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. An institution's contribution, denoted systemic expected shortfall (SES), is its propensity to be undercapitalized when the system as a whole is undercapitalized, which increases in the institution's marginal expected shortfall, *MES*, i.e., its losses in the tail of the aggregate sector's loss distribution, and in its leverage. Institutions internalize their externality if they are "taxed" based on their *SES*. We demonstrate empirically the ability of components of *SES* to predict emerging systemic risk during the financial crisis of 2007-2009, in particular, (i) the outcome of stress tests performed by regulators; (ii) the decline in equity valuations of large financial firms in the crisis; and, (iii) the widening of their credit default swap spreads.

Failures of financial institutions can impose 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. 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.[1]

Our goal in this paper is to propose a simple, alternative measure that focuses on systemic risk. To this end, we first develop a framework for formalizing and then measuring systemic risk. Second, given this framework, we formulate an optimal policy for managing systemic risk. Finally, we provide a detailed empirical analysis of the financial crisis of 2007-2009, giving support to our theoretical analysis of systemic risk.

The need for economic foundations for a systemic risk measure is more than an academic concern. We believe that the lack of an adequate systemic risk measure is at the root of practical failures of regulation. It is important to recognize that value-at-risk (VaR), the dominant form of risk measurement in the financial sector, was invented by banks as an internal risk management tool. VaR was meant to be useful for comparing risk across desks and asset classes within a bank. VaR was never meant to be a tool for regulating banks.

It is of course difficult, if not impossible, to find a systemic risk measure that is at the same time practically relevant and completely justified by a general equilibrium model. The reason is that meaningful financial regulation can only be analyzed in economies with incomplete markets, moral hazard and information asymmetries. The problem, however, is that to date the gap between the theoretical recommendations and the practical needs of regulators has been so wide that measures such as institution-level VaR have persisted in assessing risks of the financial system as a whole.

[1]See Crockett (2000) and Acharya (2001) for an early recognition of this inherent tension between micro-prudential and macro-prudential regulation of the financial sector.

Our strategy is to study a simplified theoretical model that is based on the common denominator of various general equilibrium models. We argue that two ideas are widely shared by economists and regulators. The first idea is that the main reason for regulating financial institutions is that there are externalities from their failures (or even just under-capitalization) that spill over to the rest of the economy. The second idea is that if these externalities are not internalized by financial institutions, then they manifest as excessive risk-taking, leverage and herding in business and trading decisions of financial firms.

Given these two basic ideas, the critical step is to model the externalities in a tractable manner. This is where we depart from the fully micro-founded models and instead use the stress tests of the balance-sheets of financial institutions conducted by the regulators in the Spring of 2009 as a guide to learn about the type of externality that regulators and market participants seem to view as a first-order concern. Specifically, we assume that the externality depends on the aggregate capital shortfall in the financial industry.[2] We then study the effect of externality on risk choices of banks that maximize shareholder value given limited liability. The interesting point is that even such a simple model is enough to obtain a new and interesting theory of systemic risk regulation.[3]

A detailed description of the theoretical and empirical results follows.

Theoretical results: 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 losses during an idiosyncratic bank

[2]This assumption is consistent with models that spell out the exact nature of the externality, such as models of (i) financial contagion through interconnectedness (e.g., Rochet and Tirole, 1996); (ii) pecuniary externalities through fire sales (e.g., several contributions (of and) in Allen and Gale, 2007, and Acharya and Yorulmazer, 2007), margin requirements (e.g., Garleanu and Pedersen, 2007), liquidity spirals (e.g., Brunneremeier and Pedersen, 2009), and interest rates (e.g., Diamond and Rajan, 2005 and Acharya, 2009); and, (iii) runs (e.g., Diamond and Dybvig, 1983, and Pedersen, 2009).

[3]When distilled to its essence, our modeling finds natural parallels in the early work of Stigler (1971) and Peltzman (1976) on the theory of regulation in the presence of externalities.

failure and the externality arising in a systemic crisis, that is, when the aggregate capital in the banking sector is sufficiently low.[4] 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.

We show that to align incentives, the regulator optimally imposes a tax 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.

We show that *SES*, the systemic-risk component, is equal to the expected systemic costs when the financial sector becomes undercapitalized times the financial institution's percentage contribution to this under-capitalization. *SES* is therefore measurable and we provide theoretical justification for it being related to a financial firm's marginal expected shortfall, *MES* (i.e., its losses in the tail of the aggregate sector's loss distribution), and to its leverage.

Empirical results: We empirically investigate three examples of emerging systemic risk in the financial crisis (focusing on large financial institutions based in the United States) and analyze the ability of our theoretically motivated measures to capture this risk. Specifically, we look at the relation between our measures and (i) capital shortfalls at large financial institutions estimated via stress tests performed by bank regulators during the Spring of 2009, (ii) realized systemic risk that emerged in the equity of large financial firms from July 2007 through the end of 2008, and (ii) realized systemic risk that emerged in the credit default swaps (cds) of large financial firms from July 2007 through the end of 2008.

Figures 1, 2 and 5 provide a simple illustration of the ability of the firm's *MES* to forecast realized systemic risk. In particular, the figures graph a cross-sectional scatter plot

[4] In the spirit of deposit insurance, we assume that part of the bank's liabilities are insured, but our results extend more generally to no or full insurance.

of the largest financial firm's capital shortfalls (from the stress test exercise) relative to their Tier 1 common equity capital, realized equity returns and realized cds returns during the financial crisis respectively on each firm's *MES* prior to the crisis. Each figure shows a clear relation between *MES* and systemic risk. Formal statistical analysis shows that the slope is statistically significant, and along with leverage, *MES* loads significantly on the financial firms that ran aground during the crisis.

To mention one of the salient examples, we estimate our systemic risk measures 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 B). 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 institution's systemic risk-taking, we check how well these risk measures calculated *before* the sub-prime crisis help predict which institutions fared the worst *during* the crisis period of July 2007 till December 2008. We find that both components of systemic risk - *MES* and leverage - contribute to explaining a significant proportion of the realized returns during the crisis (R^2 of 27.34%). 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, namely beta, has a modest explanatory power.

To summarize, our theoretical analysis provides a conceptual framework for measuring a financial institution's contribution to systemic risk, specifically as the losses it incurs when the system as a whole is under-capitalized. Our empirical analysis shows that such a cross-sectional measure of systemic risk can be estimated using market (equity and cds) data. Importantly, the measure is able to predict realized systemic risk contributions of financial firms during the crisis of 2007-2009.

These results have important consequences for design of future regulation. One, they suggest that systemic risk measures such as ours may be valuable aids to regulators when they "stress test" balance-sheets of individual institutions to adverse macroeconomic and financial conditions. Second, they imply that the extent to which a firm is subject to macro-prudential regulation (say a tax, a capital requirement, or forced debt-for-equity conversion) can be tied to its market-based measures of systemic risk.[5] Employing market-based measures of systemic risk such as ours to guide and aid future regulation may reduce the regulatory (and, unfortunately therefore, discretionary) burden of classifying institutions as more or less systemic.

The remainder of the paper is organized as follows. Section 1 presents a quick review of firm-level risk management. Section 2 lays out a model to define, measure and manage systemic risk. Section 3 discusses measurement issues associated with our systemic risk analysis. Of particular interest, motivation is given for two variables in particular, namely the firm's *MES* and leverage. Section 4 empirically analyzes the implications of our model for systemic risk during the financial crisis of 2007-2009. Section 5 relates our systemic risk measure to existing literature and methodologies. Section 6 concludes.

1 A Review of Firm-level Risk Management

In this section we review the standard risk measures used inside financial firms.[6] This review allows us to define some simple concepts and intuitions that will be useful in our model of systemic risk. Two standard measures of firm level risk are 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 $\alpha = 5\%$, VaR

[5] Recent proposals to contain systemic risk (based among others on Flannery, 2005, Kashyap, Rajan and Stein, 2008, Hart and Zingales, 2009, and Duffie, 2010) suggest requiring firms to issue "contingent capital", which is debt that gets automatically converted to equity when certain firm-level and systemic triggers are hit. Our systemic risk measure corresponds precisely to states in which such triggers will be hit, implying that it should be possible to use our measure to predict which firms are more systemic and therefore will find contingent capital more binding ex post.

[6] See Yamai and Yoshiba (2005) for a fuller discussion.

is the most that the bank loses with 95% confidence. Hence, VaR $= -q_\alpha$, where q_α is the α quantile of the banks return R:

$$q_\alpha = sup \left\{ z | Pr \left[R < r \right] \leq \alpha \right\} \tag{1}$$

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 a quantile:

$$ES_\alpha = -E \left[R | R \leq q_\alpha \right] \tag{2}$$

Said differently, the expected shortfall is the average of returns on days when the portfolio exceeds its VaR limit. We focus on ES because it is coherent and more robust than VaR.[7]

For risk management, transfer pricing, and strategic capital allocation, banks need to break down firm-wide losses into 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:

$$ES_\alpha = -\sum_i y_i E \left[r_i | R \leq q_\alpha \right]. \tag{3}$$

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

$$\frac{\partial ES_\alpha}{\partial y_i} = -E \left[r_i | R \leq q_\alpha \right] \equiv MES_\alpha^i, \tag{4}$$

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.

[7] 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 1% or 5% VaR 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 beyond 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).

These standard risk-management practices can be useful for thinking about systemic risk. A financial system is constituted by a number of banks, just like a bank is constituted by a number of groups. We can therefore 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*. We now present a model where we model explicitly the nature of systemic externalities.

2 Measuring Systemic Risk in an Economic Model

2.1 Banks' Incentives

The economy has N financial firms, which we denote as banks for short, indexed by $i = 1, ..N$ and two time periods $t = 0, 1$. Each bank i chooses how much x_s^i to invest in each of the available assets $s = 1, ..S$, acquiring total assets a^i of

$$a^i = \sum_{s=1}^{S} x_s^i. \tag{5}$$

These investments can be financed with debt or equity. In particular, the owner of any bank i has an initial endowment $\bar{w}_0^i$ of which w_0^i is kept in the bank as equity capital and the rest is consumed or used for other activities. The bank can also raise debt b^i. Naturally the sum of the assets a^i must equal the sum of the liabilities, equity w_0^i and the debt b^i, giving the budget constraint:

$$w_0^i + b^i = a^i. \tag{6}$$

At time 1, asset s pays off r_s^i per dollar invested for bank i (so the net return is $r_s^i - 1$). We allow asset returns to be bank-specific to capture differences in investment opportunities. The total income of the bank at time 1 is $y^i = \hat{y}^i - \phi^i$ where ϕ^i captures the costs of financial distress and y^i is the pre-distress income:

$$\hat{y}^i = \sum_{s=1}^{S} r_s^i x_s^i. \tag{7}$$

The costs of financial distress depend on the income and on the face value f^i of the outstanding debt

$$\phi^i = \Phi\left(\hat{y}^i, f^i\right). \tag{8}$$

Our formulation of distress costs is quite general. Distress costs can occur even if the firm does not actually default. This specification captures debt overhang problems as well as traditional costs of financial distress. We restrict the specification to $\phi \leq \hat{y}$ so that $y \geq 0$.

To capture various types of government guarantees, we assume that a fraction α^i of the debt is implicitly or explicitly guaranteed by the government. The face value of the debt is set so that the debt holders break even, that is,

$$b^i = \alpha^i f^i + \left(1 - \alpha^i\right) E\left[\min\left(f^i, y^i\right)\right]. \tag{9}$$

Although our focus is on systemic risk, we include government debt guarantees because they are economically important and because we want to highlight the different regulatory implications of deposit insurance and systemic risk. The insured debt can be interpreted as deposits, but it can also cover implicit guarantees. Technically, the pricing equation (9) treats the debt as homogeneous ex-ante with a fraction being guaranteed ex-post. This is only for simplicity and all of our results go through if we make the distinction between guaranteed and non-guaranteed debt from an ex-ante standpoint. (In that case, the guaranteed debt that the bank can issue would be priced at face value, while the remaining debt would be priced as above with $\alpha = 0$.)

The net worth of the bank w_1^i at time 1 is

$$w_1^i = \hat{y}^i - \phi^i - f^i \tag{10}$$

The owner of the bank equity is protected by limited liability so it receives $(1 - I_i)\, w_1^i$, where I_i is the indicator of default by bank i:

$$I_i \equiv 1_{\left[w_1^i < 0\right]}. \tag{11}$$

The owner of the bank solves the following program:

$$\max_{w_0^i, b^i, \{x_s^i\}_s} c \cdot \left(\bar{w}_0^i - w_0^i - \tau^i\right) + E\left[u\left((1 - I_i) \cdot w_1^i\right)\right], \tag{12}$$

subject to (6)–(10). Here, $u^i(.)$ is the bank owner's utility of time-1 income, $\bar{w}_0^i - w_0^i - \tau^i$ is the part of the initial endowment $\bar{w}_0^i$ that is consumed immediately (or used for outside activities). The remaining endowment is kept as equity capital w_0^i and or used to pay the bank's tax τ^i, which we describe later. The parameter c has several interpretations. It can simply be seen as a measure of the utility of immediate consumption, but, more broadly, it is the opportunity cost of equity capital. We can think of the owner as raising capital at cost c, or we can think of debt as providing advantages in terms of taxes or incentives to work hard. What really matters for us is that there is an opportunity cost of using capital instead of debt.

2.2 Welfare, Externalities, and the Planner's Problem

The regulator wants to maximize the following welfare function:

$$\sum_{i=1}^{N} c \cdot \left(\bar{w}_0^i - w_0^i - \tau^i\right) + E\left[\sum_{i=1}^{N} u^i\left((1-I_i)\cdot w_1^i\right) + g\sum_{i=1}^{N} I_i \alpha^i w_1^i + e \cdot \bar{I} \cdot \left(z\sum_{i=1}^{N} a^i - \sum_{i=1}^{N} w_1^i\right)\right] \tag{13}$$

This welfare function has three parts:

The first part, $\sum_{i=1}^{N} c \cdot \left(\bar{w}_0^i - w_0^i - \tau^i\right) + E\left[\sum_{i=1}^{N} u^i\left((1-I_i)\cdot w_1^i\right)\right]$, is the sum of the utilities of all the bank owners.

The second part, $E\left[g\sum_{i=1}^{N} I_i \alpha^i w_1^i\right]$, is the expected cost of the debt insurance program. The parameter g captures administrative costs and costs of tax collection. The cost is paid conditional on default by firm i and a fraction α^i of the shortfall is covered.

The third part of the welfare function, $E\left[e \cdot \bar{I} \cdot \left(z\sum_{i=1}^{N} a^i - \sum_{i=1}^{N} w_1^i\right)\right]$, captures the externality of financial crisis and is the main focus of our analysis. The parameter e measures the severity of the externality imposed on the economy when the financial sector is in distress. We define the indicator for the occurrence of systemic distress as capturing an event where the capital in the financial system falls below a fraction z of the aggregate assets:

$$\bar{I} \equiv 1_{\left[\sum_{i=1}^{N} w_1^i < z\sum_{i=1}^{N} a^i\right]}. \tag{14}$$

The critical feature that we want to capture is that of an aggregate threshold for capital needed to avoid early fire sales and restricted credit supply. Our specific formulation is the simplest one that captures this effect. The cost is zero as long as aggregate financial capital is above this threshold and grows linearly when it falls below. The externality depends only on the aggregate shortfall of capital in the financial sector. This is consistent with the emphasis of the stress tests performed by the Federal Reserve in the United States in the Spring of 2009, and it is the crucial difference between systemic and idiosyncratic risk. It means that a bank failure occurring in a well capitalized system imposes no externality on the economy. We believe this captures well the example of Barings Bank, for instance, whose failure in the United Kingdom in 1995 did not disrupt the global (or even the UK's) financial system. The Dutch bank ING purchased Barings and assumed all of its liabilities with minimal government involvement and no commitment of tax payer money. This stands in sharp contrast with the failures of Bear Stearns or Lehman Brothers witnessed in 2008.

The planner's problem is to choose a tax system that maximizes the welfare function (13) subject to the same technological constraints as the private agents. This ex-ante (time 0) regulation is relevant for the systemic risk debate, and this is the one we focus on. We do not allow the planner to redistribute money among the banks at time 1 because we want to focus on how to align ex-ante incentives and because there are clear operational and informational constraints that prevent the government from quickly adjusting the marginal utilities in real time.[8] In doing so, we follow the constrained efficiency analysis performed in the liquidity provision literature. In this literature, the planner is typically restricted to affect only the holding of liquid assets in the initial period (see Lorenzoni, 2008, for instance).

Lastly, we need to account for the taxes that the regulator collects at time 0 and the various costs borne at time 1. Since we focus on the financial sector and do not model the rest of the economy, we simply impose that the aggregate taxes paid by banks at time 0 add

[8]There would be three reasons for the planner to redistribute money ex post: differences in utility functions, differences in investment opportunities, and the presence of financial distress costs.

up to a constant:

$$\sum_i \tau^i = \bar{\tau}. \tag{15}$$

There are several interpretations for this equation. One is that the government charges ex-ante for the expected cost of the debt insurance program. We can also add the expected cost of the externality. At time 1, the government would simply balance its budget in each state of the world with lump-sum taxes on the non-financial sector. We can also think of equation (15) as part of a larger maximization program, where a planner would maximize utility of bank owners and other agents. This complete program would pin down $\bar{\tau}$, and we could then think of our program as solving the problem of a financial regulator for any given level of transfer between the banks and the rest of the economy.

2.3 Optimal taxation

Our optimal taxation policy has close parallels to the notion of "marginal expected shortfall" (*MES*) used to manage risk inside banks as explained carefully in Section 1. In acknowledgment of this connection, we define the default expected shortfall (DES) as the expected loss in bankruptcy for firm i:

$$DES^i \equiv -E\left[I_i \cdot w_1^i\right] \tag{16}$$

Further, we define bank i's systemic expected shortfall (*SES*) as it is the amount its equity w_1^i drops below its target level, which is a fraction z of assets a^i in case of a systemic crisis:

$$SES^i \equiv E\left[\bar{I} \cdot (za^i - w_1^i)\right] \tag{17}$$

The *SES* is the key measure of each bank's expected contribution to a systemic crisis.

Using these two functions we can characterize a tax system that would implement the optimal allocation. The regulator's problem is to choose the tax scheme τ such as to mitigate systemic risk and inefficient effects of debt guarantees. The timing of the implementation is that the banks choose their leverage and asset allocations and then pay the taxes. The taxes are therefore conditional on choices made by the banks.

Proposition 1 *The efficient outcome is obtained by a tax*

$$\tau^i = \frac{\alpha^i g}{c} \cdot DES^i + \frac{e}{c} \cdot SES^i + \tau_0, \tag{18}$$

where τ_0 is a lump sum transfer to satisfy equation (15).

Proof. Using the definition of τ^i in equation (18), the bank's problem is

$$\max_{w_0^i, b^i, \{x_s^i\}_s} c \cdot \left(\bar{w}_0^i - w_0^i - \tau_0\right) + E\left[u\left((1 - I_i) \cdot w_1^i\right)\right] - \alpha^i g \cdot DES^i - e \cdot SES^i,$$

and using (16) and (17), this becomes

$$\max_{w_0^i, b^i, \{x_s^i\}_s} c \cdot \left(\bar{w}_0^i - w_0^i - \tau_0\right) + E\left[u\left((1 - I_i) \cdot w_1^i\right) + e\bar{I}(za^i - w_1^i) + \alpha^i g I_i w_1^i\right].$$

The set of programs for $i = 1, ..., N$ is equivalent to the planer's program and the budget constraint can be adjusted ed with τ_0. ■

This result is intuitive. Each bank must first be taxed based on its expected losses in default *DES* to the extent that those losses are insured by the government, where recall that α^i is the fraction of insured debt. The tax should be lower if raising bank capital is expensive ($c > 1$) and higher the more costly is government funding (g); A natural case is simply to think of $g/c = 1$ so that this part of the tax is simply an actuarially fair deposit-insurance tax.[9] Hence, this term in equation (18) corrects the underpricing of credit risk caused by the debt insurance program. We can write it as

$$DES^i = \Pr\left(I_i\right) \cdot E\left[-w_1^i \mid I_i\right]. \tag{19}$$

DES is therefore the probability of default times the shortfall of net worth given default. The relevant point is that it is a measure of a bank's own risk, irrespective of its relation to the system. In practice, the calculation of the expected shortfall is similar to a standard Value-at-Risk calculation.

[9]Note that it is important for incentive purposes to keep charging this tax even if the deposit insurance reserve fund collected over time has happened to become over funded (in contrast to the current premium schedules of the Federal Deposit Insurance Corporation in the United States).

The second part of the tax in (18) depends on the bank's contribution to systemic risk as captured by *SES*, scaled by the severity e of the externality and scaled down by the bank's cost of capital c. This forces the private banks to internalize the externality from aggregate financial distress. We can write it as

$$SES^i = \Pr\left(\bar{I}\right) \cdot E\left[(za^i - w_1^i) \mid \bar{I}\right]. \tag{20}$$

SES is therefore the probability of an aggregate crisis times the conditional loss of firm i in such a crisis. The important point is that the expectation is conditional on a macroeconomic shortfall. This calculation is similar to that of marginal risk within financial firms. In marginal risk calculation, the risk managers ask how much a particular line of business is expected to lose on days where the firms hits its VaR constraint. Our formula applies this idea to the economy or the financial sector as a whole.

The optimal tax system holds for all kinds of financial distress costs and the planner reduces its taxes when capital is costly at time 0 (c is high). The fact that we obtain an expected shortfall measure comes from the shape of the externality function. It is important to understand the information required to implement the systemic regulation. The planner does not need to know the utility functions and investment opportunity sets of the various banks. It needs to estimate two objects: the probability of an aggregate crisis, and the conditional loss of capital of a particular firm if a crisis occurs. In practice, the planner may not be able to observe or measure these precisely. Our empirical work to follow makes a start in estimating one of the two objects, the conditional capital loss of a firm in a crisis, using market based data.

3 Measuring Systemic Risk

The optimal policy developed in Section 2 calls for a fee (i.e., a tax) equal to the sum of two components: (i) an *institution-risk* component, i.e., the expected loss on its guaranteed liabilities, and (ii) a *systemic-risk* component, namely, the expected systemic costs in a crisis (i.e., when the financial sector becomes undercapitalized) times the financial institution's percentage contribution to this under-capitalization. Some comments are in order.

There is much discussion amongst regulators, policymakers and academics of the need for a resolution fund that would be used to bailout large, complex financial institutions. This fund would be paid for by the institutions themselves and is akin to the FDIC. This resolution fund is essentially the institution-risk component of the above tax and reflects the optimal policy that government guarantees in the system (e.g., deposit insurance and too-big-to-fail) need to be priced. It does not, however, address the systemic risk of the financial firms as there is no differentiation between different economic states. Specifically, the costs associated with financial firm failures are significantly higher in a crisis.[10] The systemic-risk component of the tax deals with this particular issue.

3.1 Measuring Systemic Risk: Intuition

A large focus of regulators and policymakers on managing systemic risk has been on the size of financial institution's assets and/or liabilities. The theory described in Section II gives some support for this approach. Almost trivially, ceteris paribus, the expected losses of a financial firm conditional on a crisis are tied one-for-one to the size of the firm's assets.[11] Of course, even though a firm that doubles its size would pay, to a first approximation, twice the systemic tax, the firm would also have twice the cash flow to cover the tax. Therefore, from an economic point of view, the interesting question is what variables help explain the % expected losses (as opposed to $ losses).

[10]There is growing evidence on the large bailout costs and real economy welfare losses associated with banking crises (see, for example, Caprio and Klingebiel (1996), Honohan and Klingebiel (2000), Hoggarth, Reis and Saporta (2002), Reinhart and Rogoff (2008), and Borio and Drehmann (2009)). The bottom line from these studies is that these crises represent significant portions of GDP, on the order of 10%-20%.

[11]In fact, Appendix B of the paper provides the % contribution of each firm's $ *MES* across the 102 largest financial firms (i.e., firms with over $5 billion of market equity). The top 6 in terms of contribution (Citigroup (4.87%), JP Morgan (3.60%), Bank of America (3.54%), Morgan Stanley (2.51%), Goldman Sachs (2.41%) and Merrill Lynch (2.25%)) are also in the top 7 in terms of total number of assets.

Our theory says that the regulation of systemic risk should be based on *SES*. Equation (20) shows that there are two main pieces to estimate. The first is the probability $Pr\left(\bar{I}\right)$ of a systemic event. The unconditional risk of a systemic event can be measured using historical research as in Reinhart and Rogoff (2008) who show that there are consistent leading indicators of banking crises (some sort of asset price bubble, a corresponding credit boom, and large capital inflows into the economy). The conditional risk of a systemic event can be inferred from dynamic long-run volatility models (Engle, 2009).

We focus in our empirical analysis on the cross-sectional part. To control for each bank's size, we scale by initial equity w_0^i, which gives the following cross-sectional variation in systemic risk *SES*:

$$\frac{SES^i}{w_0^i \Pr\left(\bar{I}\right)} = \frac{za^i}{w_0^i} - 1 - E\left[\frac{w_1^i}{w_0^i} - 1 \mid \bar{I}\right].$$

The first part, $\frac{za^i}{w_0^i} - 1$, measures whether the leverage $\frac{a^i}{w_0^i}$ is initially already "too high". Specifically, since systemic crises happen when aggregate bank capital falls below z times assets, z times leverage should be less than 1. Hence, a positive value of $\frac{za^i}{w_0^i} - 1$ means that the bank is already under-capitalized at time 0.[12] The second term is the expected equity return conditional on the occurrence of a crisis. Hence, the sum of these two terms determine whether the bank will be under-capitalized in a crisis.

In practice, the planner needs to estimate the conditional expected losses before a crisis occurs. Our theory says that the regulator should use any variable that can predict capital shortfall in a crisis. In order to improve our economic intuition and to impose discipline on our empirical analysis, it is important to have a theoretical understanding of the variables that are likely to be useful for these predictions. So we want to relate *SES* to observed equity returns. Next, we explain how.

We can think of the $\bar{I}$ events in our model as extreme tail events happening once a decade or less (in the US at least). In the meantime, we observe "normal" tail events. Let us define these events as the worst 5% market outcomes at daily frequency which we denote by $I_{5\%}$.

[12] We can think of z as being in the range of 8% to 12% if all assets have risk-weighting of close to 100% under Basel I capital requirements.

Based on these events, we can define a marginal expected shortfall (*MES*) using net equity returns of firm i during these bad markets outcomes

$$MES^i_{5\%} \equiv -E\left[\frac{w^i_1}{w^i_0} - 1 \mid I_{5\%}\right].$$

We measure *MES* using a sample of negative market returns, but typically without observing a default so we can think of equity value as being always positive in the sample of $I_{5\%}$ events.

We now state our assumption regarding the tail behavior of asset returns.[13] We assume that returns follow

$$r^i_s = \eta^i_s - \delta_{i,s}\epsilon^i_s - \beta_{i,s}\epsilon_m,$$

where η^i_s follows a thin-tailed distribution (Gaussian, for instance) while ϵ^i_s and ϵ_m follow independent normalized power law distributions with tail exponent ζ. Power laws dominate in the tail so we have the following simple properties (Gabaix, 2009). First, the VaR of r^i_s at level q is $VaR\left(r^i_s; q\right) = \left(\delta^{\zeta}_{i,s} + \beta^{\zeta}_{i,s}\right)^{1/\zeta} q^{-1/\zeta}$, and the corresponding Expected Shortfall is $ES\left(r^i_s; q\right) = \frac{\zeta}{\zeta-1} VaR\left(r^i_s; q\right)$. Second, since the shock ϵ_m is the source of systemic risk, the events $I^{\%}$ and $\bar{I}$ correspond to critical values $\epsilon^{\%}_m$ and $\bar{\epsilon}_m$ respectively. Note that there is a direct link between the likelihood of an event and its tail size, since we have $\frac{\bar{\epsilon}_m}{\epsilon^{\%}_m} = \left(\frac{\Pr(I_{5\%})}{\Pr(\bar{I})}\right)^{1/\zeta}$. Using the power laws, we obtain the following proposition.

Proposition 2 *The systemic expected shortfall is related to the marginal expected shortfall according to*

$$\frac{SES^i}{\Pr\left(\bar{I}\right) w^i_0} = \frac{za^i}{w^i_0} - 1 + k \times MES^i_{5\%} + \Delta^i \tag{21}$$

where $k \equiv \frac{\bar{\epsilon}_m}{\epsilon^{\%}_m}$ *and* $\Delta^i \equiv \frac{E\left[\phi^i|\bar{I}\right] - k \cdot E\left[\phi^i|I_{5\%}\right]}{w^i_0} - (k-1)\frac{f^i - b^i}{w^i_0}$.

[13] Note that if we assume returns are multivariate normal, then the drivers of the firm's % systemic risk would be entirely determined by the expected return and volatility of the aggregate sector return and firm's return, and their correlation. However, there is growing consensus that the tails of return distributions are not described by multivariate normal processes and much more suited to that of extreme value theory (e.g., see Barro (2006), Backus, Chernov and Martin (2009), Gabaix (2009) and Kelly (2009)). Our discussion helps clarify what variables are needed to measure systemic risk in the presence of extreme values.

Proof. Equity returns are given by $\frac{w_1^i}{w_0^i}-1=\frac{\sum_{s=1}^{S}r_s^i x_s^i-\phi^i-f^i}{w_0^i}-1$. This allows us to write

$$MES_{5\%}^i=\sum_{s=1}^{S}\frac{x_s^i}{w_0^i}E\left[-r_s^i\mid I_{5\%}\right]+\frac{E\left[\phi^i\mid I_{5\%}\right]}{w_0^i}+\frac{f^i-b^i}{w_0^i}$$

In expectations we have $E\left[-r_s^i\mid I_{5\%}\right]=\beta_{i,s}\frac{\zeta}{\zeta-1}\epsilon_m^{\%}$ and therefore $E\left[-r_s^i\mid \bar{I}\right]=kE\left[-r_s^i\mid I_{5\%}\right]$. Using the definition of SES we can write

$$1+\frac{SES^i}{w_0\Pr\left(\bar{I}\right)}=\frac{za^i}{w_0^i}-E\left[\frac{w_1^i}{w_0^i}-1\mid \bar{I}\right]=\frac{za^i}{w_0^i}+\sum_{s=1}^{S}\frac{x_s^i}{w_0}E\left[-r_s^i\mid \bar{I}\right]+\frac{E\left[\phi^i\mid \bar{I}\right]}{w_0}+\frac{f^i-b^i}{w_0}$$

Under the power law assumption

$$1+\frac{SES^i}{w_0\Pr\left(\bar{I}\right)}-k\cdot MES^i=\frac{za^i}{w_0^i}+\frac{E\left[\phi^i\mid \bar{I}\right]-k\cdot E\left[\phi^i\mid I_{5\%}\right]}{w_0}+\left(1-k\right)\frac{f^i-b^i}{w_0^i}.$$

■

We see therefore that SES has three components: Excess ex ante leverage $\frac{za^i}{w_0^i}-1$, the measured marginal expected shortfall MES using pre-crisis data, scaled up by k to account for the worse performance in the true crisis, and Δ^i which comes from two sources. One source due to the term (f^i-b^i) measures the excess returns on bonds due to credit risk. This difference is fixed and does not scale up so by multiplying MES by k we would overestimate SES by $(k-1)$ times the fixed payments.

The second source due to the term $E\left[\phi^i\mid \bar{I}\right]-k\cdot E\left[\phi^i\mid I_{5\%}\right]$ measures the excess costs of financial distress. It is potentially more significant because we do not expect these costs to scale up with k as returns do. In practice, our estimation sample contains bad market days, but no real crisis. In these "normal" bad days we do not expect to pick up significant costs of distress. In other words, we are likely to measure $E\left[\phi^i\mid I_{5\%}\right]\approx 0$. On the other hand, we definitely expect $E\left[\phi^i\mid \bar{I}\right]$ to be significant, especially for highly levered firms. We therefore expect MES to underestimate SES for highly levered firms. In essence, our formula (21) assumes that the $I_{5\%}$ events capture the power law that dominates tail risk. This is probably a fair assumption in commercial and investment banking. On the other hand, there could be a more significant bias in industries such as insurance where the industry leaders were all rated AAA before the crisis and distress or tail risk can only be seen in the most extreme events.[14] Also in these cases, equity market data may be somewhat less suitable or adequate compared to cds market data: By construction, cds fee is (approximately) the price of a tail risk event, namely the firm's default, and hence conveys more direct information about tail risk of the underlying firm than the firm's equity price does. Our empirical analysis to follow will employ both equity and cds data.

4 Empirical Analysis of the Crisis of 2007-2009

To start with, we empirically estimate *MES* 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. Even though these days clearly do not capture the tails of a financial crisis, we motivate its use via our power law analysis in Section 3.1.

With respect to leverage, as shown by the current financial crisis, it is not straightforward to measure true leverage due to limited and infrequent market data, especially on the breakdown of off- and on-balance sheet financing. Nevertheless, we apply the usual approach to measuring leverage. Specifically, 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. A sample calculation here would be useful. As presented in Appendix B, in June

[14]Another way of saying this is that firms that are in the business of writing insurance against tail risks are less amenable to measurement of systemic risk using their normal time market data. Examples of such insurance are selling of deep out-of-the-money put options on the market, credit default swaps on portfolios of loans and mortgages (as were sold by A.I.G.), or liquidity puts to conduits (as was the case with Citigroup, documented by Acharya, Schnabl and Suarez, 2009). Acharya, Cooley, Richardson and Walter (2010) propose that "manufacturing tail risk" in this manner might have become the evolving business model of banking during 2004-2007 precisely to game the regulatory structure centered on measuring individual bank risks.

2007, the *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.

Then, we investigate three examples of emerging systemic risk in the financial crisis and analyze the ability of the theoretically motivated measures to capture this risk. Specifically, we look at the relation between our measures and (i) capital shortfalls at large financial institutions estimated via stress tests performed by bank regulators during the Spring of 2009, (ii) realized systemic risk that emerged in the equity of large financial firms from July 2007 through the end of 2008, and (ii) realized systemic risk that emerged in the credit default swaps (cds) of large financial firms from July 2007 through the end of 2008.

In brief summary, across all three examples, the results are consistent with implications of the theory. In particular, simple measures of systemic risk implied by the theory have useful information for which firms ran aground during the financial crisis.

4.1 The Supervisory Capital Assessment Program

At the peak of the financial crisis, in late February 2009, the government announced a series of stress tests were to be performed on the 19 largest banks over a two-month period. In particular, known as the Supervisory Capital Assessment Program (SCAP), the Federal Reserve's goal was to provide a consistent assessment of the capital held by these banks. The question asked on each bank was how much of an additional capital buffer, if any, each bank would need to make sure it had sufficient capital if the economy got worse and the financial crisis started up again.

In early May of 2009, the results of the analysis were released to the public at large. A total of 10 banks were required to raise $74.6 billion in capital. The SCAP was generally considered to be a credible test with bank examiners imposing severe loss estimates on residential mortgages and other consumer loans, not seen since the Great Depression.

The SCAP is an especially useful period to analyze to gauge the systemic risk measures described in this paper. The SCAP can be considered as close as possible to an *ex ante* estimate of expected losses of different financial firms in a financial crisis. The regulators spent two months examining the portfolios and financing of the largest banks with a particular emphasis on creating consistent valuations across these banks. Table 1 provides a summary of each bank, including its shortfall (if any) from the SCAP at the end of April 2009, its Tier 1 capital (so called core capital including common shares, preferred shares, and deferred tax assets), its tangible common equity (just its common shares), its measured *MES* (from April 2008 to March 2009) and its quasi market leverage. Five banks, as a percent of their Tier 1 capital, had considerable shortfalls, namely Regions Financial (20.66%), Bank of America (19.57%), Wells Fargo (15.86%), Keycorp (15.52%) and Suntrust Banks (12.50%).[15]

The question is how well do the systemic risk measures capture the SCAP estimates of systemic losses across these 18 firms?[16] Table 2 provides an OLS regression analysis of explaining SCAP shortfall as a percent of Tier 1 capital (panel A) and Tier 1 common or tangible common equity (panel B) with *MES* and leverage as the regressors. Because a number of firms have no shortfall, and thus there is a mass of observations at zero, we also extend the OLS regressions to a Probit analysis (which is identical for both panels and hence is shown only in Panel A).

MES is strongly significant in both the OLS and Probit regressions. For example, in the OLS regressions on *MES* of SCAP shortfall relative to Tier 1 capital and tangible common equity respectively, the t-statistics are 3.00 and 3.12 with adjusted R-squareds of 32.03% and 33.19%. When leverage is added, the adjusted R-squareds either drop or are marginally larger. The (pseudo) R-squareds jump considerably for the Probit regressions, with the SCAP shortfall by Tier 1 capital regressions reaching 40.68% and, with leverage included,

[15]The interested reader might be surprised to see that, although it required additional capital, Citigroup was not one of the leading firms. It should be pointed out, however, that towards the end of 2008 Citigroup received $301 billion of federal asset guarantees on their portfolio of troubled assets. Conversations with the Federal Reserve confirm that these guarantees were treated as such for application of the stress test. JP Morgan and Bank of America also received guarantees (albeit in smaller amounts) through their purchase of Bear Stearns and Merrill Lynch, respectively.

[16]SCAP exercise also included GMAC but it only had preferred stock trading over the period analyzed.

53.22%. The important point is that the systemic risk measures seem to capture quite well the SCAP estimates of % expected losses in a crisis.

As an additional analysis, the same regressions were run using *MES* and leverage measured prior to the failure of Lehman Brothers in mid September 2008, in other words, using information from October 2007 to September 2008. While the results are in general agreement with the earlier ones, in particular *MES* is statistically significant, the adjusted R-squareds drop considerably for both measures of capital and for both the OLS and Probit Regressions with a range of 11% to 18%. Of course, the Federal Reserve's SCAP results would also have been considerably different prior to Lehman Brother's failure.

4.2 The Financial Crisis: July 2007 to December 2008

Next, we 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 *MES* and leverage 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). While analyzing the performance of *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), our preferred measure over value at risk for a firm's own tail risk, 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 our *systemic* risk measure and *Beta* arises from the fact that systemic risk is based on tail dependence rather than average covariance. We want to compare these ex ante risk measures to the *realized SES*, that is, the ex-post return of financial firms during the period July 2007-Dec 2008.

Table 3 describes the summary statistics of all these risk measures, where Panel A reports the univariate statistics and Panel B the pair-wise correlations. The *realized SES* in Panel A illustrates how stressful this period was 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 average beta is 1.0. The power law application in Section 3.1 suggests that an important component of systemic risk is *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. All these measures however exhibit substantial cross-sectional variability, which we attempt to explain later.

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*). Naturally, the realized returns during the crisis (*realized SES*) are negatively correlated to the risk measures and, interestingly, *realized SES* is most correlated with *LVG*, *Log-Assets* and *MES*, in that order.

We also 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. [17]

Panel C 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 in theory combined into our estimate of systemic risk measure, in terms of *realized SES*, insurance firms are overall the least systemically risky, next were 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.

Table 4 and Figures 2 and 3 show the power of *MES* and leverage in explaining the realized performance of financial firms during the crisis. In particular, Table 4 contains cross-sectional regressions of realized returns during July 2007-Dec 2008 on the pre-crisis measures of risk, *ES*, *Vol*, *MES*, *Beta*, *LVG*, and *Log Assets*, respectively, and Figures 2 and 3 show the corresponding scatter plots. (We also note that Appendix B provides the firm-level data on *MES* and *LVG*.)

Figure 2 shows that *MES* does a reasonably good job of explaining the realized returns (R^2 of 6.72%), and naturally a higher *MES* is associated with a more negative return during

[17] 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.

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. Figure 3 shows that leverage does even better at explaining the realized returns (R^2 of 24.27%), and the combination of *MES* and *LVG* shows an even better fit:

$$\begin{aligned} Realized\,return &= 0.02 - 0.12\ [1_{Other}] - 0.01\ [1_{Insurance}] \\ &\quad + 0.16\ [1_{broker-dealer}] - 0.15\ MES - 0.04 \end{aligned} \tag{22}$$

with an R^2 =27.34%. Thus combining *MES* and leverage of financial firms helps understanding their systemic risk better.

In this light, 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* and leverage rankings, but this stability across measures is not a property of all other firms. For example, Countrywide is ranked 24^{th} by *MES* given its *MES* of 2.09%, but given its high leverage of 10.39 has a combined ranking of 6^{th} using equation 22 (labeled in Appendix B as "Fitted Rank"). Similarly, Freddie Mac is ranked 61^{st} by its *MES* but given its high leverage of 21 (comparable to that of investment banks), it ranks 2^{nd}, in terms of its combined ranking. On the flip side, CB Richard Ellis, a real-estate firm, has 5^{th} rank in *MES* but given low leverage of 1.55 ranks only 24^{th} in terms of combined ranking. Investment banks, Countrywide and Freddie all collapsed or nearly collapsed, whereas CB Richard Ellis survived, highlighting the importance of the leverage correction in systemic risk measurement.

In contrast to the statistically significant role of *MES* in explaining cross-sectional returns, traditional risk measures *Beta* and *ES* do not perform that well. The R^2 with *Beta* is just 3.62% and that with *ES* is basically 0.0%. These results are also summarized in Table 4 which has three additional results. First, 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. Second, in the regressions that include *LVG* and *MES* together, institutional characteristics no longer show up as significant. This suggests that the systemic risk measures do a fairly good job of capturing, for example, the risk of broker dealers. Third, column (8), however, shows that the log of assets comes in quite strong with an R^2 around 18.5%. While its significance drops substantially once leverage is included, it still shows up in the regression analysis. The negative sign on log of assets suggests that size not only affects the $ systemic risk contribution of financial firms but also the % systemic risk contribution as well. In particular, large firms create more systemic risk than a likewise combination of smaller firms.

We now consider several robustness checks. Figure 4 graphs a scatter plot of the *MES* computed during June 2006-June 2007 versus that computed during June 2005-2006. Even though there is no overlap between the return series, the plot generally shows a fair amount of stability from year to year with this particular systemic risk measure. Wide time-series variation in relative *MES* would make the optimal policy more difficult to implement. It is of interest therefore to examine how early *MES* and *LVG* predict the cross-section of realized returns during the crisis. 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 and Mar 06-Feb 07. 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.

In contrast with Figure 4, Panel A of Table 5 shows that the predictive power of *MES* progressively declines as we use lagged data for computing the measure. The overall predictive power, however, remains high as leverage has certain persistent, cross-sectional characteristics across financial firms. The coefficients on *LVG* remain unchanged throughout these periods. To better understand the *MES* decline, we repeat the Panel A regressions using two alternative measures of *MES*: (i) *W-MES*, a weighted *MES*, which uses exponentially declining weights ($\lambda = 0.94$ following the Risk Metrics parameter) on past observations to estimate the average equity returns on the 5% worst days of the market, and (ii) *D-MES*, a dynamic approach to estimating *MES*, which uses a dynamic conditional correlation (DCC) model with fat idiosyncratic tails.[18] Panel B and Panel C provide the results for *W-MES* and *D-MES*, respectively. The adjusted R^2s are generally higher and the alternative measures of *MES* better hold their predictive power even with lagged measurement. For example, the coefficients are still strongly significant using the April06-Mar07 data, with the t-statistics and R^2s equal to (-1.24, -2.94, -2.36) and (22.61%, 27.76%, 24.58%) respectively for *MES*, *W-MES* and *D-MES*. These results suggest there is some value to exploring more sophisticated methods for estimating *MES* and by and large also to including the most recent data in estimates.

4.3 Using CDS to Measure Systemic Risk

Section 4.2 above illustrated the ability of the *MES* and leverage of financial firms to forecast the equity performance of the 102 largest financial firms during the financial crisis period of July 2007 to December 2008. In this subsection, we add to this evidence by focusing on the credit default swaps (cds) of these financial firms. Of the 102 financial firms, 40 of them have enough unsecured long-term debt to warrant the existence of cds in the credit derivatives market. Appendix C provides a list of the 40 firms and their type of institution.

A few important issues arise using cds data. The first question arises how to operationalize the cds data for calculating *MES*. The cds premium resembles the spread between risky

[18]We are grateful to Christian Brownlees and Robert Engle of New York University Stern School of Business for sharing with us their dynamic measures of *MES* for our sample firms.

and riskless floating rate debt, denote this spread as s. To garner some intuition, note that $dP/P = -Dds$ and $dP/P = \xi dV/V$, where P is the bond price, V the value of the firm's assets, ξ is the elasticity of the bond price to firm value, and D is the bond's duration. Combining the two relationships, we obtain that $ds = -\xi/DdV/V$. Ignoring the duration term changes across firms/days means that measuring the firm's losses, i.e., dV/V, using the spread change ds is proportional to its bond elasticity ξ. Since we know that ξ is approximately 0 when the bond is close to risk-free and approximately 1 when the bond is virtually in default, ds attaches close to zero weight to dV/V for safe firms (when leverage is very low) and high weight (equal to 1/D) to dV/V for very risky firms (when leverage is very high). Therefore, a better measure of firm value changes is $ds/s = -\xi/(Ds)dV/V$, where s is tiny when eta is close to zero and s is large when eta is close to one.

In terms of the *cds MES*, therefore, we empirically estimate *MES* at a standard risk level of 5% using daily data of cds returns, ds/s, from the data provider Bloomberg.[19] This means that we take the 5% worst days for an equally-weighted portfolio of cds returns on the 40 financial firms from June 2006 to July 2007, and we then compute the cds return for any given firm for these days.[20] Appendix C shows stylized facts about their *MES* based on the cds market, including ranking, *MES*%, and realized CDS spread returns during the crisis period. Consider the top three financial institutions in terms of highest *cds MES* in each institutional category:

- The three insurance companies are Genworth Financial (16.40%), Ambac Financial (8.05%) and MBIA (6.71%). All of these companies were heavily involved in providing financial guaranties for structured products in the credit derivatives area.

- The top three depository institutions are Wachovia (7.21%), Citigroup (6.80%) and Washington Mutual (6.15%). These institutions are generally considered to ex post have been most exposed to the nonprime mortgage area, with two of them, Wachovia

[19]Our results are robust to the sample of firms for which data are available from Markit, and the overlapping sample of firms between Bloomberg and Markit.

[20]For comparison purposes, we also use changes in the cds spread as a measure of cds return.

and Washington Mutual, actually failing.

- The top three broker dealers are Merrill Lynch (6.3%), Lehman Brothers (5.44%) and Morgan Stanley (4.86%). Two of these three institutions effectively failed.[21]

- The top three others, SLM Corp (6.82%), CIT Group (6.80%) and Fannie Mae (5.70%), also ran into trouble due to their exposure to credit markets, with CIT going bankrupt and Fannie Mae being put into conservatorship.

Even putting these results aside, the second issue is that cds may not reflect predicted losses of the financial firm to the extent some firms have more government guarantees as part of their capital structure, such as deposit institutions, the government sponsored enterprises and so-called too-big-to-fail firms.[22] Since cds reflect estimated creditor losses, the backstop will lead to pricing distortions cross-sectionally. As a result, in terms of systemic risk, we analyze the ability of *cds MES* to forecast systemic risk in both the July 2007 to December 2008, and the July 2007 to June 2008 period (i.e., prior to many government guarantees being made explicit). To further address this issue, we also investigate the ability of *cds MES* to forecast not only future CDS returns, but also equity returns.

Figures 5-8 respectively show scatter plots of *cds MES* on realized CDS returns in the July 2007-June 2008 and July 2007-December 2008 period, and on realized equity returns in the same two periods. These results are also strongly supportive of the ability of *cds MES* to forecast future changes in firm value during a financial crisis, whether estimated by cds or equity returns. To the point above (concerning the confounding effect of government bailouts), the slope line is slightly flatter (steeper) for cds (equity) returns in the December 2008 end of sample period versus the June 2008 period. Since the crisis got considerably

[21] We note here that if Bear Stearns cds return were measured until the point of its arranged merger with J P Morgan in mid-March 2008, its realized cds return would be higher than having measured it till dates thereafter.

[22] Equity also suffers from this problem to the extent government guarantees delay bankruptcy and thus extend the option of the firm to continue. It is more likely a second order effect, however, compared to the pricing of the underlying debt of financial firms in distress.

worse during the latter 6 months of 2008, this finding is consistent with the government making a number of guarantees explicit (e..g, the government sponsored enterprises, A.I.G., and in general the capital assistance programs related to TARP).

Table 6 provides summary statistics for *cds MES* (measured using log return or arithmetic difference) and the realized returns (*realized SES*) using cds or equity returns and over the two different time periods (July 2007-June 2008 and July 2007-December 2008). Raw correlations capture the same effect as in Figures 5-8 that *cds MES* are well correlated with realized returns, for both cds and equity markets. It is to be noted that given the pre-July 2007 credit conditions, *cds MES* is rather low on average and also small in its variation across firms, whereas the realized cds and equity returns during the crisis are high and highly variable. The correlation of *cds MES* with realized returns is thus especially noteworthy.

For a more formal analysis, Table 7 provides regressions with regressors being *cds MES* based on cds returns (Panel A) or cds spread changes (Panel B) and dependent variable being the realized cds returns during different periods covering the crisis (July 2007-June 2008 / September 14, 2008 / September 30, 2008 / 0ctober 10, 2008 / December 30, 2008) related to government action on creditor guarantees. Several observations are in order. First, putting aside the date of TARP capital assistance in October, the R^2s are between 17.86% to 19.94%. Second, in terms of *cds MES* versus leverage, *cds MES* is generally the more significant variable. Because cds reflects the claim on the underlying debt, this is consistent with *cds MES* capturing more of the tail behavior and thus being less reliant on the leverage arguments provided in Section 3.1. Third, there are substantive drops in explanatory power when cds spread changes are used instead of cds returns. This is consistent with the aforementioned argument on the need to be careful with respect to operationalizing *cds MES*.

As final evidence, Table 8 provides formal statistics for regressions of both *cds MES* based on cds returns (Panel A) or cds spread changes (Panel B) on realized equity returns during the same periods as Table 7. The results are quite strong with both *cds MES* and leverage coming in at very high significant levels with adjusted R^2s of 50% or higher using cds returns (and 30% plus using cds spread changes). The important point is that the systemic risk measures prior to the crisis have important information for which firms might run into trouble, and, therefore, by inference should, according to the optimal policy, be taxed to induce them to reduce their systemic risk. While *cds MES* seems especially useful prior to the start of the crisis, it is an open question that this will continue in the future with all the government guarantees now in place.

5 Related Literature on Measuring Systemic Risk

A number of recent papers have derived measures of systemic risk, some 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. Consistent with the intuition provided in Section 2, 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 shown in Section 2 and argued in Section 3.1 above, the key variable must be 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 creditors 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.

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. Acharya and Yorulmazer (2007) and Farhi and Tirole (2009) model collective moral hazard and systemic bailouts providing a rationale for optimal regulation being tied to systemic risk contributions of firms. 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.

Compared to these papers, our contribution is to build an explicit 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, as we illustrated for the financial crisis of 2007-2009.

6 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. 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 systematic risk.

In this paper, we argued 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. We provided a simple and intuitive way to measure each bank's contribution to systemic risk, suggesting ways to limit it. In a variety of tests (stress test outcomes of 2009 and performance during 2007-08) and markets (equity and cds), our systemic risk measures appeared to be able to predict financial firms with the worst contributions in a systemic crisis.

Several extensions of our work are worthy of pursuit in future. While we estimated and tested our proposed systemic risk measure using equity and cds data, another way to obtain such information is through prices of out-of-the-money equity options and insurances against losses of individual firms when the system as a whole is in stress[23] While such insurances are not yet traded, data on firm equity options as well as market options is available and can be used to construct measures of tail dependence such as the *MES*.

Finally, we investigated the role of leverage (measured as assets to common equity ratio) in determining systemic risk of firms. The form of leverage that however had the most pernicious effect in the crisis of 2007-09 was short-term debt: the overnight secured borrowing ("repo") against risky assets (Adrian and Shin, 2008) employed heavily by the investment banks, and the short-term (overnight to week maturity) asset-backed commercial paper issued by conduits that were backed by commercial banks (Acharya, Schnabl and Suarez, 2009). In contrast, even though deposits are in principle demandable and thus short-term too, the presence of deposit insurance meant that commercial banks with access to insured deposits were in fact relatively stable in the crisis. It seems important to empirically understand how short-term leverage contributes to market-based measures of systemic risk of

[23]Acharya, Pedersen, Philippon and Richardson (2009, 2010) propose regulation of systemic risk based on mandatory purchase of such insurances by financial firms, partly from private sources (insurance companies) and rest from a systemic risk regulator.

financial firms.

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Table 1: Banks Included in the Stress Test, Descriptive Statistics.

Panel A of this table contains the values of SCAP shortfall, Tier1 capital, Tier1 Comm (tangible common equity), all in USD Billion; and, SCAP Shortfall/Tier1, SCAP Shortfall/Tier1 Comm, MES and LVG for the 18 banks who underwent stress testing. MES is the marginal expected shortfall of a stock given that the *market return* is below its 5^{th}-percentile. Leverage (LVG) 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 equity + market value of equity. All stock market data are from Datastream and book value of equity is from the merged CRSP-Compustat database. MES was measured for each individual company's stock using the period April 2008 till March 2009 and the S&P 500 as the market portfolio. LVG is as of first quarter 2009.

Panel B shows the correlation between SCAP Shortfall/Tier1, SCAP Shortfall/Tier1 Comm, MES and LVG.

Panel A

Bank Name	SCAP	Tier1	Tier1Comm	SCAP/Tier1	SCAP/Tier1Comm	MES	LVG
REGIONS FINANCIAL CORP NEW	2.5	12.1	7.6	20.66%	32.89%	14.8	44.42
BANK OF AMERICA CORP	33.9	173.2	75	19.57%	45.50%	15.05	50.38
WELLS FARGO & CO NEW	13.7	86.4	34	15.86%	40.41%	10.57	20.58
KEYCORP NEW	1.8	11.6	6	15.52%	30.00%	15.44	24.36
SUNTRUST BANKS INC	2.2	17.6	9.4	12.50%	23.40%	12.91	39.85
FIFTH THIRD BANCORP	1.1	11.9	4.9	9.24%	22.45%	14.39	67.16
CITIGROUP INC	5.5	118.8	23	4.63%	24.02%	14.98	126.7
MORGAN STANLEY DEAN WITTER & CO	1.8	47.2	18	3.81%	10.11%	15.17	25.39
P N C FINANCIAL SERVICES GRP INC	0.6	24.1	12	2.49%	5.13%	10.55	21.58
AMERICAN EXPRESS CO	0	10.1	10	0.00%	0.00%	9.75	7.8
B B & T CORP	0	13.4	7.8	0.00%	0.00%	9.57	14.78
BANK NEW YORK INC	0	15.4	11	0.00%	0.00%	11.09	6.46
CAPITAL ONE FINANCIAL CORP	0	16.8	12	0.00%	0.00%	10.52	33.06
GOLDMAN SACHS GROUP INC	0	55.9	34	0.00%	0.00%	9.97	18.94
JPMORGAN CHASE & CO	0	136.2	87	0.00%	0.00%	10.45	20.43
METLIFE INC	0	30.1	28	0.00%	0.00%	10.28	26.14
STATE STREET CORP	0	14.1	11	0.00%	0.00%	14.79	10.79
U S BANCORP DEL	0	24.4	12	0.00%	0.00%	8.54	10.53

Panel B: Correlation Matrix

	SCAP/Tier1	SCAP/Tier1Comm	MES	LVG
SCAP/Tier1	100.00%			
SCAP/Tier1Comm	95.42%	100.00%		
MES	59.48%	61.47%	100.00%	
LVG	31.58%	48.20%	53.70%	100.00%

Table 2: OLS Regression and Probit Regression Analyses.

In **Panel A** the dependent variable is SCAP Shortfall/Tier1 and in **Panel B** it is SCAP Shortfall/Tier1Comm. Models (I)-(III) are regression analyses based on MES and LVG computed respectively, during and at end-of the period, April08-March09. Models (IV)-(VI) are the equivalent Probit regression results. Models (VII)-(XII) repeat the analysis using the period Oct07-Sep08. T-stats are reported in brackets for the OLS regression coefficient estimates. In the Probit regressions the dependent variable is converted into a binary variable by only considering non-zero or zero values. The reported R^2 is then the Pseudo R^2.

Panel A: Dependent Variable is SCAP Shortfall/Tier1

	April08-March09						Oct07-Sep08					
	OLS			Probit			OLS			Probit		
	(I)	**(II)**	**(III)**	**(IV)**	**(V)**	**(VI)**	**(VII)**	**(VIII)**	**(IX)**	**(X)**	**(XI)**	**(XII)**
Intercept	-17.29	3.14	-17.33	-5.44	-2.43	-6.04	-13.46	3.94	-14.19	-2.4	-0.95	-2.03
	(-2.2)	(1.16)	(-2.00)	(-2.72)	(-2.26)	(-2.24)	(-1.50)	(1.12)	(-1.50)	(-1.37)	(-1.40)	(-1.14)
MES	1.91		1.91	0.45		0.34	3		3.29	0.37		0.21
	(3.00)		(2.46)	(2.72)		(1.65)	(2.19)		(2.04)	(1.40)		(0.67)
LVG		0.09	-0.001		0.10	0.09		0.15	-0.09		0.08	0.06
		(1.35)	(-0.01)		(2.16)	(1.61)		(0.66)	(-0.37)		(1.50)	(1.05)
Adj. R^2	32.03%	4.65%	27.5%	40.68%	45.09%	53.22%	18.27%	-3.46%	13.61%	11.06%	15.17%	17.3%
No. Obs	18	18	18	18	18	18	18	18	18	18	18	18

Panel B: Dependent Variable is SCAP Shortfall/Tier1Comm

	April08-March09			Oct07-Sep08		
	OLS			OLS		
	(I)	**(II)**	**(III)**	**(VII)**	**(VIII)**	**(IX)**
Intercept	-36.24	4.41	-30.86	-25.72	9.02	27.13
	(-2.25)	(0.85)	(-1.79)	(-1.37)	(1.24)	(-1.37)
MES	4.05		3.29	6.00		6.57
	(3.12)		(2.13)	(2.09)		(1.94)
LVG		0.27	0.12		0.31	-0.17
		(2.20)	(0.90)		(0.64)	(-0.34)
Adj. R^2	33.19%	18.44%	33.17%	16.57%	-3.56%	11.69%
No. Obs	18	18	18	18	18	18

Table 3: Summary statistics and correlation matrix of stock returns during the crisis, risk of financial firms, their systemic risk and other firm characteristics.

This table contains overall descriptive statistics (**Panel A**) and sample correlation matrix (**Panel B**) for the following measures: (1) **Realized SES**: the stock return during July 2007 till December 2008. (2) **ES**: the Expected Shortfall of an individual stock at the 5th-percentile. (3) **MES** is the marginal expected shortfalls of a stock given that the *market return* is below its 5th-percentile. (4) **Vol** is the annualized daily individual stock return volatility. (5) **Beta** is the estimate of the coefficient in a regression of a firm's stock return on that of the market's. (6) **Leverage** (LVG) 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 equity + market value of equity. (7) **Log-Assets** is the natural logarithm of total book assets. (8) **ME** is the market value of equity. We used the value-weighted market return as provided by CRSP. ES, MES, Vol and Beta were measured for each individual company's stock using the period June 2006 till June 2007. LVG, log-assets and ME are of end of June 2007. The summary statistics are also shown in **Panel C** by different institution types as described in Appendix A.

Panel A: Descriptive statistics of the measures Realized SES, ES, MES, Vol, Beta, LVG, Log-Assets and ME.

	Realized SES	ES	MES	Vol	Beta	LVG	Log-Assets	ME(blns)
Average	-47%	2.73%	1.63%	21%	1.00	5.25	10.84	31.25
Median	-46%	2.52%	1.47%	19%	0.89	4.54	10.88	15.85
Std. dev.	34%	0.92%	0.62%	8%	0.37	4.40	1.78	42.88
Min	-100%	1.27%	0.39%	10%	0.34	1.01	6.43	5.16
Max	36%	5.82%	3.36%	49%	2.10	25.62	14.61	253.70

Panel B: Sample correlation matrix of the measures Realized SES, ES, MES, Vol, Beta, LVG, Log-Assets and ME.

	Realized SES	ES	MES	Vol	Beta	LVG	Log-Assets	ME
Realized SES	1.00							
ES	-0.17	1.00						
MES	-0.30	0.71	1.00					
Vol	-0.07	0.95	0.64	1.00				
Beta	-0.25	0.76	0.92	0.72	1.00			
LVG	-0.47	-0.09	0.24	-0.17	0.18	1.00		
Log-Assets	-0.38	-0.32	-0.07	-0.40	-0.07	0.75	1.00	
ME	-0.19	-0.24	-0.08	-0.25	-0.07	0.27	0.65	1.00

Panel C: Descriptive statistics of the measures Realized SES, ES, MES, Vol, Beta and LVG by institution type.

	Realized SES					ES				
	Mean	**Median**	**Std.**	**Min.**	**Max.**	**Mean**	**Median**	**Std.**	**Min.**	**Max.**
(1) Depositories	-1.73%	-2.21%	19.96%	-35.15%	37.27%	2.23%	2.11%	0.48%	1.27%	3.58%
(2) Other	4.26%	-7.84%	35.94%	-46.21%	84.45%	3.35%	3.17%	1.06%	1.79%	5.82%
(3) Insurance	-17.35%	-24.60%	30.25%	-68.76%	51.92%	2.44%	2.29%	0.69%	1.39%	4.42%
(4) Broker-dealers	72.46%	82.62%	60.04%	3.35%	188.74%	3.61%	3.46%	0.68%	2.88%	5.24%

	MES					Vol				
	Mean	**Median**	**Std.**	**Min.**	**Max.**	**Mean**	**Median**	**Std.**	**Min.**	**Max.**
(1) Depositories	1.42%	1.31%	0.34%	0.88%	2.12%	17%	16%	4%	10%	28%
(2) Other	1.92%	1.83%	0.63%	0.92%	3.36%	26%	23%	9%	16%	49%
(3) Insurance	1.28%	1.38%	0.39%	0.39%	2.09%	18%	17%	5%	11%	32%
(4) Broker-dealers	2.68%	2.64%	0.34%	2.26%	3.29%	27%	26%	5%	21%	36%

	Beta					LVG				
	Mean	**Median**	**Std.**	**Min.**	**Max.**	**Mean**	**Median**	**Std.**	**Min.**	**Max.**
(1) Depositories	0.87	0.82	0.19	0.53	1.33	6.21	6.26	1.80	1.34	9.25
(2) Other	1.22	1.18	0.35	0.67	2.10	3.68	1.55	4.63	1.01	21.00
(3) Insurance	0.78	0.76	0.23	0.34	1.51	4.44	3.07	3.29	1.29	11.85
(4) Broker-dealers	1.61	1.60	0.24	1.21	1.96	9.58	9.25	8.26	1.03	25.62

Table 4: Stock returns during the crisis, risk of financial firms, and their systemic risk.

This table contains the results of the cross-sectional regression analyses of individual company stock returns (Realized SES) on risk (ES, Vol, LVG) and systemic risk (MES, Beta) measures. Realized SES, risk measures and leverage are as described in Table 3. All balance sheet data are based on quarterly CRSP-Compustat merged data as of end of June 2007. The industry type dummies are employed for Other, Insurance, and Broker-Dealers 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 Realized SES, the company stock returns during the crisis								
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
ES	-0.05							
	(-1.14)							
Vol		0.04						-0.07
		(0.07)						(-0.12)
MES			-0.21***			-0.15**		-0.17**
			(-2.90)			(-2.25)		(-2.08)
Beta				-0.29**				
				(-2.24)				
LVG					-0.04***	-0.04***		-0.03**
					(-5.73)	(-5.43)		(-2.29)
Log Assets							-0.09***	-0.05*
							(-4.86)	(-1.69)
Industry dummies								
Constant	-0.32***	-0.44***	-0.13	-0.18	-0.18**	0.02	0.61***	0.50
	(-2.71)	(-3.81)	(-1.09)	(-1.42)	(-2.50)	(0.20)	(2.75)	(1.61)
Other	-0.04	-0.09	0.01	0.012	-0.20**	-0.12	-0.25***	-0.15
	(-0.33)	(-0.91)	(0.14)	(0.12)	(-2.44)	(-1.35)	(-2.87)	(-1.61)
Insurance(x100)	0.43	-0.68	-3.63	-2.95	-8.86	-10.17	-0.09	-0.11
	(0.05)	(-0.08)	(-0.45)	(-0.36)	(-1.19)	(-1.39)	(-1.13)	(-1.55)
Broker-dealers	-0.09	-0.16	0.11	0.06	-0.02	0.16	-0.17	0.14
	(-0.65)	(-1.20)	(0.71)	(0.36)	(-0.18)	(1.19)	(-1.56)	(1.02)
Adj. R^2	0%	-1.36%	6.72%	3.62%	24.27%	27.34%	18.46%	28.02%
No. Obs	102	102	102	102	102	102	102	102

Table 5: 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 (Realized SES) on systemic risk: MES (**Panel A**), W-MES (**Panel B**), and D-MES (**Panel C**) measure. All measures are as described in Table 3 and Table 4, except for W-MES which is the exponentially-weighted MES and D-MES which is the dynamic MES. All three variants of MES are measured over different pre-crisis periods as indicated below. 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 columns 1 through 3 we use 2007Q1 data and for the last column we use 2006Q4 balance sheet data.

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

	June06-May07	May06-Apr07	Apr06-Mar07	Mar06-Feb07
Panel A (MES): The dependent variable is Realized SES, the company stock returns during the crisis				
Intercept	-0.14*	-0.20**	-0.20**	-0.23***
	(-1.75)	(-2.42)	(-2.48)	(-3.09)
MES	-0.10**	-0.05	-0.05	-0.04
	(-2.30)	(-1.26)	(-1.24)	(-0.98)
LVG	-0.04***	-0.04***	-0.04***	-0.04***
	(-5.06)	(-5.09)	(-5.21)	(-5.20)
Adj. R^2	24.87%	21.84%	22.61%	21.00%
No. Obs	102	102	102	102
Panel B (W-MES): The dependent variable is Realized SES, the company stock returns during the crisis				
Intercept	-0.21***	-0.09	-0.09	-0.18*
	(-3.22)	(-1.11)	(-1.15)	(-1.96)
W-MES	-0.07*	-0.10***	-0.10***	-0.03
	(-1.73)	(-2.96)	(-2.94)	(-1.30)
LVG	-0.04***	-0.03***	-0.03***	-0.04***
	(-5.01)	(-4.49)	(-4.61)	(-5.25)
Adj. R^2	23.15%	27.11%	27.76%	21.97%
No. Obs	102	102	102	102
Panel C (D-MES): The dependent variable is Realized SES, the company stock returns during the crisis				
Intercept	-0.12	-0.06	-0.11	-0.18*
	(-1.40)	(-0.66)	(-1.24)	(-2.27)
D-MES	-0.12*	-0.13**	-0.12*	-0.08
	(-2.23)	(-2.86)	(-2.36)	(-1.92)
LVG	-0.03**	-0.03**	-0.03**	-0.03**
	(-5.25)	(-4.82)	(-4.13)	(-5.02)
Adj. R^2	24.14%	26.44%	24.58%	23.15%
No. Obs	102	102	102	102

Table 6: Summary statistics and correlation matrix of the MES measures of CDS and SES measures of CDS and stock

This table contains overall descriptive statistics (**Panel A**) and sample correlation matrix (**Panel B**) for the following measures: (1) CDS MES is the average return (change) in CDS spread over the days where the return (change) in the spread of the index of 40 firms are the widest; (2) CDS SES is the total realized return (change) in the spread over the crisis; (3) Stock realized SES is the stock return measured over the crisis periods. The sample consists of 40 firms whose CDS data are available from Bloomberg.

Panel A: Descriptive statistics of the MES measures of CDS and SES measures of CDS and stock

	CDS (log returns)			CDS (arithmetic changes) in b.p			Stock	
	MES	Realized SES (1 July 06- 30 June 07)	Realized SES (1 July 06- 30 Dec 07)	MES	Realized SES (1 July 06- 30 June 07)	Realized SES (1 July 06- 30 Dec 07)	Realized SES (1 July 06- 30 June 07)	Realized SES (1 July 06- 30 Dec 2007)
Average	3.46%	167.29%	218.04%	1.02	150.96	379.53	-37.48%	-57.71%
Median	3.59%	166.91%	214.69%	0.57	64.64	187.05	-33.56%	-69.15%
Std. dev.	3.21%	99.62%	116.37%	1.54	316.68	802.39	32.90%	35.17%
Min	-0.63%	-119.93%	-103.25%	-0.25	3.00	-204.11	-98.43%	-99.82%
Max	16.40%	424.10%	436.42%	6.84	1580.27	3550.28	32.88%	13.56%

Panel B: Correlation matrix of the MES measures of CDS and SES measures of CDS and stock

		CDS (log returns)			CDS (arithmetic changes) in b.p			Stock	
		MES	Realized SES (1 Jul 06- 30 June 07)	Realized SES (1 July 06- 30 Dec 07)	MES	Realized SES (1 July 06- 30 June 07)	Realized SES (1 July 06- 30 Dec 07)	Realized SES (1 July 06- 30 June 07)	Realized SES (1 July 06- 30 Dec 07)
CDS (log returns)	MES	1.00							
	Realized SES (1 July 06- 30 June 07)	0.36	1.00						
	Realized SES (1 July 06- 30 Dec 07)	0.25	0.73	1.00					
CDS (arithmetic changes) in b.p	MES	0.52	-0.21	-0.23	1.00				
	Realized SES (1 July 06- 30 June 07)	0.34	0.57	0.28	0.33	1.00			
	Realized SES (1 July 06- 30 Dec 07)	0.60	0.40	0.64	0.28	0.45	1.00		
Stock	Realized SES (1 July 06- 30 June 07)	-0.56	-0.62	-0.38	-0.23	-0.47	-0.42	1.00	
	Realized SES (1 July 06- 30 Dec 07)	-0.50	-0.56	-0.50	-0.12	-0.30	-0.44	0.86	1.00

Table 7: CDS MES vs. Realized CDS SES

This table contains the results of the cross-sectional regression analyses of 40 companies' realized CDS SES on CDS MES. **Panel A** provides the results where CDS MES and realized CDS SES are measured in log return. **Panel B** provides the results where CDS MES and realized CDS SES are measured using arithmetic changes in CDS spreads. All measures are as described in Table 3 and Table 4, except for CDS MES, which is the average CDS returns on the worst 5% days during 1 July 2006 - 30 June 2007, where the average return on CDS spreads of the 40 companies are the highest. Leverage is based on data available at end of each period. All CDS data are from Bloomberg.

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

Panel A: The dependent variable is total realized return on CDS spread during the crisis, CDS MES is measured as log returns

	1 July07-30 June 08	1 July07-14 Sep 08	1 July07-30 Sep 08	1 July07-10 Oct 8	1 July07-30 Dec 08
CDS MES	10.21**	9.67*	13.11**	10.72	11.56*
	(2.06)	(1.83)	(2.15)	(1.65)	(2.02)
LVG	0.05	0.05	0.05	0.06	0.03
	(1.43)	(1.41)	(1.33)	(1.45)	(0.81)
Constant	1.34**	1.75**	1.80***	1.90***	1.71***
	(2.68)	(3.28)	(2.93)	(2.91)	(2.96)
Other	-0.95*	-1.29**	-1.22*	-0.97	-1.09*
	(-1.93)	(-2.46)	(-2.02)	(-1.52)	(-1.92)
Insurance	-0.14	-0.48	-0.44	-0.03	0.35
	(-0.32)	(-1.01)	(-0.81)	(-0.04)	(0.68)
Broker dealers	-0.87	-0.91	-0.72	-0.80	-0.63
	(-1.52)	(-1.49)	(-1.02)	(-1.07)	(-0.96)
Adj. R^2	17.86%	19.94%	19.37%	10.80%	19.30%
No. Obs	40	40	40	40	40

Panel B: The dependent variable is total change in CDS spread during the crisis, CDS MES is measured as changes in CDS spreads

	1 July07-30 June 08	1 July07-14 Sep 08	1 July07-30 Sep 08	1 July07-10 Oct 8	1 July07-30 Dec 08
CDS MES	90.41**	91.04**	201.35***	239.08**	228.27**
	(2.63)	(2.16)	(2.82)	(3.12)	(2.70)
LVG	-2.07	5.80	12.24	25.50	23.76
	(-0.20)	(0.45)	(0.56)	(1.09)	(0.92)
Constant	46.51	236.00	433.10	289.63	240.62
	(0.30)	(1.24)	(1.35)	(0.84)	(0.63)
Other	-131.56	-387.37*	-693.51*	-573.43	-738.60*
	(-0.78)	(-1.87)	(-1.98)	(-1.52)	(-1.78)
Insurance	104.02	-52.03	-233.95	4.30	77.11
	(0.72)	(-0.29)	(-0.78)	(0.01)	(0.22)
Broker dealers	-25.49	-183.60	-435.61	-489.86	-606.80
	(-0.14)	(-0.80)	(-1.11)	(-1.17)	(-1.31)
Adj. R^2	7.21%	5.13%	11.67%	14.09%	12.45%
No. Obs	40	40	40	40	40

Table 8: CDS MES vs. Realized stock SES

This table contains the results of the cross-sectional regression analyses of 40 companies' realized stock returns (Realized SES) on CDS MES (measured as log returns in panel A and changes in CDS spreads in panel B). All measures are as described in Table 3 and Table 4, except for CDS MES, which is the average CDS returns on the worst 5% days during 1 July 2006 - 30 June 2007, where the average changes in CDS spreads of the 40 companies are the highest. Leverage is based on data available at end of each period. All CDS data are from Bloomberg.

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

Panel A: The dependent variable is realized stock return during the crisis, CDS MES is measured as log returns

CDS MES	-4.38***	-5.20***	-6.05***	-4.48***	-4.11***
	(-3.33)	(-3.52)	(-3.83)	(-3.19)	(-2.77)
LVG	-0.03***	-0.04***	-0.04***	-0.04***	-0.03
	(-3.82)	(-4.31)	(-4.13)	(-4.17)	(-3.64)
Constant	-0.03	0.19	0.25	-0.007	-0.14
	(-0.26)	(1.29)	(1.57)	(-0.05)	(-0.91)
Other	0.09	-0.11	-0.16	-0.13	-0.09
	(0.69)	(-0.76)	(-0.99)	(-0.90)	(-0.62)
Insurance	0.03	-0.08	-0.17	-0.19	-0.06
	(0.24)	(-0.62)	(-1.19)	(-1.53)	(-0.44)
Broker dealers	0.19	0.07	0.03	0.03	0.07
	(1.26)	(0.43)	(0.19)	(0.21)	(0.39)
Adj. R^2	46.79%	51.66%	50.94%	45.52%	40.76%
No. Obs	40	40	40	40	40

Panel B: The dependent variable is realized stock return during the crisis, CDS MES is measured as changes in CDS spreads

CDS MES	-0.06**	-0.07*	-0.07*	-0.04	-0.02
	(-2.04)	(-2.00)	(-2.02)	(-1.21)	(-0.71)
LVG	-0.04	-0.05***	-0.05***	-0.05***	-0.04***
	(-4.48)	(-4.90)	(-4.70)	(-4.60)	(-4.04)
Constant	-0.17	0.03	0.06	-0.17	-0.30*
	(-1.26)	(0.19)	(0.35)	(-1.16)	(-1.98)
Other	0.20	0.02	-0.006	-0.03	-0.02
	(1.42)	(0.12)	(-0.03)	(-0.21)	(-0.11)
Insurance	0.12	0.03	-0.04	-0.09	0.04
	(0.96)	(0.19)	(-0.26)	(-0.67)	(0.28)
Broker dealers	0.33**	0.24	0.23	0.17	0.18
	(2.06)	(1.29)	(1.12)	(0.95)	(1.00)
Adj. R^2	37.16%	40.98%	37.31%	32.15%	28.49%
No. Obs	40	40	40	40	40

Figure 1: MES Vs. SCAP/Tier1Comm

Scatterplot of the marginal expected shortfall measure, MES, against SCAP/Tier1comm. MES is the marginal expected shortfall of a stock given that the *market return* is below its 5th-percentile. The sample consists of 18 US financial firms included in the Federal Reserve's stress tests of Spring of 2009. SCAP is the announced capital shortfall of each firm and Tier1comm is its tangible common equity. MES5 was measured for each individual company stock using the period Oct07-Sep08.

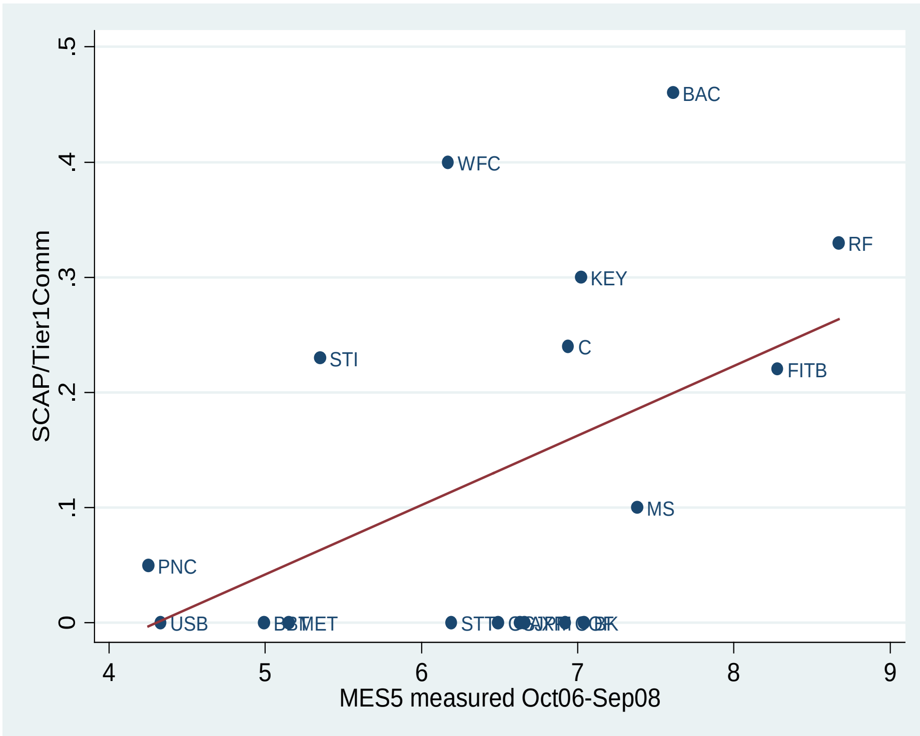


Figure 2: MES Vs. Realized SES

Scatterplot of the marginal expected shortfall measure, MES, against Realized SES, 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. Realized SES, is the stock return during July 2007 till December 2008.

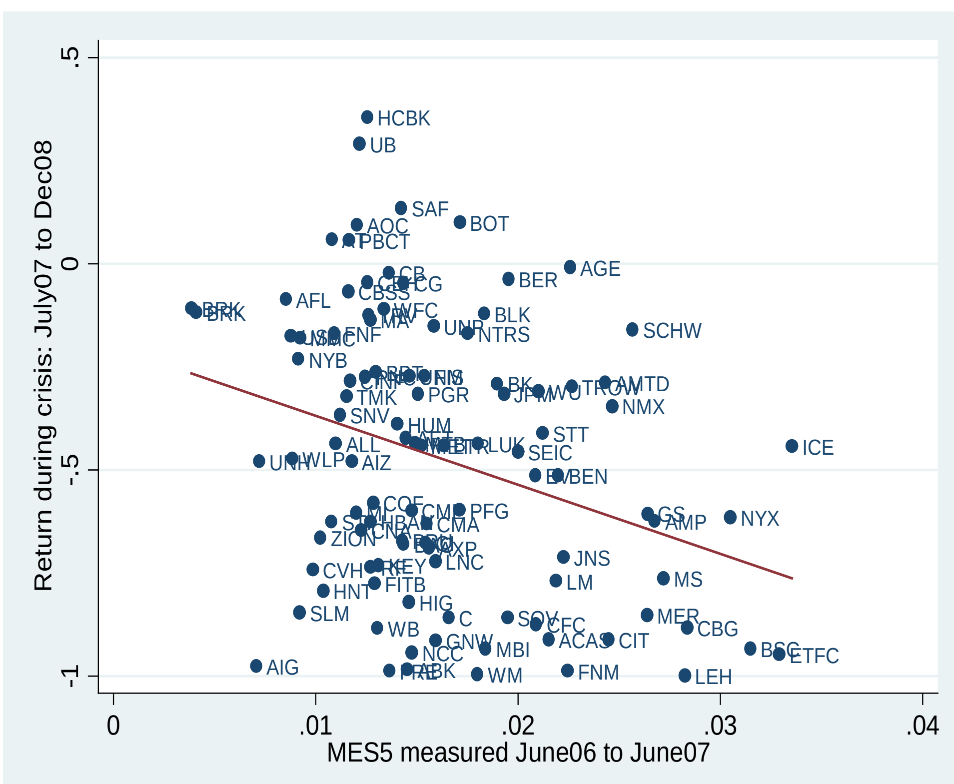


Figure 3: LVG Vs. Realized SES

Scatterplot of LVG, against Realized SES, the return during the crisis. LVG is the quasi market leverage. The sample consists of 101 US financial firms with a market cap in excess of 5 bln. dollars as of June 2007. LVG is as of June 2007. Realized SES, is the stock return during July 2007 till December 2008.

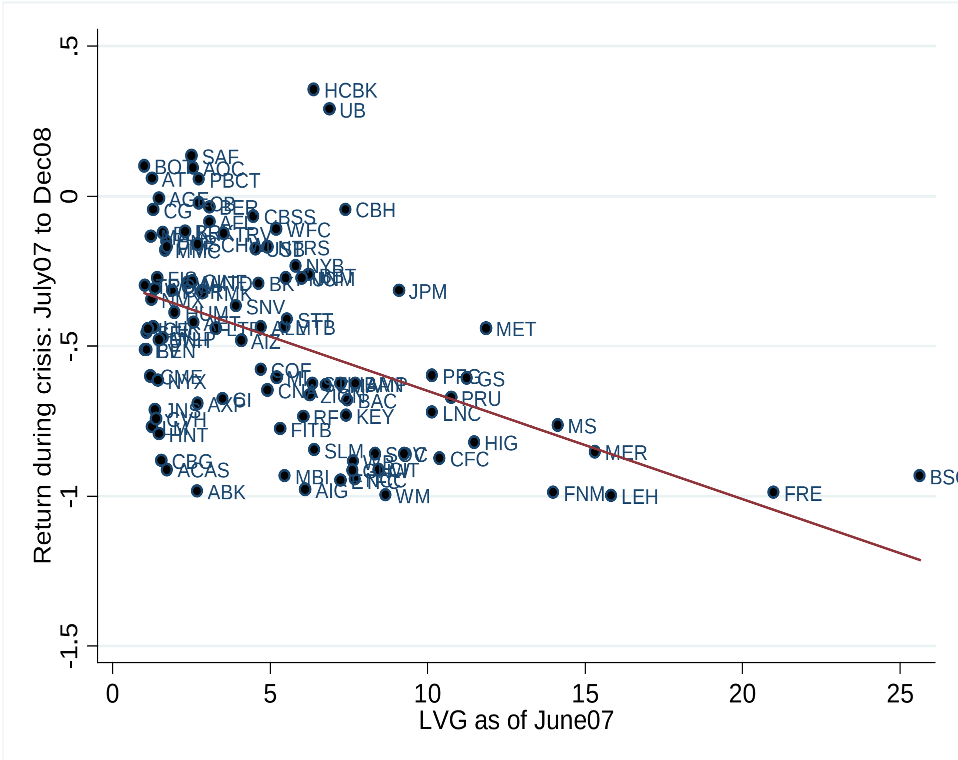


Figure 4: Stability of MES.

The graph depicts a scatter plot of the MES, marginal expected shortfall measure at the 5% level, computed during the June 2006-June 2007 period versus that computed during June 2005-June2006. MES is the marginal expected shortfall of a stock given that the *market return* is below its 5th-percentile.

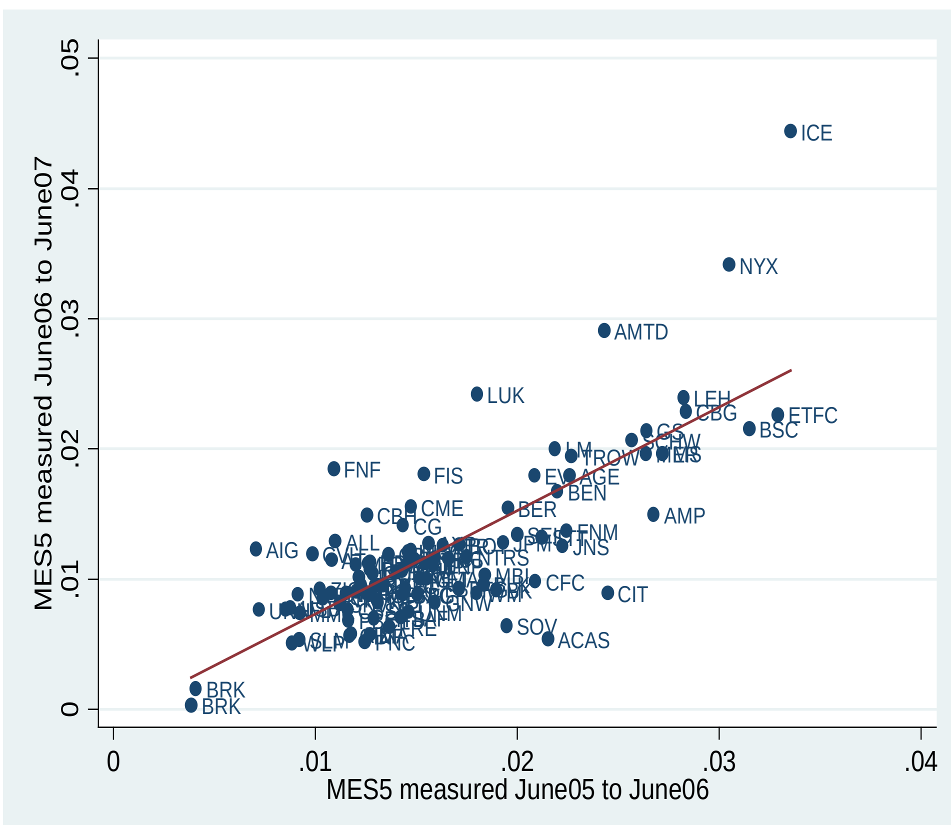


Figure 5: CDS MES vs. Total realized return in CDS spread measured during 1 July 2007- 30 June 2008

The graph depicts a scatter plot of the CDS MES computed during the period 1 July 2006-30 June 2007 period versus the total realized return on CDS spread during 1 July 2007-30 June 2008. CDS MES is the average CDS returns on the worst 5% days during 1 July 2006-30 June 2007, where the average CDS returns of the 40 companies are the highest.

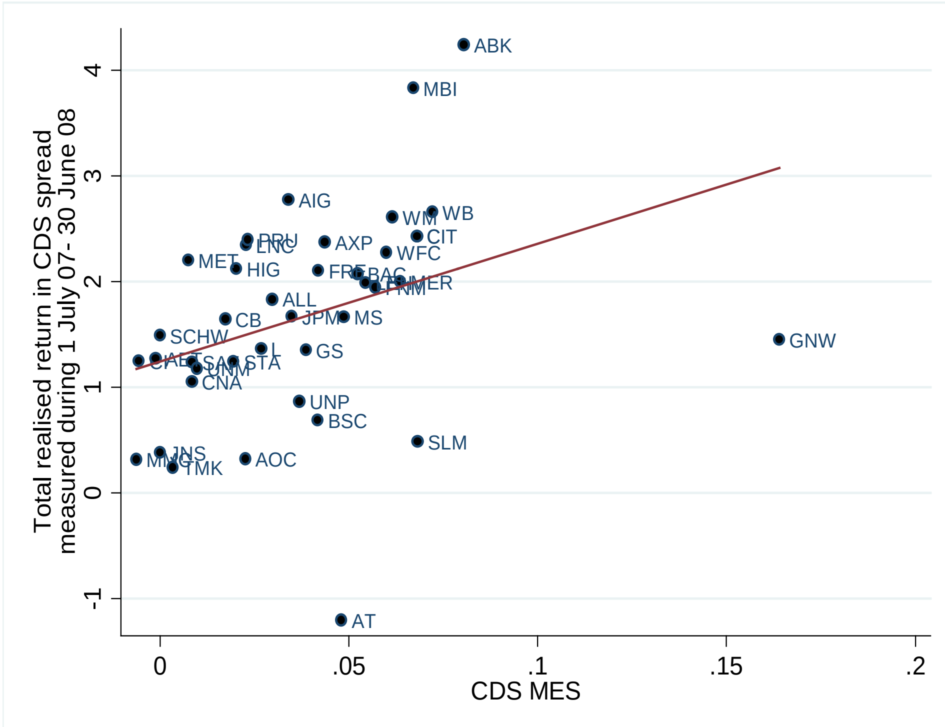


Figure 6: CDS MES vs. Total realized return in CDS spread during 1 July 2007- 30 December 2008

The graph depicts a scatter plot of the CDS MES computed during the period 1 July 2006-30 June 2007 period versus the total realized return on CDS spread during 1 July 2007-30 December 2008. CDS MES is the average CDS returns on the worst 5% days during 1 July 2006-30 June 2007, where the average CDS returns of the 40 companies are the highest.

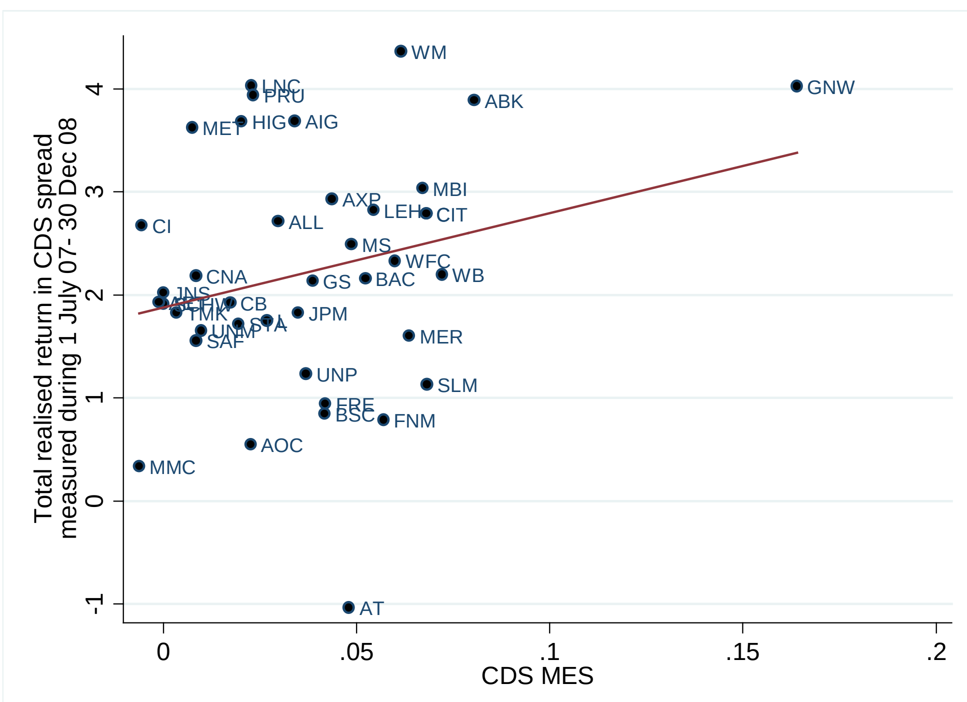


Figure 7: CDS MES vs. Total realized stock return measured during 1 July 2007- 30 June 2008

The graph depicts a scatter plot of the CDS MES computed during the 1 July 2006-30 June 2007 period versus the total realized stock return during 1 July 2007-30 June 2008. CDS MES is the average CDS returns on the worst 5% days during 1 July 2006-30 June 2007, where the average CDS returns of the 40 companies are the highest.

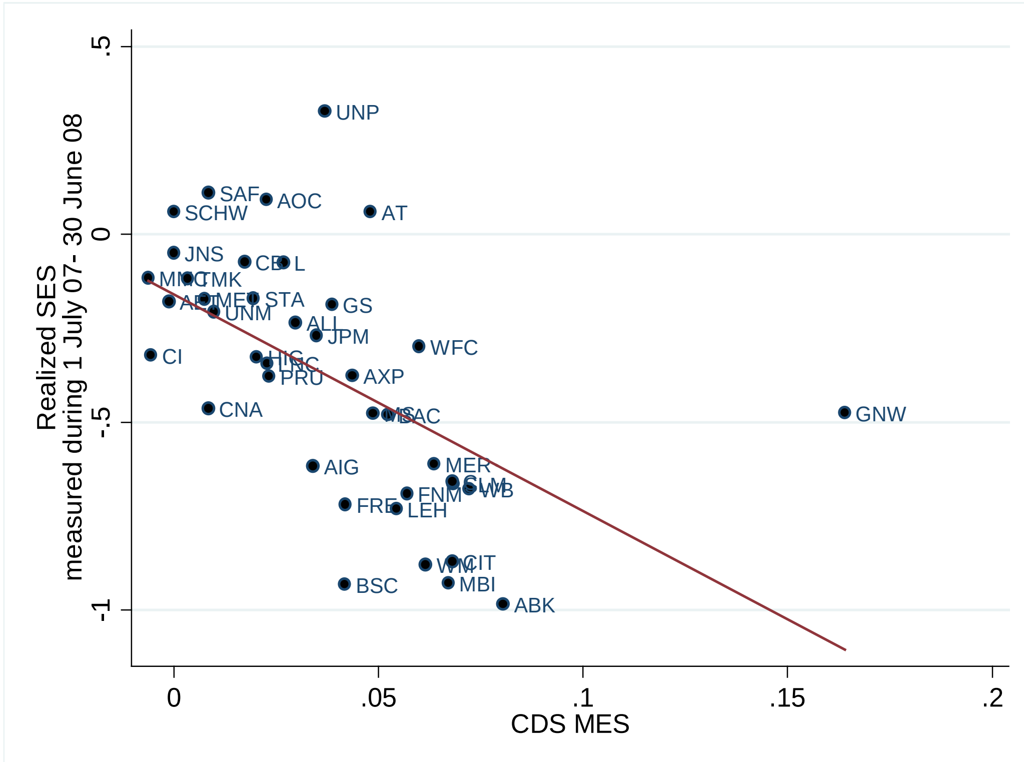
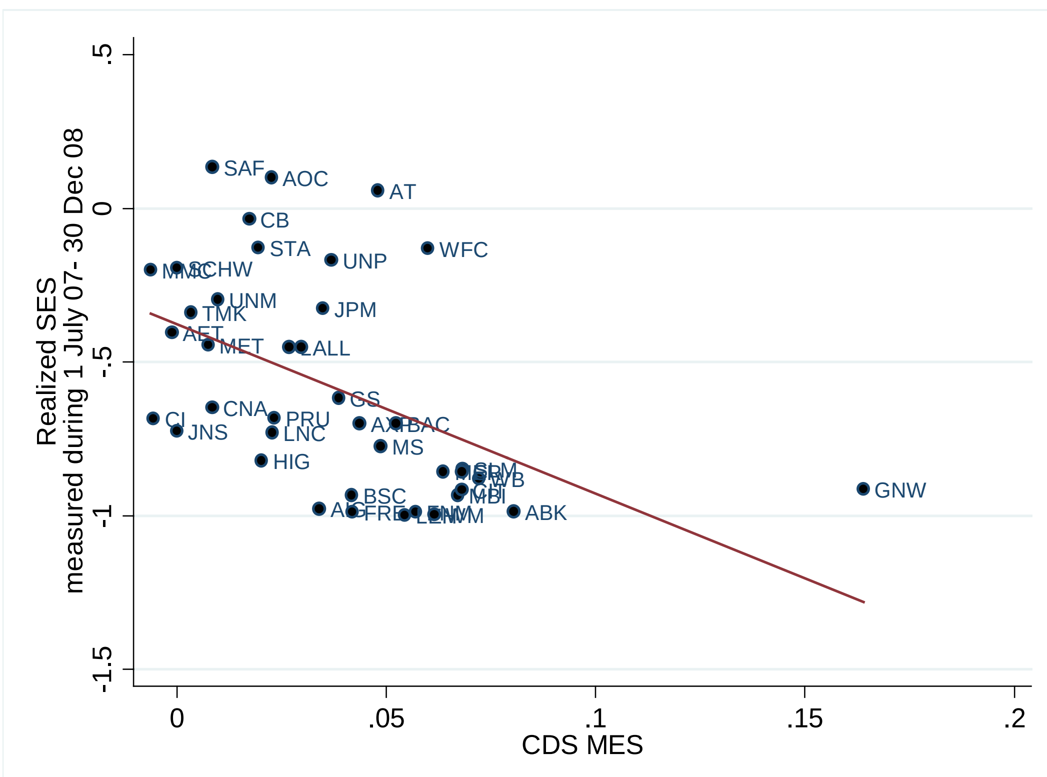


Figure 8: CDS MES vs. Total realized stock return measured during 1 July 2007- 30 December 2008

The graph depicts a scatter plot of the CDS MES computed during the 1 July 2006-30 June 2007 period versus the total realized stock return during 1 July 2007-30 December 2008. CDS MES is the average CDS returns on the worst 5% days during 1 July 2006-30 June 2007, where the average CDS returns of the 40 companies are the highest.



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: **Depositories (**JPMorgan, Citigroup, WAMU,…), **Broker-Dealers** (Goldman Sachs, Morgan Stanley,…), **Insurance** (AIG, Berkshire Hathaway, Countrywide,…) and **Insurance Agents, Brokers, Service** (Metlife, Hartford Financial,…) and a group called **Other** 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 Broker-Dealers.

Depositories: 29 companies, 2-digit SIC code=60.	**Other: Non-depository Institutions etc.: 27 Companies, 2-digit SIC code=61, 62(except 6211), 65, 67.**	**Insurance: 36 Companies, 2-digit SIC code=63 and 64.**	**Broker-Dealers: 10 Companies, 4-digit SIC code=6211.**
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	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	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	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 <u>Insurance, continued:</u> 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). Realized SES is the return during the crisis. Avg $Loss of an individual firm is the average day-to-day loss in market cap. during days in which the market return was below its 5th percentile. Avg Contribution of an individual firm is the ratio of day-to-day loss in market cap. of an individual firm relative to that of all financial firms, averaged over days where the market was below its 5th percentile. LVG is the market leverage, Fitted Rank is the ranking of firms based on the fitted values of Realized SES as obtained by the regression given below, Log-Assets is the natural logarithm of total book assets and ME is market value of equity all as of June 2007. All data are from CRSP and CRSP merged Compustat.

Realized SES= 0.02 - 0.15*MES - 0.04*LVG - 0.12*1[Other] - 0.01*1[Insurance] + 0.16*1[Broker-Dealers]

MES Ranking	Name of Company	Realized SES	MES	Avg $Loss(bln)	Avg Contribution	LVG	Fitted Rank	Assets (bln)	ME(bln)
1.	INTERCONTINENTALEXCHANGE INC	-44.24%	3.36%	0.24	0.28%	1.12	16	2.55	10.40
2.	E TRADE FINANCIAL CORP	-94.79%	3.29%	0.33	0.42%	7.24	21	62.98	9.39
3.	BEAR STEARNS COMPANIES INC	-93.28%	3.15%	0.55	0.68%	25.62	1	423.30	16.66
4.	N Y S E EURONEXT	-61.48%	3.05%	0.43	0.53%	1.43	19	16.93	19.44
5.	C B RICHARD ELLIS GROUP INC	-88.16%	2.84%	0.20	0.25%	1.55	24	5.95	8.35
6.	LEHMAN BROTHERS HOLDINGS INC	-99.82%	2.83%	1.08	1.26%	15.83	4	605.86	39.51
7.	MORGAN STANLEY DEAN WITTER & CO	-76.21%	2.72%	2.09	2.51%	14.14	9	1199.99	88.40
8.	AMERIPRISE FINANCIAL INC	-62.41%	2.68%	0.35	0.43%	7.72	7	108.13	14.95
9.	GOLDMAN SACHS GROUP INC	-60.59%	2.64%	2.13	2.41%	11.25	15	943.20	88.54
10.	MERRILL LYNCH & CO INC	-85.21%	2.64%	1.93	2.25%	15.32	5	1076.32	72.56
11.	SCHWAB CHARLES CORP NEW	-15.95%	2.57%	0.59	0.66%	2.71	88	49.00	25.69
12.	NYMEX HOLDINGS INC	-34.46%	2.47%	0.28	0.33%	1.23	98	3.53	11.57
13.	C I T GROUP INC NEW	-91.08%	2.45%	0.26	0.32%	8.45	8	85.16	10.52
14.	T D AMERITRADE HOLDING CORP	-28.75%	2.43%	0.24	0.30%	2.40	26	18.53	11.92
15.	T ROWE PRICE GROUP INC	-29.83%	2.27%	0.27	0.32%	1.03	101	3.08	13.76
16.	EDWARDS A G INC	-0.71%	2.26%	0.11	0.13%	1.46	100	5.24	6.43
17.	FEDERAL NATIONAL MORTGAGE ASSN	-98.78%	2.25%	1.24	1.51%	14.00	3	857.80	63.57
18.	JANUS CAP GROUP INC	-71.12%	2.23%	0.09	0.10%	1.34	35	3.76	5.16
19.	FRANKLIN RESOURCES INC	-51.23%	2.20%	0.62	0.66%	1.08	40	9.62	33.07
20.	LEGG MASON INC	-76.98%	2.19%	0.29	0.30%	1.25	38	10.08	12.97
21.	AMERICAN CAPITAL STRATEGIES LTD	-91.08%	2.15%	0.15	0.17%	1.73	32	12.15	7.75
22.	STATE STREET CORP	-41.07%	2.12%	0.46	0.52%	5.54	28	112.27	23.01
23.	WESTERN UNION CO	-30.84%	2.10%	0.36	0.42%	1.34	83	5.33	16.09
24.	COUNTRYWIDE FINANCIAL CORP	-87.46%	2.09%	0.48	0.57%	10.39	6	216.82	21.57
25.	EATON VANCE CORP	-51.20%	2.09%	0.09	0.10%	1.03	47	0.62	5.54
26.	S E I INVESTMENTS COMPANY	-45.61%	2.00%	0.11	0.12%	1.08	50	1.12	5.69
27.	BERKLEY W R CORP	-3.57%	1.95%	0.13	0.18%	3.07	31	16.63	6.32
28.	SOVEREIGN BANCORP INC	-85.77%	1.95%	0.21	0.25%	8.34	20	82.74	10.11
29.	JPMORGAN CHASE & CO	-31.48%	1.93%	3.19	3.60%	9.09	17	1458.04	165.51
30.	BANK NEW YORK INC	-29.05%	1.90%	0.54	0.63%	4.64	48	126.33	31.43
31.	M B I A INC	-93.34%	1.84%	0.16	0.20%	5.47	25	43.15	8.14
32.	BLACKROCK INC	-12.07%	1.83%	0.23	0.25%	1.60	53	21.99	18.18
33.	LEUCADIA NATIONAL CORP	-43.54%	1.80%	0.12	0.15%	1.28	61	6.38	7.63
34.	WASHINGTON MUTUAL INC	-99.61%	1.80%	0.72	0.84%	8.67	23	312.22	37.63
35.	NORTHERN TRUST CORP	-16.84%	1.75%	0.23	0.27%	4.92	52	59.61	14.14
36.	C B O T HOLDINGS INC	10.12%	1.71%	0.13	0.15%	1.01	69	0.89	10.92
37.	PRINCIPAL FINANCIAL GROUP INC	-59.75%	1.71%	0.27	0.29%	10.15	12	150.76	15.61
38.	CITIGROUP INC	-85.86%	1.66%	4.19	4.87%	9.25	22	2220.87	253.70
39.	LOEWS CORP	-44.08%	1.63%	0.39	0.50%	3.28	44	79.54	27.38
40.	GENWORTH FINANCIAL INC	-91.43%	1.59%	0.25	0.28%	7.62	18	111.94	14.96
41.	LINCOLN NATIONAL CORP IN	-72.08%	1.59%	0.29	0.32%	10.15	13	187.65	19.21
42.	UNION PACIFIC CORP	-15.14%	1.58%	0.45	0.51%	1.70	65	37.30	31.03
43.	AMERICAN EXPRESS CO	-69.00%	1.56%	1.08	1.27%	2.70	51	134.37	72.66
44.	COMERICA INC	-63.00%	1.55%	0.16	0.18%	6.77	36	58.57	9.27
45.	C I G N A CORP	-67.69%	1.54%	0.21	0.28%	3.50	46	41.53	15.03

46.	FIDELITY NATIONAL INFO SVCS INC	-27.15%	1.54%	0.14	0.15%	1.42	72	7.80	10.45
47.	METLIFE INC	-44.06%	1.52%	0.71	0.82%	11.85	10	552.56	47.82
48.	PROGRESSIVE CORP OH	-31.52%	1.51%	0.28	0.33%	1.89	73	21.07	17.42
49.	M & T BANK CORP	-43.46%	1.49%	0.19	0.25%	5.47	60	57.87	11.57
50.	NATIONAL CITY CORP	-94.28%	1.48%	0.34	0.37%	7.70	29	140.64	19.18
51.	CHICAGO MERCANTILE EXCH HLDG INC	-59.88%	1.47%	0.27	0.29%	1.19	78	5.30	18.64
52.	UNUM GROUP	-27.21%	1.46%	0.11	0.13%	5.99	27	52.07	8.95
53.	HARTFORD FINANCIAL SVCS GROUP IN	-82.02%	1.46%	0.45	0.50%	11.48	11	345.65	31.19
54.	AMBAC FINANCIAL GROUP INC	-98.47%	1.45%	0.13	0.18%	2.69	64	21.06	8.89
55.	AETNA INC NEW	-42.17%	1.45%	0.34	0.43%	2.58	66	49.57	25.31
56.	LOEWS CORP	-4.54%	1.44%	0.10	0.12%	1.29	82	2.84	8.38
57.	BANK OF AMERICA CORP	-68.05%	1.44%	3.27	3.54%	7.46	33	1534.36	216.96
58.	PRUDENTIAL FINANCIAL INC	-67.16%	1.43%	0.60	0.73%	10.75	14	461.81	45.02
59.	SAFECO CORP	13.56%	1.42%	0.10	0.12%	2.51	68	13.97	6.61
60.	HUMANA INC	-38.79%	1.40%	0.14	0.17%	1.97	76	13.33	10.24
61.	FEDERAL HOME LOAN MORTGAGE CORP	-98.75%	1.36%	0.60	0.74%	21.00	2	821.67	40.16
62.	CHUBB CORP	-2.24%	1.36%	0.30	0.35%	2.74	67	51.73	21.74
63.	WELLS FARGO & CO NEW	-10.88%	1.34%	1.58	1.50%	5.19	71	539.87	117.46
64.	KEYCORP NEW	-73.09%	1.31%	0.20	0.23%	7.41	41	94.08	13.47
65.	WACHOVIA CORP 2ND NEW	-88.34%	1.31%	1.32	1.40%	7.64	37	719.92	98.06
66.	B B & T CORP	-26.22%	1.30%	0.30	0.33%	6.23	59	127.58	22.07
67.	FIFTH THIRD BANCORP	-77.61%	1.29%	0.29	0.32%	5.33	30	101.39	21.30
68.	CAPITAL ONE FINANCIAL CORP	-57.90%	1.28%	0.38	0.47%	4.70	39	145.94	32.60
69.	REGIONS FINANCIAL CORP NEW	-73.55%	1.27%	0.30	0.29%	6.06	63	137.62	23.33
70.	HUNTINGTON BANCSHARES INC	-62.50%	1.27%	0.07	0.08%	7.23	45	36.42	5.35
71.	MASTERCARD INC	-13.49%	1.27%	0.13	0.14%	1.21	85	5.61	13.23
72.	TRAVELERS COMPANIES INC	-12.32%	1.26%	0.45	0.51%	3.54	62	115.36	35.52
73.	COMMERCE BANCORP INC NJ	-4.42%	1.26%	0.08	0.10%	7.40	43	48.18	7.08
74.	HUDSON CITY BANCORP INC	35.63%	1.26%	0.10	0.09%	6.39	58	39.69	6.50
75.	P N C FINANCIAL SERVICES GRP INC	-27.35%	1.24%	0.28	0.29%	5.50	74	125.65	24.69
76.	C N A FINANCIAL CORP	-64.73%	1.22%	0.14	0.16%	4.92	42	60.74	12.95
77.	UNIONBANCAL CORP	29.14%	1.22%	0.11	0.11%	6.88	54	53.17	8.25
78.	AON CORP	9.48%	1.20%	0.14	0.15%	2.55	80	24.79	12.51
79.	MARSHALL & ILSLEY CORP	-60.34%	1.20%	0.15	0.16%	5.20	79	58.30	12.34
80.	ASSURANT INC	-47.98%	1.18%	0.08	0.10%	4.08	57	25.77	7.13
81.	CINCINNATI FINANCIAL CORP	-28.29%	1.17%	0.10	0.12%	2.53	81	18.26	7.46
82.	PEOPLES UNITED FINANCIAL INC	5.77%	1.16%	0.07	0.06%	2.75	96	13.82	5.33
83.	COMPASS BANCSHARES INC	-6.70%	1.16%	0.11	0.12%	4.48	49	34.88	9.17
84.	TORCHMARK CORP	-32.18%	1.15%	0.07	0.09%	2.85	77	15.10	6.40
85.	SYNOVUS FINANCIAL CORP	-36.53%	1.12%	0.11	0.13%	3.92	90	33.22	10.04
86.	ALLSTATE CORP	-43.63%	1.10%	0.40	0.49%	4.72	55	160.54	37.36
87.	FIDELITY NATIONAL FINL INC NEW	-16.80%	1.09%	0.04	0.04%	1.73	87	7.37	5.25
88.	ALLTEL CORP	5.98%	1.08%	0.25	0.29%	1.25	89	17.44	23.23
89.	SUNTRUST BANKS INC	-62.60%	1.08%	0.34	0.33%	6.35	70	180.31	30.58
90.	HEALTH NET INC	-79.37%	1.04%	0.06	0.08%	1.47	91	4.73	5.93
91.	ZIONS BANCORP	-66.42%	1.02%	0.09	0.10%	6.26	75	48.69	8.31
92.	COVENTRY HEALTH CARE INC	-74.19%	0.99%	0.09	0.11%	1.39	94	6.41	9.01
93.	MARSH & MCLENNAN COS INC	-17.94%	0.92%	0.16	0.16%	1.67	93	17.19	17.15
94.	S L M CORP	-84.54%	0.92%	0.18	0.23%	6.40	34	132.80	23.69
95.	NEW YORK COMMUNITY BANCORP INC	-23.11%	0.92%	0.05	0.05%	5.81	84	29.62	5.33
96.	WELLPOINT INC	-47.23%	0.88%	0.43	0.50%	1.60	95	54.19	48.99
97.	U S BANCORP DEL	-17.56%	0.88%	0.53	0.54%	4.55	92	222.53	57.29
98.	A F L A C INC	-8.52%	0.85%	0.21	0.16%	3.07	86	60.11	25.14
99.	UNITEDHEALTH GROUP INC	-47.94%	0.72%	0.49	0.45%	1.47	97	53.15	68.53
100.	AMERICAN INTERNATIONAL GROUP INC	-97.70%	0.71%	1.22	1.03%	6.12	56	1033.87	181.67
101.	BERKSHIRE HATHAWAY INC DEL(A)	-11.76%	0.41%	0.49	0.53%	2.29	99	269.05	119.00
102.	BERKSHIRE HATHAWAY INC DEL(B)	-10.85%	0.39%						49.29

Appendix C: CDS MES ranking of financial firms during June 2006 to June 2007

This table contains the list of 40 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 CDS Marginal Expected Shortfall at the 5% level (MES). Realized SES is the return on CDS spread during the crisis. CDS data are from Bloomberg.

Name of company	Type of institution	CDS MES ranking	Realized CDS SES (July 07-June 08)	Realized CDS SES (July 07-Dec 08)	CDS MES
GENWORTH FINANCIAL INC	Insurance	1	145.38%	403.03%	16.40%
AMBAC FINANCIAL GROUP INC	Insurance	2	424.10%	389.12%	8.05%
WACHOVIA CORP 2ND NEW	Depository	3	266.11%	219.94%	7.21%
S L M CORP	Other	4	48.88%	113.08%	6.82%
CITIGROUP INC	Depository	5	243.16%	278.96%	6.80%
C I T GROUP INC NEW	Other	6	243.16%	278.96%	6.80%
M B I A INC	Insurance	7	383.11%	303.44%	6.71%
MERRILL LYNCH & CO INC	Broker-Dealer	8	200.27%	160.20%	6.37%
WASHINGTON MUTUAL INC	Depository	9	261.19%	436.42%	6.15%
WELLS FARGO & CO NEW	Depository	10	227.79%	233.43%	6.00%
FEDERAL NATIONAL MORTGAGE ASSN	Other	11	194.89%	78.69%	5.70%
LEHMAN BROTHERS HOLDINGS INC	Broker-Dealer	12	199.25%	282.25%	5.44%
BANK OF AMERICA CORP	Depository	13	207.86%	215.70%	5.23%
MORGAN STANLEY DEAN WITTER & CO	Broker-Dealer	14	166.88%	248.96%	4.86%
ALLTEL CORP	Other	15	-119.93%	-103.25%	4.80%
AMERICAN EXPRESS CO	Other	16	237.53%	293.40%	4.36%
FEDERAL HOME LOAN MORTGAGE CORP	Other	17	210.58%	94.57%	4.20%
BEAR STEARNS COMPANIES INC	Broker-Dealer	18	68.72%	84.96%	4.18%
GOLDMAN SACHS GROUP INC	Broker-Dealer	19	135.50%	213.68%	3.87%
UNION PACIFIC CORP	Other	20	86.69%	123.56%	3.69%
JPMORGAN CHASE & CO	Depository	21	166.95%	182.80%	3.49%
AMERICAN INTERNATIONAL GROUP INC	Insurance	22	277.42%	369.20%	3.40%
ALLSTATE CORP	Insurance	23	183.66%	271.38%	2.97%
LOEWS CORP1	Insurance	24	136.79%	175.47%	2.67%
PRUDENTIAL FINANCIAL INC	Insurance	25	240.25%	394.44%	2.33%
LINCOLN NATIONAL CORP IN	Insurance	26	234.94%	403.58%	2.27%
AON CORP	Insurance	27	32.41%	55.10%	2.26%
HARTFORD FINANCIAL SVCS GROUP IN	Insurance	28	212.09%	368.41%	2.03%
TRAVELERS COMPANIES INC	Insurance	29	124.68%	171.62%	1.95%
CHUBB CORP	Insurance	30	164.91%	192.52%	1.73%
UNUM GROUP	Insurance	31	118.33%	165.43%	0.98%
SAFECO CORP	Insurance	32	123.95%	155.92%	0.85%
C N A FINANCIAL CORP	Insurance	33	105.34%	218.89%	0.84%
METLIFE INC	Insurance	34	220.59%	362.62%	0.75%
TORCHMARK CORP	Insurance	35	24.69%	182.45%	0.34%
JANUS CAP GROUP INC	Broker-Dealer	36	38.36%	202.27%	0.00%
SCHWAB CHARLES CORP NEW	Other	37	149.45%	191.31%	0.00%
AETNA INC NEW	Insurance	38	127.42%	192.96%	-0.12%
C I G N A CORP	Insurance	39	124.73%	267.69%	-0.56%
MARSH & MCLENNAN COS INC	Insurance	40	31.82%	33.43%	-0.63%