Measuring Systemic Risk*

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First version: March 10, 2010

This version: 27 November, 2015

Abstract

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*We would like to thank Rob Engle for many useful discussions. We are grateful to Christian Brownlees, Farhang Farazmand, Hanh Le and Tianyue Ruan for excellent research assistance. We also received useful comments from Tobias Adrian, Mark Carey, Matthias Drehman, Dale Gray and Jabonn Kim (discussants), and seminar participants at several central banks and universities where the current paper and related systemic risk rankings at vlab.stern.nyu.edu/welcome/risk have been presented. Pedersen gratefully acknowledges support from the European Research Council (ERC grant no. 312417) and the FRIC Center for Financial Frictions (grant no. DNRF102).

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Abstract

We present an economic model of systemic risk in which undercapitalization of the financial sector as a whole is assumed to lead to output externality. Each financial institution's contribution to systemic risk can be measured as its systemic expected shortfall (*SES*), i.e., its propensity to be undercapitalized when the system as a whole is undercapitalized. *SES* increases in the institution's leverage and its marginal expected shortfall (*MES*), i.e., its losses in the tail of the system's loss distribution. We demonstrate empirically the ability of components of *SES* to predict emerging systemic risk during the financial crisis of 2007-2009.

Widespread failures and losses 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 seen in isolation; they are not sufficiently focused on systemic risk even though systemic risk is often the rationale provided for such regulation. As a result, while individual risks may be 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]

The goal of this paper is to propose and apply a useful and model-based measure of systemic risk. To this end, we first develop a framework for formalizing and measuring systemic risk. Using this framework, we derive an optimal policy for managing systemic risk. Finally, we provide a detailed empirical analysis of how our measure of systemic risk measured ex ante can predict the ex post losses during the financial crisis of 2007-2009 as well as the regulator's "stress test."

The need for economic foundations for a systemic risk measure is more than an academic concern since regulators around the world consider how to reduce the risks and costs of

[1]See Crockett (2000) and Acharya (2009) for a recognition of this inherent tension between micro-prudential and macro-prudential regulation of the financial sector.

systemic crises.[2] 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. In fact, the gap between theoretical models and the practical needs of regulators has been so wide that measures such as institution-level Value-at-Risk (VaR) have persisted in assessing risks of the financial system as a whole.

We bridge this gap by studying a theoretical model that is based on the common denominator of various general equilibrium models yet simple enough to provide clear recommendations relying on well-known statistical measures. Our model is based on the basic idea that the main reasons for regulating financial institutions are that (i) failing banks impose costs due to insured creditors and bailouts; (ii) under-capitalization of the financial system leads to externalities that spill over to the rest of the economy.[3] Interestingly, even a relatively simple model is enough to obtain a rich new theory of systemic risk regulation with strong empirical content.

Our theory considers a number of financial institutions ("banks") that must decide on how much capital to raise and which risk profile to choose in order to maximize their risk-adjusted return. A regulator considers the aggregate outcome of banks' actions, additionally taking into account each bank's insured losses during an idiosyncratic bank failure and the externality arising in a systemic crisis, that is, when the aggregate capital in the banking sector is sufficiently low. The pure market-based outcome differs from the regulator's preferred allocations since, due to limited liability, banks do not take into account the loss they

[2] E.g., the "crisis responsibility fee" proposed by the Obama administration and the systemic risk levy advocated by the International Monetary Fund.

[3] 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., Acharya, 2001, and Diamond and Rajan, 2005); (iii) runs (e.g., Diamond and Dybvig, 1983, and Pedersen, 2009); and, (iv) time-inconsistency of regulatory actions that manifests as excessive forbearance and induces financial firms to herd (Acharya and Yorulmazer, 2007, and Farhi and Tirole, 2009).

impose in default on guaranteed 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, which we denote the Systemic Expected Shortfall (*SES*).[4] 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 amount a bank is undercapitalized in a future systemic event in which the overall financial system is undercapitalized. Said differently, *SES* increases in the bank's expected losses during a crisis. *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.

We empirically investigate three examples of emerging systemic risk in the financial crisis of 2007-2009 and analyze the ability of our theoretically motivated measures to capture this risk *ex ante*.[5] Specifically we look at how our measures of systemic risk estimated *ex ante* predict the ex post realized systemic risk as measured, respectively, by (A) the capital shortfalls at large financial institutions as assessed in the regulator's stress tests during the Spring of 2009, (B) the drop in equity values of large financial firms during the crisis, and (C) the increase in credit risk estimated from credit default swaps (CDS) of large financial firms during the crisis.

[4]Using a variant of SES, called SRISK, the Volatility Institute at the NYU Stern School of Business publishes Systemic Risk Rankings providing estimates of the expected capital shortfall of global financial firms given a systemic crisis. (See http://vlab.stern.nyu.edu/welcome/risk/.) For recent work either using or discussing SES, see, among others, Acharya, Engle and Pierret (2013), Acharya, Engle and Richardson (2012), Allen, Bali, and Tang (2012), Brownlees and Engle (2010), Brownlees, Chabot, Ghysels and Kurz (2015), Brunnermeier, Dong, and Palia (2011), Cummins, and Weis (2014), Engle, Jondeau and Rockinger (2014, Giesecke, and Kim (2011), Hansen (2012) and Huang, Zhou, and Zhu (2009, 2012).

[5]Our systemic risk measure is provided in real-time at http://vlab.stern.nyu.edu/welcome/risk/

Figure 1 provides a simple illustration of the ability of the firm's *ex ante MES* to forecast the realized systemic risk. In particular, each of the three panels has a cross-sectional scatter plot of the largest financial firm's *ex ante* MES versus the realized systemic risk measured as in A–C enumerated above. Each panel shows a clear relation between *MES* and realized systemic risk. Formal statistical analysis shows that the slope is statistically significant, and along with leverage, *MES* has a significant explanatory power for which financial firms ran aground during the crisis.

We note that MES is very simple to estimate and therefore easy for regulators to consider: One can simply calculate each firm's average return during the 5% worst days for the market. This measures how exposed a firm is to aggregate tail shocks and, interesting, together with leverage, it has a significant explanatory power for which firms contribute to a potential crisis, consistent with our theory. On the other hand, standard measures of institution-level risk such as expected loss in an institution's own left tail and volatility have almost no explanatory power, and the standard measure of covariance, namely beta, has a modest explanatory power.

Turning to the literature, one strand of recent papers on systemic risk take a structural approach using contingent claims analysis of the financial institution's assets (Lehar, 2005, Gray, Merton and Bodie, 2008, and Gray and Jobst, 2009). 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.[6] 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 sectors total liabilities. Similarly, Adrian and Brunnermeier (2009) measure the financial sectors Value at Risk (VaR) given that a bank has had a VaR loss, which they denote *CoVaR*, using quantile regressions. Their measure uses data on market equity and book value of the debt to construct the underlying asset returns. Adrian

[6]See the survey of systemic risk methodologies by Bisias, Flood, Lo, and Valavanis (2012).

and Brunnermeiers approach has the advantage of framing the analysis using the standard regulatory tool of VaR, though regulators should also care about expected losses beyond the VaR threshold. Billio, Getmansky, Lo, and Pelizzon (2011) measure systemic risk through Granger causality (i.e., autocovariances) across and within different parts of the financial sector. De Jonghe (2010) presents estimates of tail betas for European financial firms as their systemic risk measure. Tarashev, Borio and Tsatsaronis (2009) present a game-theoretic formulation that also provides a possible allocation of capital charge to each institution based on its systemic importance. Finally, Segoviano and Goodhart (2009) also view the financial sector as a portfolio of individual financial firms, and look at how individual firms contribute to the potential distress of the system by using the CDSs of these firms within a multivariate setting.

We bridge the gap between the structural and reduced-form approaches by considering a simple economic model that gives rise to a measure of systemic risk contribution that depends on observable data and statistical techniques that are related to those in the reduced-form approaches and easily applicable by regulators. Since our systemic risk measure arises from a model, this ensures that it is logically consistent and is measured in natural units that make it useable as a basis for a systemic tax (e.g., it has naturally additivity properties if firms merge or divisions are spun off, scales naturally with the size of the firm, and so on — as opposed to many of the reduced form approaches). Our theoretical model potentially also provides an economic foundation for the systemic risk measures proposed by de Jonghe (2010), Goodhart and Segoviano (2009) and Huang, Zhou and Zhu (2009). However, Adrian and Brunnermeier (2009)'s $CoVaR$ measure is conceptually different from our measure in that it examines the system's stress conditional on an individual firm's stress, whereas we examine a financial firm's stress conditional on systemic stress. As a way of ranking the systemic risk of firms, our measure has the advantage that the conditioning set is held constant for all firms, whereas this is not the case with $CoVaR$ (different firms have different likelihoods of experiencing stress).

To summarize, our theoretical analysis provides a conceptual framework for measuring a financial institution's contribution to systemic risk, specifically as its losses in case 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 data (equity and CDS) and, importantly, that the measure is able to predict realized systemic risk contributions of financial firms during the crisis of 2007-2009. These results have significant consequences for how macro-prudential regulation can be achieved through a systemic tax and how market data can be used for "stress tests" and other recent proposals to automatically recapitalize financial firms during a systemic crisis.[7]

The remainder of the paper is organized as follows. Section 1 presents a quick review of firm-level risk management and its parallels to overall systemic risk. Section 2 present our model, showing how we define, measure, and manage systemic risk, while Section 3 lays out how to take the model to the data. Section 4 empirically analyzes the implications of our model for systemic risk during the financial crisis of 2007-2009, and Section 5 concludes.

1 A Review of Firm-level Risk Management

In this section we review the standard risk measures used inside financial firms.[8] 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, that is, $Pr\left(R < -VaR_\alpha\right) = \alpha$. The parameter α is typically taken to be 1% or 5%. E.g., with $\alpha = 5\%$, VaR is the most that the bank loses with 95% confidence. The

[7] Recent proposals (based among others on Raviv, 2004, 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 measures correspond precisely to states in which such triggers will be hit, implying that it should be possible to use our measures to predict which firms are more systemic and therefore will find contingent capital binding in more states ex post.

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

expected shortfall (ES) is the expected loss conditional on the loss being greater than the VaR:

$$ES_\alpha = -E\left[R | R \leq -VaR_\alpha\right] \tag{1}$$

Said differently, the expected shortfall is the average of returns on days when the portfolio's loss exceeds its VaR limit. We focus on ES because it is coherent and more robust than VaR.[9]

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:

$$ES_\alpha = -\sum_i y_i E\left[r_i | R \leq -VaR_\alpha\right]. \tag{2}$$

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

$$\frac{\partial ES_\alpha}{\partial y_i} = -E\left[r_i | R \leq -VaR_\alpha\right] \equiv MES_\alpha^i, \tag{3}$$

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

These standard risk-management practices can be useful for thinking about 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

[9] 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).

system by letting R be the return of the aggregate banking sector or the overall economy. 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 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_j^i to invest in each of the available assets $j = 1, ..J$, acquiring total assets a^i of

$$a^i = \sum_{j=1}^{J} x_j^i. \tag{4}$$

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 paid out as a dividend (and 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 equity w_0^i and the debt b^i, giving the budget constraint:

$$w_0^i + b^i = a^i. \tag{5}$$

At time 1, asset j pays off r_j^i per dollar invested for bank i (so the net return is $r_j^i - 1$). 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 $\hat{y}^i$ is the pre-distress income:

$$\hat{y}^i = \sum_{j=1}^{J} r_j^i x_j^i. \tag{6}$$

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

$$\phi^i = \Phi\left(\hat{y}^i, f^i\right). \tag{7}$$

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 other well-known 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,

$$b^i = \alpha^i f^i + \left(1 - \alpha^i\right) E\left[\min\left(f^i, y^i\right)\right]. \tag{8}$$

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.[10]

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

$$w_1^i = \hat{y}^i - \phi^i - f^i \tag{9}$$

The owner of the bank equity is protected by limited liability so it receives $1_{\left[w_1^i>0\right]} w_1^i$ and, hence, solves the following program:

$$\max_{w_0^i, b^i, \left\{x_j^i\right\}_j} c \cdot \left(\bar{w}_0^i - w_0^i - \tau^i\right) + E\left(u\left(1_{\left[w_1^i>0\right]} \cdot w_1^i\right)\right), \tag{10}$$

subject to (5)–(9). Here, $u^i(\cdot)$ 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

[10]Technically, the pricing equation (8) 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 $\alpha = 0$.

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 welfare function $P^1 + P^2 + P^3$, which has three parts: The first part, is simply the sum of the utilities of all the bank owners,

$$P^1 = \sum_{i=1}^{N} c \cdot \left(\bar{w}_0^i - w_0^i - \tau^i\right) + E\left[\sum_{i=1}^{N} u^i \left(1_{[w_1^i > 0]} \cdot w_1^i\right)\right].$$

The second part,

$$P^2 = E\left[g \sum_{i=1}^{N} 1_{[w_1^i < 0]} \alpha^i w_1^i\right]$$

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,

$$P^3 = E\left[e \cdot 1_{[W_1 < zA]} \cdot (zA - W_1)\right]$$

captures the externality of financial crisis and is the main focus of our analysis. Here, $A = \sum_{i=1}^{N} a^i$ are the aggregate assets in the system and $W_1 = \sum_{i=1}^{N} w_1^i$ is the aggregate banking capital to support it at time 1. A systemic crisis occurs when the aggregate capital W_1 in the financial system falls below a fraction z of the assets A. The critical feature that we want to capture as simply as possible is that of an aggregate threshold for capital needed to avoid early fire sales and restricted credit supply. The externality cost is zero as long as aggregate financial capital is above this threshold and grows linearly when it falls below. The parameter e measures the severity of the externality imposed on the economy when the financial sector is in distress.

This formulation of systemic crisis 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. This captures well examples such as the idiosyncratic failure of Barings Bank in the United Kingdom in 1995, which 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 $P^1 + P^2 + P^3$ 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.[11] 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 up to a constant:

$$\sum_i \tau^i = \bar{\tau}. \tag{11}$$

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

[11] 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.

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 (11) 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 depends on each bank's expected capital shortfall measured based on, respectively, institution-specific and systemic risk. First, it depends on its expected shortfall (ES^i) in default:

$$ES^i \equiv -E\left[w_1^i \,|\, w_1^i < 0\right] \tag{12}$$

Further, we introduce what we call a bank's *systemic expected shortfall* (SES^i). SES^i is the amount a bank's equity w_1^i drops below its target level — which is a fraction z of assets a^i — in case of a systemic crisis when aggregate banking capital W_1 is less than z times aggregate assets:

$$SES^i \equiv E\left[za^i - w_1^i \,|\, W_1 < zA\right] \tag{13}$$

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

Using ES and SES, we can characterize a tax system that implements 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*

$$\tau^i = \frac{\alpha^i g}{c} \cdot Pr(w_1^i < 0) \cdot ES^i + \frac{e}{c} \cdot Pr(W_1 < zA) \cdot SES^i + \tau_0, \tag{14}$$

where τ_0 is a lump sum transfer to satisfy equation (11).

This result is intuitive. Each bank must first be taxed based on its probability of default $Pr(w_1^i < 0)$, times the expected losses in default *ES*, to the extent that those losses are insured by the government, where we 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.[12] Hence, this term in equation (14) corrects the underpricing of credit risk caused by the debt insurance program. We note that this term is a measure of a bank's own risk, irrespective of its relation to the system, and it is similar to the current practice since the calculation of the expected shortfall is similar to a standard Value-at-Risk calculation.

The second part of the tax in (14) depends on the probability of a systemic crisis $Pr(W_1 < zA)$ and, importantly, the bank's contribution to systemic risk as captured by *SES*, namely the bank's own loss during a potential crisis. This tax is 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 note that SES is based on a calculation that is similar to that of marginal risk within financial firms discussed in Section 1. In a 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

[12]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).

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. It is useful to compare our optimal policy to some of the proposals put forward by regulators and policymakers, and then to discuss how regulators might try to implement our proposed solution.

3.1 Discussion

There is much discussion amongst regulators, policymakers and academics of the need for a resolution fund that could be used to bail out large, complex financial institutions. This fund, paid for by the institutions themselves, would be akin to the FDIC. This resolution fund is essentially the institution-risk component of the above tax and reflects the costs of the government guarantees in the system (e.g., deposit insurance and too-big-to-fail). It does not, however, fully address the systemic-risk component since it does not differentiate between different macro-economic states and does not recognize that the costs associated with the failure of a particular firm are significantly higher in a crisis.[13]

[13]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

Another important topic in the discussion of systemic risk has been the size of financial institution's assets and/or liabilities. The theory described in Section 2 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.[14] 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 percentage expected losses (as opposed to losses in dollars).

Our theory says that the regulation of systemic risk should be based on each firm's SES and the overall probability of a systemic event $Pr\,(W_1 < zA)$. The 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 and Brownlees and Engle, 2010).

We focus in our empirical analysis on the cross-sectional systemic risk, SES. 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:

$$\frac{SES^i}{w_0^i} = \frac{za^i}{w_0^i} - 1 - E\left[\frac{w_1^i}{w_0^i} - 1 \mid W_1 < zA\right].$$

The first part, $za^i/w_0^i - 1$, measures whether the leverage 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 $za^i/w_0^i - 1$ means that the bank is already under-capitalized at time 0.[15] The second term is the expected

from these studies is that these crises represent significant portions of GDP, on the order of 10%-20%.

[14]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.

[15]We can think of z as being in the range of 8% to 12% if all assets have risk-weighting of close to 100%

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.

3.2 Measurement

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. To this end, we explain the theoretical relationship between *SES* and observed equity returns.

We can think of the systemic events in our model ($W_1 < zA$) as extreme tail events that happen once or twice a decade (or less), say. In the meantime, we observe more "normal" tail events, that is, the frequent moderately bad days. Let us define these events as the worst 5% market outcomes at daily frequency which we denote by $I_{5\%}$. Based on these events, we can define a marginal expected shortfall (*MES*) using net equity returns of firm i during these bad markets outcomes

$$MES_{5\%}^{i} \equiv -E\left[\frac{w_1^i}{w_0^i} - 1 \mid I_{5\%}\right].$$

A regulator needs to use the information contained in the moderately bad days ($MES_{5\%}^{i}$) to estimate what would happen during a real crisis (SES).[16] We can use extreme value theory to establish a connection between the moderately bad and the extreme tail. Specifically, let

under Basel I capital requirements.

[16]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.

the return on security j for bank i follow

$$r_j^i = \eta_j^i - \delta_{i,j}\varepsilon_j^i - \beta_{i,j}\varepsilon_m,$$

where η_j^i follows a thin-tailed distribution (Gaussian, for instance) while ε_j^i and ε_m follow independent normalized power law distributions with tail exponent ζ. The thin-tailed factor captures normal day-to-day changes, while the power laws explain large events, both idiosyncratic (ε_j^i) and aggregate (ε_m). The sensitivity to systemic risk of activity j in bank i is captured by the loading $\beta_{i,j}$. Since power laws dominate in the tail, we have the following simple properties (Gabaix, 2009). First, the VaR of r_j^i at level α is $VaR_\alpha^{i,j} = \left(\delta_{i,j}^\zeta + \beta_{i,j}^\zeta\right)^{1/\zeta} \alpha^{-1/\zeta}$, and the corresponding Expected Shortfall is $ES_\alpha^{i,j} = \frac{\zeta}{\zeta-1} VaR_\alpha^{i,j}$. Second, the events $I_{5\%}$ and $(W_1 < zA)$ correspond to the critical values $\bar{\varepsilon}_m^{\%}$ and $\bar{\varepsilon}_m^S$ of the systemic shock ε_m and we can define the relative severity as:[17]

$$k \equiv \frac{\bar{\varepsilon}_m^S}{\bar{\varepsilon}_m^{\%}}.$$

Using the power laws, we obtain the following proposition:

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

$$\frac{SES^i}{w_0^i} = \frac{za^i - w_0^i}{w_0^i} + kMES_{5\%}^i + \Delta^i, \tag{15}$$

where $\Delta^i \equiv \frac{E\left[\phi^i | W_1 < zA\right] - k \cdot E\left[\phi^i | I_{5\%}\right]}{w_0^i} - \frac{(k-1)\left(f^i - b^i\right)}{w_0^i}$.

Proof. See appendix. ■

We see therefore that *SES* has three components: (i) Excess ex ante leverage $za^i/w_0^i - 1$, (ii) the measured marginal expected shortfall *MES* using pre-crisis data, scaled up by a factor k to account for the worse performance in the true crisis, and (iii) an adjustment term Δ^i. The main part of Δ^i is the term $E\left[\phi^i \mid W_1 < zA\right] - k \cdot E\left[\phi^i \mid I_{5\%}\right]$, which measures the excess

[17] Note that there is a direct link between the likelihood of an event and its tail size, since we have $k = \frac{\bar{\varepsilon}_m^S}{\bar{\varepsilon}_m^{\%}} = \left(\frac{5\%}{\Pr(W_1 < zA)}\right)^{1/\zeta}$.

costs of financial distress. The typical estimation sample contains bad market days, but no real crisis. We are therefore likely to miss most costs of financial distress and to measure $kE\left[\phi^i \mid I_{5\%}\right] \approx 0$. On the other hand, $E\left[\phi^i \mid W_1 < zA\right]$ is probably significant, especially for highly levered financial firms where we expect large deadweight losses in a crisis.[18]

Based on this discussion, we therefore expect *MES* and leverage to be predictors of *SES*. We now turn to the empirical analysis to test this prediction.

4 Empirical Analysis of the Crisis of 2007-2009

We consider whether our model-implied measures of systemic risk — measured before the crisis — can help predict which institutions actually did contribute to the systemic crisis of 2007-2009. We are interested in predicting the systemic expected shortfall *SES* (Section 2.3), which can be estimated using the marginal expected shortfall *MES* and leverage (Section 3).

We 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:

$$MES^b_{5\%} = \frac{1}{\#\text{days}} \sum_{t:\text{ system is in its 5\% tail}} R^b_t \tag{16}$$

Even though the tail days in this average before the crisis do not capture the tails of a true financial crisis, our power law analysis in Section 3 shows how it is linked nevertheless.

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. We apply the standard approximation of leverage, denoted LVG:

$$LVG^b = \frac{\text{quasi-market value of assets}}{\text{market value of equity}} = \frac{\text{book assets - book equity + market equity}}{\text{market value of equity}} \tag{17}$$

[18]The second part of Δ^i measures the excess returns on bonds due to credit risk $(f^i - b^i)$. This difference does not scale up when we move from bad days to tail events, so multiplying *MES* by k would overestimate *SES* by $(k-1)$ times the fixed payments. This second part is quantitatively small because ex-ante credit spreads are relatively small.

The book-value characteristics of firms are available at a quarterly frequency from the CRSP-Compustat merged dataset.

A sample calculation here would be useful. As presented in Appendix B, in June 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.

We analyze the ability of these theoretically motivated measures to capture the realized systemic risk captured in three ways: (i) the capital shortfalls at large financial institutions estimated via stress tests performed by bank regulators during the Spring of 2009; (ii) the realized systemic risk that emerged in the equity of large financial firms from July 2007 through the end of 2008; and (iii) the realized systemic risk that emerged in the credit default swaps (CDS) of large financial firms from July 2007 through the end of 2008. As we will see, the simple measures of ex ante systemic risk implied by the theory have useful information for which firms ran aground during the financial crisis.

4.1 The Stress Test: 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. 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 even worse. 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 and the market appeared to react favorably to having access to this information of the extent of systemic risk.

This stress test is very much in the spirit of our SES measure since it aims at estimating the capital shortfall in a potential future crisis. Of course, our model suggests that regulator's should use all data available to estimate SES, but it is nevertheless interesting to consider how our simple statistical measures compare to the outcome of the regulator's in depth analysis based in detailed data.

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), along with our measured *MES* (from April 2008 to March 2009) and 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%).[19]

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 question is how well do our systemic risk measures capture the SCAP estimates of systemic losses across these 18 firms?[20] 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

[19]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.

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

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, 53.22%. The important point is that the systemic risk measures seem to capture quite well the SCAP estimates of percentage 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, i.e., using information from October 2007 to September 2008. While *MES* remains statistically significant, the adjusted R-squares drop considerably for both measures of capital and for both the OLS and Probit regressions as expected. (Needless to say, the Federal Reserve's SCAP results would also have been different prior to Lehman Brother's failure.)

4.2 The Financial Crisis: July 2007 to December 2008

We next consider how *MES* and leverage estimated using data from the year prior to the crisis (June 2006 till June 2007) explain the cross-sectional variation in equity performance during the crisis (July 2007 till December 2008). To put the explanatory power of *MES* and *LVG* in perspective, we also check their incremental power relative to other measures of risk. For this, we focus on measures of firm-level risk — the expected shortfall, *ES* (i.e., the negative of the firm's average stock return in its own 5% left tail) and the annualized standard deviation of returns based on daily stock returns, *Vol* — and 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. 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 for the 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). 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. Average volatility of financial stock return is 21% and average beta is 1.0. The power law application in Section 3 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 (for CBOT Holdings Inc). 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). [21]

[21] 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

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 shows the power of *MES* and leverage in explaining the realized performance of financial firms during the crisis, both in absolute terms in relative to other measures of risk. In particular, it 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*. (We also note that Appendix B provides the firm-level data on *MES* and *LVG*.)

Figure 1B shows that *MES* does a reasonably good job of explaining the realized returns, and naturally a higher *MES* is associated with a more negative return during the crisis. A few cases illustrate the point well. We can see that Bear Stearns, Lehman Brothers, CIT and Merrill Lynch have relatively high *MES* and these firms lose a large chunk of their equity market capitalization. There are, however, also some reasons to be concerned. For example, exchanges (NYX, ICE, ETFC) have relatively high *MES* but we do not think of these as systemic primarily because they are not as leveraged as say investment banks are. Similarly, while A.I.G. and Berkshire Hathaway have relatively low *MES*, A.I.G.'s leverage at 6.12 is

institutions.

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. Thus combining *MES* and leverage of financial firms helps understanding their systemic risk better since, as predicted by the theory, financial distress costs of leveraged firms can be large in a crisis.

In this light, when combining MES and LVG using the estimated regression coefficients (column 6 in Table 4), exchanges are no longer as systemic as investment banks and A.I.G. looks far more systemic than Berkshire Hathaway. The five investment banks rank in top ten both by their *MES* and leverage rankings so they clearly appear systemically risky (Appendix B). Countrywide is ranked 24^{th} by *MES* given its *MES* of 2.09%, but due to its high leverage of 10.39, it has a combined systemic risk ranking of 6^{th} using the estimated coefficients (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*, *Vol*, and *ES* — do not perform that well. The R^2 with *Beta* is just 3.62% and those with *Vol* and *ES* are 0.0%. It is also interesting to note that, in the regressions that include *LVG* and *MES* together, the 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. Regarding the size of banks, we see that the log of assets is significant when included alone in the regression (column (7)), and while its significance drops substantially once MES and leverage are included, it remains borderline significant (column (8)). The negative sign on log of assets suggests that size may not only affect the dollar systemic risk contribution of financial firms but also the percentage systemic risk contribution as well. That is, large firms may create more systemic risk than a likewise combination of smaller firms, according to this regression, though the significance of this result is weak (and our theory does not have this implication).

As is clear from Table 3 and Figure 1B, there is a number of firms for which the realized stock return during the crisis period was −100%. This introduces a potential truncation bias in the dependent variable and in turn on estimated regression coefficients. To control for this bias, Panel B of Table 4 runs a Tobit analysis where 11 firms (listed in the caption of Table 4) that had returns worse than −90% are assumed to have in fact had returns of −100%: in all likelihood, they would have all reached that outcome but were bailed out in advance, as with Fannie, Freddie, AIG and Citigroup, or were merged through government support, as in the case of Bear Stearns. Our results are qualitatively unaffected though the coefficient on leverage increases almost two-fold, which is unsurprising given the high leverage of the firms that ran aground in the crisis.

We consider several robustness checks. Figure 2 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 estimation 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.

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.[22] 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 remain strongly significant using the April06-Mar07 data. These results suggest there is some value to exploring more sophisticated methods for estimating *MES* and to including the most recent data in estimates.

Finally, Panel D of Table 5 considers *F-MES*, which is calculated as our benchmark *MES* but instead of using the CRSP value-weighted index return as the "market return", we instead use the financial industry return series obtained from the data on 30 industry portfolios provided by Kenneth French. The financial industry return maps closer to our economic model of systemic risk wherein the externality arose when the financial sector experienced under-capitalization rather than the market as a whole. Also, *F-MES* might capture better tail dependence induced between a financial firm and other financial firms due to contagion-based systemic risk. We find that the results with using *F-MES* are virtually identical to the benchmark results in Panel A, implying little difference in using stock market or financial sector as the relevant market for computing *MES*.

[22]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, using the methodology they develop in Brownlees and Engle (2010).

4.3 Using CDS to Measure Systemic Risk

We have seen the ability of the *MES* and leverage of financial firms to forecast the outcome of the stress test and the equity performance during the financial crisis. We add to this evidence by considering the credit default swaps (CDS) data from Bloomberg for these financial firms.[23] 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 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 and riskless floating rate debt. We denote this spread by s. To garner some intuition as to how changes in the spread are related to *MES*, note that if 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, then $dP/P = -Dds$ and $dP/P = \xi dV/V$. 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 one when the bond is virtually in default, ds attaches close to zero weight to the firm value return 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, firm value changes can be approximated better than using the arithmetic change in spread ds by using instead the log change, $ds/s = -\xi/(Ds)dV/V$, where s is tiny when eta is close to zero and large when eta is close to one. Further, from an econometric standpoint, the log change is more stationary and less driven by outliers.

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. This means that we take the 5% worst days for an equally-weighted portfolio of CDS returns on the 40 financial firms from June

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

2006 to July 2007, and we then compute the CDS return for any given firm for these days. For comparison purposes, we also show results that use arithmetic changes in the CDS spread as a measure of CDS return. 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 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.[24]

- 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 enterprizes and so-called too-big-to-fail firms.[25] Since CDS reflect estimated creditor losses, the backstop

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

[25]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.

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.

Table 6 provides regressions with regressors being *CDS MES* based on CDS returns (Panel A) and CDS spread changes (Panel B) and dependent variable being respectively the realized CDS returns and changes during different periods covering the crisis (July 2007-June 2008 / September 14, 2008 / September 30, 2008 / October 10, 2008 / December 30, 2008) related to government action on creditor guarantees.

We see that our ex ante measured significantly predict the realized systemic risk. 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. 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 7 shows how *CDS MES* based on CDS returns (Panel A) or CDS spread changes (Panel B) predicts the realized *equity* returns during the same periods as Table 6. 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 information for which firms might run into trouble, and, therefore, by inference should, according to our derived optimal policy, be taxed to induce them to reduce their systemic risk.

In summary, 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. 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 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 argue that financial regulation be focused on limiting systemic risk, that is, the risk of a crisis in the financial sector and its spillover to the economy at large. We provide 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 appear to be able to predict the financial firms with the worst contributions in the 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.[26] 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 had the most pernicious

[26]Based on the theory presented here, Acharya, Pedersen, Philippon and Richardson (2009) 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.

effect in the crisis of 2007-09 was short-term debt: the overnight secured borrowing ("repo") against risky assets (Adrian and Shin, 2010) 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, 2013). 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 financial firms.

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Appendix.

Proof of Proposition 1

Using the definition of τ^i in equation (14), the bank's problem is

$$\max_{w_0^i, b^i, \left\{x_j^i\right\}_j} \quad c \cdot \left(\bar{w}_0^i - w_0^i - \tau_0\right) + E\left[u\left(1_{\left[w_1^i > 0\right]} \cdot w_1^i\right)\right]$$
$$-\alpha^i g \cdot Pr(w_1^i < 0) ES^i - e \cdot Pr(W_1 < zA) SES^i,$$

and using (12) and (13), this becomes

$$\max_{w_0^i, b^i, \left\{x_j^i\right\}_j} \quad c \cdot \left(\bar{w}_0^i - w_0^i - \tau_0\right) + E\left[u\left(1_{\left[w_1^i > 0\right]} \cdot w_1^i\right)\right]$$
$$+E\left[\alpha^i g 1_{\left[w_1^i < 0\right]} w_1^i + e 1_{[W_1 < zA]} (za^i - w_1^i)\right].$$

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

Proof of Proposition 2

Equity value satisfies: $w_1^i - w_0^i = \sum_{j=1}^{J} r_j^i x_j^i - \phi^i - f^i - w_0^i$. This allows us to write

$$MES_{5\%}^i = \sum_{j=1}^{J} \frac{x_j^i}{w_0^i} E\left[-r_j^i \mid I_{5\%}\right] + \frac{E\left[\phi^i \mid I_{5\%}\right]}{w_0^i} + \frac{f^i - b^i}{w_0^i}$$

In expectations we have $E\left[-r_j^i \mid I_{5\%}\right] = \beta_{i,j} \frac{\zeta}{\zeta - 1} \bar{\varepsilon}_m^{\%}$ and therefore $E\left[-r_j^i \mid W_1 < zA\right] = kE\left[-r_j^i \mid I_{5\%}\right]$. Using the definition of SES we can write:

$$1+\frac{SES^i}{w_0} = \frac{za^i}{w_0^i} - E\left[\frac{w_1^i}{w_0^i} - 1 \mid W_1 < zA\right] = \frac{za^i}{w_0^i} + \sum_{j=1}^{J} \frac{x_j^i}{w_0^i} E\left[-r_j^i \mid W_1 < zA\right] + \frac{E\left[\phi^i \mid W_1 < zA\right]}{w_0^i} + \frac{f^i - b^i}{w_0^i}$$

Hence, under the power law assumption:

$$1 + \frac{SES^i}{w_0} - k \cdot MES^i = \frac{za^i}{w_0^i} + \frac{E\left[\phi^i \mid W_1 < zA\right] - k \cdot E\left[\phi^i \mid I_{5\%}\right]}{w_0} + (1-k)\frac{f^i - b^i}{w_0^i}.$$

QED.

Figure 1.A MES Predicts the Stress Tests. The marginal expected shortfall measure (MES), a measure of ex ante systemic risk, plotted against the stress tests' assessed capital shortfall, SCAP/Tier1comm. MES is stock return given that the *market return* is below its 5th-percentile, measured for each individual company stock using the period Oct07-Sep08. The sample consists of 18 US financial firms included in the Federal Reserve's stress tests of Spring of 2009.

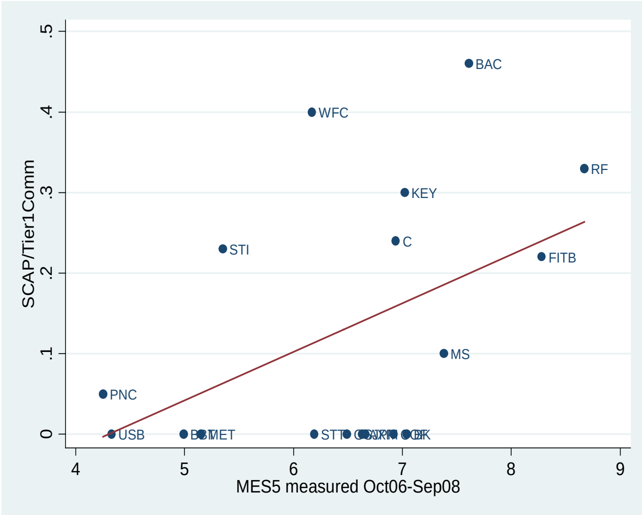

Figure 1.B: MES Predicts Realized Equity Returns During the Crisis. MES estimated ex ante over the period June 2006-June 2007 plotted against the stock return during the crisis July 2007 to December 2008. The sample consists of 102 US financial firms with a market cap in excess of 5 bln. dollars as of June 2007.

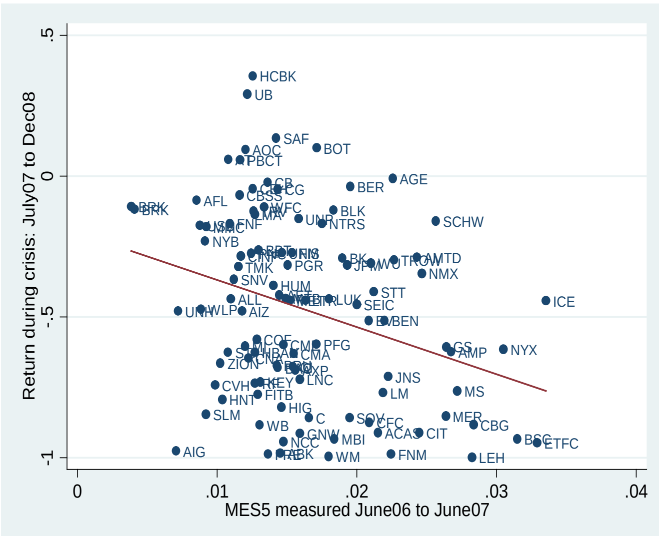

Figure 1.C: MES Predicts Realized CDS Returns During the Crisis. MES estimated ex ante from CDS returns July 2006-30 June 2007 plotted against the total realized return on CDS spread during 1 July 2007-30 June 2008.

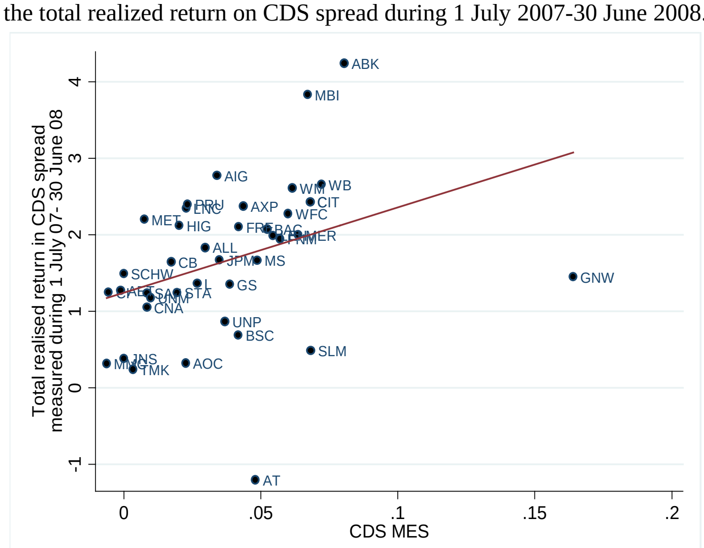

Figure 2: Stability of MES. The graph depicts a scatter plot of the MES, marginal expected shortfall measure at the 5% level, computed during the June 2006-June 2007 period versus that computed during June 2005-June2006. MES is the marginal expected shortfall of a stock given that the *market return* is below its 5th-percentile.

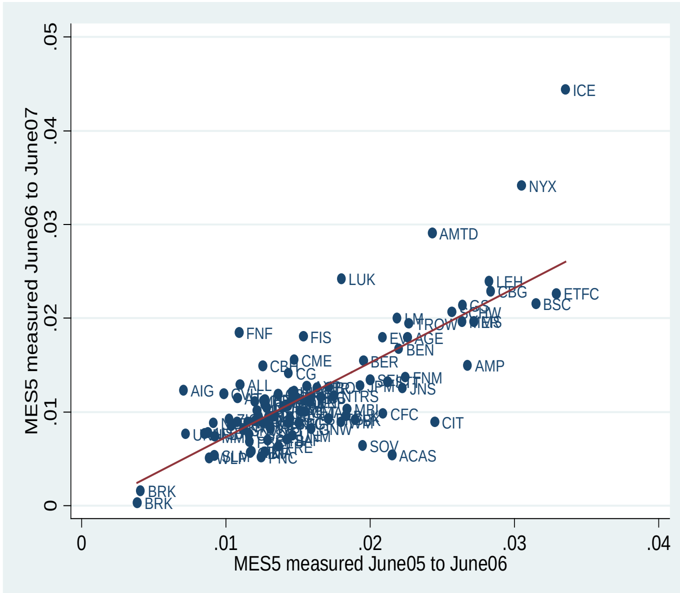

Table 1: Banks Included in the Stress Test, Descriptive Statistics.

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 5th-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. **Panel C** reports the results for estimated losses (not just the capital shortfall) as of 2008Q4 and 2009Q1 divided by Tier1 Common equity. 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. In Panels A and B, 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

Panel C: MES and LVG are measured during April08-March09 and dependent Variable is Estimated losses/Tier1Comm as of

	2008 Q4			2009 Q1		
	OLS			OLS		
	(I)	**(II)**	**(III)**	**(VII)**	**(VIII)**	**(IX)**
Intercept	-0.78	0.12	-0.06	-0.30	0.30	-0.04
	(-1.10)	(0.84)	(-0.10)	(-0.63)	(2.24)	(-0.08)
MES	0.12		0.02	0.07		0.03
	(2.07)		(0.33)	(1.75)		(0.71)
LVG		0.02	0.02		0.01	0.01
		(4.83)	(3.78)		(2.31)	(1.54)
Adj. R^2	16.21%	56.75%	54.21%	10.82%	20.36%	17.82%
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

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(**Panel A**) and Tobit analyses(**Panel B**) 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. In the Tobit regression analyses the following firms were assumed to have a Realized SES of -1: AIG, Bear Stearns, Citi-Group, Countrywide Financial Corp., Freddie Mac, Fannie Mae, Lehman Brothers, Merrill Lynch, National City Corp., Washington Mutual, and Wachovia. 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.

Panel A, OLS regression analysis: 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	101	101	101	101

Panel B, Tobit Analysis:The dependent variable is Realized SES, the company stock returns during the crisis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ES	-0.05							
	(-1.06)							
Vol		0.10						-0.26
		(0.17)						(-0.42)
MES			-0.23***			-0.001**		-0.001*
			(-2.85)			(-2.03)		(-1.69)
Beta				-0.32**				
				(-2.24)				
LVG					-0.07***	-0.06***		-0.05***
					(-6.40)	(-6.14)		(-3.18)
Log Assets							-0.12***	-0.04
							(-5.48)	(-1.18)
Industry dummies								
Constant	-0.35***	-0.48***	-0.14	-0.18	-0.06	0.12	0.87***	0.5
	(-2.66)	(-3.93)	(-1.02)	(-1.29)	(-0.69)	(1.01)	(3.48)	(1.48)
Other	-0.01	-0.08	0.04	0.04	-0.26***	-0.18*	-0.28***	-0.18*
	(-0.10)	(0.70)	(0.41)	(0.40)	(-2.92)	(-1.82)	(-2.90)	(-1.82)
Insurance(x100)	0.03	0.01	-0.02	-0.01	-0.11	-0.12	-0.09	-0.13
	(0.27)	(0.14)	(-0.21)	(-0.14)	(-1.42)	(-1.58)	(-1.03)	(-1.60)
Broker-dealers	-0.14	-0.22	0.08	0.03	-0.07	0.10	-0.23*	0.10
	(-0.87)	(-1.42)	(0.49)	(0.18)	(-0.58)	(0.68)	(-1.85)	(0.68)
Pseudo R^2	3.95%	2.95%	10.21%	7.49%	43.95%	47.70%	28.87%	49.05%
No. Obs	102	102	102	102	101	101	101	101

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**), D-MES (**Panel C**), and F-MES (**Panel D**) measure. All measures are as described in Table 3 and Table 4, except for W-MES which is the exponentially-weighted MES, D-MES which is the dynamic MES, and F-MES which is MES computed using the return on the financial industry* as the market portfolio. 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.

* The financial industry return series are obtained from the 30 industry portfolios available on Kenneth French's website http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

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

Panel A (MES): The dependent variable is Realized SES, the company stock returns during the crisis				
	June06-May07	**May06-Apr07**	**Apr06-Mar07**	**Mar06-Feb07**
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	101	101	101	101

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	101	101	101	101

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	101	101	101	101

Panel D (F-MES): The dependent variable is Realized SES, the company stock returns during the crisis				
Intercept	-0.15*	-0.19**	-0.19**	-0.22***
	(-1.84)	(-2.30)	(-2.35)	(-2.82)
F-MES	-0.09*	-0.06	-0.06	-0.04
	(-1.82)	(-1.43)	(-1.41)	(-0.94)
LVG	-0.04***	-0.04***	-0.04***	-0.04***
	(-4.80)	(-5.03)	(-5.15)	(-5.18)
Adj. R^2	23.24%	22.19%	22.96%	21.33%
No. Obs	101	101	101	101

Table 6: 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 7: 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

	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	-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

	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	-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

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.

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

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

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

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

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

Broker-Dealers: 10 Companies, 4-digit SIC code=6211.

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

<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 5^{th} 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 5^{th} 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%