Measuring Systemic Risk

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Abstract

We present a simple model of systemic risk and show how each financial institution's contribution to systemic risk can be measured and priced. A bank's contribution, denoted systemic expected shortfall (*SES*), is its propensity to be undercapitalized when the system as a whole is undercapitalized, which increases in its leverage, volatility, correlation, and tail-dependence. Institutions internalize their externality if they are "taxed" based on their *SES*, e.g. through a mandatory systemic insurance. We demonstrate empirically the ability of *SES* to predict the realized systemic risk during the financial crisis of 2007-2009, and discuss the determinants of systemic risk in the cross section and for its time evolution.

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I. Introduction

Financial firms play a critical role in the economy, acting as intermediaries between parties that need to borrow and parties willing to lend or invest. Without such intermediation, it is difficult for companies to get credit and conduct business, and for people to get student loans, auto loans, to save, and to perform a range of other financial transactions. *Systemic risk* can be thought of as widespread failures of financial institutions or freezing up of capital markets that can substantially reduce the supply of such critical intermediation.[2] Failures of financial institutions thus have an externality on the rest of the economy, and the recent crisis provides ample evidence of the importance of containing this risk. However, current financial regulations, such as Basel I and Basel II, are designed to limit each institution's risk (for example, market and credit value-at-risk) seen in isolation; they are not sufficiently focused on systemic risk.[3] This is in spite of the fact that systemic risk is often the rationale provided for such regulation. As a result, while individual risks are properly dealt with in normal times, the system itself remains, or in some cases is induced to be, fragile and vulnerable to large macroeconomic shocks.

We take on the challenge to present a framework for measuring and managing systemic risk. For this, we present a simply model of systemic risk and estimate it empirically. Our theory considers a number of financial institutions ("banks") that must decide on how much capital to raise and which risk profile to choose in order to maximize their risk-adjusted return. A regulator considers the aggregate outcome of banks' actions, additionally taking into account each bank's insured losses during an idiosyncratic bank failure and the externality arising in a systemic crisis, that is, when the aggregate capital in the banking sector is sufficiently low. The pure market-based outcome differs from the regulator's preferred allocations since, due to limited liability, banks do not take into account the loss they impose in default on creditors and the externality they impose on the society at large in a systemic crisis.

[2] For evidence on large bailout (fiscal) and output-gap costs arising from systemic crises prior to the subprime crisis, see the empirical work of Caprio and Klingebiel (1996), Claessens, Djankov and Klingebiel (1999), Honohan and Klingebiel (2000), and Hoggarth, reis and Saporta (2002). For the subprime crisis, Ivashina and Scharfstein (2008) document a sharp contraction in the bank provision of lines of credit in Fall 2008 following the failure of Lehman Brothers.

[3] Gordy (2003) formalizes the micro-foundations of Basel regulation focused on institution-level risk.

We show that to align incentives, the regulator optimally imposes a tax – capital adequacy requirement or mandatory insurance purchase – on each bank which is related to the sum of its expected default losses and its expected contribution to a systemic crisis, denoted *Systemic Expected Shortfall* (*SES*). Importantly, this means that banks have an incentive to reduce their tax (or insurance) payments and thus take into account the externalities arising from their risks and default. Additionally, it means that they pay in advance for any support given to the financial system ex post during a systemic crisis. *SES* is measurable and we show it is increasing in an institution's leverage, institution's volatility, system's volatility, tail dependence between the institution and the system, and the severity of the externality from a systemic crisis.

We estimate our proposed systemic risk measure *SES* for 102 financial firms in the US financial sector with equity market capitalization as of end of June 2007 in excess of 5bln USD (see Appendix A). We show that the *SES* of each firm can be measured as a weighted average of its expected loss when the market is in its left tail (*Marginal Expected Shortfall or MES)* and its leverage measured as quasi-market value of assets to market value of equity. We calculate the *MES* of each firm using the worst 5% days of the value-weighted market return from CRSP during the period June 2006 to June 2007, and leverage measured as of end of June 2007.

To consider our measure's ability to estimate each financial institutions systemic risk taking, we check if the *SES* estimated *before* the subprime crisis helps predict which institutions fared the worst during the crisis period of July 2007 till December 2008. We find that *SES* explains a significant proportion of the realized returns during the crisis (R^2 of 22%), as shown in Figure 1b. Importantly, standard measures of institution-level risk such as expected loss in institution's own left tail and volatility do a relatively poor job, and the standard measure of covariance, beta, has a modest explanatory power. Both components of *SES* – *MES* and leverage – contribute to its explanatory power. While the explanatory power of *MES* for realized returns during the crisis works up to a lead of one quarter, that of leverage is significant even two quarters prior to the crisis.

In the cross-section, systemic risk *SES* is the highest for security dealers, the lowest for depository institutions, and intermediate for insurance firms and remaining financial firms. The high overall systemic risk of security dealers and brokers arises from high contributions from *both* aspects of systemic risk: not only do these firms have greater tail dependence with the market (higher *MES)* but they also have substantially higher leverage (assets to equity of 25:1 for some firms such as Bear Stearns). In contrast, depository institutions have low *MES* and low leverage. Crucially, while explaining realized returns during the crisis, *MES* explains the variation *within* each type of institutions, while the leverage effect primarily drives the variation *across* types of institutions.

In time-series analysis and robustness checks, we provide several pieces of additional evidence. First, we document a striking fact that the securities dealers and brokers have been more systemically risky than other types of financials in *every* single year during 1963 to 2008 (see Figure 2a). And, finally, that systemic risk is higher during periods of macroeconomic stress – proxied by NBER recessions and spread between the commercial paper and Treasury bills, for securities brokers and dealers but not so for depository institutions. Second, we explain how to adjust the calculation of *SES* over time, for example, prior to a crisis as against during a crisis, by suitably modifying the part of the tail used to calculate the *MES* component. We show here also that the predictive power of *MES* and *SES* for the cross-section of returns exists also during the crisis period; in particular, systemic risk measures computed during July 2007 to June 2008 predict well the performance of financial firms during July 2008 to August 2009. And third, we show that the systemic risk rankings have persistence in that they are reasonably highly correlated from year to year.

Turning to the related literature, Acharya (2001, 2009) and Acharya and Yorulmazer (2007) discuss how banks have an incentive to take inefficiently high correlated risks due to the moral hazard that they are more likely to be bailed out when they fail together. Externalities from correlated failures – which we take as given – can arise due to liquidity spirals when everyone runs for the exit (Brunnermeier and Pedersen (2008), Pedersen (2009)), bank runs (Diamond and Dybvig (1983), Allen and Gale (2007)), freezes in the market for rollover debt (Acharya, Gale, and Yorulmazer (2008), He and Xiong (2009)), and risk management tightening in a feedback loop (Garleanu and Pedersen (2007)).

In terms of measurement of systemic risk, there have been a number of recent papers that explicitly derive measures, mostly related to the financial crisis of 2007-2009. These papers can broadly be separated into two categories, one based on a structural approach using contingent claims analysis of the financial institution's assets and the other on a reduced form approach focusing on the tail behavior of financial institutions' asset returns. All these approaches have the common feature of treating systemic risk in a portfolio context in which the portfolio is the financial sector, and individual assets are the financial institutions. As such, the key variable in all these papers is the comovement between financial firms when the system as a whole is distressed.

With respect to contingent claims analysis, Lehar (2005) estimates the dynamics between financial institution's assets using stock market data and a Merton model of bank liabilities. For different periods and countries, Lehar then measures the regulator's total liability (if creditor were to be bailed out) and the contribution of each institution to this liability. Gray, Merton, and Bodie (2008) also use a contingent claims approach to provide an overall way of measuring systemic risk across different sectors and countries. Gray and Jobst (2009) apply the methodology to the current financial crisis, and quantify the largest institutions' contributions to systemic risk in this crisis.

There are complexities in applying the contingent claims analysis in practice due to the strong assumptions that need to be made about the liability structure of the financial institutions. As an alternative, some researchers have used market data to back out reduced-form measures of systemic risk. For example, Huang, Zhou and Zhu (2009) use data on credit default swaps (CDS) of financial firms and stock return correlations across these firms to estimate expected credit losses above a given share of the financial sector's total liabilities. Similarly, Adrian and Brunnermeier (2009) measure the financial sector's Value at Risk (VaR) given that a bank has had a VaR loss, which they denote *CoVaR*, using quantile regressions. Their measure uses data on market equity and book value of the debt to construct the underlying asset returns. Adrian and Brunnermeier's approach has the advantage of framing the analysis using the standard regulator tool of VaR, though regulators should also care about expected losses beyond the VaR threshold. Tarashev, Borio and Tsatsaronis (2009) present a game-theoretic formulation that also provides a possible allocation of capital charge to each institution based on its systemic importance. Finally, Segoviano and Goodhart (2009) also view the financial sector as a portfolio of individual financial firms, and look at how individual firms contribute to the potential distress of the system by using the CDSs of these firms within a multivariate setting.

Our paper offers the major advantage that it builds a bridge between the structural and reduced-form approaches. On the one hand, we build a structural (albeit simple) model that provides the systemic contribution of each financial institution under reasonable assumptions. On the other hand, this systemic contribution can be written in terms of observables common to the reduced form approaches. Thus, systemic risk can be estimated using standard techniques and market data.

In terms of proposals for managing systemic risk, Acharya (2001, 2009) makes a conceptual case for capital requirements tied to correlation of bank risks rather than individual bank risks. Kashyap, Rajan, and Stein (2008), similar to the ideas in Wall (1989), Doherty and Harrington (1997) and Flannery (2005), propose that banks buy insurance against systemic crisis. In contrast, our model suggests that each bank should be taxed for its *own* losses during crisis and the taxes should go to a systemic fund. This does not create any ex post moral hazard and creates an ex ante incentive to limit systemic losses.[4] Overall, our approach to regulation of systemic risk is akin to the classical analysis of externalities such as pollution and taxes related to emissions, as proposed in Stigler (1971) and Peltzman (1976).

The ideas in this paper build upon Acharya, Pedersen, Philippon and Richardson (2009) and provide a natural way of implementing macroeconomic capital allocation. Such allocation can be viewed as a potential end goal for a "systemic risk regulator", such as the one advocated in Crockett (2000), de Larosiere (2009) and Saunders, Smith and Walter (2009).

The remainder of the paper is organized as follows. Section II lays out our model of systemic risk. Section III presents our empirical analysis. Section IV discusses issues related to the implementation of our framework, and compares our measure to other measures recently put forward. Section V concludes.

[4] One advantage of a tax-based approach relative to the insurance one is that the cost of private, rare-event insurance can rise dramatically following the incidence of claims that deplete the capital of insurance providers (Froot, 2001, Gersbach, 2001, 2009).

II. Model

We first discuss the standard techniques to manage risk within banks and how they can be adopted to consider the risk of the whole banking system. Building on these ideas, we then present an economic model that captures systemic risk more directly, and show how each bank' systemic risk contribution can be measured, priced, and managed.

II.A Managing Risk within a Bank and Across Banks: Marginal Expected Shortfall

Let us first consider the standard risk measures used inside financial firms, namely Value-at-Risk (VaR) and Expected-Shortfall (ES). These seek to measure the potential loss incurred by the firm as a whole in an extreme event. Specifically, VaR is the most that the bank loses with confidence 1-α, where α is typically taken to be 1% or 5%. For instance, with α = 5%, VaR is the most that the bank loses with 95% confidence. Hence, VaR = $-q_\alpha$, where q_α is the α quantile of the bank's return R:

$$q_\alpha = \sup\{\mathrm{z} \mid \Pr[\mathrm{R} < \mathrm{z}] \leq \alpha\}$$

The expected shortfall (ES) is the expected loss conditional on something bad happening, that is, the loss conditional on the return being less than the α quantile:

$$ES_\alpha = -E\left[R \mid R \leq q_\alpha\right]$$

Said differently, the expected shortfall is the average returns on days when the portfolio exceeds its VaR limit. We focus on ES since VaR can be gamed in the sense that asymmetric, yet very risky, bets may *not* produce a large VaR. The reason is that if the negative payoff is below the VaR 1% or 5% threshold, then VaR will not capture it. Indeed, one of the concerns in the ongoing crisis has been the failure of VaR to pick up potential "tail" losses in the AAA-tranches. ES does not suffer from this since it measures all the losses beyond the threshold. This distinction is especially important when considering moral hazard of banks, because the large losses because the VaR threshold are often born by the government bailout. In addition, VaR is not a coherent measure of risk because the VaR of the sum of two portfolios can be higher than the sum of their individual VaRs, which cannot happen with ES (Artzner et al., 1999).

For risk management, transfer pricing, and strategic capital allocation, banks need to know how their possible firm-wide losses can be broken down into its components or contributions from individual groups or trading desks. To see how, let us decompose the bank's return *R* into the sum of each group's return r_i, that is, $R = \sum_i y_i r_i$, where y_i is the weight of group i in the total portfolio. From the definition of ES, we see that

$$ES_\alpha = -\sum_i y_i E[r_i \mid R \leq q_\alpha]$$

From this expression we see the sensitivity of overall risk to exposure y_i to each group *i*:

$$\frac{\partial ES_\alpha}{\partial y_i} = -E[r_i \mid R \leq q_\alpha] \equiv MES_\alpha^i$$

where MES^i is group *i*'s *marginal expected shortfall*. The marginal expected shortfall measures how group *i*'s risk taking adds to the bank's overall risk. In words, *MES* can be measured by estimating group *i*'s losses when the firm as a whole is doing poorly.

These standard risk-management practices can be useful for thinking about the overall risk of the financial system. For this, we can consider the expected shortfall of the overall banking *system* by letting *R* be the return of the aggregate banking sector. Then each bank's contribution to this risk can be measured by its *MES*. Hence, a financial system is constituted by a number of banks, just like a bank is constituted by a number of groups, and it is helpful to consider each components risk contribution to the whole.

To take this insight further, it is instructive to consider the nature of externalities that give rise to such a measure, how the risk quantile α should depend on how well the banking sector is capitalized, and how bank's can be incentivized to reduce their externalities. We address these issues next.

II.B An Economic Model of Systemic Risk

We consider an economy with a number of banks enumerated by $b=1,\ldots,B$ who live for two periods, 0 and 1. At time 0, each bank must choose its capital (equity) w_0 and its exposures to each of S assets: $x^b = \left(x_1^b,..,x_S^b\right)$. The assets yield returns $r=(r_1,\ldots,r_S)$ so the capital evolves as:

$$w_1^b = w_0^b + r \cdot x^b$$

Each bank is subject to a tax t^b, to be discussed further below. If a bank decides to start with capital of w_0^b, then it has to raise an amount of capital equal to $w_0^b + t^b - \overline{w}_0^b$, where $\overline{w}_0^b$ is the capital endowment. The cost of raising this capital is $c\left(w_0^b + t^b - \overline{w}_0^b\right)$, where the number c can be greater than one because of financing frictions. Each bank seeks to maximize its expected utility u^b of final wealth minus its cost of capital:

$$E_0\left(u(w_1^b \cdot 1_{(w_1^b>0)})\right) - c(w_0^b + t^b - \overline{w}_0^b)$$

Here, E_0 denotes expectation conditional on the information available at time 0 (including all decision variables), and the indicator function is equal to 1 if the bank is solvent, and zero otherwise, so this expression captures that the bank has limited liability.

The economy has a regulator who maximizes the total utility of all banks, plus the value of tax revenues, minus the expected cost of bank defaults, and plus an externality e:

$$(*)\ E_0 \sum_{b=1}^{B} \{u(w_1^b \cdot 1_{(w_1^b>0)}) - c(w_0^b + t^b - \overline{w}_0^b) + c^g(w_1^b \cdot 1_{(w_1^b<0)} + t^b)\} + eE_0\left[(W_1 - \overline{W}) \cdot 1_{(W_1<\overline{W})}\right]$$

Here, W_1 is total bank capital at time 1, $W_1 = \sum_{b=1}^{B} w_1^b$ and c^g captures the regulator's cost of capital. Since we want to focus on how to handle banks' moral hazard problem, we let $c^g = c$ which eliminates the possibility that the regulator wants to tax or subsidize banks irrespective of moral hazard problems. Further, $e \geq 0$ is the externality cost. We assume that the rest of the economy suffers an externality when aggregate banking capital drops below a cutoff $\overline{W}$, and that this externality is greater, the greater is the drop in aggregate capital.

The regulator attempts to maximize this objective by designing the tax system *t*, recognizing that each bank will make its own choices of exposures and capital in light of this tax. We assume that the regulator can infer the banks' actions and can condition the tax on these actions. This makes the mechanism design relatively simple (with multiple taxes achieving first-best outcomes), but this analysis nevertheless provides a lot of intuition about how systemic risk can be handled in principle.

Proposition 1. *The regulator can achieve efficient outcomes by imposing a tax on banks consisting of two parts:*

$$t^b = DES^b + SES^b$$

where DES is the bank's expected default loss and SES is its systemic expected shortfall:

$$DES^b = -E_0(w_1^b \mid w_1^b < 0)P_0(w_1^b < 0)$$

$$SES^b = -\frac{e}{c}E_0\left(w_1^b - \overline{w}^b \mid W_1 < \overline{W}\right)P_0\left(W_1 < \overline{W}\right)$$

where $\overline{w}^b$ is a bank-specific target capital.

A bank's systemic expected shortfall is larger if (1) the externality is more severe (e); (2) the bank takes a larger exposure (x_s) in an asset s that experiences loses when other banks are in trouble; (3) the bank raises less capital initially (w_0); (4) other banks are riskier; (5) the bank's cost of capital c is lower.

This proposition is intuitive. The first part of the tax is related to each bank's own risk of default, and this captures the current practice of monitoring each bank - seen in isolation - due to costs associated with deposit insurance among other things.

The second part of the tax is the new part. It captures each bank's losses in case of a systemic crisis where the banking sector as a whole is undercapitalized and causes negative externalities.

It is natural to assume that the externality kicks in when the aggregate banking capital drops below a level that depends on the aggregate banking assets. For this, denote bank b's assets at time 0 by a^b and the aggregate assets at time 0 by A, and let the externality cut-off be $\overline{W} = kA$ and $\overline{w}^b = za^b$, where k and z are numbers, say 8%. Further, denote firm b's leverage at time 0 (i.e., debt-to-asset) ratio by $l^b = 1 - \frac{w_0^b}{a^b}$, system-wide leverage at time 0 by $L = 1 - \frac{W_0}{A}$, equity return by $R^b = \frac{w_1^b}{w_0^b} - 1$, and system-wide return by $R = \frac{\sum_b w_1^b}{\sum_b w_0^b} - 1 = \frac{W_1}{W_0} - 1$. Then a systemic event happens if $W_1 < kA$, that is, if

$$R < \frac{k}{1-L} - 1$$

Hence, *SES* can be written as

$$\begin{aligned} SES &= -\frac{e}{c} w_0^b E_0 (R^b - (\frac{z}{1-l^b} - 1) \mid R < \frac{k}{1-L} - 1) P_0 (R < \frac{k}{1-L} - 1) \\ &= \frac{e}{c} w_0^b \alpha_0 \times \left(MES_\alpha (R^b) + (\frac{z}{1-l^b} - 1) \right) \end{aligned}$$

where $\alpha_0 = P_0(R < \frac{k}{1-L} - 1)$ is the probability of systemic crisis. Using this, we get:The total systemic fee *SES* can also be written as a percent of each bank's initial capital:

Proposition 2. *The systemic expected shortfall in percent of a bank's initial capital, $SES_{\%}$, depends on the MES and the leverage l^b:*

$$SES_{\%} = SES / w_0^b = \frac{e}{c} \alpha_0 \left(MES_\alpha (R^b) + (\frac{z}{1-l^b} - 1) \right)$$

We see that the systemic expected shortfall is directly related to the *MES* with a percentile $\alpha_0 = P_0(R < \frac{k}{1-L} - 1)$ that takes leverage into account: higher aggregate leverage in the system means that the system is closer to causing externalities, and higher individual leverage means that a particular bank is more likely to contribute to the troubles.

To get more intuition about the drivers of systemic risk, suppose that returns are Normally distributed and let $\mu^b = E(r^b)$ and σ^b be bank b's expected return and volatility, $\mu = E(R)$ and σ be the aggregate sector return and volatility and $\rho^b = corr(r^b, R)$ be the correlation.

Proposition 3. *If the payoffs are jointly Normal, then the percent systemic expected shortfall is:*

$$SES_{\%} = \frac{e}{c}\left[\rho^b\sigma^b \exp\left(-\frac{1}{\sigma^2}\left(\frac{k}{1-L}-1-\mu\right)^2\right)\frac{1}{\sqrt{2\pi}} + \alpha\left(\left(\frac{z}{1-l^b}-1\right)-\mu^b\right)\right]$$

which increases in the bank's volatility σ^b*, its correlation to the aggregate system* ρ^b*, the bank's leverage* l^b*, the system volatility* σ *and leverage L, and decreases in the expected returns of the bank and the system* μ^b*,* μ*.*

Naturally, while systemic risk is generally about tail dependence, but with Normal distributions this is captured through correlations.

III. Empirical Analysis

We next turn to the empirical analysis of our approach to measuring and managing systemic risk.

III.A Estimation Methodology

We first discuss how we empirically estimate our measures of systemic risk. The marginal expected shortfall *MES* (defined in Section II.A) is estimated at a standard risk level of α=5% using daily data of equity returns from CRSP. This means that we take the 5% worst days for the market returns *(R)* in any given year, and we then compute the average return on any given firm (R^b) for these days.

The next step is to estimate our measure of systemic expected shortfall *SES*. As seen in Proposition 2, *SES* varies in the cross section depending on *MES* and leverage relative to the target-leverage parameter *z*. To estimate *SES* we need to (a) choose the parameter *z* and (b) choose the risk level α of the *MES* that corresponds to a systemic crisis.

For this, we set z= 6% based on Tier-1 Basel capital requirements, and we set the crisis-level market drop to be a 60% drop in financial firms' equity. Specifically, we estimate *SES* as follows:

$$SES^b_{\%,scaled} := \frac{60}{1.4} MES_{5\%} + \frac{0.06}{1-l^b} - 1$$

where we ignore the scaling factor ($e/c\alpha$) that is common in the cross section (Proposition 2).

Let us explain this estimation method in more detail, in particular the factor of 60/1.4. Recall first that we are interested in how each firm performs conditional on the financial sector dropping 60%. This is challenging since most samples have only much smaller drops in value. Therefore, we need to work with a percentile that gives us enough bad market days in any given year, and α=5% is a standard choice. This risk level of 5%, however, is not the one that corresponds to systemic crises. If we think that these crises occur 5 times per century, say, then they correspond to a risk level of 5% per year, which is 250 times less than the one we use for our empirical measure. Hence, we need to scale up *MES* to move further in the tail of aggregate risks. Further, while it is helpful to use daily data to have as much data as possible, the length of a systemic crisis is at least several months. A simple way to proceed is to note that the $MES_{5\%}$ for the pre-crisis period was constructed as an average return on days where the market on average dropped 1.4% (instead of a crisis drop of 60%), so we therefore scale $MES_{5\%}$ by 60/1.4.

When we run cross sectional regressions to explain realized returns during a crisis, we can also introduce $MES_{5\%}$ and leverage separately and consider the implied OLS coefficients, verifying if they imply relative weights which are similar to those employed above in the *SES* specification.

III.B Data and Descriptive Statistics

To illustrate the computation of systemic risk measure *SES* and its power in explaining the performance of firms during a systemic crisis, we initially focus on a "demo" period surrounding the subprime crisis. We consider 102 financial firms in the US financial sector with equity market capitalization as of end of June 2007 in excess of 5bln USD. Appendix A lists these firms and their "type" based on two-digit SIC code classification (Depository Institutions, Securities Dealers and Commodity Brokers, Insurance, and Others). For sake of illustration, we use the CRSP value-weighted index as the "market". Note that our model suggests the market should be the aggregate of the firms under investigation and we examine robustness of our results to financial sector aggregate as the market. We use daily stock return data from CRSP.

The overall idea is to estimate the ex ante *SES* using data from the year prior to the crisis (June 2006 till June 2007) and use it to explain the cross-sectional variation in performance during the crisis (July 2007 till December 2008). As explained in Section III.A, *SES* requires two inputs: first, the Marginal Expected Shortfall *MES,* which we choose to compute at 5% worst case days for the market, and second, the leverage of each firm l. Thus for *MES,* we simply pick the 5% worst days of the market during June 2006 to June 2007 and calculate the (negative of the) average return of each financial firm on those worst days of the market. For leverage, note that $1/(1-l)$ is the ratio of market value of assets to the market value of equity. Since market value of debt is generally unavailable, it is standard instead to use the quasi-market value of assets. This is computed as [book value of assets – book value of equity + market value of equity]. The book characteristics of firms are available at a quarterly frequency from CRSP-Compustat merged dataset. We call the ratio of quasi-market value of assets to market value of equity as *LVG* in the empirical analysis to follow.[5]

While analyzing the performance of *SES,* and its components *MES* and *LVG*, it is important to also check their incremental power relative to other measures of risk. For this, we focus on measures of firm-level risk: the expected shortfall, *ES* (i.e., the negative of the firm's average stock return in its own 5% left tail), and the annualized standard deviation of returns based on daily stock returns, *Vol*. We also look at the standard measure of systematic risk, *Beta,* which is the covariance of a firm's stock returns with the market divided by variance of market returns. Thus, the difference between *systemic* risk measure *SES* and *systematic* risk measure *Beta* arise from three sources: systemic risk is based on tail dependence rather than average covariance, it is corrected for leverage of the firm, and it is in principle only defined for firms with an externality on the rest of the economy. We want to compare these ex ante risk measures to the ex post *Event Return*, that is, the realized return of financial firms during the period July 2007-Dec 2008.

Table 1 describes the summary statistics of all these risk measures, where Panel A reports the univariate statistics and Panel B the pair-wise correlations. The *Event Return* in Panel A illustrate how stressful this period were for the financial firms, with mean (median) return being -46% (-47%) and several firms losing their entire equity market capitalization (Washington Mutual, Fannie Mae and Lehman Brothers). It is useful to compare *ES* and *MES.* While the average return of a financial in its own left tail is -2.73%, it is -1.63% when the market is in its left tail. The market itself has an *ES* of -1.4% implying that the equally-weighted average return of financials when market is in its left tail is worse than the value-weighted average return (which is of course the market itself). Average volatility of financial stock return is 21% and beta is 1.0. All these measures however exhibit substantial cross-sectional variability, which we attempt to explain later.

[5] A sample calculation here would be useful. *MES* of Bear Stearns is 3.15% and its *LVG* is 25.62. That is, its average loss on 5% worst case days of the market was 3.15% and its quasi-market assets to market equity ratio was 25.62. Thus, its *SES* is calculated as per formula in Section III.A to be 60/1.4 * 0.0315 + 0.06 * 25.62 – 1 = 1.88.

For computation of *SES,* we also need *LVG,* the quasi-market assets to market equity ratio. This measure is on average 5.26 (median of 4.59), but it has several important outliers. The highest value of *LVG* is 25.62 (for Bear Stearns) and the lowest is just 1.01. Combining *MES* and *LVG* as described in Section III.A to get *SES,* one obtains a systemic risk measure that has an average value that is close to zero with a range of -0.68 to 1.88. The positive values imply that these firms are on average undercapitalized when the market is in left tail, whereas negative values signify firms with sufficient capital.

Panel B shows that individual firm risk measures (*ES* and *Vol*) are highly correlated, and so are dependence measures between firms and the market (*MES* and *Beta*). The systemic expected shortfall *SES* is also positively correlated with the the other risk measures, but the correlation is moderate since *SES* also depends on leverage *LVG,* which in fact is not that correlated to individual firm risk and dependence measures. Naturally, the realized returns during the crisis (*Event return*) are negatively correlated to the risk measures and, interestingly, *Event return* is most correlated with *SES, LVG,* and *MES,* in that order, a theme we exploit more fully next.

III.C Does *SES* predict which institutions contributed most to the crisis of 2007-2008?

Table 2 and Figures 1a-1d show the power of *SES* in explaining the realized performance of financial firms during a systemic crisis. In particular, Table 2 contains cross-sectional regressions of realized returns during July 2007-Dec 2008 on the pre-crisis measures of risk, *MES, SES, Beta* and *ES,* respectively, and Figures 1a-1d shows the corresponding scatter plots. (We also note that Appendix B provides the firm-level data on *MES, SES* and *LVG*.)

Figure 1a shows that *MES* does a reasonably good job of explaining the realized returns (R^2 of 8.7%), and naturally a higher *MES* is associated with a more negative return during the crisis. A few cases illustrate the point well. We can see that Bear Stearns, Lehman Brothers, CIT and Merrill Lynch have relatively high *MES* and these firms lose a large chunk of their equity market capitalization. There are, however, also some reasons to be concerned. For example, exchanges (NYX, ICE, ETFC) have relatively high *MES* but we do not think of these as systemic primarily because they are not as leveraged as say investment banks are. Similarly, while A.I.G. and Berkshire Hathaway have relatively low *MES,* A.I.G.'s leverage at 6.12 is above the mean leverage whereas that of Berkshire is much lower at 2.29 and thus the two should be viewed differently from a systemic risk standpoint. Indeed, *SES* adjusts *MES* precisely for such leverage considerations.

Figure 1b shows that *SES* has an even better fit:

Realized return = – 0.47 – 0.4 SES

with an $R^2 = 23.28\%$. Thus adjusting *MES* for leverage of financial firms helps understanding their systemic risk better. As the plot shows, exchanges are no longer as systemic as investment banks and A.I.G. looks far more systemic than Berkshire Hathaway. Further inspection of the firm-level data (Appendix B) reveals that the five investment banks rank in top ten both by their *MES* or *SES* rankings, but this stability across measures is not a property of all other firms. For example, Countrywide is ranked 24th by *MES* given its *MES* of 2.09%, but given its high leverage of 10.39, ranks 11th in terms of *SES.* Similarly, Freddie Mac is ranked 61st by its *MES* but given its high leverage of 21 (comparable to that of investment banks), it ranks 6th, only after investment banks, in terms of *SES.* On the flip side, CB Richard Ellis, a real-estate firm, has 5th rank in *MES* but given low leverage of 1.55 ranks only 19th in terms of *SES.* Investment banks, Countrywide and Freddie all collapsed or nearly collapsed, whereas CB Richard Ellis survived, highlighting the importance of the leverage correction in *SES.*

In contrast to this remarkably strong role of *SES* in explaining cross-sectional returns, traditional risk measures – *Beta* (Figure 1c) and *ES* (Figure 1d) do not perform that well. The R^2 with *Beta* is just 6.19% and that with *ES* is even worse at 2.44%.

These results are also summarized in Table 2 which has two additional results. Column (3) shows that *Vol*, another measure of individual firm risk does very poorly in explaining realized returns, in fact with essentially zero R^2. Column (7) employs *MES* and *LVG* as separate regressors in explaining the realized returns. Two things are noteworthy. First, these variables are both statistically significant, controlling for the other. Second, allowing the weights on *MES* and *LVG* to vary freely in explaining returns does not produce that much of an improvement compared to employing the weights we chose in computing *SES* in Section III.A.

Put together, these facts can be summarized as implying that (i) individual firm-level risk measures such as expected shortfall and volatility do not explain the cross-section of realized returns during a systemic crisis; (ii) traditional dependence measures such as beta has some predictive power; (iii) tail-dependence measured by marginal expected shortfall (*MES)* does slightly better; and (iv) our leverage-corrected tail-dependence measure of systemic expected shortfall (*SES)* has the most predictive power.

It is of interest to examine with how early *MES* and *SES* predict the cross-section of realized returns during the crisis, as is examined in Table 3. We compute *MES* and *SES* over several periods other than the June 2006-07 "demo" period: June 06-May 07, May 06-Apr 07, Apr 06-Mar 07, Mar 06-Feb 07, and Jan 06-Dec 06. In each period, we use the entire data of daily stock returns on financial firms and the market, and the last available data on book assets and equity to calculate quasi-market measure of assets to equity ratio. Once the measures are calculated for each of these periods, the exercise is always to explain the realized returns during the same crisis period of July 2007 to December 2008.

The first panel shows that the predictive power of *MES* progressively declines as we use lagged data for computing the measure. *MES* remains significant as long as March 2007 is included in the computation period, but not thereafter. This could be due two reasons: first, simply due to the fact that more recent data contain relevant information about the tail-dependence of the firm with the market, especially since the market experienced several negative news in 2Q 2007, and second, due to the technical issue that 5% may no longer be the attractive cutoff point for going deep enough in the tail as we move backwards in time. To elaborate on the second point, as market was less stressed in earlier months of these periods, one would require a lower percentile than 5% to capture days of similar stress as in more recent months. But this of course renders the computation more difficult, as for example 2% worst case days yield only about 5 data points to compute the tail-dependence measure. This is an important issue that necessitates reliance on a structural model of risk and tail-dependence rather than a purely statistical one based on historical data, and we plan to address it in future drafts.

The second and third panels show however that this is less of a case for *SES* and when *MES* and *LVG* are employed separately to explain the realized returns. Indeed, in both these panels, the predictive power remains high in excess of R^2 of 18%, but it is also clear that this power comes even when we take lags primarily due to the explanatory role of leverage. This implies that leverage has certain persistent, cross-sectional characteristics across financial firms that aids understanding which firms suffer the most in a systemic crisis. We investigate this and related cross-sectional issues next.

III.D The cross-section of *SES*

What explains the determinants of systemic risk of a firm? This question is especially important in order to uncover the economic underpinnings of why a firm's marginal expected shortfall and leverage are high. The goal of the inquiry is also to provide an understanding of how systemic risk could be extrapolated to other institutions that do not necessarily trade in public markets, such as, private banks or hedge funds.

To this end, we first examine the behavior of risk and systemic risk across types of institutions based on the nature of their business and capital structure. As shown in Appendix A, we rely on four categories of institutions: (1) Depository institutions (29 companies with 2-digit SIC code of 60); (2) Miscellaneous non-depository institutions including real estate firms whom we often refer to as "Other" (27 companies with codes of 61, 62 except 6211, 65 or 67); (3) Insurance companies (36 companies with code of 63 or 64); and (4) Security and Commodity Brokers (10 companies with 4-digit SIC code of 6211. Note that Goldman Sachs has a SIC code of 6282 but we classify it as part of the Security and Commodity Brokers group. Some of the critical members of Other category are American Express, Black Rock, various exchanges, and Fannie and Freddie, the latter being of course significant candidates for systemically risky institutions.

Table 4 provides the univariate statistics of all the relevant risk measures by institution type. There are several interesting observations to be made. Depository institutions and insurance firms have lower absolute levels of risk, measured both by *ES* and *Vol.* These institutions also have lower dependence with the market, *MES* and *Beta.* The leverage, quasi-market assets to equity ratio, is however higher for depository institutions and securities dealers and brokers. When all this is combined into our systemic risk measure *SES,* insurance firms are overall the least systemically risky, next are depository institutions, and most systemically risky are the securities dealers and brokers. Importantly, by any measure of risk, individual or systemic, securities dealers and brokers are always the *riskiest.* In other words, the systemic risk of these institutions is high not just because they are riskier in an absolute risk sense, but they have greater tail dependence with the market (*MES)* as well as the highest leverage (*LVG*); in particular, their *MES* is about twice the median *MES* of financial firms and their leverage is twice as high as the median leverage of financial firms.

These patterns suggest that the performance of risk and systemic risk measures in explaining the realized returns during the crisis may vary significantly across types of institutions and potentially also within each type. To investigate this, Table 5 shows the regression results explaining realized returns with various risk measures, but controlling for fixed effects corresponding to these four types of institutions. Column (1) shows that on average, depository institutions lost 43% of equity market capitalization, insurance firms 44%, securities dealers and brokers 59% and other 52%. Columns (2) and (3) show that risk measures *ES* and *Vol* do not contribute to explaining realized returns at all, as in Table 2, and also do not affect much the (relative levels of) fixed effects for different institution types.

In contrast, in columns (4)-(7) we find that when *MES, Beta, SES* or *MES and LVG* are included in the regression, they remain significant by themselves in spite of the inclusion of the fixed effects. In other words, measures of systematic or systemic risk have explanatory power for explaining the variation of realized returns *within* each type of institutions. Interestingly when *MES* and *LVG* are included separately, the fixed effects are no longer significant whereas when *SES* is included directly, the fixed effects remain significant. This suggests that the relative weights chosen on *MES* and *LVG* in our specification of *SES* in Section III.A should be along the lines of estimated coefficients in column (7), or perhaps be different for different types of institutions. In particular, column (7) implies relative weight of *MES* to *LVG* of 13.93/0.03 = 464, whereas our assumed relative weight is (60/(0.06*1.4)) which is around 715. In other words, leverage seems to have played a greater role in this crisis than what we assumed in our calibration of *SES.* This can potentially be adjusted by choosing *z* (the point of under-capitalization for an individual institution) in the specification of *SES* to be 9% instead of our chosen value of 6%. That is,

$$IMPLIED\_SES = \frac{60}{1.4} MES_{5\%} + 0.09 LVG - 1$$

In column (8), we again examine the effect of *MES* and *LVG,* but allow the effect of *LVG* to be different for different institution types. In this specification again, institution type fixed effects are insignificant. The *LVG* coefficients are similar in the range of 0.03-0.04 except for depository institutions where it is 0.09. The estimated coefficient on *MES* is 15.12. Thus the implied relative weight on *MES* to *LVG* for specifying *SES* is again around 400-500 for all institutions other than depository institutions. For depository institutions, the implied relative weight on *MES* to *LVG* is only around 170, which seems rather low, in that it implies a default threshold that is higher than 25%. One reason for this difference could be that our measure of *LVG* is quasi-market value of assets to market value of equity, which does not take into account the riskiness of the underlying assets. Traditionally, credit risk assets sitting on balance-sheets of depository institutions have been deemed riskier than the tradable assets on balance-sheets of securities dealers and brokers (even though the recent crisis has made it clear that this relative riskiness could reverse itself if markets for traded assets freeze). Another reason could be that *LVG* is under-estimated in our sample for depository institutions since a large number of them had issued asset-backed commercial paper through conduits and SIVs, which under the US GAAP did not have to be consolidated on balance sheet (Acharya, Schnabl and Suarez, 2009). Hence, their effective leverage was higher than the observed leverage we employ in regressions.

While this is worthy of further investigation, analysis of this type for other crises could shed light on the optimal formulation – that is robust over time – for computing systemic risk *SES* for different types of financial institutions.

Another cross-sectional exercise that might be of interest is how to calculate the systemic risk of institutions that are not publicly traded such as private banks or hedge funds. One possible strategy we consider is to first classify such a private institution into one of the four types of institutions, and then extrapolate its systemic risk measure based on its balance-sheet characteristics. Hence, we try to understand what balance-sheet characteristics drive the systemic risk measures *MES* and *SES* within each institution type. Such understanding can also help get at the economic underpinnings of why some institutions are systemically riskier. Using

CRSP-Compustat data, we rely on four balance-sheet characteristics: book value of equity to assets (*BE/A*), long-term debt to assets (*LT/A*), other liabilities (besides equity and long-term debt) to assets (*OL/A*), and book size measured as *Log Assets*. We remind the reader that *SES* includes quasi-market assets to equity ratio, which is related to book measures, but is generally substantially driven by market value of equity.

Panel A of Table 6 summarizes average (median) of these balance-sheet characteristics for different types of institutions. We focus on medians since averages are affected significantly by values for large firms and outliers. Based on *BE/A*, securities dealers and brokers have the weakest capitalization of 5.3%, depository institutions have 8.8%, insurance firms 21% and the others 44%. Liabilities other than equity and long-term debt (*OL/A*) are also the highest for securities dealers and brokers and depository institutions, which on average are also larger in terms of balance-sheet size (*Log Assets*).

Panels B-E document the relationship between *MES* and *SES* and these balance-sheet characteristics, estimated separately for each type of institution. We employ book equity to assets and size one at a time, and the two forms of non-equity liabilities to assets together. The results are briefly summarized as follows: (i) Better *BE/A* capitalization of institutions lowers *MES,* and in turn *SES,* for all types of institutions; (ii) Larger balance-sheet does not imply higher *MES* but it does imply higher *SES*, suggesting that larger balance-sheets support higher leverage ratios, and this is true for all types of institutions except for depository institutions; (iii) Long-term debt (*LT/A*) raises systemic risk *SES* for all types of institutions, and, finally (iv) In terms of explanatory power, balance-sheet characteristics explain *MES* and *SES* best for insurance firms and securities dealers and brokers.

These results should be considered as suggestive as they are based only on the June 2006-June 2007 period. Clearly, evidence over a longer time-series, employing a fuller specification that includes together different balance-sheet characteristics, is called for. We provide some time-series analysis of *MES* and *SES* below.

III.E The time-series of *SES*

We examine over a long time-series how robust is the pattern that securities dealers and brokers are the most systemically risky institutions. We focus here on the evolution of *MES* measured at 5% year by year over the period 1963 to 2008. We now allow all financial firms to enter our analysis. In each year, we include a financial firm only if it has more than 22 trading days. Within each of the four types of institutions, we aggregate the *MES* using a value-weighted average based on market capitalization of equity of constituent firms. Figure 2a plots this time-series against the NBER recession months.

There are several salient features to the plot. One, while it is often assessed that securities dealers and firms have primarily become a source of risk in the past decade or so, the plot shows that this is not the case. In fact, securities dealers and brokers have been more systemically risky than other groups in *every* year since 1963. The other groups of institutions do not differ as substantially from each other in their *MES* measure. Two, the *MES* measure rises substantially prior to every NBER recession period. Three, the *MES* measure rises substantially also before or during the two financial crisis episodes witnessed in 1987 and 1998, even though these did not end up being recessions. And four, the *MES* of all types of institutions rose dramatically from 2006 to 2008. It should be noted that Figure 2b which shows the time-series plot of *Beta* of the different types of institutions does not reveal such clear patterns. While it is true that the beta of securities dealers and brokers has been higher than that of others, the stability of its level over time is poor and it does not necessarily peak to very high levels during the NBER recessions, prior financial crises or even the subprime crisis.

Table 8 verifies the time-series pattern formally. It regresses the time-series of *MES* of different types of institutions in a panel on two variables, namely NBER recession dummies which capture macroeconomic or real economy stress and the spread between commercial paper and Treasury bill yields which captures better financial market or financial sector stress. The broad pattern is that the systemic risk of only the securities dealers and brokers rises significantly during periods of macroeconomic and financial sector stress; the systemic risk of other types of financial firms rises too in such periods but the effect is much more muted. We conclude that the risk posed by securities dealers and brokers posed to the rest of the system and the economy went unrecognized, or certainly unaddressed (following the 1987 and 1998 episodes), because the focus of financial sector regulation had been on the risk of individual institutions rather than on the systemic risk.

While on the one hand these results confirm that our relative ranking of types of financial firms by systemic risk around the sub-prime crisis maps into their ranking over a long time-series, the results also show that our proposed systemic risk measures have the right economic properties and incremental advantage over traditional measures such as beta which measure systematic risk (but not systemic risk, which we view as being essentially about the tails).

An important issue that remains to be investigated fully is the time-series of leverage. A partial difficulty in this analysis is the poor Compustat coverage of some of these firms in earlier parts of the full sample period, many important firms being private over a part of the period, and the changing composition of different types of institutions over time.

III.F Robustness

One simple robustness check we investigate is the ability of *MES* and *SES* to predict realized performance of financial firms *during* the crisis. For this, we repeat the earlier analysis but change the computation period as well as the "event" period. We now measure *MES* and *SES* over the period July 2007 – June 2008 and study their predictive power for the cross-section of returns over the period July 2008 – August 2009. This exercise illustrates an important adjustment to be made in computing *SES* prior to a crisis versus during a crisis. The point is that expected shortfall (*ES*) of the market in the worst 5% days during the pre-crisis period of June 2006 – July 2007 was 1.4%. Since the onset of the crisis, the market volatility has clearly been higher and 1% and higher falls in market returns on a daily basis have been fairly common. In other words, the same *ES* for the market of 1.4% is observed in the worst 25% days during the crisis period of July 2007 – June 2008. Hence, the *SES* for bank b is now computed as

$$SES(b) = \frac{60}{1.4} MES_{25\%}(b) + 0.06LVG - 1$$

where we continue to make the assumption that 60% drop in the market over a year constitutes a systemic crisis and that the threshold for under-capitalization of a firm is 6% based on its Tier-1 capital ratio.

Rather than repeat the predictive analysis in a table, we use Figures 3a-3d which are variants of Figures 1a-1d, specifically showing the predictive power of *MES, SES, Beta* and *ES* for realized returns during the crisis (all tail measures being at 25% and leverage being measured as of end of June 2008). Note that we lose some of the firms in this period due to failures, mergers or data availability and end up with 85 firms (and lose one class of Berkshire Hathaway shares when we need leverage, e.g., for *SES*). The pattern in results is similar to that for the pre-crisis computation period.

Figure 3a shows that *MES* explains a significant 10% of realized returns. In contrast to the pre-crisis period, CIT has the highest *MES*, A.I.G. and Citigroup both climb up in their *MES* measures, whereas Berkshire Hathaway remains the lowest *MES* firm. As before, Figure 3b shows that *SES,* which provides a leverage-correction to *MES,* performs significantly better explaining close to 20% of realized returns. What is most striking from the plot is that the primary improvement of *SES* over *MES* comes from its ability to fit well the worst performers during the crisis, such as Fannie Mae and Freddie Mac, both of which had very high leverage, and in general, bring closer together most of the other firms to the best fit line. Figure 3c shows that *Beta* does almost as good a job as *MES* during the crisis, which is not surprising since at 25% worst case days, the tail dependence measure and the raw covariance behave similarly. Finally, Figure 3d shows that the institution-level risk measure, *ES,* performs the worst with an explanatory power that is below 5%. In other words, our proposed systemic risk measures perform as well during the crisis as they did prior to and at onset of the crisis.

The second issue we examine is the stability of tail dependence measure MES. We go back to the pre-crisis computation of MES at 5% and consider the ranking of firms it produced (Appendix B). Then, we use the entire four-year data on daily returns available during the period June 2003 to June 2007 to repeat the MES calculations, again employing the worst 5% days of the market. We then examine the correlation of firm rankings between the two measures of MES. Figure 4 shows the simple correlation of the two MES measures. They are quite highly correlated and in fact the rank correlation between the two is 75.64%. In other words, even though yearly measurement of MES at 5% worst case days relies on just 12-13 observations, the tail dependence measures so obtained are reasonably well correlated with those obtained over a longer period, using at least 50 observations for measurement.

In ongoing work, we propose to adjust the empirical calculation of *SES* for time-varying and long-term volatility based on models of historical volatility and implied volatility estimates from the options markets. Our conjecture is that the term-structure of volatility and leverage are both counter-cyclical and that adjusting the *SES* for this important fact would produce *SES* measure, and any related tax, insurance or capital requirement, to be counter-cyclical or at least muted in its pro-cyclical component.

We also intend to confirm that defining the “market” in terms of financial firms as implied by our model does not alter our results in a significant manner.

Finally, we also plan to examine the predictive power of *SES* for realized returns of financial firms during previous crises such as the Savings and Loans crisis of 80’s and the Russian default and the Long Term Capital Management episode of 1997-98.

IV. Implementation

IV.A Systemic capital controls

The propositions described in Section II showed that the *SES* of a firm was increasing in firm leverage, both through its marginal contribution to system-wide expected shortfall and its initial undercapitalization. Therefore, one way to reduce *SES* is through reducing the firm's leverage, that is, by raising the initial capital of the firms. In practice, this means that *SES* could take the form of an initial capital requirement on the firms.

Specifically, if capital cost (c) were constant cross-sectionally across firms, then capital requirements could be set as a function of a financial firm's *SES*, in particular, the systemic capital charge (SCC) could be set to *SES*, where the externality factor *e* is chosen by the regulator to achieve a given degree of aggregate safety and soundness. Forcing systemic financial firms to hold SCC is the arguably the most common, and concrete, regulatory action discussed by policymakers. The model above gives an identifiable way, especially across firms, to implement the capital requirement. While SCC gives the right incentives to firms to limit their holding of aggregate risk since keeping capital reserves is costly, it has two additional benefits: (i) it grants the firm an appropriate safety buffer in systemic crises, and (ii) it reduces the incentive to risk-shift.

In ongoing work, we intend to model the choice of capital requirements more directly in the context of Section II's model framework.

IV.B Systemic insurance

In the model presented in Section II, the regulator assesses the contribution of each firm to the downside aggregate risk of the financial sector. The firm's individual contribution to aggregate risk determines the extent of regulatory constraints which is implemented via a Pigouvian-style tax. The tax would be determined using the formulas provided in Propositions II or III (if one were to assume returns are normally distributed). The formulas would require the regulator to estimate the marginal expected shortfall, the probability of a crisis and "true" leverage. It may not be practical.

An alternative, yet equivalent, way to implement the tax would be to require each firm to buy insurance against its own losses in a scenario in which the whole financial sector is doing poorly. These individual losses would be judged against a certain level of firm capitalization, e.g., $z/(1-l^b)$ defined in Proposition II. In the event of a payoff on the insurance, the payment would not go to the firm itself, but to the regulator in charge of stabilizing the financial sector. This would provide identical incentives to the aforementioned Pigouvian tax for a company to limit systemic risk (to lower its insurance premium) and avoid moral hazard (because the firm does not get the insurance payoff).[6] Just as important, however, the market cost of this insurance would provide a market-based estimate of the systemic risk, allowing the aggregation of investors to evaluate the *MES*, leverage and probability of the next crisis.

How might this insurance scheme work in practice?

As described above, each financial institution would be required to take out insurance against its own losses during a general crisis (i.e., against its *SES*). If losses take place, the payment does not go to the financial institution, but to a systemic fund. Thus pricing of the insurance is a multivariate forward contract on the firm's losses (or gains) relative to its own capitalization conditional on the aggregate market falling.

An obvious issue is that there may not be enough capital available in the private insurance industry to cover the potential losses from a systemic event. This is a reasonable concern as the financial crisis of 2007-2009 showed that the monoline insurance companies and A.I.G. did not have sufficient capital to cover their financial guarantees. Thus, we advocate a public-private insurance plan in which the majority of the insurance be offered by the government and priced by the private market.

[6] There is no restriction that the cost of the insurance be positive. In fact, if the financial firms were to choose (i) a high enough initial capital, (iii) low volatility of its assets, and (ii) assets with low correlation with other firm's assets, then it is possible that the financial firm would get a rebate for low systemic risk.

Public-private insurance schemes of this type were seriously debated in the 1990s in response to the S&L crisis. It was determined at that time that there would not be sufficient depth in the insurance market to make it work. However, since 2002, a successful joint private-public insurance program has been in place, namely The Terrorism Risk Insurance Act (TRIA). TRIA was passed in November 2002 in the wake of the terrorist attacks of September 11, 2001. The program offers federal reinsurance for qualifying losses from a terrorist attack. TRIA is a good model for a systemic insurance program, and includes industry loss triggers and government excess of loss coverage. These features help minimize the insurance industry's losses yet also provide them with an incentive to monitor and reduce risks.[7]

There are some key differences, however, between our proposed insurance scheme and the TRIA. First, with TRIA, the government's insurance only kicks in when the industry's aggregate losses reach a certain level. Here, the government shares the losses from the start. Second, with TRIA, the insurer pays all losses up to a deductible and pays coinsurance (15%) for losses above the deductible up to an aggregate event limit ($100 billion). Above the event limit, the government covers all losses at no charge. While this might work for our case, we envision private side-by-side insurance with the government, say 1% versus 99%, yet covering all losses. The percentages can be adjusted to make sure there is enough private capital to cover the part of losses covered by private insurance. Finally, this latter point contrasts with the TRIA program. In that program, above the event limit, the government covers all losses at no charge. This would not work here as it is important to make it less attractive for financial firms to become systemic, a concern that is less relevant with terrorist attacks. For systemic financial events, market prices of insurance would need to be charged for *all* losses incurred by financial firms.

This latter point highlights a general issue the regulator faces in trying to implement insurance plans. By being charged insurance on an ex ante basis, the financial firm has an incentive to hide risky activities and pay lower insurance costs, only to deviate once the insurance is paid. This is the classic hidden action embedded in moral hazard problems. Prescott (2002) discusses this

[7] Kunreuther and Michel-Kerjan (2008) and Jaffee (2008) describe the participation of insurers in the TRIA program, as well as its applicability to other catastrophic insurance markets.

issue in the context of deposit insurance premiums, a closely related topic to ours. In general, the solution to such problems is to make the payoff state-contingent, i.e., ex post. This deserves future research. As a second-best solution, however, if the insurance (i) has a maturity that covers a long period (say business cycle lengths of five years), and (ii) is purchased on a rolling, quarterly basis to prevent such gaming of the insurance (e.g., $1/20^{th}$ of the total amount purchased each quarter), then this may be sufficient to reduce the hidden action problem.

IV.C How to improve the estimation of *SES* using regulatory data

Important components of *SES* described in Section II are both individual financial firm and sector-wide leverage. The reality of the matter is that not all leverage is equivalent, whether it is long-term debt, short-term rollover debt, life insurance premiums, deposits, and so on. Moreover, some risks may not be measured at all, especially those related to off-balance sheet financing. Off-balance sheet financing played a particular role in the current crisis (see, for example, Acharya, Schnabl and Suarez (2009)). Finally, financial firms may hold derivatives for speculative purposes or to hedge their positions. These activities may have quite different impacts on the systemic risk of the firm, but may not be treated as such in implementing *SES*. The regulator may have access, however, to better data and would be able to map out the liability structure of the financial firm. This way, each firm's expected return could be better matched to its true "capitalization".

What happens, however, if the financial firm is private and no public market data is available at all? Table 6 effectively shows that the systemic risk calculation can be performed for private firms without any stock return data based on the explanatory power of *SES* of publicly traded financial firms using the balance-sheet characteristics: book values of equity to assets, long-term debt to assets, other liabilities to assets, and size of assets. Again, this could be improved with the regulator's better access to the firm's "true" characteristics.

Nevertheless, Table 6 produces a number of interesting findings. For example, while equity to assets capitalization is the primary determinant of the *MES* component of *SES* (higher capitalization implies lower *MES*), the leverage component is significantly increasing in the institution size *within* each set of institutions and overall higher for securities dealers and brokers. Results like this could be an important guide for setting capital requirements or a Pigouvian tax for private financial firms.

IV.D Comparison to other measures

In this section, we intend to provide a direct comparison between our measure of systemic risk, and some of the alternatives currently discussed in the literature, e.g., CoVaR of Adrian and Brunnermeier, the Bank's System's Multivariate Density (BSMD) of Segoviano and Goodhart (2009), and the implied insurance premium of Huang, Zhou and Zhu (2009). But even without such a comparison, it is well-known that expected loss based risk measures, such as our proposed measure *SES,* are more attractive than Value at Risk based risk measures such as *CoVaR* from a "coherence" standpoint (see Artzner, Delbaen, Eber, and Heath (1999), Inui and Kijima (2005) and Yamai and Yoshiba (2005)). With respect to the current crisis, this distinction is especially relevant as VaR-based measures ignore tail risk beyond the VaR limit, and the current crisis is all about extreme risk. Perhaps even more importantly, VaR and CoVaR are not yet shown to be based on an explicit economic theory, while we provide a simple model-based justification for our measure of systemic risk.

Also, our paper suggests a way to manage systemic risk through a tax on (or insurance taken out) by a financial institution against the systemic risk it creates. This is related to an idea that has been around for some time, that is, to create recapitalization requirements. One way to do so is to force levered financial institutions to issue securities that provide automatic recapitalization if the firm's value decreases. The important insight is that equity capital on the balance sheet of financial institutions is expensive. Contingent capital is therefore a more efficient form of regulation. Wall (1989) proposed subordinated debentures with an embedded put option; Doherty and Harrington (1997) and Flannery (2005) proposed reverse convertible debentures. These securities limit financial distress costs ex-post without distorting bank managers' ex-ante incentives.

Kashyap, Rajan and Stein (2008) argue that the idea of automatic recapitalization can be applied to systemic risk. They propose a capital insurance scheme based on systemic risk. Each bank would issue capital insurance policies that would pay off when the overall banking sector is in bad shape, *regardless of the health of a given bank at that point*. The insurer would be a pension fund or a sovereign wealth fund that would essentially provide fully funded "banking catastrophe" insurance.

There are two issues with this proposal. First, they do not provide a link between a firm's *own contribution* to the aggregate losses and the insurance fees it must pay. The financial institution still has the incentive to lever up, take concentrated bets, and build illiquid positions which may improve the risk/return profile of the firm but nevertheless increase the systemic risk in the system. In other words, the negative externality still exists and is not priced. In fact, capital insurance policies could encourage institutions to load on aggregate risk. In contrast, our proposal in Section IV.B requires the insurance payment to go to the regulator, who then has discretion over whether the insured institution deserves the capital injection. The recent crisis has shown that moral hazard linked to aggregate risk taking is just a pervasive as moral hazard linked to specific risk. It is therefore crucial to reward firms who do not take too much aggregate risk, and to not punish those that do. Our proposal is meant to deal with precisely this issue.

V. Conclusion

Current financial regulations seek to limit each institution's risk. Unless the external costs of systemic risk are internalized by each financial institution, the institution will have the incentive to take risks that are borne by all. In other words, each individual firm may take actions to limit their own risk of collapse, but not necessarily the collapse of the system. It is in this sense that the financial institution's risk is a negative externality on the system.[8] An illustration is the current crisis in which financial institutions had levered up on similar large portfolios of securities and loans which faced little idiosyncratic risk, but large amounts of (housing-related) systematic risk.

In this paper, we argue that financial regulation be focused on limiting systemic risk, that is, the risk of a crisis in the financial sector and its spillover to the economy at large. To this end, we

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[8] An analogy can be made to an industrial company who produces emissions that might lower its costs but pollutes the environment.

provide a simple and intuitive way to measure each bank's contribution to systemic risk and suggest ways to limit it.

Our main theoretical results are (i) that each financial institution's systemic risk contribution can be measured as its expected loss in a systemic crisis, adjusted for its leverage, which we denote altogether as its *systemic expected shortfall (SES)*; (ii) *SES* increases in an institution's leverage, institution's volatility, system's volatility, tail dependence between the institution and the system, and the severity of the externality from a systemic crisis; and (iii) incentives can be aligned by imposing a tax on institutions that is based on their *SES* adjusted for their cost of capital.

We also provide an empirical methodology for calculating *SES* and apply it to the period surrounding the subprime crisis. The main empirical results are that (i) the financial institutions' ex-ante *SES* predicts their losses during the subprime crisis in a variety of specifications; (ii) *SES* is cross-sectionally related to capitalization of the institution (measured in terms of assets divided by equity) and thus higher for securities dealers and brokers; and (iii) in the extended time series beyond just the subprime crisis, *SES* is higher during periods of macroeconomic stress, especially for securities dealers and brokers.

In ongoing work, we propose to adjust the empirical calculation of *SES* for time-varying and long-term volatility based on models of historical volatility and implied volatility estimates from the options markets. We also plan to examine the predictive power of *SES* for realized returns on financial firms during previous crises such as the Savings and Loans crisis of 80's and the Russian default and the Long Term Capital Management episode of 1997-98.

Appendix: Proofs

Proof of Proposition 1. The regulators problem is to choose a tax system, letting agents choose their capital and exposures, such as to maximize overall welfare. However, it is helpful to consider the first-best solution in the case where the regulator chooses everything. Consider the first order condition when we differentiate (*) wrt. w_0^b :

$$0 = E\left(u'(w_1^b)1_{(w_1^b>0)}\partial w_1^b / \partial w_0^b\right) - c + cE(\partial w_1^b / \partial w_0^b 1_{(w_1^b<0)}) + eE(\partial w_1^b / \partial w_0^b 1_{(W_1-W<0)})$$

and the FOC wrt. x^b is

$$0 = E\left(u'(w_1^b)1_{\left(w_1^b>0\right)}\partial w_1^b / \partial x^b\right) + cE(\partial w_1^b / \partial x^b 1_{\left(w_1^b<0\right)}) + eE(\partial w_1^b / \partial x^b 1_{(W_1-W<0)})$$

and the regulator is indifferent about the pure transfer component of taxes so the optimal t is indeterminate in this case. (We note that the indicator function does not gives rise to additional Leibniz-rule terms because the integrand is everywhere continuous.)

The proof is then completed by considering the first order conditions for each bank b given the proposed tax system, and recognizing that the first order conditions are the same as above. QED

Proof of Proposition 2. In the text.

Proof of Proposition 3. The *SES* depends on the following conditional expectation:

$$\begin{aligned} E_0(R^b \mid R < \frac{k}{1-L} - 1) &= E_0(E(R^b \mid R) \mid R < \frac{k}{1-L} - 1) \\ &= E_0(\mu^b + \frac{\rho^b \sigma^b}{\sigma}(R-\mu) \mid R < \frac{k}{1-L} - 1) \\ &= \mu^b + \rho^b \sigma^b E_0(\frac{R-\mu}{\sigma} \mid \frac{R-\mu}{\sigma} < (\frac{k}{1-L} - 1 - \mu)/\sigma) \end{aligned}$$

Then, we use that $(R-\mu)/\sigma$ is a standard Normal and that, for any standard normal random variable U and number u, it holds that $E\left(U \mid U < u\right) = -\exp(-\frac{1}{2}u^2)/\sqrt{2\pi}P(U<u)$ (seen

immediately by integration by substation). Inserting these in the expression for *SES* gives the result.

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Table 1: Summary statistics and correlation matrix of stock returns during the crisis, risk (ES, Vol) and systemic risk (MES, SES, Beta).

This table contains overall descriptive statistics (Panel A) and sample correlation matrix (Panel B) for the following measures: (1) **Event return**: the stock return during July 2007 till December 2008. (2) **ES**: the Expected Shortfall of an individual stock at the 5^{th}-percentile. (3) **MES** is the marginal expected shortfalls of a stock given that the *market return* is below its 5^{th}-percentile. (4) **SES** is the leverage-corrected MES, as explained in Section III. (5) **Vol** is the annualized daily individual stock return volatility. (6) **Beta** is the estimate of the coefficient in a regression of a firm's stock return on that of the market's. (7) **Leverage** is measured as quasi-market value of assets divided by market value of equity, where quasi-market value of assets is book value of assets minus book value of debt + market value of equity. We used the value-weighted market return as provided by CRSP. ES, MES, SES, Vol and Beta were measured for each individual company's stock using the period June 2006 till June 2007.

Panel A: Descriptive statistics of the measures Event return, ES, MES, SES, Vol and Beta.

	Event Return	ES	MES	SES	Vol	Beta	LVG
Average	-47%	2.73%	1.63%	0.02	21%	1.00	5.25
Median	-46%	2.52%	1.47%	-0.07	19%	0.89	4.54
Std. dev.	34%	0.92%	0.62%	0.41	8%	0.37	4.40
Min	-100%	1.27%	0.39%	-0.69	10%	0.34	1.01
Max	36%	5.82%	3.36%	1.89	49%	2.10	25.62

Panel B: Sample correlation matrix of the measures Event return, ES, MES, SES, Vol and Beta.

	Event Return	ES	MES	SES	Vol	Beta	LVG
Event Return	1.00						
ES	-0.17	1.00					
MES	-0.30	0.71	1.00				
SES	-0.49	0.39	0.78	1.00			
Vol	-0.07	0.95	0.64	0.30	1.00		
Beta	-0.25	0.76	0.92	0.70	0.72	1.00	
LVG	-0.47	-0.09	0.24	0.79	-0.17	0.18	1.00

Table 2: Stock returns during the crisis, risk and systemic risk.

This table contains the results of the cross-sectional regression analyses of individual company stock returns (Event return) on risk (ES, Vol) and systemic risk (MES, SES, Beta) measures. Event return and risk measures are as described in Table 1. **Leverage** is measured as quasi-market value of assets divided by market value of equity, where quasi-market value of assets is book value of assets minus book value of debt + market value of equity. All balance sheet data are based on quarterly CRSP-Compustat merged data as of end of June 2007.

t-statistics are given in parentheses. ***, ** and * indicate significance at 1, 5 and 10% levels, respectively.

The dependent variable is Event return, the company stock returns during the crisis							
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Intercept	-0.47*** (-14.27)	-0.29*** (-2.80)	-0.40*** (-4.05)	-0.20** (-2.24)	-0.23** (-2.45)	-0.47*** (-16.90)	-0.13 (-1.54)
ES		-6.73* (-1.88)					
Vol			-0.37 (-0.84)				
MES				-16.78*** (-3.26)			-10.64** (-2.17)
Beta					-0.24*** (-2.77)		
SES						-0.40*** (-5.60)	
LVG							-0.03*** (-4.80)
Adj. R^2	0.00%	2.44%	-0.30%	8.70%	6.19%	23.28%	24.59%

Table 3: Stock returns during the crisis and systemic risk measured with different leads.

This table contains the results of the cross-sectional regression analyses of individual company stock returns (Event return) on systemic risk (MES, SES) measures. All measures are as described in Table 1 and Table 2. MES and SES are measured over different pre-crisis periods as indicated. The stock return during the crisis is always measured during July 2007 till December 2008. Leverage is based on data available at end of each period. Hence for coulmn1 we use balance sheet data available as of 2007Q2, columns 2 through four we use 2007Q1 data and for the last two columns we use 2006Q4 balance sheet data.

t-statistics are given in parentheses. ***, ** and * indicate significance at 1, 5 and 10% levels, respectively.

The dependent variable is Event return, the company stock returns during the crisis						
	June06-June07	**June06-May07**	**May06-Apr07**	**Apr06-Mar07**	**Mar06-Feb07**	**Jan06-Dec06**
Intercept	-0.20**	-0.26***	-0.32***	-0.32***	-0.39***	-0.38***
	(-2.24)	(-3.17)	(-3.86)	(-3.86)	(-5.41)	(-5.48)
MES	-16.78***	-13.92***	-8.62*	-8.62*	-5.43	-6.55
	(-3.26)	(-2.92)	(-1.97)	(-1.97)	(-1.27)	(-1.46)
Adj. R^2	8.70%	6.92%	2.76%	2.76%	0.60%	1.12%
Intercept	-0.47***	-0.49***	-0.46***	-0.46***	-0.49***	-0.51***
	(-16.09)	(-16.59)	(-14.83)	(-14.75)	(-15.63)	(-15.86)
SES	-0.40***	-0.40***	-0.31***	-0.32***	-0.029***	-0.32***
	(-5.60)	(-5.41)	(-4.32)	(-4.47)	(-3.82)	(-3.99)
Adj. R^2	23.28%	22.03%	15.03%	15.93%	11.98%	12.98%
Intercept	-0.13	-0.13	-0.20**	-0.20**	-0.21***	-0.20***
	(-1.54)	(-1.64)	(-2.42)	(-2.48)	(-2.85)	(-2.75)
MES	-10.64**	-10.46**	-5.08	-4.97	-4.27	-5.33
	(-2.17)	(-2.39)	(-1.26)	(-1.24)	(-1.11)	(-1.32)
LVG	-0.03***	-0.04***	-0.04***	-0.04***	-0.04***	-0.04***
	(-4.80)	(-5.08)	(-5.09)	(-5.21)	(-5.29)	(-5.20)
Adj. R^2	24.59%	25.02%	21.84%	22.61%	21.61%	21.37%

Table 4: Summary statistics of risk and systemic risk measures by institution types.

This table contains overall descriptive statistics (Panel A) and sample correlation matrix (Panel B) for the risk and systemic risk measures employed in Table 1 by institution type: Depository Institutions, Security and Commodity Brokers, Insurance, and Others, as classified in Appendix A.

Panel A: ES					
	Mean	**Median**	**Std.**	**Min.**	**Max.**
(1) Depository Institutions	2.23%	2.11%	0.48%	1.27%	3.58%
(2) Other: Non-depository	3.35%	3.17%	1.06%	1.79%	5.82%
(3) Insurance	2.44%	2.29%	0.69%	1.39%	4.42%
(4) Security and Commodity Brokers	3.61%	3.46%	0.68%	2.88%	5.24%

Panel B: MES					
	Mean	**Median**	**Std.**	**Min.**	**Max.**
(1) Depository Institutions	1.42%	1.31%	0.34%	0.88%	2.12%
(2) Other: Non-depository	1.92%	1.83%	0.63%	0.92%	3.36%
(3) Insurance	1.28%	1.38%	0.39%	0.39%	2.09%
(4) Security and Commodity Brokers	2.68%	2.64%	0.34%	2.26%	3.29%

Panel C: SES					
	Mean	**Median**	**Std.**	**Min.**	**Max.**
(1) Depository Institutions	-0.02	-0.02	0.19	-0.35	0.37
(2) Other: Non-depository	0.04	-0.08	0.36	-0.46	0.84
(3) Insurance	-0.17	-0.25	0.30	-0.69	0.52
(4) Security and Commodity Brokers	0.72	0.83	0.60	0.03	1.89

Panel D: Vol					
	Mean	**Median**	**Std.**	**Min.**	**Max.**
(1) Depository Institutions	17%	16%	4%	10%	28%
(2) Other: Non-depository	26%	23%	9%	16%	49%
(3) Insurance	18%	17%	5%	11%	32%
(4) Security and Commodity Brokers	27%	26%	5%	21%	36%

Panel E: Beta					
	Mean	**Median**	**Std.**	**Min.**	**Max.**
(1) Depository Institutions	0.87	0.82	0.19	0.53	1.33
(2) Other: Non-depository	1.22	1.18	0.35	0.67	2.10
(3) Insurance	0.78	0.76	0.23	0.34	1.51
(4) Security and Commodity Brokers	1.61	1.60	0.24	1.21	1.96

Panel F: LVG					
	Mean	**Median**	**Std.**	**Min.**	**Max.**
(1) Depository Institutions	6.21	6.26	1.80	1.34	9.25
(2) Other: Non-depository	3.68	1.55	4.63	1.01	21.00
(3) Insurance	4.44	3.07	3.29	1.29	11.85
(4) Security and Commodity Brokers	9.58	9.25	8.26	1.03	25.62

Table 5: Stock returns during the crisis and systemic risk with institution-type fixed effects.

This table contains the results of the cross-sectional regression analyses of individual company stock returns (Event return) on risk (ES, Vol) and systemic risk (MES, SES, Beta) measures. Event return, risk measures and leverage are as described in Table 1 and Table 2. The institution type fixed effects are employed for Depository Institutions, Security and Commodity Brokers, Insurance, and Others, as classified in Appendix A.

t-statistics are given in parentheses. ***, ** and * indicate significance at 1, 5 and 10% levels, respectively.

The dependent variable is Event return, the company stock returns during the crisis								
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
ES		-5.09						
		(-1.14)						
Vol			0.04					
			(0.07)					
MES				-21.10***			-13.93**	-15.12**
				(-2.90)			(-2.071)	(-2.21)
Beta					-0.29**			
					(-2.24)			
SES						-0.51***		
						(-5.769)		
LVG							-0.03***	
							(-5.273)	
Fixed Effects								
Depository	-0.43***	-0.32***	-0.44***	-0.13	-0.18	-0.44***	0.003	0.34
Institutions	(-6.93)	(-2.71)	(-3.98)	(-1.09)	(-1.42)	(-7.795)	(0.114)	(1.59)
Other: Non-	-0.52***	-0.35**	-0.53***	-0.12	-0.17	-0.50***	-0.116	-0.09
depository	(-8.10)	(-2.17)	(-3.40)	(-0.77)	(-1.00)	(-9.00)	(0.139)	(-0.59)
Insurance	-0.44***	-0.31**	-0.44***	-0.17	-0.21*	-0.53***	-0.096	-0.08
	(-7.83)	(-2.57)	(-3.88)	(-1.55)	(-1.83)	(-10.49)	(0.101)	(-0.70)
Sec. & Comm.	-0.59***	-0.41**	-0.60***	-0.02	-0.13	-0.21*	0.147	0.12
Brokers	(-5.57)	(-2.11)	(-3.31)	(-0.11)	(-0.54)	(-1.95)	(0.205)	(0.53)
Interacting with LVG								
Depository								-0.09***
Institutions								(-2.98)
Other: Non-								-0.04***
depository								(-3.20)
Insurance								-0.04**
								(-2.54)
Sec. & Comm.								-0.03***
Brokers								(-2.70)
Adj. R^2	66.42%	66.52%	66.07%	68.78%	67.74%	75.55%	75.85%	76..03%

Table 6: Determinants of systemic risk within institution types

Panel A of this table contains descriptive statistics of the measures book equity to assets (**BE/A**), long term debt to assets (**LT/A)**, other liabilities to assets (**OL/A**), given by 1 – BE/A – LT/A, and natural logarithm of assets across the groups: Depository Institutions, Security and Commodity Brokers, Insurance, and Others, as described in Appendix A. Panels B through E contain the results of cross-sectional regression analyses where each panel is defined by the companies within the four aforementioned groups. The results are those of regressing MES and SES on the different accounting measures All balance sheet data are based on latest available quarterly CRSP-Compustat merged data as of end of June 2007.

Panel A: Averages (medians) of firm characteristic variables across groups

	Book Equity to Assets	Long Term Debt to Assets	Other Liabilities to Assets	Log Assets
Depository Institutions	0.098	0.15	0.76	11.60
	(0.088)	(0.13)	(0.77)	(11.45)
Other: Non-depository	0.38	0.23	0.39	9.83
	(0.44)	(0.12)	(0.39)	(9.74)
Insurance	0.22	0.12	0.66	10.85
	(0.21)	(0.07)	(0.70)	(10.86)
Sec. & Comm. Brokers	0.19	0.11	0.73	11.45
	(0.053)	(0.15)	(0.79)	(12.00)

Panel B: Regression analysis of MES (left column) and SES (right column) on firm characteristics for Depository Institutions

	(1)		(2)		(3)	
Intercept	1.70***	0.18**	1.05*	-0.65*	-0.79	-2.76**
	(13.38)	(1.85)	(1.90)	(-2.41)	(-0.70)	(-2.56)
BE/A	-2.79**	-2.21**				
	(-2.43)	(-2.03)				
LT/A					2.81**	2.59**
					(2.43)	(2.38)
OL/A					2.39*	3.10**
					(1.84)	(2.56)
Log Assets			0.03	0.05		
			(0.67)	(2.40)		
Adj. R^2	14.90%	11.11%	-2%	16.40%	13.17%	15.91%

Panel C: Regression analysis of MES (left column) and SES (right column) on firm characteristics for Non-depository institutions(Others)

	(1)		(2)		(3)	
Intercept	1.8***	0.24**	2.74***	-0.73**	2.09***	0.26
	(8.42)	(2.18)	(4.27)	(0.34)	(6.52)	(-1.58)
BE/A	0.32	-0.54**				
	(0.69)	(-2.24)				
LT/A					-0.44	0.68**
					(-0.79)	(2.36)
OL/A					-0.19	0.38
					(-034)	(1.31)
Log Assets			-0.08	0.08**		
			(-1.30)	(2.28)		
Adj. R^2	-2.07%	12.90%	2.60%	13.91%	-5.61%	12.58%

Panel D: Regression analysis of MES (left column) and SES (right column) on firm characteristics for Insurance companies

	(1)		(2)		(3)	
Intercept	1.65***	0.22***	1.23**	-1.34***	-0.02	-1.62***
	(16.33)	(3.50)	(2.52)	(-3.80)	(-0.08)	(-8.02)
BE/A	-1.55***	-1.81***				
	(-3.90)	(-7.25)				
LT/A					2.28***	2.03***
					(4.25)	(5.77)
OL/A					1.60***	1.82***
					(4.19)	(7.27)
Log Assets			0.01	0.10***		
			(0.16)	(3.34)		
Adj. R^2	29.52%	60.26%	-2.95%	22.98%	34.94%	60.02%

Panel E: Regression analysis of MES (left column) and SES (right column) on firm characteristics for Security dealers and brokers

	(1)		(2)		(3)	
Intercept	2.84***	1.011***	1.84***	-1.52**	2.22***	-0.05
	(27.11)	(5.55)	(3.86)	(-2.58)	(7.02)	(-0.12)
BE/A	-0.84**	-1.53**				
	(-2.54)	(-2.66)				
LT/A					2.30	6.03**
					(1.65)	(3.11)
OL/A					0.36	0.26
					(0.74)	(0.390)
Log Assets			0.07	0.19**		
			(1.81)	(3.88)		
Adj. R^2	37.69%	40.34%	20.24%	60.93%	32.87%	61.27%

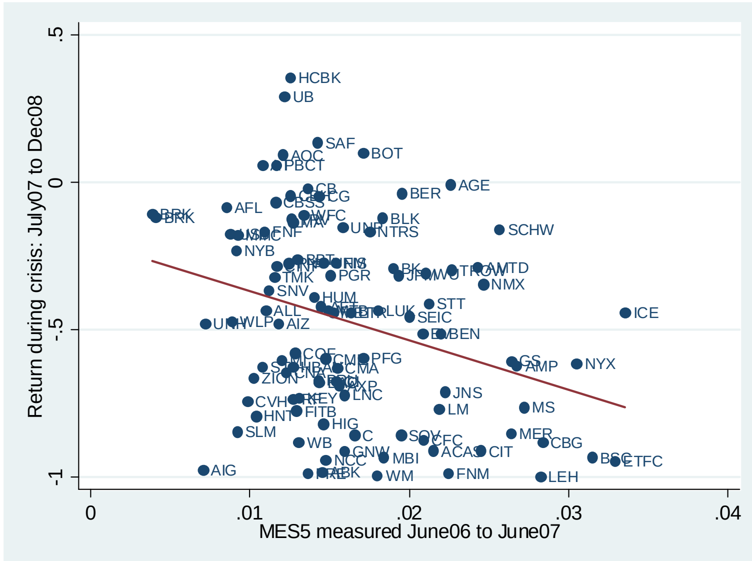
Table 7: Time-series determinants of systemic risk (MES).

All coefficient estimates have been multiplied by 100 save for those related to paper-bill spread which have been multiplied by 10000.

	Dependent variable is value weighted average of individual MESs by institution type								
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Intercept	1.71***	1.78***	2.83***	1.56***	1.62***	2.45***	1.58***	1.64***	2.55***
	(12.73)	(11.58)	(15.23)	(7.69)	(6.93)	(8.59)	(7.42)	(6.72)	(8.74)
NBER recession	0.45						0.19		
	(1.05)						(0.34)		
Depository Institutions		0.56						0.27	
		(1.13)						(0.43)	
Sec. & Comm. Brokers			1.61**						1.01
			(2.69)						(1.33)
Paperbill				0.34			0.27		
				(1.25)			(0.75)		
Depository Institutions					0.40			0.29	
					(1.27)			(0.71)	
Sec. & Comm. Brokers						1.02**			0.61
						(2.66)			(1.26)
Adj. R^2	0.28%	0.79%	15.55%	1.63%	1.74%	15.11%	-1.07%	-0.75%	17.04%
p-value of joint significance							44.96%	42.72%	1.91%

Figure 1a: MES Vs. Event Return

Scatterplot of the marginal expected shortfall measure, MES, against Event Return, the return during the crisis. MES is the marginal expected shortfall of a stock given that the *market return* is below its 5th-percentile. The sample consists of 102 US financial firms with a market cap in excess of 5 bln. dollars as of June 2007. MES5 was measured for each individual company stock using the period June 2006-June 2007. Event return, is the stock return during July 2007 till December 2008.

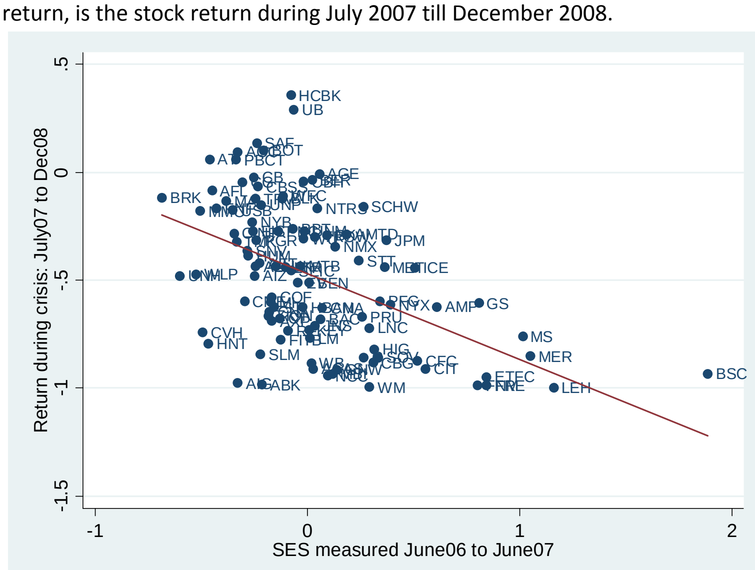


Y = - 0.2 – 16.78 * MES + error, adj R^2=8.70%

(-2.24) (-3.26)

Figure 1b: SES Vs. Event Return

Scatterplot of SES, against Event Return, the return during the crisis. SES is the leverage corrected MES. The sample consists of 101 US financial firms with a market cap in excess of 5 bln. dollars as of June 2007. SES was measured for each individual company stock using the period June 2006-June 2007. Event return, is the stock return during July 2007 till December 2008.

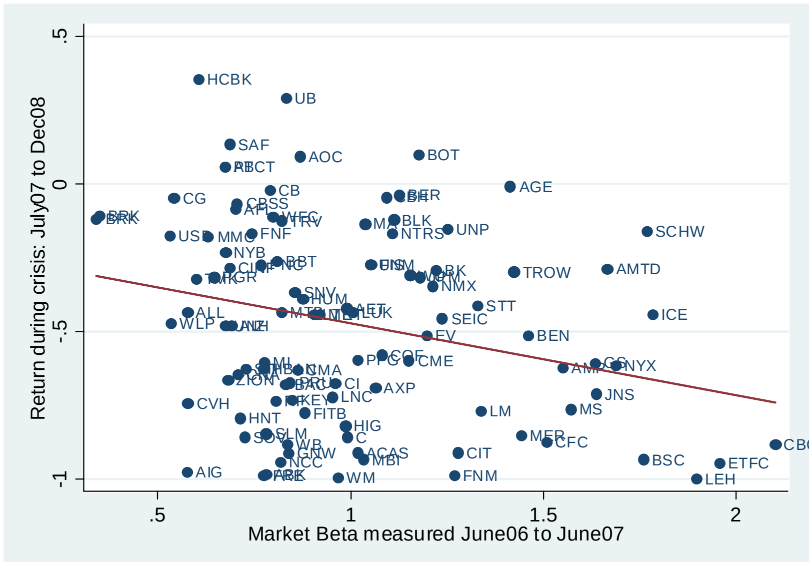


Y = - 0.47 – 0.40 * SES + error, adj R^2=23.28%

(-16.09) (-5.60)

Figure 1c: Beta Vs. Event return

Scatterplot of the market beta against Event Return, the return during the crisis. The sample consists of 102 US financial firms with a market cap in excess of 5 bln. dollars as of June 2007. Beta was measured for each individual company stock using the period June 2006-June 2007. Event return, is the stock return during July 2007 till December 2008.

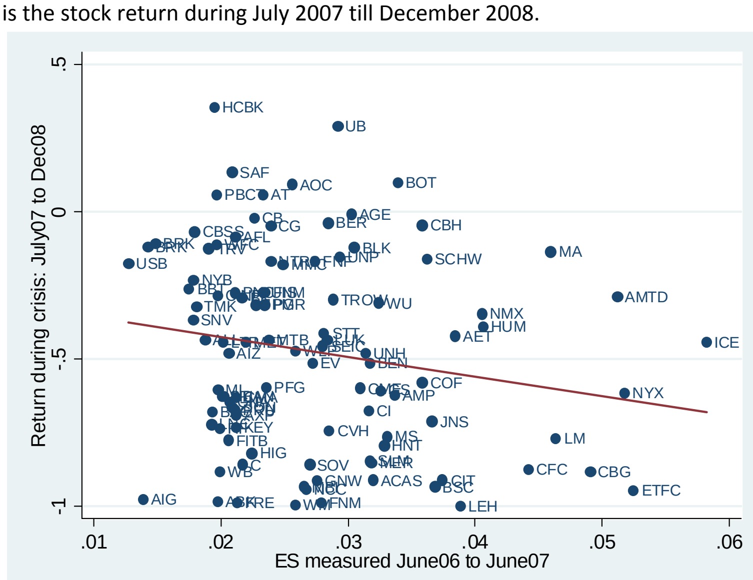


Y = -0.23 – 0.24 * beta + error, adj R^2=6.19%

(-2.45) (-2.77)

Figure 1d: ES Vs. Event Return

Scatterplot of the expected shortfall measure, ES, against Event Return, the return during the crisis. ES: is the Expected Shortfall of an individual stock at the 5th-percentile. The sample consists of 102 US financial firms with a market cap in excess of 5 bln. dollars as of June 2007. ES was measured for each individual company stock using the period June 2006-June 2007. Event return, is the stock return during July 2007 till December 2008.



Y = -0.29 – 6.73 * ES + error, adj R^2=2.44%

(-2.80) (-1.88)

Figure 2a: Annual Value-Weighted MES by Group.

The graph depicts for each calendar year from 1963 until 2008 the market-cap weighted Marginal Expected Shortfall (5%) for each of the four categories of institutions conditioned on there being more than 22 days of trading for an institution to be included within a year.

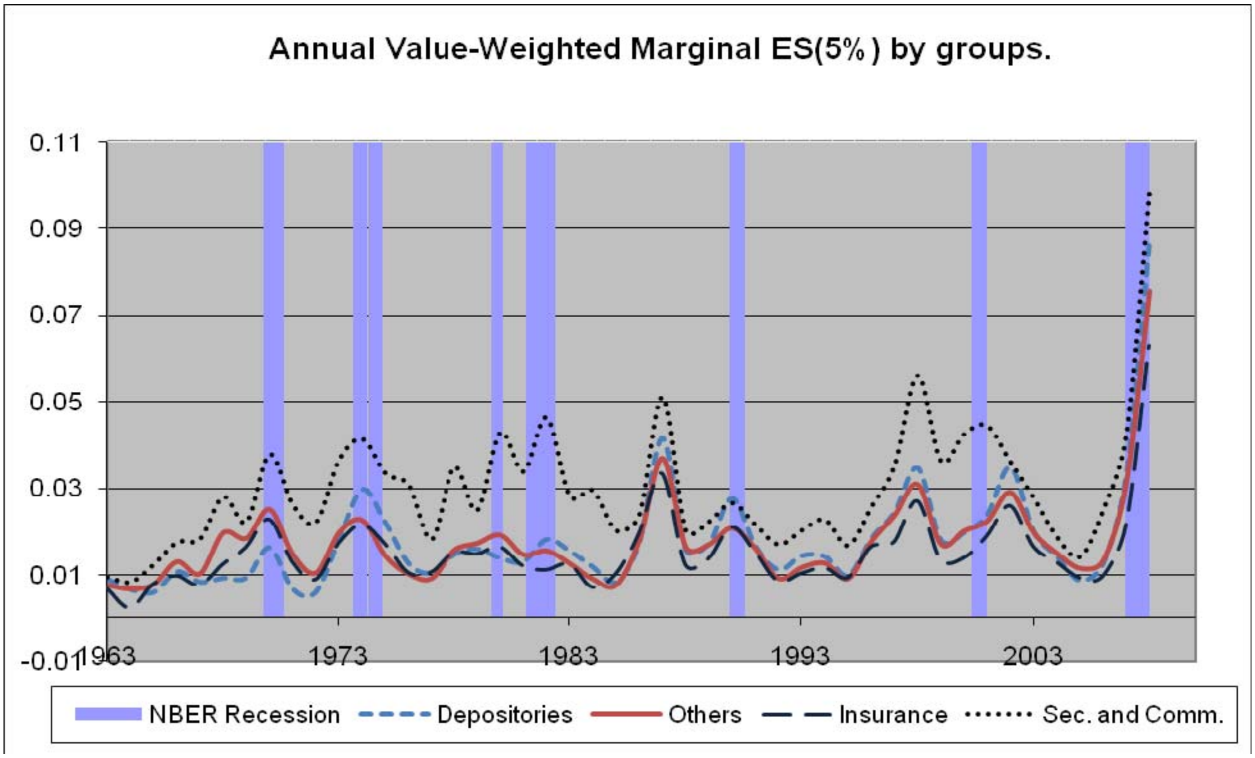


Figure 2b: Annual Value-Weighted Beta by Group.

The graph depicts for each calendar year from 1963 until 2008 the market-cap weighted market beta for each of the four categories of institutions conditioned on there being more than 22 days of trading for an institution to be included within a year.

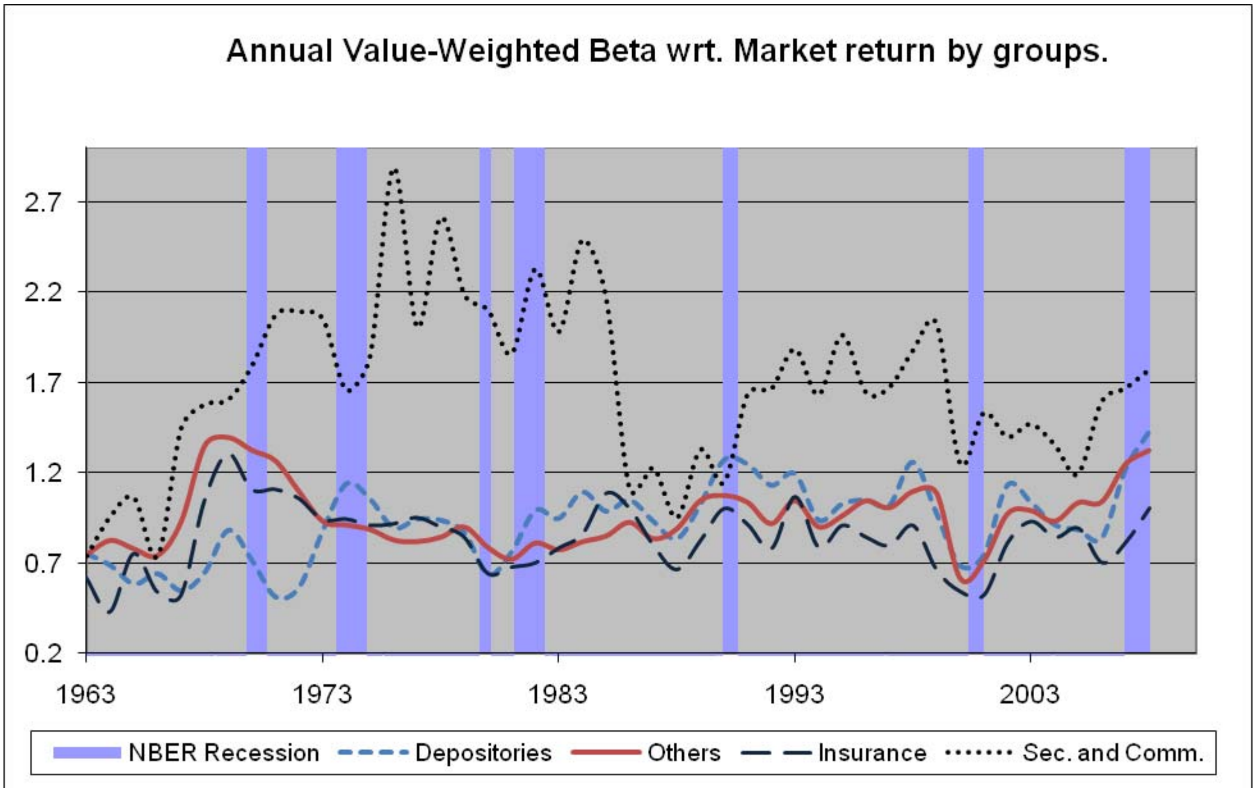
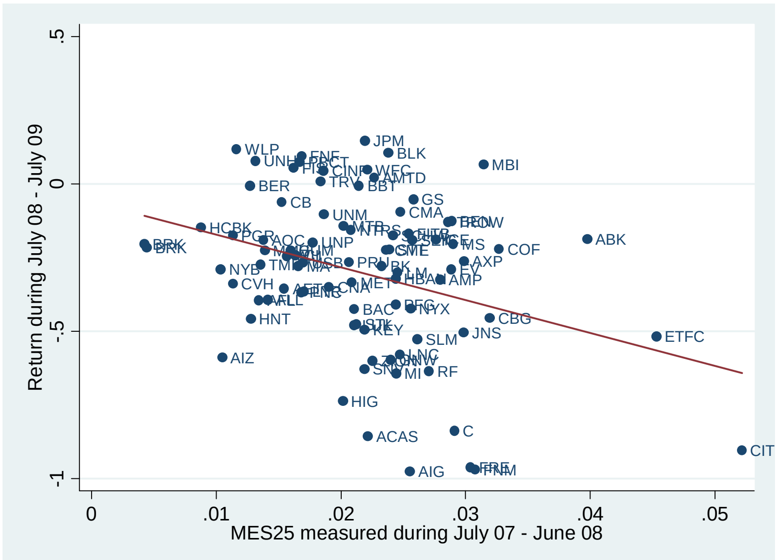


Figure 3a: $MES_{25\%}$ Vs. Post Return (return during the crisis)

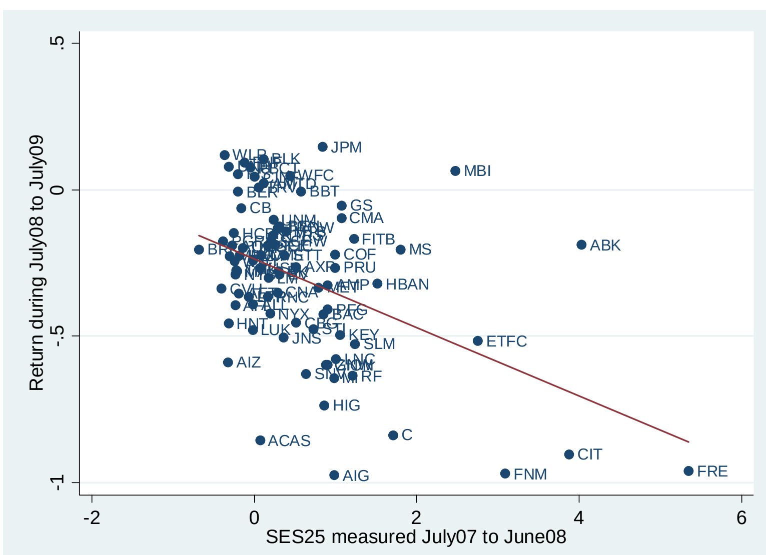
Scatterplot of the marginal expected shortfall measure, $MES_{25\%}$, against Post Return. $MES_{25\%}$ is the marginal expected shortfall of a stock given that the *market return* is below its 25th-percentile. The sample consists of 85 US financial firms with a market cap in excess of 5 bln. dollars as of June 2007 and who survived up till July 2009. $MES_{25\%}$ was measured for each individual company stock using the period July 2007-June 2008. Post return, is the stock return during July 1st 2008 till July 27th 2009. All data are from CRSP save that for Post return which uses data from Datastream.



$Y = -0.06 - 11.14 * MES_{25} + error$, adj R^2=10.01%
(-0.76) (-3.22)

Figure 3b: $SES_{25\%}$ Vs. Post Return (return during the crisis)

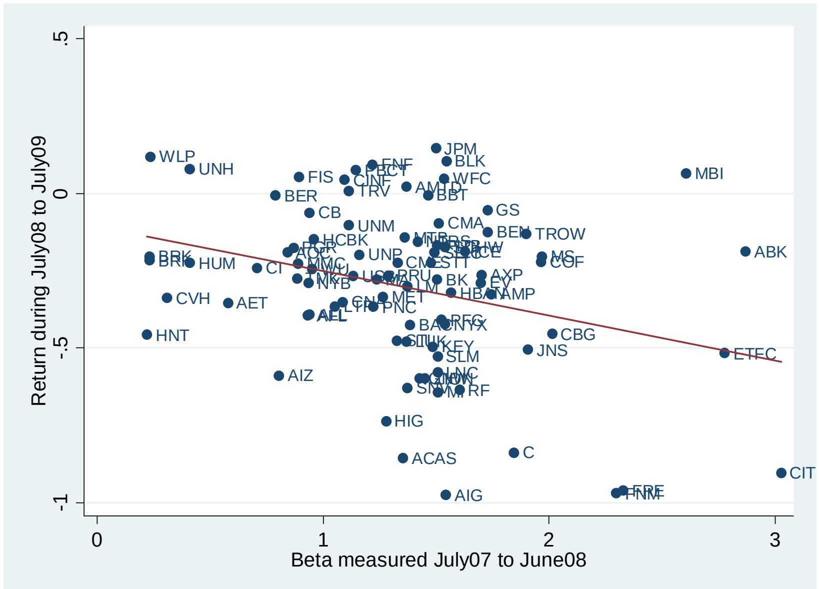
Scatterplot of $SES_{25\%}$, against Post Return. $SES_{25\%}$ is leverage adjusted $MES_{25\%}$. The sample consists of 84 US financial firms with a market cap in excess of 5 bln. dollars as of June 2007 and who survived up till July 2009. $MES_{25\%}$ was measured for each individual company stock using the period July 2007-June 2008. Post return, is the stock return during July 1st 2008 till July 27th 2009. All data are from CRSP save that for Post return which uses data from Datastream.



$Y = -0.24 - 0.12 * SES_{25} + error$, adj R^2=19.75%
(-7.96) (-4.63)

Figure 3c: Beta Vs. Post Return (return during the crisis)

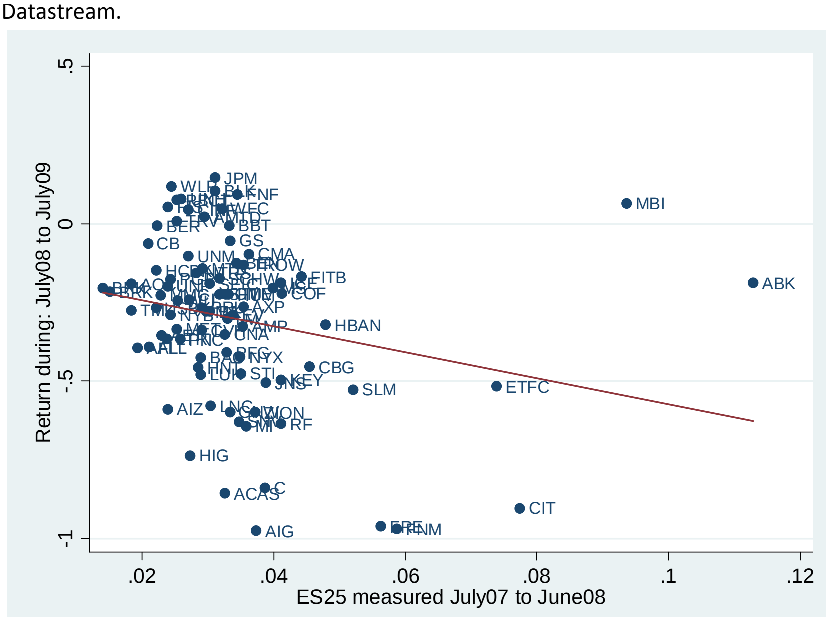
Scatterplot of market beta against Post Return. The sample consists of 85 US financial firms with a market cap in excess of 5 bln. dollars as of June 2007 and who survived up till July 2009. Beta was measured for each individual company stock against the value-weighted CRSP index using the period July 2007-June 2008. Post return, is the stock return during July 1st 2008 till July 27th 2009. All data are from CRSP save that for Post return which uses data from Datastream.



$Y = -0.11 - 0.15 * beta + error$, adj R^2=8.20%
(-1.47) (-2.92)

Figure 3d: $ES_{25\%}$ Vs. Post Return (return during the crisis)

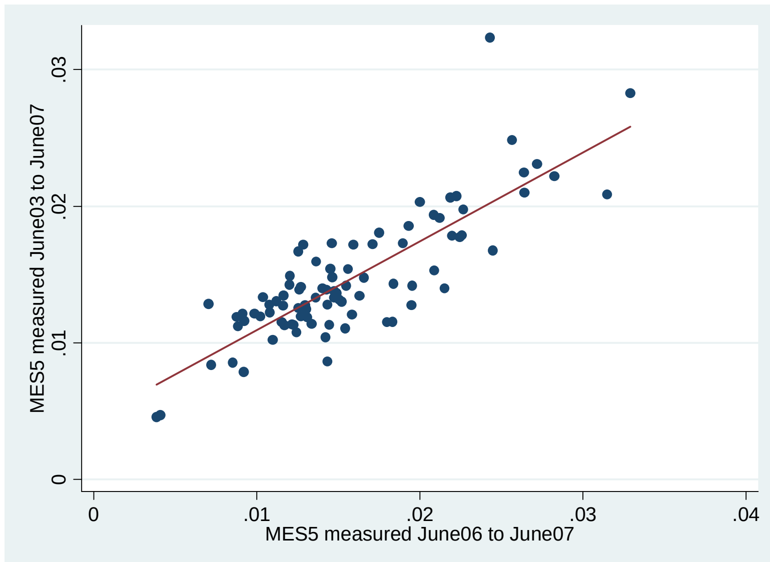
Scatterplot of expected shortfall, $ES_{25\%}$, against Post Return. $ES_{25\%}$ is the marginal expected shortfall of a stock given that the *stock return* is below its 25th-percentile The sample consists of 85 US financial firms with a market cap in excess of 5 bln. dollars as of June 2007 and who survived up till July 2009. Beta was measured for each individual company stock against the value-weighted CRSP index using the period July 2007-June 2008. Post return, is the stock return during July 1st 2008 till July 27th 2009. All data are from CRSP save that for Post return which uses data from Datastream.



$Y = -0.16 - 4.12 * ES_{25} + error$, adj R^2=4.49%
(-2.35) (-2.23)

Figure 4: Stability of MES.

The graph depicts a scatter plot of the marginal expected shortfall measure at the 5% level (MES%) computed during the June 2006-June 2007 period versus that computed during June 2003-June2007. MES is the marginal expected shortfall of a stock given that the *market return* is below its 5th-percentile.



The spearman rank correlation between the two is 75.64%

Appendix A

This appendix contains the names of the U.S. financial institutions used in the analysis of the recent crisis. The institutions have been selected according to their inclusion in the U.S. financial sector and their market cap as of end of June 2007 where all firms had a market cap in excess of 5bln USD.

The companies can be categorized into the following four groups: **Depository Institutions(**JPMorgan, Citigroup, WAMU,…), **Security and Commodity Brokers**(Goldman Sachs, Morgan Stanley,…), **Insurance Carriers**(AIG, Berkshire Hathaway, Countrywide,…) and **Insurance Agents, Brokers, Service**(Metlife, Hartford Financial,…) and a group called **others** consisting of Non-depository Institutions, Real Estate etc..

The total number of firms in the sample is 102.

Note that although Goldman Sachs has a SIC code of 6282 thus initially making it part of the group called Others we have nonetheless chosen to put in the group of Security and Commodity Brokers.

Depository Institutions: 29 companies, 2-digit SIC code=60.

1.B B & T CORP
2.BANK NEW YORK INC
3.BANK OF AMERICA CORP
4.CITIGROUP INC
5.COMERICA INC
6.COMMERCE BANCORP INC NJ
7.HUDSON CITY BANCORP INC
8.HUNTINGTON BANCSHARES INC
9.JPMORGAN CHASE & CO
10.KEYCORP NEW
11.M & T BANK CORP
12.MARSHALL & ILSLEY CORP
13.NATIONAL CITY CORP
14.NEW YORK COMMUNITY BANCORP INC
15.NORTHERN TRUST CORP
16.P N C FINANCIAL SERVICES GRP INC
17.PEOPLES UNITED FINANCIAL INC
18.REGIONS FINANCIAL CORP NEW
19.SOVEREIGN BANCORP INC
20.STATE STREET CORP
21.SUNTRUST BANKS INC
22.SYNOVUS FINANCIAL CORP
23.U S BANCORP DEL
24.UNIONBANCAL CORP
25.WACHOVIA CORP 2ND NEW
26.WASHINGTON MUTUAL INC
27.WELLS FARGO & CO NEW
28.WESTERN UNION CO
29.ZIONS BANCORP

Other: Non-depository Institutions etc.: 27 Companies, 2-digit SIC code=61, 62(except 6211), 65, 67.

1.ALLTEL CORP
2.AMERICAN CAPITAL STRATEGIES LTD
3.AMERICAN EXPRESS CO
4.AMERIPRISE FINANCIAL INC
5.BLACKROCK INC
6.C B O T HOLDINGS INC
7.C B RICHARD ELLIS GROUP INC
8.C I T GROUP INC NEW
9.CAPITAL ONE FINANCIAL CORP
10.CHICAGO MERCANTILE EXCH HLDG INC
11.COMPASS BANCSHARES INC
12.EATON VANCE CORP
13.FEDERAL HOME LOAN MORTGAGE CORP
14.FEDERAL NATIONAL MORTGAGE ASSN
15.FIDELITY NATIONAL INFO SVCS INC
16.FIFTH THIRD BANCORP
17.FRANKLIN RESOURCES INC
18.INTERCONTINENTALEXCHANGE INC
19.JANUS CAP GROUP INC
20.LEGG MASON INC
21.LEUCADIA NATIONAL CORP
22.MASTERCARD INC
23.N Y S E EURONEXT
24.S E I INVESTMENTS COMPANY
25.S L M CORP
26.T D AMERITRADE HOLDING CORP
27.UNION PACIFIC CORP

Insurance: 36 Companies, 2-digit SIC code=63 and 64.

1.A F L A C INC
2.AETNA INC NEW
3.ALLSTATE CORP
4.AMBAC FINANCIAL GROUP INC
AMERICAN
5.INTERNATIONAL GROUP INC
6.AON CORP
ASSURANT INC
7.BERKLEY W R CORP
8.BERKSHIRE HATHAWAY INC DEL
9.BERKSHIRE HATHAWAY INC DEL
10.C I G N A CORP
11.C N A FINANCIAL CORP
12.CHUBB CORP
13.CINCINNATI FINANCIAL CORP
14.COUNTRYWIDE FINANCIAL CORP
15.COVENTRY HEALTH CARE INC
16.FIDELITY NATIONAL FINL INC NEW
17.GENWORTH FINANCIAL INC
18.HARTFORD FINANCIAL
19.SVCS GROUP IN
20.HEALTH NET INC
21.HUMANA INC
22.LINCOLN NATIONAL CORP IN
23.LOEWS CORP
24.LOEWS CORP
25.M B I A INC
26.MARSH & MCLENNAN COS INC
27.METLIFE INC
28.PRINCIPAL FINANCIAL GROUP INC
29.PROGRESSIVE CORP OH
30.PRUDENTIAL

Security and Commodity Brokers: 10 Companies, 4-digit SIC code=6211.

1.BEAR STEARNS COMPANIES INC
2.E TRADE FINANCIAL CORP
3.EDWARDS A G INC
4.GOLDMAN SACHS GROUP INC
5.LEHMAN BROTHERS HOLDINGS INC
6.MERRILL LYNCH & CO INC
7.MORGAN STANLEY DEAN WITTER & CO
8.NYMEX HOLDINGS INC
9.SCHWAB CHARLES CORP NEW
10. T ROWE PRICE GROUP INC

Insurance, continued:

FINANCIAL INC
31.SAFECO CORP
32.TORCHMARK CORP
33.TRAVELERS COMPANIES INC
34.UNITEDHEALTH GROUP INC
35.UNUM GROUP
36.WELLPOINT INC

Appendix B: Systemic risk ranking of financial firms during June 2006 to June 2007

This table contains the list of US financial firms with a market cap in excess of 5 bln. dollars as of June 2007. The firms are listed in descending order according to their Marginal Expected Shortfall at the 5% level (MES). SES is the leverage adjusted MES. MES and SES are measured using the June 2006 till June 2007 period. LVG is the market leverage as of June 2007. All data are from CRSP and CRSP merged Compustat.

MES Ranking	Name of Company	MES	SES	LVG	SES Ranking
1.	INTERCONTINENTALEXCHANGE INC	3.36%	0.51	1.12	12
2.	E TRADE FINANCIAL CORP	3.29%	0.85	7.24	5
3.	BEAR STEARNS COMPANIES INC	3.15%	1.89	25.62	1
4.	N Y S E EURONEXT	3.05%	0.39	1.43	13
5.	C B RICHARD ELLIS GROUP INC	2.84%	0.31	1.55	19
6.	LEHMAN BROTHERS HOLDINGS INC	2.83%	1.16	15.83	2
7.	MORGAN STANLEY DEAN WITTER & CO	2.72%	1.01	14.14	4
8.	AMERIPRISE FINANCIAL INC	2.68%	0.61	7.72	9
9.	GOLDMAN SACHS GROUP INC	2.64%	0.81	11.25	7
10.	MERRILL LYNCH & CO INC	2.64%	1.05	15.32	3
11.	SCHWAB CHARLES CORP NEW	2.57%	0.26	2.71	23
12.	NYMEX HOLDINGS INC	2.47%	0.13	1.23	28
13.	C I T GROUP INC NEW	2.45%	0.56	8.45	10
14.	T D AMERITRADE HOLDING CORP	2.43%	0.19	2.40	26
15.	T ROWE PRICE GROUP INC	2.27%	0.03	1.03	37
16.	EDWARDS A G INC	2.26%	0.06	1.46	34
17.	FEDERAL NATIONAL MORTGAGE ASSN	2.25%	0.80	14.00	8
18.	JANUS CAP GROUP INC	2.23%	0.03	1.34	36
19.	FRANKLIN RESOURCES INC	2.20%	0.01	1.08	42
20.	LEGG MASON INC	2.19%	0.01	1.25	41
21.	AMERICAN CAPITAL STRATEGIES LTD	2.15%	0.03	1.73	38
22.	STATE STREET CORP	2.12%	0.24	5.54	25
23.	WESTERN UNION CO	2.10%	-0.02	1.34	46
24.	COUNTRYWIDE FINANCIAL CORP	2.09%	0.52	10.39	11
25.	EATON VANCE CORP	2.09%	-0.04	1.03	49
26.	S E I INVESTMENTS COMPANY	2.00%	-0.08	1.08	53
27.	BERKLEY W R CORP	1.95%	0.02	3.07	39
28.	SOVEREIGN BANCORP INC	1.95%	0.34	8.34	17
29.	JPMORGAN CHASE & CO	1.93%	0.37	9.09	14
30.	BANK NEW YORK INC	1.90%	0.09	4.64	31
31.	M B I A INC	1.84%	0.12	5.47	29
32.	BLACKROCK INC	1.83%	-0.12	1.60	57
33.	LEUCADIA NATIONAL CORP	1.80%	-0.15	1.28	61
34.	WASHINGTON MUTUAL INC	1.80%	0.29	8.67	20
35.	NORTHERN TRUST CORP	1.75%	0.05	4.92	35
36.	C B O T HOLDINGS INC	1.71%	-0.21	1.01	68
37.	PRINCIPAL FINANCIAL GROUP INC	1.71%	0.34	10.15	16
38.	CITIGROUP INC	1.66%	0.27	9.25	22
39.	LOEWS CORP	1.63%	-0.10	3.28	55
40.	GENWORTH FINANCIAL INC	1.59%	0.14	7.62	27
41.	LINCOLN NATIONAL CORP IN	1.59%	0.29	10.15	21
42.	UNION PACIFIC CORP	1.58%	-0.22	1.70	70
43.	AMERICAN EXPRESS CO	1.56%	-0.17	2.70	64
44.	COMERICA INC	1.55%	0.07	6.77	32
45.	C I G N A CORP	1.54%	-0.13	3.50	59
46.	FIDELITY NATIONAL INFO SVCS INC	1.54%	-0.26	1.42	80
47.	METLIFE INC	1.52%	0.36	11.85	15

48.	PROGRESSIVE CORP OH	1.51%	-0.24	1.89	75
49.	M & T BANK CORP	1.49%	-0.03	5.47	48
50.	NATIONAL CITY CORP	1.48%	0.09	7.70	30
51.	CHICAGO MERCANTILE EXCH HLDG INC	1.47%	-0.30	1.19	84
52.	UNUM GROUP	1.46%	-0.01	5.99	44
53.	HARTFORD FINANCIAL SVCS GROUP IN	1.46%	0.32	11.48	18
54.	AMBAC FINANCIAL GROUP INC	1.45%	-0.22	2.69	69
55.	AETNA INC NEW	1.45%	-0.23	2.58	72
56.	LOEWS CORP	1.44%	-0.31	1.29	85
57.	BANK OF AMERICA CORP	1.44%	0.06	7.46	33
58.	PRUDENTIAL FINANCIAL INC	1.43%	0.26	10.75	24
59.	SAFECO CORP	1.42%	-0.24	2.51	74
60.	HUMANA INC	1.40%	-0.28	1.97	82
61.	FEDERAL HOME LOAN MORTGAGE CORP	1.36%	0.84	21.00	6
62.	CHUBB CORP	1.36%	-0.25	2.74	79
63.	WELLS FARGO & CO NEW	1.34%	-0.12	5.19	56
64.	KEYCORP NEW	1.31%	0.01	7.41	43
65.	WACHOVIA CORP 2ND NEW	1.31%	0.02	7.64	40
66.	B B & T CORP	1.30%	-0.07	6.23	51
67.	FIFTH THIRD BANCORP	1.29%	-0.13	5.33	58
68.	CAPITAL ONE FINANCIAL CORP	1.28%	-0.17	4.70	63
69.	REGIONS FINANCIAL CORP NEW	1.27%	-0.09	6.06	54
70.	HUNTINGTON BANCSHARES INC	1.27%	-0.02	7.23	47
71.	MASTERCARD INC	1.27%	-0.38	1.21	92
72.	TRAVELERS COMPANIES INC	1.26%	-0.25	3.54	77
73.	COMMERCE BANCORP INC NJ	1.26%	-0.02	7.40	45
74.	HUDSON CITY BANCORP INC	1.26%	-0.08	6.39	52
75.	P N C FINANCIAL SERVICES GRP INC	1.24%	-0.14	5.50	60
76.	C N A FINANCIAL CORP	1.22%	-0.18	4.92	66
77.	UNIONBANCAL CORP	1.22%	-0.07	6.88	50
78.	AON CORP	1.20%	-0.33	2.55	87
79.	MARSHALL & ILSLEY CORP	1.20%	-0.17	5.20	65
80.	ASSURANT INC	1.18%	-0.25	4.08	78
81.	CINCINNATI FINANCIAL CORP	1.17%	-0.35	2.53	90
82.	PEOPLES UNITED FINANCIAL INC	1.16%	-0.34	2.75	89
83.	COMPASS BANCSHARES INC	1.16%	-0.23	4.48	73
84.	TORCHMARK CORP	1.15%	-0.34	2.85	88
85.	SYNOVUS FINANCIAL CORP	1.12%	-0.28	3.92	83
86.	ALLSTATE CORP	1.10%	-0.25	4.72	76
87.	FIDELITY NATIONAL FINL INC NEW	1.09%	-0.43	1.73	93
88.	ALLTEL CORP	1.08%	-0.46	1.25	95
89.	SUNTRUST BANKS INC	1.08%	-0.16	6.35	62
90.	HEALTH NET INC	1.04%	-0.47	1.47	96
91.	ZIONS BANCORP	1.02%	-0.19	6.26	67
92.	COVENTRY HEALTH CARE INC	0.99%	-0.49	1.39	97
93.	MARSH & MCLENNAN COS INC	0.92%	-0.50	1.67	98
94.	S L M CORP	0.92%	-0.22	6.40	71
95.	NEW YORK COMMUNITY BANCORP INC	0.92%	-0.26	5.81	81
96.	WELLPOINT INC	0.88%	-0.53	1.60	99
97.	U S BANCORP DEL	0.88%	-0.35	4.55	91
98.	A F L A C INC	0.85%	-0.45	3.07	94
99.	UNITEDHEALTH GROUP INC	0.72%	-0.60	1.47	100
100.	AMERICAN INTERNATIONAL GROUP INC	0.71%	-0.33	6.12	86
101.	BERKSHIRE HATHAWAY INC DEL(A)	0.41%	-0.69	2.29	101
102.	BERKSHIRE HATHAWAY INC DEL(B)	0.39%			