Vulnerable Banks

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Abstract

When a bank experiences an adverse shock to its equity capital, one way to return to target leverage is to sell assets. The price impact of the fire sale may impact other institutions with common exposures, resulting in contagion. We propose a simple framework that accounts for this effect. This framework explains how the distribution of leverage and risk exposures across banks contributes to systemic risk. We use it to compute a bank's exposure to sector-wide deleveraging, as well as the spillover of a bank's deleveraging onto other banks. We explain how the model can be used to evaluate a variety of policy proposals, such as caps on size or leverage, mergers of good and bad banks, and equity injections. We then apply the framework to measure (a) the vulnerability of European banks to sovereign risk in 2010 and 2011, and (b) the vulnerability of US financial institutions between 2001 and 2010. In our model, "microprudential" interventions, which target the solvency of individual banks are always less effective than "macroprudential", policies which aim to minimize spillovers across firms.

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1. Introduction

Financial stress experienced by financial institutions can contaminate others and spiral into a shock which threatens the entire financial system: this is systemic risk. The measurement of systemic risk has been high on financial regulators' priority list since the 2008 collapse of Lehman Brothers, which triggered widespread financial distress among large US financial institutions. The recent sovereign debt crisis and corresponding concerns about the solvency of European banks system have only made the need to measure system-wide stability more acute.

Two forms of linkages between financial institutions can create contagion. The first relies on contractual dependencies: when two banks write a financial contract such as a swap agreement, a negative shock to one bank can transmit to the other party as soon as one of the banks is unable to honor the contract (e.g., Allen and Babus 2009, Gorton and Metrick 2010, Giglio, 2011). Such bilateral links can create a channel for the propagation of financial distress, because the creditor bank may in turn default on its obligations to third parties (Duffie 2010, Kallestrup et al., 2011).[1] A second propagation mechanism comes from fire-sale spillovers: When an institution is forced to sell illiquid assets, it depresses prices, which in turn can prompt financial distress at other institutions holding these same assets. Such liquidation spirals have been explored in an extensive theoretical literature.[2] In a system of greater complexity, such spirals are believed by numerous economists and policy-makers to have become an important vector of systemic risk over the recent decades (Schwarcz, 2008).

This paper proposes a parsimonious and tractable model of this fire-sales channel of systemic risk. The main benefit of this framework is that it can easily be estimated with available data, used to evaluate systemic risk and simulate policy experiments. The model takes as given (1) the assets holdings of each financial institution, (2) a liquidation rule applied by institutions when they are hit by adverse shocks and (3) the liquidity of these assets on the secondary market. Using these three ingredients, we can compute how asset shocks impact leverage, liquidation, price impact, and finally the equity value of financial institutions. We derive closed form formulas for (a) the impact of shocks on the overall financial sector via fire-sales spillovers ("aggregate vulnerability", our measure of systemic risk); (b) the separate impact of each individual institution's liquidation on the overall value of the financial sector ("systemicness"); and (c) the impact of shocks on each institution separately ("vulnerability"). The model therefore makes a clear distinction between financial intermediaries that are hurt by deleveraging ("vulnerable"), and financial intermediaries that contribute to aggregate

[1] Kalemli-Ozcan(2011) investigate the impact of inter-bank linkages on business cycle synchronization.

[2] See for instance Shleifer and Vishny (1992, 2010), Gromb and Vayanos (2007), Brunnermeier and Pedersen (2009), Adrian and Shin (2010), Allen, Babus, and Carletti (2011), Wagner (2011).

deleveraging ("systemic"). It also delivers a number of intuitive properties concerning how the distribution of leverage and risk exposures across banks determines systemic risk. First, a negative return shock experienced by an asset held by relatively levered institutions has a larger aggregate impact. Second, the system is less stable when asset classes that are large tend to be held by highly levered entities. Third, assets which are both volatile and illiquid should be dispersed across banks, since shocks generate less high price impact deleveraging this way. In contrast, if illiquid assets have low price volatility, then it is better to isolate these assets in separate banks, so that they are not contaminated by other assets that are subject to larger shocks.

Though highly stylized, our framework can be used to simulate the outcome of various policy proposals to mitigate systemic risk. First, it allows to evaluate the overall impact of the failure of a given bank on each other member of the financial system. Second, the model can also simulate the effect of a size cap or forced bank mergers. These policies affect systemic risk because they redistribute existing assets held by large intermediaries to other intermediaries, which may have different exposures to shocks, different size, or different leverage. The model also allows to investigate the potential impact of a leverage cap: such a policy has the power to reduce the sensitivity of intermediaries' fire sales to shocks, but at the cost of substituting debt for equity. Last, the model also allows to explore the features and gains of an "optimal" equity injection, i.e. debt-equity swaps targeted to minimize the aggregate impact of deleveraging. In our framework, "microprudential" stabilization policies, which aim to fix insolvency at weaker banks, are almost always inferior to "macroprudential" policies which target the cross-bank spillovers directly. Put differently, optimal injections should not target banks that are directly exposed to the shock, but banks whose liquidations have the largest impact on others (high "systemicness").

We explore two concrete applications. First, we calibrate the model on European banks during the 2010-2011 sovereign debt crisis. For a large set of European banks, we have good measures of risk exposures derived from the European Banking Authority's July 2011 stress tests. The results of these tests include a set of exposures to sovereign default in a number of countries (e.g., Greece). We then use these exposures to estimate the potential spillovers which could occur during bank deleveraging. Our analysis uncovers some interesting and worrisome linkages. For example, only a few banks have direct exposure to a Greek sovereign default. However, a much larger group of banks are indirectly exposed, because they hold assets which are held by the banks which are directly exposed to Greek sovereign bonds. In the extreme event of a bank failure of a directly exposed bank, these indirectly exposed banks would suffer portfolio losses as well. Using the risk exposures as inputs, we document a correlation between our estimates of vulnerability and equity drawdowns experienced by European banks in 2010 and 2011. We then use our data to evaluate various policy actions which have the potential to reduce systemic risk. We find that size caps, or forced mergers among the most exposed entities, do not reduce systemic risk very much. However, we show that modest equity injections, if distributed appropriately between the most systemic banks, can cut the vulnerability of the banking sector by more than half.

We then apply our framework to the US financial crisis of 2007-2009. In contrast to Europe, we do not have direct measures of exposures of financial intermediaries to different assets, and thus estimate these exposures from equity returns. Despite this limitation, we find that our model performs well on three dimensions: (1) it captures the pre-Lehman build-up in financial instability, (2) it predicts the magnitude of the impact of Lehman's failure on the other banks, and (3) it predicts the maximum equity drawdown experienced by each bank during the financial crisis. These results obtain in spite of coarse estimates of each institution's holdings: a regulator in possession of detailed information on bank holdings could in principle do better. Last, we use the calibrated framework to investigate the systemic impact of various policies, fictitious (a $500bn price cap) and real (the WaMu - JP Morgan merger).

The remainder of the paper is organized as follows. We provide a short literature review in Section 2. In Section 3, we develop the model, solve it, and develop intuitions for financial sector stability under different configurations of leverage and risk exposure across banks. In Section 4, we use commercial bank exposures provided by the EBA's July 2011 stress tests to compute the vulnerability of European banks to sovereign defaults. In Section 5, we test the basic framework on US financial institutions (not just commercial banks), where we rely on historical equity returns to back out exposures. Section 6 concludes.

2. Related Literature

Our paper belongs to a growing empirical literature on systemic risk. Our main contribution is that we focus on fire sales as the channel for contagion, and we use an economic model to calibrate the contagion across financial institutions.

The recent tradition in recent papers on systemic risk has been to infer bank linkages from market price correlations. A first set of papers seeks to estimate risk from bond or CDS data (see for instance Ang and Longstaff (2011)). A recent contribution is Giglio (2011), who uses the difference between bond and CDS spreads (market estimates of counterparty risk) to estimate the joint probability that large banks (who act as CDS sellers) go broke. A second and larger set of papers measures systemic risk through comovement in the portfolios of various intermediaries, measured via equity returns (see, for instance, Billio et al (2010) and references therein). Two recent contributions focus on the extent to which financial intermediaries comove in the tail of the distribution. Adrian and Brunnermeier (2010) measure the Value at Risk of the whole financial sector conditional on a given institution being in distress. They rely on quantile regressions and historical data on stock returns to estimate the comovement of financial institutions under stress. In our model, "systemicness" (the effect of each institution on system-wide deleveraging, see Section 3.2.2) puts an economic structure on their CoVaR measure. On the other hand, Acharya et al. (2010) propose a measure closer to our concept of "vulnerability" (the effect of shocks on each bank individually, see Section 3.2.3). For each financial institution, they calculate the average of returns during the 5% worst market days. This captures the extent to which an institution performs in adverse market conditions. Like our measure of vulnerability, their measure predicts the cross-section of financial institutions' stock-returns during the crisis. Billio, Getmansky, Lo, and Pelizzon (2010) measure systemic risk using bilateral time-series dependencies between firms (see also Diebold and Yilmaz (2011)): because they identify networks, their approach is an important input for our US application. Our "cross-bank vulnerability" (effect of one bank to another, see Section 3.2.4) provide a possible economic foundation of Billio et al's bilateral connections.

We depart from this literature by making a few simple assumptions about the structure of the propagation of funding shocks across banks. The cost of this approach is that we adopt a narrower definition of systemic risk based on asset liquidation. The main benefit is that our model-based approach is to quite easy to use to do policy analysis. Another key benefit of our economic structure that we impose is that we can distinguish between a bank's *contribution* to the risk of aggregate deleveraging ("systemicness"), and that bank's *sensitivity* to deleveraging by other banks ("vulnerability"). Clearly, a bank can be quite vulnerable to deleveraging even if it does not pose much of a risk to the banking system (for example if the bank is small but highly levered). Note also that the economic structure we use in our model is similar to Acemoglu, Ozdaglar and Tahbaz-Salehi (2010), who focus on the propagation of industry shocks in the real economy. They derive conditions under which the propagation mechanism is so strong that aggregate volatility remains high even when the network is large. Assuming their asymptotic approximation is correct for some 100 banks, some of their insights could be applied here to measure systemic fragility, but our goal in this paper is to calibrate/estimate the network and use it to make policy simulations (an issue they do not look at).

Last, our analysis is closely related to policy proposals recently put forth by Duffie (2011) and Brunnermeier, Gorton, and Krishnamurthy (2011). Duffie (2011) proposes that a core group of large financial firms report for a list of stressful scenarios their gains or losses together with the large counterparties with whom the gain or loss for that scenario is the largest. Brunnermeier, Gorton, and Krishnamurthy (2011) suggest eliciting firms' sensitivities to different risk factors and scenarios. Our paper is a first attempt to use simplified economic behaviors to model these sensitivities, and to quantify how these stress scenarios could play out across the broader financial sector.

3. A Model of Bank Deleveraging

We start by describing the model. We then use it to derive easy-to-implement measures of systemic risk, at the bank and aggregate levels. We close the section by providing intuitions about how the distribution of size, leverage, and risk exposures in the system impacts systemic risk in our model.

3.1. Bank Risk Exposures and Deleveraging Behavior

t is the time subscript. There are N banks, each indexed by i. Each bank holds a portfolio of K assets which is financed with a mix of debt d_i and equity e_i. The total value of bank i's portfolio of assets is a_i. The returns of the K underlying assets is given the random $K \times 1$ vector F_t. M is the $N \times K$ matrix of banks' returns exposure to the various assets. Then, the vector of banks' (unlevered) portfolio returns R_t is given by:

$$R_t = MF_t + \epsilon_t, \tag{1}$$

where ϵ_t is a vector of idiosyncratic shocks.

To model the propagation of shocks through assets liquidations, we need to define (1) the total dollar amount sold by each bank following the shock and (2) in what proportion each asset is sold, and last (3) the price-impact of asset sales. In practice, more complex assumptions can be made on each of these three dimensions: For instance, in the Section 4.5, we explore an alternative liquidation rule to that of the canonical model, whereby liquidations are restricted to the most liquid class of assets.

Assumption 1: Size of Asset Sales: Leverage Targeting

When banks experience shocks to their net worth, we assume that they respond by scaling up or down their assets to maintain a fixed level of leverage. Such leverage-targetting is in line with Adrian and Shin (2010), who show that banks manage leverage to offset shocks to their assets' values.[3] Let

[3] They provide evidence that commercial banks target a constant leverage ratio, while investment banks have procyclical leverage, which means that their leverage adjustments more than offset the changes in leverage induced by shocks to asset values.

B be the $N \times N$ diagonal matrix such that B_{ii} is the desired ratio of debt to equity of a given bank, i.e., $B_{ii} = d_i/e_i$. Let A_t be the $N \times N$ diagonal matrix such that $A_{ii,t} = a_{i,t}$ is equal to the total assets in dollars of bank i.

Assume a bank experiences an unlevered return of $R_{i,t-1}$, but seeks to maintain its target leverage at B_{ii}. In this case, it is easy to show that the bank will have to scale up its assets by $B_{ii}A_{ii,t-1}R_{i,t-1}$. For example, suppose a bank with equity of 1 and debt of 9 experiences a 10% return on its assets, bringing its equity to 2. The bank will have to borrow an additional 9 and buy assets to return to the prior leverage of 9-to-1.[4] Hence, if we define ϕ as the vector of net inflows of capital required to maintain constant leverage:

$$\phi_t = BA_{t-1}R_{t-1}. \tag{2}$$

When $\phi < 0$, this means that banks with negative asset returns have to sell assets to deleverage.[5]

In writing Eq. (2) we implicitly assume that banks do not raise equity in response to a negative shock. While the assumption is extreme, the basic analysis does not change if we instead assume that banks return to target leverage using a combination of asset sales and equity issues in fixed proportion. In this case, the magnitude of our results is dampened by the willingness to issue equity. We note, however, that in situations where debt overhang is severe, banks will be unwilling to raise new equity without government intervention, and thus our analysis serves as a useful benchmark. We also abstract away from the specific dynamics of the adjustment process, which could be quite slow if the bank is reluctant to recognize losses. The analysis remains qualitatively identical if banks return only partially to their leverage target.

Assumption 2: Composition of Asset Sales

Which of their assets do banks sell when they deleverage? The second main assumption of the model is that banks sell (or buy) the different assets in proportion to their dollar holdings, so as to keep their exposures (as defined by the M matrix) relative to total assets constant. For example, if a bank portfolio consists of 10 percent cash, 20 percent in stocks and 70 percent in mortgage backed securities, if the bank scales down its portfolio by ten units, it will sell 2 units of stocks, 7 units of mortgage backed securities, and take its cash down by 1.[6] Accordingly, let $\phi_{i,t}^k$ denote bank i's the

[4] Essentially we are treating banks as similar to leveraged exchange traded funds (ETFs) which must readjust to their target leverage at the close of trading each day.

[5] See Greenlaw, Hatzius, Kashyap, and Shin (2008) and Adrian and Shin (2009) for further discussion of this point and related evidence.

[6] This assumption has been widely used in the mutual fund literature: investor flows have been shown to cause mutual funds to scale up and down their portfolios, but otherwise keep their portfolio weights constant. See Coval and Stafford (2007), Greenwood and Thesmar (2010), and Lou (2011). We have experimented with more complicated liquidation rules,

dollar net buys of asset k, so that $\phi_{i,t} = \sum_k \phi_{i,t}^k$. To maintain constant relative dollar exposures, net buys of asset k must satisfy:

$$\phi_{i,t}^k = m_{ik}\phi_{i,t}, \tag{3}$$

where we implictly assume that the bank holds a fraction $1 - \sum_k m_i^k$ of cash, which it buys or sells like the other assets. In vector terms, the $K \times 1$ vector of total net dollar order purchases is given by $M'\phi_t$.

Assumption 3: Price Impact of Asset Sales

We make the reduced-form assumption that asset sales generate price impact according to:

$$F_t = LM'\phi_t, \tag{4}$$

where L is a diagonal matrix of price impact ratios, expressed in units of returns per dollar of net purchase. For instance, Pulvino (1998) estimates the discount associated with fire sales of commercial aircraft by distressed airlines. In equity markets, Coval and Stafford (2007) estimate the L coefficient using forced purchases and sales of stock by mutual funds (see also Ellul et al, 2011, and Jotikasthira et al, 2011 who use similar methodologies in other asset markets).

Given these three assumptions, the model is solved by combining equations (4), (2) and (1). Let S be the vector of shocks to assets in $t-1$, then, returns R_t should be given by:

$$R_t = (MLM'BA_{t-1}) \times S. \tag{5}$$

In principle, one can iterate for multiple rounds of deleveraging following an initial shock through further multiplying by $MLM'BA_{t-1}$. In this paper, we restrict our attention to the first round.

3.2. Measuring Systemic Risk

We use Equations (1) through (5) to derive four measures of bank vulnerability and systemic risk that capture the contagion effect of bank deleveraging.

in which banks first rank assets by liquidity, and start selling their most liquid assets first, or equivalently drawing down their cash assets before engaging in asset sales. While this analysis yields some additional theoretical insights, it is less amenable to calibration in our data.

3.2.1. Aggregate vulnerability

Let us first define the direct effect of a shock S. The response of bank returns is given by MS. By pre-multiplying this vector by aggregate bank assets $1'A_{t-1}$, we obtain the aggregate dollar *direct* impact of the shock, which is $1'A_{t-1}MS$. This direct effect does not involve any contagion between banks. The direct effect can also be expressed as a levered equity return by pre-multiplying by B, i.e., $BA_{t-1}MS$.

Following equation (5), the dollar effect of shock S on bank assets through fire-sales is given by premultiplying $MLM'BA_{t-1}MS$ by $1'A_{t-1}$. We normalize this by total bank equity and define "aggregate vulnerability" as:

$$AV = \frac{1'A_{t-1}MLM'BA_{t-1}MS}{E_{t-1}}, \tag{6}$$

AV measures the percentage of aggregate bank equity that would be wiped out by banks' subsequent deleveraging if there was a shock S to economic factors. Note that this formula crucially omits the direct impact of the shock on net worth, thereby emphasizing only the spillovers across banks. If all assets are perfectly liquid (i.e., all elements of the L matrix are zero), then $AV = 0$: there is no fire-sales and therefore no contagion, even though there is still a direct effect $BA_{t-1}MS$. on equity returns.

To understand the core intuitions of our model, using $R = MS$, we can expand Equation (6):

$$\begin{aligned} AV \times E_{t-1} &= \sum_{i,j,k} \Big(a_{i,t-1} m_{i,k} l_k m_{j,k} b_j a_{j,t-1} r_j \Big) \\ &= \sum_k \Big[\Big(\sum_i m_{i,k} a_{i,t-1} \Big) \Big(\sum_i l_k m_{i,k} b_i a_{i,t-1} r_i \Big) \Big]. \end{aligned} \tag{7}$$

where r_i is the i^{th} element of bank return vector R. Suppose that bank j is impacted by a return shock $r_j < 0$, so its total assets go down by $a_j r_j$ dollars. To maintain target leverage, that bank thus has to liquidate a dollar amount $b_j a_j r_j$. A fraction $m_{j,k}$ of that amount will be in asset k, leading to a return impact of liquidation $(l_k m_{j,k}) b_j a_j r_j$ on asset k. Bank i, which owns $m_{i,k} a_i$ dollars of this asset k will make a loss equal to $m_{i,k} a_i m_{j,k} a_j b_j r_j$. Our measure of aggregate vulnerability adds up *across all assets and banks* these liquidation-generated losses.

The expansion in Eq. (7) highlights another key feature of our model: vulnerability is high when asset classes for which aggregate dollar holdings $\sum_i m_{i,k} a_i$ are large are also assets which are held by large, levered highly exposed banks $\sum_i m_{i,k} a_i b_i r_i$.

With constant leverage ($b = b^*$) and constant shocks across banks ($r_i = r$ for all i), the distribution of assets across banks does not matter for aggregate vulnerability. In particular, having all assets in one bank, or having assets equally distributed across banks does not change aggregate vulnerability since the fire sale spillovers add up linearly. The distribution of assets across banks matters *only* when leverage or portfolio composition (M) differ across banks.

3.2.2. Systemic Banks

We can calculate the contribution that each bank has– through liquidation spirals – on the aggregate value of the banking system. To do this, we again focus on the impact of a shock to factors S, but assume it only affects bank i. In this case, it is easy to see that the impact coming from the liquidations of bank i on the aggregate of the banking system is:

$$
\begin{aligned}
S(i) &= \frac{1' A_{t-1} M L M' B A_{t-1} e_i e_i' M S}{E_{t-1}} && (8) \\
&= b_i \times \left(\frac{a_{i,t-1}}{E} \right) \times \left(e_i M S \right) \times \left(1' A_{t-1} M L M' e_i \right) && (9) \\
&= \underbrace{b_i}_{\text{Higher leverage}} \cdot \underbrace{\frac{a_{i,t-1}}{E_{t-1}}}_{\text{Size}} \cdot \underbrace{\left(\sum_{k=1}^{K} m_{i,k} s_k \right)}_{\text{Exposure to shocked assets}} \cdot \underbrace{\sum_{k=1}^{K} l_k m_{i,k} \left(\sum_{j=1}^{N} a_{j,t-1} m_{j,k} \right)}_{\text{Holds illiquid assets held by rest of system}} && (10)
\end{aligned}
$$

where e_i is the vector with all zeros except for the i^{th} element, which is equal to 1. We call $S(i)$ the "systemicness" of bank i.

Eq. (10) shows that a bank can be more systemic for four distinct reasons:

- *It is more levered:* A shock to a more levered bank is going to induce it to sell more, which generates more price-impact.
- *It is bigger:* A given shock on a larger bank leads to more fire sales which in turn leads to a large price impact.
- *Is is more exposed to shocked assets:* If this is the case, a given factor shock will lead to more deleveraging, which increases the price impact.
- *It is more connected:* This happens when bank i owns more illiquid assets held by other banks. In our approach of systemic risk, contagion occurs through liquidation spirals; thus interconnections through common holdings are weighted by illiquidity. This is the meaning of the last term in Eq. (10).

Note that aggregate vulnerability is simply the sum over all banks of their systemicness, i.e., $AV = \sum_i S(i)$. Hence, systemicness can be interpreted as the contribution of each bank to aggregate vulnerability.

3.2.3. Vulnerable Banks

A bank's systemicness is not the same as its *exposure* to the deleveraging of other banks. We define a bank's "vulnerability" as the impact on its equity of the aggregate deleveraging following a shock S according to:

$$V(i) = \frac{e_i' A_{t-1} M L M' B A_{t-1} M S}{E_{i,t-1}} \tag{11}$$

$$= (1+b_i) \times \left(e_i' M L M' B A_{t-1} M S\right) \tag{12}$$

$$= (1+b_i) \times \sum_{k=1}^{K} \left[m_{i,k} \left(\sum_{j=1}^{N} l_k m_{j,k} b_j a_{j,t-1} r_j \right) \right]. \tag{13}$$

$V(i)$ represents the effect of the aggregate shock on bank i as a percentage of its equity. The first term stands for the pure leverage effect: a more levered bank is more vulnerable. The second term measures the importance of connections between banks. The price impact on asset k of deleveraging by all banks is $\left(\sum_{j=1}^{N} l_k m_{j,k} b_j a_{j,t-1} r_j\right)$. These price impacts are then multiplied by bank i's exposure: an individual bank's vulnerability to deleveraging risk depends on its leverage and exposures to illiquid factors that lots of other highly levered banks are exposed to.

For each bank, it is natural to compare "vulnerability" and "direct exposure", which can be calculated by pre-multiplying MS by $e_i' A_{t-1}$. Direct exposure $e_i' A_{t-1} M S$ measures the immediate impact of the shock on bank i, while vulnerability captures the indirect effect of fire-sales spillovers.

3.2.4. Cross-Bank Vulnerability

So far we have emphasized vulnerability to deleveraging occurring because a broad set of banks receives a set of potentially correlated shocks. A special case of this is to compute the vulnerability of a bank to liquidations induced by a negative shock to any another bank. We later do this empirically where we estimate the impact of the Lehman Brothers failure on other US banks. The impact of a 100 % shock to bank j's assets on the assets of bank i, normalized by bank i's equity is given by:

$$V(i,j) = \frac{e_i' A_{t-1} M L M' B A_{t-1} e_j}{E_{i,t-1}} \tag{14}$$

$$= b_j \times a_{j,t-1} \times (1+b_i) \times e_i' M L M' e_j \tag{15}$$

$$= b_j \times a_{j,t-1} \times (1+b_i) \times \left(\sum\nolimits_{k=1}^{K} l_k m_{i,k} m_{jk}\right). \tag{16}$$

The four terms can be interpreted as follows. If bank j (the sender of the shock) is bigger or more levered, its dollar impact on each bank i will be bigger. This is because bank i will have to sell a larger quantity of assets. The first two terms are the same for all receiving banks i. The third component measures the leverage effect on bank i. Since fire sales by bank j impact the assets of i, their impact on equity value will be bigger if the bank is more levered. The last term measures the liquidity weighted linkages between banks i and j.

3.3. Ex-ante Vulnerability

The different vulnerability measures developped above are relative to a given shock to assets S. To measure *ex-ante* vulnerability, a first approach consists in mputing for S the vector of asset returns' volatilities This approach basically corresponds to analyzing the impact of a one standard deviation shock to all assets simultaneously. This way of stress-testing the system is robust in that it doesn't rely on any assumption on the stability of correlations between asset classes. An alternative measure of ex-ante vulnerability uses the variance-covariance matrix of asset returns Ω to compute the standard deviation of AV. [7]

3.4. Determinants of Banking System Vulnerability

Here we build intuition for the determinants of aggregate vulnerability through a few simple examples. The examples illustrate how the distribution of size, leverage, and risk exposures across banks contributes to systemic risk. In these examples, we fix $n = K = 2$, i.e., two banks and two assets (1 and 2). Dollar holdings of assets are given by $H_1 = H_2 = H$. We define l_k as the price impact associated with asset k (return effect of one dollar of net buys). s_k is the volatility of asset k and b_i is the debt-equity ratio of bank i. For any variable θ, we follow the convention that $\theta^* = (\theta_1 + \theta_2)/2$.

[7] More precisely, since $AV = \frac{1' A_{t-1} M L M' B A_{t-1} M}{E_{t-1}} S$, the variance of AV is $\left(\frac{1' A_{t-1} M L M' B A_{t-1} M}{E_{t-1}}\right) \Omega \left(\frac{1' A_{t-1} M L M' B A_{t-1} M}{E_{t-1}}\right)'$.

3.4.1. Systems in which banks have identical leverage

We start by studying a system in which banks have identical leverage b^*. We consider two sub cases. In the first ("same"), banks have similar portfolio compositions, i.e. $m_{1,k} = m_{2,k}$. This implies that asset returns are perfectly correlated across banks. Because each asset exists in similar quantity in the economy, it is easy to see that $M^{Same} = \frac{1}{2}11'$.[8] Existing methodologies that measure systemic risk based on historical returns correlations, such as Adrian and Brunnermeier (2010) or Acharya et al (2011), would tend to consider systemic risk in this case to be high, since banks are all highly distressed when the whole system is in distress. But, as we will show below, it is not automatically true that systemic risk is high, in the sense that these banks are strongly exposed to deleveraging shocks.

In the second subcase ("Segregated Assets"), each category of assets is segregated into a single bank: The first bank holds only asset 1, and the second bank holds only asset 2. i.e. $M^{Segregated} = I$. Total assets of bank i, A_{ii}, is equal to the supply of bank i, H. This banking system has very different properties from the symmetric one, e.g. since banks have no assets in common, their historical returns will look less correlated than in the first case.

These two banking systems have different aggregate vulnerabilities. We compute ex-ante aggregate vulnerabilities by looking at the impact of a one standard deviation shocks to all assets, i.e. $S_i = s_i$. Plugging into Eq. (6) leads to:

$$\begin{cases} AV^{Same} & = & b^* H^2 \cdot 2l^* s^* \\ AV^{Segregated} & = & b^* H^2 \cdot (l_1 s_1 + l_2 s_2) \end{cases}$$

AV^{Same} does not depend on the relative size of the two banks. If one big bank holds all of the assets and a second bank holds none (i.e., a void bank), this is equivalent in terms of aggregative vulnerability to a symmetric system in which the two banks each hold half of the assets. This is because of the linearity of the liquidation rule and the common leverage assumption: a dollar shock Δ to asset i leads to the total liquidation of a dollar quantity of assets $b^*\Delta$, split equally across both assets. Our measure captures the total aggregate value destruction induced by the liquidation of assets: thus the split among banks does not matter when leverage is constant and the banks hold similar portfolios of assets.

We also note that $AV^{Same} < AV^{Segregated} \Leftrightarrow (l_1 - l_2)(s_1 - s_2) > 0$. Making the banks more similar in their exposures makes the system stronger when the less liquid (higher l) asset is also the most volatile. The intuition is that there are two opposing forces at work:

[8] Indeed, if we call $m = m_{1,1} = m_{2,1}$, then $m_{1,2} = m_{2,2} = 1 - m$ and the total quantity of asset 1 is $m(A_1 + A_2) = H$, while that of asset 2 is $(1 - m)(A_1 + A_2) = H$, which finally implies $m = 1/2$.

- The benefit of spreading the volatile asset across banks is that when an asset (say asset 1) is hit with a shock, less of it has to be liquidated in aggregate. Namely, for a shock Δ_1 to the value of asset 1, only a quantity $b^*\Delta_1/2$ of asset 1 has to be liquidated (and a similar quantity of asset 2) whereas under segregated assets that quantity is $b^*\Delta_1$.
- The cost of spreading the volatile asset across the banks is that when asset 2 is hit by a dollar shock Δ_2, some of the less liquid asset must get liquidated, in amount $b^*\Delta_2/2$ which is relatively costly.

When asset 1 is more volatile ($\Delta_1 > \Delta_2$), the expected benefit dominates the cost because on average asset 1 is subject to larger shocks. When liquidity *or* volatility of both assets are identical, the segregated and symmetric systems are equally vulnerable to deleveraging pressures. If liquidity is the same, it does not matter which asset is liquidated. And if volatilities are identical, then return shocks have similar magnitude, so the gain from shielding asset 1 from its own shocks is exactly offset by the cost of getting exposed to liquidating asset 1 because of shocks to asset 2.

3.4.2. Heterogeneous leverage

Suppose we now assume that banks have different levels of leverage, $b_1 \neq b_2$. Now it is no longer true that all systems where the banks hold the same asset mix have similar aggregate vulnerability.

We distinguish between "Symmetric" systems (in which both banks have an asset portfolio of identical size) and "Single Bank" systems, in which all assets are held by the lowest leverage bank (say, Bank 1). We then compute the corresponding measures for aggregate vulnerability:

$$\begin{cases} AV^{Symmetric} & = & 2H^2 \times b^* l^* s^* \\ AV^{One\ Bank} & = & 2H^2 \times b_1 s^* l^* \\ AV^{Segregated} & = & 2H^2 \times \left(\frac{l_1 b_1 s_1 + l_2 b_2 s_2}{2}\right). \end{cases}$$

Isolating all assets under the umbrella of the lowest leverage bank is more stabilizing than splitting them equally across the two banks. This is because there will be less liquidations in aggregate for a given shock when the assets are held by the lowest leverage bank.

When one asset is volatile but liquid, it can be optimal to ring-fence it. To see this, consider the limiting case where $l_2 = 0$, i.e., liquidations of asset 2 have no price impact. Then $AV^{Segregated} < AV^{One\ Bank}$ *iff* $s_1 < s_2$. The intuition is that if the price pressure associated with liquidations of asset 2 is zero, but asset 2 is subject to large shocks, then mixing the two assets in a low-leverage bank is counter-productive in terms of aggregate vulnerability, because it makes asset 1 subject to the larger shocks experienced by asset 2. Under these assumptions, segregating assets leads to lowest aggregate vulnerability.

3.4.3. The impact of bank mergers on systemic risk

We now show how the merger of two banks can affect aggregate vulnerability.

Start from a segregated system in which all of asset i is in Bank i. Consider the merger of the two banks which have identical size A and leverages of b_1 and $b_{2.}$. Liabilities of the two banks are combined into $D = D_1 + D_2$. The new bank has size $2A$ and leverage of:

$$b^{merged} = \frac{\sum_{i=1,2} D_i}{\sum_{i=1,2} A_i - D_i} = \frac{\frac{1}{1+b_1}b_1 + \frac{1}{1+b_2}b_2}{\frac{1}{1+b_1} + \frac{1}{1+b_2}}.$$

The last equation uses $b_i = \frac{D_i}{A_i - D_i}$ (which rewrites $A_i - D_i = \frac{A_i}{1+b_i}$) and the assumption that $A_1 = A_2$. Note that the leverage of the merged bank is not the same as *asset-weighted* leverage: $b^{merged} < (b_1 + b_2)/2$ as relative weight on the smallest leverage is smaller, a simple manifestation of Jensen's Inequality. This effect can be surprisingly large when pre-merger leverages differs significantly. Consider the example in Figure 1. A risky Bank had debt of 90 and equity of 10, and a safer Bank had debt of 10 and equity of 90. The merged bank has leverage of 1, compared to the average leverage of 4.55.

To determine whether the merger is stabilizing, we compare aggregate vulnerability before and after the merger:

$$\begin{cases} AV^{Before} & = & 2H^2 \times \left(\frac{b_1 l_1 s_1 + b_2 l_2 s_2}{2}.\right) \\ AV^{After} & = & 2H^2 \times b^{merged} l^* s^*. \end{cases}$$

Intuitions for this formula can be developed by distinguishing two effects:

- First, merging banks of similar leverage (such that $b^{merged} = b_1 = b_2$) creates a more stable system iff $(s_1 - s_2)(l_1 - l_2) > 0$, i.e. iff the most illiquid asset is also the most volatile. Under this assumption, the merger creates stability, because the illiquid asset will be subject to smaller shocks on average.
- Second, suppose we assume the two assets have identical liquidity and volatility : $l_1 = l_2 = l^*$, $s_1 = s_2 = s^*$. Then $AV^{After} < AV^{Before}$ because the leverage of the merged entity (b^{merged}) is below the average leverage of pre-merger entities.

3.5. Extending the analysis to large shocks

So far, we have looked at the vulnerability of banks to shocks whose direct effect did not lead to insolvency. If a shock makes a bank's asset value smaller than its liability, there is no self-financed deleveraging that can bring the bank back to solvency, and thus our liquidation rule needs to be adjusted. We do this here by making the natural assumption that once a bank is insolvent, its assets are immediately liquidated.

Consider an initial shock S to factors. Banks' assets returns following the shock are $R_{t-1} = MS$. Any bank such that post-shock asset value $a_{i,t-1}(1 + R_{i,t-1})$ is smaller than its debt d_i liquidates all of its assets. Going back to Eq. (2), this translates into the following adjusted liquidation rule:

$$\phi_{i,t} = \begin{cases} b_i a_{i,t-1} R_{i,t-1} & \text{if} \quad a_{i,t-1}(1 + R_{i,t-1}) > d_i \\ -a_{i,t-1}(1 + R_{i,t-1}) & \text{if} \quad a_{i,t-1}(1 + R_{i,t-1}) \leq d_i \end{cases}$$

This liquidation rule remains a continuous function of assets returns $R_{i,t-1}$ and can simply be written as a function of our key parameters:

$$\phi_{i,t} = a_{i,t-1} \max\left(b_i R_{i,t-1}, -(1 + R_{i,t-1})\right)$$

All our vulnerability concepts, such as aggregate vulnerability or individual bank vulnerability, can be redefined vis-à-vis the shock S in a straightforward manner: one just needs to replace the previously linear liquidation rule by this generalized liquidation rule. Calling "*max*" the point-wise maximum matrix operator, defined by $\max(X, Y) = (\max(X_i, Y_i))$, we obtain the following expression for aggregate vulnerability to S :

$$AV = \frac{1' A_{t-1} M L M' A_{t-1} \max(BMS, -1 - MS)}{E_{t-1}}. \tag{17}$$

We use this formula to define vulnerability and systemicness in the next section.

4. Measuring Vulnerability of European Banks

Europe is a natural testing ground for the model because detailed holdings data per bank are available through the European Banking Authority (EBA) as a result of the 2011 bank stress tests. Given the role that sovereign debt has played in the European banking crises, we focus our analysis on banks' sovereign bond holdings.

4.1. Data

Risk exposures M are taken directly from the results of the European stress tests published in July 2011 on the EBA website, which provides detailed accounts for the 90 largest banks in the EU27 countries. We focus on the following 42 asset classes: sovereign debt of each of the 27 EU countries plus 10 others, commercial real estate, mortgages, corporate loans, retail SME and retail revolving credit lines. [9] Looking at overall exposure, the EBA data reveal that banks' total exposure to commercial real estate is 1.2 tn euros (5% of aggregate banking assets); small business lending is 744bn euros (3.2%); mortgages are 4.7 tn euros (20%); and corporate loans are 6.7 tn euros (29%). Sovereign bonds are a modest fraction of the aggregate bank balance sheet: 2.3 tn euros, or about 13% of total banking assets.

To populate the leverage matrix B, we use the book values for total assets and equity which are reported in the stress tests. This approach contrasts with our US analysis in the next section where we use market leverage. Using book leverage, however, does allow us to include a number of non-listed banks (see Appendix A for the full lists the European banks in our sample.[10]) For each bank, we divide total banking assets *minus* common equity divided by common equity. Last, we calculate the A matrix using total bank exposures from the EBA. For price impact, we assume price impact of $L = 10^{-13} Id$.

4.2. Model Validation on the Sovereign Crisis.

Between Dec 31, 2009 and September 16, 2011, European bank stocks (the subset of our sample which is publicly traded) fell by an average of 54%. In this Section, we ask if this meltdown comes from market perception of direct and indirect exposures to losses on sovereign debt from Greece, Italy, Ireland, Portugal and Spain (GIIPS).

We first calculate the vulnerability of each european bank using equation (11). As our hypothetical shock S_{GIIPS} to risk factors, in our baseline specifications, we assume a 50% write-down on GIIPS debt, with no impact on the debt prices of other sovereigns.[11]

We first provide in Table 1 the ranking of banks by indirect vulnerabilities ($V(i)$). Rankings in terms of indirect and direct effect do not correlate very much, which suggests that they provide different information. The Spearman rank correlation between direct and indirect exposure to GIIPS

[9] http://stress-test.eba.europa.eu/

[10] These non listed banks are far from being negligible in size: they hold 20% of total banking assets. This is due to the large number of mutual and savings banks, in particular in Germany and Spain.

[11] In alternative specifications, we have used, as shock S, a 50% write-down on Greek banks only, as well as a shock to Greece, Ireland and Portgual. Measuring expected losses under these alternative scenario led to similar results. This is not surprising since yields of all five GIIPS countries tend to comove.

is .14, and not significantly different from zero. Indirect vulnerability is not correlated with size (Spearman rank correlation =-.03), and negatively correlated with leverage (with a Spearman rank correlation of -.59, statistically significant at 1%). All in all, indirect vulnerability, which forms the core of our analysis, is not obviously correlated with available measures. On average, the direct impact of a full-blown GIIPS crisis would be to wipe out 1.6 times the equity for the average banks, which represents some 380bn euros in aggregate. The indirect effect is even bigger, since it averages 3.4 times the bank's equity (2300bn euros), even assuming that european sovereigns are as liquid as US stocks.

We then regress cumulative returns over 2010 - Sep 2011 on our measures of exposure:

$$R_{it} = a + bV(i) + cDirectExposure_{it} + u_{it}. \tag{18}$$

These estimates are reported in Table 2. In these regressions, it is important to recognize that vulnerability $V(i)$ only captures *indirect* exposure, after one round of deleveraging. There is, however, a more direct impact of the Greek write-down which comes through *direct* exposure. We control for this direct effect $V_0(i) = e_i' AMS_{GIIPS}/E_i$. We also control for bank size and leverage, to capture easily available proxies of exposure, and make sure our indirect vulnerability measure indeed adds something to available proxies of exposure.

The first three columns are simple OLS regressions. Out of 90 banks covered by the stress tests, only 51 are publicly listed, and we have complete data for 49 observations only. To reduce sensitivity to outliers, we therefore report median regression results in column 4-6. Both sets of results confirm that the differences in indirect vulnerabilities explain part of the cross-section of bank returns during the crisis. In OLS results, the R^2 of indirect vulnerability alone is 8%, against 13% when direct exposure is also included. Size and leverage do not have any independent explanatory power. The direct and indirect vulnerabilities have the same economic impact on stock returns. If indirect vulnerability increases by 4 times bank equity (sample standard deviation for both direct and indirect measures), cumulative return drop by 4 percentage points.

4.3. Systemicness Ranking.

In this Section, we briefly discuss the properties of our "systemicness" measure on European Data. Table 8 reports the systemicness ranking for the 20 most systemic banks in Europe, along with size and leverage. The shock we consider is a 50% write-off on of GIIPS sovereign debt. Given equation (10), we know that $S(i)$ can be interpreted as the impact of the shock on aggregate banking equity, coming from the liquidations of some assets by bank i.

Our model has the natural feature that large and levered banks should mechanically be systemic. Indeed, banks, when facing a shock to their assets, sell a fraction of their assets equal to the debt-to-equity ratio. So the larger the bank, the more euros of assets it will sell, which will trigger a larger price impact and therefore a stronger impact on other banks' balance sheets. The more levered it is, the more assets it will need to sell, given size. Table 3 confirms the intuition that systemicness and size are strongly correlated, but size is not the entire story. Overall, the correlation coefficient between size and systemicness is .47. For the 20 most systemic banks, systemicness ranking differs somewhat from size. For instance, Intesa SanPaolo appears more systemic than BNP Paribas even though BNP is nearly three times as large, and both have the same leverage. In the cross-section, however, leverage is statistically uncorrelated with systemicness.

4.4. Policy experiments

In this Section, we use our model to evaluate a number of different policies which have the potential to reduce systemic risk. The results of these experiments are reported in Table 4. For each policy "experiment", we calculate the aggregate vulnerability to three different types of shocks. The first is a 50% write-down on Greek sovereign debt. The second is a 50% write-down on the debt of Greece, Ireland, and Portugal. The third is a 50% write-down on all GIIPS debt.

The first line of Table 4 corresponds to the baseline estimates of aggregate vulnerability under no intervention. In this case, a 50% write-down on Greek debt alone would lead to a 27% reduction in aggregate equity. A 50% reduction in all GIIPS debt leads to a reduction by 285% of aggregate bank equity. Note that these are the indirect effets of the write-downs, coming from the price-impact of liquidations.

4.4.1. Size cap

The first policy we consider is a size cap. Assume a bank i holds $a_i m_{i,k}$ euros of asset k. If assets $a_i > c$, where c is the cap, we set the bank's assets to c, and redistribute residual asset holdings $(a_i - c)m_{i,k}$ equally among non-capped banks. This procedure does not affect the portfolio structure of the capped banks, but does affect the portfolios of the other banks. Since after one iteration some previously uncapped banks end up above the cap (this happens in particular when the cap is low), we iterate this process until all banks are below or at the cap.

We report the results of this experiment for caps at 500, 900 and 1300 bn euros in the first three rows of Table 4. The various columns of the table correspond to different types of shock. For example, results in the first column always concern a writedown to Greek debt only.

The table shows that capping at 500bn requires to cap 17 banks, while only 2 banks are above the 1300bn cap. The main lesson from this "experiment" is that the overall impact of size caps on aggregate vulnerability is small, and sometimes even negative. Capping size does not have the power of reducing systemic risk as we measure it. In this experiment, the leverage of each bank is kept constant.

4.4.2. Leverage cap

We next study the impact of capping leverage. Here, the policy is much simpler: if x is the cap, then, for all banks with leverage above x, we set $D/E = x$. We implicitly assume these banks can costlessly raise equity to reach the maximum leverage. This assumption is a bit unrealistic, but it allows us to investigate quantitatively the effect of leverage on vulnerability.

We try three different caps (knowing we capped leverage to 30 in the data): 15, 20 and 25. We calculate the amount of equity capped banks need to raise to reach this cap: for instance capping leverage at 15 (25^{th} percentile) requires banks to raise a staggering 480bn euros. This experiment shows that, to obtain a significant reduction in systemic risk, the regulator would need to set a very drastic cap. For instance, capping leverage to 25 (63^{rd} percentile) only reduces vulnerability to a GIIPS shock from 285 to 270% of aggregate equity. A blind leverage cap does not achieve much either.

4.4.3. Merging the riskiest banks together

Perhaps more targeted policies can make the most systemic banks safer? Suppose the regulator merges the most exposed banks into a single one. For each bank, we define as "exposure" the fraction of bank equity that would be lost directly in a 50% write-down of GIP debt. We then study three scenarios: merge all banks whose exposure is above 50%, above 100% and above 150% of their own equity. This means merging respectively 14, 8 and 4 banks. table 4 shows that the effect is nearly zero. The intuition is that, vis a vis the shocks considered, these banks have "similar" portfolios. They will sell the same total amounts of assets, whether merged or separate: the overall price impact will be the same. In our model, merging two banks with identical portfolio structure into a single bank (with the same structure) has no impact on aggregate vulnerability is these banks have the same leverage. This is what happens here: ring fencing does not reduce systemic risk.

4.4.4. Merge exposed banks with unexposed ones

As an alternative to ring-fencing, we therefore look at the impact of merging the 8 most exposed banks with the banks that are unexposed to the GIP write-down (16 of our 90 banks have this feature). To isolate the impact of merging the two groups, we first merge the exposed banks (and report the impact on AV), then merge the unexposed banks, and then perform the full merger. Merging unexposed banks does not change AV at all, because of the effect discussed in the previous experiment: they are identical with respect to the shock. Merging exposed banks does not change things much either, also as discussed previously. Merging the two groups into one bank does, however, increase systemic risk (not very much, but consistently so). The intuition is that the assets of unexposed banks, who were previously not sold in response to the shock, are now contaminated by the poor performance if GIP debt: they are now sold which reduces their returns and has a stronger impact on all banks. This policy experiment illustrates this channel of transmission.

4.4.5. Dismantling exposed banks

As an alternative to the proposal considered above, we might ask what would happen if we dismantled the banks most exposed to a 50% write-down on GIP debt. We reshuffle their assets equally among the remaining banks. We start by focusing our attention on the 17 banks for which this shock is larger than 100% of their equity. If we do this, Table 4 shows that aggregate vulnerability *increases* slightly. By reshuffling GIP sovereigns into previously unexposed banks, we induce these banks to sell assets. The reason is that GIP sovereign exposures contaminate previously healthy balance sheets.

4.4.6. Optimizing capital injection

The above experiments suggest that very little can be gained from capping leverage, and that all other policies have ambiguous, or even adverse, impacts on systemic risk. In this last exercise, we explore the power of an optimal targeted policy. Recall that aggregate vulnerability to a shock vector S can be written as:

$$AV_t = \sum_i b_i \times \left(\frac{a_{i,t-1}}{E} \times \left(e_i MS\right) \times 1' A_{t-1} MLM' e_i \right) \tag{19}$$

so that AV is a weighted average of debt to equity ratios b_i's. Weights measure the extent to which leverage of i is really bad for aggregate vulnerability. This is the case when (1) the bank is large (it will sell a lot of assets), (2) the bank is exposed to the shock we consider (its asset returns will be low) and (3) linkages are strong.

We assume the regulator has a given amount of cash F to invest in bank equity. Equity injection into bank i is given by the vector $f = (f_1, ..., f_n)$, so that $1'f = F$. When a bank receives f_i euros of fresh equity, we assume the entire amount is used to repay existing debt, so that its debt to equity ratio becomes $(D_i - f_i)/(E_i + f_i)$.

We minimize Eq. (19) subject to the constraints that $1'f = F$ and $b_i = (D_i - f_i)/(E_i + f_i)$. We also impose the third constraint that the regulator cannot withdraw cash from equity-rich banks (see below), so that $f_i > 0$, for all i.

The first lesson of this exercise is that optimizing equity injection across banks allows us to reduce aggregate vulnerability a lot more than any of the policy experiments we considered in Table 4. We can see this visually in Figure 2, where we report the optimal AV obtained for various levels of aggregate investment F. Panel A shows the aggregate vulnerability to a GIP shock, while Panel B shows aggregate vulnerability to a GIIPS shock (both assuming a 50% write-down). Data from panel A shows a reduction by a third in systemic risk: AV goes down from 47% to 31% using only 50 bn euros of equity.

Then, the impact of additional injections decreases: 200 bn leads to an AV of 23%and 500 bn to 18%. The effect on aggregate vulnerability to GIIPS is smaller in relative terms, and decreases more slowly, as more banks are exposed to GIIPS debt than to GIP debt. 50 bn euros only buy a reduction from 285% to 240% of aggregate equity. Still, the effect is large compared to previous policies considered in this paper. The size of AV reduction is comparable to capping debt to equity at 20 for all banks, which would require banks to raise some 170 bn euros of equity. Optimizing capital injections therefore reduces the cost of stabilizing the system.

Table 5 then reports cross-sectional optimal equity injections. Here, we assume the regulator invests 200 bn euros, and seeks to minimize aggregate vulnerability to a 50% write-down on GIIPS debt. Table 10 only reports the 20 largest banks by equity issue. This list consists mostly of Italian, Spanish and Greek banks. These banks are not the largest, but the most exposed to the write-down. By construction, optimal injection has a very strong correlation with systemicness (.91). Correlation with the four components of systemicness is lower: .16 (leverage), .16 (Size), 38 (direct exposure), .21 (linkage). This shows that when deciding to inject fresh capital into banks, the regulator should consider all components of systemicness to minimize taxpayer's investment.

4.5. Robustness of results to an alternative liquidation rule

While our model delivers a number of useful intuitions, it relies on a few simplifying assumptions. In this section, we relax one of these: the fact that all assets have the same price impact ratio (the

L matrix has identical diagonal elements). If some assets are less liquid than others, then it is not optimal for banks to sell assets in proportion of their holdings as we have thus far assumed. In this case, banks will first sell their most liquid securities. We do not relax this assumption in the general case here, but focus on a polar case to simplify exposition.

We posit that all non sovereign assets are infinitely illiquid, so that banks have to concentrate liquidation on sovereigns alone. In this case, the formula for Aggregate Vulnerability to a shock S is modified:

$$AV = \frac{1' A_{t-1} M L M^{*'} B A_{t-1} M S}{E_{t-1}}, \tag{20}$$

where M^* is a weight matrix that accounts for the fact that non-sovereigns are not liquidated. Each element is given by: $m^*_{ik} = m_{ik} / \big(\sum_k m_{ik} \big)$. We only focus on factors k which corresponds to sovereign holdings. Hence, elements of M^* are bigger: banks will liquidate more sovereigns in response to an adverse shock to their balance sheets.

The striking feature of these simulations is that aggregate vulnerability is much lower under this alternative liquidation rule. The aggregate vulnerability of banks to a Greek write-down goes from 25% of aggregate equity (core specification) to just 1.4%. AV to a GIP writedown goes from 47% to 2.6%; and AV to a GIIPS write-down is now 23%, instead of 285%. Changing the liquidation rule has two opposite effects. One the one hand, banks liquidate much more sovereign bonds, which has a stronger price impact on other banks. But on the other, they don't liquidate the other assets, which are the majority of assets held in balance sheets.

To understand this further we report, in Table 6, values of AV for alternative liquidation rules. We progressively add other asset classes to the list of liquid assets. As can be seen from Table 6, as long as the list of liquid assets is small enough (i.e. corresponds to less than 41% of banks' assets), aggregate vulnerability is reduced by illiquidity of the other assets. The intuition is that illiquidity prevents banks from transmitting their shocks to otherwise immune banks. When, however, sellable assets take up a larger fraction of the balance sheet (in our simulations, this happens as soon as we include corporate loans), then the fire sale concentration effect starts dominating the "ring fencing" effect: because banks cannot liquidate everything, they have to liquidate more liquid assets, which increases the price impact and therefore contagion. Table 6 illustrate the ambiguity of alternative liquidation rules on AV.

5. Measuring Vulnerability of US Banks

In this section we use the model to measure the vulnerability of US banks between 2001 and 2010. We start by describing the sample and how we estimate the factor exposures. We then validate the model by looking at the build-up of systemic risk during the 2007 pre-crisis period. We also analyze the predicted effect of the Lehman Brothers failure on other banks. After these checks, we present three sets of outputs, including (a) the most vulnerable banks at various points in time, (b) the most systemic banks in terms of their contribution to potential deleveraging, and (c) an analysis of the impact of the WaMu and JP Morgan merger on systemic risk.

5.1. Sample Description and Data

We select the largest US-listed 100 financial firms by market capitalization in 2006 on the CRSP database. Financial firms have SIC codes between 6000 and 7000. The complete list is shown in the Appendix, and includes commercial banks, investment banks, insurance companies, and money managers. Citigroup and Bank of America are the largest firms in December 2006, but investment banks form the next group of large firms. For this sample, we collect weekly and monthly stock returns from January 2001 through March 2011. Because firms list, delist, and merge through the 2001-2011 period, the average number of firms with complete data at any point in time is 88. Finally, we merge financial firm stock returns data from year t with annual balance sheet data at the end of year $t-1$ from COMPUSTAT.

To compute the systemic risk measures, we need estimates of M, L, B, and A, which we obtain as follows.

Asset Matrix A_{t-1}: We compute market value of the firm's assets (i.e., enterprise value) on a weekly basis by adding book assets (Compustat item AT) and the market value of equity from CRSP, and subtracting book common equity (Compustat item CEQ). Because the accounting data refresh annually, this means that our estimates of enterprise value are increasingly stale as we approach the end of each calendar year. For fast growing firms, this introduces some lumpiness in our measures. We define debt as the difference between book assets and book equity and compute market leverage d_i/e_i by taking the ratio of debt to market equity.

Target Leverage Matrix B: We assume that target leverage is the same as lagged leverage. Equivalently, we assume that firms adjust their capital structures quickly in response to shocks. This assumption may be too extreme during deleveraging scenarios, particularly for the most levered firms. For example, consider how a bank with D/E = 19 might behave following a 2 percent drop in the value of its portfolio. Realized leverage increases to 31.7 (=19/(1-2%x20)). To return to target leverage of 19, the bank would have to sell 41% of the remaining assets in the portfolio. In practice, the bank may do this slowly, remaining over-levered in the short-run, and perhaps raising equity or lowering dividends.. In order to maintain realism and prevent our measures from blowing up, we cap target leverage at 20.

Liquidity Matrix L: This diagonal matrix measures for each asset, the price impact in percentage terms of a one dollar liquidation. For non-financial equities, one can estimate this number following previous research on price impact in equity markets. For each stock, we compute individual Amihud (2002) price impact ratios based on the first 90 trading days of 2002, and then aggregate these to yield a a market-wide price impact of 6.24x10^{-13}. This means that to depress the market by one percent would require order flow of $16 billion, approximately 10% of weekly trading volume.[12]

The most challenging part of this exercise is determining how to compute liquidity ratios for factors other than equity. We suspect, for example, that a bank selling a specialized loan portfolio might incur a larger fire sale discount than a bank selling a portfolio of liquid S&P 500 stocks. But, absent other data on price impact, we take a conservative approach and assign these factors the same price impact parameter as that of equities. This has the effect of making L matrix proportional to the identity matrix. While we view this simplification as unfortunate, we believe it to be conservative, and also somewhat unavoidable.

Factor Selection and the Portfolio Matrix M: The portfolio matrix M contains, for each bank i the weights m_{ik} of each asset k in the portfolio. Here we do not observe banks' portfolios directly, so we estimate M with a factor model. For each bank i, we run the following regression on a rolling basis:

$$R_{i,t} = \sum_k m_{i,k} F_{k,t} + \epsilon_{it}. \tag{21}$$

Each week, we run this regression over the past 104 weeks, thereby obtaining rolling estimates of M. Provided we have the full vector of asset returns $F_{k,t}$, the estimated $m_{i,k}$ is equal to the weight of each asset in the bank's portfolio. To be able make this inference, $R_{i,t}$ has to be obtained through unlevering the equity returns according to $R_{it} = (A/D)R_{it}^{equity}$. Implicitly, we assume that: (1) we have the adequate set of factor returns to represent each bank's portfolio, (2) that holdings are fairly stable (i.e. did not move too much over the past 2 years), and (3) that the stock market has some understanding of each bank's exposure to each asset.

In selecting factors, we adopt the following principles. First, we were careful to select a series

[12]We compute the implied price impact of the complete stock market by aggregating the individual ratios according to $\sum_i w_i^2 Amihud_i^2$ where w_i is the weight of equity of stock i in the aggregate stock market.

of factors which were not too collinear (for example, it would be challenging to estimate a bank's separate exposure to AA and A bonds from a stock return regression). Second, it is important to select factors which proxy for the returns of the underlying assets held by each institution.[13] Third, we sought a sufficiently large list of factors so as to be able to capture diversity in the holding of the different banks. These considerations in mind, the factors we use are based on the returns of (1) non-financial firms in the S&P 500; (2) mortgage REITs; (3) 10-year nominal US Treasuries; (4) Commodities, proxied using the Goldman Sachs Commodity Index; and (5) High Yield Bonds based on the Morgan Stanley High Yield Bond Index.[14] Table 1 summarizes the five factors, both during the full sample and during the March 2007-June 2011 crisis subperiod. To reduce the impact of measurement error, we zero out elements of the M matrix for which the estimated coefficient has a t-statistic less than 1.5.

Since much of the cross-sectional variation between banks' contributions to systemic risk comes from their different risk exposures, we have verified that there is enough interesting variation across firms. A simple way to see this is to compute time-series average exposures for each of the banks, and then compare banks. State Street bank, for example, has sample average factor exposures of (0.12, 0.03, 0.02, 0.00, and 0.02) while Mellon Bank has exposures of (0.25, 0.01, 0.16, 0.00, and 0.14) The nature of the exposures differs across banks, with State Street having greater exposure to non-financial firm equity and Mellon Bank having higher exposure to mortgage REITs.

5.2. Validating the Model

We start by performing a series of simple exercises to validate the empirical relevance of the model. We start by showing time-series measures of aggregate vulnerability AV, as well as the contributions (the systemicness $S(i)$) of a few important firms such as Lehman Brothers and Citigroup. We show that bank-specific vulnerabilities are useful for predicting the maximum drawdown of these firms during the 2007-2009 financial crisis. We then show that the model is quite useful for predicting how individual bank stocks respond to the failure of Lehman Brothers.

[13]This led us to exclude, on principle, factors which were associated with bank equity returns but were unlikely related to the underlying assets held by the bank. For example, changes in the TED spread are significantly correlated with bank equity returns during the financial crisis, but are more likely related to the cost associated with the bank's liabilities rather than its assets.

[14]Because these factors were chosen with hindsight bias, we perform a robustness test in which the factors are estimated directly from principle components of bank stock returns. The main drawback is that statistical factors are harder to interpret economically: factors are not "assets" so the elements of the M matrix cannot be interpreted as portfolio weights. This is why we rely primarily on the economic factors for most of our analysis, but show in the appendix that using the statistical factors estimated through PCA over 2001-2006 produces similar insights.

5.2.1. Time series measures of aggregate vulnerability AV

Figure 3 shows aggregate vulnerability AV, which recall is the total (i.e., systemwide) dollar price impact of deleveraging resulting from a one standard deviation shock to each of the five factors, calculated according to equation (6). The series starts low in early 2001, drops in mid 2005, and then rises quickly in 2007.

We remind the reader that while the magnitude of these results depends on the scaling matrix L, the time-series behavior is unlikely much affected. To the extent that we believe price impact went up during the crisis; or that price impact varies significantly across asset classes, the dollar magnitude is impacted.

Equation (10) tells us how to compute the extent to which shocks to a given bank can affect the entire system. Figure 4 plots time-series of contributions to vulnerability, ie., the systemicness $S(i)$ of six important banks in our sample: Wells Fargo, JP Morgan Chase, Bank of America, Citigroup, Lehman Brothers, and Goldman Sachs. The figure shows that many of these individual bank series share the common characteristic of systemicness $S(i)$ rising through the crisis to a peak in January 2009, subsequently falling as equity markets rebound and factor volatility drops.

Figure 5 shows that systemicness is related to size and leverage in the cross-section, but that each of these variables explains less than 60 percent of the variation: differential exposures in the M matrix explain the rest.

To be clear, a bank's contribution to total systemic risk $S(i)$ is not the same as its vulnerability to common shocks. For example, a small levered bank may by highly susceptible to common shocks, while not imposing much in the way of spillovers. Notwithstanding, the two are correlated in the data.

5.2.2. Bank Sensitivity to Deleveraging: Lehman bankruptcy

Eq. (14) shows how to compute the impact of a shock to the assets of bank i on any other bank j. In this section, we study the impact of the failure of Lehman Brothers on September 15, 2008. Before markets opened that day, Lehman Brothers announced that it would file for bankruptcy protection, citing debt of \$768 billion and assets with a market value of \$639 million. Although the company filed for reorganization under the US bankruptcy code, market participants could have reasonably expected substantial liquidations of its asset portfolio.

Taking the liquidation rule of our model literally, we would expect banks with high exposures to the same assets would experience reductions in their portfolio value as a fraction of equity described by equation (14). Since pre-failure, Lehman had market leverage of approximately 20-to-1, a -5% shock to its assets would result in complete liquidation of its portfolio. We thus multiply the expression in equation (14) by 0.05. To normalize the equation, we take equity value on the Friday before the announcement.

We then compare this predicted equity shock to the actual return. This is shown graphically in Figure 6. As can be seen, there is a discernible positive correlation between the predicted return and the actual stock return on Monday September 15, 2008. [15]

We would expect the relationship between vulnerability $V(i)$ and realized returns in Figure 6 to be quite noisy, as the Lehman failure was also a significant information event, both on the magnitude of losses faced by the banking sector, and on the willingness of the government to intervene to stem those losses. Table 8 shows the results of cross-sectional regressions of realized stock returns on September 15, 2008 on vulnerability to Lehman deleveraging. One possible concern with our vulnerability measure is that it does not add much information to size and leverage, since large banks, or levered banks are the most adversely affected the Lehman bankruptcy. We include bank leverage and bank size as controls in our regressions of Table 8.

5.2.3. Bank vulnerability and market performance during the crisis

Although our firm-specific vulnerability measures $V(i)$ are not forecasters of stock returns per se, they might be useful for for explaining the cross-section of returns following a systemwide deleveraging shock. To operationalize this, here we study the relationship between the maximum drawdown in stock returns experienced by each firm during the crisis, and $V(i)$. Maximum drawdown is the minimum cumulative rolling return from July 2007 through March 2011 (i.e., the cumulative return corresponding to the lowest price experienced during that period).

Figure 7 plots this relationship, revealing a negative correlation of -28%. The corresponding regression, also shown in the figure, yields a t-statistics of -3.88 on bank vulnerability. Interestingly, this result is not driven by leverage alone. In a multivariate regression of drawdowns on vulnerability and bank leverage, vulnerability retains a similar coefficient and a t-statistic of -3.12.

5.3. Outputs

5.3.1. Bank Contributions to Systemic Risk

The most systemic banks are large levered financial institutions which tend to have similar sets of exposures. Table 9 lists the top 10 systemic banks in January 2007, January 2008, and January 2009.

[15] We analyze returns over a short window because of significant financial news the next day: on September 16, 2008, the Federal Reserve Board authorized lending of up to $85 billion to insurance company AIG.

In the table we show the "systemicness" $S(i)$. In a separate column, we show $S(i)$ scaled by AV. This rescaled numbers tells us how important a given bank is in relative contribution to aggregate vulnerability. Of course, a bank may have a relatively large contribution to AV when the level of AV is low, in which case the scaling is less meaningful.

As can be seen, this exercise turns up the usual crowd of large levered financial institutions. In January 2007, AIG, JP Morgan, and Morgan Stanley are at the top of the list; by January 2009, the dollar impact of their deleveraging is much greater (JP Morgan rises from \$1.4 billion to \$16 billion), and the rankings change somewhat, with Wells Fargo, JP Morgan, and Bank of American topping the list.

A possible concern is that the rankings in Table 9 do not capture much more than the product of size and leverage. To be sure, size and leverage are important inputs in equation (10). However, we find only a 0.7 correlation between $S(i)$ and the product of size and leverage in January 2009, and lower correlations still for the other two panels. We provide graphical evidence of such imperfect correlation in Figure 8, where we plot systemicness against leverage or bank size. While indeed systemicness appears correlated with both size and leverage, they are far from explaining the full cross section of our measure. For instance, BofA is the biggest bank but scores low on systemicness.

5.3.2. Bank Vulnerability to Deleveraging

Bank vulnerability is the impact of a shock to all factors on each single bank. As in equation (11), we can express this in dollar terms or normalize it as a percentage of bank's equity. Panel A of Table 10 shows dollar vulnerability in January 2007, January 2008, and January 2009. We show the top 10 most vulnerable banks, meaning the ten banks which would suffer the largest reduction in net worth if there were a simultaneous shock to each of the factors. According to this measure, AIG, JP Morgan, and Citigroup are the most vulnerable banks in early 2007; the rankings do not change much over time: by 2009, Wells Fargo, JP Morgan and Citigroup are the most vulnerable.

Panel B of Table 10 shows vulnerability for the same set of dates, except now we scale by each firm's equity value. Although AIG still appears among the top banks according to this scaling, the list otherwise looks quite different. For example, Radian Group, a highly levered bond insurer, shows up as the most vulnerable institution in both 2007 and early 2008. Although it is difficult to generalize as to which firm characteristics land them on this list, cursory inspection reveals a number of insurance companies specialized in insuring mortgage-related securities.

5.3.3. Analysis of the JP Morgan acquisition of Washington Mutual.

On September 25, 2008, JP Morgan Chase acquired the assets of Washington Mutual Bank (WaMu). Did this make the bank system more or less fragile? The merged bank may be safer than the sum of the individual contributions, if there are large differences in bank leverage, or if the banks have quite different sets of factor exposures. We can run this thought experiment using our model to generate a counterfactual.

In Table 11, Panel A, we calculate: the systemicness $S(i)$ for WaMu, of JP Morgan, for the hypothetical merged bank. The merged bank inherits the assets of both banks and takes on the asset-weighted capital structure of the original banks (i.e., it inherits total debt and total equity from the individual banks). Just prior to the merger, the market value of JP Morgan assets was \$194 billion, while that of Washington Mutual was \$314 billion. On a market value basis, Washington Mutual had leverage of 42.6, while JP Morgan had leverage of 12.75. Following our earlier convention, we assume that target leverage for Washington Mutual was 20, and use this number to form a blended leverage for the two banks of 16.5, and total assets of \$508 billion.

Taking each bank separately and computing equation (6), WaMu contributed \$7,761 to aggregate vulnerability AV, making it one of the most systemic banks in the sample on this date. JPM contributed \$2,061 to deleveraging. When we combine the banks, we see that the hypothetical merged bank is slightly safer than the two banks individually, because \$9,060<\$2,061+\$7,761.

We next compute hypothetical bank mergers of WaMu with each of the remaining US financial institutions in our sample. Table 11, Panel B lists the ten safest acquirors from the perspective of systemic risk; a merger with each of these banks would reduce systemic risk relative to the banks operating standalone. Panel C lists the ten riskiest acquirors; a merger with each of these banks would increase systemic risk relative to the banks remaining standalone.

6. Conclusions

During the financial crisis of 2007-2009, regulators in the United States and Europe have been frustrated at the difficulty of understanding the complete set of risk exposures of the largest and most levered financial institutions. Yet, at the time, it was unclear how such data might have been used to make the financial system safer. Our paper is an attempt to show show how such information can be used in an analytically coherent way.

The key assumption in our model is that banks use asset liquidations to return to target leverage. We use this assumption to predict how individual banks will behave following shocks to their net worth, and how the resulting fire sales may spillover to other banks.

While the model is quite stylized, it generates a number of useful insights concerning the distribution of risks in the financial sector. For example, the model suggests that regulators should pay close attention to risks which are concentrated in the most levered banks. The model also suggests that policies which explicitly target bank solvency may be suboptimal from the perspective of controlling contagion.

We then apply the model to the largest financial institutions in the United States and Europe, and use it to evaluate a number of policy proposals to reduce systemic risk. When analyzing the European banks in 2011, we show how a policy of targeted equity injections, if distributed appropriately across the most systemic banks, can significantly reduce systemic risk.

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Appendix A. European Banks Involved in the 2011 stress tests. The sample includes the banks included in the EBA stress tests and thus considered in our European analysis.

Publicly listed banks	Non-public banks
Irish Lf.& Perm.Ghg.	Banque Et Caisse D epargne De L etat
Bank Of Cyprus	Bayerische Landesbank
Marfin Popular Bank	Bpce
Otp Bank	Caixa D estalvis De Catalunya,
Swedbank A	Caixa D estalvis Unio De Caixes De
Banco De Sabadell	Caixa De Aforros De Galicia, Vigo,
Dnb Nor	Caixa Geral De Depîsitos, Sa
Efg Eurobank Ergasias	Caja De Ahorros Y M.P. De Gipuzkoa Y
Bank Of Piraeus	Caja De Ahorros Y M.P. De Zaragoza,
Bnp Paribas	Caja De Ahorros Y Pensiones De
Abn Amro Holding	Caja Espa„A De Inversiones, Salamanca
Ing Groep	Dekabank Deutsche Girozentrale,
Nordea Bank	Dz Bank Ag Dt. Zentral-
Banca Monte Dei Paschi	Effibank
Banco Popolare	Grupo Bbk
Banco Santander	Grupo Bmn
Banco Bpi	Grupo Caja3
Alpha Bank	Hsh Nordbank Ag, Hamburg
Societe Generale	Landesbank Baden
Banco Pastor	Monte De Piedad Y Caja De Ahorros
Banco Comr.Portugues R	Norddeutsche Landesbank
Bankinter R	Nova Ljubljanska Banka
Bbv.Argentaria	Nykredit
Espirito Santo Financial	Oesterreichische Volksbank Ag
Dexia	Powszechna Kasa Oszcz_Dno_Ci Bank
Erste Group Bank	Rabobank Nederland
Lloyds Banking Group	Raiffeisen Bank International
Barclays	Skandinaviska Enskilda Banken Ab
Royal Bank Of Sctl.Gp.	Westlb Ag, Dusseldorf
Commerzbank	Wgz Bank Ag Westdt. Geno. Zentralbk,
Allied Irish Banks	
Deutsche Bank	
Bank Of Ireland	
National Bk.Of Greece	
Kbc Group	
Hsbc Holdings	
Unicredit	
Intesa Sanpaolo	
Banco Popular Espanol	
Danske Bank	
Svenska Handbkn. A	
Landesbank Bl.Hldg.	
Agri.Bank Of Greece	
Credit Agricole	
Ubi Banca	
Hypo Real Estate Hldg	
Sns Reaal	
Tt Hellenic Postbank	
Caja De Ahorros Del Mediterraneo	
Bankia	
Banca Civica	

Appendix B. US Financial firms in sample. The sample includes the largest 100 financial firms by market capitalization in December 2006.

Name	MV Equity	Name	MV
Citigroup Inc	$273,691	C I G N A Corp	$13,495
Bank Of America Corp	239,758	Northern Trust Corp	13,273
American International Group Inc	186,296	Ameriprise Financial Inc	13,187
Jpmorgan Chase & Co	167,551	Marshall & Ilsley Corp New	12,590
Wells Fargo & Co New	120,049	Legg Mason Inc	12,491
Wachovia Corp 2Nd New	114,542	Sovereign Bancorp Inc	12,007
Morgan Stanley Dean Witter & Co	85,410	T Rowe Price Group Inc	11,597
Goldman Sachs Group Inc	84,890	C I T Group Inc New	11,059
Merrill Lynch & Co Inc	82,050	Aon Corp	10,944
American Express Co	73,094	C N A Financial Corp	10,924
U S Bancorp Del	63,617	Nymex Holdings Inc	10,788
Federal National Mortgage Assn	57,908	Synovus Financial Corp	10,019
Federal Home Loan Mortgage Corp	47,035	M B I A Inc	9,849
Berkshire Hathaway Inc Del	45,920	T D Ameritrade Holding Corp	9,709
Metlife Inc	44,861	E Trade Financial Corp	9,558
Washington Mutual Inc	42,725	Ambac Financial Group Inc	9,450
Lehman Brothers Holdings Inc	41,408	Comerica Inc	9,322
Prudential Financial Inc	40,955	Zions Bancorp	8,798
Allstate Corp	40,690	Unionbancal Corp	8,597
Travelers Companies Inc	37,047	C B O T Holdings Inc	8,004
Capital One Financial Corp	31,397	Coventry Health Care Inc	7,976
Suntrust Banks Inc	29,907	Cincinnati Financial Corp	7,839
Bank Of New York Mellon Corp	29,601	Compass Bancshares Inc	7,837
Hartford Financial Svcs Grp Inc	29,573	Hudson City Bancorp Inc	7,742
Franklin Resources Inc	27,932	C B Richard Ellis Group Inc	7,481
Countrywide Financial Corp	26,365	T D Banknorth Inc	7,374
Schwab Charles Corp New	24,469	Safeco Corp	7,222
B B & T Corp	23,763	Unum Group	7,118
National City Corp	23,092	American Capital Ltd	6,828
Fifth Third Bancorp	22,767	Assurant Inc	6,818
A F L A C Inc	22,747	Commerce Bancorp Inc Nj	6,614
Aetna Inc New	22,540	Berkley W R Corp	6,613
State Street Corp	22,395	Peoples United Financial Inc	6,345
Chubb Corp	21,780	Torchmark Corp	6,253
P N C Financial Services Grp Inc	21,754	Intercontinentalexchange Inc	6,198
S L M Corp	19,935	Mercantile Bankshares Corp	5,872
Bear Stearns Companies Inc	19,112	Health Net Inc	5,672
Lincoln National Corp In	18,418	Huntington Bancshares Inc	5,593
Progressive Corp Oh	18,221	Old Republic International Corp	5,366
Regions Financial Corp New	17,996	Fidelity National Finl Inc New	5,223
C M E Group Inc	17,746	First Horizon National Corp	5,200
Blackrock Inc	17,686	M G I C Investment Corp Wis	5,192
Mellon Financial Corp	17,504	First Marblehead Corp	5,159
Western Union Co	17,184	Popular Inc	5,003
Marsh & Mclennan Cos Inc	16,897	Edwards A G Inc	4,777
Principal Financial Group Inc	15,835	New York Community Bancorp Inc	4,752
Genworth Financial Inc	15,470	Markel Corp	4,639
Keycorp New	15,272	Associated Banc Corp	4,495
N Y S E Euronext	15,186	Radian Group Inc	4,344
M & T Bank Corp	13,519	Janus Cap Group Inc	4,279

Figure 1. Bank mergers and aggregate vulnerability. This figure shows what happens when two banks with different leverage marge. The merged bank has less than or equal leverage to the asset-weighted leverage of the two merging banks.

Risky Bank
D/E = 9

A 100	E 10 D 90

+

Safe Bank
D/E = 0.11

A 100	E 90 D 10

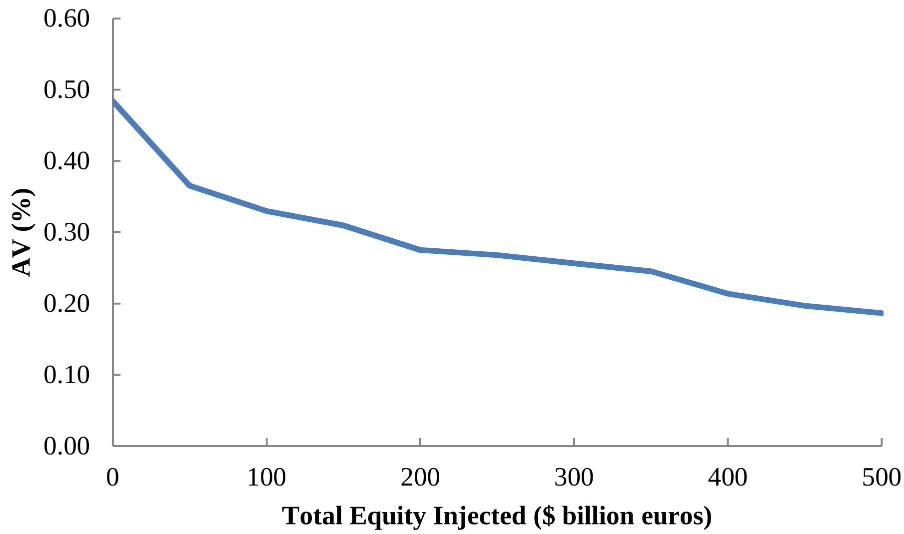
Merged Bank
D/E = 1

A 200	E 100 D 100

.

Figure 2. Optimal Aggregate Vulnerability, as a Function of Aggregate Equity Injected (in bn euros). This figure reports the optimal AV to a 50% write-off on GIP debt (Panel A), GIIPS debt (Panel B). Such optimal AV is obtained assuming the social planner can freely allocate 200bn euros of equity into banks, keeping their sizes constant, so the equity injection serves to reduce debt. In Panel A, for 0bn, we obtain AV of 0.47. This means that, absent a capital injection, a 50% write-off on GIP debt would reduce aggregate bank equity by 47%.

Panel A: Aggregate vulnerability to a 50% write-off to GIP debt (per euro of aggregate equity)



Panel B: Aggregate vulnerability to a 50% write-off to GIIPS debt (per euro of aggregate equity)

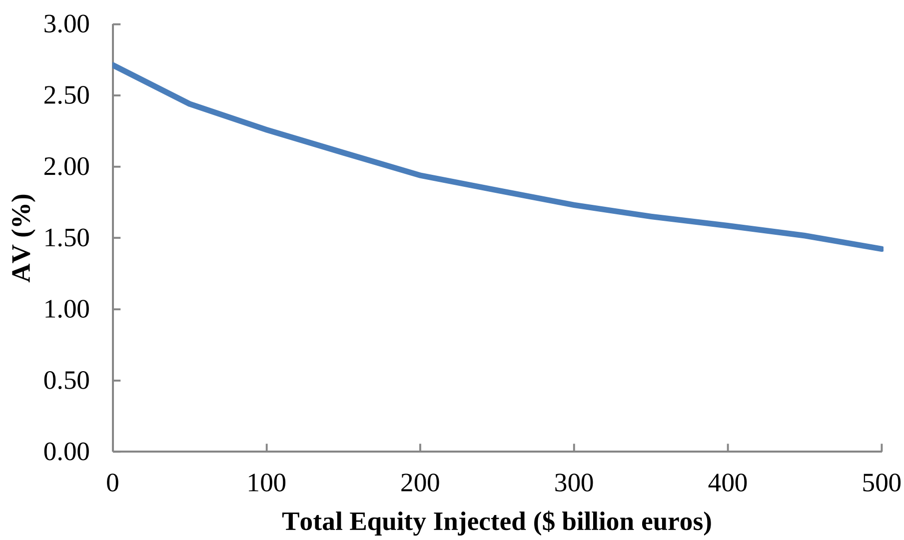


Figure 3. Aggregate vulnerability, United States financial institutions. Aggregate vulnerability AV is defined according to Eq. (6) in the text. The sample includes the top-100 US financial firms listed on CRSP in 2006.

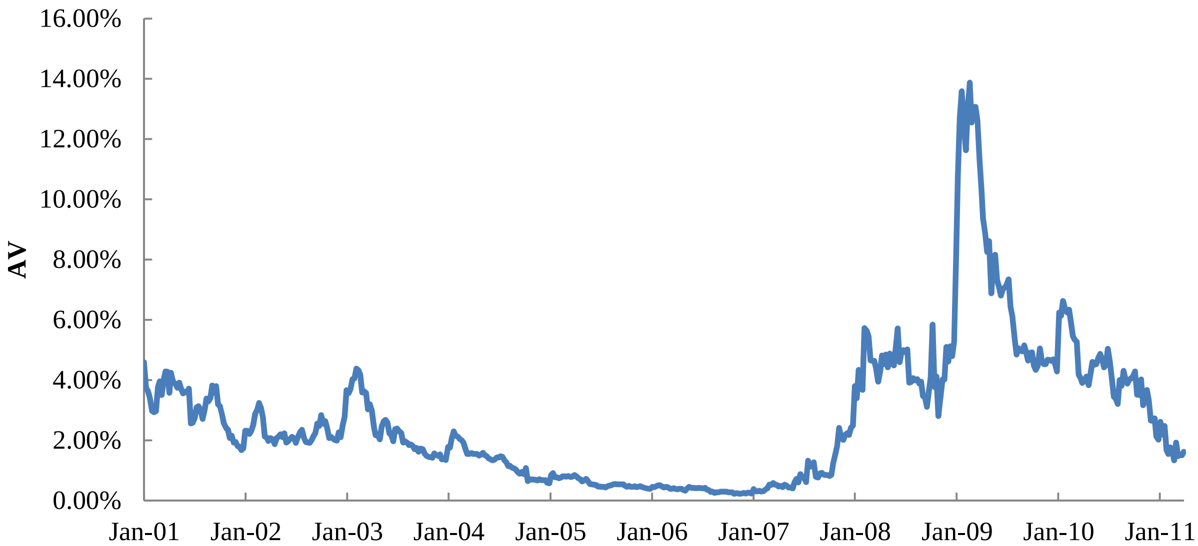


Figure 4. Contributions to time series vulnerability from various financial institutions. Vulnerability of bank i, $V(i)$, is expressed as a percentage of the bank's total equity value of all financial institutions, as in Equation (11) in text. The figure shows a few of the most important banks.

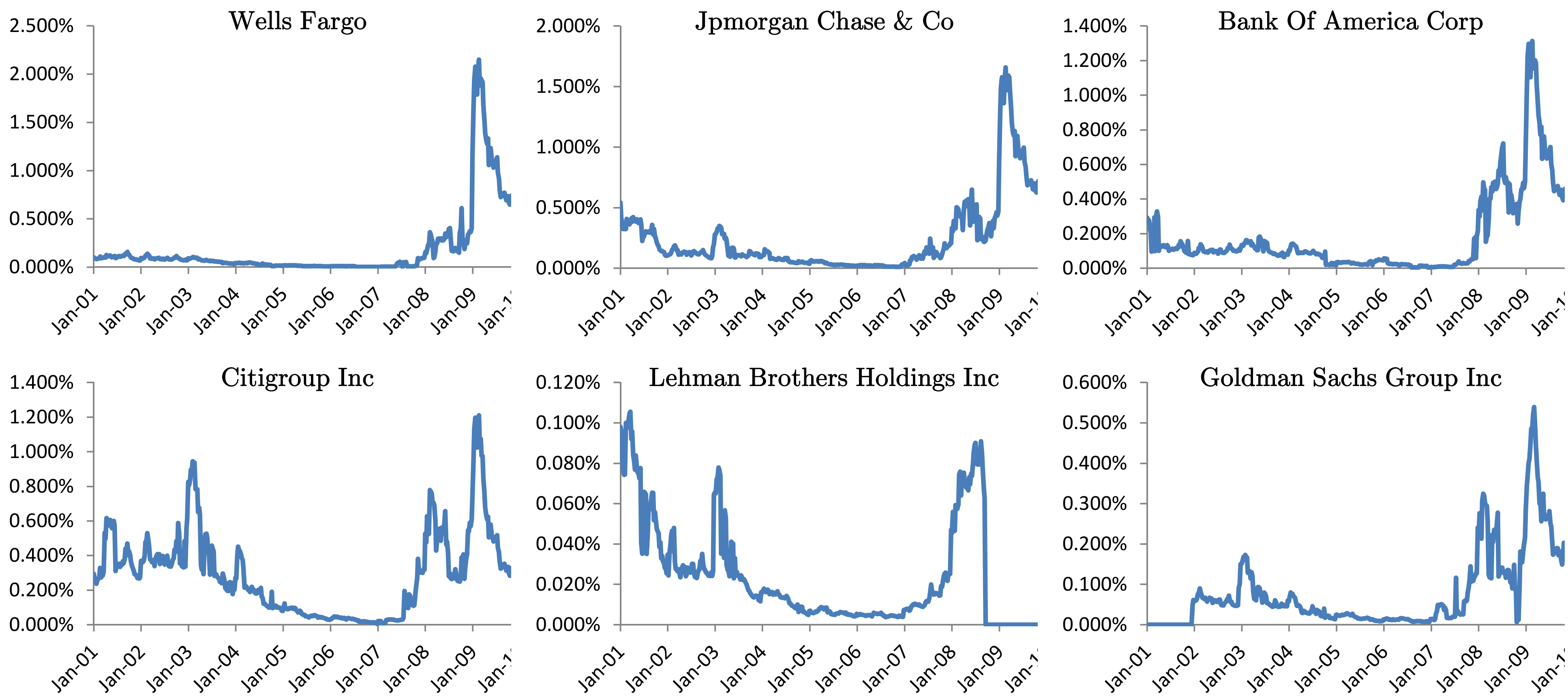
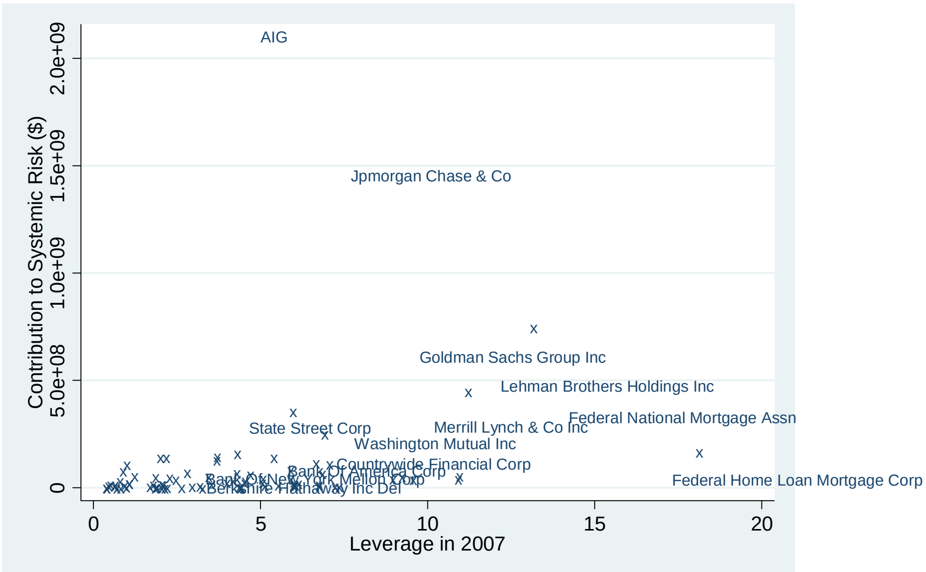


Figure 5. What drives individual banks' systemicness? We plot systemicness S(i) (in January 2008) against leverage (Panel A), and against Size (Panel B).

Panel A. Leverage vs. Systemicness



Panel B. Size vs. Systemicness

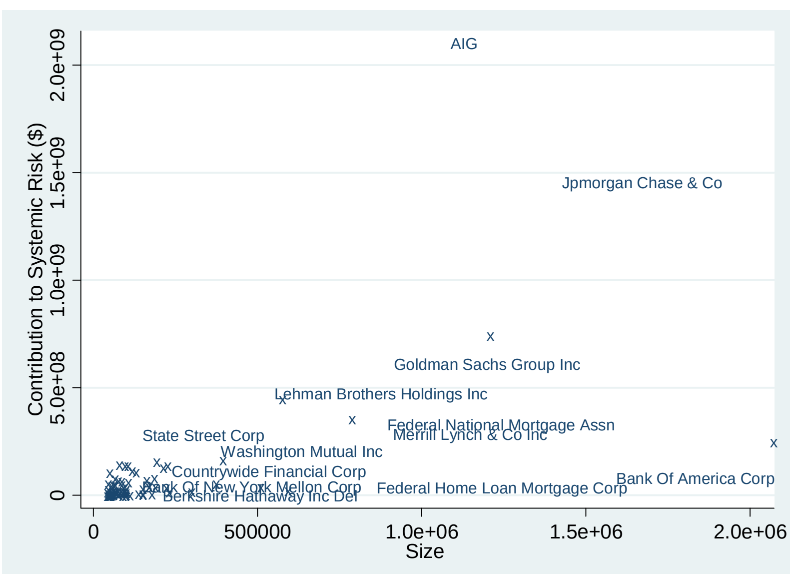


Figure 6. Bank Stocks vulnerability to Lehman Brothers collapse. Vulnerability $V(i,\text{Lehman})$ is the dollar price impact of predicted deleveraging driven by an expected liquidation of Lehman Brothers holdings on September 15, 2008.

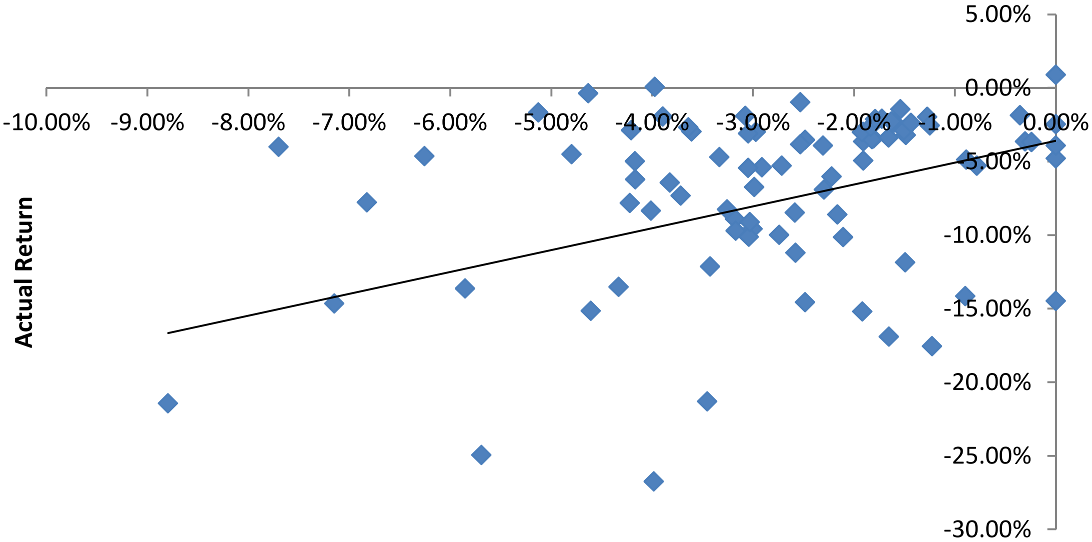


Figure 7. Vulnerability and Maximum Crisis Drawdown. We plot the maximum drawdown during the crisis against the ranking of the bank's vulnerability in January 2008. Maximum drawdown is the minimum cumulative rolling return from July 2007 through March 2011. We also show the corresponding regression, above the picture.

$$\text{Maximum Drawdown(i)} = \text{-0.65} - \text{2.88 Vulnerability(i) [t=-3.68]}$$

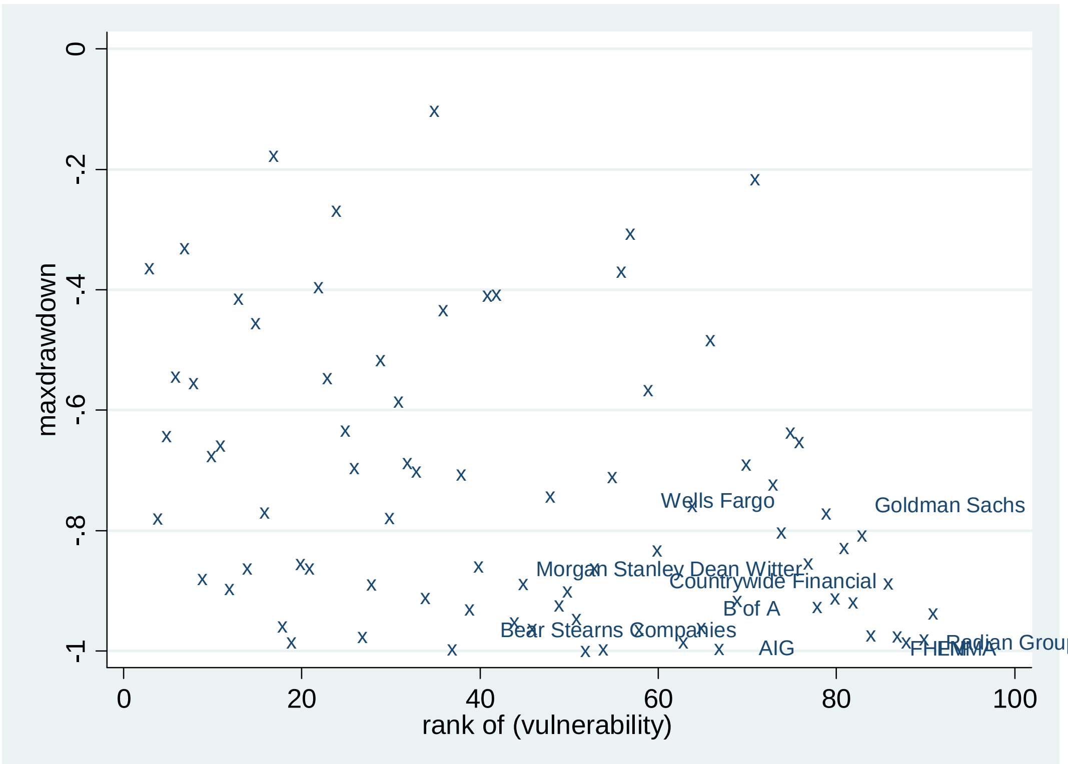


Figure 8. Vulnerability and Direct Exposure. Vulnerability $V(i)$ is a bank's exposure to deleveraging following an initial shock S. Direct Exposure (called "Round-0 exposure on the picture) is the simple levered exposure to the initial shock. The plot is drawn based on data as of January 2008.

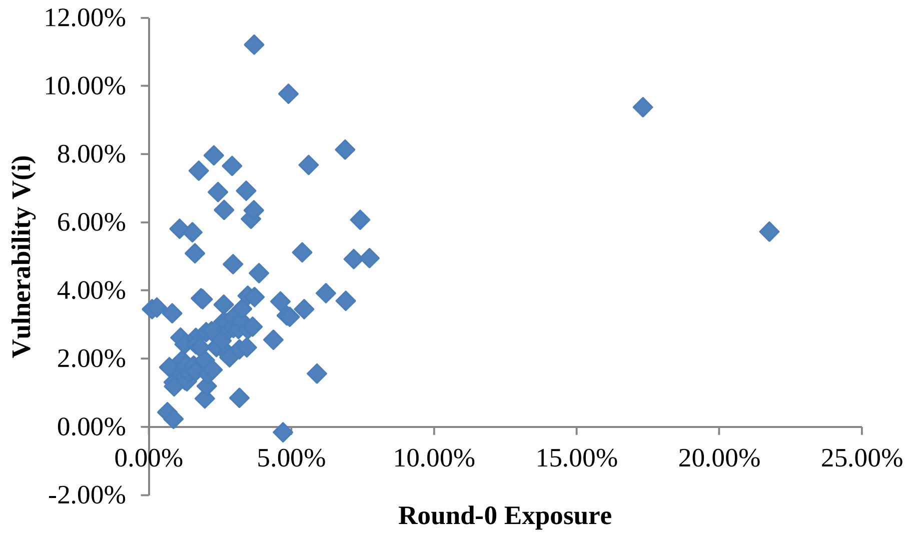


Table 1. Vulnerability Ranking to a 50% write-off on all GIIPS Debt (Listed banks). We compute the vulnerability of the major European banks to a 50% write-down on all sovereign debt of Greece, Italy, Ireland, Portugal, and Spain. The vulnerability has two parts. The first is the direct exposure of each bank to the loss. The second part is the exposure of each bank to liquidations from exposed banks. The table also shows the size of each bank as well as its target leverage. Target leverage is actual leverage or 30, whichever is smaller.

Bank_Name	Vulnerability $V(i)$ (%)	Rank	Direct Exposure (%)	Rank	Size	Rank	Target leverage	Rank
Allied Irish Banks Plc	-41.30	1	-11.86	2	0.01	27	30	1
Agricultural Bank Of Greece S.A.	-15.50	2	-33.55	1	0.00	48	30	1
Banca Monte Dei Paschi Di Siena	-5.94	3	-3.75	3	0.01	23	30	1
Sns Bank Nv	-5.59	4	-0.31	33	0.00	38	30	1
Commerzbank Ag	-5.27	5	-0.96	16	0.03	12	30	1
Caja De Ahorros Del Mediterráne	-4.72	6	-1.53	6	0.00	37	30	1
Banco Popolare - S.C.	-4.51	7	-1.50	7	0.01	30	30	1
Danske Bank	-4.50	8	-0.06	43	0.02	17	30	1
Bankinter	-4.38	9	-0.94	17	0.00	40	25	14
Ing Bank Nv	-4.34	10	-0.20	36	0.04	8	30	1
Deutsche Bank Ag	-4.20	11	-0.21	35	0.05	5	30	1
Banco De Sabadell	-4.12	12	-1.06	14	0.00	34	25	13
Banco Comercial Português	-3.71	13	-1.06	15	0.00	33	27	10
Svenska Handelsbanken Ab	-3.71	14	-0.00	46	0.01	19	26	12
Bank Of Ireland	-3.68	15	-0.54	28	0.01	26	29	8
Abn Amro Bank Nv	-3.54	16	-0.07	41	0.01	18	24	16
Dnb Nor Bank Asa	-3.50	17	0.00	48	0.01	22	21	28
Irish Life And Permanent	-3.38	18	-0.55	27	0.00	42	27	9
Nordea Bank Ab	-3.23	19	-0.00	44	0.02	16	23	22
Societe Generale	-3.14	20	-0.33	32	0.03	11	25	15
Banco Santander S.A.	-3.13	21	-0.60	26	0.04	7	23	17
Banco Pastor	-3.06	22	-0.91	18	0.00	47	20	32
Swedbank Ab (Publ)	-3.05	23	0.00	48	0.01	25	23	21
Banco Bpi	-2.96	24	-1.28	9	0.00	41	22	25
Intesa Sanpaolo S.P.A	-2.89	25	-1.18	12	0.02	13	21	26

Table 2. Vulnerability to GIIPS and Cumulative Stock Returns. For each publicly listed bank in our sample, we calculate the cumulative return between Dec 31, 1999 and Sep 16, 2011. We then regress this return on our measure of indirect vulnerability, controlling for direct exposure to a 50% write-off on GIIPS debt, bank size and leverage. Columns 1-3 report plain OLS estimates. Columns 4-6 report median regressions to account for outliers.

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable = Cumulative Stock Return: 2009/12 - 2011/9					
Vulnerability: $V(i)$	0.015***	0.007**	0.008**	0.012**	0.009**	0.007*
	[4.34]	[2.58]	[2.48]	[2.68]	[2.58]	[1.89]
Direct exposure to GIIPS		0.016***	0.014***		0.010***	0.006
		[2.91]	[2.73]		[2.70]	[1.36]
Assets / total bank assets			2.682			4.763
			[1.45]			[1.25]
Debt to Equity			0.003			-0.006
			[0.38]			[-0.50]
Constant	-0.435***	-0.441***	-0.545***	-0.472***	-0.468***	-0.441
	[-9.25]	[-9.61]	[-3.64]	[-6.43]	[-6.53]	[-1.51]
N	49	49	49	49	49	49
R^2	0.089	0.136	0.164			

Table 3. Systemicness ranking in a response to a GIIPS shock. We calculate the contribution to aggregate vulnerability of each individual banks behavior, assuming a 50% write-off on GIIPS sovereign debt. Column 1 reports systemicness as computed in equation (8-9). Column 2 reports total exposure, in billions of euros. Column 3 reports the debt to equity ratio. Banks are sorted by systemicness. Only the 25 most systemic banks are reported here. In the whole sample, correlation between size and systemicness is 0.47, while correlation between leverage and systemicness is 0.12.

Rank	Name	Systemicness $S(i)$	Debt to Equity (b_i)	Assets / Aggregate Equity (a_i/E)	Exposure to shock (e_iMS)	Linkage effect ($1\ AMLM\ e_i$)
1	Intesa Sanpaolo S.P.A	0.23	21.43	0.62	0.05	0.33
2	Banco Bilbao Vizcaya Argentaria	0.22	20.87	0.57	0.06	0.33
3	Banco Santander S.A.	0.21	23.00	1.06	0.03	0.34
4	Unicredit S.P.A	0.19	22.39	0.88	0.03	0.31
5	Banca Monte Dei Paschi Di Siena	0.17	30.00	0.22	0.08	0.32
6	Caja De Ahorros Y Pensiones De Barcelona	0.16	22.38	0.27	0.07	0.38
7	Bfa-Bankia	0.16	28.63	0.29	0.05	0.42
8	Bnp Paribas	0.15	22.62	1.37	0.02	0.30
9	Societe Generale	0.07	24.56	0.75	0.01	0.32
10	Commerzbank Ag	0.07	30.00	0.66	0.02	0.23
11	Banco Popolare - S.C.	0.07	30.00	0.13	0.05	0.36
12	Barclays Plc	0.06	17.52	0.90	0.01	0.34
13	Ing Bank Nv	0.06	30.00	0.95	0.01	0.36
14	Deutsche Bank Ag	0.06	30.00	1.15	0.01	0.30
15	Credit Agricole	0.06	27.01	1.36	0.01	0.25
16	Dexia	0.05	29.37	0.54	0.02	0.14
17	Banco De Sabadell	0.04	25.26	0.10	0.04	0.40
18	Ubi Banca	0.04	20.37	0.15	0.04	0.33
19	Banco Comercial Português	0.04	27.16	0.10	0.04	0.34
20	National Bank Of Greece	0.03	12.64	0.11	0.09	0.28
21	Hsbc Holdings Plc	0.03	15.62	1.52	0.01	0.29
22	Banco Popular Español	0.03	18.50	0.14	0.04	0.35
23	Royal Bank Of Scotland Group Plc	0.03	18.02	1.18	0.00	0.31
24	Caja España De Inversiones	0.03	27.38	0.05	0.09	0.28
25	Caja De Ahorros Del Mediterráneo	0.03	30.00	0.07	0.04	0.34

Table 4. Impact of Various Policies on Aggregate Vulnerability of European Banking Sector. The first line reports the aggregate vulnerability of the European banks to a 50% write-down of Greek sovereign debt (column 1), a 50% write-down of Greek, Irish, and Portugese debt (column 2), and a 50% write-down of Greek, Irish, Italian, Portguse, and Spanish sovereign debt (column 3). The remaining rows of the table show this calculation under different hypothetical policy implementations. We start by capping size of the banks, and distributing any excess assets equally across the remaining banks. We then cap leverage. We also consider merging some of the most systemic banks, or destroying banks with systemic impact greater than a certain amount.

Policy:			Aggregate Vulnerability AV:		
			Greece	GIP	GIIPS
Baseline			-0.25	-0.47	-2.85
		Number of banks capped:			
Size cap (bn euros)	500	17	-0.27	-0.49	-2.81
	900	8	-0.26	-0.48	-2.84
	1300	2	-0.25	-0.47	-2.85
		Equity required:			
Cap leverage, set max D/E equal to:	15	480	-0.18	-0.32	-1.84
	20	173	-0.22	-0.40	-2.38
	25	45	-0.24	-0.45	-2.70
		Total banks merged:			
Merge banks on which a GIP shock:	50%	14	-0.29	-0.49	-2.87
is at least xx% of equity	100%	8	-0.28	-0.48	-2.86
	150%	4	-0.26	-0.48	-2.86
		Total banks merged:			
Merge banks on which a GIP shock:	Only exposed banks	8	-0.28	-0.48	-2.86
is at least 100% of equity	Only unexposed banks	16	-0.25	-0.47	-2.84
with banks totally unexposed	Both exposed and unexposed	24	-0.30	-0.52	-2.89
		Total banks destroyed:			
Destroy banks with systemic impact/ own equity > xx%	100%	17	-0.31	-0.51	-2.86
Split their assets equally among others	Assets>500bn	17	-0.27	-0.49	-2.76
	Both	1	-0.25	-0.47	-2.82

Table 5. Optimal Equity Allocation to Reduce Aggregate Vulnerability to a GIIPS shock. We assume the social planner has 200bn euros to inject, and seeks the allocation of capital increases that maximizes the reduction in Aggregate Vulnerability. We only report here the top 20 receivers. Column 1 reports optimal equity injection in bn euros. Column 2 reports systemicness as in equation (8). Columns 3-6 provide the four components of systemicness as in equation (9): their product equals systemicness: debt to common equity ratio (col 4), total assets relative to aggregate bank equity (col. 5), bank exposure w.r.t. to the GIP shock (col. 6), and the linkage term (col. 7).

Bank	Equity Injection (bn euros)	Systemic ness	Target leverage	Size (ai / Agg. E)	Exposur e to GIP shock (ei MS)	Linkage effect (1 AML M ei)
Banca Monte Dei ...Siena	18.20	0.17	30	0.22	0.08	0.32
Intesa Sanpaolo S.P.A	18.20	0.23	21.43	0.62	0.05	0.33
Caja De Ahorros Y Pensiones De Barcelona	17.90	0.16	22.38	0.27	0.07	0.38
Banco Bilbao Vizcaya Argentaria	17.77	0.22	20.87	0.57	0.06	0.33
Bfa-Bankia	17.40	0.16	28.63	0.29	0.05	0.42
Banco Santander S.A.	12.04	0.21	22.99	1.06	0.03	0.34
Unicredit S.P.A	12.00	0.19	22.39	0.88	0.03	0.31
Banco Popolare	8.11	0.07	30.00	0.13	0.05	0.36
Bnp Paribas	6.04	0.15	22.62	1.37	0.02	0.3
Banco De Sabadell	4.68	0.04	25.26	0.10	0.04	0.4
Banco Comercial Português	4.34	0.04	27.16	0.10	0.04	0.34
Ubi Banca	4.13	0.04	20.37	0.15	0.04	0.33
Banco Popular Español	3.53	0.03	18.5	0.14	0.04	0.35
National Bank Of Greece	3.52	0.03	12.64	0.11	0.09	0.28
Efg Eurobank Ergasias	3.26	0.03	22.88	0.08	0.06	0.26
Commerzbank Ag	3.14	0.07	30.00	0.66	0.02	0.23
Bank Of Ireland	2.98	0.03	29.36	0.17	0.02	0.32
Caja De Ahorros Del Mediterráneo	2.96	0.03	30.00	0.07	0.04	0.34
Piraeus Bank Group	2.69	0.02	16.69	0.05	0.09	0.34
Caixa De Aforros De Galicia	2.66	0.03	30.00	0.07	0.04	0.36

Table 6: Robustness to Liquidation Rules. In this Table we calculate the aggregate vulnerability AV under three scenarios (Greek, GIP and GIIPS 50% write-down). We make 7 different assumptions on the liquidation rules. In line 1, we report the baseline. In line 2, we assume only sovereigns can be sold. In line 3, we assume sovereigns and commercial real estate only can be sold. In line 4, we add mortgages to the list of assets that can be sold. In line 7, we include all known assets (typically about 80 % of total exposure). Implicitly, the different here with the first line is that we assume banks have no cash to adjust.

	Greek debt only	GIP	GIIPS	Liquid assets / total
Benchmark	-0.25	-0.47	-2.85	1.00
Sovereigns only	-0.01	-0.03	-0.23	0.12
+ commercial real estate	-0.04	-0.08	-0.47	0.18
+ mortgages	-0.21	-0.42	-2.40	0.41
+ corporate loans	-0.38	-0.71	-4.11	0.68
+ consumer loans	-0.36	-0.69	-4.02	0.70
+ SME loans	-0.35	-0.67	-3.84	0.75

Table 7. Risk factors used to proxy for bank holdings. The factors consist of the weekly returns on S&P non-financial firms, returns on US Mortgage REITs, returns on the US10yr Treasury, the return on the GSCI Commodities index, and the return on high yield bonds. The data span 2001 through March 2011.

Panel A. Summary Statistics

	Full sample		Crisis period (March 2007-May 2009)	
	Mean Return (%)	Volatility (%)	Mean Return (%)	Volatility (%)
SP Returns	0.19	3.21	-0.28	4.55
Mortgage REITs	-0.01	3.64	-0.74	5.82
US 10 yr Return	-0.02	0.55	-0.05	0.69
Commodities	0.12	3.59	-0.16	4.62
High Yield Returns	0.15	1.26	-0.05	2.13

Panel B. Correlations

	SP Returns	Mortgage REITs	US 10 yr Return	Commodities	High Yield Returns
SP Returns	1.00				
Mortgage REITs	0.57	1.00			
US 10 yr Return	0.28	0.07	1.00		
Commodities	0.24	0.06	0.14	1.00	
High Yield Returns	0.54	0.37	0.21	0.25	1.00

Table 8. The impact of the Lehman Brothers failure on other banks. We regress stock returns on September 15, 2008 on V(I,Lehman) which is the impact of Lehman induced fire sales on each bank. T-statistics are shown in brackets.

	Dep. Var = Return on September 15, 2008	
Predicted Return from deleveraging $V(i, \text{Lehman})$	1.48	1.31
	[3.04]	[2.44]
Log(Size)		-0.01
		[-1.86]
Log(Leverage)		-0.09
		[-0.11]
R^2	0.10	0.16

Table 9. Top 10 Systemic Banks, selected dates. We show $S(i)$ as well as $S(i)/AV$. $S(i)$ is systemicness, and is the impact of each bank on aggregate vulnerability AV. It is defined in Equation (9).

Jan-07			Jan-08			Jan-09		
Name	S(i)	S(i)/AV % of total	Name	S(i)	S(i)/AV % of total	Name	S(i)	S(i)/AV % of total
AIG	0.07%	19.6%	Citigroup Inc	0.66%	17.4%	Wells Fargo	1.60%	20.4%
Jpmorgan Chase	0.05%	13.6%	Goldman Sachs	0.49%	12.9%	Jpmorgan Chase	1.26%	16.0%
Morgan Stanley	0.03%	7.0%	Jpmorgan Chase	0.36%	9.4%	Bank Of America	0.88%	11.3%
Goldman Sachs	0.02%	5.7%	FNMA	0.33%	8.6%	Citigroup	0.74%	9.4%
Lehman Brothers	0.02%	4.4%	Bank Of America	0.19%	5.0%	Intercontinentalexchange	0.23%	3.0%
Metlife Inc	0.02%	4.2%	AIG	0.17%	4.5%	BONY Mellon	0.18%	2.2%
Wachovia Corp	0.01%	3.3%	American Express	0.13%	3.5%	Merrill Lynch & Co Inc	0.18%	2.2%
FNMA	0.01%	3.1%	FHLM	0.13%	3.4%	Goldman Sachs	0.15%	1.9%
Merrill Lynch	0.01%	2.7%	Lehman Brothers	0.10%	2.5%	Regions Financial	0.15%	1.9%
State Street Corp	0.01%	2.6%	Metlife Inc	0.09%	2.4%	Capital One Financial	0.14%	1.8%

Table 10. Top 10 Vulnerable Financial Institutions, selected dates. We show vulnerability expressed as a percentage of equity value. Vulnerability is the impact of an aggregate shock to all factors on each single bank. We a;sp sjpw the direct exposure of each bank to the shocks considered. For each date and in each panel, we show the 10 most vulnerable banks in the sample. Banks are ranked by Vulnerability V(i)

2007			2008			2009		
Name	Round 0 Exposure	V(i) %	Name	Round 0 Exposure	V(i) %	Name	Round 0 Exposure	V(i) %
Radian Group	2.31%	1.19%	Radian Group	20.33%	19.43%	M G I C Investment Wis	38.09%	30.49%
AIG	1.06%	1.18%	Federal National Mortgage	3.27%	11.68%	Intercontinentalexchange	19.00%	24.18%
M G I C Investment	1.75%	1.15%	C B Richard Ellis Group	7.57%	9.09%	American Capital Ltd	21.27%	23.94%
Sovereign Ban	0.86%	1.10%	Citigroup	2.87%	8.23%	C B Richard Ellis Group	11.46%	23.18%
M B I A	1.88%	0.95%	Federal Home Loan Mortgage	2.07%	7.95%	C M E Group	6.20%	16.47%
Ambac Financial	1.12%	0.84%	American Capital Ltd	3.01%	7.24%	Fifth Third Ban	10.18%	15.78%
Metlife	1.26%	0.79%	E Trade Financial	11.38%	6.96%	Legg Mason	10.80%	14.14%
State Street	1.80%	0.76%	Synovus Financial	1.90%	6.88%	Regions Financial New	14.06%	13.94%
C B Richard Ellis	4.32%	0.75%	Goldman Sachs Group	4.72%	6.65%	Wells Fargo New	9.43%	13.87%
Jpmorgan Chase	1.35%	0.74%	Fifth Third Ban	2.11%	6.57%	M B I A	8.57%	13.66%

Table 11. The impact of bank mergers on systemic risk. On September 25, 2008, JP Morgan Chase acquired the assets of Washington Mutual Bank (WaMu). The impact of a 1% shock to the assets of bank *i* to total deleveraging is given by $1'AMLM'BAe_i$. In Panel A, we compare the contributions of WaMu to that of JP Morgan to that of the hypothetical merged bank. The merged bank inherits the assets of both banks and takes on the asset-weighted capital structure of the original banks. We then compute hypothetical bank mergers of WaMu with each of the remaining US financial institutions in our sample. Panel B lists the ten safest acquirors from the perspective of systemic risk; a merger with each of these banks would reduce systemic risk relative to the banks operating standalone. Panel C lists the ten riskiest acquirors; a merger with each of these banks would increase systemic risk relative to the banks remaining standalone.

Panel A: Deal Statistics

	WaMu	JPM	Hypothetical Merged Bank
Contribution to deleveraging ($m)	$7,761	$2,061	$9,060
Leverage (market)	42.609	12.746	22.781
Assumed target leverage	20	12.746	16.479
Assets, MV ($m)	$313,940	$194,820	$507,760

Panel B: Safest potential acquirors from perspective of systemic risk (safest on top)

Rank	Name	Leverage	Assets ($m)
Safest	BERKSHIRE HATHAWAY INC DEL	2.31	218,320
2	U S BANCORP DEL	3.28	283,750
3	INTERCONTINENTALEXCHANGE INC	0.21	7,441
4	PROGRESSIVE CORP OH	1.17	25,764
5	ALLSTATE CORP	5.22	160,300
6	AETNA INC NEW	2.23	58,885
7	BANK OF NEW YORK MELLON CORP	4.11	209,170
8	BLACKROCK INC	0.44	35,757
9	C M E GROUP INC	0.29	35,173
10	STATE STREET CORP	5.02	157,340

Panel C: Least safe potential acquirors from perspective of systemic risk (least safe on top)

Rank	Name	Leverage	Assets ($m)
Least safe	REGIONS FINANCIAL CORP	8.81	134,980
2	MARSHALL & ILSLEY CORP	6.90	60,469
3	FIFTH THIRD BANCORP	9.33	112,710
4	WACHOVIA CORP	17.49	748,800
5	B B & T CORP	5.30	142,590
6	SUNTRUST BANKS INC	7.73	182,960
7	KEYCORP NEW	12.53	99,597
8	POPULAR INC	13.03	44,163
9	ASSOCIATED BANC CORP	5.82	22,568
10	FIRST HORIZON NATIONAL CORP	11.92	37,805