Fire-Sale Spillovers and Systemic Risk

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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 ΔCoVaR. The balance sheet-based measures we propose are therefore useful early indicators of when and where vulnerabilities are building up.

Keywords: Systemic risk, fire-sale externalities, leverage, linkage, concentration.

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

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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] The empirical literature, in contrast, is thinner, as it is difficult to conclusively identify fire sales. A few notable papers document 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 arguably more concerned with fire sales that affect a large portion of the financial sector and many different markets simultaneously, especially in high marginal utility states — crises being the paradigmatic example. Clean identification during such turbulent times is difficult at best. Even if it were possible to identify fire sales in real time, 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 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 occur 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, however. What are the factors that make the financial system vulnerable to fire sales? Can we track them over time? And is it possible to predict not only when vulnerabilities develop, but also

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

[2]See Shleifer and Vishny (1992), Allen and Gale (1994), Mitchell, Pedersen, and Pulvino (2007), Acharya, Shin, and Yorulmazer (2009), Brunnermeier and Pedersen (2009), Gromb and Vayanos (2010), and Diamond and Rajan (2011).

[3]See Coval and Stafford (2007), Mitchell, Pedersen, and Pulvino (2007), Ellul, Jotikasthira, and Lundblad (2011), Merrill et al. (2012), Feldhütter (2012), and Mitchell and Pulvino (2012).

where in the financial sector they lurk?

In this paper we address these questions by constructing an index of large bank holding companies' (BHCs') aggregate vulnerability to fire sales. The index decomposes additively into each bank's "systemicness" (its contribution to a fire sale) and multiplicatively into aggregate and cross-sectional factors that drive fire-sale vulnerability. We find that the aggregate vulnerability index (AV) increases slowly starting in 2000 and accelerates in 2004, before many other major systemic risk measures. It then rises steadily, more than doubling by the end of 2006 and peaking at three times its initial level in 2008. After the crisis, AV decreases equally dramatically before stabilizing in 2015 at roughly 40% 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% of AV growth and 50% 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 an individual bank's systemicness is an excellent five-year-ahead predictor of five prominent and widely used measures of firm-specific systemic risk (SRISK, ΔCoVaR, marginal expected shortfall (MES), systemic expected shortfall (SES), and systemic expected losses from a contingent claims analysis (CCA)). For example, even after controlling for contemporaneous SRISK and several bank characteristics, a 1% increase in systemicness is associated with a 3.24% increase in SRISK five years later, highly statistically significant. In addition, the exposure of each bank to fire-sale spillovers — which we refer to as "vulnerability" — predicts actual capital shortfalls during the financial crisis as early as the last quarter of 2004: a 1% increase in bank vulnerability in the last quarter of 2004 is associated with a 16.5% increase in troubled asset relief program (TARP) injections. Thus, had they been available at the time, our measures would 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 pattern that we refer to as 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 Greenwood, Landier, and Thesmar (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 that we refer to as "illiquidity concentration." While it is well known that size and leverage — two of the aggregate factors — are relevant to systemic risk for various reasons, the illiquidity concentration factor 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, Landier, and Thesmar (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 a sample period as long as ours and would (i) implicitly inter-

[4]That different measures of "portfolio overlap" or "interconnectedness" are important for fire sales has been widely recognized in the literature (Falato et al. (2019), Acharya, Shin, and Yorulmazer (2009), Acharya et al. (2009), Allen and Carletti (2008), Bernanke (2009), Cont and Schaanning (2017), Greenwood, Landier, and Thesmar (2015)).

pret observed time-variation in a bank's leverage as variation in the bank's leverage target and (ii) rule out time-variation 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 in both the target and the adjustment speed. Importantly, we are able to seamlessly integrate the partial adjustment behavior of banks into the AV framework of Greenwood, Landier, and Thesmar (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. BHCs from 1999 to 2016. We focus on BHCs for several reasons: they comprise 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, Mandel, and Mollineaux (2012), Adrian, Ashcraft, and Cetorelli (2015)); detailed regulatory data on their balance sheets are publicly available; they were forced to fire-sell assets in the face of deteriorating equity capital during the financial crisis (Bernanke (2009)); and they have been the focus of government interventions. Of course, other parts of the financial sector that are beyond the scope of our analysis can generate large spillovers, either by themselves or when their linkages with banks are considered. For example, Falato et al. (2019) 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 changes 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-

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

section of bank systemicness.

Leverage adjustment speed is roughly constant until 2006, before increasing by over 50% 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% until early 2007. We confirm the importance of illiquidity concentration with two further exercises. First, we run 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 consists of homogeneous banks. Over the majority of our sample, AV is over 20% higher due to the heterogeneity of banks in the data.

AV has other unique features that complement and improve upon 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 et al. (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 before the crisis, highlighting the usefulness of adding AV to the suite of existing measures. 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 account for 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 that a financial firm be designated a SIFI when, among other standards, 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 managers' cases.[7] It has also been adapted to other countries and markets.[8]

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

[7] See U.S. Department of the Treasury (2012), Financial Stability Oversight Council (2015), Financial Stability Board (2016), and U.S. House of Representatives (2016).

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

Bank stress testing has become another standard regulatory tool. However, current implementations focus largely on initial individual losses at large financial institutions, all but ignoring 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 each quarter, which allows us to understand in a consistent way if changes in the system from one quarter to the next affect the vulnerability of the system to fire sales.

Finally, 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 TARP and without the post-crisis tightening in capital and liquidity regulation.

The rest of the paper is structured as follows. In Section I, we present the framework used to calculate fire-sale spillovers. In Section II, we describe the estimation of leverage targets and adjustment speeds. In Section III, we present and discuss the results on fire-sale spillovers. In Section IV, we document the predictive power of the measures. Appendix A summarizes the variables used in the partial adjustment model and Appendix B summarized those used in the calculation fire-sale spillovers calculation.

I. Framework

To calculate potential spillovers from fire sales, we build on the "vulnerable banks" framework of Greenwood, Landier, and Thesmar (2015). The framework assumes a simple fire-sale scenario following a sequence of steps:

(i) Initial shock: An initial exogenous shock hits the banking system. This can be a shock

et al. (2018).

to one or several asset classes, or to equity capital.

(ii) Delevering: Banks affected by the shock delever and partially return to their leverage targets.

(iii) Asset sales: To delever, banks sell assets proportionally and pay off debt.

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

(v) Spillover losses: Banks holding the fire-sold assets suffer spillover losses.

The spillover losses in Step (v) — as opposed to the direct losses in Step (i) — are the focus of the analysis.

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 make no further assumptions on banks' liabilities.

A. *Partial Adjustment to Target Leverage*

Greenwood, Landier, and Thesmar (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

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

where the new level of leverage b_{it+1} is a convex combination of a passive leverage b^p_{it+1} 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

$$b^p_{it+1} = \frac{d_{it}}{e_{it} + \Delta e^s_{it+1} + \Delta e^{\text{iss}}_{it+1}}, \tag{2}$$

where Δe^s_{it+1} is the change in equity due to the shock s and $\Delta e^{\text{iss}}_{it+1}$ 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 II.[9]

B. 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 shocks $(f_{1t}, \ldots, f_{Kt})^\top > 0$ across asset classes that hits all banks at the end of period t. 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.[10] During the episodes of systemic risk that we are interested in, which

[9] We show how alternative assumptions about leverage adjustment affect the calculation of fire-sale spillovers in Internet Appendix Section I.A. The internet appendix is available in the online version of the article on the *Journal of Finance* website.

[10] In Internet Appendix Section I.B we show that not marking-to-market assets that are usually not marked-to-market in practice (such as loans) does not significantly affect our results.

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 setting 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 be reduced only 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, that is, 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_{it}^f 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, that is, $x_{ikt}^f = \widetilde{m}_{ikt} x_{it}^f$. We assume for our benchmark that banks sell in proportion to their existing portfolio weights, $\widetilde{m}_{ikt} = m_{ikt}$ (as in Greenwood, Landier, and Thesmar (2015)), to be agnostic about the relative importance of several opposing forces that could lead to more sales of relatively liquid or illiquid assets.[11] Summing the sales of asset k across banks implies that aggregate sales of asset k are given by

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

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.[12] In addition, we assume there are no cross-asset price impacts; for example, selling agency mortgage-backed securities (MBS) has no direct impact on the price of corporate bonds. The asset classes we construct in our empirical implementation are sufficiently different for the first-order effects to be consistent with no cross-asset price impacts. The price impact of asset k is assumed to be proportional to its illiquidity ℓ_k and inversely proportional to the wealth w_t of potential buyers of fire-sold assets (motivated by

[11] We discuss these forces in Internet Appendix Section I.C together with several alternatives for the liquidation strategy $\widetilde{m}_{ikt}$ and how they affect the results. For sufficiently large shocks, some banks may be selling all of their assets. We take this into account in our empirical implementation by using $x_{it}^f = \min\{a_{it}, \lambda_{it} b_{it}^* a_{it} \sum_k m_{ikt} f_{kt}\}$.

[12] Almost all empirical papers identifying 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 nonlinear 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)). However, over many days — which is the relevant horizon for our study — the nonlinearities tend to smooth out and make price impacts much closer to linear (Bouchaud (2010)).

Shleifer and Vishny (1992)). Aggregate 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

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

Finally, the price impact of the fire sales lead to spillover losses for 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 $\mathscr{L}_t$ suffered by the banking system as a whole. Written in matrix form, we have

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

where $1^\top$ is a row vector of ones, $F_t = (f_{1t},\dots,f_{Kt})^\top$ is the vector of shocks, M_t is an $N\times K$ matrix of portfolio weights, A_t, B^*_t and Λ_t are $N\times N$ diagonal matrices of total assets, leverage targets, and adjustment speeds, respectively, and L is a $K\times K$ diagonal matrix of price impacts. It is important to note that $\mathscr{L}_t$ only captures the *indirect* losses due to spillovers — it 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.[13]

We want to distinguish between 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 $\widetilde{\lambda}_{it} =$

[13]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 Internet Appendix Section I.D, we verify that our main results are virtually unchanged under this kind of multi-round liquidation setup.

$\lambda_{it}/\overline{\lambda}_t$ 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 $\mathscr{L}_t$ in (7) can then be rewritten as

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

Price impacts ℓ_k are notoriously hard to estimate and differ across the limited number of available studies by orders of magnitude.[14] We therefore normalize $\mathscr{L}_t$ 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 the 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 $\mathscr{L}_t$ 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 $\mathscr{L}_t$ 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 $\mathscr{L}_t$, we define the following three measures of systemic risk.[15]

[14] Ellul, Jotikasthira, and Lundblad (2011) find a median price impact of 7.5 bps per $10 billion for corporate bonds, with several bps 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, Lundblad, and Ramadorai (2012) for emerging market stock indices, and Merrill et al. (2012) for nonagency residential MBS. They find price impact estimates that are much larger than those for corporate bonds. To the best of our knowledge, no empirical estimates exist of price impact for bank fire sales or for bank loans, which constitute a large proportion of their balance sheet.

[15] Internet Appendix Section II compares our framework and decompositions with those in Greenwood, Landier, and Thesmar (2015).

Aggregate vulnerability. The fraction of system equity capital lost due to spillovers, $\mathscr{L}_t/e_t$, captures the "aggregate vulnerability" 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:

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

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 $\overline{b}_t^* = \frac{1}{N}\sum_i b_{it}^*$, since 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," shows 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 would collapse to a liquidity-weighted Herfindahl–Hirschman index on portfolio shares $\sum_k \ell_k m_{kt}^2$. In Section III.C, we find that heterogeneity across banks increases AV by roughly 20% over most of our sample.

Systemicness of bank i. We define the systemicness of bank i as the contribution of bank i to AV, which is obtained by dropping the summation over i in expression (8). It is also equal to 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 is large with a high α_{it}, adjusts quickly with high $\widetilde{\lambda}_{it}$, has a high leverage target β_{it}^*, and 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 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

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

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

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

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

II. 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, Landier, and Thesmar (2015). Since our framework for calculating 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, Roberts, and Zender (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 use data only 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 I.A but does not use the hypothetical fire-sale scenario in Section I.B. The fire-sale scenario is not used until Section III, where we quantify the spillovers under the scenario using the estimated leverage targets and adjustment speeds.

A. 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 BHCs, savings and loans associations, and securities holding companies. For convenience, we refer to all of these financial institutions as banks. The information in the form is publicly available and is generally used by regulators to assess and monitor the condition of the 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, we have 688 banks per quarter that account 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.

B. 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.[16]

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 nonfinancial 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, Kuehn, and Strebulaev (2010), Korteweg and Strebulaev (2015)), as well as bank fixed effects (Flannery and Rangan (2006), Lemmon, Roberts, and Zender (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 AI and AII provide a list of the explanatory variables for the leverage target and adjustment speed, respectively. The roles and details of the explanatory variables are discussed with the estimation results in Section II.D.

C. *Estimation Procedure*

The partial adjustment model specified by equations (12) to (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

[16] In Internet Appendix Section III.A we show how treating equity issuance as an active adjustment affects our estimates of adjustment speed. Since banks reduce payouts to shareholders only very slowly and very late, even during 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 banks commonly use instead of cash dividends (Hirtle (2004)). In Internet Appendix Section III.A we show that not adjusting for past dividends does not materially affect our results.

get

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

We can estimate equation (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 equation (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 we use 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) to (14) on rolling 16-quarter windows.[17] We use the resulting rolling estimates $\left(\widehat{\delta}, \widehat{\gamma}\right)$ to construct bank i's leverage target and adjustment speed that will be used in the fire-sale scenario of Section III. The leverage target used for the scenario in period t is bank i's predicted leverage target for

[17] 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, $\sum_i \sum_t b^p_{it} = \sum_i \sum_t \widehat{b}^*_{it} = \sum_i \sum_t b_{it}$.

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)), and 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.[18]

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 correlated, by construction, 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 Internet Appendix Section III.C, we compare the estimated adjustment speed 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 potential finite-sample bias — and find that both have very similar evolution over time.

[18]In Internet Appendix Section III.B we show how alternative treatments of the windows affects our estimates of adjustment speed and leverage target.

D. Estimation Results

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

Full sample regressions. Table I reports results from regressions on the full 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 Comprehensive Capital Analysis and Review (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 their targets are 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, while recessions are associated with lower leverage targets.

Column (2) shows results for the variables determining the adjustment speed and are broadly consistent with faster adjustment speed for banks under different forms of pressure (supporting, for example, 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 omitted category). For banks zero 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).

Table I

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 $\left(b_{it+1} - b^p_{it+1}\right) / \left(\widehat{b}^*_{it} - b^p_{it+1}\right)$ as a function of explanatory variables w_{it}, $b_{it+1} - b^p_{it+1} = \gamma^\top \left[w_{it} \times \left(\widehat{b}^*_{it} - b^p_{it+1}\right)\right] + \nu_{it+1}$, estimated using OLS (column (2)) with $\widehat{b}^*_{it} = \left(\widehat{\phi} / \left(1 - \widehat{\psi}\right)\right)^\top z_{it}$, where the estimates $\widehat{\phi}$ and $\widehat{\psi}$ come from step 1. For details on the explanatory variables, see Table AI. 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^2	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^2	0.16
Observations	55008

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 "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 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 II.C, 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 average actual leverage in the data. In the pre-crisis period, the two measures are very close. Starting in 2007, as banks'

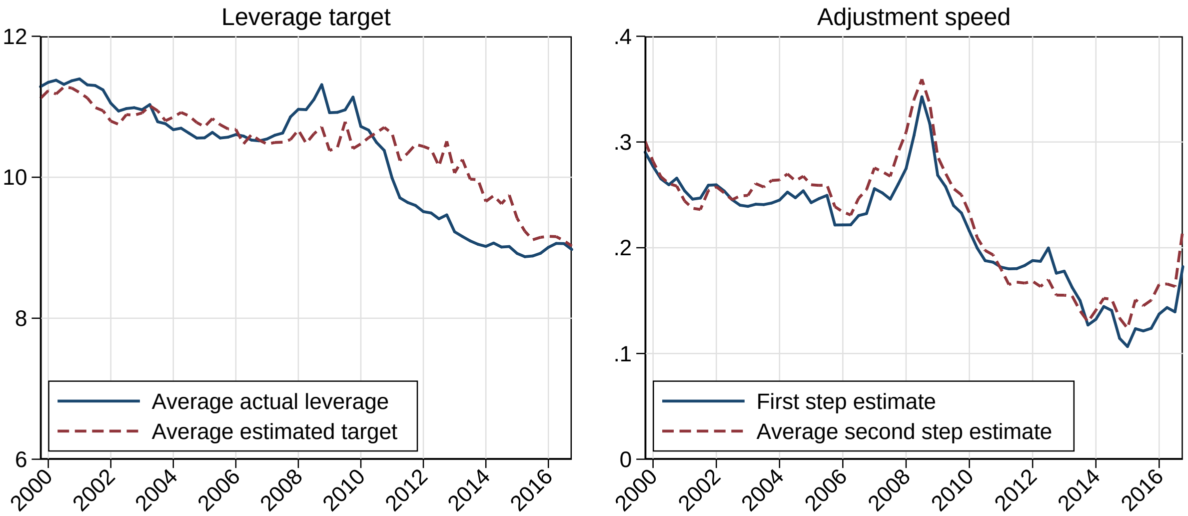

Figure 1. Leverage target and adjustment speed. The figure reports results from 16-quarter rolling regressions estimating the dynamic adjustment model in two steps. Step 1 models leverage b_{it+1} as a function of explanatory variables z_{it} and passive leverage b^p_{it+1}, $b_{it+1} = \phi^\top z_{it} + \psi b^p_{it+1} + \varepsilon_{it+1}$. 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}, $b_{it+1} - b^p_{it+1} = \gamma^\top [w_{it} \times (\widehat{b}^*_{it} - b^p_{it+1})] + \nu_{it+1}$, with $\widehat{b}^*_{it} = (\widehat{\phi}/(1-\widehat{\psi}))^\top z_{it}$, where the estimates $\widehat{\phi}$ and $\widehat{\psi}$ come 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 each 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 sample quarter.

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 II.C). 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 I, column (2), we know that the capital buffer is the main driver of adjustment speed, with adjustment speed inversely related to capital buffer. Consistent with this observation, 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 in the other direction.

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, which means that there is more cross-sectional than time-series variation, and about 0.7 for adjustment speed, which implies somewhat more time-series than cross-sectional variation. See Table BI for additional summary statistics for the leverage target and adjustment speed.

III. Calculation of Fire-Sale Spillovers

We now present 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 II. We then study the role of the individual factors of AV in equation (8) and evaluate the effect of key regulatory policies on AV.

A. 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 II.A. We group assets into the 17 categories listed in Table BI to construct the matrix of portfolio weights M_t; Internet Appendix Section IV contains the mapping between these asset classes and 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 II) 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.[19] There are no readily available estimates for the liquidity of most bank assets. Greenwood, Landier, and Thesmar (2015) therefore assume the same price impact for all assets, $\ell_k = \ell$ for all k. Taking a different approach, 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 employ the NSFR instead of the Liquidity Coverage Ratio (LCR) because it distinguishes asset classes more

[19]For robustness, in Internet Appendix Section I.E we also consider constant outside wealth as well as outside wealth scaled by GDP.

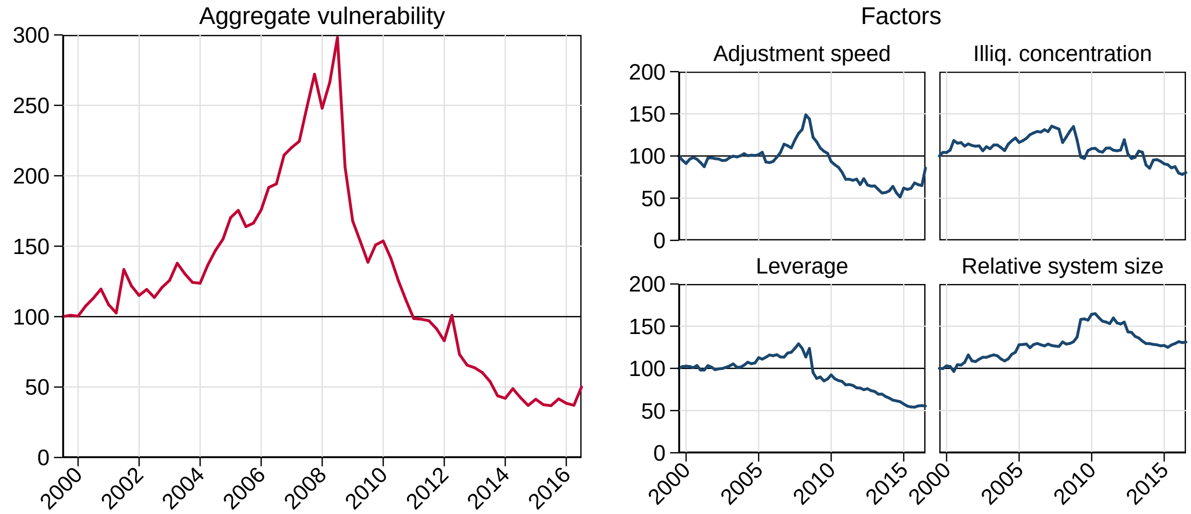

Figure 2. Aggregate vulnerability index and decomposition into factors. The figure shows the aggregate vulnerability index (left panel) and the decomposition into multiplicative factors based on equation (8) (right panel). All series are normalized to 100 at the beginning of the sample.

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 BI shows the value 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).[20] To calculate AV, we include the top 100 banks each quarter that have estimates for leverage target and adjustment speed from Section II.[21]

B. Results

Figure 2 shows the evolution of AV, our main measure of systemic fire-sale risk, as well as its constituent factors from equation (8), which we also normalize to 100 at the beginning of

[20]Internet Appendix Section V provides details on 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, Landier, and Thesmar (2015)) in Internet Appendix Section I.E.

[21]For robustness, in Internet Appendix Section I.F we show that results with a balanced panel are very similar.

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 IV. AV decreases sharply over the course of 2009 and returns to its initial level in 2011. In the post-crisis period, it declines further before stabilizing in 2015 at around 40% of its initial level.

Studying the four AV factors in the right panel of Figure 2, we see that each factor contributes differently to the total and that the contributions change over time. The relative size of the banking system (compared to the rest of the financial sector) and leverage show the 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, due mostly to bank recapitalizations (TARP, see Section III.D), 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 that became BHCs.

Size and leverage are known to be potential contributors of systemic risk, 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% through 2008, causing AV to spike. This is notable since, as discussed in Section II, we control for adjustments via equity issuance. The estimated increase in adjustment speed during the crisis therefore 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 large, we see a positive trend starting in 2004 — between 2004 and 2007, illiquidity concen-

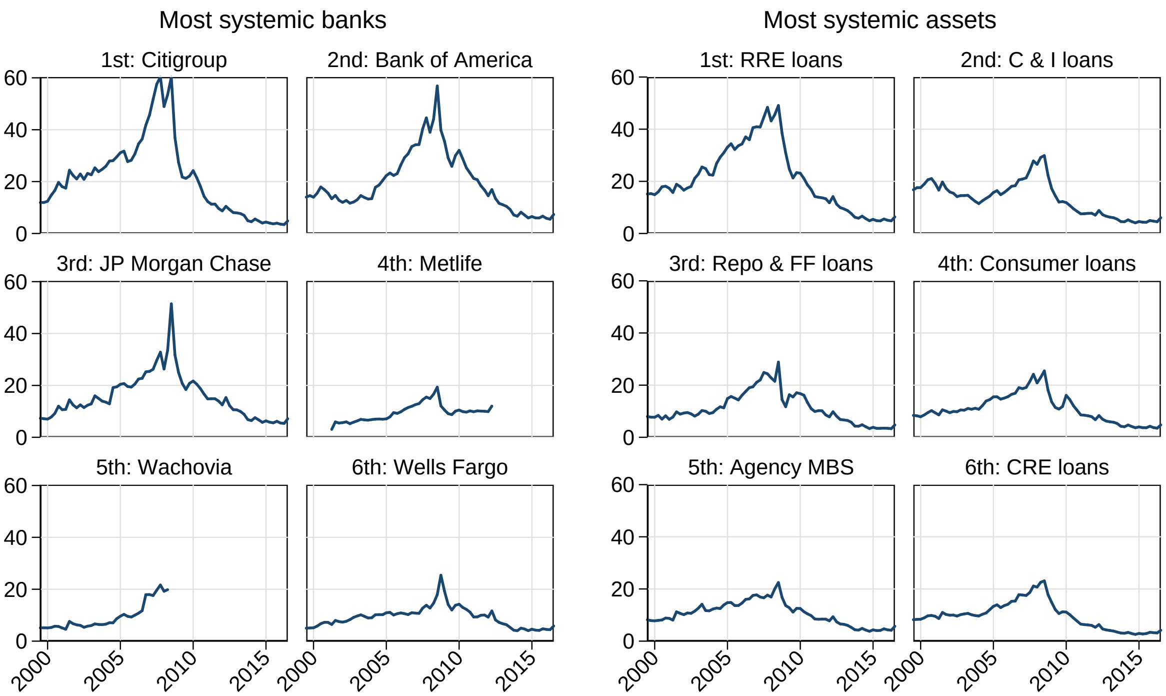

Figure 3. Fire-sale externality of most systemic banks and assets. The figure shows the most systemic banks and assets, plotting the evolution of the measures SB_{it} and SA_{kt} from equations (9) and (10), respectively. Which banks and assets are most systemic is determined by sample averages. Series are normalized to sum to 100 at the beginning of the sample. Abbreviations: "RRE" is residential real estate, "C & I" is commercial and industrial, "Repo & FF loans" is federal funds sold and securities purchased under agreements to resell, "CRE" is commercial real estate.

tration increases by roughly 25%. 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% of the increase in AV from 2000 until its peak in 2008.

Figure 3 plots the evolution over time of the measures SB_{it} and SA_{kt} from equations (9) and (10) for the six banks and the six 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.

Table II

Most Systemic Banks Post-Crisis and G-SIB Surcharge

The table lists the top 10 banks by average systemicness (SB_i) in the post-crisis period (2008Q4 to 2016Q3) as well as any bank not in the top 10 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 to 2016Q3). G-SIB surcharge is the maximum surcharge assigned to each bank between 2011 and 2016, in percent. The sample 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

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 patterns due to differences in the evolution of the bank-specific factors in decomposition (9).

Table II lists the top 10 banks by average fire-sale systemicness in the post-crisis period (2008Q4 to 2016Q3) as well as any bank not in the top 10 by systemicness that has been designated 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 due primarily 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 ranks only seventh by size. In line with our measure's ranking, Metlife was designated as systemically important by the FSOC in December 2014. The designation was based in part 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 (RRE) 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 BI). 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, commercial and industrial (C & I) loans, are as systemic as RRE 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.

C. *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 decompose the variance of log AV into the variances and co-variances of the logs of its factors — relative size, leverage, adjustment speed, and illiquidity

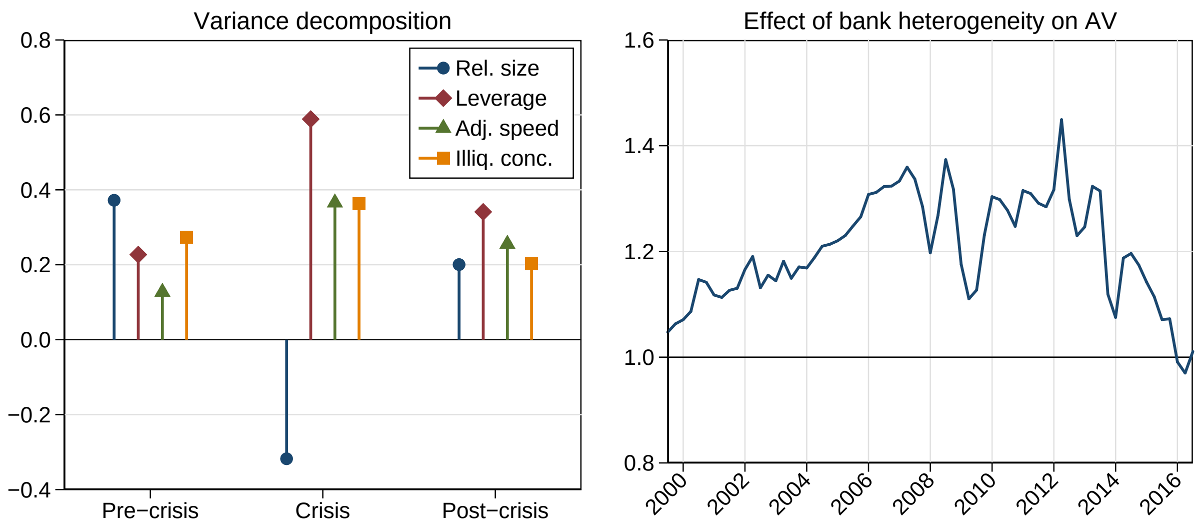

Figure 4. Effect of factors on AV. The left panel shows the contribution of the four factors in equation (8) to the variance of log AV, using the variance decomposition given by equation (18). The right panel shows the ratio of actual AV to a counterfactual AV in which all banks are homogeneous. "Pre-crisis" is 1999Q3 to 2006Q4, "Crisis" is 2007Q1 to 2009Q4, and "Post-crisis" is 2010Q1 to 2016Q3.

concentration — according to

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

We then sum the contributions of each log factor, that is, its variance and all covariances, and express the total relative to the variance of log AV,

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

Figure 4 (left panel) shows the results of this variance decomposition across three sub-periods of our sample: before the crisis (before 2007Q1), during the crisis (2007Q1 to 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 adjustment 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 as the most stable contributor over the entire sample. Jointly, the fire-sale-specific factors adjustment speed and illiquidity concentration account for 40% 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),

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

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% 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.

D. 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 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, for example, 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 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% 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.[22] For simplicity, we leave unchanged each

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

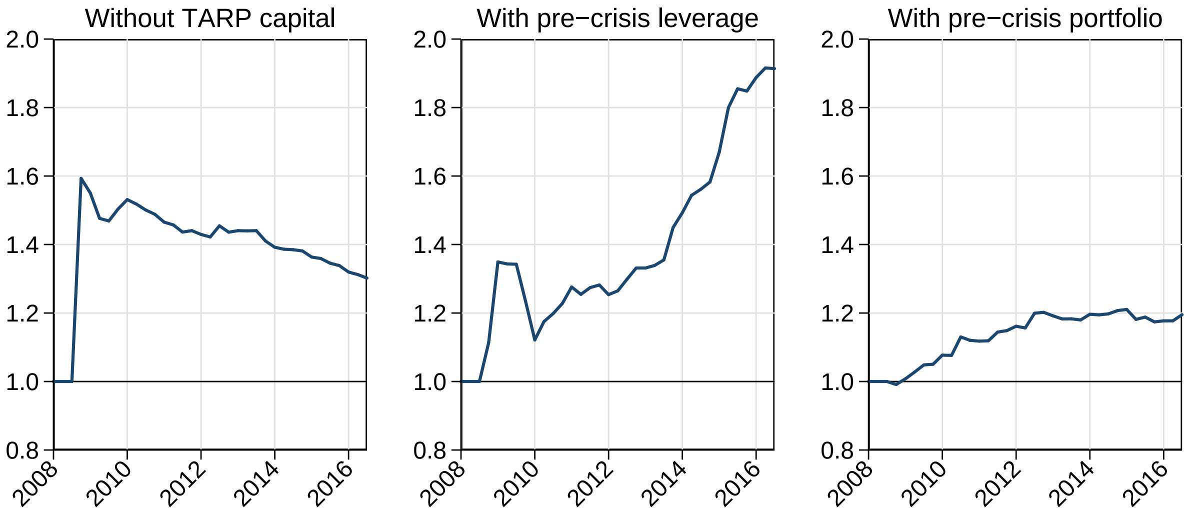

Figure 5. Effects of TARP, capital regulation, and liquidity regulation on AV. The figure shows the ratio of benchmark AV to a counterfactual AV in which each bank's leverage is adjusted by the capital injection it received through TARP (left panel), a counterfactual AV in which, starting in 2008Q4, 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).

bank's estimated adjustment speed; since adjustment speed varies inversely with capital (Section II), 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% in 2008Q4 and 43% higher on average over the entire post-crisis period.

Capital regulation. After the recapitalization through TARP, leverage in the post-crisis period 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% 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. Our counterfactual finds a larger effect for G-SIBs, consistent with their more tightened regulation: while systemicness with pre-crisis leverage in the post-crisis period would have been 37% higher on average across all banks, it would have been 47% higher for banks designated as G-SIBs and 68% 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 LCR and the 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 to this regulation, 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 to be constant at their pre-crisis levels (as of 2006Q4, analogous to the capital regulation analysis above). In Figure 5 (right panel) we see that without the post-crisis changes in asset portfolios, AV would have been about 15% higher over the entire post-crisis period. Among individual banks, systemicness would have been 6% higher on average across all banks, 8% higher for banks designated as G-SIBs, and 23% 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 skewed more towards the most systemic banks.

Regulatory lenience. Regulators have some discretion in implementing and enforcing regulations, which affects a 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. To address this question, we 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); we leave everything else unchanged. We find that this hypothetical regulatory lenience would have reduced AV by 8% on average during 2007 and 2008, with the effect largest in 2008Q3, when AV is reduced by 20%. Thus, temporary regulatory lenience can reduce the costs of fire sales during times of stress, although the magnitude of the effect is smaller than that of the capital and liquidity regulations discussed above.

E. Robustness

In Internet Appendix Section I we consider extensive robustness checks and show that the qualitative behavior of AV remains the same; its evolution over time is essentially unchanged. Specifically, we consider alternative assumptions about leverage adjustment, not marking loans to market, alternative rules for liquidating assets, multiple rounds of fire sales, alternative assumptions about asset liquidities, a balanced panel of banks, and an initial shock to equity instead of assets.

IV. 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 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 those used to construct AV and SB.

A. *Aggregate Early-Warning Properties*

Systemic risk does not emerge overnight. Identifying the steady buildup of systemic risk is crucial to be able to respond to it — detecting trends and implementing policy actions can take time. Figure 6 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.[23]

The top two panels show that 31 out of the 35 measures fail to identify any buildup 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 than lower-frequency trends; they appear rather noisy over the multi-year sample we consider.

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 refer to as "network analysis and systemic financial linkages" and "bank funding risk and shock transmission," are conceptually related to AV, as they are designed to capture the interconnectedness of the financial system and banking system, respectively. The "network

[23]More details on these measures, including how they are constructed and individual plots without any transformations, are provided in Internet Appendix Section VIII.

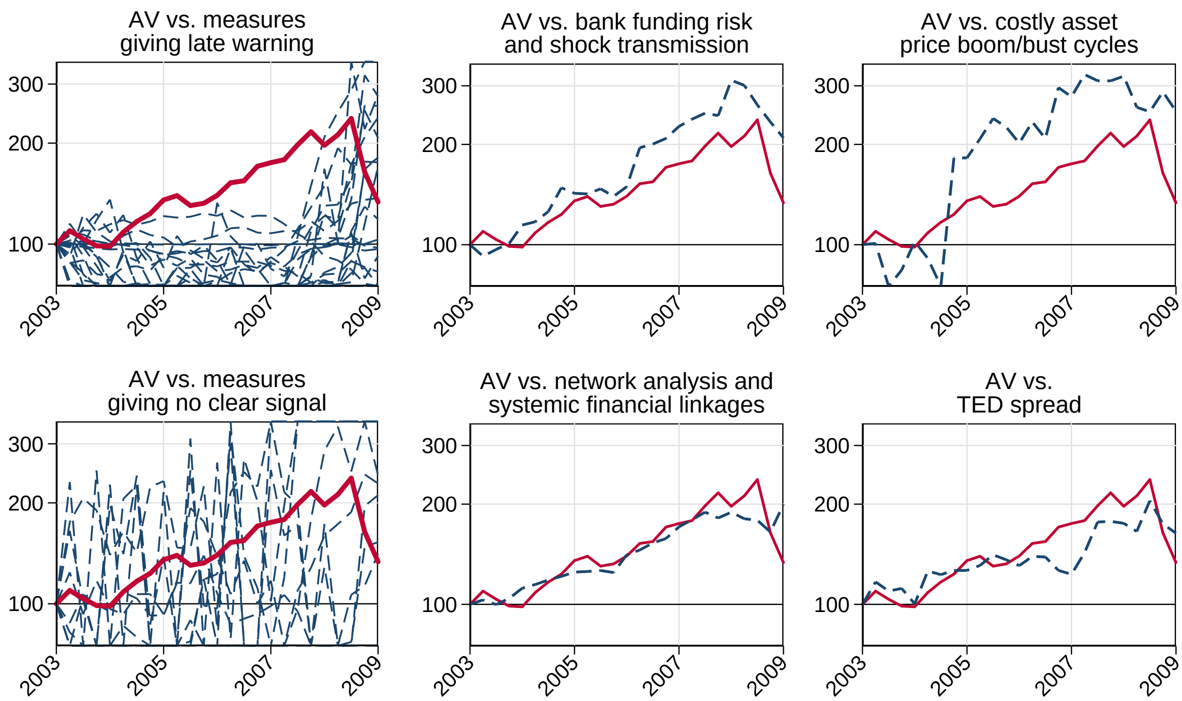

Figure 6. Comparison of AV to other systemic risk measures leading up to the crisis. The figure plots time-series evolution of AV (solid line) and 35 systemic risk measures (dashed lines) surveyed in Bisias et al. (2012) and Giglio, Kelly, and Pruitt (2016) between 2003Q1 and 2009Q1. All measures are normalized to 100 in 2003Q1 and shown in log-scale, winsorized for values lower than 50 and higher than 350. The top left panel compares AV to the 22 measures that give late warning of systemic risk, starting to rise in mid-2007 or later. The bottom left panel shows AV and the nine measures that provide neither a clear trend nor any discernible signal of a crisis. The middle and right panels compare AV to each of the four systemic risk measures that have an increasing pre-crisis trend similar to the one that AV displays. Internet Appendix Section VIII provides plots identifying each measure as well as details on how they were constructed.

analysis and systemic financial linkages" measure is the only one surveyed in BFLV that includes fire sales as a factor contributing 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 refer to as "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 to 2008 period, the asset price boom predicted to adversely affect the real economy is in real estate. As discussed in Section III, RRE loans are also the most systemic class of assets in our analysis and one of the main elements driving the increase in AV in this period, making AV also closely related to this measure. Additionally, BFLV classify the "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, which highlights 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 though are conceptually related to AV. We interpret this as helping to externally validate AV and as additional evidence that the mechanism through which systemic risk increased before the crisis is related to the fire-sale channel we consider.

B. 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 that in Figure 6 effectively relies on a single identifying observation. Figure 6 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 6, 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, SES, MES, CCA, distressed insurance premium (DIP), and Co-Risk. The aggregate versions of all of these measures are in the "late-warning" category plotted in the top left panel of Figure 6. 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 thus 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 seven other cross-sectional systemic risk measures.

In our framework, the distinction between systemicness (SB) and vulnerability (VB) is more transparent. The contemporaneous correlation between SB and VB is 13%, which implies that the two measures contain different information.[24] SB shows a positive correlation with all other measures, which provides further external validation that SB does indeed

[24]See Internet Appendix Table IA.I for the contemporaneous correlations of SB, VB, and the seven other measures we consider.

capture a notion of systemicness. It is most correlated with DIP (87%) and CCA (67%). VB, in contrast, is generally uncorrelated with the other measures. It has a correlation of 17% 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

$$\text{OtherMeasure}_{it+\tau} = \beta\,\text{SB}_{it} + \delta\,\text{OtherMeasure}_{it} + \gamma\,\text{controls}_{it} + \nu_i + \eta_t + \varepsilon_{it+\tau} \tag{20}$$

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 II). The variable $\text{OtherMeasure}_{it+\tau}$ is the value of one of the seven systemic risk measures to be predicted for bank i at time $t+\tau$, 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, namely, conditional CAPM beta, stock returns, volatility of stock returns, physical probability of default over the next year, conditional value-at-risk at the 95% 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 broadly speaking are not directly related to the specific fire-sale mechanism we consider.

Because regression (20) contains a lag of the dependent variable as a regressor, naive estimators — like OLS and the within-groups estimator — can be biased. We therefore use the system GMM estimator of Arellano and Bover (1995) and Blundell and Bond (1998), which, in addition to helping mitigate the bias, has been shown to have high asymptotic efficiency and excellent performance in finite samples (Kiviet, Pleus, and Poldermans (2017)). We assume that all regressors are endogenously determined except for the time fixed effects, which are assumed to be exogenous.[25] Consistent with these assumptions, we use as GMM instruments for the difference equation all lags of order one and higher for the time fixed effects 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 employed in the difference equation. We "collapse" the instrument matrix to keep the number of instruments small as recommended by Roodman (2009) and Kiviet, Pleus, and Poldermans (2017), which, among other benefits, helps mitigate the weak instruments problem.[26]

The coefficient of interest in regression (20) is β. Panel A of Table III 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 reports the $\widehat{\beta}$ obtained by running a different regression. Panel B of Table III 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-value < 0.01 except for CCA at the one-year horizon with p-value < 0.05). SB predicts DIP only at the one-year horizon (p-value < 0.01) despite the two measures having a high contemporaneous correlation (Internet Appendix Table IA.I). 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

[25] 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.

[26] Internet Appendix Section VI.D 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 Internet 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 estimators, consistent with the assumptions in Arellano and Bover (1995) and Blundell and Bond (1998).

Table III

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% 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 horizons) × (7 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 the 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 Internet Appendix Section VI.A.

	(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)

(SRISK) implies that an increase in systemicness SB equal to one percentage point of equity capital at time t is associated with an increase in SRISK of 3.24 percentage points five years later. MES is in 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 III), 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 DIP at the three- to five-year horizon. This confirms the view that, in contrast to SB, the other measures are more likely to capture risk realization rather than ex-ante buildup of risk.

In Internet Appendix Section VI.B, we show that our measure of fire-sale vulnerability VB_{it} from equation (11) is also an excellent predictor of SRISK, ΔCoVaR, SES, and MES.

Predicting with fire-sale factors. In Internet Appendix Section VI.A, we examine the results of running the same regression as equation (20) but replacing SB by its constituent factors from equation (9). The first goal is to further understand what economic forces drive the predictive 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(size$_{it}$), log(leverage$_{it}$), log(illiquidity linkage$_{it}$), and log(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, for example, log(size$_{it}$) × log(leverage$_{it}$).

We find that the different factors of SB drive predictability at different horizons and that the predictive power of the 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). The predictability of ΔCoVaR comes mostly from the size factor. 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 between the factor and size is also a good predictor of the same measure at the same horizon.

C. 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 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 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, this exercise allows us to show that our framework is relevant not only on average over the sample period considered 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

$$\log \mathrm{CI}_i^* = \alpha_\tau + \beta_\tau \log \mathrm{VB}_{i\tau} + \gamma_\tau \,\mathrm{controls}_{i\tau} + \varepsilon_{i\tau}, \tag{21}$$

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 includes no controls and the second includes the controls $\mathrm{SRISK}_{i\tau}$, $\Delta\mathrm{CoVaR}_{i\tau}$, $\mathrm{MES}_{i\tau}$, volatility of stock returns, log assets, and decrease in equity capital between 2007Q2 and 2008Q2 as a share of assets.[27] Brownlees and Engle (2016) further assume that 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 (21) is a Tobit regression that can be estimated consistently by maximum likelihood.

Table IV reports the estimated coefficients for $\tau \in \{2004\mathrm{Q}4, 2005\mathrm{Q}4, 2006\mathrm{Q}4\}$, that is four, three, and two years ahead of 2008Q4, when capital injections start. Each column presents results of a single cross-sectional regression. At the four-year horizon, τ = 2004Q4, our measure of bank vulnerability predicts capital injections, both with and without controls (columns (1) and (2), p-value < 0.05). In addition, the magnitude of the coefficient is eco-

[27]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 underlying and interpretation of equation (21).

Table IV

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 vulnerability of bank i at time τ, $\log \mathrm{VB}_{i\tau}$, predicts the log 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 decrease in equity capital 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 capture 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 $\log \mathrm{CI}_i = \max\left\{\log \mathrm{CI}_i^*, 0\right\}$. To estimate the coefficients, we run six versions of the resulting Tobit regression (using $\tau \in \{2004\mathrm{Q}4, 2005\mathrm{Q}4, 2006\mathrm{Q}4\}$ with and without controls), which we estimate consistently by maximum likelihood. The t-statistics in parentheses are computed using standard errors robust to heteroskedasticity and autocorrelation. Significance: $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

	τ = 2004Q4		τ = 2005Q4		τ = 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 $\mathrm{Decrease}_i$ (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

nomically large and similar in the two specifications: a 1% increase in bank vulnerability in 2004Q4 is associated with either a 13.69% or a 16.50% increase in TARP injections depending on whether controls are included. In terms of the controls, ΔCoVaR is weakly significant (p-value < 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. In contast, 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, and the coefficient on ΔCoVaR is significantly positive only at the four-year horizon.

Internet Appendix Section VI.C shows that vulnerability VB also predicts the probability of receiving a TARP injection in a Probit regression with a TARP indicator as the dependent variable.

V. 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 BHCs 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% 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 in both 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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Appendix A: Variables in Partial Adjustment Model

Table AI

Explanatory Variables for Leverage Target

The table provides 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, $b_{it+1} = \lambda_{it} b^*_{it} + (1-\lambda_{it}) b^p_{it+1} + \varepsilon_{it+1}$. 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-to-equity according to $\left(\rho^{e/d}_{it}\right)^{-1} = \left(\rho^{e/\text{rwa}}_t \text{rwa}_{it}/d_{it}\right)^{-1}$. We winsorize the quarterly return on assets at the 1st and 99th percentiles before calculating the eight-quarter average and the eight-quarter standard deviation used as the variables "Profitability" and "Risk." 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 sample quarter. In the last two columns, "p5" and "p95" denote, 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-to-equity implied by the minimum tier-1 capital ratio requirement.	32.137	11.629	20.062	44.887
CCAR	Dummy equal to one 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	Eight-quarter average of return on assets (net income-to-assets, annualized).	0.009	0.008	-0.003	0.019
Risk	Eight-quarter standard deviation of return on assets (annualized).	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 one 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 two-year Treasury yields.	0.012	0.009	-0.001	0.026
Recession	Dummy equal to one for NBER recessions.	0.095	0.295	0	1

Table AII

Explanatory Variables for Adjustment Speed

The table provides 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 variable "Average capital buffer" varies at the bank level since it is constructed omitting bank i's capital buffer: $(\text{Average capital buffer})_{it} = \frac{1}{N_t-1}\sum_{j\neq i}(\text{Well capitalized 0-20pp})_{jt}$. 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 sample quarter. In the last two columns, "p5" and "p95" denote, 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 one for tier-1 capital ratio below the "well capitalized" threshold (two percentage points above the minimum requirement).	0.013	0.112	0	0
Well capitalized 0-20pp	Dummy equal to one for tier-1 capital ratio zero 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 one for existing bond rating.	0.078	0.269	0	1
Investment grade	Dummy equal to one 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 (omitting bank i).	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	Three-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 three-month LIBOR and three-month Treasury bill yield.	0.005	0.004	0.002	0.011

Appendix B: Variables in Fire-Sale Spillovers Calculation

Table BI

Summary Statistics for Balance Sheet Data

The table provides summary statistics for the variables used in the calculation of fire-sale spillovers. The sample includes the largest 100 banks by assets each 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 II). "SW avg." denotes the size-weighted average (weighted by total assets); "EW avg." denotes the equal-weighted average. "p5" and "p95" denote, 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 one (Internet Appendix Section V). Abbreviations: "C & I" is commercial and industrial, "Repo & fed funds loans" is federal funds sold and securities purchased under agreements to resell, "MBS" is mortgage-backed securities, and "ABS" is agency-backed securities. Source: FR Y-9C and estimation in Section II.

	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
Nonagency 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

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