Vulnerable Banks*

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Abstract

When a bank experiences a negative shock to its equity, one way to return to target leverage is to sell assets. If asset sales occur at depressed prices, then one bank's sales may impact other banks with common exposures, resulting in contagion. We propose a simple framework that accounts for how this effect adds up across the banking sector. Our framework explains how the distribution of bank leverage and risk exposures contributes to a form of systemic risk. We compute bank exposures to system-wide deleveraging, as well as the spillover of a single bank's deleveraging onto other banks. We use the model to evaluate a variety of crisis interventions, such as mergers of good and bad banks, and equity injections. We apply the framework to European banks vulnerable to sovereign risk in 2010 and 2011.

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I. Introduction

Financial stress experienced by banks can contaminate other banks and spiral into a shock that threatens the broader 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.

Recent literature has emphasized two main channels by which the 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). Bilateral links of this kind can propagate distress, because the creditor bank may in turn lack the funds needed to deliver on its on its obligations to third parties (Duffie 2010, Kallestrup et al., 2011).[1]

A second type of linkage comes from fire-sale spillovers: when a bank is forced to sell illiquid assets, the sale may depress prices because of a lack of unconstrained buyers, which in turn can prompt financial distress at other banks that hold the same assets. Liquidation spirals of this sort 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 contributor to systemic risk over recent years.

[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), Allen, Babus, and Carletti (2011), Wagner (2011).

This paper puts forth a simple model of fire-sales spillovers that can be readily estimated using available data. The model takes as given (1) the asset holdings of each financial institution, (2) an adjustment rule applied by institutions when they are hit by adverse shocks and (3) the liquidity of these assets on the secondary market (i.e., the ability of banks to sell these assets quickly with little price discount). Our main objective is to develop simple formulas of how fire sale spillovers add up across the financial sector, and how susceptible individual banks are to episodes of deleveraging by other banks.

An appealing feature of our approach is that we distinguish between a bank's *contribution* to financial sector fragility (which we call its "systemicness"), and a bank's *vulnerabilty* to deleveraging by other banks. Our model allows us to compute formulas for both. To see the difference, consider a small but highly levered bank with a portfolio of risky assets. Such a bank may be quite vulnerable to financial sector deleveraging, yet is unlikely to be systemic. This is because asset sales triggered by its potential distress will be modest in size, thus not triggering much in the way of spillovers.

The model delivers a number of intuitive properties concerning how the distribution of leverage and risk exposures across banks determines systemic risk. For instance, consider a negative return shock experienced by an asset that is held by relatively levered banks. This shock has a larger aggregate impact than if the same asset was held by the less levered institutions. More generally, we show that the banking system is less stable to shocks when asset classes that are large in dollar terms are also held by the most levered banks. If the goal is to reduce fire sale spillovers, then assets that are both volatile and illiquid should be dispersed across banks, since the same shocks generate less price impact in a deleveraging cycle. 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, which in turn are subject to larger shocks.

Though the model is highly stylized, we can use it to simulate the outcome of various policies to reduce fire sale spillovers in the midst of a crisis. The model takes as exogenous bank reaction functions to net worth shocks, and therefore there is no presumption that bank capital structures are optimal ex ante.[3] Nevertheless, the model can help predict how deleveraging can play out once banks are up against binding leverage constraints. As an example of policy analysis, consider a forced bank merger between two vulnerable banks—Sorkin (2009) suggests this was one of the initiatives entertained by the New York Federal Reserve during the US financial crisis. Such a policy may affect systemic risk because it redistributes existing assets across banks, which may have different exposures to shocks, different sizes, or different leverage ratios. As another example, consider the policy question of how to distribute a fixed amount of equity across a large set of distressed banks. It should not be surprising that stabilization policies that aim to fix insolvency at individual banks can be inferior to policies that directly target the cross-bank spillovers.

We apply the model to European banks during the 2010-2011 sovereign debt crisis. For a large set of these banks, we have measures of sovereign bond exposures derived from the European Banking Authority's (EBA) July 2011 stress tests. We then use these exposures to estimate the potential spillovers which could occur during bank deleveraging precipitated by sovereign downgrades or defaults. Using the risk exposures as inputs, we document a correlation between our estimates of bank vulnerability and equity drawdowns experienced by European banks in 2010 and 2011. We then use our data to evaluate various policy interventions. We find that size caps, or forced mergers among the most exposed banks do not reduce systemic risk very much. However, we show

[3] For example, it may be optimal for banks to retain a buffer stock so that they are less subject to small shocks.

that modest equity injections, if distributed appropriately between the most systemic banks, can cut the vulnerability of the banking sector to deleveraging by more than half.

The remainder of the paper is organized as follows. We first develop the model, solve it, and build intuition for financial sector stability under different configurations of leverage and risk exposure across the banks. In Section III, we explain how our approach fits into, and contributes to, a growing literature on systemic risk. In Section IV, we use commercial bank exposures provided by the EBA's July 2011 stress tests to compute the vulnerability of European banks to sovereign defaults. Section V explains how the model can be adapted to monitor vulnerability on a more dynamic basis using factor exposures. The final section concludes.

II. A Model of Bank Deleveraging

We start by describing the framework. We then use it to derive easy-to-implement measures of systemic risk, at the bank and aggregate levels.

A. Setup

There are two periods t=1,2, and N banks. Each bank n is financed with a mix of debt d_{nt} and equity e_{nt}. A_t is the $N \times N$ diagonal matrix of banks' assets so that each diagonal term $a_{nt} = e_{nt} + d_{nt}$ at date t. B is the $N \times N$ diagonal matrix of leverage ratios, such that each diagonal term $b_n = d_{nt}/e_{nt}$.

Each bank n holds a portfolio of K assets: m_{nk} is the weight of asset k in bank n's portfolio. M is the $N \times K$ matrix of these weights. In each period, the vector of banks' unlevered returns is given by:

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

where the $K \times 1$ vector F_t denotes asset net returns.

Assumption 1: Asset trading in response to bank return shock

Suppose banks receive an exogenous shock R_1 to their assets at t=1. Because banks are levered, these shocks move banks away from their current leverage. We assume that banks respond by scaling up or down their total assets in period 2 so as to maintain a fixed target leverage. Such leverage-targeting is in line with empirical evidence in Adrian and Shin (2010), who show that banks manage leverage to offset shocks to asset values.[4] Adrian and Shin's evidence implicitly suggests that banks do not raise equity in response to a negative shock.[5] However, the analysis that follows does not change much if we instead assume that banks return to target leverage using a combination of asset sales and equity issues in fixed proportion.

If banks target leverage ratios given by the matrix B, then the $N\times 1$ vector of dollar net asset increases is simply $A_1 B R_1$. When $R_1<0$, banks with negative asset returns have to sell assets to deleverage. When $R_1>0$, banks with positive returns need to borrow more to preserve leverage. The intuition of this formula is simple: 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.[6] In practice, banks will have more flexibility in dealing with a positive shock to bank equity, and so our model will be more useful for thinking about dynamics following negative

[4] 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.

[5] In situations where debt overhang is severe, issuing equity dilutes existing shareholders as the gains from the reduction in risk accrue disproportionately to debt holders.

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

If some elements of R_1 are negative and very large, then it is possible that the A_1BR_1 vector may have some negative elements that are bigger in absolute value than banks' assets. This happens if the initial shock is large enough to wipe out all of the equity of the bank, in which case no amount of asset sales will return the bank to target leverage. To prevent this from happening, we can modify the vector of net asset increases by replacing it by $A_1.\max(BR_1,-1-R_1)$, where "max" is the point-wise maximum matrix operator, defined by $\max(X,Y)=(\max(X_n,Y_n))$. In Section IV we use this modified formula, because the shocks we consider in Europe are large enough to wipe out some banks. But to simplify the exposition that follows, for now we keep the simpler linear formula.

Assumption 2: Target exposures remain fixed in percentage terms

Second, we must describe how banks sell individual assets to return to target leverage. We make the simplest assumption that banks sell assets so as to keep their exposures constant in a proportional sense. More formally, this means that they sell assets in such a way as to hold the M matrix constant between dates 1 and 2. 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, 2011, and Lou, 2011). Let ϕ be the $K\times 1$ vector of net asset (dollar) purchases by all banks in period 2. If banks keep their portfolios constant, then:

$$\phi = M' A_1BR_1. \tag{2}$$

To see the intuition, consider a bank with holdings 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. Equation (2) describes this in matrix form, summed over all banks: for each bank n facing a shock R_{1n}, total net asset purchase (i.e., the increase in assets net of returns) will be given by $a_n b_n R_{1n}$. Net purchases of asset k by the bank will be proportional to its holdings of asset k, i.e., $m_{nk} a_n b_n R_{1n}$. Equation (2) sums this expression across all n banks.

We have experimented with variations of this assumption (which is admittedly strong), because in practice, banks may optimally sell their most liquid assets first. The constant portfolio assumption simplifies the algebra and the intuition below, but we show later (Section IV F) that the framework can be quite easily modified to account for more sophisticated liquidation rules.

Assumption 3: Fire sales generate price impact

Third, we assume that asset sales in the second period ϕ generate price impact according to a linear model:

$$F_2 = L\phi \,, \tag{3}$$

where L is a matrix of price impact ratios, expressed in units of returns per dollar of net purchase.[7] We start by assuming that L is diagonal, meaning that fire sales in one asset do not directly affect prices in other assets.[8]

For assets with uncorrelated payoffs, equation (3) can be easily microfounded. Suppose there are outside investors with a fixed dollar amount of outside wealth W who provide liquidity to the banking sector during a fire sale, but trade off the returns to outside projects with the returns to investing in fire sold assets. In such a setting, the equilibrium discount will be an increasing function of the total dollar amount of fire sold assets (See Stein (2012)).

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[7] 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). Bank loans can also be sold on fairly liquid markets (Drucker and Puri, 2008).

[8] Greenwood (2005) develops a model in which price impact spreads across similar assets. To the extent that off-diagonal elements are positive, this would further amplify the effects discussed below.

We combine equations (1), (2) and (3) to calculate the effect of bank unlevered asset returns in t=1 on returns in t=2:

$$R_2 = MF_2 = ML\phi = (MLM'BA_1)R_1. \tag{4}$$

In principle, one can iterate multiple rounds of deleveraging following an initial shock, by further multiplying by the transition matrix $MLM'BA_1$. Taken to the limit, the deleveraging process ends at a fixed point, which is a function of the eigenvalues of the transition matrix. For simplicity, we restrict our attention to the first round of deleveraging, because this delivers most of the useful intuitions about the relevant linkages between banks.

B. Measuring Aggregate Exposures to Deleveraging ("Aggregate Vulnerability")

We start with a negative shock $-F_1=(-f_1,\ldots,-f_n)$ to asset returns: this translates into dollar shocks to banks' assets given by A_1MF_1. The aggregate *direct* effect on all bank assets the quantity is then $1'A_1MF_1$, where 1 is the $N\times 1$ vector of ones. This direct effect does not involve any contagion between banks, it is simply the change in asset value.

Following equation (4), To compute the dollar effect of shock F_1 on bank assets through fire sales, we pre-multiply $MLM'BA_1MF_1$ by $1'A_1$. We normalize this by total bank equity pre-delevering E_1 and define "aggregate vulnerability" as:

$$AV = \frac{1'A_1MLM'BA_1MF_1}{E_1}. \tag{5}$$

AV measures the percentage of aggregate bank equity that would be wiped out by bank deleveraging if there was a shock F_1 to asset returns. As a reminder, this formula omits the *direct* impact of the shock on net worth, 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 contagion across banks because delivering does not involve price impact, even though there is still a direct effect of the shock on banks asset values given by $1'A_1MF_1$.

To understand the intuition behind Eq. (5), using $-R_1=-MF_1=(-r_{1t},...,-r_{nt})'$, we can rearrange terms slightly and expand:

$$AV\times E_1=\sum_n \gamma_n b_n a_{n1} r_{n1}, \tag{6}$$

where $\gamma_n=\sum_k\left(\sum_m a_m m_{mk}\right)l_k m_{nk}$ measures the "connectedness" of bank n. This is the extent to which bank n owns large ($s_k=\sum_n a_n m_{nk}$ large) or illiquid (l_k large) asset classes. Where this is the case, one dollar of fire sales by bank n will lead to a larger amount of the banking system's holdings, since it will reduce by more the price of larger asset classes.

Equation (6) shows that the systemic risk is large when large banks (banks with large a_{n1}) are levered (large b_{n1}), exposed to the shock in question (r_{n1}), or connected (large γ_n). These properties are intuitive: if large banks are levered and/or exposed, a given shock will trigger larger asset sales. In addition, if exposed banks hold assets that are illiquid and/or widely held, then price impact is large and the overall system is more vulnerable. More generally, the four elements of equation (6) – connectedness, leverage, size, and exposure – enter multiplicatively in determining AV. This means that the *distribution* of these elements across the financial system matters enormously for systemic risk. For example, the formula tells us that from the perspective of spillovers, the covariance between bank size and leverage is an important input.

C. Contribution of each Bank to Deleveraging: "Systemicness"

We can calculate the contribution that each bank has -- through contagion -- on the aggregate vulnerability of the banking system. To do this, we again focus on the impact of a shock F_1, but assume it only affects bank n. In this case, it is easy to see that the impact coming from the liquidations of bank n on the aggregate of the banking system is:

$$S(n) = \frac{1' A_1 MLM' BA_1 \delta_n \delta'_n MF_1}{E_1}, \tag{7}$$

where δ_n is the $N \times 1$ vector with all zeros except for the n^{th} element, which is equal to 1. We call $S(n)$ the "systemicness" of bank n. Systemicness can be interpreted as the contribution of bank n to aggregate vulnerability, as $AV = \sum_n S(n)$.

As we did for aggregate vulnerability, we can develop intuition by expanding terms in equation (7):

$$S(n) = \gamma_n \times \left(\frac{a_n}{E_1} \right) \times b_n \times r_{n1}, \tag{8}$$

which is the bank-level equivalent of Equation (6). Thus, a bank is more systemic if:

- *It is more connected* (*γ_n is bigger*): the bank owns assets that are both illiquid and widely held by other banks.
- *It is bigger* (*a_n/E_1 is bigger*): a given shock on a larger bank leads to more fire sales, which in turn leads to a large price impact.
- *It is more levered* (*b_n is bigger*): a shock to a more levered bank is going to induce it to sell more, which generates more price-impact.
- *It receives a bigger shock r_{n1}.*

D. Impact of Deleveraging on each Bank: Indirect Vulnerability

We define a bank's "indirect vulnerability" with respect to shock F_1 as the impact of the shock on its equity through the deleveraging of other banks:

$$IV(n) = \frac{\delta'_n A_1 MLM' BA_1 MF_1}{e_{n1}}. \tag{9}$$

$IV(n)$ measures the fraction of equity of bank n that disappears when other banks deleverage following shock F_1. It differs from *direct* vulnerability, which measures the direct exposure of bank n's assets to shock F_1:

$$DV(n) = \frac{\delta'_n A_1 M F_1}{e_{n1}}. \tag{10}$$

In our empirical applications, we will systematically contrast the two measures: IV involves the deleveraging spiral, while DV does not.

To understand the intuition behind $IV(n)$, we can expand terms in equation (9):

$$IV(n) = \underbrace{(1+b_n)}_{\text{leverage}} \times \sum_k \left[\underbrace{l_k m_{nk}}_{\substack{\text{illiquidity- weighted}\\ \text{exposure to asset k}}} \times \underbrace{\left(\sum_{n'} m_{n'k} a_{n'} b_{n'} r_{n'} \right)}_{\text{fire sales of asset k}} \right]. \tag{11}$$

The first term stands for the pure leverage effect: a given asset shock has a bigger impact on equity if the bank is more levered. The second term measures the importance of connections between banks. It is large when the bank is exposed to assets that are illiquid and exposed to heavy fire sales.

E. Indirect Vulnerability to a specific bank

Suppose one is interested in the impact of a single bank deleveraging (for example, if it were to fail and its assets were liquidated). In this case, we can compute IV in the special case where the vector of banks' returns $R_1 = \sigma.\delta_m$, i.e. assuming that bank m (and only bank m) will deleverage following a shock σ to it assets. Then, following equation (9), the indirect vulnerability of bank n to this shock is:

$$IV(n,m) = \sigma \frac{\delta'_n A_1 M L M' B A_1 \delta_m}{e_{n1}}. \tag{12}$$

This measure captures the interdependence through deleveraging of banks n and m. $IV(n,m)$ is large when sender bank m is large and levered, when receiver bank n is levered, and more interestingly when the term $\delta_n' MLM' \delta_m$ is big, i.e., when n and m own similar illiquid assets.

F. Theoretical Properties

i. Heterogeneity and Systemic Risk

One implication of equation (6) is that making the banks more similar may reduce fire sale spillovers, and thus AV. This contrasts with much of the existing literature on systemic risk, which assumes that systemic risk is high when banks have correlated stock returns.[9] The economic intuition for this comes from two opposing effects. First, because banks liquidate all assets they hold when they are shocked, shocks to liquid assets trigger fire sales of illiquid assets when banks own both types. This can make it stabilizing to ring-fence the illiquid assets into specific banks. There is, however, also an effect that makes diversification desirable: when all banks own all assets, any shock to asset prices will spread the fire sales across all asset markets, which tends to reduce the total price impact. The diversification effect dominates when illiquid (high l_k) assets receive stronger shocks (high f_k): diversified (correlated) banks are better, because they can react to these shocks by partly selling liquid assets which reduces global price impact. But when liquid (low l_k) assets receive bigger shocks (high f_k), the contagion effect is more important. In this case, stability can be increased by isolating the illiquid assets into specific banks.

To illustrate this intuition more formally, consider the case of N assets and N banks of identical size a and leverage b. Suppose that assets are equally spread across banks (heterogeneity),

[9] A notable exception is Wagner (2011) who considers a similar set of issues about the distribution of risks between banks.

we have $M=(11')/N$ (this is a matrix where all coefficients are equal to $1/N$) and $AV = a^2 b \sum_{i=1}^{N} \bar{l} f_i$ where $\bar{l}=(\sum_{i=1}^{N} l_i)/N$ is the average liquidity of assets. In contrast, if each asset is exclusively held by one bank dedicated to that asset (homogeneity) $M=Id.$, and $AV = a^2 b \sum_{i=1}^{N} l_i f_i$. Thus homogeneity leads to lower AV than heterogeneity if $\sum_{i=1}^{N}(\bar{l}-l_i) f_i > 0$, i.e. when assets with large shocks tend to be more illiquid.

ii. Absence of "Too Big to Fail" effect

Another somewhat surprising property of our framework is that AV is not directly impacted by the size of banks. For instance, we can prove that slicing a bank into n smaller banks, with the same asset mix and leverage as the original bank, leaves AV unchanged (see appendix). This is because each of these new banks reacts to shocks exactly as the original bank, scaled by the ratio of their sizes. Thus, the combined impact on the rest of the system is exactly identical to that of the original banks. Conversely, merging banks with same asset mix and leverage also leaves AV unchanged.

III. Relation to Literature

We follow a growing literature that studies linkages between financial institutions and the implications for systemic risk. The tradition in recent papers has been to infer bank linkages from correlations in market prices. A first set of papers seeks to estimate risk directly from bond or CDS (see for instance Ang and Longstaff (2011)). Giglio (2011), for example, uses the difference between bond and CDS spreads to estimate the joint probability of failure of large banks who are sellers of protection. A second set of papers measures systemic risk through comovement in the equity returns of financial intermediaries (Adrian and Brunnermeier (2010), Acharya, Pedersen, Philippon and Richardson (2010), Billio, Getmansky, Lo, and Pelizzon (2010), Diebold and Yilmaz (2011)).

Our framework departs from some of this literature by making simple assumptions about how funding shocks propagate across banks, i.e., we posit an economic structure to the propagation mechanism of initial shocks. To do so comes at some cost—we adopt a narrow definition of systemic risk based on banks' common exposures, thus deemphasizing bilateral risks such as counterparty risk. On the other hand, the benefits are that our model-based approach can be used to do policy analysis.

The structure of our model is similar to Acemoglu, Ozdaglar and Tahbaz-Salehi (2010), who study the propagation of shocks in the real economy. They derive conditions under which aggregate volatility remains high even when the network is large. Assuming their asymptotic approximation is correct for a large universe of banks, some of their insights could conceivably be applied here.

A contribution of our model relative to existing work is that it distinguishes between a bank's *contribution* to the risk of aggregate deleveraging ("systemicness"), and a bank's *sensitivity* to deleveraging by other banks ("indirect vulnerability"). Adrian and Brunnermeier (2010) define and estimate the "CoVaR" of institution n as the Value at Risk of the *whole financial sector* conditional on bank n being in distress. In our model, "systemicness" $S(n)$ is similar to their CoVaR measure; the main difference being that, while CoVaR is estimated using comovement in stock returns, we put structure on the propagation mechanism, which could result in patterns of return comovement that differ from comovement of returns observed during ordinary times. On the other hand, Acharya et al. (2010) propose a measure closer to "indirect vulnerability" $IV(n)$. For each bank, they estimate average returns during the 5% worst days of market conditions. They combine this estimate with bank leverage to compute the "marginal expected shortfall (MES)," which captures how much capital a bank must raise when faced with adverse market conditions. Finally, Billio, Getmansky, Lo, and Pelizzon (2012) measure systemic risk using bilateral time-series dependencies between firms. Diebold and Yilmaz (2011) discuss the relationship between cross-bank linkages estimated in this way and measures of network connectedness. Our cross-bank indirect vulnerability measure $IV(n,m)$ may provide a foundation for some of these connections.

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 their losses vis-à-vis their largest counterparties for a list of stressful scenarios. Brunnermeier, Gorton, and Krishnamurthy (2011) suggest eliciting firms' sensitivities to different risk factors and scenarios. We build on this work by modeling these sensitivities, and quantifying how these stress scenarios could play out across the broader financial sector.

IV. The Vulnerability of European Banks

As the US financial crisis subsided in 2009, investor attention shifted to the fiscal positions of a handful of European governments that were running large euro-denominated deficits. As the crisis in Europe unfolded between 2009 and 2011, one area of growing concern was the holdings of sovereign debt by national banks. To assess exposure to potential sovereign defaults, in 2011 the newly formed European Banking Authority (EBA) conducted stress tests across euro banks.

We use data disseminated by the EBA to test our model, and show how our model can be used to do policy simulations during a crisis. The main question we ask is: What the potential spillovers are across banks in the event of a sovereign default or writedown? Our task is made easier by the detailed bank-level holdings made available during the stress tests. Given the role that sovereign debt has played in the European banking crises, we focus on banks' sovereign bond holdings, and consider as shocks writedowns of Greek, Irish, Italian, Portugese, and Spanish debt (henceforth GIIPS debt).

A. Data

Published on the EBA website in July 2011, the European stress tests provide harmonized balance sheet composition for the 90 largest banks in the EU27 countries. The complete list of banks is in the Appendix.

Matrix A_1: The matrix of assets is obtained directly from the EBA data by summing over all banking exposures to loans of each bank *n*. Diagonal elements a_{nn} are the "total exposure" in euros of bank *n*. The average exposure is €260 billion. The biggest bank is HSBC (€1440bn), the smallest one is Caixa d'Estalvis de Pollensa (€338 million).

Matrix *M*: To calculate the exposure matrix *M*, we collapse the EBA data into 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. The *M* matrix is thus a 90 x 42 matrix, where m_{nk} is the fraction of exposure to asset *k* of bank *m*. Aggregate exposure to commercial real estate across the 90 banks is €1.2 tn (5% of banking sector assets); small business lending is €744 bn (3.2%); mortgages are €4.7 tn (20%); and corporate loans are €6.7 tn (29%). Sovereign bonds account for €2.3 tn (13%).

An alternative way to compute *M*, which may be helpful in other applications, is to estimate it from asset return data by regressing unlevered bank stock returns on the returns of assets in the bank portfolio. Adopting this approach is reasonable if we believe the stock market fully recognizes all of the assets and risks in a bank's portfolio. And, the advantage of such an approach, particularly visible in Acharya et al (2010), is that it allows researchers or policymakers to monitor *M* dynamically. On the other hand, because factor returns are quite noisy and may be collinear, having direct measures of *M* is clearly preferable wherever possible.

Matrix *B*: The leverage matrix B is the diagonal matrix of debt-to-equity ratio. We use book leverage because the EU data does not lend itself to the use of market leverage (half of the 90 banks are not listed, and EBA exposure data are mostly not marked-to-market), and because measures of risk weighted leverage are strongly affected by regulatory arbitrage (Acharya, Schnabl and Suarez, 2011). To obtain each element b_{nn}, we divide total exposure (the a_{nn} element of A) *minus* book equity by book equity. Because some EU banks are very levered, this number has a few outliers (540 for Allied Irish Banks, 228 for the Agricultural Bank of Greece). Because we do not want our results to be driven by these outliers, we cap target leverage b_{nn} at 30: this cap is imposed on 20 banks.

Matrix *L*: We assume L=10^{-13} x Id, where Id is a 42 x 42 diagonal matrix of ones. We therefore assume that all 42 assets have the same price impact. 10^{-13} means that €10bn of trading imbalances lead to a price change by 10bp. This is in the neighborhood of recent empirical estimates of price impact in the bond market, but probably an underestimate for some other asset classes.

Shock F_1: We study a 50% write-off of all GIIPS debt. Hence, the shock vector F_1 is equal to zero for all 42 assets, except for the five GIIPS sovereign debts, for which we assume a return of -50%. Given banks' exposures, the *direct* effect of this shock on aggregate bank equity is given by -$1'A_1MF_1$, which is equal to 381bn €, or 40.1% of aggregate bank equity.

B. Validation using stock returns during the sovereign debt crisis

We first validate our deleveraging model using past data on bank returns during the 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 exposures $DV(n)$ and indirect vulnerabilities $IV(n)$ to losses on

GIIPS sovereign debt. If the market prices bank interdependence via deleveraging, *IV*(*n*) should explain the cross-section of bank returns during the crisis, even controlling for *DV*(*n*).

To calculate *DV*(*n*) we use equation (10). To compute *IV*(*n*), we use a modified version of equation (9), where we account for the fact the fire sales cannot exceed the total assets of a bank (see Section II.A.). This adjustment is necessary as some banks are severely hit by the large shock we assume, so as to entirely wipe out their equity. This leads to the following definition of *IV*(*n*):

$$IV\left(n\right)=\frac{\delta'_n A_1 MLM'\max\left(BA_1MF_1, A_1(I-MF_1)\right)}{e_n},$$

where *max(X,Y)* is the element-by-element max operator. In this definition, we plug in the above matrices and the GIIPS shock vector F_1.

Table 1 lists the top 10 banks, sorted according to *IV*(*n*). To see how *IV*(*n*) differs from more direct exposures *DV*(*n*), we also report direct vulnerability, along with each bank's leverage. Rankings in terms of indirect and direct effect are far from being perfectly correlated: the Spearman rank correlation between DV and IV with respect to a GIIPS shock is 0.17, and is not significantly different from 0 at the 5% level. On average, the direct impact of a full-blown GIIPS crisis would be to wipe out 1.11 times the equity for the average bank. To this direct effect, the impact of the subsequent deleveraging would further wipe out some 302% of the equity of the average bank. As a reminder, all estimates of the impact of deleveraging are contingent on our price impact estimate discussed earlier.

We then regress cumulative returns over 2010 and September 2011 of each bank on indirect vulnerability, controlling for direct vulnerability, bank size (as measured by log of bank total exposure *log*(a_{nn})) and leverage. These controls ensure that vulnerability to the deleveraging process *IV*(*n*) adds explanatory power beyond a bank's direct exposure. Table 2 shows these results.

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 returns data for 49 of them. To reduce sensitivity to outliers, we also report median regression results in columns 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 9%, compared with 14% when direct exposure is also included. The bank size control does not affect the estimated impact of *IV*(*n*) on returns. The direct and indirect vulnerabilities have the same explanatory power on the cross-section of bank returns. For two banks that are one sample standard deviation apart in terms of *IV*(*n*), cumulative returns drop by 5 percentage points more in the bank most exposed to sector-wide deleveraging.

C. Systemicness

In this Section, we briefly discuss the properties of our systemicness measure *S*(*n*) on European Data. As for vulnerability, we need to amend equations (7) and (8) to ensure that bank-level total fire sales are less than total assets (see Section II.A).

$$
\begin{aligned}
S(n) &= \frac{1' A_1 M L M' \delta_n \delta'_n A_1 \max\left(BMF_1, (I - MF_1)\right)}{E_1} \\
&= \gamma_n \times \left(\frac{a_{nn}}{E_1}\right) \times \max\left(b_{nn}\delta'_n MF_1, 1 - \delta'_n MF_1\right).
\end{aligned}
$$

which shows that the systemicness of bank *n* can be decomposed into the product of three scalars: γ_n, which captures the impact of bank *n* on other banks through deleveraging, a_{nn}/E_1, which captures the relative size of bank *n*, and $\max\left(b_{nn}\delta'_n MF_1, 1 - \delta'_n MF_1\right)$, which reflects the size of fire sales by bank *n*.

Table 3 reports the systemicness ranking for the 10 most systemic banks in Europe, along with the three components of the decomposition above. Unsurprisingly, in the overall sample, systemicness is correlated with size (spearman correlation of .52, statistically significant at 1%), but this correlation is far from perfect, as can be seen among the 10 most systemic banks. For example, HSBC, the largest EU bank, does not appear in this ranking. BNP Paribas, which is the second largest, is only the fifth most systemic bank. Size does not explain everything because there is substantial heterogeneity across banks in terms of necessary fire sales. Bankia, which is relatively small, is among the most systemic banks because fire sales would be enormous (92% of its assets), and it is highly connected with the rest of the financial system through its asset holdings (its linkage component equals 0.42). Assuming, for instance, that Bankia had an average linkage level (0.30 instead of 0.42), its systemicness would be equal to 0.29x0.95x0.30=0.08, which would make it the 8^{th} most systemic bank instead of the 6^{th}.

The sum of systemicness across all 90 banks is equal to 2.45, which means that through the deleveraging process, our model predicts that 245% of aggregate bank equity would be wiped out. This is sizeable, since the direct impact of the GIIPS writedown total 40.1% of EU bank equity. The deleveraging effect is therefore 6 times larger than the direct shock. In what follows, we focus on deleveraging.[10]

D. Policy simulations

We now use the model to evaluate a number of different policies which have the potential to reduce spillovers from fire sales when banks are deleveraging. As a reminder, the model does not

[10] To properly calibrate this effect, we would need to amend our exercise in two directions: change the L matrix so as to account for the fact that assets are less liquid, and change the liquidation rule of banks so as to account for the fact that banks fire-sell liquid assets more. The first change would make estimates of systemic risk bigger, while the second one (making banks smarter) would reduce it.

take a position on whether banks are behaving optimally, and assumes that all banks face currently binding leverage constraints, meaning that they adjust immediately to reach new target leverage. Thus, the interventions that follow should be interpreted as potential ex post interventions that could be used in a moment of crisis. The results of the experiments are reported in Table 4. For each policy intervention, we calculate the aggregate vulnerability to the 50% write-down on all GIIPS debt.[11]

Limiting Bank Size: We start by considering the effect of a cap on bank size, holding constant leverage. We do this as follows. Suppose a bank n holds $a_n m_{nk}$ euros of asset k. If assets $a_n > c$, where c is the cap, we set the bank's assets to c, and redistribute residual asset holdings $(a_n - c)m_{nk}$ equally among non-capped banks. This procedure does not affect the portfolio structure of the capped bank, but does affect the portfolios of the other banks, which become richer in the assets held by the capped bank. After one iteration, some previously uncapped banks end up with size greater than c. We iterate this process until all banks are below or at the size cap.

In calculating the new AV, we keep leverage constant. This means we are implicitly assuming that receiving banks can issue enough equity to absorb the new assets, while capped banks reduce their equity when they downsize. The intention is to isolate the effect of size capping separately from deleveraging.

We report the results of this experiment for caps of €500 bn, €900 bn and €1300 bn euro in the first three rows of Table 4. The table shows that capping at €500 bn requires us to redistribute assets out of 17 banks; only two banks would be downsized if we set the cap to be €1300 bn. The main lesson from this analysis is that the overall impact of size caps on aggregate vulnerability is small, and, if anything, tends to increase AV.

[11] Similar qualitative insights obtain using alternative, "less extreme" shocks, such as a 50% write-down on Greek debt only, or a 50% write-down on Greece, Ireland and Portugal.

The intuition for this can be understood by using the definition of AV and taking the difference before and after the policy has been implemented:

$$
\begin{aligned}
\Delta AV &= \sum_n \Delta\left(\gamma_n \frac{a_{n1}}{E_1} r_{n1}\right) \\
&= \underbrace{\sum_n b_n \overline{\gamma_n r_{n1}} \Delta \frac{a_{n1}}{E_1}}_{\text{size reallocation}} + \underbrace{\sum_n b_n \overline{\frac{a_{n1}}{E_1} r_{n1}} \Delta \gamma_n}_{\text{connection reallocation}} + \underbrace{\sum_n b_n \overline{\frac{a_{n1}}{E_1} \gamma_{n1}} \Delta r_{n1}}_{\text{exposure reallocation}}
\end{aligned}
\tag{13}
$$

where Δx measures the change in x between before and after the policy, and $\bar{x}$ measures the average of x between before and after the policy. r_{n1} is the adjusted levered exposure given by $\max\left(b_{nn}\delta'_n MF_1, 1-\delta'_n MF_1\right)$. AV changes because the size cap reallocates assets across banks. The overall effect can be decomposed into three pieces. First, there is a size reallocation effect, in which AV is increased if banks that are more connected or more exposed/levered receive more assets. Second is a "connection reallocation" effect, in which AV increases when large, exposed/levered banks become more connected. The third effect is "exposure reallocation", which increases systemic risk if it makes large connected banks more exposed.

We report this decomposition in Table 4, next to the size cap simulation. The net increase in systemic risk is driven by two opposing forces. These two forces are the strongest for the most drastic cap (€500 bn), so we focus on this one. On the one hand, average (size- and connectedness-weighted) exposure decreases, which reduces systemic risk. This happens because large banks tend to be significantly less exposed: GIIPS debt accounts for 3.2% of their assets, against 5.8% for banks below €500 bn.[12] As a result, the average large banks has less GIIPS exposure: the transfer of one euro from large to small banks will reduce the average exposure of smaller banks, while keeping the average exposure of larger banks constant. Through this effect, the €500bn cap policy reduces

[12] This difference also holds for levered exposure r. A 50% GIIPS debt write-down would wipe out 35% of the book equity of large banks on average, against 46% for banks below the €500 bn threshold.

exposure at smaller banks by 10.5 percentage points, on average. This "risk dilution effect" (further amplified by the fact that the smaller banks get relatively larger) decreases AV.

On the other hand, AV goes up because more exposed banks (which happen to be the smaller banks) receive more assets. Through this "contamination effect", safe assets which were previously held by relatively sheltered institutions are now held by more exposed banks, increasing AV. Overall, in the €500 bn cap policy, the contamination effect dominates the risk dilution effect.

<u>*GIIPS debt re-nationalization*</u>: We also look at the effect of reallocating GIIPS sovereign debt to banks in their home country. This exercise is motivated by two facts. First, between July and December 2011, under pressure of markets and regulators, GIIPS-based banks increased their holdings of GIIPS debt by about 1%, while non GIIPS-based banks reduced them by about 22%. Second, between December 2011 and January 2012, while the ECB lent about €500 bn to euro-area banks, Spanish banks bought about 23bn euro of government debt and Italian banks some €20 bn. A partially intended consequence of prudential and monetary policies over the fall of 2011 has thus been to re-nationalize GIIPS debt.

We thus implement the reallocation of 20% of aggregate holdings of each sovereign back to the balance sheets of banks of its own country. First, for each sovereign k, we aggregate euro holdings by all banks according to $s_k = \sum_n m_{nk} a_n$. For each bank n outside country k, we then remove

$20\% \times s_k \times \frac{a_n m_{nk}}{\sum_{m \in foreign} a_m m_{mk}}$ euro of sovereign k from its balance sheet. Then, for each domestic bank n' in country k, we inject the holdings in proportion of its holdings of the sovereign among banks of country k: $20\% \times s_k \times \frac{a_{n'} m_{n'k}}{\sum_{m \in domestic} a_m m_{mk}}$. This reallocation never leads to negative holdings as long as foreign banks own at least 20% of the aggregate holdings of sovereign *k*, which is the case in our simulation.[13]

Table 4 reports the results of this simulation. We find that it *reduces* systemic risk by about 8%, an effect larger than the €500 bn size cap. This effect is large: the amount of sovereign debt reallocated in the process is only €96 bn, while the €500 bn size cap reallocates trillion of euro of assets.

What drives the reduction in AV? We can break down the overall impact into three components. Most of the effect comes through the aggregate reduction in exposure. When reallocating GIIPS debt, we are reducing GIIPS exposure of non-GIIPS banks (on average, by 0.2% of total assets), while increasing the exposure of most GIIPS banks (on average, by some 0.03% of their total assets).[14] Given that GIIPS banks are on average less levered than non-GIIPS banks (with a debt-to-equity ratio of 21 against 23), this implements an overall reduction in fire sales and hence AV.

<u>Euro-bonds:</u> Our next intervention replicates the effect of substituting all the different sovereign bonds in Europe for one debt security that has the same payoff. The intuition behind the experiment is to break the loop between banks and their sovereigns (Acharya, Dreschler and Schnabl, 2010). Some recent proposals have suggested replacing part of individual sovereign bonds

[13] The only country in our sample where domestic banks own more than 80% of the aggregate bank holdings is the UK (81.6%).

[14] Some GIIPS banks experience a decrease in exposure. This happens because these banks own a lot of GIIPS debt but relatively little of their own sovereign (for instance most Italian banks own much a lot of non-Italian debt, and relatively less Italian debt). As a result, the policy reduces overall exposure to GIIPS for these banks.

in the eurozone with the equivalent amount of a euro-level sovereign bond.[15] According to these authors, this would make banks less sensitive to their own sovereign default.

Suppose we could substitute the sovereign portfolio of each bank with a new portfolio of sovereigns which has (1) the same size and (2) weights that are the same across banks. Each bank thus receives an identical portfolio. More precisely, we change the exposure m_{nk} into $sharesov_k \times \%sov_n$ where $sharesov_k$ is the share of sovereign k in aggregate sovereign holdings, while $\%sov_n$ is the share of sovereign holdings in bank n's portfolio. This reshuffling of bonds across banks preserves each bank's total sovereign exposure, and aggregate exposure (holdings) to each sovereign. But it makes banks more similar in terms of individual country exposure. In the context of our model, it is as if all banks are holding Eurobonds.

Table 4 shows that this policy involves a considerable reshuffling of assets across banks: some 1.6tn euro of bonds change owners. It also increases AV. As in the previous experiment, the reason is that exposure is reallocated to firms that are more levered, so that only the "exposure change" components appears. The intuition is that non-GIIPS banks are both less exposed but more levered in the data. The eurobond experiment transfers GIIPS debt from GIIPS banks to non-GIIPS banks, and therefore increases exposure of the most levered banks.

Ring-fencing risky assets: Perhaps more targeted policies can make the most systemic banks safer? To understand the effect of a merger, let us assume that banks indexed by n are merged together into a bank denoted by *. Noting that the merger preserves the quantity of each holding, it is straightforward to show that:

[15] See Delpla and Von Weizacker (2010), Brunnermeier et al (2011), Hellwig and Philippon (2011) among others.

$$\Delta AV = \sum_{n \text{ merged}} b_m \frac{a_m}{E} \gamma_m \left(r^* - r_m \right) \tag{14}$$

The interpretation of this equation is simple: if banks that are larger or more connected have an exposure lower than the merged entity, the merger increases systemic risk. The intuition is that the merger creates contagion: banks who were relatively large and connected, but less exposed, were protected against the shock. By being merged into an entity with larger exposure, these assets become vulnerable to fire sales, increasing AV.

Suppose now that the regulator merges the most exposed banks into a single large bank. For each bank, we define as 'exposure' the fraction of bank equity that would be lost directly in a 50% write-down of GIIPS debt. We then study three scenarios: merge all banks with exposure above 50%, above 100% and above 150% of their own equity. This means merging respectively 47, 20 and 9 banks.

Table 4 shows that the effect of the bank mergers is nearly zero. The reason is that the policy regroups banks that have very similar exposure-to-equity r_{n1}. And, as equation (14) demonstrates, the expected change in AV is small when expected leverage adjusted-exposure r_{n1} is the same across merged firms. In this case, ring-fencing does not reduce systemic risk: the policy simply transforms several similar small banks into one big bank with the same exposure.

Merging exposed banks with unexposed ones: Suppose we merge the 20 most exposed banks with the banks that are unexposed to the GIIPS write-down (6 of the 90 banks are unexposed). To isolate the impact of merging the two groups, we first merge the exposed banks together, then merge the unexposed banks together, and then finally perform the full merger. Merging unexposed banks does not change AV, because of the effect discussed in the previous experiment: they are identical with respect to the shock. For the same reason, merging exposed banks does not change things much either. Merging the two groups into one bank does, however, increase systemic risk by 20% of aggregate equity. The intuition is that the assets of unexposed banks, which were previously not sold in response to the shock, become contaminated by the poor performance of GIIPS debt. This is because, in the data, the measure of connectedness of bank n, $\sum_k m_{nk} s_k$, is larger for initially unexposed banks than for exposed banks. As a result, merging the two categories of banks exposes the connected balance sheet of unexposed banks to the GIIPS shock.[16]

<u>Leverage cap:</u> 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 raise equity to reach the maximum leverage, but do not change their sizes. Economically in our model, such a policy reduces the need for banks to fire-sell assets, so it unambiguously reduces AV. From Equation (6) we see that:

$$\Delta AV \times E_1 = l \sum_n \left[\Delta b_n \times \underbrace{a_{n1}}_{\text{n is large}} \times \underbrace{(-r_{n1})}_{\text{n is large}} \times \underbrace{\left(\sum_k m_{nk} s_k \right)}_{\text{n holds large asset classes}} \right], \text{ with } s_k = \sum_{n'} m_{n'k} a_{n'1}$$

The policy is more effective when targeted banks are either (1) bigger, (2) more exposed, or (3) hold large asset classes.

---

[16] This effect of increasing AV after merger shows up even in simulations where we assume that all banks have the same leverage b_n and the same size a_n. If in equation (13) we set $a_n = a^*$ and $b_n = b^*$, we obtain:

$$\Delta AV \times E_1 = la^* b^* \sum_{i \text{ merged}} \left[((-r_1^*) - (-r_{i1})) \times \sum_k m_{ik} s_k \right]$$

where $r^* = (1/N_{\text{merged}}) \cdot \sum_{i \text{ merged}} r_{i1}$. It appears from this expression that the increase in AV is positive if banks with above average exposure $-r_{i1}$ have below average connectedness $\sum_k m_{ik} s_k$. This is the case in the data, where exposed banks have a connectedness level 13% below unexposed banks.

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 of €480 bn. The table shows that, to obtain a significant reduction in systemic risk, the regulator would need to set a very drastic cap. For instance, capping leverage at 25 (this is leverage at the 63^{rd} percentile bank) only reduces vulnerability to a GIIPS shock from 245 to 238% of aggregate equity. The impact of reducing leverage to 20 is much larger.

E. Optimizing capital injection

The policy interventions discussed above are disappointing in that they suggest that capping leverage yields only modest improvements in AV, and that other policies have ambiguous, or even adverse, impacts on AV. In a moment of crisis, what tools can reduce contagion at minimal expense to the regulator? In this last exercise, we explore the power of an optimal targeted policy. Recall from Eq. (8) that aggregate vulnerability to a shock vector S can be written as a weighted average of the debt-to-equity ratios b_n's. The weights measure the extent to which the leverage of a particular bank n is bad for aggregate vulnerability. This happens when the bank is large, the bank is exposed to shocks, and linkages are strong.

Suppose the regulator has a given amount of cash F available to invest in bank equity, and cares only about reducing spillovers between banks in a deleveraging cycle. Equity injection into bank n is given by the vector $f = (f_1,\ldots,f_n)$, so that $1'f = F$. When a bank receives f_n 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. (8) subject to the constraints that $1'f = F$ and $(D_i - f_i)/(E_i + f_i)$=b_i ?. We also impose the constraint that the regulator cannot withdraw cash from equity-rich banks, so that f_n>0 for all i.

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 result 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 declines from 47% to 31% using only €50 bn of equity.

The marginal impact of additional euros of equity injections decreases: €200 bn leads to an AV of 23%; €500 bn leads to an AV of 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 only buy a reduction from 285% to 240% of aggregate equity. Still, the effect is large compared to previous policies considered in this paper.

Table 5 then reports the optimal equity injections for each bank. Here, we use the scenario in which the regulator invests €200 bn, and seeks to minimize aggregate vulnerability to a 50% write-down on GIIPS debt. Table 10 only reports the 20 largest banks, ranked by the size of their equity injection. 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 taxpayers' investment.

F. Extension-- considering different liquidation rules

Earlier we suggested that the model could be adjusted for different liquidation rules. A natural one to consider is one in which banks first sell off their most liquid assets. Here we focus on an extreme case and show its impact on the empirical results.

Suppose that banks have the flexibility to sell their sovereign bonds, but that their other assets (primarily loans) are infinitely illiquid, meaning that their early disposal would yield zero proceeds. In this case, the banks would have to concentrate their liquidations of sovereign bonds alone. In this case, we can write down a modified version of the formula for aggregate vulnerability AV to a shock S:

$$AV = \frac{1' A_{t-1} MLM^{*\prime} M' B A_{t-1} MS}{E_{t-1}}, \tag{15}$$

where M^* is a weight matrix that accounts for the fact that non-sovereigns are not liquidated. Each element is given by: $m_{ik}^{*} = m_{ik} / \left(\sum_k m_{ik} \right)$. 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.

A striking feature of these simulations is that aggregate vulnerability is much lower under this alternative liquidation rule. The aggregate vulnerability of banks to a GIIPS write-down is now 23%, instead of 285%.

Changing the liquidation rule has two opposite effects. On the one hand, banks liquidate much more sovereign bonds, which has a stronger price impact on other banks. On the other hand, fire sales don't contaminate other assets, which in this case are the majority of assets held on bank balance sheets.

Table 6 reports 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 sell more liquid assets, which increases the price impact and therefore contagion. Table 6 illustrates the ambiguity of alternative liquidation rules on AV.

V. Dynamic Estimation of Vulnerability and Systemicness

In our analysis thus far, we have used data on bank holdings and leverage to compute the M and B matrices, which are the key inputs in our calculations of vulnerability and systemicness. This approach has the advantage of precision: we can study how shocks may propagate across many different types of assets on bank balance sheets. The main disadvantage is that it requires granular data that may not always be available, or data that is only available to regulators.

An alternate approach is to compute M using stock returns. Consider the M matrix, which captures banks' ownership of different asset classes such as mortgages, sovereign debt, or securities. We can estimate exposures to these assets by regressing unlevered stock returns on the underlying returns of the factors. For each bank n, we can run rolling regressions of the form:

$$R_{n,t} = \sum_k m_{nk} F_{kt} + \varepsilon_{n,t} \tag{16}$$

Provided we have the full vector of asset returns $F_{k,t}$, the estimated m_{nk} is equal to the weight of each asset in the bank's portfolio. Armed with a conditional estimate of M, we can compute systemicness and vulnerability on a dynamic basis, which is potentially valuable from the perspective of monitoring.

To be able make the inference in equation (16), R_{nt} has to be obtained through unlevering the equity returns. 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 span of the data used to estimate the regression), and (3) that the stock market has some understanding of each bank's exposure to each asset. Similar market-based approaches are adopted by many of the recent efforts to monitor systemic risk, including Adrian and Brunnermeier (2010) and Acharya et al (2010). A challenge in regressions of this type is the lack of power when bank assets have correlated returns. For example, suppose one wanted to estimate a bank's exposures to Italian and Spanish bonds. Since the returns of these bonds are highly correlated, one requires long time-series of data to obtain reliable estimates. But, the longer is the time-series, the more likely our estimate of M is to be stale.

VI. Conclusions

Since the beginning of the US financial crisis in 2007, regulators in the United States and Europe have been frustrated by the difficulty in identifying the risk exposures at 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 simple ways in which this information can be used to understand how deleveraging scenarios could play out.

The key assumption in our model is that distressed 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 that are concentrated in the most levered banks. The model also suggests that policies which explicitly target bank solvency, such as was implicit in both the European and US stress tests, may be suboptimal from the perspective of controlling contagion.

We then apply the model to the largest financial institutions in Europe, focusing on banks' exposure to sovereign bonds. We use the model 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, Tarragona..
Swedbank 'A'	Caixa D'estalvis Unio De Caixes De Manll..
Banco De Sabadell	Caixa De Aforros De Galicia, Vigo, Ouren..
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 Barcelona
Abn Amro Holding	Caja Espa,,A De Inversiones, Salamanca Y ..
Ing Groep	Dekabank Deutsche Girozentrale, Frankfurt
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, Ddf
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	

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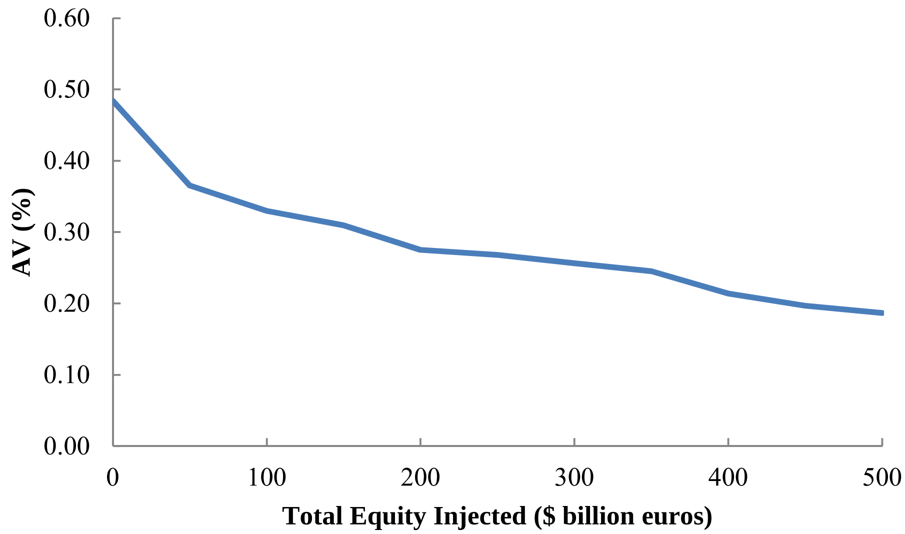
Figure 1. Aggregate Vulnerability as a Function of Aggregate Equity Injected (in billions of euros). This figure reports the optimal aggregate vulnerability AV to a 50% write-off on GIP debt (Panel A), GIIPS debt (Panel B). AV is defined in Equation (5) of the paper and denotes the deterioration in bank equity that comes from fire sales that follow an initial shock. We minimize equation (5) by allowing the social planner to freely allocate euros into the banks, subject to the constraint that equity cannot be withdrawn from banks. 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 result in fire sales that 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)

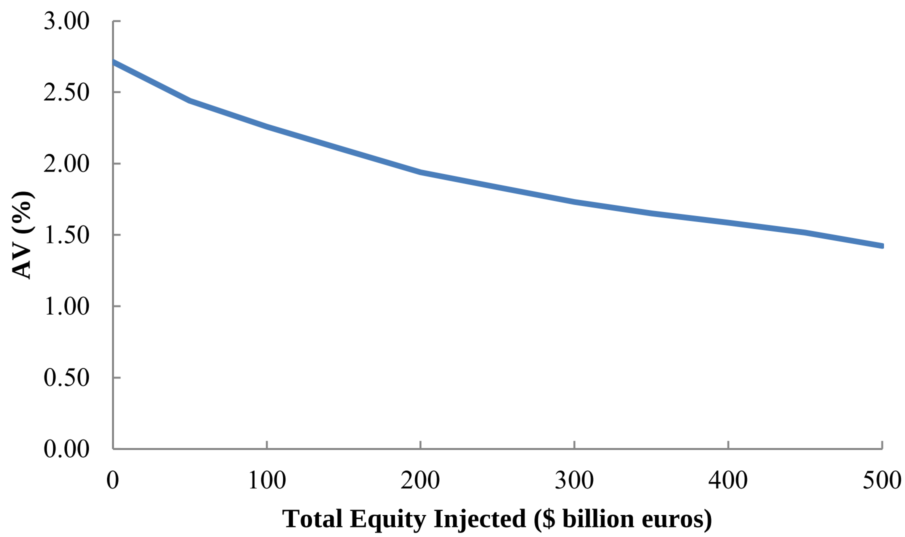


Table 1. Vulnerability to a 50% write-off on all GIIPS Debt. We compute the vulnerability of the major European banks to a 50% write-down on all sovereign debt of Greece, Italy, Ireland, Portugal, and Spain. In column 1, *IV(n)* denotes the indirect vulnerability via sector-wide deleveraging as we define it in Equation (10), adjusted for the fact that total fire sales are capped by total assets (see Section II.A.). In column 3, *DV(n)* denotes the direct vulnerability to the write-down on balance-sheets, as defined in Equation (9), adjusted for maximal fire sales. Both measures are normalized by bank equity. In column 5, the table also reports the leverage, capped at 30. We only report bank-by-bank values for the 10 largest banks in terms of deleveraging vulnerability. In the last line of the table, we also report sample averages: Hence, a 50% write-down on all GIIPS debt would wipe out 111% of the equity of the average bank through the direct impact, while the indirect impact via deleveraging would create an additional loss of 302% of equity.

Bank Name	**Indirect Vulnerability as a Fraction of Equity**		**Direct Vulnerability as a Fraction of Equity**		**Leverage Ratio**
	$IV(n)$	Rank	$DV(n)$	Rank	Leverage Ratio $\boldsymbol{b_{nn}}$
Allied Irish Banks	35.24	1	11.9	2	30
Agricultural Bank of Greece	12.98	2	33.5	1	30
West LB	8.80	3	0.9	25	30
Banca Monte Dei Baschi di Siena	5.08	4	3.7	3	30
Oesterreichische Volksbank	4.83	5	0.2	56	30
SNS Bank	4.71	6	0.3	55	30
Caixa de Aforros	4.70	7	1.4	11	30
NordDeustche Landesbank	4.61	8	0.4	51	30
Commerzbank AG	4.54	9	1.0	21	30
Caixa d’Estalvis de Catalunya	4.36	10	0.8	31	30
Full sample average	3.02		1.11		22.1

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. Robust t-statistics in brackets.

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable : Cumulative return: 2009/12 - 2011/9					
Indirect Vulnerability	-0.017***	-0.008**	-0.010***	-0.013***	-0.010**	-0.010**
	[-4.34]	[-2.58]	[-2.92]	[-2.70]	[-2.59]	[-2.52]
Direct Vulnerability		-0.016***	-0.010*		-0.010***	-0.003
		[-2.93]	[-1.96]		[-2.74]	[-0.51]
log(assets)			0.069***			0.081
			[2.70]			[1.46]
Debt to Equity			-0.001			-0.004
			[-0.08]			[-0.33]
Constant	-0.435***	-0.441***	-0.099	-0.472***	-0.467***	-0.037
	[-9.24]	[-9.60]	[-0.47]	[-6.42]	[-6.53]	[-0.08]
Observations	49	49	49	49	49	49
R-squared	0.088	0.136	0.213			

*** p<0.01, ** p<0.05, * p<0.1

Table 3. Systemicness ranking in a response to a GIIPS shock. We calculate the systemicness *S(n)* of each individual bank, assuming a 50% write-off on GIIPS sovereign debt. Column 1 reports systemicness as computed in equation (7). We only report detailed information for the top 10 banks in terms of systemicness. Columns 2-4 report the element of the decomposition of systemicness as in equation (8), except that we take into account the fact that fire sales induced by the write-off are capped by total assets (see Section II.A.). Column 2 reports total exposure of each bank, normalised by aggregate equity. Column 3 reports the fraction of assets that would be fire-sold as a fraction of total exposure. Because of our cap, it is always smaller than 1. Column 4 focuses on the linkage effect. By virtue of equation (8), systemicness is the product of the elements in columns 2,3 and 4. Banks are sorted by systemicness. Through Santander, a GIIPS write-off would lead, through deleveraging, to a 21% reduction in aggregate bank equity. The last line present the aggregate sum (over the 90 banks) of systemicness, which is equal to Aggregate Vulnerability (equation (5)). A 50% write-down on GIIPS debt would wipe out, through deleveraging 245% of total bank equity.

Bank Name	Systemicness $S(n)$	Assets / Aggregate Equity (a_{nn}/E)	Fire sales $min(-b_{nn.}\square'_n MF_1, 1+\square'_n MF_1)$	Linkage effect $(1'AMLM'\square_n)$
Banco Santander	0.21	1.06	0.58	0.34
Unicredit	0.19	0.88	0.69	0.31
Intesa SanPaolo	0.19	0.62	0.95	0.33
BBVA	0.18	0.57	0.94	0.33
BNP Paribas	0.15	1.37	0.36	0.30
BFA-Bankia	0.12	0.29	0.95	0.42
Caja de Ahorros Y Pensiones de Barcelona	0.10	0.27	0.93	0.38
Societe Generale	0.07	0.75	0.32	0.32
Commerzbank AG	0.07	0.66	0.48	0.23
Banca Monte Dei Baschi di Siena	0.06	0.22	0.92	0.32
Full Sample Average	0.03	0.27	0.44	0.30
Full Sample Total *AV*	2.45			

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% GIIPS write-down: induced deleveraging would destroy 245% of aggregate bank equity. The remaining rows of the table show this calculation under different hypothetical policy interventions.

Policy intervention	Detail	Summary Statistics	Aggregate Vulnerability (deviation / benchmark)	Contribution of change in distribution of: Asset	Connectedness	Exposure
Baseline			0.00			
		Number of banks capped				
Size cap (bn euros)	500	17	0.06	0.16	0.00	-0.09
	900	8	0.04	0.07	0.00	-0.03
	1300	2	0.00	0.01	0.00	0.00
GIIPS debt re-nationalization (bn euros)		*Fraction of total renationalized*				
	96	0,2	-0.08	0.01	-0.01	-0.08
Eurobonds (swap individual sov. holdings		*Total amount of sovereign reshuffled (in bn €)*				
for the same basket of sovereigns)		1672	0.08	0.00	0.00	0.09
		Number of banks merged				
Merge banks on which a GIIPS shock	*x* = 50%	47	0.13			
is at least *x*% of equity	*x* = 100%	20	0.01			
	x = 150%	9	0.00			
		Number of Banks Merged				
Merge banks on which a GIIPS shock	Merge exposed only	20	0.01			
is at least 100% of equity	Merge unexposed only	6	0.00			
with banks totally unexposed	Merge all	26	0.08			
		Equity Injection (in bn €)				
Leverage cap	max D/E = 15	480	-0.28			
	max D/E = 20	173	-0.11			
	max D/E = 25	45	-0.03			
Optimized equity injection of €200bn		*Countries*				
	200	All Europe	-0.26			
	200	German banks	-0.05			
	200	German + French	-0.09			
	200	GIIPS	-0.24			

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 billions of euros. Column 2 reports systemicness S(n). Columns 3-6 provide the four components of systemicness as in equation (8) from the text: target leverage, size, exposure to the shock, and connectedness to other banks.

Bank	Equity Injection (bn euros)	Systemic ness $S(n)$	Assumed Target Leverage	Size (a_i/E_1)	Exposure to GIP shock $(e_i'MS)$	Linkage effect $(1'AMLM'e_i)$
Banca Monte Dei ...Siena	18.20	0.17	30.00	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	0.30
Banco De Sabadell	4.68	0.04	25.26	0.10	0.04	0.40
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	18.50	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. We calculate the aggregate vulnerability AV to a 50% writedown of GIIPS debt. In line 1, we report the baseline AV. 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). The difference here with the first line is that we assume banks have no cash to adjust.

	GIIPS	**Liquid assets / total**
Benchmark AV	-2.85	1.00
Liquidate Sovereigns only	-0.23	0.12
+ Commercial real estate	-0.47	0.18
+ Mortgages	-2.40	0.41
+ Corporate loans	-4.11	0.68
+ Consumer loans	-4.02	0.70
+ SME loans	-3.84	0.75

Table 7. 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*, 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, and the Top 10 more Vulnerable Banks, selected dates.

Jan-07			Jan-08			Jan-09		
Name	**S(n)**		**Name**	**S(n)**		**Name**	**S(n)**	
AIG	0.07%		Citigroup Inc	0.66%		Wells Fargo	1.60%	
Jpmorgan Chase	0.05%		Goldman Sachs	0.49%		Jpmorgan Chase	1.26%	
Morgan Stanley	0.03%		Jpmorgan Chase	0.36%		Bank Of America	0.88%	
Goldman Sachs	0.02%		FNMA	0.33%		Citigroup	0.74%	
Lehman Brothers	0.02%		Bank Of America	0.19%		Intercontinentalexchange	0.23%	
Metlife Inc	0.02%		AIG	0.17%		BONY Mellon	0.18%	
Wachovia Corp	0.01%		American Express	0.13%		Merrill Lynch & Co Inc	0.18%	
FNMA	0.01%		FHLM	0.13%		Goldman Sachs	0.15%	
Merrill Lynch	0.01%		Lehman Brothers	0.10%		Regions Financial	0.15%	
State Street Corp	0.01%		Metlife Inc	0.09%		Capital One Financial	0.14%	
Name	**DV**	**IV**	**Name**	**DV**	**IV**	**Name**	**DV**	**IV**
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	3.27%	11.68%	Intercontinentalexchange	19.00%	24.18%
M G I C Investment	1.75%	1.15%	C B Richard Ellis	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	2.07%	7.95%	C M E Group	6.20%	16.47%
Ambac Financial Group	1.12%	0.84%	American Capital	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 Group	4.32%	0.75%	Goldman Sachs	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%

APPENDIX

We prove below that when some banks have similar leverage and similar asset mix, merging them has no impact on aggregate *AV*. Equivalently, dividing a bank into several banks having the same levels of leverage and the same asset mix has no impact on *AV*.

Assume there are *N+s-1* banks and that the last *s* banks all have same leverage b_N and same portfolio weights $m_{n,k}$. Since they have the same mix of assets, they also have same asset returns r_N

Developing formula (6) yields:

$$AV \times E_1 = \sum_{n\in[1,N+s]} \sum_{k\in[1,K]} \sum_{m\in[1,N+s]} a_m m_{m,k} l_k m_{n,k} b_n a_n r_n$$

$$AV \times E_1 = \sum_{n\in[1,N-1]} \sum_{k\in[1,K]} \sum_{m\in[1,N-1]} a_m m_{m,k} l_k m_{n,k} b_n a_n r_n$$

$$+ \sum_{n\in[N,N+s]} \sum_{k\in[1,K]} \sum_{m\in[N,N+s]} a_N m_{N,k} l_k m_{N,k} b_N a_n r_N$$

$$AV \times E_1 = \sum_{n\in[1,N-1]} \sum_{k\in[1,K]} \sum_{m\in[1,N-1]} a_m m_{m,k} l_k m_{n,k} b_n a_n r_n$$

$$+ \sum_{k\in[1,K]} \left(\sum_{m\in[N,N+s]} a_m \right) \quad m_{N,k} l_k m_{N,k} b_N \left(\sum_{n\in[N,N+s]} a_n \right) r_N$$

This expression is strictly identical to the *AV* of a system where the first *N-1* banks are similar to the previous system ($\tilde{a}_m = a_m; m \in [1, N-1]$) and the last one, bank *N*, is the combination of the previous last *s* banks: $\left(\tilde{a}_N = \sum_{n\in[N,N+s]} a_n \,;\ \tilde{b}_N = b_N; \quad \tilde{m}_{N,k} = m_{N,k}\right)$.