Measuring Systemic Risk

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We present an economic model of systemic risk in which undercapitalization of the financial sector as a whole is assumed to harm the real economy, leading to a systemic risk externality. Each financial institution's contribution to systemic risk can be measured as its systemic expected shortfall (SES), that is, 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), that is, 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. (*JEL* G01, G21, G28, D62, H23)

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Widespread failures and losses of financial institutions can impose an externality on the rest of the economy, and the global financial crisis of 2007–2009 provides ample evidence of the importance of containing this risk. However, current financial regulations, such as Basel capital requirements, are designed to limit each (or representative) institution's risk seen in isolation; they are not sufficiently focused on systemic risk even though systemic risk is

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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 ex ante measure of systemic risk can predict the ex post losses during the financial crisis of 2007–2009 as well as the regulators' "stress test" in the spring of 2009.

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 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), designed to address the risk of an individual institution, have persisted in regulation-assessing risks of the financial system as a whole (Allen and Saunders 2002).

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; and (ii) undercapitalization 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

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[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.

[2] Some examples are the "crisis responsibility fee" proposed by the Obama administration (White House press release, January 14, 2010) and the systemic risk levy advocated by the International Monetary Fund (Global Financial Stability Report, International Monetary Fund, April 2010).

[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 in Allen and Gale 2007 and Acharya and Yorulmazer 2007), margin requirements (e.g., Garleanu and Pedersen 2007), liquidity spirals (e.g., Brunnermeier and Pedersen 2009), and interest rates (e.g., Acharya 2009; Diamond and Rajan 2005); (iii) runs (e.g., Diamond and Dybvig 1983; Pedersen 2009); and (iv) time-inconsistency of regulatory actions that manifests as excessive forbearance and induces financial firms to herd (Acharya and Yorulmazer 2007; Farhi and Tirole 2009).

losses during an idiosyncratic bank failure and the externality arising in a systemic crisis, that is, when the aggregate capital in the banking sector is sufficiently low. The pure market-based outcome differs from the regulator's preferred allocations since, due to limited liability, banks do not take into account the loss they impose in default on guaranteed creditors and the externality they impose on the economy at large in a systemic crisis.

We show that to align incentives, the regulator optimally imposes a tax on each bank that 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 (i) the capital shortfalls at large financial institutions as assessed in the regulator's stress tests during the spring of 2009, (ii) the actual drop in equity values of large financial firms during the crisis, and (iii) the increase in credit risk estimated from credit default swaps (CDS) of large financial firms during the crisis.

We note that MES is very simple to estimate: 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, interestingly, 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, we find that standard measures of institution-level risk such as expected loss in an institution's own left tail and volatility have little explanatory power. Moreover,

[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), Bostandzic and Weiss (2015), Brownlees and Engle (Forthcoming), Brownlees et al. (2015), Brunnermeier, Dong, and Palia (2011), Cummins and Weiss (2014), Engle, Jondeau, and Rockinger (2014), Giesecke and Kim (2011), Hansen (2014), 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/.

the standard measure of covariance, namely beta, also has less explanatory power than the measures we propose.

Turning to the literature, one strand of recent papers on systemic risk takes a structural approach using contingent claims analysis of the financial institutions' assets (Lehar 2005; Gray, Merton, and Bodie 2008; Gray and Jobst Forthcoming). 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 (CDSs) of financial firms and stock return correlations across these firms to estimate expected credit losses above a given share of the financial sector's total liabilities. Similarly, Adrian and Brunnermeier (Forthcoming) measure the financial sector's 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. Adrian and Brunnermeier's 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 et al. (2012) 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. Borio, Tarashev, 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 usable as a basis for a systemic tax. For example, it has natural 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's (forthcoming) *CoVaR* measure is conceptually different from

[6] See the survey of systemic risk methodologies by Bisias et al. (2012).

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 (i.e., the existence of a financial crisis), whereas this is not the case with *CoVaR* (i.e., conditional on a given firm's stress, which varies cross-sectionally). This can lead to some undesirable properties in the rankings. For example, Acharya, Engle, and Richardson (2012) show that, under certain distributional assumptions about firm's returns, *CoVaR* treats two firms identically in terms of systemic risk if the firms have the same return correlation with the aggregate market even though they might have very different return volatilities.

In conclusion, we provide a simple economic framework for measuring systemic risk, and our results have consequences for how macro-prudential regulation can be achieved through a systemic tax, stress tests, or recapitalization of financial firms during systemic crises.[7]

1. Systemic Risk in an Economic Model

1.1 Definitions and preliminary analysis

We start by reviewing the standard risk measures used inside financial firms and discuss how these measures can be extended to apply for the whole financial system.[8] This preliminary analysis allows us to define some simple concepts and generate an intuition that is 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 $1-\alpha$, that is, $Pr(R<-VaR_\alpha)=\alpha$. The parameter α is typically taken to be 1% or 5%. For example, with $\alpha = 5\%$, *VaR* is the most that the bank loses with 95% confidence. The ES is the expected loss conditional on the loss being greater than the *VaR*:

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

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 rather than *VaR* for several reasons. First, *VaR* is not robust 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

[7] Recent proposals (based among others on Raviv (2004), Flannery 2005; Kashyap, Rajan, and Stein 2008; Hart and Zingales 2009; 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 Lehar (2005) and Yamai and Yoshiba (2005) for a fuller discussion.

VaR does 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 of collateralized debt obligations (CDOs) and other structured products. In contrast, ES does not suffer from this problem, 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 borne by the government bailout. Second, *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 *VaR*s, which cannot happen with ES (Artzner et al. 1999).

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:

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

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

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

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 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*.

1.2 Banks' incentives

We next present an economic model in which we consider the incentives of financial firms and their systemic externalities. The economy has N financial firms, which we denote as banks, indexed by $i=1,..N$ and two time periods $t=0,1$. Each bank i chooses how much x^i_j to invest in each of the available assets $j=1,..J$, acquiring total assets a^i of

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

These investments can be financed with debt or equity. In particular, the owner of any bank i has an initial endowment $\bar{w}^i_0$ of which w^i_0 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 market value of the bank assets 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 market value of bank assets 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 $y \geq 0$.

What is special about banks (versus other corporations) is that (i) they enjoy government guarantees of parts of their debt, and (ii) their financial distress can impose systemic-risk externalities. We first discuss the issue of guaranteed debt and turn to systemic risk in the next section.

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.[9]

[9] 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 $\alpha = 0$. We adopt the general formulation as it allows us to span the setting where a portion of bank debt, e.g., retail deposits up to a threshold size, is guaranteed by a national deposit insurance agency.

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:

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

subject to Equations (5)–(9), where, $u^i(\times)$ 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), and the remaining endowment is kept as equity capital w_0^i or used to pay the bank's tax τ^i, which we describe later. The parameter c has several interpretations. It can simply be seen as a measure of the utility of immediate consumption, but, more broadly, it is the opportunity cost of equity capital. We can think of the owner as raising capital at cost c, or we can think of debt as providing advantages in terms of taxes or incentives to work hard. What matters for us is that there is an opportunity cost of using capital instead of debt.

1.3 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,

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

The second part,

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

is the expected cost of the debt insurance program, where 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 is the main focus of our analysis since

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

captures the externality of financial crisis, where each term is defined as follows. First, $A = \sum_{i=1}^{N} a^i$ 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, where the slope parameter e measures the severity of the externality imposed on the economy when the financial sector is in distress.[10]

This formulation of a systemic crisis is consistent with the emphasis of the stress tests performed by the Federal Reserve in the United States starting in the spring of 2009,[11] and in understanding the crucial difference between systemic and institution-specific risk. It means that a bank failure occurring in a well-capitalized system imposes no externality on the economy. This captures well-known examples such as the idiosyncratic failure of Barings Bank in the United Kingdom in 1995, which did not disrupt the global (or even the United Kingdom's) financial system. (That is, the Dutch bank ING purchased Barings and assumed all of its liabilities with minimal government involvement and no commitment of taxpayer money.) This stands in sharp contrast with the failures of Bear Stearns or Lehman Brothers witnessed in 2008. When the whole financial system has too little capital, then firms and consumers face a credit crunch, which can lead to job losses, a recession, or perhaps even a depression (see, for instance, the discussion in Acharya et al. 2009).

The planner's problem is to choose a tax system τ^i 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. Indeed, adding capital ex post to troubled banks creates moral hazard, and here we focus on measuring and managing systemic risk ex ante. 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

10 There is growing evidence on the large bailout costs and real economy welfare losses associated with banking crises (see, for example, Caprio and Klingebiel 1996; Honohan and Klingebiel 2000; Hoggarth, Reis, and Saporta 2002; Reinhart and Rogoff 2008; Borio and Drehmann 2009; and more recently, Laeven and Valencia 2013; Chodorow-Reich 2014; Acharya et al. 2015). The bottom line from these studies is that these crises represent significant portions of GDP, on the order of 10–20%.

11 The Federal Reserve states on their website that "the Comprehensive Capital Analysis and Review (CCAR) is an annual exercise by the Federal Reserve to assess whether the largest bank holding companies operating in the United States have sufficient capital to continue operations throughout times of economic and financial stress and that they have robust, forward-looking capital-planning processes that account for their unique risks." As part of this exercise, the Federal Reserve evaluates institutions' capital adequacy, internal capital adequacy assessment processes, and their individual plans to make capital distributions, such as dividend payments or stock repurchases. Dodd-Frank Act stress testing (DFAST)—a complementary exercise to CCAR—is a forward-looking component conducted by the Federal Reserve and financial companies supervised by the Federal Reserve to help assess whether institutions have sufficient capital to absorb losses and support operations during adverse economic conditions. For more details, see the Federal Reserve Board's stress test website: http://www.federalreserve.gov/bankinforeg/stress-tests-capital-planning.htm.

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, making it a self-funded entity. We can also add the expected cost of the externality. At time 1, the government would simply balance its budget in each state of the world with lump-sum taxes on the non-financial sector. We can also think of Equation (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.

1.4 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 "required" 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:

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

Recall that a crisis happens when the aggregate capital W_1 is below z times aggregate assets A. This condition can be avoided if each bank keeps its own capital above z times its own assets—hence, the "required" capital is the same fraction z of assets for all banks. A bank that has positive *SES* is expected to contribute to a future systemic crisis in the sense of failing to meet this requirement during a future crisis. Therefore, *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 $\{\tau_i\}_{i=1,\ldots N}$ 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 conditional on choices made by the banks, which captures the idea that a regulator can impose a higher tax on banks that take more systemic risk (or require certain actions based on stress tests).

Proposition 1. The efficient outcome is obtained by a tax

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

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

Proof. See Appendix A. ■

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, the first 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 Equation (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 1.1. In a marginal risk calculation, the risk managers ask how much a particular line of business is expected to lose on days where the bank as a whole has a large loss (i.e., how much that particular line of business is expected to contribute to the overall loss). Our formula applies this idea more broadly, namely to the financial system as a whole.

The optimal tax system holds for all kinds of financial distress costs, and the planner reduces its taxes when capital is costly at time 0 (c is high). The fact that we obtain an expected shortfall measure comes from the shape of the externality function. It is important to understand the information required to implement the systemic regulation. The planner does not need to know the utility functions and investment opportunity sets of the various banks. It needs to estimate two

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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 overfunded (in contrast to the current premium schedules of the Federal Deposit Insurance Corporation [FDIC] in the United States). See, for example, the theoretical arguments and the empirical evidence in Acharya, Santos, and Yorulmazer (2010).

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 bank in a crisis, using market-based data.

2. Measuring Systemic Risk

The optimal policy developed in Section 1.4 calls for a fee (i.e., a tax) equal to the sum of two components: (i) an institution-risk component, that is, 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 undercapitalization.

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 more 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 market outcomes

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

A regulator needs to use the information contained in the "moderately bad days" ($MES^i_{5\%}$) to estimate what would happen during a real crisis (*SES*).[13] We can use extreme value theory to establish a connection between the moderately bad and the extreme tail. Specifically, let the return on security j for bank i follow

$$r^i_j = \eta^i_j - \delta_{i,j}\varepsilon^i_j - \beta_{i,j}\varepsilon_m,$$

where η^i_j follows a thin-tailed distribution (Gaussian, for instance), while ε^i_j and ε_m follow independent normalized power law distributions with tail exponent ζ.

[13] Note that if we assume returns are multivariate normal, then the drivers of the firm's systemic risk would be entirely determined by the expected return and volatility of the aggregate sector return and the 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; Jiang and Kelly 2014). Our discussion helps clarify what variables are needed to measure systemic risk in the presence of extreme values.

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, for α sufficiently small, is $VaR_\alpha^{i,j} \approx \left(\delta_{i,j}^\zeta + \beta_{i,j}^\zeta\right)^{1/\zeta} \alpha^{-1/\zeta}$, and the corresponding expected shortfall is $ES_\alpha^{i,j} \approx \frac{\zeta}{\zeta-1} VaR_\alpha^{i,j}$. 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:

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

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

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

Proof. See Appendix A. ■

We see therefore that *SES* has three components: (i) the excess ex ante degree of undercapitalization $za^i / w_0^i - 1$, (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 $E\left[\phi^i \mid W_1 < zA\right] - k \times E\left[\phi^i \mid I_{5\%}\right]$, which measures the excess 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 large financial firms where we expect large deadweight losses in a crisis.[14]

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.

[14] The second part of Δ^i measures the excess returns on bonds due to credit risk ($f^i - b^i$). This second part is likely to be quantitatively small because ex ante credit spreads are relatively small.

3. 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* (see Section 1.4). Using the results of Section 2, we show below that *SES* can be estimated using the marginal expected shortfall *MES* and leverage.

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 undercapitalized at time 0 in the sense that the capital w_0^i is low relative to the assets a^i.[15] The second term is the expected equity return conditional on the occurrence of a crisis. Hence, the sum of these two terms determine whether the bank will be undercapitalized in a crisis and by what magnitude.

We estimate *MES* at a standard risk level of α=5% using daily data of equity returns from the Center for Research in Security Prices (CRSP). This means that we take the 5% worst days for the market returns (R) in any given year, and we then compute the equal-weighted 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 2 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*:

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

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

[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% under Basel I capital requirements.

As a first look at the data, Appendix C lists the U.S. financial firms with a market capitalization of at least \$5 billion as of June 2007. For each of these firms, Appendix C provides the realized *SES* during the financial crisis, the *MES* using the prior year of data, the leverage of the firm using Equation (17), the quasi-market value of the assets, and the firm's fitted *SES* rank from a cross-sectional regression of realized *SES* on *MES*, leverage, and industry characteristics. As an illustration, consider Bear Stearns, the first of the major financial firms to effectively fail during the crisis. As of June 2007, Bear Stearns ranked third in *MES* (i.e., its average loss on 5% worst-case days of the market was 3.15%), first in leverage (i.e., its quasi-market assets to market equity ratio was 25.62), and not surprisingly, first in fitted *SES* rank.

Going into the crisis, the next four highest ranked firms in terms of fitted *SES* are Freddie Mac, Fannie Mae, Lehman Brothers, and Merrill Lynch. Aside from the insurance giant AIG, these were the next four largest financial firms to run aground during the crisis, either through government receivership, bankruptcy, or sale. Of some note, unlike Bear Stearns, Lehman Brothers, and Merrill Lynch, Freddie Mac and Fannie Mae rank high in leverage, yet less so in *MES*. This observation highlights the importance of both *MES* and leverage in terms of systemic risk. While *MES* measures the firm's expected capital losses during a crisis, these losses matter most in the aggregate to the extent the firm is poorly capitalized as Freddie Mac and Fannie Mae were. As a final comment, note that *SES* is on a per-dollar basis. The level of systemic risk is scaled up by the firm's assets. For example, while Bear Stearns had considerable assets (i.e., \$423 billion), Freddie Mac, Fannie Mae, and Merrill Lynch all had twice the assets of Bear Stearns (i.e., \$822 billion, \$858 billion, and \$1.076 billion, respectively), leading to a higher level of absolute systemic risk.

These observations are suggestive of the potential use of the methodology of Section 2. In this section, we take a more thorough look at systemic risk using this methodology. Specifically, we analyze the ability of our theoretically motivated measure to capture realized systemic risk 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 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.

3.1 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 of 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 the sense of specific stress scenarios defined by the Fed and then supervised by its examiners. In early May of 2009, the results of the analysis were released to the public at large. A total of 10 banks were required to raise $74.6 billion in capital. The SCAP was generally considered to be a credible test with bank examiners imposing severe loss estimates on residential mortgages and other consumer loans, not seen since the Great Depression. The market appeared to react favorably to having access to this information on the extent of systemic risk.

At first glance, the "bottom-up" risk assessment of the SCAP would seem to be very different from our *SES* measure. However, this stress test is very much in the spirit of *SES* since it aims at estimating each bank's capital shortfall in a common potential future crisis and the total shortfall across banks. Hence, it is interesting to consider how our simple statistical measures of systemic capital shortfall compare to the outcome of the regulator's in-depth analysis. Of course, we must naturally recognize that our measures are based on much less data than the detailed data available to regulators. It nevertheless is interesting to compare and, more broadly, to note that the regulators are essentially computing systemic risk as in our model when they perform stress tests, just based on other data and statistical methods.

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, Panel A, provides a summary of each bank, including (i) its shortfall (if any) from the SCAP at the end of April 2009, (ii) its Tier 1 capital (so-called core capital including common shares, preferred shares, and deferred tax assets), (iii) its tangible common equity (just its common shares), along with our measured *MES* (from April 2008 to March 2009), and (iv) its quasi-market leverage. Five banks, as a percentage 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%).[16]

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 in the spirit of our measure of systemic risk. Panel B of Table 1 provides the correlation across firms between the banks' SCAP/Tier 1 and the banks' MES and leverage. The correlations are large and positive, 59.5% and 31.6%, respectively. Consistent

[16] The interested reader might be surprised to see that, although it required additional capital, Citigroup was not one of the most undercapitalized. It should be pointed out, however, that toward the end of 2008 (and thus prior to the SCAP), 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. JPMorgan and Bank of America also received guarantees (albeit in smaller amounts) through their purchase of Bear Stearns and Merrill Lynch, respectively. We also note that the SCAP exercise also included GMAC, but it only had preferred stock trading over the period analyzed.

Table 1
Banks included in the stress test, descriptive statistics

Panel A

Bank Name	SCAP	Tier1	Tier1 Comm	SCAP/ Tier1	SCAP/Tier1 Comm	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%

Panel A of this table contains the values of SCAP shortfall, Tier1 capital, Tier1Comm (tangible common equity), all in U.S. $billion, and SCAP Shortfall/Tier1, SCAP Shortfall/Tier1Comm, 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 to 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/Tier1Comm, MES, and LVG.

with this result, Figure 1 shows our measure of MES is linked positively in the cross-section of stress-tested financial institutions to their capital shortfall assessed by the stress test.[17]

To further test the link between the capital shortfall assessed by the stress test and our measures of systemic risk, Table 2 provides an OLS regression analysis of explaining SCAP shortfall as a percent of Tier 1 capital (Panel A) and Tier 1 common or tangible common equity (Panel B) with *MES* and leverage as the regressors. Because a number of firms have no shortfall, and thus there is a mass of observations at zero, we also extend the OLS regressions to a probit analysis (which is identical for both panels and hence is shown only in Panel A).

MES is strongly significant in both the OLS and probit regressions. For example, in the OLS regressions of *MES* on SCAP shortfall relative to Tier

[17] Appendix E provides the map between abbreviated and full financial institution names.

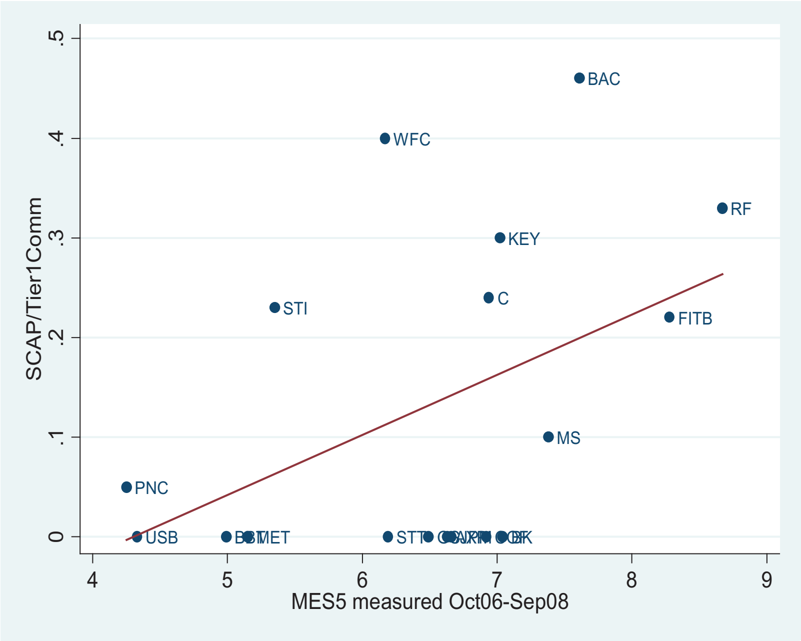

Figure 1
MES predicts the stress tests
The marginal expected shortfall measure (MES), a measure of ex ante systemic risk, plotted against the stress tests' assessed capital shortfall, SCAP/Tier1comm. MES is stock return given that the market return is below its 5th percentile, measured for each individual company stock using the period October 2007–September 2008. The sample consists of 18 U.S. financial firms included in the Federal Reserve's stress tests of spring of 2009.

1 capital and tangible common equity, respectively, the t-statistics are 3.00 and 3.12 with adjusted R^2s of 32.03% and 33.19%. When leverage is added, the adjusted R^2s either drop or are marginally larger. The (pseudo) R^2s 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.

The above regressions use information up to March 2009 to coincide with the timing of the Federal Reserve's SCAP. As an additional analysis, the same regressions are run in the right columns of Panels A and B using *MES* and leverage measured prior to the failure of Lehman Brothers, that is, using information from October 2007 to September 2008. While *MES* remains statistically significant, the adjusted R^2 drops considerably for both measures of capital and for both the OLS and probit regressions as expected.

3.2 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 through June 2007) explain the cross-sectional

Table 2
OLS regression and probit regression analyses

Panel A: Dependent variable is SCAP Shortfall/Tier1

	April 2008–March 2009						October 2007–September 2008					
	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

	April 2008-March 2009			October 2007-September 2008		
	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)
	4.05		3.29	6.00		6.57
	(3.12)		(2.13)	(2.09)		(1.94)
		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

In Panel A the dependent variable is SCAP Shortfall/Tier1, and in Panel B it is SCAP Shortfall/Tier1Comm. Models (I)–(III) are regression analyses based on MES and LVG computed respectively, during and at end of the period, April 2008–March 2009. Models (IV)–(VI) are the equivalent Probit regression results. In Panels A and B, Models (VII)–(XII) repeat the analysis using the period October 2007–September 2008. 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.

variation in equity performance during the crisis (July 2007 through 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 (i) two 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 (ii) the standard measure of systemic 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–December 2008.

Table 3 describes the summary statistics of all these risk measures for the 102 financial firms in the U.S. financial sector with equity market capitalization as of the end of June 2007 in excess of U.S.$5 billion. Appendix B lists these firms and their "type" based on two-digit SIC code classification (Depository Institutions,

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

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

Panel C: Descriptive statistics of the average of the measures Realized SES, ES, MES, Vol, Beta, LVG for different industry types

Depository institutions	–42%	2.23%	1.42%	17%	0.87	6.21
Other: Non-depository	—52%	3.35%	1.92%	26%	1.22	3.68
Insurance	–44%	2.44%	1.28%	18%	0.78	4.44
Security dealers	–59%	3.61%	2.68%	27%	1.61	9.58

This table contains overall descriptive statistics (Panel A) and sample correlation matrix (Panel B) for the following measures: (i) *Realized SES*: the stock return during July 2007 to December 2008. (ii) *ES*: the Expected Shortfall of an individual stock at the 5th percentile. (iii) *MES* is the marginal expected shortfall of a stock given that the market return is below its 5th percentile. (iv) *Vol* is the annualized daily individual stock return volatility. (v) *Beta* is the estimate of the coefficient in a regression of a firm's stock return on that of the market's. (vi) 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. (vii) *Log-Assets* is the natural logarithm of total book assets. (viii) *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 to 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 B.

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 a financial stock's return is 21% and average beta is 1.0. The power law application in Section 2 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 mentioned above, in Appendix B, we rely on four categories of institutions: (i) Depository institutions (29 companies with two-digit SIC code of 60); (ii) 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); (iii) Insurance companies (36 companies with codes of 63 or 64); and (iv) Security and Commodity Brokers (10 companies with four-digit SIC code of 6211).[18] These risk measures are reported in Panel C of Table 3.

When these risk measures are observed across 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*. Financial leverage, that is, quasi-market assets to equity ratio, is, however, higher for depository institutions than for insurance firms. When all this is in theory combined into our estimate of the systemic risk measure, in terms of realized SES, insurance firms are overall the least systemically risky, next are depository institutions, and most systemically risky are the securities dealers and brokers. Importantly, by any measure of risk, individual or systemic, securities dealers and brokers are always the riskiest. In other words, the systemic risk of these institutions is high not just because they are riskier in an absolute risk sense, but they have greater tail dependence with the market (*MES*) as well as the highest leverage (*LVG*). In particular, both their *MES* and leverage are about twice the median of other 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 as well as relative to other measures of risk. In particular, it contains cross-sectional regressions of realized returns during July 2007–December 2008 on the pre-crisis measures of risk: *ES*, *Vol*, *MES*, *Beta*, *LVG*, and *Log Assets*. (As described earlier, we also note that Appendix C provides the firm-level data on *MES* and *LVG*.)

Figure 2 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

[18] Note that Goldman Sachs has an 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 Mae and Freddie Mac, the latter firms being of course significant candidates for systemically risky institutions.

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

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($\times$100)	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)	(0.3)	(−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

(*continued*)

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 AIG and Berkshire Hathaway have relatively low *MES*, AIG's leverage at 6.12 is above the mean leverage, whereas that of Berkshire is much lower at 2.29. Thus, the two should be viewed differently from a systemic risk standpoint. As described in the beginning of Section 3, combining *MES* and leverage of financial firms helps explain systemic risk better since, as predicted by the theory, financial distress costs of leveraged firms can be large in a crisis.

To understand this point, consider the estimated systemic risk ranking of financial firms (i.e., Model 6 in Table 4, which coincides with the label "Fitted Rank," in Appendix C). In this light, when combining *MES* and *LVG* using the estimated regression coefficients, exchanges are no longer as systemic as investment banks and AIG looks far more systemic than Berkshire Hathaway. The five investment banks rank in the top ten by both their *MES* and leverage rankings, so they clearly appear systemically risky (Appendix C). Countrywide is ranked 24th 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 6th using the estimated

Table 4
Continued

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

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)	(−1.02)	(−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(×100)	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

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

coefficients from Model 6 in Table 4. Similarly, Freddie Mac is ranked 61st by its *MES*, but given its high leverage of 21 (comparable to that of investment banks), it ranks 2nd in terms of its combined ranking. On the flip side, CB Richard Ellis, a real-estate firm, ranks 5th in *MES*, but given its low leverage of 1.55, it ranks only 24th in terms of combined ranking. Investment banks, Countrywide, and Freddie Mac 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 R^2s 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 (Model

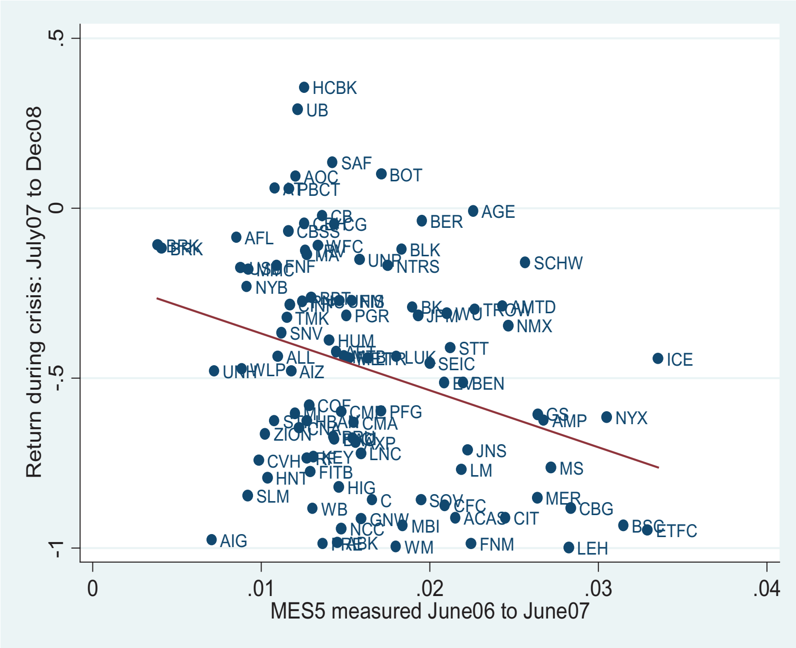

Figure 2
MES predicts realized equity returns during the crisis
MES estimated ex ante over the period June 2006–June 2007 plotted against the stock return during the crisis July 2007 to December 2008. The sample consists of 102 U.S. financial firms with a market cap in excess of $5 billion as of June 2007.

(7)), and while its significance drops substantially once *MES* and leverage are included, it remains borderline significant (Model (8)). The negative sign on log of assets suggests that size may affect not only 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).[19]

As is clear from Table 3 and Figure 2, there are 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 will affect the model's 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, these firms would have all reached that

[19] The R^2s from Columns (1), (3), and (6) of Table 4, Panel A, imply that the explanatory power of leverage is about four times as high as that of *MES* in explaining the realized *SES*.

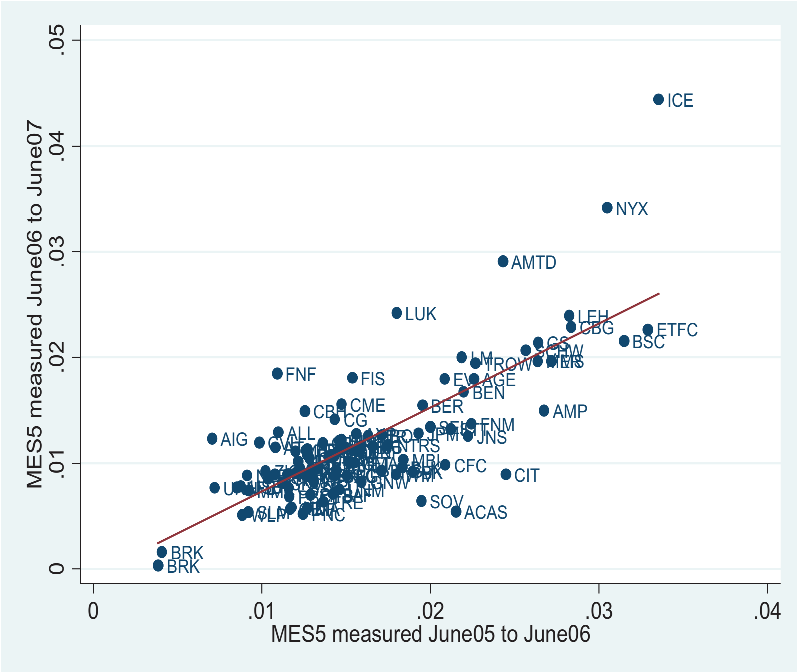

Figure 3
Stability of MES
The graph depicts a scatter plot of the MES, marginal expected shortfall measure at the 5% level, computed during the June 2006–June 2007 period versus that computed during June 2005–June 2006. MES is the marginal expected shortfall of a stock given that the market return is below its 5th percentile

outcome but were bailed out in advance, as with Fannie Mae, Freddie Mac, 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 twofold, which is unsurprising given the high leverage of the firms that ran aground in the crisis.

We consider several robustness checks. Figure 3 graphs a scatter plot of the *MES* computed during June 2006–June 2007 versus that computed during June 2005–June 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-June 2007 estimation period: June 2006–May 2007, May 2006–April 2007, April 2006–March 2007, and March 2006–February 2007. 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 the quasi-market measure of the assets to equity ratio. Once the measures are calculated for each of these periods, the exercise involves explaining the same realized returns during the 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.[20] Panels B and 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 April 2006–Mar 2007 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 because the externality arises when the financial sector experiences undercapitalization rather than the market as a whole. Also, *F-MES* might capture better tail dependence induced between a financial firm and other financial firmns due to contagion-based systemic risk. We find that the results 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*.

3.3 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.[21] On the one hand, CDS data

[20] 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 (Forthcoming).

[21] 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.

Table 5
Stock returns during the crisis and systemic risk measured with different leads

Panel A (*MES*): The dependent variable is *Realized SES*, the company stock returns during the crisis				
	June 2006–May 2007	**May 2006–April 2007**	**April 2006–March 2007**	**March 2006–February 2007**
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

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 to December 2008. Leverage is based on data available at the 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.

might be preferred to equity data because CDS might better capture estimates of losses of the market value of the financial firm's assets, as opposed to just its equity. On the other hand, CDS data reflects the underlying value of the financial firm's debt, which may be subject to government guarantees. Of the 102 financial firms we have looked at so far, 40 of them have enough unsecured long-term debt to warrant the existence of CDS in the credit derivatives market. Appendix D provides a list of the 40 firms and their type of institution.

A 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 $ds=-(\xi/D)(dV/V)$. Ignoring the duration term changes across firms/days means that measuring the firm's losses, that is, 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 small when ξ is close to zero and large when ξ is close to one. Further, from an econometric standpoint, the log change is more stationary and less driven by outliers. Therefore, when using CDS data, we empirically estimate *MES* at a standard risk level of 5% using daily data of CDS returns, ds/s.

Thus, practically, we take the 5% worst (i.e., highest CDS return) days for an equally weighted portfolio of CDS returns on the 40 financial firms from June 2006 to July 2007, and we then compute the CDS return for any given firm for these days. This measure is used against realized *SES* during the crisis. For comparison purposes, we also show results that use arithmetic changes in the CDS spread as a measure of CDS return.

As a first pass at the data, Appendix D presents stylized facts about the financial firms' *MES* based on the CDS market, including ranking, *MES%*, and realized CDS spread returns during the crisis period.[22] 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 guarantees for structured products in the credit derivatives area.

[22] We can compare the *MES* CDS ranking of Appendix D to the *MES* equity ranking of Appendix C for the 40 coincident firms. The rank correlation is 23%, which suggests there is different potential information in CDS and equity markets. This could be possibly due to CDS *MES* better capturing asset losses from a positive viewpoint or being a biased measure due to government guarantees from a negative point of view.

- 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.[23]
- 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.

The above anecdotal observations illustrate the potential for using *MES* based on CDS data. That said, as mentioned previously, note that CDS in a pre-crisis period may not relate well to the realized losses of financial firms during a crisis if some firms receive greater government guarantees, for example, deposit institutions, the government-sponsored enterprises, and the so-called too-big-to-fail firms.[24] To address this issue in part, 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 periods (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 (which accrue the benefit of government guarantees to a much lesser extent than creditor returns).

In terms of a more thorough analysis using *CDS*, Figure 4 shows that there is a positive relation between the ex ante measure of systemic risk based on CDS and the ex post CDS return during the crisis (as measured from July 2007 to June 2008). To test this relation more rigorously, Table 6 reports regressions in which the regressors are, respectively, *CDS MES* based on CDS returns (Panel A) and CDS spread changes (Panel B). The dependent variables are, respectively, the realized CDS returns and changes during different periods covering the crisis related to government action on creditor guarantees (July 2007-June 2008/September 14, 2008/September 30, 2008/October 10, 2008/December 30, 2008). Table 6 demonstrates that our ex ante measure significantly predicts 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

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

[24] Equity also suffers from this problem to the extent government guarantees delay bankruptcy preferentially for some financial firms, extending the option of their equity to continue relative to the option for some other firms. It is more likely a second-order effect, however, compared to the pricing of the underlying debt and CDS of financial firms in distress.

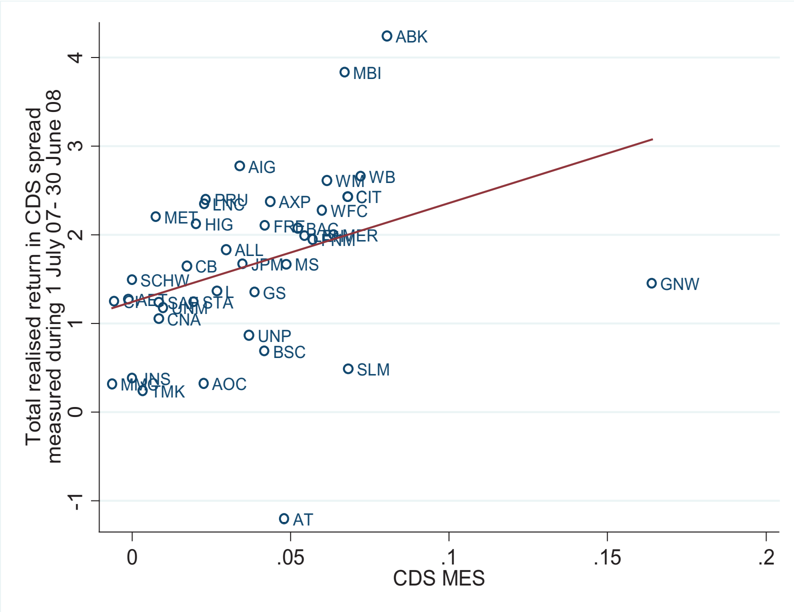

Figure 4
MES predicts realized CDS returns during the crisis
MES estimated ex ante from CDS returns July 2006–June 30, 2007, plotted against the total realized return on CDS spread during July 1, 2007–June 30, 2008.

CDS MES capturing more of the tail behavior and thus being less reliant on the leverage arguments provided in Section 2. Third, there are substantive drops in explanatory power when CDS spread changes are used instead of CDS returns (Panel B). This is consistent with the aforementioned argument on the need to be careful with respect to operationalizing *CDS MES*.[25]

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 ex ante systemic risk measures (i.e., prior to the crisis) have information for which firms might run into trouble. Therefore, by inference, these are the firms that should, according to our derived optimal policy, be taxed in order 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* may have been useful

25 Note that unlike in Table 4, leverage is statistically insignificant in explaining realized *SES* in the presence of *CDS MES*.

Table 6
CDS MES vs. realized CDS SES

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

	July 1, 2007–June 30, 2008	July 1, 2007–September 14, 2008	July 1, 2007–September 30, 2008	July 1, 2007–October 10, 2008	July 1, 2007–December 30, 2008
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

	July 1, 2007–June 30, 2008	July 1, 2007–September 14, 2008	July 1, 2007–September 30, 2008	July 1, 2007–October 10, 2008	July 1, 2007–December 30, 2008
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

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 July 1, 2006–June 30, 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.

prior to the start of the crisis, it is an open question whether this will continue in the future with all the government guarantees in place.

4. Discussion

Before we conclude, it is useful to compare our optimal policy of Section 1.4 for regulating systemic risk to some of the proposals put forward by regulators and policymakers. We then end with a discussion of important features not analyzed in this paper.

Table 7
CDS MES vs. realized stock SES

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

	July 1, 2007–June 30, 2008	July 1, 2007–September 14, 2008	July 1, 2007–September 30, 2008	July 1, 2007–October 10, 2008	July 1, 2007–December 30, 2008
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

	July 1, 2007–June 30, 2008	July 1, 2007–September 14, 2008	July 1, 2007–September 30, 2008	July 1, 2007–October 10, 2008	July 1, 2007–December 30, 2008
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

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 July 1, 2006–June 30, 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.

There is much discussion among 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 Federal Deposit Insurance Corporation (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.

Another important topic in the discussion of systemic risk has been the size of financial institutions' assets and/or liabilities. The theory described in Section 1.4 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.[26] 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 of 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 $Pr(W_1 < zA)$. We focused our empirical analysis on the cross-section of systemic risk, *SES*. The risk of a systemic event $Pr(W_1 < zA)$ can be measured using historical research, as in Reinhart and Rogoff (2008), who show that there are consistent leading indicators of banking crises, for example, an asset price bubble, a corresponding credit boom, and large capital inflows into the economy (see also Laeven and Valencia 2013). The conditional risk of a systemic event can then be inferred from dynamic long-run volatility models (Engle 2009; Brownlees and Engle Forthcoming).

Finally, there have been recent discussions as to whether non-banking institutions such as insurance companies and asset managers can be systemically important. In our model, we did not introduce specific features distinguishing banks from such non-banking entities. It is best to think of our model as being most applicable to banks because we treat all liabilities as short-term, whereby there is no distinction in the model between liquidity and solvency risks. Acharya, Philippon, and Richardson (Forthcoming) extend our model where some of the financial firm liabilities are long-term, allowing for a distinction between liquidity and solvency risks. Their extended model decomposes the negative externality of the financial sector's distress into two components: (i) a fire-sale externality that arises due to asset liquidations in response to runs on short-term liabilities; and (ii) a going-concern externality that is a disruption of new intermediation activities and which arises from solvency risk. While banks likely contribute to systemic risk via both of these externalities, some non-banking entities such as insurance companies that have less short-term debt are likely to contribute to systemic risk primarily through the going-concern externality.

[26] In fact, Appendix C of the paper provides the contribution of each firm's average dollar loss in market capitalization during the worst 5% of market return days as a percentage of the average dollar loss across all of the 102 largest financial firms (i.e., firms with over $5 billion of market equity). The top 6 in terms of contribution (Citigroup (8.81%), JPMorgan (6.70%), Bank of America (6.87%), Morgan Stanley (4.39%), Goldman Sachs (4.48%) and Merrill Lynch (4.06%)) are also in the top 7 in terms of total number of assets.

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 that 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 (e.g., stress test outcomes of 2009 and firm performance during the crisis of 2007-08) using market data from equity and CDS, our systemic risk measures appear to be able to predict the financial firms with the worst contributions in systemic crises.

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 insurance contracts against losses of individual firms when the system as a whole is in stress.[27] 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 *MES*.

Finally, we investigated the role of leverage (measured as the ratio of assets to common equity) in determining the systemic risk of firms. The form of leverage that had the most pernicious effect in the crisis of 2007-08 was arguably short-term debt, such as the overnight secured borrowing ("repo") against risky assets employed heavily by the investment banks (Adrian and Shin 2010), 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 therefore to empirically understand how short-term leverage contributes to market-based measures of systemic risk of financial firms.

[27] Based on the theory presented here, Acharya et al. (2009) propose regulation of systemic risk based on mandatory purchase of such insurance contracts by financial firms, partly from private sources (insurance companies), and the rest from a systemic risk regulator.

Appendix A

Proof of Proposition 1
Using the definition of τ^i in Equation (14), the bank's problem is

$$\max_{w_0^i, b^i, \left\{x_j^i\right\}_j} \times\left(\bar{w}_0^i - w_0^i - \tau_0\right) + E\left[u\left(1_{\left[w_1^i>0\right]} \times w_1^i\right)\right]$$

$$-\alpha^i g \times Pr(w_1^i<0)ES^i - e \times Pr(W_1<zA)SES^i,$$

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

$$\max_{w_0^i, b^i, \left\{x_j^i\right\}_j} c\times\left(\bar{w}_0^i - w_0^i - \tau_0\right) + E\left[u\left(1_{\left[w_1^i>0\right]} \times w_1^i\right)\right]$$

$$+E\left[\alpha^i g 1_{\left[w_1^i<0\right]} w_1^i + e1_{[W_1<zA]}(za^i - w_1^i)\right].$$

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

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:

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

■

Appendix B

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 U.S.$5 billion.

The companies can be categorized into the following four groups: Depositories (JPMorgan, Citigroup, WAMU, …), Broker-Dealers (Goldman Sachs, Morgan Stanley, etc.), Insurance (AIG, Berkshire Hathaway, Countrywide, etc.) and Insurance Agents, Brokers, Service (Metlife, Hartford Financial, etc.) and a group called Other consisting of non-depository institutions, real estate, and so on.

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.

Table A.1

Depositories: 29 companies, 2-digit SIC code = 60	**Other: Non-depository institutions etc.: 27 companies, 2-digit SIC code = 61, 62 (except 6211), 65, 67**	**Insurance: 36 companies, 2-digit SIC code = 63 and 64**	**Broker-Dealers: 10 companies, 4-digit SIC code = 6211**
1. B B & T CORP	1. ALLTEL CORP	1. A F L A C INC	1. BEAR STEARNS COMPANIES INC
2. BANK NEW YORK INC	2. AMERICAN CAPITAL STRATEGIES LTD	2. AETNA INC NEW	2. E TRADE FINANCIAL CORP
3. BANK OF AMERICA CORP	3. AMERICAN EXPRESS CO	3. ALLSTATE CORP	3. EDWARDS A G INC
4. CITIGROUP INC	4. AMERIPRISE FINANCIAL INC	4. AMBAC FINANCIAL GROUP INC AMERICAN	4. GOLDMAN SACHS GROUP INC
5. COMERICA INC	5. BLACKROCK INC	5. INTERNATIONAL GROUP INC	5. LEHMAN BROTHERS HOLDINGS INC
6. COMMERCE BANCORP INC NJ	6. C B O T HOLDINGS INC	6. AON CORP ASSURANT INC	6. MERRILL LYNCH & CO INC
7. HUDSON CITY BANCORP INC	7. C B RICHARD ELLIS GROUP INC	7. BERKLEY W R CORP	7. MORGAN STANLEY DEAN WITTER & CO
8. HUNTINGTON BANCSHARES INC	8. C I T GROUP INC NEW	8. BERKSHIRE HATHAWAY INC DEL	8. NYMEX HOLDINGS INC
9. JPMORGAN CHASE & CO	9. CAPITAL ONE FINANCIAL CORP	9. BERKSHIRE HATHAWAY INC DEL	9. SCHWAB CHARLES CORP NEW
10. KEYCORP NEW	10. CHICAGO MERCANTILE EXCH HLDG INC	10. C I G N A CORP	10. T ROWE PRICE GROUP INC
11. M & T BANK CORP	11. COMPASS BANCSHARES INC	11. C N A FINANCIAL CORP	
12. MARSHALL & ILSLEY CORP	12. EATON VANCE CORP	12. CHUBB CORP	
13. NATIONAL CITY CORP	13. FEDERAL HOME LOAN MORTGAGE CORP	13. CINCINNATI FINANCIAL CORP	
14. NEW YORK COMMUNITY BANCORP INC	14. FEDERAL NATIONAL MORTGAGE ASSN	14. COUNTRYWIDE FINANCIAL CORP	
15. NORTHERN TRUST CORP	15. FIDELITY NATIONAL INFO SVCS INC	15. COVENTRY HEALTH CARE INC	
16. P N C FINANCIAL SERVICES GRP INC	16. FIFTH THIRD BANCORP	16. FIDELITY NATIONAL FINL INC NEW	
17. PEOPLES UNITED FINANCIAL INC	17. FRANKLIN RESOURCES INC	17. GENWORTH FINANCIAL INC	
18. REGIONS FINANCIAL CORP NEW	18. INTERCONTINEN-TALEXCHANGE INC	18. HARTFORD FINANCIAL	
19. SOVEREIGN BANCORP INC	19. JANUS CAP GROUP INC	19. SVCS GROUP IN	

(*continued*)

Table A.1
Continued

Depositories: 29 companies, 2-digit SIC code = 60	Other: Non-depository institutions etc.: 27 companies, 2-digit SIC code = 61, 62 (except 6211), 65, 67	Insurance: 36 companies, 2-digit SIC code = 63 and 64	Broker-Dealers: 10 companies, 4-digit SIC code = 6211
20. STATE STREET CORP	20. LEGG MASON INC	20. HEALTH NET INC	
21. SUNTRUST BANKS INC	21. LEUCADIA NATIONAL CORP	21. HUMANA INC	
22. SYNOVUS FINANCIAL CORP	22. MASTERCARD INC	22. LINCOLN NATIONAL CORP IN	
23. U S BANCORP DEL	23. N Y S E EURONEXT	23. LOEWS CORP	
24. UNIONBANCAL CORP	24. S E I INVESTMENTS COMPANY	24. LOEWS CORP	
25. WACHOVIA CORP 2ND NEW	25. S L M CORP	25. M B I A INC	
26. WASHINGTON MUTUAL INC	26. T D AMERITRADE HOLDING CORP	26. MARSH & MCLENNAN COS INC	
27. WELLS FARGO & CO NEW	27. UNION PACIFIC CORP	27. METLIFE INC	
28. WESTERN UNION CO		28. PRINCIPAL FINANCIAL GROUP INC	
29. ZIONS BANCORP		29. PROGRESSIVE CORP OH	
		30. PRUDENTIAL FINANCIAL INC	
		31. SAFECO CORP	
		32. TORCHMARK CORP	
		33. TRAVELERS COMPANIES INC	
		34. UNITEDHEALTH GROUP INC	
		35. UNUM GROUP	
		36. WELLPOINT INC	

Appendix C

Table C.1
Systemic risk ranking of financial firms during June 2006 to June 2007

Realized SES $=0.02-0.15\times \text{MES}-0.04\times \text{LVG}-0.12\times 1[\text{Other}]-0.01\times 1[\text{Insurance}]+0.16\times 1[\text{Broker}-\text{Dealers}]$

MES ranking	Name of company	Realized SES	MES	Avg. $Loss(bln)	Avg. contribution	LVG	Fitted rank	Assets (bln)	ME(bln)
1.	INTERCONTINENTAL EXCHANGE INC	−44.24%	3.36%	0.24	0.50%	1.12	16	2.55	10.40
2.	E TRADE FINANCIAL CORP	−94.79%	3.29%	0.33	0.69%	7.24	21	62.98	9.39
3.	BEAR STEARNS COMPANIES INC	−93.28%	3.15%	0.55	1.16%	25.62	1	423.30	16.66
4.	N Y S E EURONEXT	−61.48%	3.05%	0.43	0.90%	1.43	19	16.93	19.44
5.	C B RICHARD ELLIS GROUP INC	−88.16%	2.84%	0.20	0.42%	1.55	24	5.95	8.35
6.	LEHMAN BROTHERS HOLDINGS INC	−99.82%	2.83%	1.08	2.27%	15.83	4	605.86	39.51
7.	MORGAN STANLEY DEAN WITTER & CO	−76.21%	2.72%	2.09	4.39%	14.14	9	1199.99	88.40
8.	AMERIPRISE FINANCIAL INC	−62.41%	2.68%	0.35	0.74%	7.72	7	108.13	14.95
9.	GOLDMAN SACHS GROUP INC	−60.59%	2.64%	2.13	4.48%	11.25	15	943.20	88.54
10.	MERRILL LYNCH & CO INC	−85.21%	2.64%	1.93	4.06%	15.32	5	1076.32	72.56
11.	SCHWAB CHARLES CORP NEW	−15.95%	2.57%	0.59	1.24%	2.71	88	49.00	25.69
12.	NYMEX HOLDINGS INC	−34.46%	2.47%	0.28	0.59%	1.23	98	3.53	11.57
13.	C I T GROUP INC NEW	−91.08%	2.45%	0.26	0.55%	8.45	8	85.16	10.52
14.	T D AMERITRADE HOLDING CORP	−28.75%	2.43%	0.24	0.50%	2.40	26	18.53	11.92
15.	T ROWE PRICE GROUP INC	−29.83%	2.27%	0.27	0.57%	1.03	101	3.08	13.76
16.	EDWARDS A G INC	−0.71%	2.26%	0.11	0.23%	1.46	100	5.24	6.43
17.	FEDERAL NATIONAL MORTGAGE ASSN	−98.78%	2.25%	1.24	2.61%	14.00	3	857.80	63.57
18.	JANUS CAP GROUP INC	−71.12%	2.23%	0.09	0.19%	1.34	35	3.76	5.16
19.	FRANKLIN RESOURCES INC	−51.23%	2.20%	0.62	1.30%	1.08	40	9.62	33.07
20.	LEGG MASON INC	−76.98%	2.19%	0.29	0.61%	1.25	38	10.08	12.97
21.	AMERICAN CAPITAL STRATEGIES LTD	−91.08%	2.15%	0.15	0.32%	1.73	32	12.15	7.75
22.	STATE STREET CORP	−41.07%	2.12%	0.46	0.97%	5.54	28	112.27	23.01
23.	WESTERN UNION CO	−30.84%	2.10%	0.36	0.76%	1.34	83	5.33	16.09
24.	COUNTRYWIDE FINANCIAL CORP	−87.46%	2.09%	0.48	1.01%	10.39	6	216.82	21.57
25.	EATON VANCE CORP	−51.20%	2.09%	0.09	0.19%	1.03	47	0.62	5.54
26.	S E I INVESTMENTS COMPANY	−45.61%	2.00%	0.11	0.23%	1.08	50	1.12	5.69
27.	BERKLEY W R CORP	−3.57%	1.95%	0.13	0.27%	3.07	31	16.63	6.32
28.	SOVEREIGN BANCORP INC	−85.77%	1.95%	0.21	0.44%	8.34	20	82.74	10.11
29.	JPMORGAN CHASE & CO	−31.48%	1.93%	3.19	6.70%	9.09	17	1458.04	165.51
30.	BANK NEW YORK INC	−29.05%	1.90%	0.54	1.13%	4.64	48	126.33	31.43
31.	M B I A INC	−93.34%	1.84%	0.16	0.34%	5.47	25	43.15	8.14
32.	BLACKROCK INC	−12.07%	1.83%	0.23	0.48%	1.60	53	21.99	18.18
33.	LEUCADIA NATIONAL CORP	−43.54%	1.80%	0.12	0.25%	1.28	61	6.38	7.63
34.	WASHINGTON MUTUAL INC	−99.61%	1.80%	0.72	1.51%	8.67	23	312.22	37.63

(*continued*)

Table C.1
Continued

MES ranking	Name of company	Realized SES	MES	Avg. $Loss(bln)	Avg. contribution	LVG	Fitted rank	Assets (bln)	ME(bln)
35.	NORTHERN TRUST CORP	−16.84%	1.75%	0.23	0.48%	4.92	52	59.61	14.14
36.	C B O T HOLDINGS INC	10.12%	1.71%	0.13	0.27%	1.01	69	0.89	10.92
37.	PRINCIPAL FINANCIAL GROUP INC	−59.75%	1.71%	0.27	0.57%	10.15	12	150.76	15.61
38.	CITIGROUP INC	−85.86%	1.66%	4.19	8.81%	9.25	22	2220.87	253.70
39.	LOEWS CORP	−44.08%	1.63%	0.39	0.82%	3.28	44	79.54	27.38
40.	GENWORTH FINANCIAL INC	−91.43%	1.59%	0.25	0.53%	7.62	18	111.94	14.96
41.	LINCOLN NATIONAL CORP IN	−72.08%	1.59%	0.29	0.61%	10.15	13	187.65	19.21
42.	UNION PACIFIC CORP	−15.14%	1.58%	0.45	0.95%	1.70	65	37.30	31.03
43.	AMERICAN EXPRESS CO	−69.00%	1.56%	1.08	2.27%	2.70	51	134.37	72.66
44.	COMERICA INC	−63.00%	1.55%	0.16	0.34%	6.77	36	58.57	9.27
45.	CIGNA CORP	−67.69%	1.54%	0.21	0.44%	3.50	46	41.53	15.03
46.	FIDELITY NATIONAL INFO SVCS INC	−27.15%	1.54%	0.14	0.29%	1.42	72	7.80	10.45
47.	METLIFE INC	−44.06%	1.52%	0.71	1.49%	11.85	10	552.56	47.82
48.	PROGRESSIVE CORP OH	−31.52%	1.51%	0.28	0.59%	1.89	73	21.07	17.42
49.	M & T BANK CORP	−43.46%	1.49%	0.19	0.40%	5.47	60	57.87	11.57
50.	NATIONAL CITY CORP	−94.28%	1.48%	0.34	0.71%	7.70	29	140.64	19.18
51.	CHICAGO MERCANTILE EXCH HLDG INC	−59.88%	1.47%	0.27	0.57%	1.19	78	5.30	18.64
52.	UNUM GROUP	−27.21%	1.46%	0.11	0.23%	5.99	27	52.07	8.95
53.	HARTFORD FINANCIAL SVCS GROUP IN	−82.02%	1.46%	0.45	0.95%	11.48	11	345.65	31.19
54.	AMBAC FINANCIAL GROUP INC	−98.47%	1.45%	0.13	0.27%	2.69	64	21.06	8.89
55.	AETNA INC NEW	−42.17%	1.45%	0.34	0.71%	2.58	66	49.57	25.31
56.	LOEWS CORP	−4.54%	1.44%	0.10	0.21%	1.29	82	2.84	8.38
57.	BANK OF AMERICA CORP	−68.05%	1.44%	3.27	6.87%	7.46	33	1534.36	216.96
58.	PRUDENTIAL FINANCIAL INC	−67.16%	1.43%	0.60	1.26%	10.75	14	461.81	45.02
59.	SAFECO CORP	13.56%	1.42%	0.10	0.21%	2.51	68	13.97	6.61
60.	HUMANA INC	−38.79%	1.40%	0.14	0.29%	1.97	76	13.33	10.24
61.	FEDERAL HOME LOAN MORTGAGE CORP	−98.75%	1.36%	0.60	1.26%	21.00	2	821.67	40.16
62.	CHUBB CORP	−2.24%	1.36%	0.30	0.63%	2.74	67	51.73	21.74
63.	WELLS FARGO & CO NEW	−10.88%	1.34%	1.58	3.32%	5.19	71	539.87	117.46
64.	KEYCORP NEW	−73.09%	1.31%	0.20	0.42%	7.41	41	94.08	13.47
65.	WACHOVIA CORP 2ND NEW	−88.34%	1.31%	1.32	2.77%	7.64	37	719.92	98.06
66.	B B & T CORP	−26.22%	1.30%	0.30	0.63%	6.23	59	127.58	22.07
67.	FIFTH THIRD BANCORP	−77.61%	1.29%	0.29	0.61%	5.33	30	101.39	21.30
68.	CAPITAL ONE FINANCIAL CORP	−57.90%	1.28%	0.38	0.80%	4.70	39	145.94	32.60
69.	REGIONS FINANCIAL CORP NEW	−73.55%	1.27%	0.30	0.63%	6.06	63	137.62	23.33
70.	HUNTINGTON BANCSHARES INC	−62.50%	1.27%	0.07	0.15%	7.23	45	36.42	5.35
71.	MASTERCARD INC	−13.49%	1.27%	0.13	0.27%	1.21	85	5.61	13.23

(*continued*)

Table C.1
Continued

MES ranking	Name of company	Realized SES	MES	Avg. $Loss(bln)	Avg. contribution	LVG	Fitted rank	Assets (bln)	ME(bln)
72.	TRAVELERS COMPANIES INC	−12.32%	1.26%	0.45	0.95%	3.54	62	115.36	35.52
73.	COMMERCE BANCORP INC NJ	−4.42%	1.26%	0.08	0.17%	7.40	43	48.18	7.08
74.	HUDSON CITY BANCORP INC	35.63%	1.26%	0.10	0.21%	6.39	58	39.69	6.50
75.	P N C FINANCIAL SERVICES GRP INC	−27.35%	1.24%	0.28	0.59%	5.50	74	125.65	24.69
76.	C N A FINANCIAL CORP	−64.73%	1.22%	0.14	0.29%	4.92	42	60.74	12.95
77.	UNIONBANCAL CORP	29.14%	1.22%	0.11	0.23%	6.88	54	53.17	8.25
78.	AON CORP	9.48%	1.20%	0.14	0.29%	2.55	80	24.79	12.51
79.	MARSHALL & ILSLEY CORP	−60.34%	1.20%	0.15	0.32%	5.20	79	58.30	12.34
80.	ASSURANT INC	−47.98%	1.18%	0.08	0.17%	4.08	57	25.77	7.13
81.	CINCINNATI FINANCIAL CORP	−28.29%	1.17%	0.10	0.21%	2.53	81	18.26	7.46
82.	PEOPLES UNITED FINANCIAL INC	5.77%	1.16%	0.07	0.15%	2.75	96	13.82	5.33
83.	COMPASS BANCSHARES INC	−6.70%	1.16%	0.11	0.23%	4.48	49	34.88	9.17
84.	TORCHMARK CORP	−32.18%	1.15%	0.07	0.15%	2.85	77	15.10	6.40
85.	SYNOVUS FINANCIAL CORP	−36.53%	1.12%	0.11	0.23%	3.92	90	33.22	10.04
86.	ALLSTATE CORP	−43.63%	1.10%	0.40	0.84%	4.72	55	160.54	37.36
87.	FIDELITY NATIONAL FINL INC NEW	−16.80%	1.09%	0.04	0.08%	1.73	87	7.37	5.25
88.	ALLTEL CORP	5.98%	1.08%	0.25	0.53%	1.25	89	17.44	23.23
89.	SUNTRUST BANKS INC	−62.60%	1.08%	0.34	0.71%	6.35	70	180.31	30.58
90.	HEALTH NET INC	−79.37%	1.04%	0.06	0.13%	1.47	91	4.73	5.93
91.	ZIONS BANCORP	−66.42%	1.02%	0.09	0.19%	6.26	75	48.69	8.31
92.	COVENTRY HEALTH CARE INC	−74.19%	0.99%	0.09	0.19%	1.39	94	6.41	9.01
93.	MARSH & MCLENNAN COS INC	−17.94%	0.92%	0.16	0.34%	1.67	93	17.19	17.15
94.	S L M CORP	−84.54%	0.92%	0.18	0.38%	6.40	34	132.80	23.69
95.	NEW YORK COMMUNITY BANCORP INC	−23.11%	0.92%	0.05	0.11%	5.81	84	29.62	5.33
96.	WELLPOINT INC	−47.23%	0.88%	0.43	0.90%	1.60	95	54.19	48.99
97.	U S BANCORP DEL	−17.56%	0.88%	0.53	1.11%	4.55	92	222.53	57.29
98.	A F L A C INC	−8.52%	0.85%	0.21	0.44%	3.07	86	60.11	25.14
99.	UNITEDHEALTH GROUP INC	−47.94%	0.72%	0.49	1.03%	1.47	97	53.15	68.53
100.	AMERICAN INTERNATIONAL GROUP INC	−97.70%	0.71%	1.22	2.56%	6.12	56	1033.87	181.67
101.	BERKSHIRE HATHAWAY INC DEL(A)	−11.76%	0.41%	0.49	1.03%	2.29	99	269.05	119.00
102.	BERKSHIRE HATHAWAY INC DEL(B)	−10.85%	0.39%						49.29

This table contains the list of U.S. financial firms with a market cap in excess of $5 billion as of June 2007. The firms are listed in descending order according to their marginal expected shortfall at the 5% level (MES) measured over the period June 2006 to June 2007. Realized SES is the return during the crisis. *Avg $Loss* of an individual firm is the average day-to-day loss in market cap during days in which the market return was below its 5th percentile. *Avg Contribution* of an individual firm is the ratio of day-to-day loss in market cap of an individual firm relative to that of all financial firms, averaged over days where the market was below its 5th percentile. *LVG* is the market leverage, *Fitted Rank* is the ranking of firms based on the fitted values of *Realized SES* as obtained by the regression given below, *Log-Assets* is the natural logarithm of total book assets, and *ME* is market value of equity all as of June 2007. All data are from CRSP and CRSP merged Compustat.

Appendix D

Table D.1
CDS MES ranking of financial firms during June 2006 to June 2007

Name of company	Type of institution	CDS MES ranking	Realized CDS SES (July 2007– June 2008)	Realized CDS SES (July 2007– December 2008)	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%

This table contains the list of 40 U.S. financial firms with a market cap in excess of $5 billion 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.

Appendix E

Table E.1
List of Institutions' names and tickers

TICKER	Institution's Name
ABK	AMBAC FINANCIAL GROUP INC
ACAS	AMERICAN CAPITAL STRATEGIES LTD
AET	AETNA INC NEW
AFL	A F L A C INC
AGE	EDWARDS A G INC
AIG	AMERICAN INTERNATIONAL GROUP INC
AIZ	ASSURANT INC
ALL	ALLSTATE CORP
AMP	AMERIPRISE FINANCIAL INC
AMTD	T D AMERITRADE HOLDING CORP
AOC	AON CORP
AT	ALLTEL CORP
AXP	AMERICAN EXPRESS CO
BAC	BANK OF AMERICA CORP
BBT	B B & T CORP
BEN	FRANKLIN RESOURCES INC
BER	BERKLEY W R CORP
BK	BANK NEW YORK INC
BLK	BLACKROCK INC
BOT	C B O T HOLDINGS INC
BRK	BERKSHIRE HATHAWAY INC DEL(A)
BRK	BERKSHIRE HATHAWAY INC DEL(B)
BSC	BEAR STEARNS COMPANIES INC
C	CITIGROUP INC
CB	CHUBB CORP
CBG	C B RICHARD ELLIS GROUP INC
CBH	COMMERCE BANCORP INC NJ
CBSS	COMPASS BANCSHARES INC
CFC	COUNTRYWIDE FINANCIAL CORP
CG	LOEWS CORP2
CI	C I G N A CORP
CINF	CINCINNATI FINANCIAL CORP
CIT	C I T GROUP INC NEW
CMA	COMERICA INC
CME	CHICAGO MERCANTILE EXCH HLDG INC
CNA	C N A FINANCIAL CORP
COF	CAPITAL ONE FINANCIAL CORP
CVH	COVENTRY HEALTH CARE INC
ETFC	E TRADE FINANCIAL CORP
EV	EATON VANCE CORP
FIS	FIDELITY NATIONAL INFO SVCS INC
FITB	FIFTH THIRD BANCORP
FNF	FIDELITY NATIONAL FINL INC NEW
FNM	FEDERAL NATIONAL MORTGAGE ASSN
FRE	FEDERAL HOME LOAN MORTGAGE CORP
GNW	GENWORTH FINANCIAL INC
GS	GOLDMAN SACHS GROUP INC
HBAN	HUNTINGTON BANCSHARES INC
HCBK	HUDSON CITY BANCORP INC
HIG	HARTFORD FINANCIAL SVCS GROUP IN

(*continued*)

Table E.1
Continued

TICKER	Institution's Name
HNT	HEALTH NET INC
HUM	HUMANA INC
ICE	INTERCONTINENTALEXCHANGE INC
JNS	JANUS CAP GROUP INC
JPM	JPMORGAN CHASE & CO
KEY	KEYCORP NEW
L	LOEWS CORP1
LEH	LEHMAN BROTHERS HOLDINGS INC
LM	LEGG MASON INC
LNC	LINCOLN NATIONAL CORP IN
LUK	LEUCADIA NATIONAL CORP
MA	MASTERCARD INC
MBI	M B I A INC
MER	MERRILL LYNCH & CO INC
MET	METLIFE INC
MI	MARSHALL & ILSLEY CORP
MMC	MARSH & MCLENNAN COS INC
MS	MORGAN STANLEY DEAN WITTER & CO
MTB	M & T BANK CORP
NCC	NATIONAL CITY CORP
NMX	NYMEX HOLDINGS INC
NTRS	NORTHERN TRUST CORP
NYB	NEW YORK COMMUNITY BANCORP INC
NYX	N Y S E EURONEXT
PBCT	PEOPLES UNITED FINANCIAL INC
PFG	PRINCIPAL FINANCIAL GROUP INC
PGR	PROGRESSIVE CORP OH
PNC	P N C FINANCIAL SERVICES GRP INC
PRU	PRUDENTIAL FINANCIAL INC
RF	REGIONS FINANCIAL CORP NEW
SAF	SAFECO CORP
SCHW	SCHWAB CHARLES CORP NEW
SEIC	S E I INVESTMENTS COMPANY
SLM	S L M CORP
SNV	SYNOVUS FINANCIAL CORP
SOV	SOVEREIGN BANCORP INC
STA	TRAVELERS COMPANIES INC
STI	SUNTRUST BANKS INC
STT	STATE STREET CORP
TMK	TORCHMARK CORP
TROW	T ROWE PRICE GROUP INC
UB	UNIONBANCAL CORP
UNH	UNITEDHEALTH GROUP INC
UNM	UNUM GROUP
UNP	UNION PACIFIC CORP
USB	U S BANCORP DEL
WB	WACHOVIA CORP 2ND NEW
WFC	WELLS FARGO & CO NEW
WLP	WELLPOINT INC
WM	WASHINGTON MUTUAL INC
WU	WESTERN UNION CO
ZION	ZIONS BANCORP

This appendix contains the tickers and names of the 102 U.S. financial institutions used in the analysis of the recent crisis.

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