2013; Kyle and Obizhaeva, 2016). On the other hand, over many days — which is the relevant horizon for our study — the non-linearities tend to smooth out and make price impacts much closer to linear (Bouchaud, 2010).

sales of y_{kt} dollars of asset k therefore have price impact $\left(\ell_k/w_t\right) y_{kt}$. Combining with the expression for aggregate sales in (5), the fire-sale price impact for asset k is given by

$$\widehat{f}_{kt} = \frac{\ell_k}{w_t} \textstyle\sum_i m_{ikt} \lambda_{it} b^*_{it} a_{it} \sum_{k'} m_{ik't} f_{k't}. \tag{6}$$

Finally, the price impact of the fire-sales cause spillover losses to all banks holding the assets that were fire-sold, which we can calculate analogously to the very first step above as $a_{it} \sum_k m_{ikt} \widehat{f}_{kt}$. Summing spillovers over all banks, we arrive at the total spillover losses $\mathcal{L}_t$ suffered by the banking system as a whole. Written in matrix form, we have

$$\begin{aligned} \mathcal{L}_t &= \textstyle\sum_{i'} a_{i't} \sum_k m_{i'kt} \frac{\ell_k}{w_t} \sum_i m_{ikt} \lambda_{it} b^*_{it} a_{it} \sum_{k'} m_{ik't} f_{k't} \\ &= \frac{1}{w_t} 1^\top A_t M_t L M_t^\top \Lambda_t B^*_t A_t M_t F_t, \end{aligned} \tag{7}$$

where $1^\top$ is a row vector of ones, $F_t = (f_{1t}, \ldots, f_{Kt})^\top$ is the vector of shocks, M_t the $N \times K$ matrix of portfolio weights, A_t, B^*_t and Λ_t are $N \times N$ diagonal matrices of, respectively, total assets, leverage targets and adjustment speeds, and L is a $K \times K$ diagonal matrix of price impacts. It is important to note that $\mathcal{L}_t$ captures only the *indirect* losses due to spillovers. It therefore does not include the *direct* losses due to the initial shock, given by $\sum_i a_{it} \sum_{k'} m_{ik't} f_{k't}$. This makes our analysis different but complementary to the typical microprudential stress-test analysis that focuses on the direct losses for a given shock.

In principle, we could restart the delevering sequence in response to the "endogenous shocks" $\widehat{f}_{kt}$ in equation (6). The process could then be repeated, potentially until convergence. In Section 5.4, we verify that our main results are virtually unchanged in this kind of multi-round liquidation setup.

We want to distinguish between the effects stemming from aggregate characteristics of the banking system and effects that arise due to the distribution of characteristics across banks. To do so, we denote by $\alpha_{it} = a_{it}/a_t$ bank i's assets as a share of system assets, by $\beta^*_{it} = b^*_{it}/\overline{b}^*_t$ bank i's leverage target relative to the average leverage target $\overline{b}^*_t = \frac{1}{N}\sum_i b^*_{it}$ and by $\widetilde{\lambda}_{it} = \lambda_{it}/\overline{\lambda}_t$ bank i's adjustment speed relative to the average adjustment speed $\overline{\lambda}_t = \frac{1}{N}\sum_i \lambda_{it}$. For the portfolio weights, we denote by $m_{kt} = \sum_i m_{ikt} a_{it}/a_t$ the system portfolio weight for asset k and by $\mu_{ikt} = m_{ikt}/m_{kt}$ bank i's portfolio weight for asset k

relative to the system portfolio weight. The expression for total spillover losses $\mathcal{L}_t$ in (7) can then be rearranged as

$$\mathcal{L}_t = \frac{a_t^2 \overline{b}_t^* \overline{\lambda}_t}{w_t} \sum_k \left[m_{kt}^2 \ell_k \sum_i \left(\mu_{ikt} \widetilde{\lambda}_{it} \beta_{it}^* \alpha_{it} \sum_{k'} m_{ik't} f_{k't} \right) \right].$$

Price impacts ℓ_k are notoriously hard to estimate and differ across the limited number of available studies by orders of magnitude.[11] We therefore normalize $\mathcal{L}_t$ to 100 at the beginning of our sample period and treat it as an index, focusing on its changes over time rather than its level. Further, we choose the same shock across all assets, $f_{kt} = f_t$ for all k, to calculate an overall vulnerability of the system to spillovers while being agnostic about where a particular fire-sale episode may originate. In this case $\sum_k m_{ikt} f_t = f_t$ so the exogenous shock f_t affects $\mathcal{L}_t$ linearly. Since we are interested in studying changes in vulnerability over time, we need the shock to be constant, $f_t = f$ for all t to make estimates directly comparable across time periods. Because we normalize $\mathcal{L}_t$ to 100 at the beginning of our sample period, the actual magnitude of f has no effect on the evolution of the index so we drop it from the expressions below.

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

Aggregate vulnerability: The fraction of system equity capital lost due to spillovers, $\mathcal{L}_t / e_t$, captures the "aggregate vulnerability" (AV) of the system to fire-sale spillovers. This is the main measure of systemic risk that we propose. It can be decomposed into four factors:

$$\mathrm{AV}_t = \underbrace{\frac{a_t}{w_t}}_{\text{rel. size}} \times \underbrace{(b_t + 1)\, \overline{b}_t^*}_{\text{leverage}} \times \underbrace{\overline{\lambda}_t}_{\text{adj. speed}} \times \underbrace{\sum_k \left[m_{kt}^2 \ell_k \sum_i \left(\mu_{ikt} \widetilde{\lambda}_{it} \beta_{it}^* \alpha_{it} \right) \right]}_{\text{illiquidity concentration}}. \tag{8}$$

[11] 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 much larger than those for corporate bonds. To the best of our knowledge, there exist no empirical estimates of price impact for bank fire sales or for bank loans, which constitute a large proportion of their balance sheet.

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, then aggregate liquidity is lower and fire sales are more severe. The second factor combines two measures of leverage: aggregate leverage $b_t + 1 = \sum_i a_{it} / \sum_i e_{it}$ since spillover losses *relative to system equity* are increasing in system leverage; and the average leverage target $\overline{b}_t^* = \frac{1}{N} \sum_i b_{it}^*$ which captures how asset sales are increasing in the average leverage target. The third factor is the average leverage adjustment speed since spillovers are larger if banks, on average, adjust more quickly towards target leverage.

The fourth factor, "illiquidity concentration," captures how the cross-sectional distribution of assets, size, and leverage adjustment across heterogeneous banks affects fire-sale vulnerability. Illiquidity concentration is high if assets with a high aggregate share are illiquid and are held by banks that, relative to the average bank, are large, have a high leverage target and adjust their leverage quickly. If all banks were the same, equal to a representative bank with $\alpha_{it} = 1/N$ and $\beta_{it}^* = \widetilde{\lambda}_{it} = \mu_{it} = 1$ for all i and k, then illiquidity concentration collapses to a liquidity-weighted Herfindahl–Hirschman index on portfolio shares $\sum_k \ell_k m_{kt}^2$. In Section 4.3, we find that heterogeneity across banks increases AV by roughly 20 percent over most of our sample.

Systemicness of bank i: We define the systemicness of bank i as the contribution to AV of bank i, obtained by dropping the summation over i in expression (8). It also equals the aggregate vulnerability resulting from a shock exclusively to bank i. Highlighting the terms that are specific to bank i we have:

$$\mathrm{SB}_{it} = \underbrace{\frac{a_t}{w_t}(b_t+1)\,\overline{b}_t^*\overline{\lambda}_t}_{\text{aggregate factor}} \times \underbrace{\alpha_{it}}_{\text{size}} \times \underbrace{\widetilde{\lambda}_{it}}_{\text{adj. spd.}} \times \underbrace{\beta_{it}^*}_{\text{lev. tar.}} \times \underbrace{\textstyle\sum_k \left[m_{kt}^2 \ell_k \mu_{ikt}\right]}_{\text{illiquidity linkage}}. \tag{9}$$

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_{it}, (ii) adjusts quickly with high $\widetilde{\lambda}_{it}$, (iii) has a high leverage target β_{it}^*, and (iv) has high "illiquidity linkage" by holding large and illiquid asset classes.

Systemicness of asset k: Similar to the measure for individual banks, we define the systemicness of asset k as the contribution of asset k to AV, equivalently obtained either by dropping the summation over k in expression (8), or as the aggregate vulnerability for a shock exclusively to asset k (with $f_{k't} = 0$ for $k' \neq k$). Highlighting the terms that are specific to asset k we have:

$$\mathrm{SA}_{kt} = \underbrace{\frac{a_t}{w_t}\left(b_t + 1\right)\overline{b}_t^* \overline{\lambda}_t}_{\text{aggregate factor}} \times \underbrace{m_{kt}}_{\text{size}} \times \underbrace{\textstyle\sum_{k'} \left[m_{k't}^2 \ell_{k'} \sum_i \left(\mu_{ik't} \widetilde{\lambda}_{it} \beta_{it}^* \alpha_{it} \mu_{ikt}\right)\right]}_{\text{held by systemic banks}}. \tag{10}$$

Similar to SB_{it}, SA_{kt} can be decomposed into an aggregate factor that is constant across assets and asset-specific factors. Asset class k is systemic if it is large in aggregate and if it is held by systemic banks. Although the shock we consider is constant across assets ($f_{kt} = f_t = f$ for all k), the AV for any general scenario with different shock sizes for different asset classes can be easily obtained by taking a linear combination of the systemicness of each asset class SA_{kt}. Therefore, once SA_{kt} is constructed and known, the linearity of the framework implies that our assumption of a constant shock across assets is without loss of generality.

Vulnerability of bank i: Instead of summing the spillover losses across all banks as in equation (7) and taking the ratio to total equity capital, we can consider the spillover losses suffered by an individual bank relative to its individual equity capital. Highlighting the terms that are specific to bank i, this vulnerability of bank i is given by

$$\mathrm{VB}_{it} = \underbrace{\frac{a_t}{w_t}\overline{b}_t^* \overline{\lambda}_t}_{\text{agg. factor}} \times \underbrace{\left(b_{it} + 1\right)}_{\text{leverage}} \times \underbrace{\textstyle\sum_k \left[\mu_{ikt} m_{kt}^2 \ell_k \sum_{i'} \left(\mu_{i'kt} \widetilde{\lambda}_{i't} \beta_{i't}^* \alpha_{i't}\right)\right]}_{\text{holding systemic assets}}. \tag{11}$$

Bank i is more vulnerable if it (i) is more levered, or (ii) holds assets that are large, illiquid, or held by banks that are larger, have a higher leverage target, or adjust leverage more quickly.

Appendix A compares our framework and decompositions with those in Greenwood et al. (2015).

3 Estimation of leverage targets and adjustment speeds

In this section, we estimate bank-specific leverage targets and adjustment speeds as required by our generalization of Greenwood et al. (2015). Since our framework to calculate fire-sale spillovers is highly stylized, we aim to keep the estimation procedure as simple and transparent as possible. We therefore rely heavily on existing literature and opt for a standard empirical implementation of a partial adjustment model (e.g. Flannery and Rangan, 2006; Lemmon et al., 2008) with bank-specific leverage targets and adjustment speeds that can be estimated in two steps (e.g. Öztekin and Flannery, 2012). Further, since the goal of our paper is to track fire-sale vulnerabilities in real time, we aim to minimize look-ahead bias. We therefore estimate leverage targets and adjustment speeds on rolling windows and only use data up to period t when calculating potential fire-sale spillovers in period t. We note that the estimation of leverage targets and adjustment speeds makes use of the partial adjustment framework in Section 2.1 but does not use the hypothetical fire-sale scenario of Section 2.2. The fire-sale scenario is not used until Section 4, where we quantify the spillovers under the scenario using the estimated leverage targets and adjustment speeds.

3.1 Data

We use quarterly 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 banks. The information in the form is publicly available and is generally used by regulators to assess and monitor the condition of banking sector. Banks with total assets over \$150 million before 2006q1, over \$500 million between 2006q1 and 2014q4, and over \$1 billion starting in 2015q1, are required to file.We include in our sample large banks (any bank that is ever in the top 500 by total assets in a quarter) because they have the most complete and uniform data and account for almost all assets (on average, 688 banks per quarter accounting for 98% of system assets). Our measure of equity is tier 1 capital, which becomes available in the data in 1996q1. Our sample therefore runs from 1996q1 to 2016q4. We subtract equity from total assets to obtain our measure of debt. To simplify the analysis, and because cash is not subject to fire sales, we subtract all cash holdings from both assets and debt. We cap leverage at 30 whenever it exceeds this threshold.

3.2 Econometric model

The econometric model corresponding to the partial adjustment model in equation (1) is

$$b_{it+1} = \lambda_{it} b^*_{it} + (1 - \lambda_{it})\, b^p_{it+1} + \varepsilon_{it+1}, \tag{12}$$

$$b^*_{it} = \delta^\top z_{it}, \tag{13}$$

$$\lambda_{it} = \gamma^\top w_{it}. \tag{14}$$

In equation (12), ε_{it+1} is a random error term. Bank i's actual leverage b_{it+1} is obtained at the end of each period directly from the balance sheet data. Passive leverage b^p_{it+1} is constructed according to equation (2) with Δe^s_{it+1} measured by net income (Faulkender et al., 2012) while net issuance $\Delta e^{\text{iss}}_{it+1}$, debt d_{it}, and equity e_{it} are directly obtained from the balance sheet data. We show in Appendix B.1 how treating equity issuance as active adjustment affects our estimates of adjustment speed.[12]

The bank's leverage target for period t and its adjustment speed over period t are modeled in equations (13) and (14), respectively, as functions of explanatory variables. As explanatory variables z_{it} for the leverage target, we use bank-level characteristics commonly used in the empirical literature on capital structure (for banks, see Berger et al. (2008); Gropp and Heider (2010); for non-financial firms, see Titman and Wessels (1988); Rajan and Zingales (1995); Frank and Goyal (2009)). We also include a set of aggregate variables, given their importance in capital structure decisions (Korajczyk and Levy, 2003; Bhamra et al., 2010; Korteweg and Strebulaev, 2015), as well as bank fixed effects (Flannery and Rangan, 2006; Lemmon et al., 2008). As explanatory variables w_{it} for the adjustment speed, we use variables capturing both costs of adjusting leverage as well as regulatory pressures to adjust it (Berger et al., 2008; Öztekin and Flannery, 2012). Tables 1 and 2 provide a list of the explanatory variables for the leverage target and adjustment speed, respectively. The

[12]Since banks cut dividends only very slowly and very late, even in the financial crisis (Hirtle, 2016), we adjust net issuance by lagged average dividends paid over the previous eight quarters. In addition to cash dividends, we include stock repurchases (gross purchases of treasury stocks) which are commonly used by banks instead of cash dividends (Hirtle, 2004). We show in Appendix B.1 that not adjusting for past dividends does not materially affect our results.

Table 1: Explanatory variables for leverage target. The table shows descriptions and summary statistics for the explanatory variables for the leverage target, $b_{it}^{*} = \delta^{\top} z_{it}$, used in the partial adjustment model of leverage, $b_{it+1} = \lambda_{it} b_{it}^{*} + (1 - \lambda_{it})\, b_{it+1}^{p} + \varepsilon_{it+1}$. The sample consists of quarterly data from 1996q1 to 2016q4 and includes any bank that is ever in the top 500 by assets in a given quarter of the sample. In the last two columns, p5 and p95 stand for, respectively, the 5th and 95th percentiles of the distribution. Sources: FR Y-9C, CRSP, Compustat, FRED.

Bank-specific variables		Mean	St. dev.	p5	p95
Regulatory max	Maximum debt/equity implied by the minimum tier-1 capital ratio requirement[a]	32.137	11.629	20.062	44.887
CCAR	Dummy equal to 1 for banks subject to SCAP/CCAR stress tests	0.012	0.107	0	0
Size	Log of real assets (2016q4 dollars)	21.415	1.425	19.864	24.489
Profitability	8-quarter average of return on assets (net income/assets, annualized)[b]	0.009	0.008	-0.003	0.019
Risk	8-quarter standard deviation of return on assets (annualized)[b]	0.004	0.005	0.001	0.017
Loan share	Loans and lease financing receivables, as a share of assets	0.687	0.138	0.437	0.875
Retail deposits	Money-market and savings accounts, and small time deposits, as a share of liabilities	0.567	0.206	0.296	0.795
Public	Dummy equal to 1 for publicly traded banks	0.467	0.499	0	1
Market-to-book	Log market-to-book ratio	7.258	0.576	6.174	8.036
Aggregate variables					
GDP growth	Quarterly real GDP growth (annualized)	0.024	0.025	-0.017	0.065
Term spread	Difference between 10- and 2-year Treasury yields	0.012	0.009	-0.001	0.026
Recession	Dummy equal to 1 for NBER recessions	0.095	0.295	0	1

[a] The tier-1 capital requirement is on the ratio of tier-1 capital (our measure of equity) to risk-weighted assets. We convert it to a maximum requirement on debt over equity as $(\rho_{it}^{e/d})^{-1} = (\rho_t^{e/\mathrm{rwa}}\, \mathrm{rwa}_{it}/d_{it})^{-1}$.

[b] We winsorize the quarterly return on assets at the 1st and 99th percentiles before calculating the 8-quarter average and the 8-quarter standard deviation used as the variables "Profitability" and "Risk".

Table 2: Explanatory variables for adjustment speed. The table shows descriptions and summary statistics for the explanatory variables for the adjustment speed, $\lambda_{it} = \gamma^{\top} w_{it}$, used in the partial adjustment model of leverage, $b_{it+1} = \lambda_{it} b^*_{it} + (1 - \lambda_{it})\, b^p_{it+1} + \varepsilon_{it+1}$. The sample consists of quarterly data from 1996q1 to 2016q4 and includes any bank that is ever in the top 500 by assets in a given quarter of the sample. In the last two columns, p5 and p95 stand for, respectively, the 5th and 95th percentiles of the distribution. Sources: FR Y-9C, CRSP, Compustat, FRED.

Bank-specific variables		Mean	St. dev.	p5	p95
Not well capitalized	Dummy equal to 1 for tier-1 capital ratio below the "well capitalized" threshold (2 percentage points above the minimum requirement)	0.013	0.112	0	0
Well capitalized 0-20pp	Dummy equal to 1 for tier-1 capital ratio 0 to 20 percentage points above the "well capitalized" threshold	0.955	0.208	1	1
Capital buffer	Difference between tier-1 capital ratio and "well capitalized" threshold	0.068	0.073	0.017	0.143
Asset growth	Year-over-year change in assets	0.120	0.254	-0.072	0.435
Rated	Dummy equal to 1 for existing bond rating	0.078	0.269	0	1
Investment grade	Dummy equal to 1 for rated investment grade (BBB– or better)	0.863	0.344	0	1
Stock return	Quarterly average of daily stock return (annualized)	0.167	0.735	-0.835	1.201
Return volatility	Realized volatility of daily stock return over the quarter (annualized)	0.366	0.258	0.153	0.826
Aggregate variables					
Average capital buffer	Average difference between tier-1 capital ratio and "well capitalized" threshold across banks (leaving out bank i)[a]	0.068	0.010	0.055	0.088
Stock index return	Quarterly average of daily CRSP value-weighted index return (annualized)	0.097	0.336	-0.523	0.623
VIX	Quarterly average of daily VIX/100	0.207	0.076	0.127	0.307
3m Treasury yield	3-month Treasury yield	0.023	0.022	0.000	0.052
Credit spread	Difference between Moody's seasoned Aaa and Baa corporate bond yields	0.010	0.004	0.006	0.014
TED spread	Difference between 3-month LIBOR and 3-month Treasury Bill yield	0.005	0.004	0.002	0.011

[a] The variable "Average capital buffer" varies at the bank level since it is constructed leaving out bank i's capital buffer: $(\text{Average capital buffer})_{it} = \frac{1}{N_t - 1} \sum_{j \neq i} (\text{Well capitalized 0-20pp})_{jt}$

roles and details of the explanatory variables are discussed with the estimation results in Section 3.4.

3.3 Estimation procedure

The model (12)–(14) can be estimated in two steps (e.g. Öztekin and Flannery, 2012). In the first step, we obtain an estimate of target leverage, b^*_{it}. Substituting the expression for target leverage (13) into the partial adjustment equation (12) and assuming that the adjustment speed is constant, $\lambda_{it} = \lambda$ for all i and t, we get

$$b_{it+1} = \lambda\delta^\top z_{it} + (1-\lambda)\, b^p_{it+1} + \varepsilon_{it+1}. \tag{15}$$

We can estimate the model (15) with the fixed-effects panel regression

$$b_{it+1} = \phi^\top z_{it} + \psi b^p_{it+1} + \varepsilon_{it+1}, \tag{16}$$

which yields estimates for λ and δ by using the estimated coefficients $\widehat{\phi}$ and $\widehat{\psi}$ to set $\widehat{\lambda} = 1 - \widehat{\psi}$ and $\widehat{\delta} = \widehat{\phi}/\widehat{\lambda}$. Using equation (13), we arrive at the estimate of target leverage $\widehat{b}^*_{it} = \widehat{\delta}^\top z_{it}$.

In the second step, armed with the estimate $\widehat{b}^*_{it}$, we find an estimate for λ_{it}. Substituting the expression for adjustment speed (14) and the estimated leverage target $\widehat{b}^*_{it}$ from the first step into the partial adjustment equation (12) and rearranging, we obtain:

$$b_{it+1} - b^p_{it+1} = \gamma^\top \left[w_{it} \times \left(\widehat{b}^*_{it} - b^p_{it+1} \right) \right] + \nu_{it+1}. \tag{17}$$

We can estimate the model (17) with an ordinary least squares (OLS) regression where the dependent variable is the difference between actual and passive leverage, $b_{it+1} - b^p_{it+1}$ and the independent variables are the explanatory variables w_{it} multiplied by the difference between estimated target and passive leverage, $\widehat{b}^*_{it} - b^p_{it+1}$. From this regression, we retain $\widehat{\gamma}$, which will be used to construct λ_{it}.

Our framework is intended to allow for financial stability monitoring in real time. To minimize any look-ahead bias, we estimate the econometric model (12)–(14) on rolling

16-quarter windows.[13] We use the resulting rolling estimates $(\widehat{\delta}, \widehat{\gamma})$ to construct bank i's leverage target and adjustment speed that will be used in the fire-sale scenario of Section 4. The leverage target used for the scenario in period t is bank i's predicted leverage target for the last date of the estimation window ending at t, $b^*_{it} = \widehat{\delta}^\top z_{it}$. The adjustment speed used for the scenario in period t is bank i's average adjustment speed over the estimation window that ends at t,

$$\lambda_{it} = \hat{\gamma}^\top \left(\frac{1}{16} \sum_{\tau=t-15}^{t} w_{i\tau} \right).$$

Using the average predicted adjustment speed — rather than the last value in the window — is intended to make it consistent with the leverage target: the leverage target is estimated in step 1 under the assumption of a constant adjustment speed across banks and periods (equation 15); using the average across periods from step 2 as bank i's adjustment speed ensures that the average adjustment speed across banks is close to the constant adjustment speed λ from step 1. We show in Appendix B.2 how alternative treatments of the windows affects our estimates of adjustment speed and leverage target.

While the estimation in step 2 (equation 17) is a simple linear regression that we can estimate with OLS, the estimation in step 1 (equation 16) is very similar to a dynamic panel regression with bank fixed effects, low T, and large N, where standard fixed-effects estimation can incur finite-sample bias because the within-group mean of the lagged dependent variable is, by construction, correlated with the error term (Nickell, 1981; Baltagi, 2008). The estimation in step 1 is not literally a dynamic panel regression since it has passive leverage b^p_{it+1} instead of the lagged dependent variable b_{it} as an explanatory variable. However, by construction of b^p_{it+1} as a transformation of b_{it}, the two are correlated. In Appendix B.3, we compare the estimated adjustment speeds from a fixed-effects regression to that from a system GMM approach (Arellano and Bover, 1995; Blundell and Bond, 1998) — which is designed to address the potential finite-sample bias — and find that both have a very similar evolution over time.

[13] We apply a constant correction to all b^p_{it} to ensure that the averages of passive leverage and estimated target leverage equal the overall average of actual leverage within each estimation window, $\sum_i \sum_t b^p_{it} = \sum_i \sum_t \widehat{b}^*_{it} = \sum_i \sum_t b_{it}$.

3.4 Estimation results

We first present results from regressions on the whole sample and then turn to the results from rolling regressions that provide the estimated leverage targets and adjustment speeds used in our AV analysis.

Full sample regressions. Table 3 shows results from regressions on the whole sample from 1996q1 to 2016q4. Column 1 shows results from the fixed-effects regression that corresponds to step 1 of our estimation (equation 16). Column 2 shows results from the OLS regression that yields coefficients of the adjustment speed and corresponds to step 2 of our estimation (equation 17). For the variables determining the leverage target in column 1, most coefficients are significant and all have the expected sign. Leverage targets are higher for looser capital requirements (higher regulatory max) and lower for banks subject to CCAR stress tests. Banks that are larger, more profitable and riskier have lower leverage targets. "Traditional" banks with high loan shares and deposit funding have lower leverage targets. Publicly traded banks have lower leverage targets on average but increasing in their market-to-book ratio. In terms of the aggregate variables, leverage targets increase after higher GDP growth and a reduction in the term spread; recessions are associated with lower leverage targets.

Column 2 shows results for the variables determining the adjustment speed, broadly indicating faster adjustment speed for banks under different forms of pressure (consistent with, e.g. Berger et al., 2008). In the regression, we model the effect that the regulatory capital constraint has on adjustment speed with a piece-wise linear function of the capital buffer. The function is equal to a constant value for banks below the well capitalized threshold ("not well capitalized" dummy) and another constant value for banks more than 20 percentage points above that threshold (the left-out category). For banks 0 to 20 percentage points above the threshold, the function is affine (the "well capitalized 0-20pp" dummy is the intercept and its interaction with "capital buffer" is the slope).

The leverage adjustment speed of banks above the well-capitalized threshold increases as they get closer to the threshold (the coefficient on the interaction "WC 0-20pp x capital buffer" is negative). This result is consistent with regulators putting increasing pressure on banks to delever when their capital buffers are low. Once the threshold is breached and the bank is no longer well capitalized, adjustment speed drops (the coefficient on the

Table 3: Full sample results for estimation of the leverage partial adjustment model. The table shows results from estimating the partial adjustment model in two steps. Step 1 models leverage b_{it+1} as a function of explanatory variables z_{it} and passive leverage b^p_{it+1}, $b_{it+1} = \phi^\top z_{it} + \psi b^p_{it+1} + \varepsilon_{it+1}$, estimated with a fixed-effects regression (column 1). Step 2 models the adjustment speed $(b_{it+1} - b^p_{it+1})/(\widehat{b}^*_{it} - b^p_{it+1})$ as a function of explanatory variables w_{it}, $b_{it+1} - b^p_{it+1} = \gamma^\top [w_{it} \times (\widehat{b}^*_{it} - b^p_{it+1})] + \nu_{it+1}$, estimated with OLS (column 2) with $\widehat{b}^*_{it} = \left(\widehat{\phi}/\left(1-\widehat{\psi}\right)\right)^\top z_{it}$ using the estimates $\widehat{\phi}$ and $\widehat{\psi}$ from step 1. For details on the explanatory variables, see Table 1. The sample consists of quarterly data from 1996q1 to 2016q4 and includes any bank that is ever in the top 500 by assets in a given quarter of the sample. t-statistics are reported in parentheses, computed using standard errors robust to heteroskedasticity and autocorrelation clustered at the bank level; significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)
Constant	5.669***
	(14.13)
Regulatory max	0.001***
	(3.34)
CCAR	-0.038
	(-0.74)
Size	-0.202***
	(-10.93)
Profitability	-6.352***
	(-2.78)
Risk	-10.306***
	(-4.65)
Loan share	-0.009
	(-0.09)
Retail deposits	-0.041*
	(-1.72)
Public	-1.420***
	(-6.85)
Public x MTB	0.197***
	(7.10)
GDP growth	0.419**
	(2.00)
Term spread	-4.301***
	(-7.31)
Recession	-0.031
	(-1.55)
Passive leverage	0.901***
	(120.21)
Adj. R-squared	0.84
Observations	55008

	(2)
Constant	0.115**
	(2.53)
Not well capitalized	-0.027*
	(-1.87)
Well capitalized 0-20pp	0.051***
	(5.42)
WC 0-20pp x Capital buffer	-0.203**
	(-2.18)
Asset growth	0.025***
	(2.89)
Public	0.001
	(0.15)
Public x Stock return	-0.010*
	(-1.78)
Public x Return volatility	0.010
	(0.94)
Rated	0.093
	(1.59)
Rated x Investment grade	-0.078
	(-1.31)
Average capital buffer	-1.059***
	(-2.83)
S&P 500 return	-0.017*
	(-1.92)
VIX	0.009
	(0.14)
3m Treasury yield	0.113
	(0.36)
Term spread	0.699
	(1.61)
Credit spread	0.229
	(0.15)
TED spread	1.771
	(1.09)
Adj. R-squared	0.16
Observations	55008

“not well capitalized” dummy is negative). In this case, the operational regime of the bank changes and with it the adjustment speed, possibly due to regulatory intervention.

Also consistent with the idea that banks adjust leverage faster under different forms of pressure is the negative coefficient on banks’ individual stock returns. Adjustment speed is higher for banks with high asset growth, which seems contrary to the general pattern of higher adjustment speeds for banks under pressure. We interpret this relation as being instead due to the fact that concurrent large changes in assets and the capital structure are dominated, holding the other covariates constant, by mergers and acquisitions — of which there are plenty in our sample.

Finally, the coefficients on the average capital buffer across banks (leaving out bank *i*’s own capital buffer) and on S&P 500 returns are negative and significant. A low aggregate capital buffer and low aggregate stock returns increase bank *i*’s adjustment speed, even after controlling for bank *i*’s own capital buffer and its own stock returns. Therefore, aggregate conditions are important for the individual leverage adjustment speed of banks, with bad aggregate conditions accompanied on average by faster adjustment speeds.

Rolling regressions. Figure 1 summarizes the leverage targets and adjustment speeds resulting from estimating steps 1 and 2 (equations 16 and 17, respectively) on rolling 16-quarter windows. As discussed in Section 3.3, each estimation window results in a leverage target and an adjustment speed for each bank. The left panel of Figure 1 compares the evolution over time of the average estimated bank-level target to the average actual leverage in the data. In the pre-crisis period, the two measures are very close. Starting in 2007, as banks’ actual leverage increases due to losses, the two diverge with target leverage remaining flat. Starting in 2010, actual and target leverage decline, consistent with tighter post-crisis regulation.

The right panel of Figure 1 shows the evolution over time of the average estimated bank-level adjustment speed (from step 2), comparing it to the estimate in step 1 which is constant across banks. As expected, the two measures are very close (see the discussion in Section 3.3). The estimated adjustment speed is fairly stable until 2006 and then increases by more than 50% between 2006q1 and its peak in 2008q3. After the crisis, adjustment speed declines quickly until 2014, before leveling off at about 60% of its pre-crisis level. From the results in Table 3, column 2, we know that the capital buffer is the main

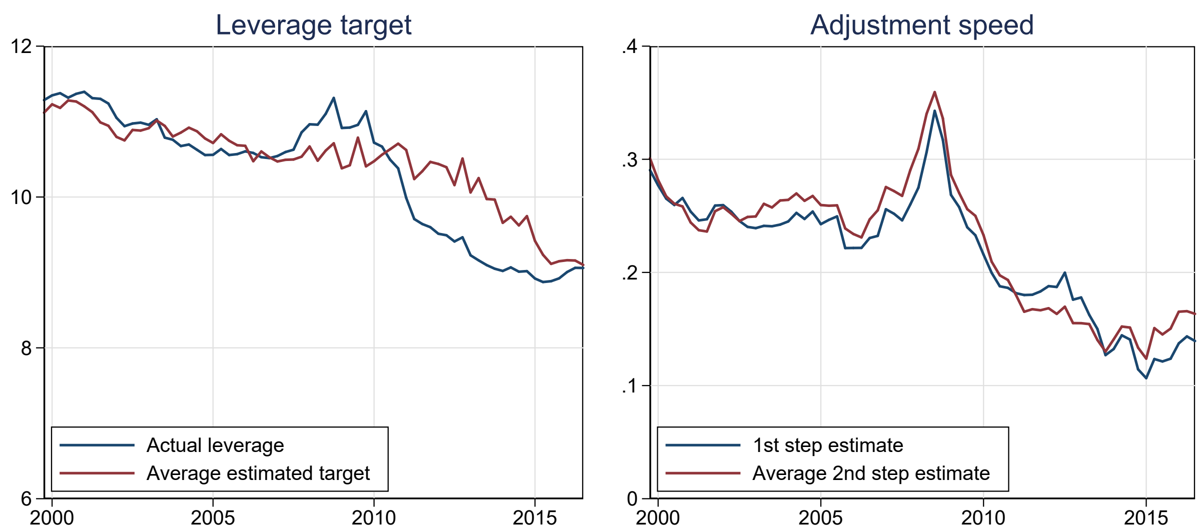

Figure 1: Leverage target and adjustment speed. The figure shows results from 16-quarter rolling regressions estimating the dynamic adjustment model in two steps. Step 1 models leverage b_{it+1} as a function of explanatory variables z_{it} and passive leverage b^p_{it+1}, $b_{it+1} = \phi^\top z_{it} + \psi b^p_{it+1} + \varepsilon_{it+1}$. Step 2 models the adjustment speed $(b_{it+1} - b^p_{it+1})/(\widehat{b}^*_{it} - b^p_{it+1})$ as a function of explanatory variables w_{it}, $b_{it+1} - b^p_{it+1} = \gamma^\top \left[w_{it} \times \left(\widehat{b}^*_{it} - b^p_{it+1}\right)\right] + \nu_{it+1}$ with $\widehat{b}^*_{it} = \left(\widehat{\phi}/\left(1 - \widehat{\psi}\right)\right)^\top z_{it}$ using the estimates $\widehat{\phi}$ and $\widehat{\psi}$ from step 1. The left panel shows the average actual leverage and the average estimated leverage target from step 1, using the leverage target predicted for the last period $t = 16$ of every window. The right panel shows the adjustment speed $\widehat{\lambda}$ estimated in step 1 and the average adjustment speed estimated in step 2, using the bank-level average predicted adjustment speed $\frac{1}{16}\sum_{t=1}^{16} \gamma^\top w_{it}$ within each window. The sample consists of quarterly data from 1996q1 to 2016q4 and includes any bank that is ever in the top 500 by assets in a given quarter of the sample.

driver of adjustment speed with adjustment speed inversely related to capital buffer. Consistent with that, the low-frequency movements in average adjustment speed in Figure 1 are related to corresponding low-frequency movements in the capital buffer: between 2005 and 2008, bank capital was eroding with the average capital buffer declining by over 20%, which is consistent with the increase in adjustment speed in the run-up to the crisis. Between 2008 and 2011, the post-crisis increases in bank capital raised the average capital buffer by over 60%, which is consistent with the concurrent sharp drop in adjustment speed. Our result that the speed of leverage adjustment is negatively related to the level of bank capital also adds an interesting asymmetry to the cyclicality of leverage first documented by Adrian and Shin (2010) since it implies faster adjustments "on the way down" (delevering from high leverage) than vice versa.

At the bank level, there is meaningful variation in leverage targets and adjustment speeds in both the cross-section and the time series. The ratio of between-variation to within-variation for target leverage is about 1.5, i.e. more cross-sectional than time-series variation, and about 0.7 for adjustment speed, i.e. somewhat more time-series than cross-sectional variation. See Table 4 for additional summary statistics of leverage target and adjustment speed.

4 Calculation of fire-sale spillovers

We now present the results of calculating fire-sale spillovers in the form of AV, bank systemicness, and asset systemicness (equations 8, 9, and 10, respectively), using the estimates for leverage targets and adjustment speeds from Section 3. We then study the role of the individual factors of AV in equation (8) and evaluate the effect of key regulatory policies on AV.

4.1 Data

We calculate spillover losses using equation 7. The matrices of total assets A_t and portfolio weights M_t come directly from the FR Y-9C balance sheet data described in Section 3.1. We group assets into the seventeen categories listed in Table 4 to construct the matrix of portfolio weights M_t; Appendix C contains the mapping between these asset classes and

Table 4: Summary statistics for balance sheet data. The table shows summary statistics for the variables used in the calculation of fire-sale spillovers. The sample includes the largest 100 banks by assets every quarter that have estimates for leverage target and adjustment speed available, resulting in a sample period from 1999q3 to 2016q3 at the quarterly frequency (Section 3). "SW avg." denotes the size-weighted average (weighted by total assets); "EW avg." denotes the equal-weighted average. "p5" and "p95" stand for, respectively, the 5th and 95th percentiles of the distribution. The last column shows the price impact for each asset class based on the Net Stable Funding Ratio, where the price impact of U.S. Treasuries is normalized to 1 (Appendix D). Source: FR Y-9C and estimation in Section 3.

	SW avg.	EW avg.	St. dev.	p5	p95	ℓ_k
Total assets ($ billions)	834.6	105.1	295.3	6.3	481.4	
Leverage target	13.6	11.5	3.9	6.8	16.9	
Adjustment speed (percent)	24.1	23.3	6.2	13.6	33.5	
Portfolio shares (percent):						
Residential real estate loans	15.3	16.8	10.8	0.2	36.3	12.0
C & I loans	10.9	13.2	8.4	0.4	27.2	15.0
Repo & fed funds loans	9.9	2.7	7.2	0.0	14.9	2.0
Agency MBS	8.8	12.3	9.3	0.8	29.9	3.0
Consumer loans	8.7	7.0	10.1	0.1	18.2	15.0
Commercial real estate loans	7.6	19.3	13.4	0.2	43.6	15.0
ABS & other debt securities	6.7	2.7	5.5	0.0	11.7	7.0
U.S. Treasuries	2.2	1.4	2.9	0.0	6.7	1.0
Equities & other securities	1.9	0.8	2.7	0.0	2.6	11.0
Non-agency MBS	1.8	1.6	3.2	0.0	7.5	13.0
Agency securities	1.7	3.7	5.5	0.0	14.5	3.0
Lease financings	1.5	1.5	2.4	0.0	6.1	15.0
Municipal securities	1.2	2.0	2.9	0.0	7.6	12.0
Other real estate loans	1.0	1.1	3.7	0.0	3.6	15.0
Residual loans	4.6	3.7	5.2	0.0	10.9	15.0
Residual securities	4.3	0.8	2.7	0.0	4.1	20.0
Residual assets	11.7	9.4	6.5	3.1	19.9	20.0

entries in form FR Y-9C. We choose this particular categorization of asset classes so as to have the finest possible subdivision while reasonably maintaining the assumption of no cross-asset price impacts of fire sales. Banks' leverage targets and adjustment speeds (estimated in Section 3) are collected in the diagonal matrices B_t^* and Λ_t. To measure the wealth w_t of potential buyers of fire-sold assets, we use the value of total financial sector assets from the Financial Accounts of the United States (formerly Flow of Funds) minus the assets in our sample. For robustness, we also consider in Appendix E.1 constant outside wealth as well as outside wealth that scales with GDP. There are no readily available estimates for the liquidity of most assets of banks. Greenwood et al. (2015) therefore assume

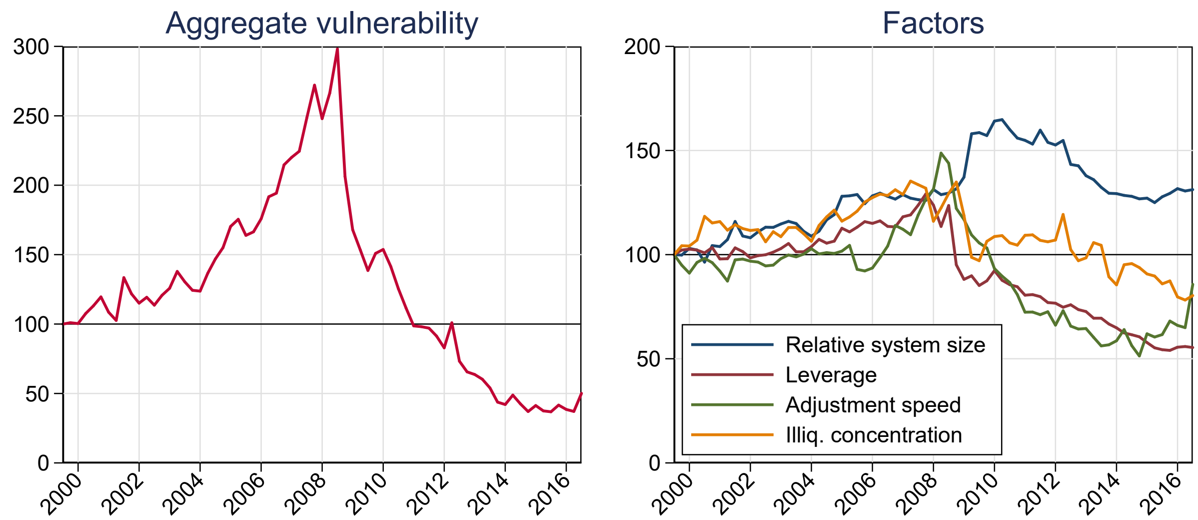

Figure 2: Aggregate vulnerability index and decomposition into factors. The figure shows the aggregate vulnerability index (left panel) and the decomposition into multiplicative factors based on equation (8) (right panel). All series are normalized to 100 at the beginning of the sample.

the same price impact for all assets, $\ell_k = \ell$ for all k. Instead, we introduce heterogeneity in the liquidity of asset classes by using the information contained in the Net Stable Funding Ratio (NSFR) of the Basel III regulatory framework. We use the NSFR instead of the Liquidity Coverage Ratio (LCR) since it distinguishes asset classes more finely. The NSFR involves applying haircuts to different asset classes to account for differences in liquidity over a horizon of one year. The last column of Table 4 shows the values of price impact ℓ_k, normalized to the value for Treasuries (since the absolute value does not affect the AV which is normalized to 100 at the beginning of the sample). Appendix D shows in detail how we impute liquidity values for different assets using the NSFR guidelines. We consider the case in which all assets have the same liquidity (as in Greenwood et al., 2015) in Appendix E.1. To calculate AV, we include the top 100 banks every quarter that have estimates for leverage target and adjustment speed from Section 3. For robustness, we show in Appendix E.2 that results with a balanced panel are very similar.

4.2 Results

Figure 2 shows the evolution of AV, our main measure of systemic fire-sale risk, as well as its comprising factors from equation (8), which we also normalize to 100 at the beginning of the sample. AV shows a weakly increasing trend between 2000 and the end of 2003. Starting in 2004, it increases quickly until the financial crisis, more than doubling by the end of 2006 and peaking at three times its initial level in 2008q3. If available at the time, our measure would have been useful as an early indicator of vulnerabilities building up; we explore this issue more formally with predictive regressions in Section 6. The measure decreases sharply over the course of 2009 and returns to its initial level in 2011. In the post-crisis period, the measure declines further before stabilizing in 2015 at around 40 percent of its initial level.

Studying the four comprising factors of AV in the right panel of Figure 2, we see that each factor contributes differently to the total and that the contributions change over time. Relative size of the banking system (compared to the rest of the financial sector) and leverage show expected trends, increasing in the pre-crisis period and decreasing towards the end of the sample. Of note are the sharp decline in leverage in late 2008 mostly due to bank recapitalizations (TARP, see Section 4.4) and the increase in relative size in early 2009 due to the addition to the sample of firms such as Morgan Stanley and Goldman Sachs which became bank holding companies. As mentioned above, Appendix E.2 shows that our measure is robust to using a balanced panel, so that firms that enter and exit the sample do not drive our results.

Size and leverage are known to be potential contributors of systemic risk, also through mechanisms different from fire sales. It is therefore crucial for the importance of the fire-sale channel that the two factors more specific to fire-sale spillovers — adjustment speed and illiquidity concentration — also play important roles in the evolution of AV. Average adjustment speed is roughly constant between 2000 and 2006, and then increases by over 50 percent through 2008, causing AV to spike. This is notable since, as discussed in Section 3, we have controlled for any adjustments via equity issuance so the estimated increase in adjustment speed during the crisis reveals greater leverage adjustment that explicitly excludes the adjustments that resulted from raising equity.

Turning to illiquidity concentration, which captures the concentration of more illiquid assets among banks that are relatively levered, adjust relatively quickly, and are relatively

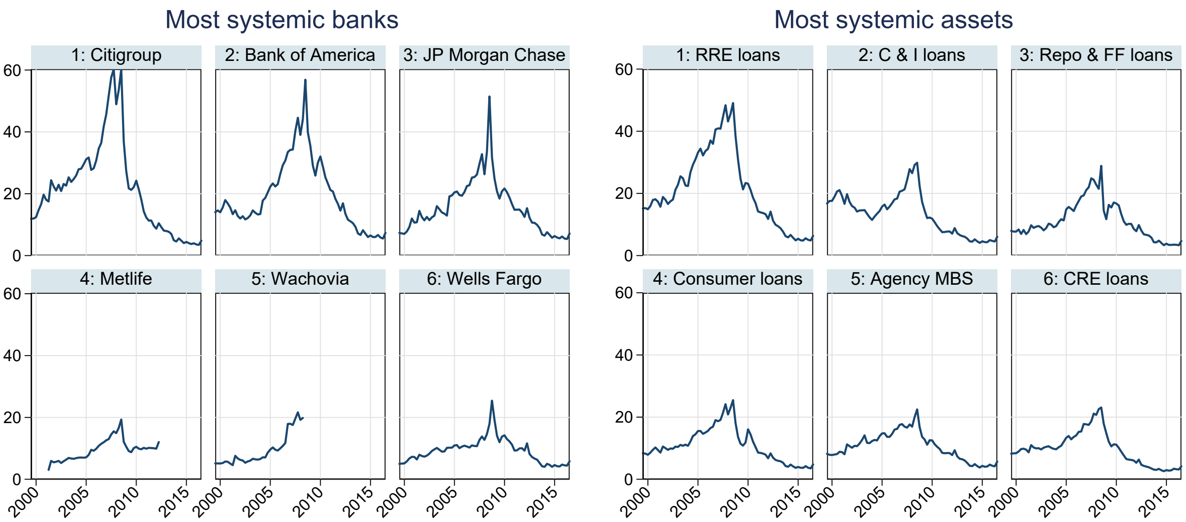

Figure 3: Fire-sale externality of most systemic banks and assets. The figure shows the most systemic banks and assets, plotting the evolution of the measures SB_{it} and SA_{kt} from equations (9) and (10), respectively. Which banks and assets are most systemic is determined by sample averages. Series are normalized to sum to 100 at the beginning of the sample.

large, we see a positive trend starting in 2004; between 2004 and 2007, illiquidity concentration increases by roughly 25 percent. In the post-crisis period, it remains fairly stable before starting a downward trend in 2013. Jointly, the two fire-sale specific factors of adjustment speed and illiquidity concentration account for over 60 percent of the increase in AV from 2000 until its peak in 2008.

Figure 3 reports the evolution over time of the measures SB_{it} and SA_{kt} from equations (9) and (10) for the six banks and assets that have the highest average systemicness in our sample. Since we normalize AV to 100 at the beginning of the sample and SB and SA themselves sum up to AV, we normalize them so that they sum to 100 at the beginning of the sample.

Among banks, Citigroup is the most systemic for the majority of the sample, with Bank of America and JP Morgan Chase following closely behind. Despite their overall systemicness measures being highly correlated, there are clear differences in the patterns due to differences in the evolution of the bank specific factors in decomposition (9).

Table 5 lists the top ten banks by average fire-sale systemicness in the post-crisis period (2008q4–2016q3) as well as any bank not in the top ten by systemicness that has been des-

Table 5: Most systemic banks post crisis and G-SIB surcharge. The table lists the top ten banks by average systemicness (SB_i) in the post-crisis period (2008q4–2016q3) as well as any bank not in the top ten by systemicness that has a G-SIB surcharge. Systemicness is normalized to sum to 100 at the beginning of the sample (1999q3). Asset (a_i) rank is also based on the average in the post-crisis period (2008q4–2016q3). G-SIB surcharge is the maximum surcharge assigned to each bank between 2011 and 2016, in percent. Excludes foreign banks.

SB_i rank	a_i rank	Name	SB_i	G-SIB
1	2	Bank of America	16.0	2.0
2	1	JP Morgan Chase	12.8	2.5
3	3	Citigroup	11.4	2.5
4	7	Metlife	10.2	.
5	4	Wells Fargo	8.8	1.5
6	6	Morgan Stanley	3.1	1.5
7	5	Goldman Sachs	2.5	1.5
8	8	U.S. Bancorp	2.1	.
9	9	PNC	1.8	.
10	10	Capital One	1.6	.
13	11	Bank of NY Mellon	1.1	1.5
21	14	State Street	0.6	1.0

ignated as a Global Systemically Important Bank (G-SIB) by the Financial Stability Board, resulting in a regulatory capital surcharge. While broadly consistent, there are differences between our systemicness measure and the one implied by the G-SIB surcharge. For example, our systemicness ranks Bank of America first while it is only second in terms of size and third in terms of G-SIB surcharge. Further, Bank of NY Mellon and State Street are G-SIBs even though our systemicness measure ranks them below several non-G-SIBs. Both of these differences are primarily due to the fact that the G-SIB designation considers additional factors such as international scope and substitutability that are unrelated to fire sales. Finally, our measure assigns high systemicness to Metlife at rank 4 while it only ranks 7th by size. Consistently, Metlife was designated by the FSOC in December 2014 as systemically important. The designation was partly based on the systemic threat Metlife could pose through the "asset liquidation channel", using an earlier version of our measure (Financial Stability Oversight Council, 2015). Overall, fire-sale systemicness highlights slightly different institutions than size alone or the G-SIB framework.

Among assets, residential real estate loans stand out in Figure 3 as the most systemic and with the fastest growth in the run-up to the crisis. This is not just because they have a large average portfolio share, but also because they are held in large amounts by the most systemic banks (as can be inferred by the difference between size-weighted and equal-weighted averages in the portfolio shares in Table 4). They are also a key determinant of the illiquidity concentration factor of AV: between 2002 and 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 2002 when the bifurcation in their aggregate portfolio shares occurs. By the end of our sample, no asset class stands out as particularly more systemic than the rest.

4.3 Effect of factors on AV

To further disentangle the contribution of the individual factors of AV in equation (8), we first do a variance decomposition and then consider a hypothetical version of AV in which banks are homogeneous.

Variance decomposition. We can decompose the variance of log AV into the variances and covariances of the logs of the factors relative size, leverage, adjustment speed, and illiquidity concentration according to

$$\text{var}\left(\log \text{AV}\right) = \text{var}\left(\textstyle\sum_n \log X_n\right) = \textstyle\sum_n \text{var}\left(\log X_n\right) + \textstyle\sum_n \textstyle\sum_{m \neq n} \text{cov}\left(\log X_n, \log X_m\right). \quad (18)$$

We then sum the contributions of each log factor, i.e. its variance and all covariances and express the total relative to the variance of log AV according to

$$\text{contribution of factor } X_n \equiv \frac{\text{var}\left(\log X_n\right) + \sum_{m \neq n} \text{cov}\left(\log X_n, \log X_m\right)}{\text{var}\left(\sum_m \log X_m\right)}. \quad (19)$$

Figure 4 (left panel) shows the results of this variance decomposition across three subperiods of our sample: before the crisis (before 2007q1), during the crisis (2007q1–2009q4), and after the crisis (after 2009q4). We see that the contribution of relative size is large pre-crisis but much smaller post-crisis and even negative during the crisis (due to negative covariances with the other factors). In contrast, the contribution of leverage is greatest during the crisis and only about half as large in the pre and post period. Variation in ad-

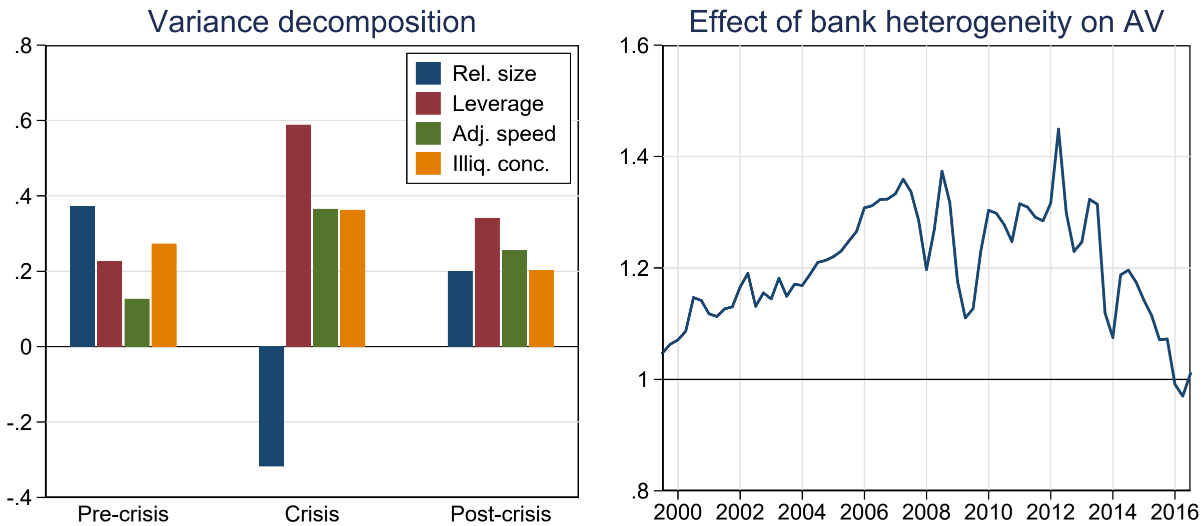

Figure 4: Effect of factors on AV. The left panel shows the contribution of the four factors in equation (8) to the variance of log AV, using the variance decomposition given by equation (18). The right panel shows the ratio of actual AV to a counterfactual AV in which all banks are homogeneous. "Pre-crisis" is 1999q3–2006q4, "Crisis" is 2007q1–2009q4, and "Post-crisis" is 2010q1–2016q3.

justment speed contributes little to variation in AV pre-crisis but increases its contribution during the crisis and is the second largest contributor post-crisis. Finally, illiquidity concentration stands out as the second largest contributor to variation in AV pre-crisis and the most stable contributor over the whole sample. Jointly, the fire-sale specific factors adjustment speed and illiquidity concentration account for 40 percent of the variance of AV during the pre-crisis period until 2006q4.

Effect of heterogeneity on AV. An important element of the AV framework is the non-neutrality with respect to the distribution of a given "aggregate balance sheet" across different institutions, as captured by the illiquidity concentration factor in the decomposition (8). We can study this effect of bank heterogeneity by constructing a counterfactual system in which banks are homogeneous and comparing the resulting fire-sale vulnerability to benchmark AV. To construct such a counterfactual measure we assume that all banks are equally sized, have the same leverage target and adjustment speed, and hold the same asset portfolio — effectively creating a representative bank. This requires setting $\alpha_{it} = 1/N$, $\beta^*_{it} = 1$, $\widetilde{\lambda}_{it} = 1$ and $\mu_{ikt} = 1$ for all i, k in the expression for aggregate vulnerability in equation (8):

$$\mathrm{AV}_t^{\mathrm{hom}} = \frac{a_t}{w_t}\left(b_t+1\right)\overline{b}_t^*\overline{\lambda}_t \textstyle\sum_k \left(m_{kt}^2 \ell_k\right).$$

Taking the ratio of actual AV to the hypothetical homogeneous $\mathrm{AV}^{\mathrm{hom}}$, the first three factors (which depend on aggregate variables only) cancel and we are left with a ratio of the respective illiquidity concentration factors:

$$\frac{\mathrm{AV}_t}{\mathrm{AV}_t^{\mathrm{hom}}} = \frac{\sum_k \left[m_{kt}^2 \ell_k \sum_i \left(\mu_{ikt}\widetilde{\lambda}_{it}\beta_{it}^*\alpha_{it}\right)\right]}{\sum_k \left(m_{kt}^2 \ell_k\right)}.$$

Figure 4 (right panel) shows the evolution of this ratio over time, highlighting that the effect of heterogeneity on AV can be large and variable over the sample. From the beginning of the sample until the crisis, the effect of heterogeneity increases steadily, leaving AV in 2007 over 30 percent higher due to heterogeneity. Starting in 2013, the effect declines and eventually disappears with AV almost unchanged by bank heterogeneity at the end of the sample in 2016.

4.4 Effect of regulatory policies on AV

The crisis led to a strong regulatory response intended to reduce acute systemic stress as well as vulnerability to future systemic risk. In this section, we consider the effects of three regulatory policies with potential effects on the fire-sale vulnerabilities that are the focus of our paper. First, we consider the effect of the Troubled Asset Relief Program (TARP) which involved a significant recapitalization of U.S. banks in late 2008 and early 2009. Second, we consider the effect of the post-crisis tightening of capital regulation, especially for G-SIBs. Third, we consider the effect of the post-crisis change in bank asset portfolios due to new liquidity regulation. Finally, since regulators may try to slow down deleveraging during crises, e.g. by being more lenient with respect to low capital buffers, we also consider the effect of hypothetically lower adjustment speeds during the crisis period.

TARP recapitalization. At the high-point of the financial crisis in the fall of 2008, the U.S. government initiated TARP, which included a recapitalization of U.S. banks. For the

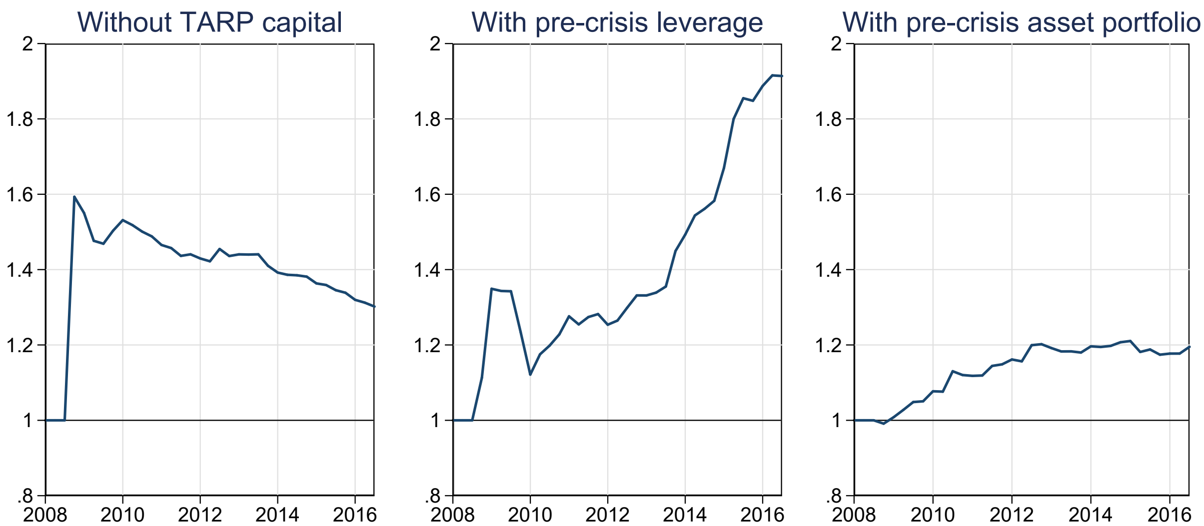

Figure 5: Effects of TARP, capital regulation and liquidity regulation on AV. The figure shows the ratio of benchmark AV to a counterfactual AV in which each bank's leverage is adjusted by the capital injection it received through TARP (left panel), a counterfactual AV in which, starting in 2008q4, each bank's leverage is kept constant at its 2006q4 level (middle panel), and a counterfactual AV in which, starting in 2008q4, each bank's asset portfolio weights are kept constant at their 2006q4 levels (right panel).

banks in our sample, TARP increased equity by $155 billion in 2008q4 and by a further $11 billion in 2009q1, which is close to 70 percent of their net equity issuance in these quarters. To assess the effect of this crisis recapitalization, we calculate a counterfactual AV without the extra equity capital from TARP. To do so, we reduce each bank's equity and increase its actual and target leverage as if it had not been recapitalized.[14] For simplicity, we leave unchanged each bank's estimated adjustment speed; since adjustment speed varies inversely with capital (Section 3) this means we likely underestimate the decrease in AV arising from the TARP recapitalization. Figure 5 (left panel) shows the ratio of benchmark AV to the counterfactual without the TARP recapitalization in 2008q4 and 2009q1. AV without TARP would have been considerably higher, 59 percent in 2008q4 and 43 percent higher on average over the entire post-crisis period.

[14]For equity, we just subtract cumulative TARP injections, $e_{it}^{\text{notarp}} = e_{it} - \sum_{s \le t} \Delta e_{is}^{\text{tarp}}$. For target leverage, we first infer a target equity e_{it}^* from target leverage b_{it}^* and assets a_{it} as $e_{it}^* = a_{it}/(b_{it}^* + 1)$. Then we subtract TARP injections, $e_{it}^{*\text{notarp}} = e_{it}^* - \sum_{s \le t} \Delta e_{is}^{\text{tarp}}$, and create the counterfactual target leverage as $b_{it}^{*\text{notarp}} = \left(a_{it} - e_{it}^{*\text{notarp}}\right)/e_{it}^{*\text{notarp}}$.

Capital regulation. After the recapitalization through TARP, leverage post-crisis declines further due to, among other factors, stress testing and tightened capital regulation under the Basel III framework. To assess the effect of this decline in leverage, we calculate a counterfactual AV where, starting in 2008q4, we set each bank's leverage constant at its pre-crisis level (as of 2006q4, before the increase in leverage due to crisis losses). The middle panel of Figure 5 plots the ratio of benchmark AV to this counterfactual with pre-crisis leverage. Similar to the effect of TARP, we see that AV under pre-crisis leverage would have been considerably higher, 43 percent on average over the entire post-crisis period and almost double toward the end of the sample. Among individual banks, regulation was tightened even more for G-SIBs. Consistent with that, our counterfactual finds a larger effect for G-SIBs: while systemicness with pre-crisis leverage in the post-crisis period would have been 37 percent higher on average across all banks, it would have been 47 percent higher for banks designated as G-SIBs and 68 percent higher for those in the highest G-SIB capital surcharge bucket.

Liquidity regulation. The post-crisis regulation under the Basel III framework also includes new liquidity requirements. The liquidity coverage ratio (LCR) and the net stable funding ratio (NSFR) require large banks to hold sufficiently liquid assets relative to the liquidity of their liabilities. Roberts, Sarkar, and Shachar (2019) show that, in response, the affected banks changed the composition of their assets toward more liquid holdings. To assess the effect of this policy change, we calculate a counterfactual AV where, starting in 2008q4, we set each bank's asset portfolio weights constant at their pre-crisis levels (as of 2006q4, analogous to the capital regulation analysis above). We see in Figure 5 (right panel) that without the post-crisis changes in asset portfolios, AV would have been about 15 percent higher over the entire post-crisis period. Among individual banks, systemicness would have been 6 percent higher on average across all banks, 8 percent higher for banks designated as G-SIBs, and 23 percent higher for those in the highest G-SIB bucket. On average, the effect of liquidity regulation on AV is therefore less than half of the effect of capital regulation but the effect is relatively more skewed towards the most systemic banks.

Regulatory lenience. Regulators have some discretion in implementing and enforcing regulations, which affects bank's behavior (e.g. Eisenbach, Lucca, and Townsend, 2019). This raises the question of how much AV, especially during the crisis period, would have been reduced if regulators had been more lenient and allowed slower adjustments. We therefore calculate a counterfactual AV where, during the years 2007 and 2008, we cap each bank's adjustment speed at its pre-crisis level (as of 2006q4) and leave everything else unchanged. We find that this hypothetical regulatory lenience would have reduced AV by 8 percent on average during 2007 and 2008, with the effect largest in 2008q3 where AV is reduced by 20 percent. Temporary regulatory lenience can therefore reduce the costs of fire sales during times of stress but the magnitude of the effect is smaller than that of the capital and liquidity regulations discussed above.

5 Robustness

We present four sets of robustness checks: (i) alternative assumptions about leverage adjustment, (ii) not marking loans to market, (iii) alternative rules for liquidating assets, and (iv) conducting multiple rounds of fire sales. Several additional robustness checks are in Appendix E.

5.1 Different assumptions about leverage adjustment

In our calculation of AV, we assume that, following a shock, banks adjust partially back to a target leverage and that the adjustment speed varies across banks and time. We now consider the effects of these assumptions by comparing our benchmark AV to three versions with alternative assumptions about leverage adjustment. First, we assume that the adjustment speed is constant across banks and equal to the estimate from step 1 of our estimation (Section 3). The left panel of Figure 6 shows the resulting time series of AV. We see a similar evolution over time as in benchmark AV but a smaller increase from the beginning of the sample to the peak of the crisis. While benchmark AV triples in magnitude, the alternative with constant adjustment speed across banks only doubles. This difference means that, in benchmark AV, individual banks' adjustment speed interacts with their leverage and asset holdings in a way that increases overall vulnerability to fire-sale spillovers.

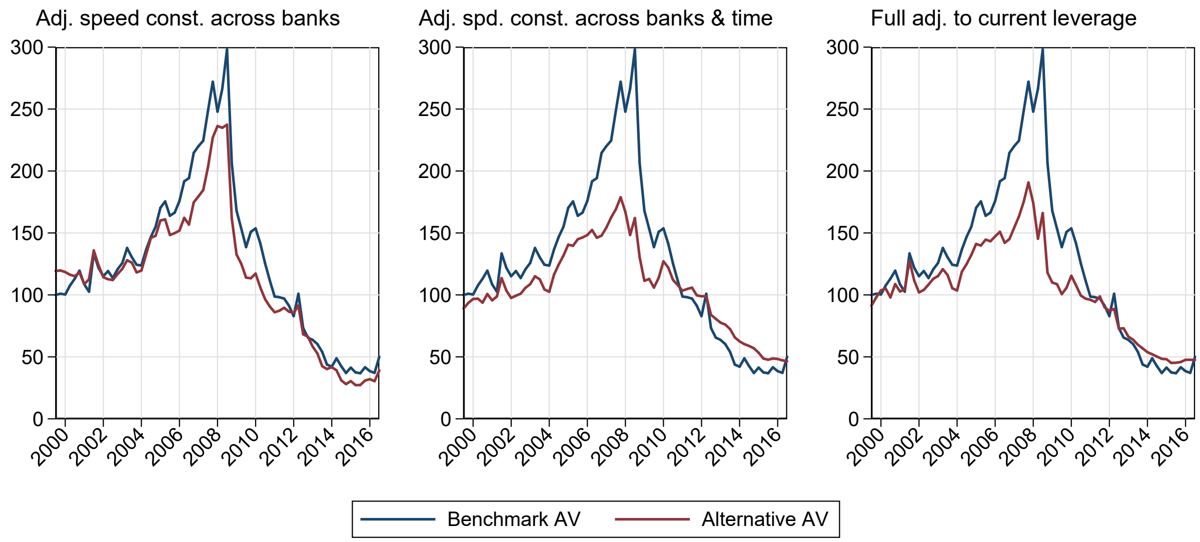

Figure 6: Comparison of benchmark AV to AV with different assumptions about leverage adjustment. The figure shows the effects on AV of assuming (i) constant adjustment speed across banks, equal to the estimate in step 1 of the estimation in Section 3 (left panel); (ii) constant adjustment speed across banks and time (middle panel); and (iii) constant adjustment speed with pre-shock leverage as the target (right panel). Alternative AV series are normalized by the relative size of the raw AV values at the beginning of the sample.

Second, we assume that the adjustment speed is not only constant across banks, as in the previous exercise, but also constant over time and equal to the overall average. The middle panel of Figure 6 shows the resulting time series of AV, with an almost identical evolution to benchmark AV until 2006, when the increase in adjustment speed leads benchmark AV to increase considerably more before its peak.

Finally, we completely eliminate the effects of our partial adjustment estimation on AV by assuming that adjustment speed is constant across banks and time, as in the previous exercise, and that banks' target leverage is their current (pre-shock) leverage. Under these assumptions, our framework is equivalent to the original "vulnerable banks" framework of Greenwood et al. (2015). The right panel of of Figure 6 shows the resulting time series of AV, which is almost identical to the previous exercise in the middle panel where the leverage target was still the one estimated in Section 3. In sum, we see that our assumption of a partial adjustment model for bank leverage has a sizable effect on AV and mainly through the bank-specific adjustment speed.

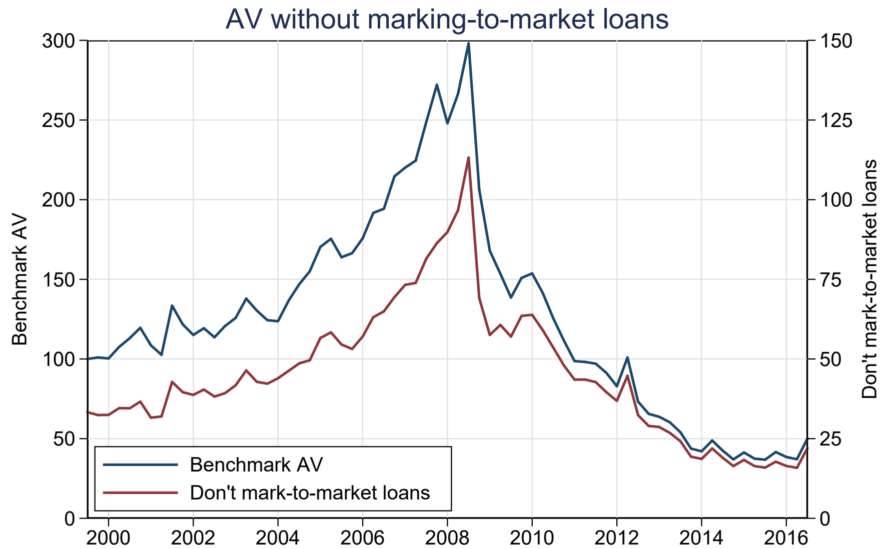

Figure 7: Comparison of benchmark AV to AV without marking-to-market loans. The figure shows the effect on AV of not marking to market loans (as well as residual securities and residual assets). AV without marking-to-market is normalized by the relative size of the raw AV values at the beginning of the sample.

5.2 Not marking-to-market loans

Banks do not 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. In such cases, when confronted with a negative shock, banks may not recognize the full extent of the economic losses on their balance sheets. 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 therefore consider the extreme case in which banks simply do not mark down any loans, residual securities, or residual assets (and mark-to-market the rest of their balance sheet). Figure 7 displays the results, comparing the benchmark AV to the version without marking-to-market. We normalize the latter index by the same initial value that we use to normalize AV, so that the difference in magnitude and not just evolution over time, can be compared. When banks do not mark down illiquid assets at all, AV is cut by more than half. However, the behavior of the index over time hardly changes.

5.3 Alternative liquidation rules

Selling the most liquid assets first has the important advantage of minimizing the price impact of fire sales, which reduces immediate 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). 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 (Brown et al., 2009; Krishnamurthy, 2010). Regulatory requirements on risk-weighted assets as well as post-crisis liquidity regulations (LCR and NSFR) create an incentive to sell assets with high risk-weights first (Cifuentes et al., 2005; Hameed et al., 2010; 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 higher liquidation costs – and selling assets that have low risk-weights but are more liquid.

For robustness, we calculate AV under three alternative liquidation rules: (i) sell liquid assets first, (ii) sell liquid assets last, (iii) sell assets proportional to liquidity, and (iv) minimize price impact subject to a risk-based capital requirement.

Sell liquid assets first. We first assume a simple "waterfall" strategy, whereby banks sell assets in decreasing order of liquidity until they achieve their desired leverage. The results are in Figure 8 (left panel), where, for level comparison to the benchmark index, we have normalized the alternative AV indices by the relative size of the raw AV values at the beginning of the sample, as we did before. When selling liquid assets first, the level of AV is cut by roughly 90 percent on average but the behavior of the index over time does not materially change.

Sell liquid assets last. This strategy is the reverse of the previous one so assets are now sold in *increasing* order of liquidity. As shown in Figure 8 (left panel), this assumption increases the level of AV by roughly 30 percent on average but in terms of the behavior of

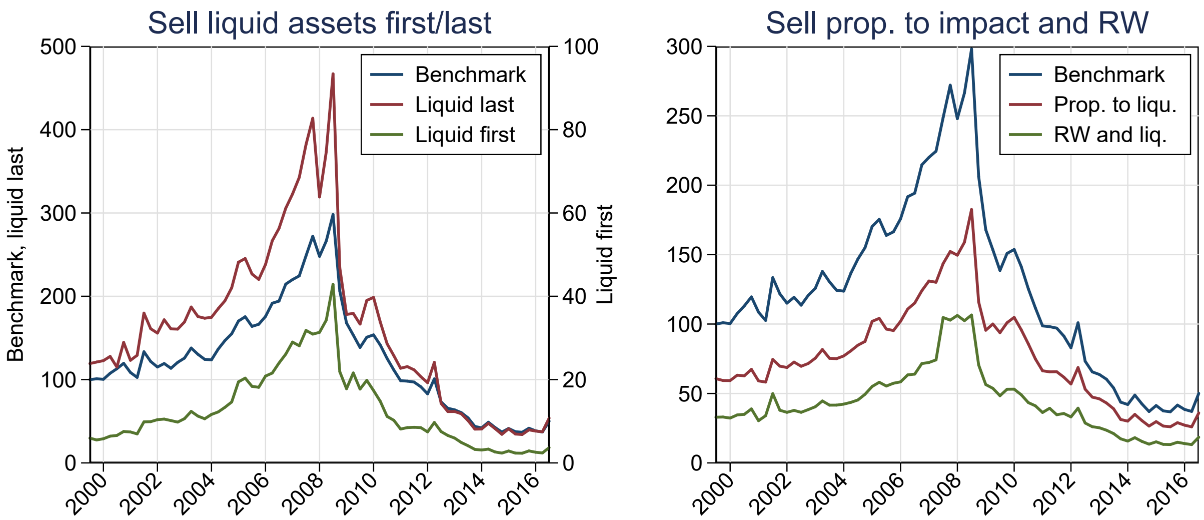

Figure 8: Comparison of benchmark AV to AV with alternative rules for selling assets. The figure shows the effects on AV of selling liquid assets first or last (left panel) and of selling assets proportionally to liquidity or when minimizing the price impact of fire sales subject to a risk-based capital requirement (right panel). Alternative AV series are normalized by the relative size of the raw AV values at the beginning of the sample.

the index over time, the results again hardly change.

Sell proportional to liquidity. We now assume that banks sell assets proportionally to asset liquidity (inversely proportional to price impact). Figure 8 (right panel) shows that that under the assumption of selling proportional to asset liquidity, the level of AV is roughly 40 percent lower on average but, in terms of the index over time, the results hardly change.

Risk weights and liquidity. We now assume that banks minimize the price impact of their fire sales subject to a realistically calibrated risk-based capital requirement; the details of the analysis are in Appendix E.4. Figure 8 (right panel) shows that AV under the resulting trade-off between risk weights and liquidity is considerably smaller than the benchmark (roughly 70 percent on average), but not as small as under the simple liquid first strategy (left panel). However, as before, the profile of vulnerability over time retains its shape.

5.4 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 as a new endogenous "shock" $\widehat{f}$ that triggers a second round of fire sales, given in equation (6). 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.[15]

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 decrease following each round of fire sales. Once we explicitly allow assets at the beginning of the round, A_1, and assets at the end of the round, A_2, to differ, the first-round fire-sale spillovers are:

$$\mathrm{AV}_1 = \frac{1}{e}\frac{1}{w} 1^\top A_2 M L M^\top \Lambda B^* A_1 M F_1. \tag{20}$$

The assumption that all fire-sold assets exit the system implies that A_2 is given by the following relation:

$$A_2 1 = A_1 1 - \Lambda B^* A_1 M F_1,$$

Using A_2 as initial assets for the second round and the first-round fire-sale spillover losses $F_2 = \frac{1}{w} L M^\top \Lambda B^* A_1 M F_1$ as the new shock, we find second-round spillover losses:

$$\mathrm{AV}_2 = \mathrm{AV}_1 + \frac{1}{e}\frac{1}{w} 1^\top A_3 M L M^\top \Lambda B^* A_2 M F_2.$$

We can iterate this process indefinitely with resulting fire-sale spillovers given by $\mathrm{AV}_\infty = \sum_{r=1}^{\infty} \mathrm{AV}_r$. Figure 9 (left panel) shows how multiple rounds of fire sales affect AV (normalized by the relative size of the raw AV values at the beginning of the sample). We see that convergence is achieved fairly quickly and that the shape of AV is preserved. Interestingly, the fraction of converged AV_∞ not accounted for by the first round AV_1 is not constant over time (Figure 9, right panel). There is a positive relationship between the effect of multiple

[15] Tepper and Borowiecki (2014) and Capponi and Larsson (2015) develop systemic risk measures based on how close the banking system is to being explosive due to high leverage and asset concentration. Braouezec and Wagalath (2017) study the fixed-point like equilibrium in a one-asset version of Greenwood et al. (2015).

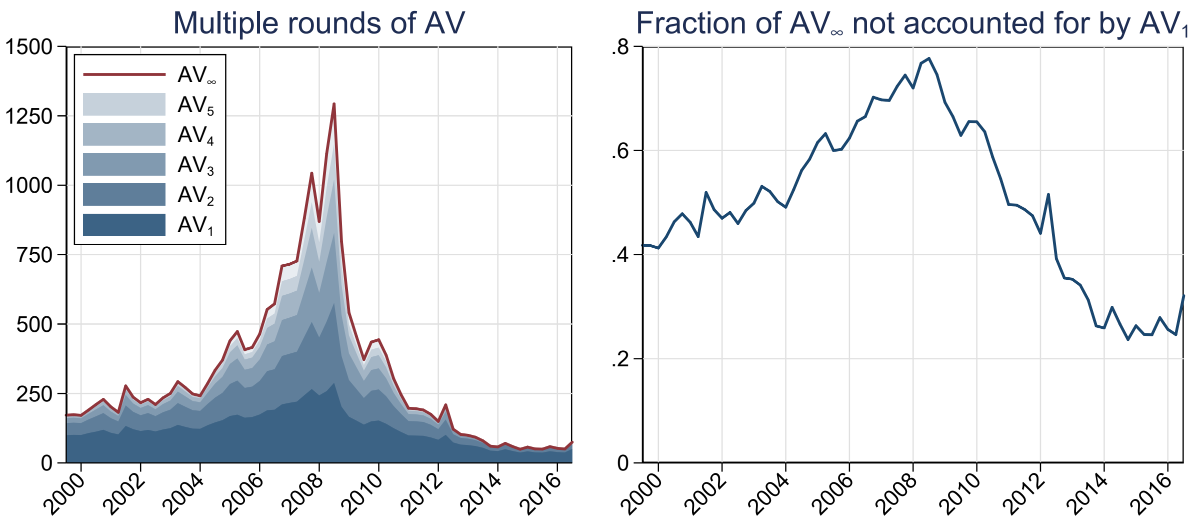

Figure 9: Effect of multiple rounds of fire sales on AV. The figure shows the effects on AV of additional rounds of fire sales until convergence (left panel) and the fraction of converged AV_∞ not accounted for by the first round AV_1 (right panel). Alternative AV indices are normalized by their relative size to raw benchmark AV at the beginning of the sample.

rounds and the level of AV. Among the factors of AV, the contribution of additional rounds is highly correlated with leverage (0.82), adjustment speed (0.87), and illiquidity concentration (0.84), but not with size (0.17). In terms of the behavior of the index over time, however, the one-round benchmark captures the essence of vulnerability to fire sales.

5.5 Other robustness checks

We consider several additional robustness checks in the appendix and show that the qualitative behavior of AV remains the same; its evolution over time is essentially unchanged. In Appendix E.1, instead of liquidity varying across assets according to NSFR weights, we consider constant liquidity across assets; and, instead of liquidity varying across time according to the wealth of potential buyers, we consider liquidity constant across time and liquidity varying according to GDP. In Appendix E.2, instead of including the top 100 banks every quarter, we consider a balanced panel. In Appendix E.3, instead of a shock to assets, we consider a shock that directly reduces the equity capital of banks.

6 Comparison with other systemic risk measures

Since the financial crisis, a large number of systemic risk measures have been proposed and analyzed. In this section, we compare AV, our measure based on systemic fire-sale spillovers, to 35 other measures of aggregate systemic risk. We show that, besides AV, only four other aggregate measures signal increasing systemic risk in the five years prior to the crisis. We also compare SB, our measure of individual bank systemicness, to seven other measures of bank-specific systemic risk. We then show that SB is an excellent predictor of five of these measures across horizons from one to five years, even controlling for bank-specific characteristics and the current value of the other systemic risk measures themselves. These results highlight the usefulness of our measures as early-warning indicators. Comparing AV and SB to other measures is also a useful way to externally validate them, as these other measures are constructed using data (mainly asset prices) and methodologies that differ from the ones used in AV and SB.

6.1 Aggregate early-warning properties

Systemic risk does not emerge overnight. Identifying the steady build-up of systemic risk is crucial to be able to respond to it — detecting trends and implementing policy actions can take time. Figure 10 shows the time evolution of AV and 35 other prominent measures of systemic risk from 2003q1 to 2009q1 taken from Bisias, Flood, Lo, and Valavanis (2012, "BFLV") and Giglio, Kelly, and Pruitt (2016). To make the growth rates easier to visualize, all measures are normalized to 100 in 2003q1, plotted in a log-scale, and winsorized for values lower than 50 and higher than 350. More details on these measures, including how they are constructed and individual plots without any transformations, are in Appendix H.

The top two panels show that 31 out of the 35 measures fail to identify any build-up of risk before the crisis. The top left panel shows in gray the 22 measures that signal no increased systemic risk until mid-2007 or later. In contrast, the red line that shows AV has a clear increasing trend. The top right panel shows in gray the nine measures that provide neither a clear trend nor any discernible signal of the crisis. These measures may be better suited to detect short-run bouts of systemic risk rather than lower frequency trends; they appear rather noisy over the multi-year sample we consider.

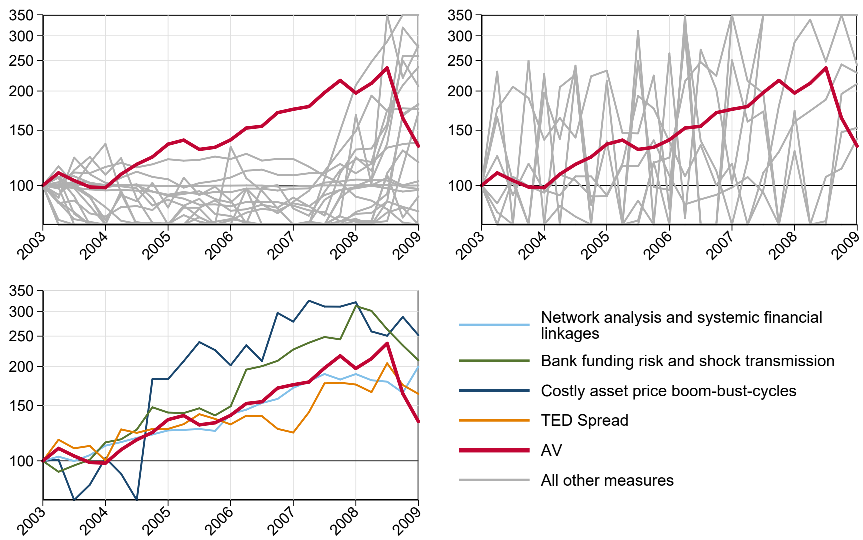

Figure 10: Comparison of AV to other systemic risk measures leading up to the crisis. Time-series evolution of AV and 35 systemic risk measures surveyed in Bisias et al. (2012) and Giglio et al. (2016) between 2003q1 and 2009q1. All measures are normalized to 100 in 2003q1 and shown in a log-scale, winsorized for values lower than 50 and higher than 350. The top left panel shows, in gray, the 22 measures that do not signal increased systemic risk until mid-2007 or later. The top right panel shows, in gray, the nine measures that provide neither a clear trend nor any discernible signal of a crisis. The bottom left panel shows the four systemic risk measures that have an increasing pre-crisis trend similar to the one that AV displays. Appendix H shows plots identifying each measure and gives details on how they were constructed.

The bottom left panel shows the four measures out of the 35 we consider that do have a clear increasing trend like AV between 2003 and the crisis. Two of the measures, which BFLV label "network analysis and systemic financial linkages" and "bank funding risk and shock transmission," are conceptually related to AV, as they are constructed to capture the interconnectedness of the financial system and banking system, respectively. The "network analysis and systemic financial linkages" measure is the only one surveyed in BFLV that has fire sales as a contributor to systemic risk; to the extent that other measures capture fire sale spillovers, they do so in an indirect or implicit way without any mention of them. The third measure, which BFLV label "costly asset price boom-bust-cycles," uses many macroeconomic and financial series to predict asset price booms that have serious negative consequences for the real economy. For the 2003–2008 period, the asset price boom predicted to adversely affect the real economy is in real estate. As discussed in Section 3, residential real estate loans are also the most systemic class of assets in our analysis and one of the main drivers of the increase in AV in this period, making AV also closely related to this measure. Additionally, BFLV classify this "costly asset price boom-bust-cycles" measure as an ex-ante, early warning, macroprudential measure, all of which also apply to AV. The fourth measure is the TED spread (three-month LIBOR minus three-month T-bill rate), which is mainly an indicator of credit risk in the interbank market. While this measure declines heading into 2007, it displays an overall low-frequency increasing trend between 2003 and the crisis. It does not have as clear-cut a relation to AV as the three other measures discussed above.

The takeaway is that only a minority of aggregate systemic risk measures are able to capture the slow and steady buildup of risk that accrued before the crisis, highlighting the usefulness of adding AV to the suite of existing measures. Of the four measures that do successfully capture the buildup, three are constructed using different data and methodologies than AV yet are conceptually related to AV. We interpret this, first, as helping to externally validate AV and, second, as additional evidence that the mechanism through which systemic risk increased before the crisis is related to the fire-sale channel we consider.

6.2 Predicting bank-level systemic risk

There is just one crisis in our sample, so any time-series analysis that reveals a consistent buildup in vulnerability like the one in Figure 10 effectively relies on a single identifying observation. Figure 10 also shows that the majority of measures react so late that they are effectively measures of risk realization rather than ex-ante measures that are predictive of risk. To more systematically analyze the early warning properties suggested by Figure 10, we exploit the panel data underlying the construction of AV and show that individual bank systemicness, SB_{it} from equation (9), predicts other bank-level systemic risk measures proposed in the literature at one- to five-year-ahead horizons. For this exercise, we use the seven measures that, out of the 35 considered above, have a cross-sectional dimension and thus allow for bank-specific measures of risk: SRISK, ΔCoVaR, systemic expected shortfall (SES), marginal expected shortfall (MES), systemic expected losses from a contingent claims analysis (CCA), distressed insurance premium (DIP) and Co-Risk. The aggregate versions of all of these are in the "late warning" category plotted in the top left panel of Figure 10. Conversely, none of the "early warning" measures in the bottom left panel have a cross-sectional dimension, so AV is the only measure that has early warning properties both in the time-series and, as we shall see, in the cross-section. This makes our framework unique in predicting not only when but also where systemic risk is building up.

Some of the measures we aim to predict reflect not only the systemicness of a bank but also its vulnerability to systemic risk. For example, SRISK is the expected capital shortfall of a given financial institution conditional on a severely adverse scenario for the entire financial system. SRISK can then be straightforwardly understood as a measure of vulnerability, since a large capital shortfall is associated with a higher risk of bankruptcy. Therefore, we also study how individual bank vulnerability, VB_{it} from equation (11), predicts the other seven cross-sectional systemic risk measures.

In our framework, the distinction between systemicness (SB) and vulnerability (VB) is more transparent. Table 6 shows the contemporaneous correlation between SB and VB, which at 13 percent implies that the two measures contain different information. Table 6 also displays the contemporaneous correlations of SB and VB with the seven other measures we consider. SB shows a positive correlation with all other measures, which provides further external validation that SB does indeed capture a notion of systemicness. It is most

Table 6: Correlations among bank-level systemic risk measures. The table shows pairwise correlations (pooling across time and banks) for bank systemicness SB, bank vulnerability VB, and the seven bank-specific systemic risk measures from Bisias et al. (2012) and Giglio et al. (2016): SRISK, ΔCoVaR, systemic expected shortfall (SES), marginal expected shortfall (MES), systemic expected losses from a contingent claims analysis (CCA), distressed insurance premium (DIP), and Co-Risk. All correlations are computed using quarterly data. For each pair of measures, we compute the correlation using all the observations for which both measures have non-missing data and that are included in the sample used to construct our measure of systemicness SB (1999q3 to 2016q3 for the top 100 banks by assets each quarter).

	SRISK	ΔCoVaR	SES	MES	CCA	DIP	CoRisk	SB	VB
SRISK	1.00								
ΔCoVaR	0.17	1.00							
SES	0.73	0.36	1.00						
MES	0.37	0.50	0.52	1.00					
CCA	0.39	0.34	0.57	0.24	1.00				
DIP	0.23	0.37	0.72	0.28	0.68	1.00			
CoRisk	0.09	0.22	0.06	0.13	0.07	0.06	1.00		
SB	0.16	0.37	0.56	0.23	0.67	0.87	0.12	1.00	
VB	-0.01	0.06	0.04	-0.05	0.04	0.03	0.17	0.13	1.00

correlated with DIP (87 percent) and CCA (67 percent). VB, in contrast, is generally uncorrelated with the other measures. It has a correlation of 17 percent with Co-Risk and a correlation of around zero with all other measures.

Predicting with fire-sale systemicness. To formally test for the ability of SB to predict another bank specific systemic risk measure, we run the dynamic panel regression

$$\text{OtherMeasure}_{it+\tau} = \beta\,\text{SB}_{it} + \delta\,\text{OtherMeasure}_{it} + \gamma\,\text{controls}_{it} + \nu_i + \eta_t + \varepsilon_{it+\tau}, \qquad (21)$$

using our full sample of quarterly data spanning 1999q3 to 2016q3 (SB_{it} is estimated with rolling regressions that use data starting in 1996q1 as explained in Section 3). The variable $\text{OtherMeasure}_{it+\tau}$ is the value for bank i at time $t+\tau$ of one of the seven systemic risk measures to be predicted, τ is the prediction horizon, ν_i are bank fixed effects, η_t are time fixed effects, $\varepsilon_{it+\tau}$ is an error term assumed to be uncorrelated with the regressors, and controls_{it} is a vector of bank-specific controls: conditional CAPM beta, stock returns, volatility of stock returns, physical probability of default over the next year, conditional value-at-risk at the 95 percent level, maturity mismatch between assets and liabilities, and number of subsidiaries. These controls are meant to capture bank characteristics that could, in principle, affect the systemicness of each bank but are, broadly speaking, not directly related to the specific fire-sale mechanism we consider.

Because regression (21) contains a lag of the dependent variable as a regressor, naive estimators — like OLS and the within-groups estimator — can be biased. We use the system GMM estimator of Arellano and Bover (1995) and Blundell and Bond (1998) which, in addition to helping with the bias, has been shown to have high asymptotic efficiency and excellent performance in finite samples (Kiviet et al., 2017). We assume that all regressors are endogenously determined except for the time fixed effect, which is assumed exogenous.[16] Consistent with these assumptions, we use as GMM instruments for the difference equation all lags of order one and higher for the time fixed effect, and of order two and higher for all other regressors. For the level equation, we use as instruments the first differences of the respective instruments used for the difference equation. We "collapse" the instrument matrix to keep the number of instruments small as recommended by Roodman (2009) and Kiviet et al. (2017) which, among other benefits, helps with the weak instruments problem. Appendix F.4 shows that the null hypothesis that the instruments are valid cannot be rejected at high confidence levels by using the Arellano and Bond (1991) test. The appendix also shows that results are robust to using various similar specifications and that the system GMM estimator is between the OLS and the within-groups estimator, consistent with the assumptions in Arellano and Bover (1995) and Blundell and Bond (1998).

The coefficient of interest in regression (21) is β. Panel A of Table 7 shows the estimated coefficients $\widehat{\beta}$ obtained by running the regression using prediction horizons $\tau \in \{20, 16, 12, 8, 4\}$ quarters (shown in the table as "5 yr ahead", "4 yr ahead", and so on) and each of the systemic risk measures we consider for $\text{OtherMeasure}_{it+\tau}$. Each cell contains an estimate $\widehat{\beta}$ obtained by running a different regression. Panel B of Table 7 shows the estimated coefficients $\widehat{\delta}$ on OtherMeasure_{it}, the measure being predicted, lagged by τ quarters.

Fire-sale systemicness SB significantly predicts SRISK, ΔCoVaR, SES, MES, and CCA at all horizons (p-val < 0.01 except for CCA at the one-year horizon with p-val < 0.05). SB predicts DIP only at the one-year horizon (p-val < 0.01) despite the two measures having

[16] A regressor x_{it} is endogenously determined if, for all t, $E[x_{it}\varepsilon_{it+s}] = 0$ for $s \geq 1$ and $E[x_{it}\varepsilon_{it+s}] \neq 0$ for $s \leq 0$. It is exogenous if, for all t, $E[x_{it}\varepsilon_{it+s}] = 0$ for all s.

Table 7: Predicting other systemic risk measures with bank systemicness. We run the predictive dynamic panel regression $\text{OtherMeasure}_{it+\tau} = \beta\,\text{SB}_{it} + \delta\,\text{OtherMeasure}_{it} + \gamma\,\text{controls}_{it} + \nu_i + \eta_t + \varepsilon_{it+\tau}$ using the system GMM estimator of Blundell and Bond (1998) and quarterly data from 1999q3 to 2016q3. OtherMeasure_{it} is one of the measures for bank i at time t from the set {SRISK, ΔCoVaR, SES, MES, CCA, DIP, Co-Risk}. SB_{it} is our measure of bank-specific systemicness. The vector controls_{it} contains bank-specific: conditional CAPM beta, stock returns, volatility of stock returns, physical probability of default over the next year, conditional value-at-risk at the 95 percent level, maturity mismatch between assets and liabilities, and number of subsidiaries. The regression contains bank and time fixed effects ν_i and η_t. We run one regression for each combination of prediction horizon $\tau \in \{20, 16, 12, 8, 4\}$ quarters (shown in the table as "5 yr ahead", "4 yr ahead", and so on) and choice of OtherMeasure_{it}, for a total of $(5\text{ horizons}) \times (7\text{ measures}) = 35$ regressions. Panel A reports the estimated coefficient $\widehat{\beta}$ on SB_{it} and Panel B reports the estimated coefficient $\widehat{\gamma}$ on OtherMeasure_{it}, for each of these 35 regressions. The corresponding t-statistics are in parentheses, computed using standard errors robust to heteroskedasticity and autocorrelation, clustered at the bank level, and adjusted for small samples using the Windmeijer (2005) correction; significance: $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$. Results for all other regression coefficients are in Appendix F.1.

	(1) SRISK	(2) ΔCoVaR	(3) SES	(4) MES	(5) CCA	(6) DIP	(7) CoRisk
	Panel A: Coefficient $\hat{\beta}$ on systemicness (SB_{it})						
5 yr ahead	3.24***	0.43***	5.34***	0.28***	0.04***	-4.81	-0.00*
	(4.30)	(3.29)	(4.29)	(3.52)	(7.78)	(-0.52)	(-1.85)
4 yr ahead	3.95***	0.87***	6.90***	0.40***	0.08***	-1.95	0.00
	(5.01)	(3.13)	(5.00)	(3.38)	(7.42)	(-0.17)	(0.80)
3 yr ahead	3.25***	1.03***	6.49***	0.31***	0.09***	0.93	0.00
	(5.08)	(3.75)	(5.00)	(2.84)	(4.88)	(0.09)	(0.68)
2 yr ahead	2.69***	0.86***	7.12***	0.42***	0.09***	5.09	0.00
	(4.98)	(4.08)	(8.66)	(4.23)	(4.25)	(0.87)	(0.50)
1 yr ahead	2.54***	0.83***	5.73***	0.57***	0.06**	9.88***	0.00*
	(10.34)	(5.35)	(7.34)	(5.71)	(2.23)	(6.19)	(1.81)
	Panel B: Coefficient $\hat{\delta}$ on OtherMeasure_{it}						
5 yr ahead	-0.12*	0.17***	-0.04	0.05	-0.07	0.50***	-0.08**
	(-1.66)	(3.48)	(-0.37)	(0.84)	(-1.13)	(4.71)	(-2.19)
4 yr ahead	-0.02	0.01	-0.04	-0.07	-0.19***	0.44**	-0.00
	(-0.36)	(0.26)	(-0.33)	(-1.38)	(-4.65)	(2.22)	(-0.08)
3 yr ahead	0.23***	0.14**	0.14*	-0.07	-0.26***	0.32**	0.05
	(7.50)	(2.25)	(1.66)	(-1.20)	(-8.69)	(2.02)	(1.34)
2 yr ahead	0.29***	0.26***	0.12*	-0.13	0.03	0.16	-0.12*
	(6.97)	(4.94)	(1.73)	(-1.46)	(0.61)	(1.28)	(-1.65)
1 yr ahead	0.58***	0.44***	0.28***	0.12**	-0.07	0.26***	-0.13***
	(13.40)	(15.78)	(3.46)	(2.29)	(-1.18)	(3.82)	(-3.28)

a high contemporaneous correlation (Table 6). SB does not predict Co-Risk at any of the horizons considered.

The magnitude of $\widehat{\beta}$ is also of interest. SB as well as SRISK, ΔCoVaR, SES, CCA, and DIP are measured in units of dollars divided by equity capital, making the interpretation straightforward. For example, the number 3.24 in the first row ($\tau = 5\text{y}$) and first column (SRISK) implies that an increase in systemicness SB equal to 1 percentage point of equity capital at time t is associated with an increase in SRISK of 3.24 percentage points five years later. MES has units of return (it is the average return of a firm during the 5% worst days for the market within the period) while Co-Risk is an elasticity (it is the percentage increase in a bank's CDS spread when all other banks experience a 1% increase in their CDS spread), so one must adjust the interpretation accordingly. Whenever SB predicts SRISK, ΔCoVaR, SES, MES, or DIP in a statistically significant way (with p-val < 0.05), the magnitude of $\widehat{\beta}$ is also economically large. For CCA, despite the high significance, the magnitude of $\widehat{\beta}$ is economically small.

Turning to the estimated coefficients $\widehat{\delta}$ on OtherMeasure$_{it}$ (Panel B of Table 7), we see that the measures themselves are much worse predictors of their future values than systemicness SB. The coefficients $\widehat{\delta}$ are significant in fewer instances or with a lower level of significance, and generally smaller in magnitude, than the coefficients $\widehat{\beta}$ in Panel A. Overall, SB is a better predictor of the measures than lags of the measures themselves for all cases except for DIP at the three to five year horizon. This confirms the notion that, in contrast to SB, the other measures are more prone to capture risk realization rather than ex-ante build-up of risk.

Predicting with fire-sale vulnerability. In Table 8, we repeat the predictability exercise but use our measure of fire-sale vulnerability VB$_{it}$ from equation (11) instead of our measure of systemicness SB$_{it}$ when running regression (21). Overall, VB is an excellent predictor of SRISK, ΔCoVaR, SES, and MES. Compared to SB, VB does not predict MES as strongly, and predicts neither CCA nor DIP.

Predicting with fire-sale factors. In Appendix F.1, we examine the results of running the same regression as equation (21) but replacing SB by its constituent factors from equation (9). The first goal is to further understand what economic forces drive the good predictive

Table 8: Predicting other systemic risk measures with bank vulnerability. We run the same predictive regressions as in Table 7 but replace bank systemicness, SB_{it}, by bank vulnerability, VB_{it}. We only report the coefficient $\widehat{\beta}$ on VB_{it}, with t-statistics in parentheses that are computed as in Table 7; significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Results for all other regression coefficients are in Appendix F.2.

	(1) SRISK	(2) ΔCoVaR	(3) SES	(4) MES	(5) CCA	(6) DIP	(7) CoRisk
5 yr ahead	40.29**	15.63***	79.88***	5.99***	0.09	2.20	-0.01***
	(2.48)	(4.53)	(2.68)	(2.91)	(0.91)	(0.37)	(-2.94)
4 yr ahead	38.95**	17.33***	95.25***	7.13***	0.12	-0.17	0.01
	(2.37)	(4.28)	(2.78)	(3.28)	(0.95)	(-0.02)	(1.13)
3 yr ahead	25.12**	10.50***	91.60**	2.29*	0.09	3.22	0.02
	(2.17)	(2.93)	(2.53)	(1.71)	(0.96)	(0.32)	(1.57)
2 yr ahead	10.20*	5.63**	97.35**	1.32	0.10	7.68	0.01
	(1.87)	(2.43)	(2.12)	(0.84)	(1.03)	(0.70)	(0.77)
1 yr ahead	25.69***	8.39***	54.00**	6.59***	0.05	12.99	0.01
	(3.22)	(3.52)	(2.09)	(2.74)	(0.81)	(0.81)	(0.78)

properties of our measure SB. The second goal is to assess the usefulness of the decomposition in equation (9) and the overall measure SB. For example, if only one factor were the single source of predictability, then one could dispense of SB in favor of that simpler factor. We use logs to adapt the multiplicative decomposition of equation (9) to the additive form of the regression and use $\log(\text{size}_{it})$, $\log(\text{leverage}_{it})$, $\log(\text{illiquidity linkage}_{it})$ and $\log(\text{adjustment speed}_{it})$ as regressors. To allow for the possibility that the covariances between factors, and not just their levels, drive predictability, we also include the six interaction terms, e.g., $\log(\text{size}_{it}) \times \log(\text{leverage}_{it})$.

We find that the different factors of SB drive predictability at different horizons and that the predictive power of different factors varies across the measures predicted. Overall, when illiquidity linkage and its interactions with other factors are strong predictors, the predictability tends to be at horizons of three years or less. In contrast, size, leverage, and adjustment speed show predictive power at all horizons.

Regarding different factors' predictive power across measures, SRISK and CCA are predicted by all factors (with different factors important at different horizons). ΔCoVaR loads most heavily on size. The predictability of SES comes from leverage and adjustment speed. MES is predicted by size and illiquidity linkage. DIP and Co-Risk are not meaningfully predicted by any of the factors, consistent with their lack of predictability with SB.

In terms of covariances, the only meaningful pattern we find is that if a factor other than size is a good predictor of a particular measure at a particular horizon, then it is likely that the interaction of the factor with size is also a good predictor of the same measure at the same horizon.

6.3 Predicting actual recapitalization needs

We now use our measure of individual bank vulnerability, VB_{it}, to predict a direct measure of realized bank-level vulnerability, the capital injections of the Troubled Asset Relief Program (TARP) during the crisis. We view this exercise as an important complement to the predictive panel regressions discussed above. First, it tests a different dimension of the fire-sale framework — whether more vulnerable banks do indeed have worse outcomes, as opposed to what banks contribute the most to systemic risk and do not necessarily have poor outcomes themselves. Second, in contrast to fire-sale externalities and systemic risk, the negative outcomes associated with vulnerability have a much closer empirical proxy, providing a more direct empirical test of the framework (in this case, recapitalization through TARP is a proxy for equity needs during the crisis). Third, it allows us to show that our framework is relevant not solely on average over the sample period we consider but also during a crisis, when it matters most.

We use the econometric assumptions and specification in Brownlees and Engle (2016), who conduct the same exercise of predicting capital needs but using their measure SRISK as the predictor. For a given time τ, we run the cross-sectional regression

$$\log \mathrm{CI}_i^* = \alpha_\tau + \beta_\tau \log \mathrm{VB}_{i\tau} + \gamma_\tau \, \mathrm{controls}_{i\tau} + \varepsilon_{i\tau}, \tag{22}$$

where $\log \mathrm{CI}_i^*$ are the log capital needs of bank i during 2008q4 and 2009q1, $\log \mathrm{VB}_{i\tau}$ is log vulnerability for bank i at time τ, $\mathrm{controls}_{i\tau}$ is a vector of control variables and $\varepsilon_{i\tau}$ is a Gaussian error term assumed to be uncorrelated with the regressors. We run two specifications. The first one includes no controls and the second one includes the controls $\mathrm{SRISK}_{i\tau}$, $\Delta\mathrm{CoVaR}_{i\tau}$, $\mathrm{MES}_{i\tau}$, volatility of stock returns, log assets, and equity capital fall between 2007q2 and 2008q2 as a share of assets.[17] Brownlees and Engle (2016) further assume that

[17]Unlike Brownlees and Engle (2016), we do not include industry dummies because our sample consists only of banks. See Brownlees and Engle (2016) for a more detailed discussion of the assumptions and inter-

Table 9: Predicting TARP capital injections with bank vulnerability. We estimate the cross-sectional equation $\log \mathrm{CI}_i^* = \alpha_\tau + \beta_\tau \log \mathrm{VB}_{i\tau} + \gamma_\tau \,\mathrm{controls}_{i\tau} + \varepsilon_{i\tau}$ to evaluate whether the log of vulnerability of bank i at time τ, $\log\mathrm{VB}_{i\tau}$, predicts the log of capital needs of bank i during 2008q4 and 2009q1, denoted by $\log \mathrm{CI}_i^*$. The vector $\mathrm{controls}_{i\tau}$ contains the control variables $\mathrm{SRISK}_{i\tau}$, $\Delta\mathrm{CoVaR}_{i\tau}$, $\mathrm{MES}_{i\tau}$, volatility of stock returns, log assets, and equity capital fall between 2007q2 and 2008q2 as a share of assets, while $\varepsilon_{i\tau}$ is a Gaussian error term assumed to be uncorrelated with the regressors. Capital needs, CI_i^*, are unobserved. We measure them by TARP capital injections, CI_i, which we assume are carried out only if the capital need is positive, leading us to observe the censored variable $\log \mathrm{CI}_i = \max\{\log \mathrm{CI}_i^*, 0\}$. To estimate the coefficients, we run six versions of the resulting Tobit regression (using $\tau \in \{2004q4, 2005q4, 2006q4\}$ with and without controls), which we estimate consistently by maximum likelihood. The t-statistics in parenthesis are computed using standard errors robust to heteroskedasticity and autocorrelation; significance: $^{*}\, p < 0.10$, $^{**}\, p < 0.05$, $^{***}\, p < 0.01$.

	$\tau = 2004q4$		$\tau = 2005q4$		$\tau = 2006q4$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\log \mathrm{VB}_{i\tau}$	13.69**	16.50**	6.84	21.39***	8.56	13.94**
	(2.48)	(2.46)	(1.09)	(3.32)	(1.43)	(2.15)
$\mathrm{SRISK}_{i\tau}$		-0.16		-2.00*		-1.21
		(-0.20)		(-1.70)		(-0.82)
$\mathrm{MES}_{i\tau}$		9.29		18.28**		14.37
		(1.28)		(2.31)		(1.56)
$\Delta\mathrm{CoVaR}_{i\tau}$		11.33*		6.53		2.37
		(1.74)		(1.08)		(0.27)
Equity Fall_i (07q2-08q2)		415.75		303.83		128.80
		(1.48)		(1.15)		(0.39)
Stock $\mathrm{Vol}_{i\tau}$		-15.15		-6.18		-17.57
		(-1.30)		(-0.60)		(-1.16)
log $\mathrm{Assets}_{i\tau}$		-1.54		-4.42		-1.72
		(-0.65)		(-1.60)		(-0.58)
Num Obs	100	38	100	40	100	40

capital needs are measured by TARP capital injections, CI_i, which are carried out only if the capital need is positive, leading the econometrician to observe the censored variable $\log \mathrm{CI}_i = \max\{\log \mathrm{CI}_i^*, 0\}$. Under these conditions, equation (22) is a Tobit regression that can be estimated consistently by maximum likelihood.

Table 9 shows the estimated coefficients for $\tau \in \{2004q4, 2005q4, 2006q4\}$, i.e. four, three and two years ahead of 2008q4, when capital injections start. Each column shows the results of a single cross-sectional regression. At the four-year horizon, $\tau = 2004q4$, our measure of bank vulnerability predicts capital injections, both with and without controls (columns 1 & 2, p-val < 0.05). In addition, the magnitude of the coefficient is economically

pretation of equation (22).

large and similar in the two specifications: a one percent increase in bank vulnerability in 2004q4 is associated with either a 13.69 or a 16.50 percent increase in TARP injections depending on whether controls are included. In terms of the controls, ΔCoVaR is weakly significant (p-val < 0.1) while SRISK and MES are not significant. Columns 3 through 6 repeat the exercise for the three- and two-year-ahead horizons. Without controls, the coefficient on (log) vulnerability VB is now insignificant. On the other hand, when controls are included, the coefficient is significant and remains economically large. The other measures are much less consistent in their ability to predict: the coefficient on SRISK is uniformly negative, significantly so at the three-year horizon; the coefficient on MES is significantly positive only at the three-year horizon; the coefficient on ΔCoVaR only at the four-year horizon. Appendix F.3 shows that vulnerability VB also predicts the probability of receiving a TARP injection by running a Probit regression with a TARP indicator as the dependent variable.

7 Conclusion

In this paper, we study the factors that make the financial system vulnerable to fire sales. We construct an index of aggregate vulnerability to fire sales of large bank holding companies that decomposes additively into each bank's "systemicness" as well as multiplicatively into aggregate versus cross-sectional factors that drive fire-sale vulnerability.

We use this framework to track vulnerability and its drivers over time. Our AV index starts increasing quickly in 2004, before most other major systemic risk measures, and reaches its peak in 2008. We identify the fire-sale specific factors of delevering speed and illiquidity concentration, and find that they account for the majority of the pre-crisis increase in AV. After the crisis, the index decreases equally dramatically, ending in late 2016 at roughly 40 percent of its initial 1999 level. This indicates that the the U.S. banking system materially reduced its vulnerability to fire sales during the post-crisis period.

We show that it is possible to predict systemic risk both in the time-series and the cross-section of banks. Individual banks' contributions to AV are excellent five-year-ahead predictors of five widely used measures of firm-specific systemic risk. Had they been available at the time, our measures would have been useful early-warning indicators of risk building up.

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Internet Appendix

A Comparison to Greenwood et al. (2015)

Greenwood et al. (2015) use an additive decomposition of AV into the sum of individual banks' systemicness,

$$\text{AV}_t = \sum_i \text{SB}_{it} = \sum_i \gamma_{it}^{\text{GLT}} \lambda_{it} b_{it}^{*} \frac{a_{it}}{e_t}, \tag{23}$$

where γ_{it}^{GLT} is the Greenwood et al. (2015) connectedness of bank i:

$$\gamma_{it}^{\text{GLT}} = \sum_k \left(\sum_{i'} a_{i't} m_{i'kt}\right) \frac{\ell_k}{w_t} m_{ikt}$$

Substituting γ_{it}^{GLT} into (23) and separating aggregate terms from cross-sectional terms, we arrive at our mulitplicative decomposition of AV already shown in equation (8),

$$\text{AV}_t = \underbrace{\frac{a_t}{w_t}}_{\text{rel. size}} \times \underbrace{(b_t + 1)\,\overline{b}_t^{*}}_{\text{leverage}} \times \underbrace{\overline{\lambda}_t}_{\text{adj. speed}} \times \underbrace{\sum_i \gamma_{it} \widetilde{\lambda}_{it} \beta_{it}^{*} \alpha_{it}}_{\text{illiquidity concentration}},$$

where γ_{it} is our "illiquidity linkage" for bank i (from equation 9), which differs from connectedness in Greenwood et al. (2015) by a factor $(a_t/w_t)^{-1}$:

$$\gamma_{it} = \sum_k m_{kt}^2 \ell_k \mu_{ikt} = \left(\frac{a_t}{w_t}\right)^{-1} \gamma_{it}^{\text{GLT}}$$

We choose this multiplicative decomposition for four reasons: (i) it separates aggregate determinants of fire-sale vulnerability from cross-sectional determinants (illiquidity concentration); (ii) it lends itself more readily to our focus on changes in AV over time since it allows us to track the evolution of each multiplicative factor; (iii) it separates the fire-sale specific factors of adjustment speed and illiquidity concentration from the size and leverage factors, which are known to affect systemic risk for various reasons; and (iv) the fire-sale specific factors empirically account for a large share of the variance of AV. Note that the shock part is analogous to the expression in Greenwood et al. (2015), $x_{it}^{\text{GLT}} = b_{it} a_{it} \sum_k m_{ikt} f_{kt}$, where banks are simply assumed to return to their pre-shock leverage. The difference in our framework is that the adjustment is partial and to a target, $\lambda_{it} \times b_{it}^{*}$, instead of full and to pre-shock leverage, $1 \times b_{it-1}$.

Greenwood et al. (2015) discuss a partial adjustment model in their Appendix B.2, but it features variation in neither b_{it}^{*} nor λ_{it}.

B Robustness checks for adjustment speed estimation

B.1 Construction of passive leverage

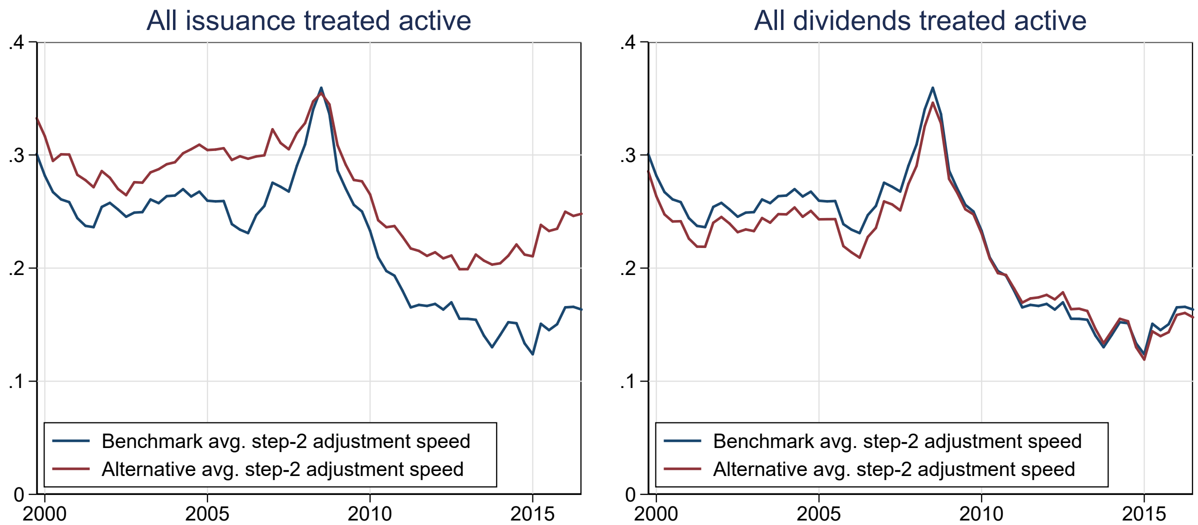


Figure IA-1: Comparison of average estimated adjustment speed $\overline{\lambda}_t$ under different assumptions for equity issuance (left panel) and for the persistence of dividends (right panel). The benchmark includes all equity issuance and the previous eight-quarter average dividends in passive leverage. The left panel compares to treating all equity issuance as active; the right panel treats all dividends as active. Sample includes any bank that is ever in the top 500 by assets.

In our estimation of the adjustment speed λ_{it}, we need to construct a passive leverage from which the bank adjusts to the observed actual leverage. We now consider the effects of two adjustments we make in the construction of passive leverage. First, the benchmark specification includes all equity issuance in passive leverage, emphasizing active leverage adjustments through balance sheet contraction. For robustness, we consider the effect of treating all equity issuance as active leverage adjustment (Figure IA-1, left panel). As expected, we see that this increases the average estimated adjustment speed but leaves the evolution over time largely unaffected. Second, the benchmark specification uses the previous eight-quarter average dividends as the baseline dividend payment in period t. We now consider treating all dividend payments as active leverage adjustments (Figure IA-1, right panel). We see that these alternatives have negligible effects on the evolution of the average estimated adjustment speed $\overline{\lambda}_t$.

B.2 Choice of estimates from windows

From each window of our rolling estimation, we use the last period's predicted bank-level leverage target from step 1 and the bank-level average predicted adjustment speed from

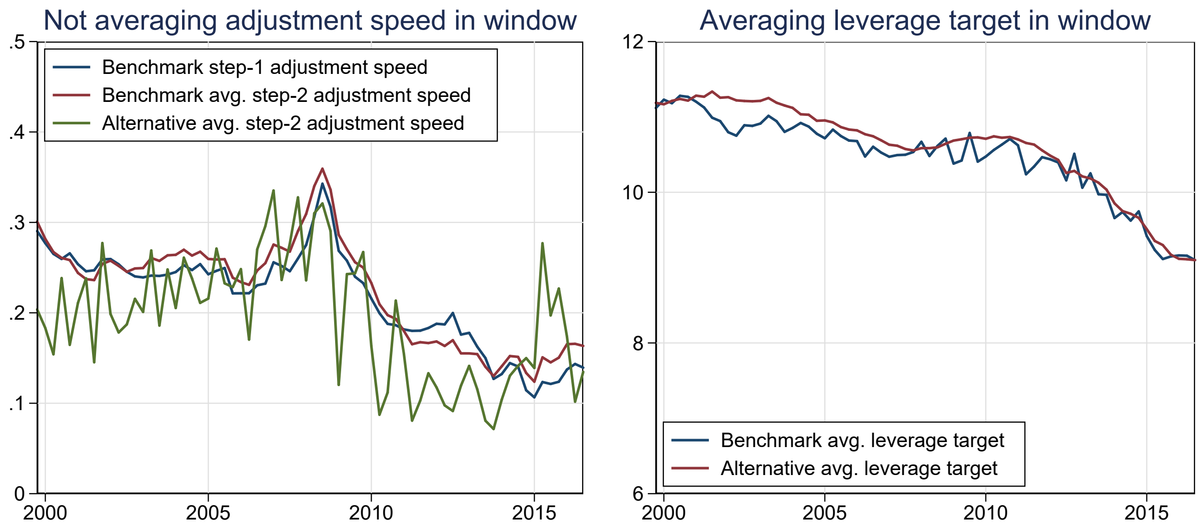


Figure IA-2: Comparison of average estimated adjustment speed $\overline{\lambda}_t$ (left panel) and average estimated leverage target $\overline{b}_t^*$ (right panel) under different treatment of the predicted values in each estimation window. In the benchmark, the predicted bank-level adjustment speed is first averaged within each window; the left panel compares to taking the predicted value for the last period of the window. In the benchmark, the predicted leverage target is as of the last period of the window; the right panel compares to first averaging the predicted bank-level leverage target. Sample includes any bank that is ever in the top 500 by assets.

step 2. In Figure IA-2, we show the results from reversing this treatment. The left panel compares the benchmark average step-2 adjustment speed $\overline{\lambda}_t$ to the version using the last period's predicted bank-level adjustment speed as well as the step-1 adjustment speed. We see that the benchmark average step-2 adjustment speed is very similar to the step-1 adjustment speed; in contrast, while the alternative average step-2 adjustment speed shows a similar overall trend, it is considerably more noisy quarter-to-quarter. The right panel of Figure IA-2 compares the benchmark average leverage target $\overline{b}_t^*$ to the version first averaging the bank-level predicted leverage target within each window. We see that the two are very similar with the alternative slightly smoother, as expected.

B.3 Dynamic panel estimation

In step 1 of our adjustment speed estimation, we use a standard fixed-effects regression. We now consider the effect on the estimated adjustment speed of using a system GMM approach (Arellano and Bover, 1995; Blundell and Bond, 1998). In the difference equation, we instrument the change in passive leverage with one lag of passive leverage; in the level equation, we instrument passive leverage with one lag of the change in passive leverage. We see a level difference in the estimates, consistent with a finite-sample bias in the fixed-effects regression. However, the evolution of the estimated adjustment speed is

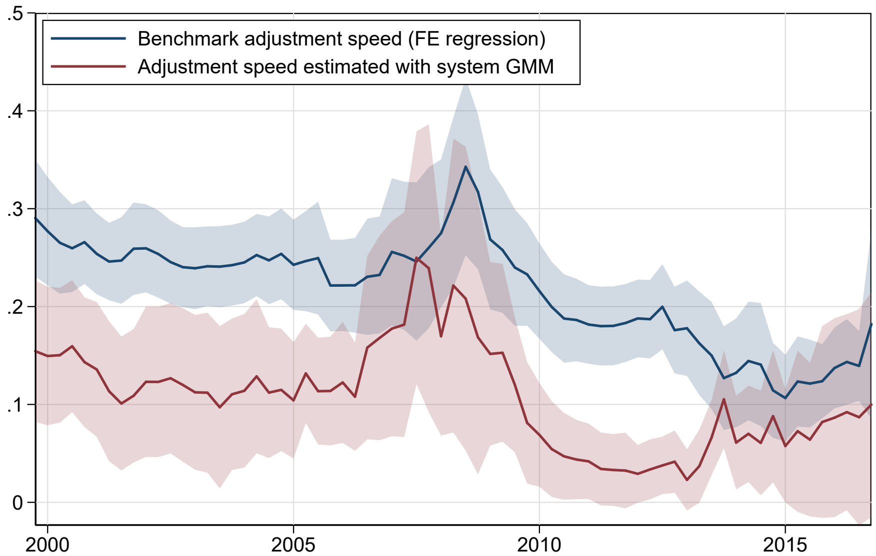


Figure IA-3: Comparison of adjustment speed from equation (15) using different estimation techniques. The benchmark uses a standard fixed-effects regression; the alternative uses a system GMM approach. Shaded areas indicate 95 percent confidence intervals computed using robust standard errors clustered at the bank level (FE regression) and based on the robust VCE estimator of Arellano and Bond (1991) (system GMM). Sample includes any bank that is ever in the top 500 by assets.

very similar under both approaches. Consistent with less precision due to the instrumental variable approach, the system GMM estimates have larger confidence intervals and are more volatile across the rolling windows — in particular in the run-up to the financial crisis.

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

Category	Codes on FR Y-9C (http://www.federalreserve.gov/apps/reportforms/)	
Total assets	Entire sample	bhck2170
Equity	Starting 2014q1	bhck8274 or bhca8274
	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 (http://www.federalreserve.gov/apps/reportforms/)	
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
Other real estate loans	Starting 2007q1	bhck1410 – (bhdm1797 + bhdm5367 + bhdm5368 + bhckf158 + bhckf159 + bhdm1460 + bhckf160 + bhckf161) + bhckf610 – (bhdmf606 + bhdmf607 + bhdmf611 + bhdmf604 + bhdmf612 + bhdmf613)

Category	Codes on FR Y-9C (http://www.federalreserve.gov/apps/reportforms/)	
	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.

D NSFR weights

We use price impacts ℓ_k based on the weights laid out under the Net Stable Funding Ratio (NSFR). The NSFR is fully described in "Basel III: The Net Stable Funding Ratio," issued in October 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

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.

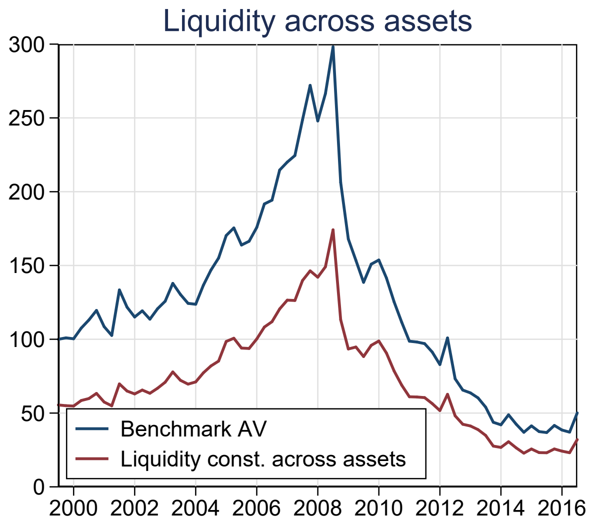
We determine liquidity weights based on the NSFR as follows:

Asset class	NSFR haircut	Notes
U.S. Treasuries	5%	See section II.B, paragraph 37.
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 32 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 39.
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 37–42.
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 40 and 43.
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 40–41.
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 40–41.
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 40–42.

Asset class	NSFR haircut	Notes
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 40–42.
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
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 43.
Residual securities	100%	See section II.B, paragraph 43.

E Robustness checks for spillovers calculation

E.1 Liquidity across assets and time



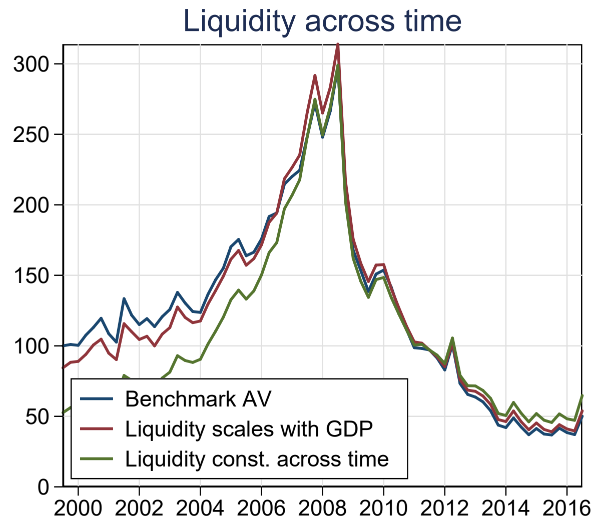


Figure IA-4: Effect of different liquidity assumptions across assets and time.

For BHCs, the benchmark specification has liquidity of asset classes based on the Net Stable Funding Ratio (NSFR) of the Basel III regulatory framework. Greenwood et al. (2015) instead assume the same price impact for all assets, $\ell_k = \ell$ for all k, and base the estimate on the liquidity of corporate bonds. Figure IA-4 (left panel) shows that AV is lower under this assumption (since most bank assets are less liquid than corporate bonds).

In our benchmark, we adjust liquidity across time by the wealth w_t of potential buyers of fire-sold assets. We proxy for w_t using total financial sector assets net of BHCs, 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. 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 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.[18] For this scenario, we set $w_t = \text{const.}$ in all periods t. Figure IA-4 (right panel) shows the implications of the two scenarios.[19]

[18]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.

[19]By construction, AV under all three scenarios is the same in 2011q3, the quarter we use to normalize absolute asset liquidity, to be consistent with Greenwood et al. (2015).

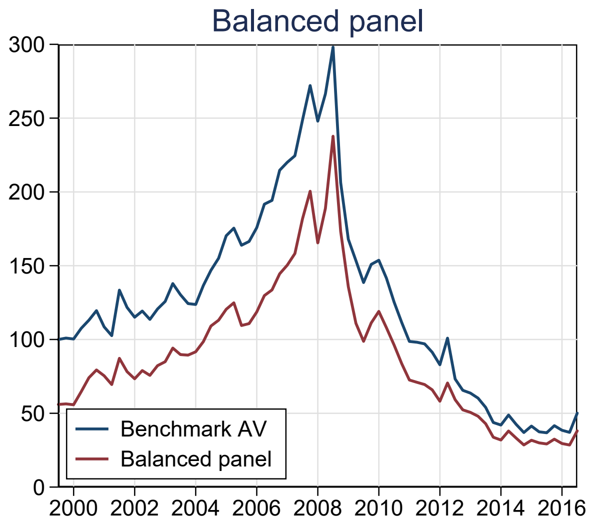


Figure IA-5: Comparison of benchmark AV to AV with a balanced panel of banks (left panel) and with equity shocks (right panel).

There is a notable difference only for the constant liquidity scenario and only in the pre-crisis period, where the growth in AV is faster than in the benchmark. This is due to the fact that over this period, 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.

E.2 Balanced panel of institutions

In our main analysis, we include the top 100 banks every quarter that have leverage target estimates from Section 3, which may be different sets in each period. Figure IA-5, left panel, displays AV when we only keep banks that have been present throughout the entire sample. 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.

E.3 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).[20]

We calibrate the equity shock to have the same average initial direct losses as our benchmark of a one percent uniform asset shock.[21] To do so, we first compute the size g_{it} 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:

$$g_{it} = \frac{0.01 \times a_{it}}{e_{it}}.$$

Then, we take the average of g_{it} 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.

Figure IA-5, right panel, 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, therefore amplifying and transmitting less externalities.

E.4 Details on risk-based capital requirements

We capture the trade-off between risk weights and price impact in a simple model. Bank i's equity capital must exceed a fixed percentage of its risk-weighted assets

$$e_{it} \geq \kappa a_{it}^{\omega} = \kappa \sum_{k=1}^{K} \omega_k m_{ikt} a_{it}, \tag{24}$$

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

[21]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.

where $\kappa \in (0, 1)$ is a fixed number picked by the regulator and $\omega_k \geq 0$ is the risk weight of asset k.

We maintain the partial adjustment model for leverage and the implied cash amount x_{it}^f, but assume that the bank wants to minimize the total price discount it suffers when selling assets but still satisfy the capital requirement (equation (24)) and the budget constraint (that it has to raise x_{it}^f). The price impact for bank i of selling a share $\rho_{ikt} \in [0, 1]$ of its holdings in asset k is $\ell_k \rho_{ikt} m_{ikt} a_{it}$ basis points, since $\rho_{ikt} m_{ikt} a_{it}$ 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 $\ell_k \left(\rho_{ikt} m_{ikt} a_{it}\right)^2$ dollars. The amount of asset k remaining on the balance sheet is $\left(1 - \rho_{ikt}\right) m_{ikt} a_{it}$ dollars. The bank's optimization problem is then

$$\min_{\rho_{ikt}} \sum_{k=1}^{K} \ell_k \left(\rho_{ikt} m_{ikt} a_{it}\right)^2 \tag{25}$$

$$\text{s.t.} \quad e_{it} \geq \kappa \sum_{k=1}^{K} \omega_k \left(1 - \rho_{ikt}\right) m_{ikt} a_{it},$$

$$x_{it}^f = \sum_{k=1}^{K} \rho_{ikt} m_{ikt} a_{it} - \sum_{k=1}^{K} \ell_k \left(\rho_{ikt} m_{ikt} a_{it}\right)^2 \tag{26}$$

$$0 \leq \rho_{ikt} \leq 1 \tag{27}$$

We calibrate risk weights ω_k by using the "standardized approach" of capital requirements in Basel III.[22] 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.

F Appendix to Section 6

F.1 Predictive dynamic panel regressions of other systemic risk measures using systemicness and its factors as predictors

[22] Appendix G 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.

Table IA-1: $\text{SRISK}_{it+\tau} = \beta \text{SB}_{it} + \delta \text{SRISK}_{it} + \gamma \text{controls}_{it} + \nu_i + \eta_t + \varepsilon_{it+\tau}$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$\tau = 20$q	$\tau = 16$q	$\tau = 12$q	$\tau = 8$q	$\tau = 4$q	$\tau = 20$q	$\tau = 16$q	$\tau = 12$q	$\tau = 8$q	$\tau = 4$q
SB_{it}	3.24***	3.95***	3.25***	2.69***	2.54***					
	(4.30)	(5.01)	(5.08)	(4.98)	(10.34)					
Rel. Assets_{it}						1.46**	-0.40	-1.00**	-1.20**	-0.62**
						(2.16)	(-0.93)	(-2.27)	(-2.44)	(-2.35)
Rel. Leverage_{it}						16.69***	14.35*	7.81	4.62	4.30
						(2.68)	(1.99)	(1.33)	(1.06)	(1.63)
Illiquidity Link_{it}						-9.74	5.38	9.48**	10.53***	6.24***
						(-1.62)	(1.20)	(2.23)	(3.07)	(3.36)
Adj speed_{it}						-8.99	-5.06	12.45**	20.78**	3.50
						(-0.85)	(-0.40)	(2.06)	(2.37)	(0.75)
$\text{Assets}_{it} \times \text{Lev}_{it}$						2.88***	2.36*	1.18	0.67	0.63
						(2.78)	(1.94)	(1.32)	(0.98)	(1.49)
$\text{Assets}_{it} \times \text{Illiq}_{it}$						-2.18*	0.70	1.66**	1.88***	1.08***
						(-1.75)	(0.88)	(2.20)	(2.94)	(2.93)
$\text{Lev}_{it} \times \text{Illiq}_{it}$						5.04**	3.02	0.90	0.18	0.33
						(2.04)	(1.16)	(0.63)	(0.15)	(0.38)
$\text{Assets}_{it} \times \lambda_{it}$						-0.59	-0.15	2.46*	3.67**	0.37
						(-0.42)	(-0.07)	(1.88)	(2.26)	(0.42)
$\text{Lev}_{it} \times \lambda_{it}$						-4.16	-3.63	-4.08	-3.36*	-0.91
						(-1.39)	(-1.19)	(-1.57)	(-1.80)	(-1.17)
$\lambda_{it} \times \text{Illiq}_{it}$						4.48	3.93	3.57	1.66	-1.39
						(0.59)	(0.75)	(1.12)	(0.41)	(-0.42)
SRISK_{it}	-0.12	-0.02	0.23***	0.29***	0.58***	-0.01	0.09**	0.28***	0.33***	0.64***
	(-1.66)	(-0.36)	(7.50)	(6.97)	(13.40)	(-0.11)	(2.19)	(12.19)	(10.82)	(20.26)
Stock Ret_{it}	0.00	-0.00	0.00	0.00	-0.00	0.00	-0.00	-0.00	-0.00	-0.00
	(0.90)	(-1.08)	(0.59)	(0.58)	(-0.60)	(0.81)	(-0.92)	(-0.19)	(-1.04)	(-1.22)
Stock Vol_{it}	0.30*	0.32	0.25	-0.06	-0.18	0.26	0.33	0.25	0.04	-0.10
	(1.82)	(1.63)	(1.27)	(-0.44)	(-1.06)	(1.49)	(1.64)	(1.25)	(0.26)	(-0.75)
CAPM beta_{it}	-1.38**	-1.71**	-1.52*	-0.44	0.11	-0.92**	-1.20*	-1.22	-0.40	0.08
	(-2.46)	(-2.22)	(-1.75)	(-0.85)	(0.68)	(-2.40)	(-1.95)	(-1.48)	(-0.73)	(0.48)
Prob Def_{it}	2.07	2.78	3.52	1.37	2.48	5.24	1.58	-0.95	-6.87	-2.52
	(0.26)	(0.68)	(1.12)	(0.36)	(0.28)	(0.44)	(0.30)	(-0.44)	(-1.30)	(-0.30)
95% VaR_{it}	-1.64*	-2.77*	-2.43*	-1.56	-1.14	-1.25*	-2.47*	-2.28*	-1.81	-1.45
	(-1.89)	(-1.99)	(-1.78)	(-1.27)	(-1.11)	(-1.69)	(-1.92)	(-1.85)	(-1.55)	(-1.38)
Mat Mismatch_{it}	-0.50	-1.04	-2.27	-1.55	-1.90	-1.47	-1.71	-2.82	-1.89	-0.90
	(-0.69)	(-1.09)	(-1.01)	(-1.17)	(-1.45)	(-0.88)	(-0.79)	(-1.14)	(-1.16)	(-1.12)
# $\text{Subs}_{it} \times 10^{-3}$	-0.87	0.02	0.08	0.58	0.00	-0.12	1.06**	1.12*	1.39***	0.72***
	(-1.44)	(0.05)	(0.19)	(1.51)	(0.01)	(-0.20)	(2.09)	(1.79)	(2.68)	(3.62)
AR(2) p-value	0.96	0.61	0.74	0.52	0.93	0.79	0.83	0.74	0.90	0.59
Num Obs	1,453	1,675	1,904	2,139	2,283	1,448	1,666	1,892	2,125	2,269

t-statistics in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Table IA-2: $\Delta\text{CoVaR}_{it+\tau} = \beta\text{SB}_{it} + \delta\Delta\text{CoVaR}_{it} + \gamma\text{controls}_{it} + \nu_i + \eta_t + \varepsilon_{it+\tau}$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$\tau = 20q$	$\tau = 16q$	$\tau = 12q$	$\tau = 8q$	$\tau = 4q$	$\tau = 20q$	$\tau = 16q$	$\tau = 12q$	$\tau = 8q$	$\tau = 4q$
SB_{it}	0.43***	0.87***	1.03***	0.86***	0.83***					
	(3.29)	(3.13)	(3.75)	(4.08)	(5.35)					
Rel. Assets_{it}						1.27***	0.97***	0.54***	0.38***	0.50***
						(7.49)	(6.04)	(3.94)	(2.73)	(4.16)
Rel. Leverage_{it}						-2.00	-0.93	0.43	-1.39	-1.76***
						(-1.44)	(-0.94)	(0.34)	(-1.41)	(-2.74)
Illiquidity Link_{it}						-3.84**	-0.83	0.95	2.08	0.48
						(-2.36)	(-0.54)	(0.68)	(1.59)	(0.41)
Adj speed_{it}						-2.43	-2.55**	-0.14	1.55	-2.56**
						(-1.42)	(-2.17)	(-0.11)	(1.05)	(-2.22)
$\text{Assets}_{it} \times \text{Lev}_{it}$						-0.27	-0.03	0.12	-0.21	-0.26***
						(-1.21)	(-0.17)	(0.53)	(-1.22)	(-2.62)
$\text{Assets}_{it} \times \text{Illiq}_{it}$						-0.61**	-0.09	0.29	0.55**	0.25
						(-2.17)	(-0.35)	(1.39)	(2.47)	(1.17)
$\text{Lev}_{it} \times \text{Illiq}_{it}$						0.06	0.86	0.26	-0.17	-0.30
						(0.13)	(1.48)	(0.39)	(-0.25)	(-0.72)
$\text{Assets}_{it} \times \lambda_{it}$						-0.16	-0.24	-0.15	-0.02	-0.53***
						(-0.49)	(-0.92)	(-0.68)	(-0.07)	(-2.85)
$\text{Lev}_{it} \times \lambda_{it}$						-0.06	-0.71	-0.75**	-0.01	-0.18
						(-0.13)	(-1.40)	(-2.18)	(-0.04)	(-0.67)
$\lambda_{it} \times \text{Illiq}_{it}$						1.11	1.59	0.28	-1.91*	-2.40***
						(0.64)	(0.87)	(0.21)	(-1.85)	(-2.94)
ΔCoVaR_{it}	0.17***	0.01	0.14**	0.26***	0.44***	-0.12***	-0.23***	-0.01	0.11**	0.33***
	(3.48)	(0.26)	(2.25)	(4.94)	(15.78)	(-3.05)	(-5.17)	(-0.24)	(2.58)	(12.49)
Stock Ret_{it}	0.00*	0.00**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(1.75)	(2.07)	(1.33)	(1.42)	(1.35)	(1.38)	(0.41)	(0.11)	(0.77)	(0.92)
Stock Vol_{it}	0.04	-0.02	-0.01	-0.11***	-0.08***	0.04	-0.05	-0.00	-0.10***	-0.09***
	(0.94)	(-0.56)	(-0.28)	(-3.30)	(-2.69)	(1.13)	(-1.45)	(-0.19)	(-3.26)	(-2.94)
CAPM beta_{it}	-0.45***	-0.19**	-0.07	0.04	0.12*	-0.39***	-0.17**	-0.10	0.05	0.11
	(-4.26)	(-2.35)	(-0.99)	(0.51)	(1.96)	(-4.30)	(-2.08)	(-1.25)	(0.77)	(1.61)
Prob Def_{it}	-1.31	-0.60	-0.55	1.66	2.61**	-0.23	0.78	-1.16	2.76**	2.87**
	(-0.82)	(-0.57)	(-0.74)	(1.61)	(2.33)	(-0.19)	(0.67)	(-1.41)	(2.19)	(2.43)
95% VaR_{it}	-0.81***	-0.30*	-0.52***	-0.37*	-0.10	-0.19	-0.13	-0.47***	-0.17	-0.02
	(-4.08)	(-1.94)	(-4.34)	(-1.69)	(-0.76)	(-1.06)	(-0.64)	(-3.13)	(-1.09)	(-0.23)
Mat Mismatch_{it}	-0.68	-0.50	-0.49	-0.28	-0.98**	-0.46	-0.87**	-0.52	-0.51	-0.26
	(-1.24)	(-1.40)	(-1.15)	(-0.75)	(-2.22)	(-1.09)	(-2.54)	(-0.88)	(-0.96)	(-0.61)
# $\text{Subs}_{it} \times 10^{-3}$	0.62**	1.00***	0.92**	0.94***	0.38*	-0.61***	-0.13	0.21	0.17	-0.09
	(2.54)	(2.76)	(2.19)	(2.75)	(1.76)	(-3.63)	(-0.86)	(0.93)	(0.87)	(-0.50)
AR(2) p-value	0.40	0.55	0.09	0.87	0.05	0.55	0.15	0.08	0.33	0.13
Num Obs	2,240	2,652	3,060	3,425	3,826	2,238	2,646	3,050	3,412	3,812

t-statistics in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Table IA-3: $\text{SES}_{it+\tau} = \beta\text{SB}_{it} + \delta\text{SES}_{it} + \gamma\text{controls}_{it} + \nu_i + \eta_t + \varepsilon_{it+\tau}$

	(1) $\tau = 20q$	(2) $\tau = 16q$	(3) $\tau = 12q$	(4) $\tau = 8q$	(5) $\tau = 4q$	(6) $\tau = 20q$	(7) $\tau = 16q$	(8) $\tau = 12q$	(9) $\tau = 8q$	(10) $\tau = 4q$
SB_{it}	5.34***	6.90***	6.49***	7.12***	5.73***					
	(4.29)	(5.00)	(5.00)	(8.66)	(7.34)					
Rel. Assets_{it}						0.93	1.96	0.25	-0.21	0.25
						(0.81)	(1.05)	(0.17)	(-0.15)	(0.32)
Rel. Leverage_{it}						25.85***	27.99***	29.96***	34.73***	24.38***
						(3.90)	(4.20)	(4.68)	(3.33)	(3.13)
Illiquidity Link_{it}						9.78	15.00*	17.12*	17.93	12.18*
						(1.29)	(1.93)	(1.89)	(1.58)	(1.77)
Adj speed_{it}						19.21**	-24.04*	7.38	7.87	-22.00**
						(2.17)	(-1.82)	(0.70)	(0.53)	(-2.16)
$\text{Assets}_{it} \times \text{Lev}_{it}$						6.33***	7.10***	7.39***	7.76***	5.67***
						(5.18)	(6.89)	(5.37)	(3.74)	(3.40)
$\text{Assets}_{it} \times \text{Illiq}_{it}$						1.93	3.06*	3.75*	3.64	2.57*
						(1.17)	(1.86)	(1.89)	(1.52)	(1.75)
$\text{Lev}_{it} \times \text{Illiq}_{it}$						10.61	12.34	10.57	3.91	3.36
						(1.26)	(1.17)	(1.18)	(0.45)	(0.45)
$\text{Assets}_{it} \times \lambda_{it}$						5.20**	-7.05*	1.06	1.88	-6.02**
						(2.24)	(-1.86)	(0.36)	(0.51)	(-2.08)
$\text{Lev}_{it} \times \lambda_{it}$						-3.35	-0.74	-5.18	0.27	9.21
						(-0.51)	(-0.08)	(-0.60)	(0.03)	(1.39)
$\lambda_{it} \times \text{Illiq}_{it}$						16.33	-11.68	6.62	10.93	-5.93
						(1.66)	(-0.76)	(0.52)	(0.77)	(-0.64)
SES_{it}	-0.04	-0.04	0.14	0.12*	0.28***	-0.08	0.01	0.12**	0.15**	0.43***
	(-0.37)	(-0.33)	(1.66)	(1.73)	(3.46)	(-1.16)	(0.15)	(2.22)	(2.45)	(7.76)
Stock Ret_{it}	0.00	0.00	0.00	0.00	-0.00	0.00**	0.00	0.00*	0.00	-0.00
	(1.32)	(1.56)	(1.44)	(0.12)	(-1.60)	(2.56)	(1.31)	(1.84)	(0.36)	(-1.42)
Stock Vol_{it}	0.15	0.11	0.18	0.14	-0.20	0.12	0.30*	0.31	0.21	-0.11
	(1.01)	(0.64)	(1.45)	(0.33)	(-0.53)	(0.88)	(1.84)	(1.50)	(1.25)	(-0.34)
CAPM beta_{it}	-1.00	-1.11*	-1.10*	-0.16	2.04	-0.11	-0.83	-0.70	-0.05	1.54
	(-1.71)	(-1.82)	(-1.83)	(-0.62)	(1.45)	(-0.16)	(-1.44)	(-1.08)	(-0.08)	(1.27)
Prob Def_{it}	6.74	1.53	-9.21	-22.20	-39.54	7.76	-9.19	-1.37	-25.07***	-57.95**
	(0.43)	(0.08)	(-1.20)	(-1.08)	(-1.32)	(1.10)	(-0.95)	(-0.22)	(-3.02)	(-2.33)
95% VaR_{it}	0.57	0.58	0.99	-1.61	0.40	1.49	1.95	1.12	0.10	1.05
	(0.59)	(0.55)	(1.23)	(-0.58)	(0.44)	(1.29)	(1.46)	(0.82)	(0.06)	(1.07)
Mat Mismatch_{it}	-0.33	-1.10	-2.68	-3.92	-1.02	-1.32	-3.52	-3.58	-4.11	-1.56
	(-0.28)	(-0.56)	(-1.27)	(-1.27)	(-0.77)	(-0.79)	(-1.12)	(-1.33)	(-1.43)	(-0.73)
# $\text{Subs}_{it} \times 10^{-3}$	0.84*	1.06	0.43	0.17	0.20	0.46	-0.21	0.43	0.57	0.28
	(1.84)	(1.54)	(1.21)	(0.41)	(0.59)	(0.87)	(-0.21)	(0.45)	(0.70)	(0.57)
AR(2) p-value	0.24	0.18	0.41	0.19	0.20	0.20	0.06	0.21	0.26	0.36
Num Obs	550	646	719	724	732	550	646	719	724	732

t-statistics in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

Table IA-4: $\text{MES}_{it+\tau} = \beta \text{SB}_{it} + \delta \text{MES}_{it} + \gamma \text{controls}_{it} + \nu_i + \eta_t + \varepsilon_{it+\tau}$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$\tau = 20q$	$\tau = 16q$	$\tau = 12q$	$\tau = 8q$	$\tau = 4q$	$\tau = 20q$	$\tau = 16q$	$\tau = 12q$	$\tau = 8q$	$\tau = 4q$
SB_{it}	0.28***	0.40***	0.31***	0.42***	0.57***					
	(3.52)	(3.38)	(2.84)	(4.23)	(5.71)					
Rel. Assets_{it}						0.71***	0.21	0.12	0.05	0.06
						(4.23)	(1.61)	(1.49)	(0.55)	(0.61)
Rel. Leverage_{it}						-0.31	-0.81	-0.46	-0.55	-0.36
						(-0.33)	(-0.92)	(-0.58)	(-0.70)	(-0.58)
Illiquidity Link_{it}						-3.53**	-0.21	0.43	0.89	0.72
						(-2.56)	(-0.19)	(0.57)	(1.16)	(0.76)
Adj speed_{it}						-2.50	-3.27	1.29	2.31*	-1.41
						(-1.14)	(-1.14)	(1.42)	(1.77)	(-1.54)
$\text{Assets}_{it} \times \text{Lev}_{it}$						0.11	-0.06	-0.11	-0.14	-0.01
						(0.69)	(-0.38)	(-0.88)	(-1.14)	(-0.05)
$\text{Assets}_{it} \times \text{Illiq}_{it}$						-0.76***	-0.07	0.14	0.23	0.17
						(-2.78)	(-0.39)	(0.96)	(1.42)	(0.97)
$\text{Lev}_{it} \times \text{Illiq}_{it}$						1.37*	0.51	-0.59*	-0.56**	0.30
						(1.77)	(0.93)	(-1.83)	(-2.19)	(1.02)
$\text{Assets}_{it} \times \lambda_{it}$						-0.43	-0.39	0.40*	0.51**	-0.38**
						(-1.11)	(-0.87)	(1.90)	(2.14)	(-2.10)
$\text{Lev}_{it} \times \lambda_{it}$						-0.53	-0.17	-0.89**	0.26	-0.13
						(-0.97)	(-0.36)	(-2.18)	(0.51)	(-0.66)
$\lambda_{it} \times \text{Illiq}_{it}$						0.24	0.89	1.84*	1.52	-1.46
						(0.15)	(0.54)	(1.67)	(1.42)	(-1.36)
MES_{it}	0.05	-0.07	-0.07	-0.13	0.12**	0.10*	0.01	0.01	0.00	0.20***
	(0.84)	(-1.38)	(-1.20)	(-1.46)	(2.29)	(1.76)	(0.15)	(0.15)	(0.02)	(4.14)
Stock Ret_{it}	-0.00	-0.00***	-0.00	-0.00*	-0.00***	-0.00	-0.00***	-0.00	-0.00*	-0.00***
	(-0.15)	(-4.59)	(-1.22)	(-1.70)	(-2.94)	(-0.03)	(-4.04)	(-0.73)	(-1.70)	(-3.19)
Stock Vol_{it}	-0.03	0.08**	0.09**	0.06*	-0.01	-0.03	0.06*	0.07*	0.04	-0.03
	(-0.91)	(2.57)	(2.21)	(1.72)	(-0.15)	(-0.98)	(1.87)	(1.84)	(1.32)	(-0.96)
CAPM beta_{it}	0.13	-0.21**	-0.18	-0.00	0.13*	0.02	-0.14	-0.19*	0.02	0.18**
	(1.43)	(-2.24)	(-1.63)	(-0.03)	(1.78)	(0.30)	(-1.55)	(-1.72)	(0.30)	(2.57)
Prob Def_{it}	-1.70*	-0.40	1.53	-3.62**	-4.09**	-2.11	-1.22	0.08	-5.57***	-4.11**
	(-1.92)	(-0.37)	(1.13)	(-2.06)	(-2.33)	(-1.55)	(-1.25)	(0.06)	(-4.51)	(-2.38)
95% VaR_{it}	-0.30**	-0.22	-0.00	-0.10	0.42***	-0.34**	-0.28**	-0.06	-0.22	0.37***
	(-2.24)	(-1.64)	(-0.03)	(-0.59)	(3.10)	(-2.33)	(-2.53)	(-0.45)	(-1.35)	(2.95)
Mat Mismatch_{it}	-0.25	-0.48	-0.64	-0.42	-0.15	-0.67***	-0.79*	-1.09***	-0.75**	-0.64***
	(-0.82)	(-1.25)	(-1.39)	(-0.85)	(-0.44)	(-2.73)	(-1.77)	(-3.45)	(-2.51)	(-3.04)
# $\text{Subs}_{it} \times 10^{-3}$	0.13	0.03	0.17**	0.22	0.11	-0.26**	0.07	0.02	0.13	0.11
	(1.32)	(0.23)	(2.04)	(1.65)	(0.90)	(-2.21)	(0.60)	(0.18)	(1.30)	(0.74)
AR(2) p-value	0.08	0.09	0.04	0.05	0.02	0.09	0.07	0.04	0.04	0.01
Num Obs	1,453	1,675	1,904	2,139	2,283	1,448	1,666	1,892	2,125	2,269

t-statistics in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Table IA-5: $CCA_{it+\tau} = \beta SB_{it} + \delta CCA_{it} + \gamma controls_{it} + \nu_i + \eta_t + \varepsilon_{it+\tau}$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$\tau = 20$q	$\tau = 16$q	$\tau = 12$q	$\tau = 8$q	$\tau = 4$q	$\tau = 20$q	$\tau = 16$q	$\tau = 12$q	$\tau = 8$q	$\tau = 4$q
SB_{it}	0.04***	0.08***	0.09***	0.09***	0.06**					
	(7.78)	(7.42)	(4.88)	(4.25)	(2.23)					
Rel. $Assets_{it}$						0.02**	0.01	-0.04***	-0.05***	-0.03***
						(2.24)	(1.43)	(-3.53)	(-3.41)	(-2.76)
Rel. $Leverage_{it}$						0.32***	0.36***	0.13*	0.05	-0.08
						(2.64)	(3.30)	(1.80)	(0.47)	(-1.20)
Illiquidity $Link_{it}$						-0.06	0.08	0.45***	0.53***	0.43***
						(-0.91)	(1.06)	(3.81)	(3.88)	(3.13)
Adj $speed_{it}$						-0.32***	-0.28*	-0.13	0.13	0.30
						(-2.83)	(-1.71)	(-1.14)	(1.28)	(1.52)
$Assets_{it} \times Lev_{it}$						0.05**	0.06***	0.02**	0.01	-0.01
						(2.55)	(3.26)	(2.02)	(0.70)	(-1.11)
$Assets_{it} \times Illiq_{it}$						-0.01	0.02	0.08***	0.09***	0.07***
						(-0.88)	(1.42)	(3.67)	(3.64)	(3.15)
$Lev_{it} \times Illiq_{it}$						0.06*	0.06**	0.03	0.01	-0.01
						(1.97)	(2.37)	(1.17)	(0.54)	(-0.29)
$Assets_{it} \times \lambda_{it}$						-0.05***	-0.05**	-0.03*	0.01	0.05
						(-3.55)	(-2.11)	(-1.71)	(1.00)	(1.64)
$Lev_{it} \times \lambda_{it}$						-0.04	-0.05*	-0.00	-0.02	0.01
						(-1.04)	(-1.78)	(-0.25)	(-0.96)	(0.40)
$\lambda_{it} \times Illiq_{it}$						-0.03	-0.09	-0.15*	-0.02	0.11
						(-0.32)	(-1.15)	(-1.82)	(-0.41)	(1.53)
CCA_{it}	-0.07	-0.19***	-0.26***	0.03	-0.07	-0.05	-0.16***	-0.21***	0.09***	-0.00
	(-1.13)	(-4.65)	(-8.69)	(0.61)	(-1.18)	(-0.70)	(-8.73)	(-10.14)	(7.68)	(-0.04)
Stock Ret_{it}	0.00	-0.00	0.00**	-0.00	0.00*	0.00*	0.00	0.00*	-0.00	0.00*
	(1.46)	(-1.10)	(1.99)	(-0.70)	(1.80)	(1.88)	(0.28)	(1.82)	(-0.75)	(1.73)
Stock Vol_{it}	-0.00	-0.00	-0.00*	-0.00*	0.00	0.00	0.00	-0.00	-0.00*	-0.00
	(-0.06)	(-0.48)	(-1.88)	(-1.75)	(0.90)	(0.02)	(0.50)	(-1.16)	(-1.93)	(-1.38)
CAPM $beta_{it}$	-0.01	-0.01	-0.00	0.00	0.00	-0.01	-0.01*	-0.00	0.01	0.01**
	(-1.09)	(-1.64)	(-1.65)	(0.75)	(1.09)	(-0.97)	(-1.82)	(-0.87)	(1.40)	(2.14)
Prob Def_{it}	-0.08	0.00	0.11	0.01	0.08	0.04	0.07	0.10	0.00	0.10
	(-0.80)	(0.12)	(1.35)	(0.23)	(0.98)	(0.49)	(1.31)	(1.29)	(0.02)	(1.29)
95% VaR_{it}	-0.00	-0.02*	-0.01*	0.00	0.00	-0.00	-0.01	-0.00	0.01	0.01*
	(-0.61)	(-1.96)	(-1.89)	(0.36)	(0.59)	(-0.16)	(-1.31)	(-0.33)	(1.21)	(1.69)
Mat $Mismatch_{it}$	0.02	-0.00	0.01	0.01	0.04	0.01	0.01	0.02	0.02	0.01
	(1.31)	(-0.03)	(0.72)	(0.60)	(1.43)	(0.55)	(0.48)	(1.46)	(1.12)	(0.46)
# $Subs_{it} \times 10^{-3}$	-0.02*	-0.01	0.02**	0.02	0.05**	-0.02	0.01	0.07***	0.06***	0.06***
	(-1.79)	(-0.86)	(2.17)	(1.27)	(2.20)	(-1.65)	(0.39)	(3.86)	(3.76)	(4.87)
AR(2) p-value	0.77	0.80	0.54	0.54	0.40	0.74	0.73	0.59	0.68	0.64
Num Obs	2,814	3,235	3,624	3,820	4,034	2,809	3,226	3,612	3,806	4,020

t-statistics in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

Table IA-6: $\text{DIP}_{it+\tau} = \beta \text{SB}_{it} + \delta \text{DIP}_{it} + \gamma \text{controls}_{it} + \nu_i + \eta_t + \varepsilon_{it+\tau}$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$\tau = 20$q	$\tau = 16$q	$\tau = 12$q	$\tau = 8$q	$\tau = 4$q	$\tau = 20$q	$\tau = 16$q	$\tau = 12$q	$\tau = 8$q	$\tau = 4$q
SB_{it}	-4.81	-1.95	0.93	5.09	9.88***					
	(-0.52)	(-0.17)	(0.09)	(0.87)	(6.19)					
Rel. Assets_{it}						9.99	9.43	5.99	4.90	2.97
						(1.36)	(1.54)	(1.33)	(1.08)	(1.37)
Rel. Leverage_{it}						-2.30	-2.32	12.04	24.75	28.83
						(-0.10)	(-0.11)	(0.79)	(1.34)	(1.24)
Illiquidity Link_{it}						-18.26	-20.82	-8.87	5.77	6.71
						(-0.37)	(-0.50)	(-0.28)	(0.17)	(0.34)
Adj speed_{it}						-54.03	-85.31	-77.79*	-40.32	-38.44
						(-1.64)	(-1.54)	(-1.66)	(-1.32)	(-1.50)
$\text{Assets}_{it} \times \text{Lev}_{it}$						1.55	0.81	2.48	4.46	5.14
						(0.42)	(0.24)	(1.00)	(1.53)	(1.37)
$\text{Assets}_{it} \times \text{Illiq}_{it}$						-2.55	-2.61	0.00	1.94	1.66
						(-0.33)	(-0.40)	(0.00)	(0.38)	(0.53)
$\text{Lev}_{it} \times \text{Illiq}_{it}$						7.56	3.91	2.00	2.08	4.45
						(1.20)	(0.78)	(0.53)	(0.64)	(1.56)
$\text{Assets}_{it} \times \lambda_{it}$						-10.16*	-14.21	-12.28*	-7.27*	-6.62*
						(-1.88)	(-1.65)	(-1.87)	(-1.77)	(-1.75)
$\text{Lev}_{it} \times \lambda_{it}$						2.71	2.84	2.99	-2.42	-0.34
						(0.49)	(0.48)	(0.69)	(-1.34)	(-0.25)
$\lambda_{it} \times \text{Illiq}_{it}$						-17.79	-10.93	-6.71	-9.01	-4.78
						(-1.10)	(-0.66)	(-0.41)	(-0.57)	(-0.45)
DIP_{it}	0.50***	0.44**	0.32**	0.16	0.26***	0.32***	0.33***	0.26***	0.17**	0.36***
	(4.71)	(2.22)	(2.02)	(1.28)	(3.82)	(3.28)	(4.66)	(4.85)	(2.22)	(6.23)
Stock Ret_{it}	0.00	-0.00	0.00	0.00	-0.00	0.01*	0.00**	0.00**	0.00*	0.00
	(1.38)	(-1.16)	(0.02)	(0.28)	(-0.68)	(1.95)	(2.05)	(2.05)	(1.69)	(0.07)
Stock Vol_{it}	0.08	-0.06	-0.02	-0.07	-0.07	-0.45*	-0.46*	-0.01	0.01	-0.05
	(0.25)	(-0.30)	(-0.12)	(-0.30)	(-0.50)	(-1.68)	(-1.87)	(-0.04)	(0.03)	(-0.21)
CAPM beta_{it}	0.98	0.09	-0.74	-0.57	-0.08	1.35	-0.21	-1.16	-0.59	-0.07
	(0.41)	(0.09)	(-0.81)	(-0.45)	(-0.22)	(0.76)	(-0.26)	(-1.21)	(-0.51)	(-0.14)
Prob Def_{it}	-35.53	-7.65	-9.27	-10.38	-17.06	5.81	23.80*	8.54	-5.46	-16.74
	(-1.34)	(-0.77)	(-0.97)	(-0.76)	(-0.84)	(0.54)	(1.74)	(1.04)	(-0.66)	(-0.86)
95% VaR_{it}	2.68	-0.66	-1.47	-3.88*	-3.02	3.56	0.83	0.61	-3.73**	-2.84
	(0.75)	(-0.48)	(-1.63)	(-1.95)	(-1.20)	(1.19)	(0.54)	(0.47)	(-1.98)	(-1.17)
Mat Mismatch_{it}	9.04	6.74	-4.42	-4.49	-3.63	17.34	8.21	4.33	2.39	3.90
	(1.53)	(1.33)	(-1.27)	(-1.15)	(-1.38)	(1.44)	(1.13)	(1.32)	(0.73)	(1.54)
# $\text{Subs}_{it} \times 10^{-3}$	2.04	0.08	2.31	6.96**	4.27	-0.86	-2.33	0.97	4.71	5.99
	(0.56)	(0.02)	(0.63)	(2.19)	(0.90)	(-0.16)	(-0.37)	(0.17)	(0.75)	(1.30)
AR(2) p-value	0.13	0.08	0.05	0.12	0.19	0.04	0.05	0.03	0.04	0.13
Num Obs	2,814	3,235	3,624	3,820	4,034	2,809	3,226	3,612	3,806	4,020

t-statistics in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Table IA-7: $\text{CoRisk}_{it+\tau} = \beta\text{SB}_{it} + \delta\text{CoRisk}_{it} + \gamma\text{controls}_{it} + \nu_i + \eta_t + \varepsilon_{it+\tau}$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$\tau = 20$q	$\tau = 16$q	$\tau = 12$q	$\tau = 8$q	$\tau = 4$q	$\tau = 20$q	$\tau = 16$q	$\tau = 12$q	$\tau = 8$q	$\tau = 4$q
SB_{it}	-0.00*	0.00	0.00	0.00	0.00*					
	(-1.85)	(0.80)	(0.68)	(0.50)	(1.81)					
Rel. Assets_{it}						-0.00	0.00	0.00	-0.00	0.00
						(-0.56)	(1.02)	(1.04)	(-0.27)	(0.34)
Rel. Leverage_{it}						-0.00	-0.00	0.00	0.00*	0.00
						(-1.26)	(-0.99)	(0.61)	(1.71)	(1.05)
Illiquidity Link_{it}						0.00	-0.00	-0.00	0.00	-0.00
						(1.05)	(-1.07)	(-0.61)	(0.33)	(-0.64)
Adj speed_{it}						0.00	-0.00	-0.01*	0.00	0.00
						(0.69)	(-0.96)	(-1.80)	(0.06)	(0.47)
$\text{Assets}_{it} \times \text{Lev}_{it}$						-0.00***	-0.00	0.00	0.00	0.00***
						(-3.65)	(-0.20)	(0.27)	(0.85)	(3.28)
$\text{Assets}_{it} \times \text{Illiq}_{it}$						0.00	-0.00	-0.00	0.00	-0.00
						(1.19)	(-1.08)	(-0.79)	(0.31)	(-0.51)
$\text{Lev}_{it} \times \text{Illiq}_{it}$						-0.00***	0.00**	0.00	-0.00	0.00***
						(-4.01)	(2.67)	(0.08)	(-0.72)	(3.95)
$\text{Assets}_{it} \times \lambda_{it}$						0.00	-0.00	-0.00	-0.00	0.00
						(0.69)	(-0.22)	(-0.67)	(-0.13)	(0.40)
$\text{Lev}_{it} \times \lambda_{it}$						0.00	0.00	0.00	0.00	-0.00**
						(1.69)	(1.28)	(1.05)	(1.07)	(-2.20)
$\lambda_{it} \times \text{Illiq}_{it}$						0.00	0.00*	0.01	0.00	-0.00
						(0.70)	(1.77)	(1.54)	(0.64)	(-0.65)
CoRisk_{it}	-0.08**	-0.00	0.05	-0.12	-0.13***	-0.06*	-0.01	0.06*	-0.11	-0.15***
	(-2.19)	(-0.08)	(1.34)	(-1.65)	(-3.28)	(-2.02)	(-0.22)	(1.87)	(-1.35)	(-4.56)
Stock Ret_{it}	0.00	0.00**	-0.00	0.00	0.00	0.00	0.00***	-0.00	0.00	0.00
	(0.46)	(2.15)	(-0.23)	(0.76)	(0.87)	(0.65)	(3.08)	(-1.56)	(0.18)	(0.66)
Stock Vol_{it}	0.00	0.00	-0.00	0.00	0.00**	0.00	0.00	-0.00*	0.00	0.00***
	(0.53)	(0.18)	(-1.26)	(1.21)	(2.19)	(0.55)	(1.07)	(-1.83)	(1.26)	(3.16)
CAPM beta_{it}	-0.00**	-0.00	0.00	-0.00	-0.00***	-0.00***	-0.00*	0.00	-0.00	-0.00***
	(-2.23)	(-0.37)	(0.88)	(-1.42)	(-4.01)	(-3.21)	(-1.96)	(0.66)	(-1.55)	(-4.46)
Prob Def_{it}	-0.00	0.00	0.00	-0.01	-0.00	-0.00	-0.00	0.00	-0.01	-0.00
	(-0.36)	(0.18)	(0.87)	(-0.95)	(-0.26)	(-0.30)	(-0.62)	(0.67)	(-1.02)	(-1.04)
95% VaR_{it}	0.00	0.00	0.00	-0.00	-0.00*	0.00	0.00	-0.00	-0.00	-0.00
	(0.85)	(0.52)	(0.68)	(-0.78)	(-1.83)	(1.33)	(1.48)	(-0.03)	(-1.31)	(-1.13)
Mat Mismatch_{it}	0.00	-0.00	0.00	0.00	0.00	-0.00	0.00	-0.00	0.00	0.00
	(1.68)	(-0.96)	(0.45)	(0.90)	(0.98)	(-0.27)	(0.29)	(-0.31)	(0.39)	(1.68)
# $\text{Subs}_{it} \times 10^{-3}$	0.00	-0.00	-0.00	0.00	-0.00	0.00	0.00	-0.00	0.00	-0.00
	(1.65)	(-0.64)	(-0.43)	(0.06)	(-0.62)	(0.68)	(0.26)	(-0.17)	(0.52)	(-0.22)
AR(2) p-value	0.70	0.06	0.01	0.27	0.55	0.68	0.07	0.01	0.36	0.55
Num Obs	551	641	729	774	824	546	632	717	760	810

t-statistics in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

F.2 Predictive dynamic panel regressions of other systemic risk measures using vulnerability as predictor

Table IA-8: $\text{SRISK}_{it+\tau} = \beta\,\text{VB}_{it} + \delta\,\text{SRISK}_{it} + \gamma\,\text{controls}_{it} + \nu_i + \eta_t + \varepsilon_{it+\tau}$

	(1)	(2)	(3)	(4)	(5)
	$\tau = 20$q	$\tau = 16$q	$\tau = 12$q	$\tau = 8$q	$\tau = 4$q
VB_{it}	40.29**	38.95**	25.12**	10.20*	25.69***
	(2.48)	(2.37)	(2.17)	(1.87)	(3.22)
SRISK_{it}	-0.04	0.05	0.24***	0.29***	0.61***
	(-0.85)	(1.51)	(4.93)	(4.54)	(10.57)
Stock Ret_{it}	0.00	-0.00	0.00	-0.00	-0.00
	(1.29)	(-0.53)	(1.48)	(-0.19)	(-0.44)
Stock Vol_{it}	0.28*	0.33*	0.24	-0.03	-0.12
	(1.95)	(1.80)	(1.47)	(-0.30)	(-0.97)
CAPM beta_{it}	-1.00**	-1.14*	-0.84	-0.22	0.07
	(-2.30)	(-1.73)	(-1.24)	(-0.53)	(0.52)
Prob Def_{it}	-6.64*	-8.23	-4.32	-6.42**	-3.10
	(-1.71)	(-1.49)	(-0.55)	(-2.48)	(-0.63)
95% VaR_{it}	-1.10	-1.79*	-1.50	-1.22	-0.82
	(-1.35)	(-1.72)	(-1.60)	(-1.33)	(-1.02)
Mat Mismatch_{it}	-2.59*	-1.59	-0.85	-0.81	-1.59
	(-1.75)	(-1.36)	(-0.61)	(-0.78)	(-1.25)
# Subs_{it} $\times 10^{-3}$	0.66	1.40***	1.31***	1.33**	0.36
	(1.03)	(2.72)	(2.82)	(2.49)	(1.16)
AR(2) p-value	0.76	0.74	0.76	0.55	0.70
Num Obs	1,453	1,675	1,904	2,139	2,283

t statistics in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Table IA-9: $\text{CoVaR}_{it+\tau} = \beta\,\text{VB}_{it} + \delta\,\text{CoVaR}_{it} + \gamma\,\text{controls}_{it} + \nu_i + \eta_t + \varepsilon_{it+\tau}$

	(1)	(2)	(3)	(4)	(5)
	$\tau = 20$q	$\tau = 16$q	$\tau = 12$q	$\tau = 8$q	$\tau = 4$q
VB_{it}	15.63***	17.33***	10.50***	5.63**	8.39***
	(4.53)	(4.28)	(2.93)	(2.43)	(3.52)
ΔCoVaR_{it}	0.13**	-0.03	0.15***	0.27***	0.45***
	(2.61)	(-0.50)	(3.01)	(5.31)	(14.59)
Stock Ret_{it}	0.00**	0.00***	0.00	0.00*	0.00*
	(2.52)	(3.12)	(1.25)	(1.77)	(1.73)
Stock Vol_{it}	0.02	-0.05	-0.01	-0.12***	-0.09***
	(0.48)	(-1.36)	(-0.31)	(-3.90)	(-2.77)
CAPM beta_{it}	-0.40***	-0.16**	-0.10	0.02	0.09*
	(-4.32)	(-2.38)	(-1.42)	(0.28)	(1.66)
Prob Def_{it}	-1.52	0.11	-2.94**	1.48	1.25
	(-1.52)	(0.10)	(-2.41)	(1.06)	(0.90)
95% VaR_{it}	-0.60***	-0.20	-0.35**	-0.21	0.08
	(-2.88)	(-1.05)	(-2.52)	(-1.05)	(0.73)
Mat Mismatch_{it}	-1.05*	-1.01**	-0.40	-0.28	-0.63**
	(-1.79)	(-2.09)	(-0.68)	(-0.59)	(-1.99)
# Subs_{it} $\times 10^{-3}$	0.76**	1.60***	1.52***	1.46***	0.90***
	(2.47)	(2.85)	(2.95)	(3.25)	(3.02)
AR(2) p-value	0.27	0.30	0.20	0.75	0.04
Num Obs	2,240	2,652	3,060	3,425	3,826

t statistics in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Table IA-10: $\text{SES}_{it+\tau} = \beta\,\text{VB}_{it} + \delta\,\text{SES}_{it} + \gamma\,\text{controls}_{it} + \nu_i + \eta_t + \varepsilon_{it+\tau}$

	(1)	(2)	(3)	(4)	(5)
	$\tau = 20$q	$\tau = 16$q	$\tau = 12$q	$\tau = 8$q	$\tau = 4$q
VB_{it}	79.88**	95.25**	91.60**	97.35**	54.00**
	(2.68)	(2.78)	(2.53)	(2.12)	(2.09)
SES_{it}	0.10	0.15	0.32***	0.34***	0.47***
	(1.04)	(1.23)	(3.67)	(3.69)	(4.70)
Stock Ret_{it}	0.01**	0.01**	0.01*	0.00	-0.00
	(2.21)	(2.38)	(2.04)	(1.54)	(-0.58)
Stock Vol_{it}	-0.22	-0.08	-0.02	-0.04	-0.33
	(-0.55)	(-0.36)	(-0.11)	(-0.06)	(-0.65)
CAPM beta_{it}	0.51	-1.05	-1.31	-0.43	1.81
	(0.88)	(-1.46)	(-1.44)	(-0.81)	(1.33)
Prob Def_{it}	-1.77	-18.22	-25.24**	-42.71	-62.37
	(-0.07)	(-0.79)	(-2.08)	(-1.37)	(-1.69)
95% VaR_{it}	2.88*	1.96	3.18**	0.33	2.48
	(1.76)	(1.25)	(2.34)	(0.12)	(1.41)
Mat Mismatch_{it}	1.58	5.16	-0.80	-0.41	4.64
	(0.49)	(0.83)	(-0.19)	(-0.10)	(1.14)
# Subs_{it} $\times 10^{-3}$	2.87**	3.69**	2.42*	2.45*	2.30**
	(2.44)	(2.21)	(1.99)	(1.95)	(2.42)
AR(2) p-value	0.45	0.09	0.28	0.30	0.41
Num Obs	550	646	719	724	732

t statistics in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Table IA-11: $\text{MES}_{it+\tau} = \beta\,\text{VB}_{it} + \delta\,\text{MES}_{it} + \gamma\,\text{controls}_{it} + \nu_i + \eta_t + \varepsilon_{it+\tau}$

	(1)	(2)	(3)	(4)	(5)
	$\tau = 20$q	$\tau = 16$q	$\tau = 12$q	$\tau = 8$q	$\tau = 4$q
VB_{it}	5.99***	7.13***	2.29*	1.32	6.59***
	(2.91)	(3.28)	(1.71)	(0.84)	(2.74)
MES_{it}	0.08	0.03	0.00	-0.08	0.19***
	(1.49)	(0.44)	(0.01)	(-0.91)	(3.53)
Stock Ret_{it}	0.00	-0.00***	-0.00	-0.00*	-0.00**
	(0.16)	(-3.66)	(-0.70)	(-1.74)	(-2.38)
Stock Vol_{it}	-0.05*	0.04	0.06*	0.04	-0.02
	(-1.67)	(1.27)	(1.74)	(1.29)	(-0.52)
CAPM beta_{it}	0.09	-0.16*	-0.15	0.03	0.11
	(1.10)	(-1.92)	(-1.54)	(0.44)	(1.64)
Prob Def_{it}	1.15	-0.34	1.07	-4.40**	-4.74***
	(0.72)	(-0.29)	(0.80)	(-2.46)	(-3.43)
95% VaR_{it}	-0.25*	-0.06	0.12	-0.07	0.48***
	(-1.99)	(-0.46)	(0.95)	(-0.42)	(3.48)
Mat Mismatch_{it}	-0.68**	-0.98**	-0.68	-0.42	-0.23
	(-2.61)	(-2.05)	(-1.54)	(-0.90)	(-0.62)
# Subs_{it} $\times 10^{-3}$	0.12	0.13*	0.19**	0.26**	0.13
	(1.25)	(1.70)	(2.55)	(2.02)	(1.48)
AR(2) p-value	0.07	0.08	0.04	0.05	0.02
Num Obs	1,453	1,675	1,904	2,139	2,283

t statistics in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

Table IA-12: $\text{CCA}_{it+\tau} = \beta\,\text{VB}_{it} + \delta\,\text{CCA}_{it} + \gamma\,\text{controls}_{it} + \nu_i + \eta_t + \varepsilon_{it+\tau}$

	(1)	(2)	(3)	(4)	(5)
	$\tau = 20$q	$\tau = 16$q	$\tau = 12$q	$\tau = 8$q	$\tau = 4$q
VB_{it}	0.09	0.12	0.09	0.10	0.05
	(0.91)	(0.95)	(0.96)	(1.03)	(0.81)
CCA_{it}	-0.09***	-0.10**	-0.19***	0.13**	0.01
	(-3.36)	(-2.13)	(-3.06)	(2.16)	(0.06)
Stock Ret_{it}	0.00	-0.00	0.00*	-0.00	0.00**
	(1.36)	(-1.26)	(1.89)	(-1.03)	(2.04)
Stock Vol_{it}	0.00	0.00	0.00	-0.00	0.00
	(0.23)	(0.12)	(0.40)	(-0.86)	(0.97)
CAPM beta_{it}	-0.01	-0.00*	-0.01*	-0.00	0.00
	(-1.05)	(-1.71)	(-1.83)	(-0.31)	(0.65)
Prob Def_{it}	-0.11	-0.05	0.08	-0.02	0.07
	(-1.08)	(-0.93)	(0.88)	(-0.49)	(0.74)
95% VaR_{it}	-0.00	-0.01	-0.00	0.01	0.01
	(-0.55)	(-1.25)	(-0.22)	(0.86)	(0.84)
Mat Mismatch_{it}	0.03	0.04	0.06	0.06*	0.04
	(1.48)	(1.35)	(1.48)	(1.68)	(1.32)
# Subs_{it} $\times 10^{-3}$	-0.01	0.01	0.03***	0.03***	0.07***
	(-0.65)	(0.89)	(2.99)	(2.69)	(2.78)
AR(2) p-value	0.74	0.70	0.54	0.70	0.53
Num Obs	2,814	3,235	3,624	3,820	4,034

t statistics in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

Table IA-13: $\text{DIP}_{it+\tau} = \beta\,\text{VB}_{it} + \delta\,\text{DIP}_{it} + \gamma\,\text{controls}_{it} + \nu_i + \eta_t + \varepsilon_{it+\tau}$

	(1) $\tau = 20$q	(2) $\tau = 16$q	(3) $\tau = 12$q	(4) $\tau = 8$q	(5) $\tau = 4$q
VB_{it}	2.20	-0.17	3.22	7.68	12.99
	(0.37)	(-0.02)	(0.32)	(0.70)	(0.81)
DIP_{it}	0.47***	0.42***	0.36***	0.30***	0.54***
	(2.82)	(5.73)	(3.68)	(2.95)	(17.09)
Stock Ret_{it}	0.00	-0.00*	0.00	0.00	-0.00
	(1.26)	(-1.78)	(0.86)	(0.86)	(-0.97)
Stock Vol_{it}	0.20	0.15	0.06	-0.03	-0.00
	(0.56)	(0.60)	(0.51)	(-0.12)	(-0.02)
CAPM beta_{it}	0.76	-0.02	-1.15	-1.09	-0.57
	(0.39)	(-0.02)	(-1.23)	(-0.73)	(-0.94)
Prob Def_{it}	-35.24	-14.08	-14.16	-15.63	-22.40
	(-1.35)	(-1.05)	(-1.42)	(-1.01)	(-1.01)
95% VaR_{it}	2.74	-0.56	-1.50	-3.27**	-2.80
	(0.67)	(-0.25)	(-1.30)	(-2.22)	(-1.40)
Mat Mismatch_{it}	5.87	5.32*	-4.65	-4.38	-1.04
	(1.64)	(1.84)	(-0.93)	(-0.80)	(-0.37)
# Subs_{it} $\times 10^{-3}$	0.14	-1.41	-1.89	4.64	4.71
	(0.03)	(-0.19)	(-0.21)	(0.69)	(0.96)
AR(2) p-value	0.10	0.06	0.04	0.05	0.11
Num Obs	2,814	3,235	3,624	3,820	4,034

t statistics in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Table IA-14: $\text{CoRisk}_{it+\tau} = \beta\,\text{VB}_{it} + \delta\,\text{CoRisk}_{it} + \gamma\,\text{controls}_{it} + \nu_i + \eta_t + \varepsilon_{it+\tau}$

	(1) $\tau = 20$q	(2) $\tau = 16$q	(3) $\tau = 12$q	(4) $\tau = 8$q	(5) $\tau = 4$q
VB_{it}	-0.01***	0.01	0.02	0.01	0.01
	(-2.94)	(1.13)	(1.57)	(0.77)	(0.78)
CoRisk_{it}	-0.08**	-0.00	0.06	-0.13*	-0.13**
	(-2.23)	(-0.01)	(1.65)	(-1.76)	(-2.74)
Stock Ret_{it}	0.00	0.00*	-0.00	0.00	0.00
	(0.65)	(1.95)	(-0.25)	(1.02)	(0.89)
Stock Vol_{it}	0.00	0.00	-0.00	0.00	0.00*
	(0.95)	(1.10)	(-1.19)	(1.17)	(1.96)
CAPM beta_{it}	-0.00***	-0.00	0.00	-0.00	-0.00***
	(-3.19)	(-1.12)	(1.13)	(-1.44)	(-3.30)
Prob Def_{it}	-0.00	-0.00	0.00	-0.01	-0.00
	(-0.84)	(-0.60)	(0.72)	(-0.97)	(-0.56)
95% VaR_{it}	0.00	0.00	0.00	-0.00	-0.00**
	(0.80)	(0.08)	(0.74)	(-0.45)	(-2.51)
Mat Mismatch_{it}	0.00**	-0.00	-0.00	0.00	0.00
	(2.23)	(-0.82)	(-1.14)	(0.37)	(0.21)
# Subs_{it} $\times 10^{-3}$	0.00	-0.00	-0.00	0.00	-0.00
	(0.64)	(-0.81)	(-0.74)	(0.23)	(-0.67)
AR(2) p-value	0.69	0.06	0.00	0.30	0.56
Num Obs	551	641	729	774	824

t statistics in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

F.3 Probit regression of TARP injections on indirect vulnerability

Table IA-15: Probit regression $1_{\text{TARP}_i} = \alpha_\tau + \beta_\tau \log \text{VB}_{i\tau} + \gamma_\tau \text{controls}_{i\tau} + \varepsilon_{i\tau}$

	$\tau = 2004q4$		$\tau = 2005q4$		$\tau = 2006q4$	
$\log \text{VB}_{i\tau}$	0.66**	1.89***	0.32	3.19***	0.43	1.40*
	(2.27)	(2.61)	(1.01)	(3.04)	(1.31)	(1.81)
$\text{SRISK}_{i\tau}$		-0.12		-0.55**		-0.17
		(-0.53)		(-2.00)		(-0.89)
$\text{MES}_{i\tau}$		1.07		2.98**		1.50
		(1.38)		(2.35)		(1.56)
$\Delta\text{CoVaR}_{i\tau}$		1.45*		1.05		0.40
		(1.91)		(1.43)		(0.46)
Equity Fall_i (07q2-08q2)		61.03*		52.35		25.33
		(1.77)		(1.25)		(0.72)
Stock $\text{Vol}_{i\tau}$		-1.64		-0.94		-1.58
		(-1.42)		(-0.75)		(-1.09)
log $\text{Assets}_{i\tau}$		-0.24		-0.91**		-0.29
		(-0.76)		(-2.15)		(-0.88)
Num Obs	100	38	100	40	100	40

t statistics in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

F.4 Robustness of predictive regressions

Table IA-16

	Pooled OLS			Fixed Effects						Dynamic Panel	
SB_{it}	2.33***	2.07***	2.23***	5.52***	5.15***	5.23***	4.90***	5.12***	4.92***	2.90***	3.25***
	(9.25)	(6.72)	(6.33)	(4.55)	(4.18)	(4.18)	(3.85)	(4.61)	(4.18)	(3.45)	(5.08)
$SRISK_{it}$		0.37***	0.39***			0.17***	0.16***		0.16***	0.16***	0.23***
		(7.29)	(7.38)			(3.85)	(4.05)		(4.18)	(7.21)	(7.50)
Stock Ret_{it}			-0.00					0.00	0.00		0.00
			(-0.69)					(0.23)	(0.45)		(0.59)
Stock Vol_{it}			0.09*					0.19	0.20		0.25
			(1.73)					(1.29)	(1.16)		(1.27)
CAPM $beta_{it}$			-0.23**					-0.94	-1.18		-1.52*
			(-1.99)					(-1.48)	(-1.54)		(-1.75)
Prob Def_{it}			-3.27					21.81***	15.09***		3.52
			(-0.69)					(3.24)	(4.37)		(1.12)
95% VaR_{it}			-0.90***					-1.20	-1.39		-2.43*
			(-4.01)					(-1.43)	(-1.29)		(-1.78)
Mat $Mismatch_{it}$			-0.04					-2.91	-2.41		-2.27
			(-0.34)					(-1.18)	(-1.13)		(-1.01)
# $Subs_{it}$ $\times 10^{-3}$			-0.07					-0.05	-0.00		0.08
			(-0.48)					(-0.09)	(-0.00)		(0.19)
Adj. R^2	0.19	0.36	0.37	0.29	0.38	0.33	0.42	0.41	0.45		
AR(2) p-value										0.55	0.74
FE (Bank,Time)	N, N	N, N	N, N	Y, N	Y, Y	Y, N	Y, Y	Y, Y	Y, Y	Y, Y	Y, Y
Num Obs	2,069	1,940	1,904	2,069	2,069	1,940	1,940	2,029	1,904	1,940	1,904

t-statistics in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

Table IA-17

	Pooled OLS			Fixed Effects						Dynamic Panel	
SB_{it}	1.37***	0.94***	0.80***	0.84***	0.47***	0.92***	0.50***	0.48***	0.50***	1.37***	1.03***
	(14.57)	(9.35)	(6.88)	(6.51)	(4.62)	(5.59)	(4.15)	(3.98)	(3.58)	(4.27)	(3.75)
$\Delta CoVaR_{it}$		0.32***	0.39***			-0.24***	-0.27***		-0.27***	0.19***	0.14**
		(17.17)	(19.52)			(-12.61)	(-11.11)		(-9.30)	(3.47)	(2.25)
Stock Ret_{it}			0.00					0.00	0.00		0.00
			(1.61)					(0.98)	(0.67)		(1.33)
Stock Vol_{it}			-0.05**					0.05**	0.07***		-0.01
			(-2.11)					(2.50)	(2.94)		(-0.28)
CAPM $beta_{it}$			0.15***					-0.15**	-0.09		-0.07
			(3.35)					(-2.19)	(-1.30)		(-0.99)
Prob Def_{it}			-2.49**					0.34	0.06		-0.55
			(-2.55)					(0.37)	(0.09)		(-0.74)
95% VaR_{it}			-0.72***					-0.38***	-0.15*		-0.52***
			(-7.77)					(-2.69)	(-1.82)		(-4.34)
Mat $Mismatch_{it}$			-0.32***					0.21	0.21		-0.49
			(-3.64)					(0.77)	(0.96)		(-1.15)
# $Subs_{it} \times 10^{-3}$			0.07					-0.08	-0.05		0.92**
			(1.36)					(-1.13)	(-0.63)		(2.19)
Adj. R^2	0.15	0.25	0.31	0.03	0.61	0.08	0.64	0.61	0.64		
AR(2) p-value										0.06	0.09
FE (Bank,Time)	N, N	N, N	N, N	Y, N	Y, Y	Y, N	Y, Y	Y, Y	Y, Y	Y, Y	Y, Y
Num Obs	3,141	3,141	3,060	3,141	3,141	3,141	3,141	3,060	3,060	3,141	3,060

t-statistics in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

Table IA-18

	Pooled OLS			Fixed Effects						Dynamic Panel	
SB_{it}	7.03***	6.71***	6.52***	4.32**	4.04**	2.25**	2.17**	4.30**	2.10***	6.06***	6.49***
	(12.90)	(7.98)	(7.44)	(2.64)	(2.34)	(2.77)	(2.53)	(2.52)	(2.92)	(4.17)	(5.00)
SES_{it}		0.16***	0.16***			-0.11***	-0.11***		-0.05	0.22***	0.14
		(3.05)	(2.76)			(-8.34)	(-7.64)		(-0.84)	(3.63)	(1.66)
Stock Ret_{it}			0.01***					0.00*	0.00		0.00
			(4.33)					(1.85)	(1.56)		(1.44)
Stock Vol_{it}			0.22*					0.16	0.14		0.18
			(1.95)					(0.69)	(0.52)		(1.45)
CAPM $beta_{it}$			-1.90***					-1.04	-1.23*		-1.10*
			(-4.31)					(-1.54)	(-1.76)		(-1.83)
Prob Def_{it}			8.20					15.58	13.63		-9.21
			(0.76)					(1.68)	(0.69)		(-1.20)
95% VaR_{it}			-0.36					-0.80	-0.30		0.99
			(-0.94)					(-0.77)	(-0.36)		(1.23)
Mat $Mismatch_{it}$			-0.83					-8.06**	7.64		-2.68
			(-0.79)					(-2.09)	(1.62)		(-1.27)
# $Subs_{it}$ $\times 10^{-3}$			0.36**					0.30	-2.05**		0.43
			(2.08)					(0.56)	(-2.20)		(1.21)
Adj. R^2	0.58	0.62	0.64	0.12	0.30	0.07	0.23	0.32	0.26		
AR(2) p-value										0.34	0.41
FE (Bank,Time)	N, N	N, N	N, N	Y, N	Y, Y	Y, N	Y, Y	Y, Y	Y, Y	Y, Y	Y, Y
Num Obs	973	747	719	973	973	747	747	933	719	747	719

t-statistics in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

Table IA-19

	Pooled OLS			Fixed Effects						Dynamic Panel	
SB_{it}	0.58***	0.42***	0.36***	0.65***	0.18	0.73***	0.25**	0.23**	0.29***	0.08	0.31***
	(8.34)	(5.45)	(3.73)	(3.75)	(1.36)	(4.67)	(2.41)	(2.30)	(3.80)	(0.76)	(2.84)
MES_{it}		0.28***	0.22***			0.02	-0.02		-0.07	0.00	-0.07
		(12.38)	(5.67)			(0.58)	(-0.57)		(-1.25)	(0.07)	(-1.20)
Stock Ret_{it}			0.00					-0.00	-0.00		-0.00
			(1.37)					(-0.14)	(-1.19)		(-1.22)
Stock Vol_{it}			-0.09***					0.11***	0.13***		0.09**
			(-3.97)					(4.09)	(3.59)		(2.21)
CAPM $beta_{it}$			0.33***					-0.25**	-0.25**		-0.18
			(5.56)					(-2.60)	(-2.37)		(-1.63)
Prob Def_{it}			0.64					1.19	1.95		1.53
			(0.34)					(1.23)	(1.45)		(1.13)
95% VaR_{it}			0.15*					-0.30**	-0.25**		-0.00
			(1.66)					(-2.55)	(-2.16)		(-0.03)
Mat $Mismatch_{it}$			-0.50***					-0.16	-0.19		-0.64
			(-8.75)					(-0.74)	(-0.86)		(-1.39)
# $Subs_{it}$ $\times 10^{-3}$			0.04					-0.17**	-0.12*		0.17**
			(0.86)					(-2.45)	(-1.81)		(2.04)
Adj. R^2	0.09	0.17	0.20	0.03	0.63	0.04	0.65	0.65	0.67		
AR(2) p-value										0.03	0.04
FE (Bank,Time)	N, N	N, N	N, N	Y, N	Y, Y	Y, N	Y, Y	Y, Y	Y, Y	Y, Y	Y, Y
Num Obs	2,069	1,940	1,904	2,069	2,069	1,940	1,940	2,029	1,904	1,940	1,904

t-statistics in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Table IA-20

	Pooled OLS			Fixed Effects						Dynamic Panel	
SB_{it}	0.09***	0.10***	0.10***	0.07***	0.07***	0.08***	0.08***	0.07***	0.08***	0.09***	0.09***
	(12.42)	(9.21)	(8.13)	(4.35)	(4.21)	(5.02)	(4.89)	(3.91)	(4.27)	(4.15)	(4.88)
CCA_{it}		-0.17***	-0.22***			-0.31***	-0.30***		-0.29***	-0.26***	-0.26***
		(-3.08)	(-3.84)			(-6.01)	(-6.14)		(-6.54)	(-4.87)	(-8.69)
Stock Ret_{it}			0.00					0.00*	0.00**		0.00**
			(0.33)					(1.85)	(2.00)		(1.99)
Stock Vol_{it}			-0.00					0.00	-0.00		-0.00*
			(-1.35)					(1.02)	(-0.01)		(-1.88)
CAPM $beta_{it}$			-0.00					-0.01**	-0.00*		-0.00
			(-0.35)					(-2.09)	(-1.79)		(-1.65)
Prob Def_{it}			0.07**					0.09	0.07		0.11
			(2.07)					(1.03)	(1.18)		(1.35)
95% VaR_{it}			0.00					-0.01	-0.01		-0.01*
			(0.23)					(-1.34)	(-1.64)		(-1.89)
Mat $Mismatch_{it}$			-0.00					0.01	0.01		0.01
			(-0.00)					(0.78)	(0.50)		(0.72)
# $Subs_{it}$ $\times 10^{-3}$			0.01***					-0.01	-0.01		0.02**
			(2.64)					(-1.53)	(-0.55)		(2.17)
Adj. R^2	0.48	0.50	0.52	0.11	0.14	0.20	0.22	0.16	0.23		
AR(2) p-value										0.55	0.54
FE (Bank,Time)	N, N	N, N	N, N	Y, N	Y, Y	Y, N	Y, Y	Y, Y	Y, Y	Y, Y	Y, Y
Num Obs	4,670	4,670	3,624	4,670	4,670	4,670	4,670	3,624	3,624	4,670	3,624

t-statistics in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

Table IA-21

	Pooled OLS			Fixed Effects						Dynamic Panel	
SB_{it}	41.89***	3.51	4.67	5.81	5.86	4.76	4.68	5.89	4.40	3.40	0.93
	(17.42)	(1.24)	(1.51)	(1.46)	(1.45)	(0.64)	(0.60)	(1.26)	(0.51)	(0.41)	(0.09)
DIP_{it}		0.85***	0.76***			0.06	0.06		0.08	0.28***	0.32**
		(20.04)	(12.80)			(0.31)	(0.34)		(0.42)	(2.74)	(2.02)
Stock Ret_{it}			0.00					0.00**	0.00**		0.00
			(0.75)					(2.14)	(2.07)		(0.02)
Stock Vol_{it}			-0.21*					0.13	0.15		-0.02
			(-1.66)					(1.09)	(0.96)		(-0.12)
CAPM $beta_{it}$			-0.52**					-0.99	-1.07		-0.74
			(-2.11)					(-1.40)	(-1.35)		(-0.81)
Prob Def_{it}			-7.10					-10.45	-11.43		-9.27
			(-1.20)					(-1.01)	(-0.92)		(-0.97)
95% VaR_{it}			0.59					-1.11	-1.23		-1.47
			(1.29)					(-1.10)	(-1.00)		(-1.63)
Mat $Mismatch_{it}$			1.34***					8.91	9.01		-4.42
			(2.92)					(1.13)	(1.14)		(-1.27)
# $Subs_{it} \times 10^{-3}$			2.88***					-0.89	-1.30*		2.31
			(2.76)					(-0.76)	(-1.93)		(0.63)
Adj. R^2	0.72	0.86	0.86	0.03	0.03	0.04	0.04	0.05	0.05		
AR(2) p-value										0.06	0.05
FE (Bank,Time)	N, N	N, N	N, N	Y, N	Y, Y	Y, N	Y, Y	Y, Y	Y, Y	Y, Y	Y, Y
Num Obs	4,670	4,670	3,624	4,670	4,670	4,670	4,670	3,624	3,624	4,670	3,624

t-statistics in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

Table IA-22

	Pooled OLS			Fixed Effects						Dynamic Panel	
SB_{it}	0.00	0.00	0.00	-0.00	-0.00	-0.00	0.00	-0.00	0.00	0.00	0.00
	(1.58)	(0.71)	(0.91)	(-0.62)	(-0.93)	(-0.46)	(1.11)	(-0.47)	(0.22)	(0.54)	(0.68)
$CoRisk_{it}$		0.03	0.06**			0.04	0.06*		0.07**	0.04	0.05
		(1.29)	(2.04)			(1.39)	(2.03)		(2.06)	(1.01)	(1.34)
Stock Ret_{it}			-0.00					0.00	-0.00		-0.00
			(-0.79)					(1.16)	(-0.89)		(-0.23)
Stock Vol_{it}			-0.00					-0.00	-0.00		-0.00
			(-0.60)					(-0.31)	(-1.59)		(-1.26)
CAPM $beta_{it}$			-0.00					-0.00	0.00		0.00
			(-1.00)					(-0.00)	(1.11)		(0.88)
Prob Def_{it}			-0.00					0.00	0.00		0.00
			(-0.51)					(0.23)	(0.98)		(0.87)
95% VaR_{it}			-0.00					0.00	0.00		0.00
			(-0.61)					(0.42)	(1.55)		(0.68)
Mat $Mismatch_{it}$			0.00					0.00	0.00		0.00
			(1.42)					(0.37)	(1.10)		(0.45)
# $Subs_{it}$ $\times 10^{-3}$			-0.00					-0.00**	-0.00		-0.00
			(-0.61)					(-2.05)	(-0.18)		(-0.43)
Adj. R^2	0.00	-0.00	0.01	-0.00	0.20	-0.00	0.30	0.20	0.30		
AR(2) p-value										0.01	0.01
FE (Bank,Time)	N, N	N, N	N, N	Y, N	Y, Y	Y, N	Y, Y	Y, Y	Y, Y	Y, Y	Y, Y
Num Obs	1,031	766	729	1,031	1,031	766	766	968	729	766	729

t-statistics in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

G 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.[23] 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.

[23] 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).

H Systemic Risk Measures

The systemic risk measures that we examine in Section 6 come from two sources. The first source is Giglio, Kelly, and Pruitt (2016). We thank Stefano Giglio, Bryan Kelly and Seth Pruitt for generously sharing with us the time-series of all the systemic risk measures they use. The time-series of the 19 measures they use can be downloaded from Stefano Giglio's website or from Seth Pruitt's website. See Table 1 in Giglio, Kelly, and Pruitt (2016) for a list of the 19 measures they use.

The second source is Bisias et al. (2012), who provide a public code base and a detailed appendix to reconstruct the systemic risk measures they survey. They provide neither the underlying raw data nor the time series of the constructed measures. We follow their construction as closely as possible. In this Appendix, we only document instances in which we deviate from their construction (usually because of data availability) or make assumptions (usually because they provide several alternatives, do not provide enough detail, or do not provide the relevant code to construct the measure). If any details in the construction of the measures are not documented below, it means they are exactly as in Bisias et al. (2012). We use their notation and nomenclature without defining or explaining terms, all of which can be found in Bisias et al. (2012), its code base or its appendix. Whenever the measures are constructed at a frequency higher than quarterly, we convert to quarterly frequency by taking the average of all observations within the quarter, with the exception of the two measures constructed in section *F.5 (Equity Market Illiquidity) where we take the largest value of all daily observations in the quarter (to preserve the dynamics highlighted in Bisias et al., 2012). We number the following sections in accordance with the numbering in Bisias et al., 2012, prefaced with a star to distinguish from the section numbering of our paper.

*A Macroeconomic Measures

*A.1 Costly Asset-Price Boom/Bust Cycles

Data. We only conduct the analysis for the U.S. We use the method in Filardo et al. (2018) to generate the aggregate asset price index that defines when an asset price boom occurs. The index is the first principal component of two variables: the ratio of total U.S. private sector credit to potential GDP and a real house price index. Total private sector credit is from the BIS and nominal potential GDP data is from FRED. The house price index is a weighted average of the real residential housing price index and the real equity price

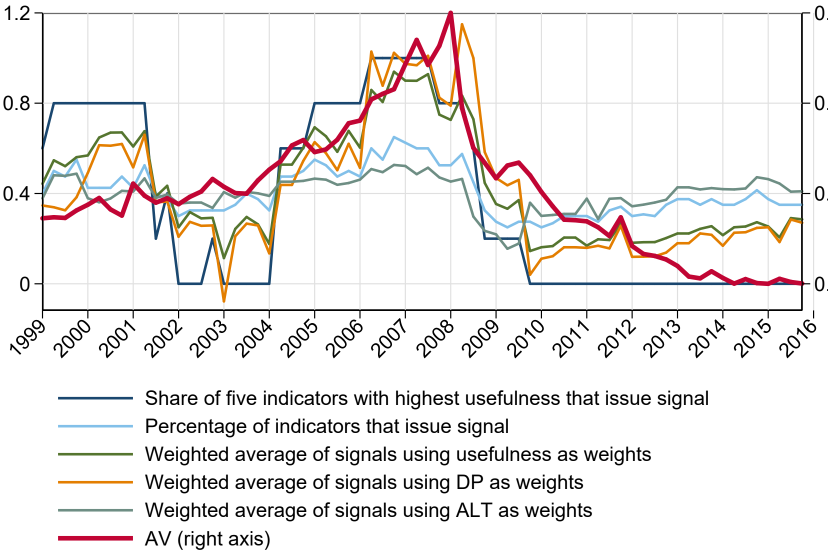


Figure IA-6

index, both from the OECD. To weight the two components, we use the real estate market value for the U.S. from FRED and the total market capitalization from the World Bank.

Code. We add a calculation for the average lead time (ALT). We also construct the optimal percentile threshold selection for each indicator variable, which is determined as the percentile that minimizes the loss function.

Output. We construct five systemic risk measures, shown in Figure IA-6: the sum of the warnings for the five signals that have the highest usefulness indicator, the percentage of signals that flash a warning, and the weighted average of all signals with weights calculated using the usefulness indicator in equation (A.2), dp in equation (A.5), and ALT. In Figure 10 from Section 6, we show the weighted average of signals using the usefulness indicator as weights.

*A.2 Property-Price, Equity-Price, and Credit-Gap Indicators

Data. We use the specification for the property index from the appendix of Aldasoro et al. (2018), using real residential property prices data for the U.S. from the BIS, rather than taking a weighted average of residential and commercial property price indices from the BIS with weights given by their share in private sector wealth. We only conduct the analysis for the U.S.

Figure IA-7

Code. We adapt the gap definition to the percent change from the trend, i.e.(Observed – Trend)/Trend, rather than the (additive) difference, i.e. (Observed – Trend).

Output. We construct three systemic risk measures, shown in Figure IA-7. These measures are the "warning signals" based on: credit-to-GDP and property prices, credit-to-GDP and equity prices, or property prices and equity prices. In Figure 10 from Section 6, we show the warning signal of credit-to-GDP and property prices.

*B Granular Foundation and Network Measures

*B.1 The Default Intensity Model

Output. We thank Kay Giesecke and Baeho Kim for generously sharing their constructed measures with us. Figure IA-8 shows the 95% and 99% VaR of the economy-wide and system-wide (financial sector) default rates. In Figure 10 from Section 6, we show the economy-wide 99% VaR of default rates.

*B.2 Network Analysis and Systemic Financial Linkages

Data. For the country capital stocks, BIS data starts in 2013. For pre-2013 capital stocks, we use GDP growth rates (also from the BIS) to proxy for capital growth rates.

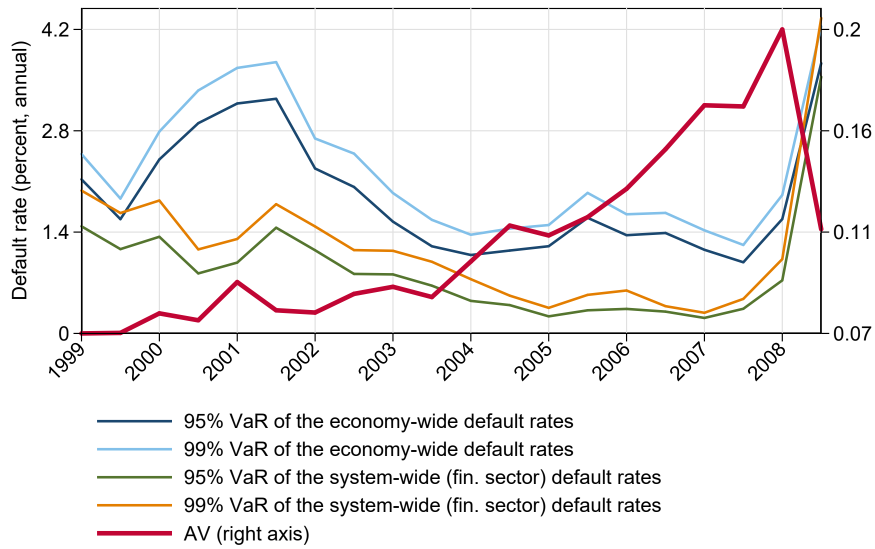


Figure IA-8

Output. Figure IA-9 shows the two systemic risk measures we construct: the mean capital loss for the U.S. across isolated international defaults (one country at a time), and the number of simulations in which the U.S. defaults (which turns out to always be zero). In Figure 10 from Section 6, we show the mean capital loss for the U.S.

*B.3 PCA and Granger-Causality Networks

Data. For the individual institution case, we compute ranks every three years beginning in January 1994 (matches analysis in original paper). We use the largest 25 banks, broker-dealers, hedge funds, and insurers, for a total of 100 firms. Banks, broker-dealer, and insurer data is from CRSP and hedge fund data is from TASS.

Output. The Granger networks are calculated for the four industries. b3 Institution Commonality: percent of variation explained by the first principal component of sector/institution returns over a 36 month rolling window. Figure IA-10 shows the three systemic risk measures we construct: the DCI from equation (A.17) at the index level, "Institution Commonality" from equation (A.18) also at the index level, and the average of firm-level DCI. In Figure 10 from Section 6, we show the DCI at the index level.

*B.4 Bank Funding Risk and Shock Transmission

Code. We generate an undirected network for each quarter and a directed network for each year, which was not constructed by the code provided in Bisias et al. (2012).

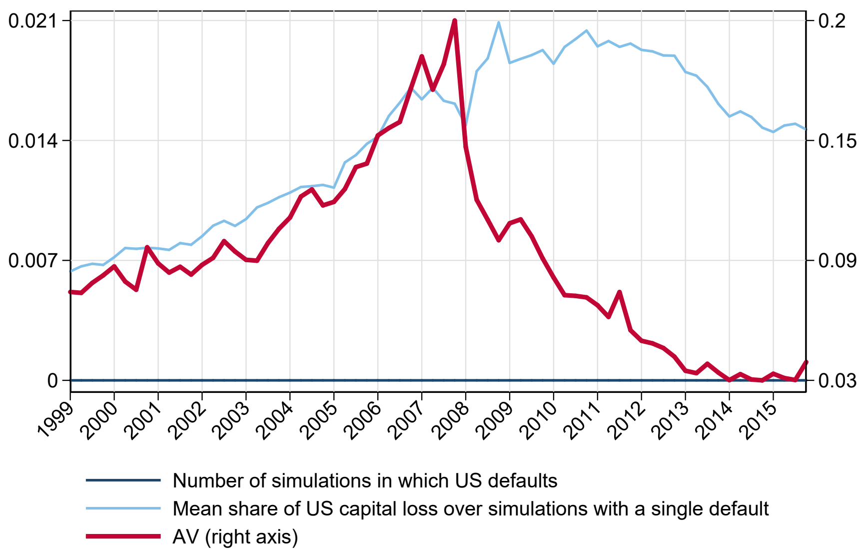


Figure IA-9

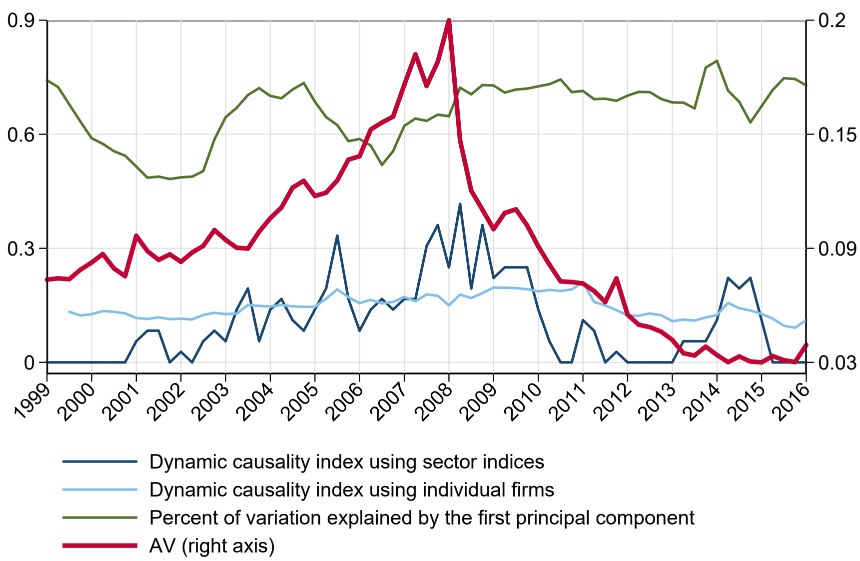


Figure IA-10

Output. We construct ten measures of systemic risk, shown in Figure IA-11. Four of these measures are the upper and lower bounds for USD funding risk at the group-level and for the sum of USD funding risks at the office-location level. The other six measures are constructed by using the directed and undirected networks. For the directed network, two of the measures are given by the sum of upper and lower bounds of funding risks across linkages with positive net flows from the U.S. The third measure is the annual change in U.S. net claims. For the undirected network, two of the measures are given by the sum of upper and lower bounds of funding risks across linkages with the U.S. The third measure is the sum over all U.S. linkages. In Figure 10 from Section 6, we show the sum of upper bounds of funding risks across linkages with the U.S.

*C Forward-Looking Risk Measurement

*C.1 Contingent Claims Analysis

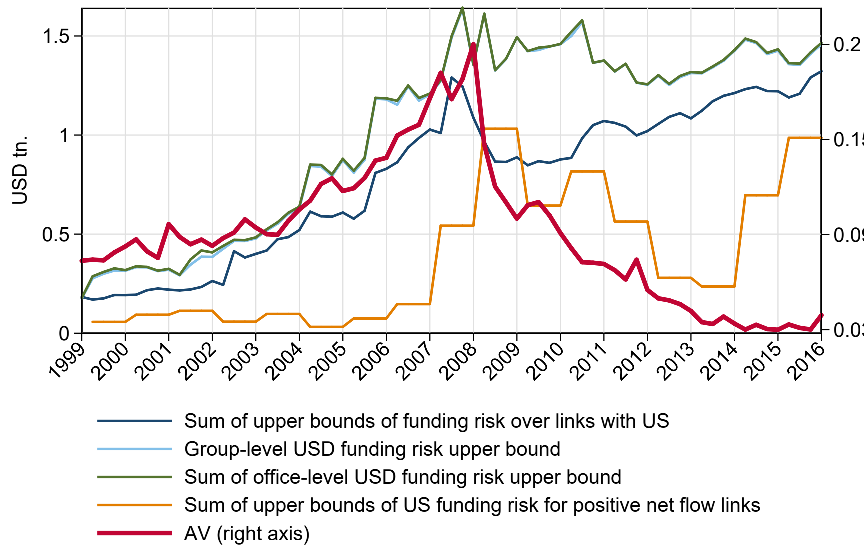
Data. Equity prices are from Bloomberg and CDS spreads from Markit. Bloomberg data was used to construct the default barrier, rather than Moody's KMV CreditEdge. The original paper uses the "36 largest financial institutions (banks, insurance companies and asset managers)" though the exact firms are not specified. We use a sample of 20 large financial institutions with liquid CDS contracts.

Output. We construct the systemic risk measure from equation (A.29), which is the sum of implicit guarantees across all institutions in the sample, shown in Figure IA-12 and Figure 10 in Section 6.

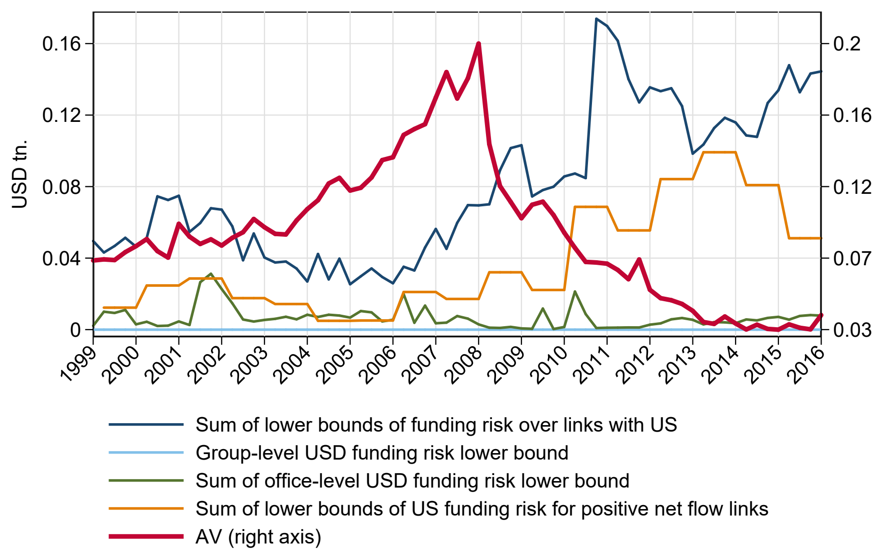
*C.2 Mahalanobis Distance

Data. The authors are not specific about what bond, commodity, and real estate returns they use. We pick three commodities: gold, oil, and natural gas; the Wilshire REIT Index for real estate; and Moody's BAA relative to the 10Y treasury for bonds.

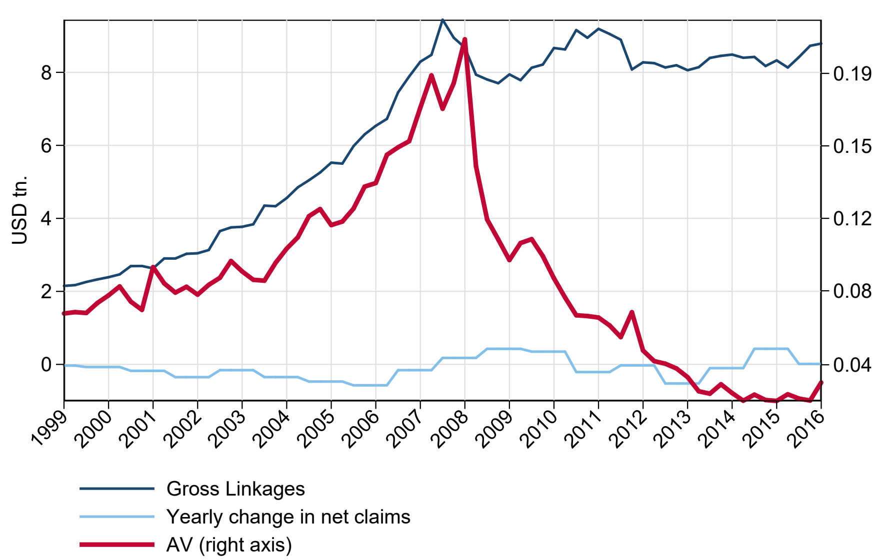
Output. We construct the "financial turbulence" systemic risk measure from equation (A.30), shown in Figure IA-12 and Figure 10 in Section 6.



USD tn.
1.5
1
0.5
0
0.2
0.15
0.09
0.03
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
Sum of upper bounds of funding risk over links with US
Group-level USD funding risk upper bound
Sum of office-level USD funding risk upper bound
Sum of upper bounds of US funding risk for positive net flow links
AV (right axis)



USD tn.
0.16
0.12
0.08
0.04
0
0.2
0.16
0.12
0.07
0.03
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
Sum of lower bounds of funding risk over links with US
Group-level USD funding risk lower bound
Sum of office-level USD funding risk lower bound
Sum of lower bounds of US funding risk for positive net flow links
AV (right axis)



USD tn.
8
6
4
2
0
0.19
0.15
0.12
0.08
0.04
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
Gross Linkages
Yearly change in net claims
AV (right axis)

Figure IA-11

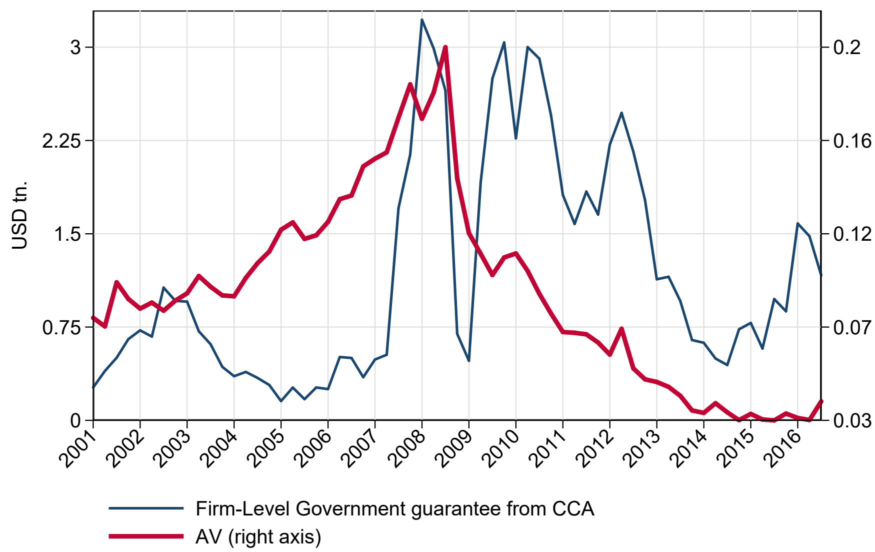


Figure IA-12

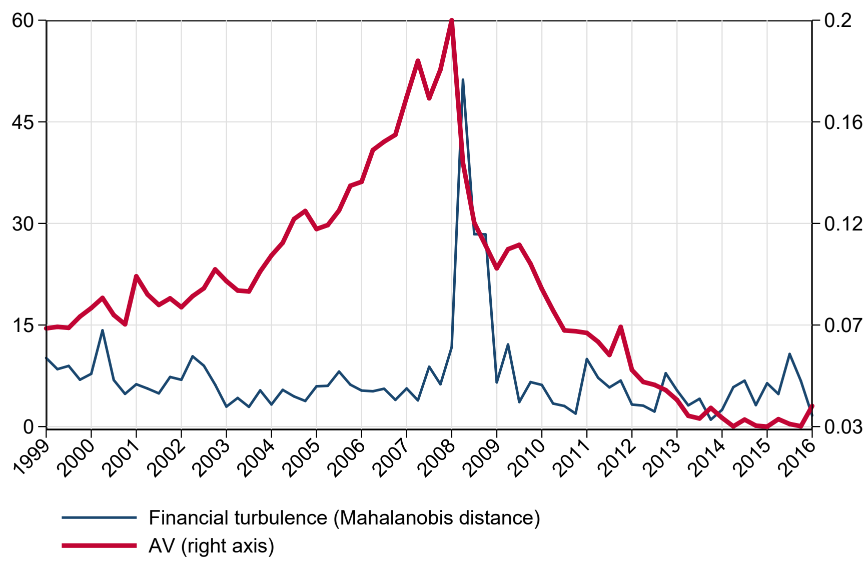


Figure IA-13

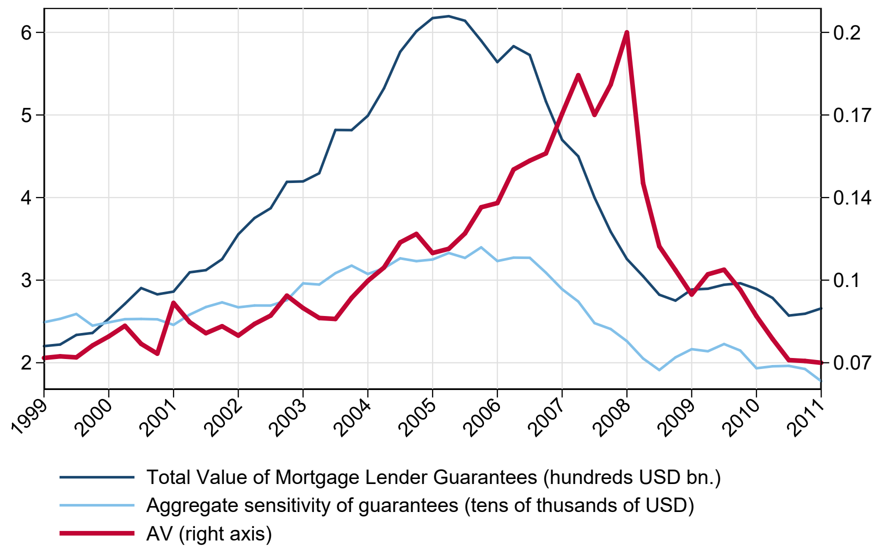


Figure IA-14

*C.5 Simulating the Housing Sector

Data. We use Average Sales Price for New Houses Sold in the United States rather than "New One-Family Houses Sold."

Output. We construct two systemic risk measures, shown in Figure IA-14: the total value of mortgage lender guarantees from equation (A.52), and the aggregate sensitivity of guarantees from equation (A.53). In Figure 10 from Section 6, we show the sensitivity of guarantees.

*C.6 Consumer Credit

Data. We use actual consumer credit variables, instead of using those predicted by a machine learning model. We lag the realized measures by the window of prediction (six months). Observed consumer credit measures mirror the model-predicted ones quite closely (the machine learning algorithm used in the original model had an R^2 of 85%). We use data from the Federal Reserve Bank of New York's Quarterly Report on Household and Credit.

Output. Figure IA-15 shows the four systemic risk measures we construct: percent of total balances 90+ days delinquent, percent of credit card balances 90+ days delinquent, transition into seriously delinquency for credit cards as a percent of total balances, and transition into seriously delinquency for all loan types as a percent of total balances. In

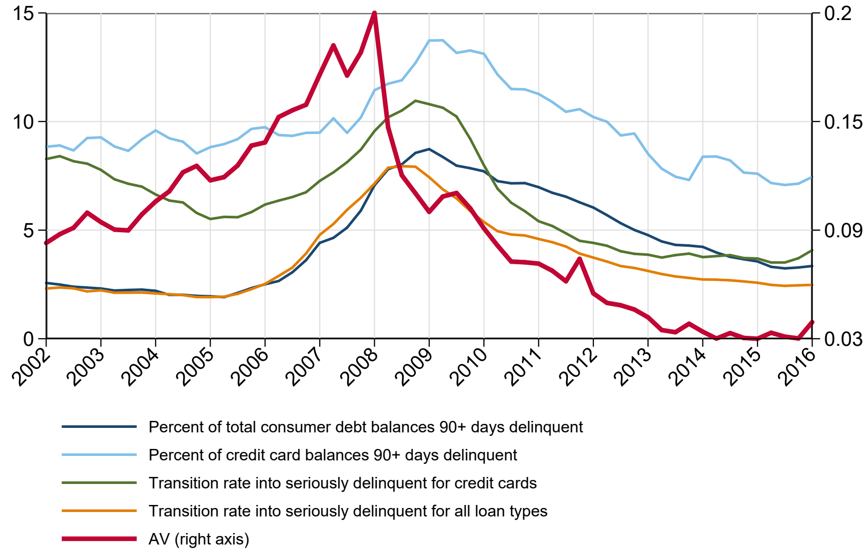


Figure IA-15

Figure 10 from Section 6, we show the percent of credit card balances 90+ days delinquent.

*C.7 Principal Components Analysis (PCA)

Data. We use MSCI indices from the MSCI website and Case-Shiller subindices from Bloomberg. [24]

Output. Figure IA-17 shows the four systemic risk measures we construct: the absorption ratio and the change in the absorption ratio for either 11 MSCI subindices or 14 Case-Shiller city subindicies. In Figure 10 from Section 6, we show the absorption ratio for the 11 MSCI subindices.

*D Stress Tests

*D.1 GDP Stress Tests

Code. For each crisis period (i.e. 2007q3 in the U.S.), we determine the forecast error for that crisis period and construct a time series where we conduct a stress test for each quarter using the forecast error for the crisis as the shock. Therefore, the shock is identical for each stress-tested quarter. When generating the time series of stress test results, we iterate

[24]For robustness we pull the universe of MSCI indicies from Bloomberg (32 indicies) and find similar results.

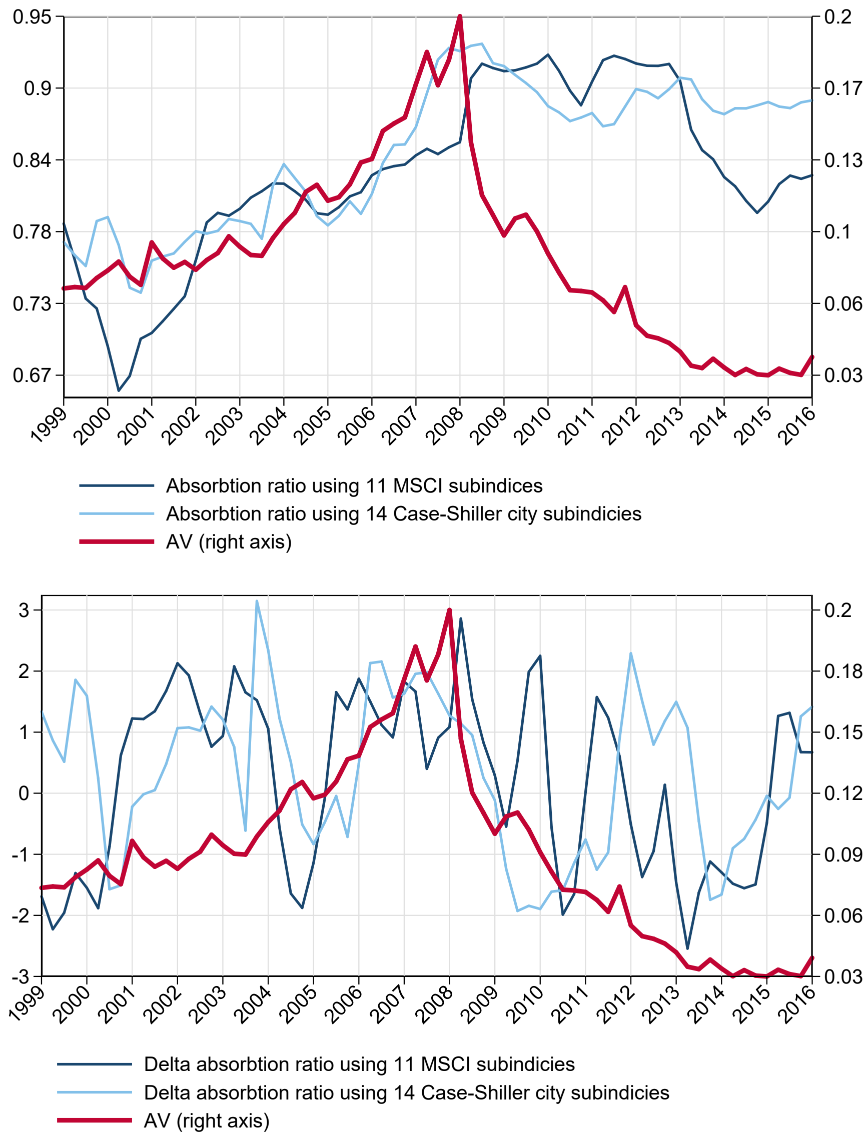

0.95
0.9
0.84
0.78
0.73
0.67
0.2
0.17
0.13
0.1
0.06
0.03
1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016
Absorbtion ratio using 11 MSCI subindices
Absorbtion ratio using 14 Case-Shiller city subindicies
AV (right axis)
3
2
1
0
-1
-2
-3
0.2
0.18
0.15
0.12
0.09
0.06
0.03
1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016
Delta absorbtion ratio using 11 MSCI subindicies
Delta absorbtion ratio using 14 Case-Shiller city subindicies
AV (right axis)

Figure IA-16

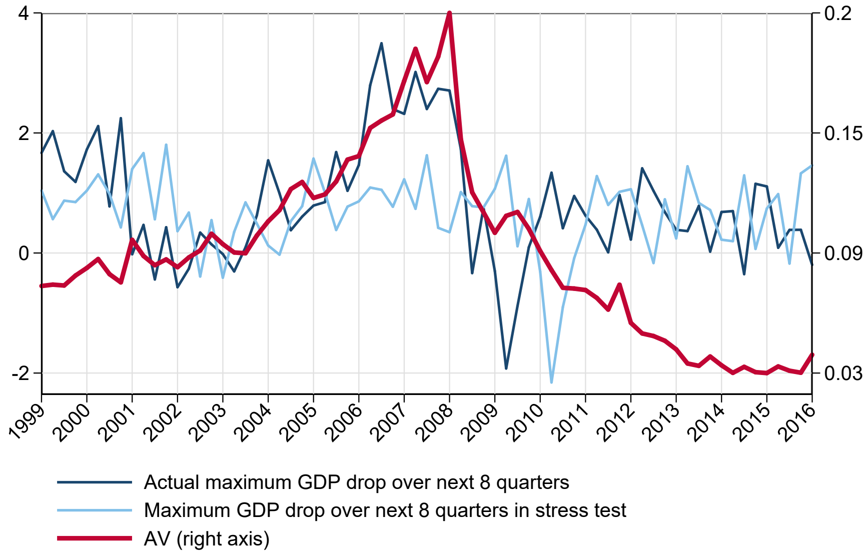


Figure IA-17

quarter by quarter and for each iteration we estimate an AR model using GDP growth data up until the quarter in question. We shock GDP growth four quarters prior to the quarter, project the series forward using the estimated AR process, and compute maximum drops in GDP for the stress test period and drops in actual GDP for the quarter in question. We also generate a forecast error that is specific to each quarter, which returns a time series of forecast errors. We then conduct the stress test for each quarter using the forecast error corresponding to that quarter rather than a fixed forecast error corresponding to a specific crisis period.

Output. We run the same stress test exercise for forecast error shocks that are unique to each quarter. Figure IA-17 shows the two systemic risk measures we construct. They both correspond to the difference between the maximum drop in GDP growth during the hypothetical stress test and actual GDP growth in the data. The two measures differ in the assumed shock: one uses the the forecast error for the U.S. 2007q3 crisis while the other uses the forecast error of the current quarter. In Figure 10 from Section 6, we show the measure that uses the 2007q3 scenario.

*E Cross-Sectional Measures

*E.1 CoVaR

Data. We obtain CoVaR from two sources: the Board of Governors of the Federal Reserve (for a sample of large and medium banks), and the online supplementary materials from

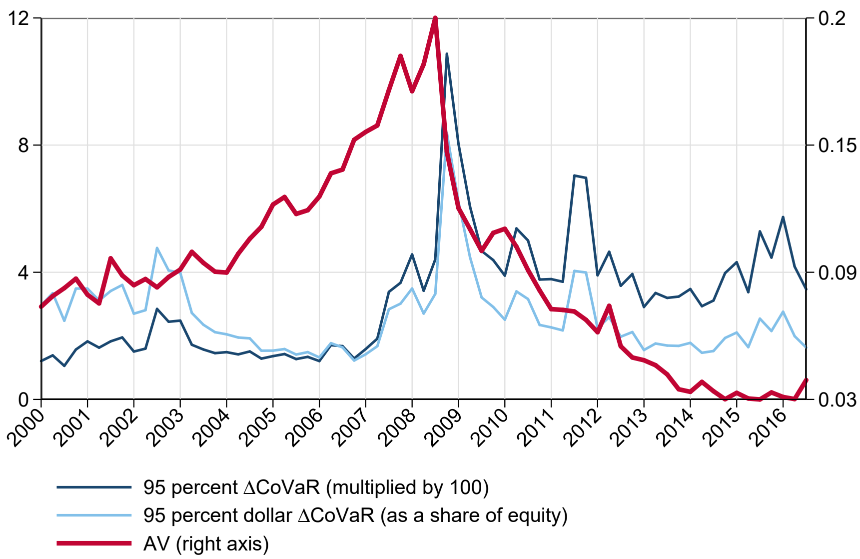


Figure IA-18

Adrian and Brunnermeier (2016) (for publicly traded firms).

Output. Figure IA-18 shows four systemic risk measures: the average across firms of CoVaR and of dollar CoVaR computed using either the Board of Governor's data or the data from Adrian and Brunnermeier (2016). In Figure 10 from Section 6, we show the average across firms of CoVaR constructed by the Board of Governors.

*E.2 Distressed Insurance Premium

Data. Instead of using CDS-implied probabilities of default, we use the risk neutral default probabilities from Moody's KMV. Then, rather than using daily intra-day correlations, we use end-of-day return correlations over the course of the previous year, calculated on a rolling basis each quarter. We keep firms with at least 120 days of observations during the previous year.

Code. In addition to the economy-wide DIP measure, we compute a firm-specific DIP measure, using liabilities data from Moody's KMV.

Output. Figure IA-19 shows the economy-wide DIP measure, which is also shown in Figure 10 from Section 6.

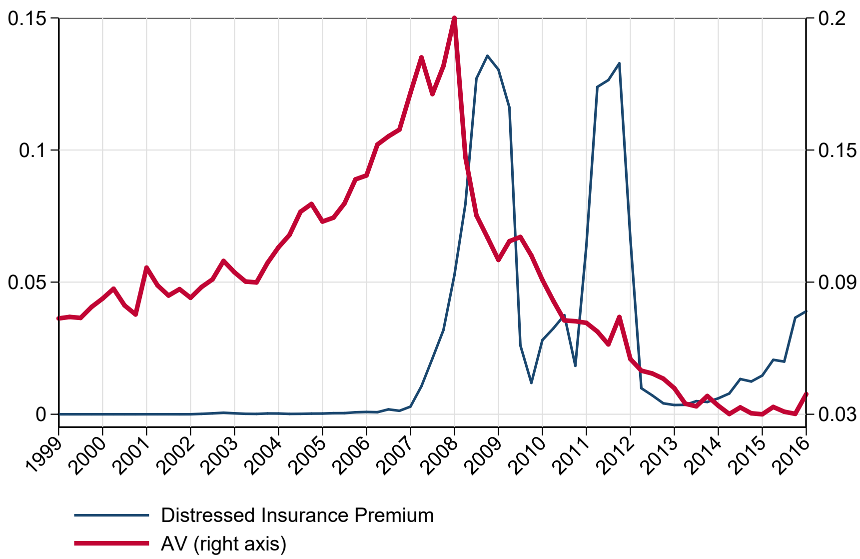


Figure IA-19

*E.3 Co-Risk

Data. Instead of using the 3-month GCF Repo Rate, we use the overnight Treasury GC Repo Primary Dealer Survey Rate. For CDS Spreads, we use the Markit quoted 5-year spreads. Where possible, we use traditional documentation clauses (XR, XR14); for entity-date combinations on which there is no traditional clause available, we use another documentation clause if the quote is distinct to that day. The original paper used a sample of 25 representative institutions. We use the subset of those original 25 institutions that are BHCs (firms that have Y-9C data), and add additional financial institutions for which Markit provides the requisite data and identifiers.

Code. Instead of computing Co-Risk at a single point in time using the full history of spreads going back five years, we compute Co-Risk in every month of our sample. Specifically, for each month, we run the quantile regressions on every combination of banks for which there are at least 63 days in common with non-missing observations in the previous year (63 is the number of trading days in a quarter).[25] We construct Co-Risk(i) for firm i by taking the average of Co-Risk(i, j) across all j, and aggregate Co-Risk by taking the average of Co-Risk(i) across all firms i.

Output. Figure IA-20 shows aggregate Co-Risk, which is also shown in Figure 10 from Section 6.

[25] We changed the last line of the MATLAB source code co_risk.m provided by Bisias et al. (2012) so that the computation matches the one given by equation (A.77); the input and output CDS spreads were incorrectly switched in the code.

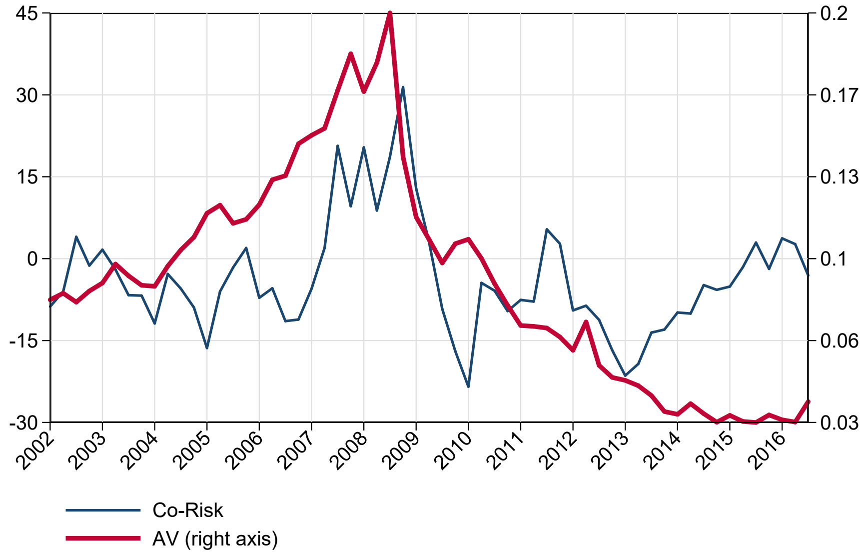


Figure IA-20

*E.4 Marginal and Systemic Expected Shortfall

Output. We thank Asani Sarkar and Robert Engle for sharing data on MES, SES and SRISK with us. Figure IA-21 shows aggregate MES, SES and SRISK, obtained by taking the average of their firm-level counterparts. In Figure 10 from Section 6, we show aggregate SRISK.

*F Measures of Illiquidity and Insolvency

*F.3 Noise as Information for Illiquidity

Data. We download the output directly from Jun Pan's website.

Output. Figure IA-22 shows the noise measure, also shown in Figure 10 from Section 6.

*F.4 Crowded Trades in Currency Funds

Data. We thank Pierre Lequeux for sharing an updated series of his AFX Currency Management Index. Pierre has a blog post with details on the index's construction. We use TASS for firm-level statistics (aggregated at the monthly level rather than weekly).

Code. We calculate the alternative crowdedness measure in equation (A.90) using $X = 1$.

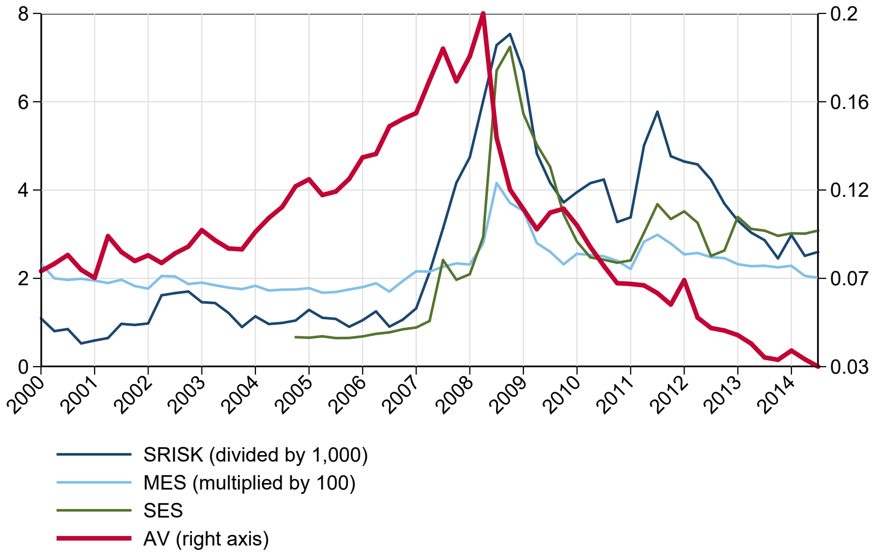


Figure IA-21

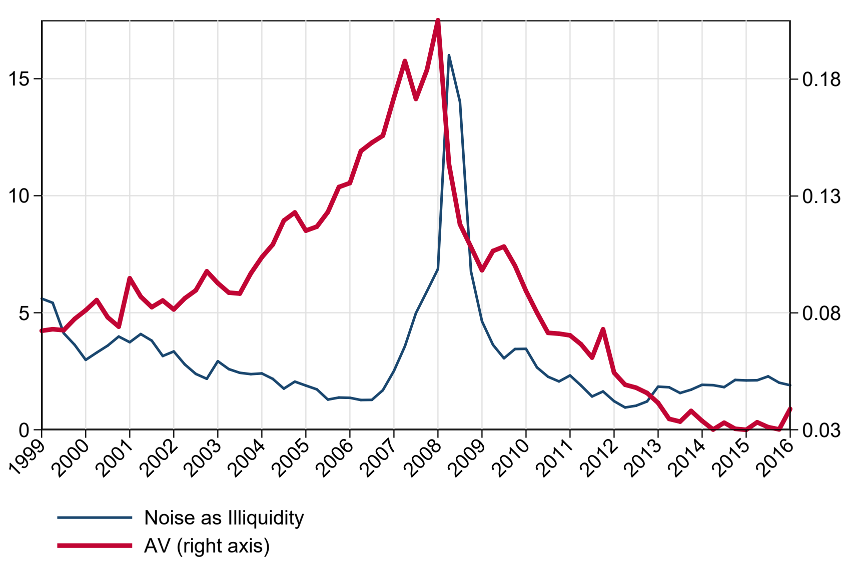


Figure IA-22

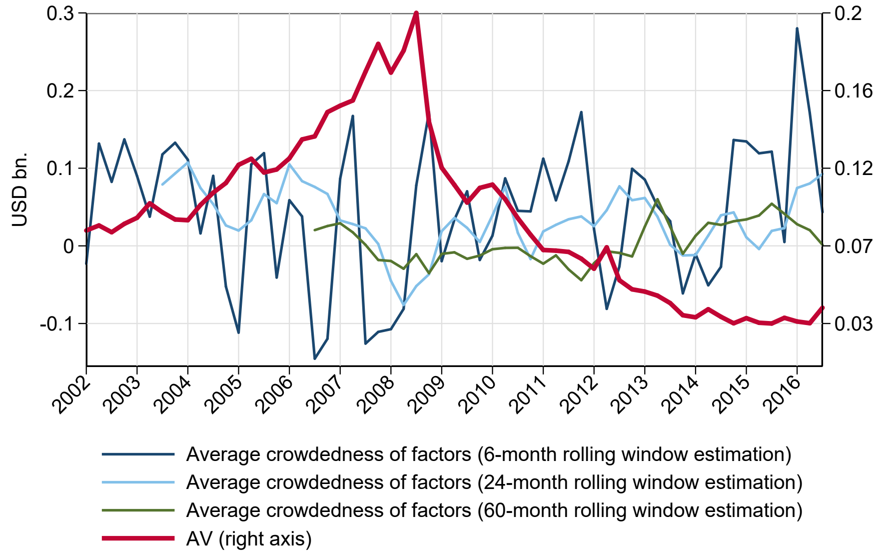


Figure IA-23

Output. We produce each crowdedness measure using 6, 24, and 60-month rolling windows. We then construct three systemic risk measures, shown in Figure IA-23, by taking the average of all measures that use 6, 24, and 60-month rolling windows, respectively. In Figure 10 from Section 6, we show the measure based on 24-month rolling windows.

*F.5 Equity Market Illiquidity

Data. For the contrarian trading strategy measure, we use hourly intra-day tick data from Thomson Reuters Intraday database and construct one-hour returns (rather than examining all five minute intervals from five minutes up to one hour). We use all stocks from the S&P500 rather than the S&P1500. For our price impact liquidity measure, we use preconstructed lambdas from WRDS Intraday database.

Output. We construct two systemic risk measures, shown in Figure IA-24. The first measure is given by the returns of the contrarian trading strategy, constructed by taking the average daily returns of the long minus short portfolio strategy, where the long and short are equally weighted. The second measure is the price-liquidity measure, which is the equal weighted mean of lambdas by day across all companies available on the given date, winsorizing the sample at the 1% level by day to exclude outliers. In Figure 10 from Section 6, we show the return on the contrarian trading strategy.

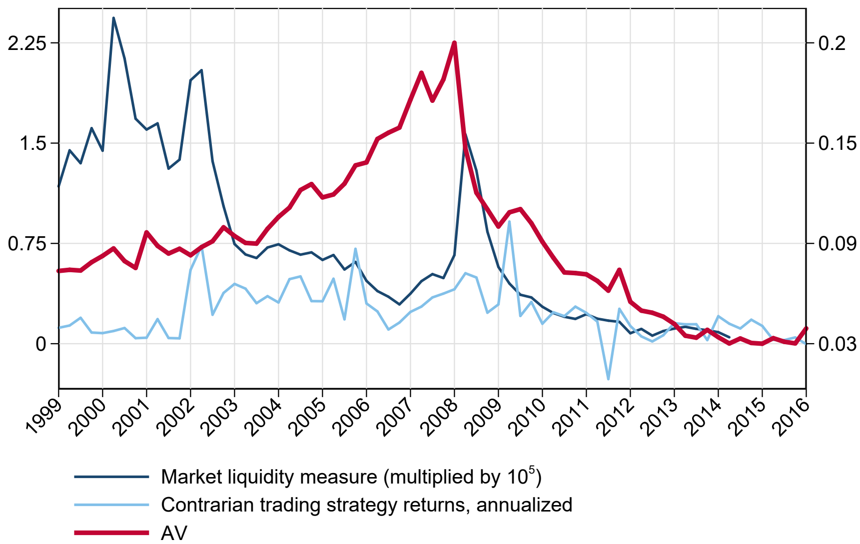


Figure IA-24

*F.6 Serial Correlation and Illiquidity in Hedge Fund Returns

Data. We construct the measure for indices only. All indices and S&P data are from Bloomberg.

Output. We construct three systemic risk measures, shown in Figure IA-25. The first measure is the value-weighted average (across funds) of the first-order autocorrelation of fund returns. The other two measures are analogous but use second- and third-order autocorrelations. In Figure 10 from Section 6, we show the measure based on first-order autocorrelations.

*F.7 Broader Hedge-Fund Based Systemic Risk Measures

Data. For the autocorrelation measures, we a use 5-year rolling window to generate a time series of the Q-statistic and the Systemicness Indicator. For the probability of liquidation, we assume the liquidation year of a fund to be the fund's performance end date. We keep all observations for which there exists two years (24 months) of non-missing data.

Code. We set Q-statistics that equal zero to missing before taking the median for the aggregate time series measure. To generate the aggregate systemicness indicator, we output a panel of first-order autocorrelations for fund returns and calculate the cross-sectional weighted average each month weighted by assets under management where the code in Bisias et al. (2012) uses the same weight over the entire time series. For the probability of

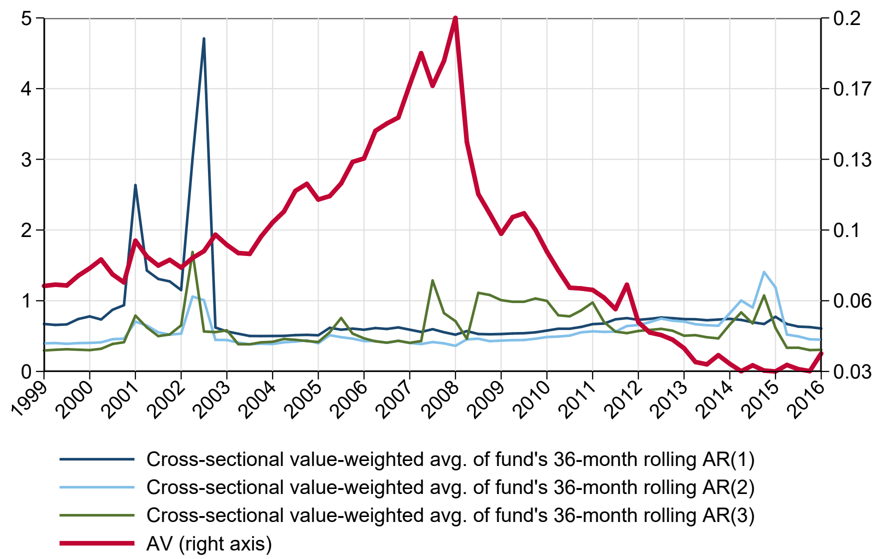


Figure IA-25

liquidation measure, we produce a yearly time series. We also calculate the age of a fund as the number of months from inception to the end of the corresponding year.

Output. We construct five systemic risk measures, shown in Figure IA-26: the mean and median probability of liquidation across funds, the median Q-statistic across funds, and the value-weighted average of the systemic liquidity indicator defined in equation (A.104), using as weights either the AUM of each fund for the current period or the average AUM of each funds over the entire lifetime of the fund. In Figure 10 from Section 6, we show the AUM-weighted average of the systemic liquidity indicator.

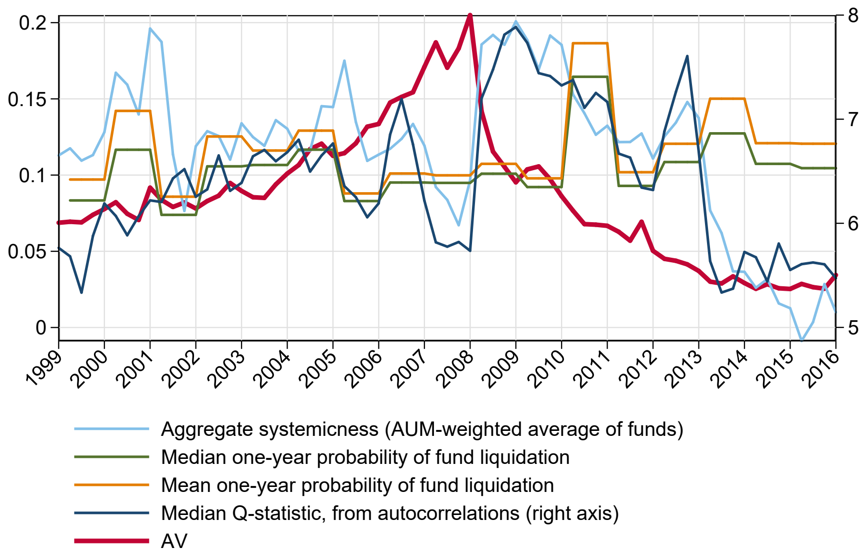

0.2
0.15
0.1
0.05
0
8
7
6
5
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
Aggregate systemicness (AUM-weighted average of funds)
Median one-year probability of fund liquidation
Mean one-year probability of fund liquidation
Median Q-statistic, from autocorrelations (right axis)
AV

Figure IA-26