Extending a Market-Based Measure of Systemic Risk

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Abstract

This thesis extends a market-based measure of systemic risk, developed by Acharya et al. (2016). Their systemic risk measure, the systemic expected shortfall (SES) has three components: a firm's marginal risk contribution (MES), leverage and excess distress costs. In their empirical implementation, the authors leave out the estimation of excess distress costs.

The excess costs of financial distress can be approximated through the distress costs during the 5% worst market days scaled by equity capital to account for firm size.

We estimate the expected costs of financial distress using an approach by Breitkopf and Elsas (2012) who develop a framework to directly estimate expected distress costs from CDS and stock price data.

We find that the expected excess cost of financial distress scaled by equity capital does not explain returns during the crisis nor has it any explanatory power in explaining the outcome of the 2009 SCAP stress test. However, we find that when changing the scaling to unlevered asset value, distress costs have significant explanatory power even when measured two years before the crisis.

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List of Abbreviations

ES	Expected shortfall
LTCM	Long Term Capital Management
PD	Probability of default
BHC	Bank holding company
CDS	Credit default swap
BCBS	Basel Committee on Banking Supervision
IMF	International Monetary Fund
RWA	Risk weighted assets
IRB	Internal-ratings-based approach
SCAP	Supervisory Capital Assessment Program
US	United States
GDP	Gross Domestic Product
EBA	European Banking authority
BoE	Bank of England
TBTF	Too big to fail
LT	Leland and Toft
RMSE	Root Mean Square Error
DD	Distance to default
CAPM	Capital Asset Pricing Model
SIC	Security Identifier Code
FED	Federal Reserve System
CRSP	Center for Research in Security Prices
E	Market value of equity
T	Debt maturity
VaR	Value at risk
SES	Systemic expected shortfall
MES	Marginal expected shortfall

LGD	Loss given default
LVG	Quasi - leverage ratio
DC	Expected distress costs
AIC	Akaike Information Critereon
V	Unlevered asset value
$PV(\ldots)$	Present value

1 Introduction

Systemic risk has been a widely discussed topic in financial and economic literature. The risk of a financial system breaking down has increasingly been in the focus since the subprime crisis, which illustrated the high welfare costs due to distortions in the banking system[1].

The purpose of banking regulation is to secure the stability of the financial system. In other words, the objective is not to prevent individual banks from bankruptcy but to prevent a systemic crisis. Regulation should therefore focus on a bank's systemic risk contribution (rather than on a bank's own default risk) and make it internalize this risk by e.g. taxing banks based on their contribution.

As a risk prevention measure, banking supervision authorities have introduced banking stress tests in the aftermath of the subprime crisis (Mishkin, 2011). Stress tests are designed to test whether a bank has sufficient regulatory capital to absorb losses during stressful conditions. To this end, a bank's capital losses are projected in a potential worst case scenario, representing primarily credit and market risk. In the current framework, these projections are based mostly on book values, as is regulatory capital (Fed Board of Governors, 2017).

Several weaknesses of the current stress test methodology have been discussed in academic literature. The current framework implies several assumptions. First, by focusing on individual risk, it is assumed that all individual risks simply add up to systemic risk. Second, it is assumed that the imposed regulatory capital limits individual default risk of a bank and therefore a bank's systemic risk contribution. However, as pointed out by Flannery (2014), regulatory capital ratios are insensitive to actual default risk of banks. Furthermore, the expected shortfall (ES) of banks does not necessarily reflect banks' systemic risk contribution. In stress tests, the expected shortfall is based on book values and it is being assessed irrespective of other banks' losses. As Mishkin (2011) points out, a firm can be systemically important due to either its size or its interconnectedness. He provides LTCM as an example, a hedge fund of a relatively small size whose failure had a large systemic impact. On the other hand, the failure of Continental Illinois Bank in 1984, which was the largest bank failure in American history until Washington Mutual,

[1] In the U.S., for example, GDP decreased by about 4%, unemployment increased by 4 percentage points, and capital investments were reduced by 15% in 2009. For an overview on the subprime crisis, see e.g. Reinhart/Rogoff (2008) and Mishkin (2011). Gros/Alcidi (2010) provide a detailed analysis of the welfare implications of the crisis by comparing pre-crisis long-term GDP growth rates to actual GDP changes (the so-called output gap).

did not have any significant impact on the economy. This shows that for systemic stability it is rather the risk that a bank's default poses to the financial system instead of the bank's own risk of default which matters.

Alternatives to the current stress testing procedure have been developed which target a market-value based evaluation of banks' systemic risk contribution. Assuming markets are informationally efficient, these approaches have the advantage to promptly incorporate changes in probabilities of default and interconnected risks between banks.

One alternative has been proposed by Acharya et al. (2016), who developed a theoretically motivated framework for taxing bank holding companies (BHCs) according to their overall risk contribution. Besides idiosyncratic risk, the model captures the contribution to systemic risk (SES). In their publication, the focus is on the unobservable systemic part, SES, which, according to the authors, can be explained through three factors: leverage, a company's marginal risk contribution in a systemic downturn (MES) and excess costs of financial distress. In this context, they define the excess costs of financial distress as the difference between expected distress costs during a crisis and expected distress costs that can be observed on normal bad days.

In their empirical implementation, the authors argue that although distress costs are probably very significant in a crisis, they would be approximately zero in non-crisis times. Thus, the authors ignore this factor in their estimation. Overall, they expect MES and leverage to sufficiently explain SES.

MES and leverage are measured in the pre-crisis year to test the predictive power of the SES measure. The authors find that both variables – in contrast to common risk measures such as ES and variance – are highly significant in explaining banks' equity returns and CDS spread changes during the financial crisis, as well as the SCAP results in 2009. Acharya et al. (2016) conclude that their SES measure (combining MES and leverage) "appear(s) to be able to predict the financial firms with the worst contributions in systemic crises" (p. 35).

However, according to the theoretical model, a bank's systemic risk contribution, SES, also depends on the excess costs of financial distress. Thus, if an empirical measure of this variable was available, incorporating it into the estimation of SES could potentially improve the predictive performance of the empirical systemic risk measure suggested by Acharya et al. (2016).

In fact, distress costs can be estimated using the framework of structural models. Building on the Leland and Toft (1996) model, Breitkopf and Elsas (2012) develop a framework to directly estimate distress costs from CDS and stock price data. The distinctive feature about their approach is that they do not use any ad-hoc values for model exogenous parameters, in particular loss given default (LGD) and debt maturity, but instead estimate these parameters from CDS spreads. In contrast to the assumption by Acharya et al. (2016), the authors find that expected distress costs are significantly and economically different from zero. In fact, they found average expected distress costs amounting to 6.95% of unlevered asset value in the period 2003-2011 even if firms were not in financial distress.

Thus, it seems very likely that distress costs are highly relevant for banks, so that taking distress costs into account potentially offers a possibility to improve the SES measure.

For this reason, the objective of this thesis is to extend the empirical analysis of market-based measures of banks' systemic risk contribution by building on the Acharya et al. (2016) framework, empirically estimate and analyze the relevance of distress costs for banks, and test whether distress costs can improve the predictive power of the SES measure for banks' actual risk contribution. For reasons of comparison, the sample for testing the predictive power of the improved SES measure will be the same as in Acharya et al. (2016).

The rest of this thesis proceeds as follows. In section 2, we give an overview of the regulatory developments that led to the introduction of supervisory stress tests, after which we provide a short description of the current stress testing framework and describe some important shortfalls of the procedure. Section 3 outlines the measure for systemic expected shortfall by Acharya et al. (2016). In section 4, we describe the Breitkopf and Elsas (2012) method for estimating expected costs of financial distress. Section 5 describes our empirical implementation. Section 6 presents descriptive statistics of our estimated parameters and those that we implement in the model. Section 7 contains the empirical analysis of the implemented estimators and a robustness check. In section 8 we discuss the findings and section 9 concludes.

2 Bank Regulation and Regulatory Stress Tests

2.1 Banking Regulation

The current regulation builds on a set of rules developed by the Basel Committee on Banking Supervision (BCBS). At the end of 1982, during the Latin-American debt crisis, the ten largest American banks held about $ 50 billion in loans on their balance sheets from countries like Mexico, Brazil and Argentina which were about to default. To avoid bankruptcy and a crisis which would spread over to the whole financial system, the United States and the International Monetary Fund (IMF) had to grant billions of dollars in loans to the countries in trouble. The American banks who were lenders to these countries started rescheduling the loans and, due to massive undercapitalization, were forced to increase their loss reserves by a new regulation, the International Lending Supervision Act of 1983 (see Markham, 2002 pp. 128 - 130). This new law has been regarded as a major threat to competition and urged the need for a global standard for banking supervision and for certain requirements for the capitalization of banks. With the focus on strengthening the international banking system and reducing possible competitive inequalities, the Basel Capital Accord, better known as Basel I, has been released in 1988 by the BCBS. (Goodhart, 2011)

Basel I was designed to assess the credit risk of internationally active banks and to set minimum capital requirements in relation to that risk. Thus, banks had to fund their assets with enough equity capital that would absorb losses arising due to credit risk, i.e. counterparty default risk, during stressful conditions.

For this purpose, the BCBS designed a risk-weight approach which would relate capital to different risk categories of assets. Four different categories of assets were defined and risk weights between 0% and 100% were assigned to the different asset classes. Multiplying book value of the assets with the corresponding risk weights determined the risk weighed assets (RWA). After assessing RWA, book equity capital was to be divided into two classes (or "Tiers"): Tier 1 capital (or core capital), at that time comprising only permanent shareholders' equity and disclosed reserves (created by retained earnings or other surpluses) and Tier 2 capital which consists of reserves, hybrid debt capital, subordinated debt and other kinds of supplementary capital. The minimum capital requirement prescribed that 8% of RWA were to be held in capital of which at least 4%

would have to be core capital. To meet the proposed regulatory capital ratio of 8%, banks could thus either reduce the (apparent) risk on the asset side by shifting to assets in low risk asset classes, or increase their capital base. (BCBS, 1988)

As an extension to Basel I, the Market Risk Amendment was released in 1996. This document defined a framework to quantify market risk in addition to credit risk, addressing the risk of a decline in market prices of equities, interest rate related and foreign-exchange positions, commodities, and options. Similar capital requirements applied to market risk. (see BCBS, 2005)

Within an asset class, no distinction in terms of riskiness of the assets was made. This gave banks incentives to shift from low to high risk assets within an asset class[2]. Banks could thus keep their regulatory risk measure low and at the same time substantially increase their economic risk – a term called regulatory arbitrage (see Jones, 2000). The BCBS acknowledged banks' practices to employ in regulatory arbitrage and recognized that banks' internal models of assessing credit risk might produce better estimates of credit risk and thus better reflect the riskiness of assets (BCBS 2009).

To counteract the problem of regulatory arbitrage, Basel II was introduced in 2004. The concept of Basel II is a three-pillar approach, consisting of the following parts (BCBS, 2004):

1. Minimum Capital Requirements: Defines capital requirements.
2. Supervisory Review Process: Encourages bank supervision authorities to impose capital charges beyond the minimum capital requirements based on risks not (or not adequately) accounted for through Pillar 1. Furthermore, authorities are encouraged to intensify supervisory review processes.
3. Market Discipline: Introduction of disclosure requirements about capital and capital structure, risk exposures and risk assessment processes. This allows market participants to better assess capital adequacy of banks.

A major difference in the assessment of the required capital under Basel II is that credit risk weights are not determined solely based on asset classes. Rather, risk weights would depend on

[2] For example, Acharya, Schnabl and Suarez (2013) find that banks were engaged in regulatory arbitrage by setting up special purpose vehicles (SPVs) to securitize their assets but were still providing liquidity guarantees for these assets.

ratings. Banks could rely on credit ratings determined by recognized external credit assessment institutions or they could use their own internal models to generate their credit assessment, the so-called internal-ratings-based (IRB) approach. (BCBS, 2004)

Under the IRB approach, banks use internal risk models to project possible losses over a one-year time horizon. In this context, banks have to assess the 99.9% Value at Risk (VaR), that is the amount of losses that would not be exceeded with a probability of 99.9%. In this context, the minimum capital requirements for credit risk are specified to correspond to a probability of default (PD) of less than 0.1%. (see Federal Register September 25, 2006, p. 55833)

Figure 1: Loss Distribution (Source: Federal Register)

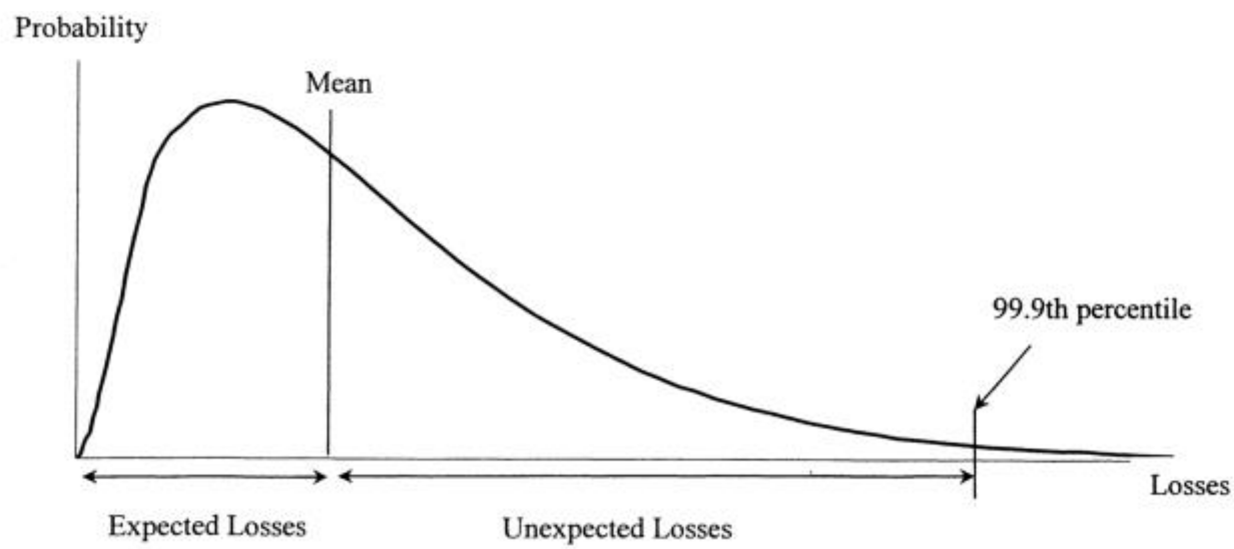

Figure 1 illustrates the concept of the IRB approach. It illustrates the one-year loss distribution. The loss amount at the 99.9^{th} percentile determines the capital requirement.

Before the financial crisis in 2008/2009, the BCBS started working on a revised framework (Basel III), which would further strengthen the capital base of banks. The revised set of rules has been published at the end of 2010 with the scope of strengthening the three Basel II pillars and to extend the rules to "improve the banking sector's ability to absorb shocks arising from financial or economic stress […] thus reducing the risk of spillover from the financial sector to the real economy" (BCBS, 2010).

Basel III basically stipulates the implementation of stricter capital requirements. The required amount of Tier 1 capital to RWA increases from 4% to 6%, and at least 4.5% of all RWA must be Tier 1 common equity capital (which is essentially non-preferred shares)[3]. Additionally, banks are required to hold a capital conservation and a countercyclical buffer[4]. (BCBS, 2011)

Basel III also regulates the leverage ratio through minimum leverage standards of 3% in Tier 1 common equity to total 'on and off' balance sheet assets. Further, an important kind of risk not accounted for in the prevailing framework is liquidity risk, i.e. the risk that an institution is not able to meet cash flow commitments and collateral needs (BCBS, 2011). Banks are particularly sensitive to this risk because they tend to fund long term loans with short term deposits. Therefore, Basel III introduces a global liquidity standard that most importantly demands that banks need to hold enough liquid assets (cash or cash-like) to cover all cash outflows of 30 days under stress[5]. The changes are to be implemented gradually until 2019. (BCBS, 2013)

In 2007, when the subprime crisis started, Basel II regulation was in force. At that time, most banks had regulatory capital ratios that exceeded minimum requirements and, under Basel Pillar 2, were under a constant supervisory monitoring process (see Flannery, 2014). Nevertheless, the crisis has not been prevented. As a consequence of the crisis, regulatory institutions introduced frequent regulatory stress tests for the banking sector.

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[3] The exact definition of Tier 1 common equity capital is "Tier 1 capital less the non-common elements of Tier 1 capital, including perpetual preferred stock and related surplus, minority interest in subsidiaries, trust preferred securities and mandatory convertible preferred securities" (Clark and Ryu, Federal Reserve Board, 2015).

[4] The capital conservation buffer imposes banks to build up ex-ante capital buffers that can be drawn upon in stressful times, the countercyclical buffer imposes banks to hold more capital during economic good times (BCBS, 2011)

[5] Stress scenario comprises a significant downgrade of the bank's credit rating, a partial loss of deposits, partial loss of unsecured wholesale funding, a significant increase in secured funding haircuts, increases in derivative collateral calls and substantial calls on contractual and non- contractual off-balance sheet exposures, including committed credit and liquidity facilities. (BCBS, 2010)

2.2 Regulatory Stress Tests

Stress tests in general are scenario based analyses of a firm's asset values. Within the framework of financial risk modelling, scenario analysis has been and continues to be a common tool. It is conducted by individual companies for their own risk management. In contrast to the "internal stress tests" conducted by banks, regulatory stress tests differ as they enable comparisons across banks and, as a macro-prudential tool taking all banks' results into account, also aim at giving an impression of the systemic risk prevalent within the banking sector (Petrella & Resti, 2013).

The financial crisis of 2007-2009 can be seen as the motivation behind the regulatory stress tests. After numerous bank failures and bailouts of banks[6], regulatory authorities around the world launched several initiatives to regain and preserve system stability. The first supervisory stress test, the Supervisory Capital Assessment Program (SCAP), has been conducted by the Federal Reserve System in early 2009. (Mishkin, 2011)

The SCAP (as well as the following stress tests) was a supervisory assessment on the 19 largest US banking institutions and had two main purposes: First, it was supposed to assess whether banks have sufficient capital to withstand losses and still meet their customers' credit needs in adverse macroeconomic conditions. Sufficient capital in this context referred to a common equity ratio of 4% and a tier 1 risk-based capital ratio of 6%[7]. Second, the SCAP was supposed to provide information to regulators and the market through the disclosure of results on a bank-by-bank level in order to facilitate market discipline (as is the purpose of Basel Pillar 3). This was also supposed to enable a bank to raise - if required - additional capital by making a bank's condition more transparent.

The results of the SCAP were disclosed in March 2009 and 10 out of 19 banks failed the test (i.e. they were undercapitalized in the adverse scenario of the stress test) but almost all of them were able to raise the required amount[8] . This fact shows that the stress test has been successful in terms

[6] The most prominent bailouts are probably those of Fannie Mae, Freddie Mac, American International Group (AIG) and Bear Stearns, Lehman Brothers' bankruptcy in September 2008 was the largest bank failure in American history (Mishkin, 2011)

[7] The Tier 1 common capital ratio is defined as the ratio between Tier 1 common equity capital to risk weighted assets, (see Clark and Ryu, Federal Reserve Board, 2015).

[8] General Motors Acceptance Corporation (GMAC) was the only bank not able to raise enough capital by November 2009 (Federal Reserve, 2009)

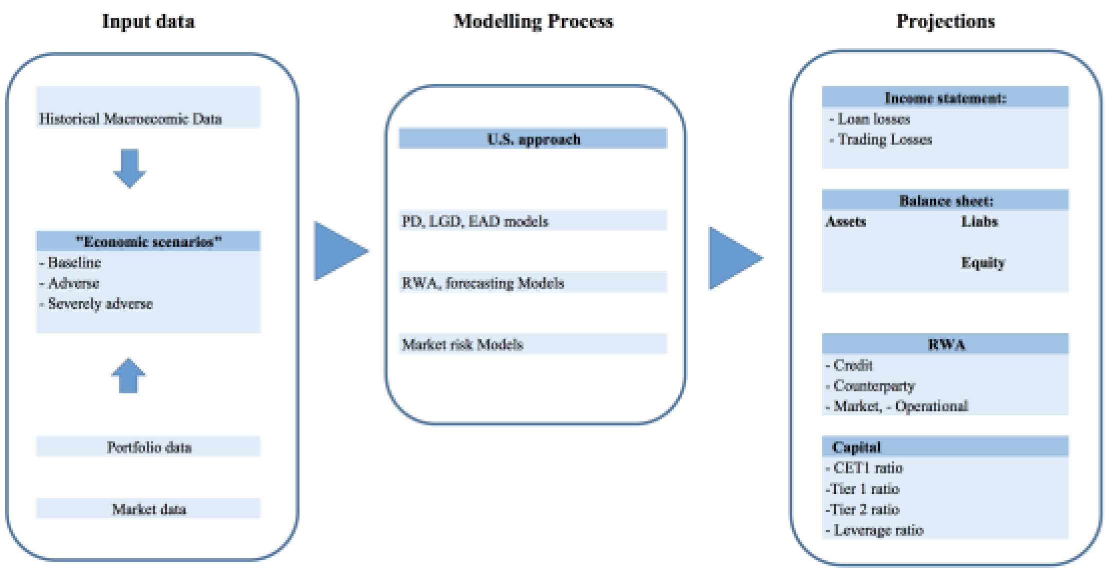
of fostering transparency and trust in the banking system. Mishkin (2011) argues that stress tests are a key element in the recovery of the economy[9].

With the SCAP, a whole series of other regulatory stress tests around the world was initiated. The most prominent stress tests are those conducted in Europe and the United States.

The current stress testing process in the U.S. basically has the following structure: Regulatory authorities design a baseline, an adverse and a severely adverse scenario that describe a hypothetical macroeconomic environment over a three-year horizon. Participating institutions, usually the system's largest banks in terms asset value, provide the data necessary to assess their financial development within the different scenarios such as net income and balance sheet data. Lastly, profitability and capital ratios over the three-year time frame are projected. (Fed Board of Governors, 2017)

The following figure illustrates the stress testing procedure, after which we will shortly describe some of the components in more detail.

Figure 2: Stress Testing Procedure (Source: Capgemini)



[9] In a similar manner, Hoshi and Kashyap (2011) argue that the 2003 stress test conducted in Japan after years of economic recession significantly contributed to the economic recovery

The foundation of regulatory stress tests are one or more hypothetical bad-case scenarios that represent an economic downturn caused by various simultaneous shocks to the macroeconomic environment. For this purpose, supervisory institutions define a set of conditions that affect the economy and financial markets for three subsequent years. This set of conditions captures factors like economic activity, asset prices (e.g. housing prices and stock indices), interest rates, GDP growth, inflation, and unemployment rates. Besides the stress scenario, or the adverse scenario, the tests usually comprise a baseline scenario, representing an economic forecast of what regulators consider as realistic given the prevailing economic conditions. U.S. stress tests comprise two stress scenarios, an adverse and a severely adverse scenario. Furthermore, the conditions are adjusted for each test to what regulators consider as adequate. (Dent el al, 2016)

The following figure shows a comparison of selected projected economic variables between the U.S. severely adverse scenario and the European Adverse Scenario in 2016.

Figure 3: Stress Test Scenarios of the 2016 U.S. Stress Test

Figure 3 illustrates the three-year projections of the changes in unemployment rate, house price index, stock market index and real GDP as a part of the severely adverse scenario in the 2016 U.S. stress test.

The macroeconomic scenarios affect banks' capital positions in several ways. For example, the increase in the unemployment rate could lead to more people having difficulties paying off their loans. In this case, a bank, being the lender, will possibly have to record losses. Another example would be a decline in the house price index, pointing at decreasing housing prices, that results in the deterioration of banks' asset values as the value of the collateral falls below the loan amount. All these losses lead to a decline in equity capital. If the overall loss in equity leads to an equity capital position below a certain threshold (which is the regulatory capital ratio), the bank fails the test. (Dent et al., 2016)

Generally, the impact of the scenario depends on the correlation of the economic variables with the bank's assets. For example, if assets only consist of mortgage loans, the correlation to house prices is likely to be very high and losses due to credit risk are likely to be very high. The projection of capital ratios to future values requires banks and supervisors to make assumptions about the development of asset values. In this sense, regulatory institutions have decided to keep values constant (such as RWA and dividend policy). (Dent el al, 2016)

All participating banks send the required data to the supervisory institution which then uses its own risk models to quantify the risks. The advantage of the approach applied is that it truly makes the stress impact comparable across institutions and that it eliminates incentives for banks to play down potential losses using their own models (Hirtle and Lehnert, 2014).

One important factor of the regulatory stress testing procedure that is supporting system stability is the disclosure of test results. Banks' assets in their nature are opaque, meaning banks do not provide sufficient information about their assets' risk exposures (Flannery, 2010). Consequently, the market's ability to assess the true value of banks' assets is limited (Flannery, 2014). The disclosure of test results on a detailed level aims at providing more information to market participants and thus to mitigate bank opaqueness. Petrella and Resti (2013) examine whether the disclosure of stress test results evokes market reactions. If markets are efficient, any new information is reflected in market prices (Fama, 1969). They find that markets do react to the disclosure of results and conclude, that it in fact does provide new information and mitigates bank opaqueness.

In summary, regulatory stress tests are a tool used for the quantitative assessment of banks' risks. They are used to assess whether banks can also comply with regulatory standards in times of economic downturn. To banking regulation they are an important complement that improves system stability. The results can be used as an input for both, micro- and macroprudential regulation. On a microprudential level, regulatory institutions can use the results to make sure that banks are sufficiently capitalized. On a macroprudential level, i.e. concerning the system as a whole, authorities can evaluate the capital adequacy of the entire financial system. (Dent el al, 2016)

However, the test results can only be considered in conjunction with the assumptions made in the modelling process. In the following section, we argue that these assumptions are incorrect and therefore the current stress tests are subjected to a couple of weaknesses.

2.3 Weaknesses of Regulation and the Stress Testing Procedures

Although the existence of stress tests and regulation is justified, the question remains to what extent they are capable of ensuring system stability and preventing another financial crisis.

Despite the positive contribution of regulatory stress tests and banking regulation to a more stable system as stated above, the current stress test methodology is flawed by a number of weaknesses, which we elaborate in the following.

Firstly, as stress tests aim at assessing risk on a macroprudential level, i.e. at assessing systemic risk, the regulators assume that systemic risk is simply the sum of individual risks of all banks. To understand why this is not the case, we first need to properly define systemic risk: Billio et al. (2012) give a formal definition, as "any set of circumstances that threatens the stability of […] the financial system" (p. 537). According to them, systemic risk comprises four factors: leverage, liquidity, losses and interconnectedness. Basel III and the stress test together capture the first three factors. However, the fourth factor, interconnectedness, is the crucial factor to systemic risk that is not covered by either as it cannot be measured on a microprudential level, which is where Basel III and the stress test are really employed.

Cai et al (2017) define interconnectedness as common exposures among financial institutions which lead to a higher correlation among their portfolios. Liu et al. (2015) find that these common exposures can arise from direct and indirect connections. Direct connections are for example credit exposures and financial infrastructure dependencies between financial institutions. Indirect connections could among others stem from marked-to-market losses, triggered by e.g. fire sales[10]. Acharya and Yorulmazer (2008) analyze another interesting example of indirect interconnectedness, namely information spillover. They state that when distressing news of a single bank are interpreted as a bad signal for the whole financial sector, other similar banks' costs of borrowing debt will increase.

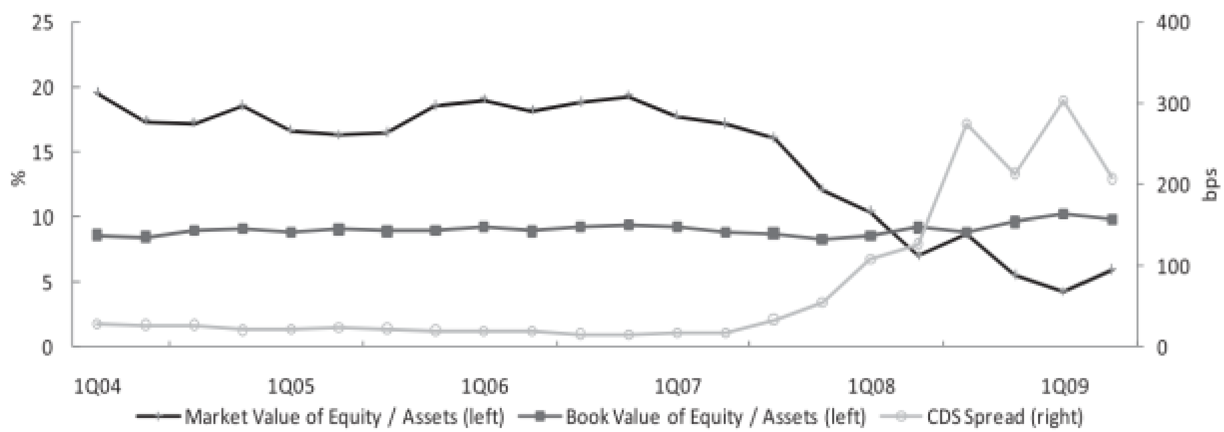
Acemoglu et al. (2015) argue that, when negative shocks (e.g. bank failures) pass a certain threshold, a higher degree of interconnectedness promotes the spread of financial distress from one institution to the other. Therefore, interconnectedness increases the probability of one institution going bankrupt in times when other interlinked institutions experience financial distress.

Interconnectedness is the key to understand why individual banks' risks don't just add up to systemic risk. To illustrate this, imagine a system with three banks, Bank A, Bank B and Bank C. They are highly interconnected, i.e. Bank A has large credit exposure to both, Bank B and Bank C, and Bank B also has credit exposure to Bank C. A stress test makes sure that Bank A can carry all losses arising from both banks' credit risks seen in isolation. But what it would not capture is the increased probability of default of Bank B, when Bank C defaults. This example can be modified to illustrate the effect of other channels of interconnectedness. Let us assume Bank B is the only clearing bank in the system. Bank A and Bank C depend on the financial services offered by Bank B but do not have any credit exposure to it, so these connections do not show in any balance sheets and therefore are not taken into account by the stress test. If Bank B goes bankrupt, Bank A and Bank C would quickly have to come up with a substitute for Bank B. The default risk is not considered by the stress test, even though a default would significantly affect Bank A and Bank C and maybe even the rest of the economy. Both examples illustrate the systemic risk that arises from interconnectedness that is not captured by regulatory stress tests.

[10] Fire sales occur when a failing bank does not have enough liquid assets and might be forced to sell a large amount of illiquid assets in a short period of time at a discount.

A further weakness is that regulation and stress tests rely on regulatory capital ratios to limit a bank's default risk and thus their contribution to systemic risk. However, as pointed out by Flannery (2014) regulatory capital measures are insensitive to actual default risks of banks because they are based on book values. He adds that the five largest U.S. banks that failed or were acquired in 2008 (Bear Stearns, Lehman Brothers, Wachovia, Washington Mutual and Merrill Lynch) reported high Tier 1 book capital ratios in their last financial statements, while their market values of equity had already declined and CDS spreads had already increased as shown in Figure 4.

Figure 4: Book Capital Ratios versus Market Solvency Indicators (Source: Flannery, 2014)



Book values and regulatory risk weights, can be subject to accounting distortions because banks are able to manipulate book data and regulatory risk weights. Acharya, Engle and Pierret (2014) state that banks are not interested in holding the economic efficient amount of capital because they do not bear the costs of bailouts and "externalities they impose to the rest of the economy […] when the financial sector is undercapitalized". The risk weight estimates produced by banks under the IRB approach are a result of strategic risk modelling and do not reflect the actual risk. This can lead to excessive economic leverage despite having adequate regulatory capital ratios.

The alternative to using capital ratios based on book values is the use of market values instead. Flannery (2014) states that regulators do not see an advantage in the use of market values, as they can also be flawed due to the opaqueness of banks and therefore the market is not able to assess the true value of their assets. In response to this argument, Flannery (2014) states that even though market values might not be able to predict deteriorating conditions much in advance, they still adjust much sooner than book capital ratios. Figure 4 illustrates this. Their quicker adjustment is due to their reflection of all publicly available information under the assumption that markets are efficient (Fama, 1969).

This leads to the next argument in favor of market values compared to book values: the current regulation and stress tests have a tedious risk assessment framework. Credit risk, market risk, liquidity risk etc. must be assessed separately using sophisticated models, the information must then be put together to obtain the final measure for capital adequacy. The advantage of market values is that they include an overall risk assessment based on the information that is available.

Furthermore, in contrast to book values, market values are forward-looking and not a reflection of the past.

In the following section, we explain an alternative measure for a bank's contribution to systemic risk that takes the described weaknesses into account.

3 Market Based Measures of Systemic Risk

3.1 Systemic expected short fall

Acharya et al. (2016) develop a theoretical framework for taxing bank holding companies (BHCs) according to their overall risk contribution. Instead of taking into account only BHCs' individual default risk, as done in supervisory stress tests and banking regulation, they also consider their contribution to systemic risk. The framework is based on the idea, that BHCs should be taxed ex-ante for their expected risk contribution because – due to their limited liability feature – they incur costs to society in case of a default. Such costs include the amount necessary for a bailout which, in the end, is carried by taxpayers but also the costs of a debt insurance program. In an interconnected system, the default of a bank that is systemically important can trigger other banks' defaults, a credit crunch and in consequence an economic downturn. If banks have to pay for this risk in advance through a tax, they may find it optimal to reduce the risk by choosing a different (less levered) capital structure.

The model implies that BHCs choose a mix between equity and debt that maximizes the net worth for equity holders. The regulator in turn chooses a tax rate, that maximizes the welfare of the whole financial system considering the sum of all BHC owners' utilities, the expected cost of the debt insurance program (that depends on the BHC's choices) and the externalities that would spill over to the rest of the economy in case of a systemic downturn.

An important assumption in this model is that a systemic crisis occurs when the whole financial system is undercapitalized. Thus, when a single bank is undercapitalized in times when the system as a whole is not, this one bank's default will not impose any externalities to the whole economy because it could, for example, just be purchased by another BHC.

Acharya et al. (2016) state that a financial system is undercapitalized when the aggregate capital falls below a fraction z of the aggregate assets in the system. Thus, if all banks hold at least this much capital to cover the fraction z of their assets, the system is not undercapitalized. In our current regulatory framework z in size is comparable to the required amount of 8% of RWA that needs to be held in Tier 1 capital by banks. As explained in the previous section, 8% of RWA is what regulators define as capital adequacy.

The tax rate has two main components: idiosyncratic risk and a bank's contribution to systemic risk (SES). It is the idiosyncratic part, that the current regulation and supervisory stress tests address, but both, the idiosyncratic and the systemic terms, that supervisory institutions actually want to regulate. The focus of this thesis is on the systemic part SES.

SES – the systemic expected shortfall - has the following form:

$$(1)\ SES = E[za^i - w_1 |\, W_1 < zA]$$

where z is a fraction that determines capital adequacy, a^i is firm i's asset value, w_1 is firm i's available equity capital at time 1, W_1 is the aggregated amount of capital in the whole system and A are the aggregated assets in the whole system.

Thus, SES is a measure for the expected difference between the fraction z of a bank's assets and its equity capital w_1 when the system is undercapitalized. This difference shows how much a firm contributes to the shortfall of the system when a crisis occurs.

Because the tax will be set ex-ante, the systemic expected shortfall must be known in advance, which is unfortunately not the case as z is not predictable. Hence, SES cannot be calculated the way it is described in equation (1) and therefore Acharya et al. (2016) derive a relationship between SES and market based data. For this purpose, they introduce a measure called marginal expected shortfall, or MES, that has the following form:

$$(2)\ MES_{5\%}^{i} = -E\left[\frac{w_1^i}{w_0^1} - 1 |\ I_{5\%}\right]$$

where $\frac{w_1^i}{w_0^1} - 1$ is firm i's return on equity capital, $I_{5\%}$denotes the 5% worst market days during a certain period. MES is therefore the negative average of daily equity returns during the 5% worst market days. The negative sign makes MES in total a positive number as average returns will most likely be negative during the 5% worst market days[11].

Crisis returns are not predictable, but what can be observed are returns and values during the worst days of a year. By employing Extreme – Value – Theory, these can be translated to extreme day returns, thus approximating crisis returns. Acharya et al. (2016) use this connection and derive a relationship between systemic expected shortfall (SES) and $MES_{5\%}^{i}$. The relationship looks as follows:

$$(3)\ \frac{SES^i}{w_0^i} = \frac{za^i - w_0^i}{w_0^i} + kMES_{5\%}^{i} + \Delta^i\ ,$$

where a^i is a firm's pre-crisis amount of assets, z is the capital adequacy threshold, as explained above, k is the extreme-value-scaling factor and Δ^i are the excess costs of financial distress, which will be described further below. For the remainder of the thesis we will refer to this term as SES.

[11] To be precise, this term should use the following notation: $-E\left[\frac{w_{t+1}^i}{w_t^1} - 1 |\ I_{5\%}\right]$ as otherwise it refers to the whole period instead of the 5% worst sub-periods of one day.

As can be seen, SES^i relative to equity capital w_0^i is explained by three summands, which are in their own right. The first term, $\frac{za^i - w_0^i}{w_0^i}$, describes to what extent the company meets its capital threshold, za^i , in relation to how much equity capital a company holds. If this term is positive, firm *i* is already undercapitalized and the firm's systemic expected shortfall increases.

The second term is $MES_{5\%}^i$ (referred to as MES from now on) and is scaled by factor *k*, which is the power law translation from normal bad-day-returns to returns in a systemic crisis.[12]

The third factor has the following form:

$$(4)\ \Delta^i = \frac{E\left[DC^i \middle| W_1 < zA\right] - kE\left[DC^i \middle| I_{5\%}\right]}{w_0^i} - \frac{(k-1)(f^i - b^i)}{w_0^i}$$

where DC^i are BHC i's costs of financial distress, f^i is its face value of debt, and b^i is its market value of debt. $E\left[DC^i \mid W_1 < zA\right]$ are therefore the expected distress costs in a crisis for BHC i, $kE\left[DC^i \mid I_{5\%}\right]$ are the scaled expected distress costs during the 5% worst market days.

Distress costs are costs to a firm that arise when the firm experiences financial difficulties. Despite the costs that arise after a bankruptcy, such as the costs of hiring lawyers and accountants, filing for bankruptcy or restructuring costs, distress costs also arise from actions like cutting down capital expenditures or selling assets at a discount (see Andrade and Kaplan, 1998). In a theoretical Trade-Off framework, expected distress costs increase with leverage because with increasing leverage, a firm's probability of default (PD) increases (and the present value of distress costs is roughly the product of PD and distress costs).

Thus, the first part of Δ^i measures the excess costs of financial distress, i.e. the expected amount that will exceed the distress costs predicted for the crisis. If the true distress costs in a crisis are higher than the distress costs translated from normal days, this term is positive and Δ^i and SES^i increase. If they are actually lower, the opposite is the case.

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[12] As aforementioned, we can use Extreme Value Theory to derive a direct relationship between tail distributions and values during a crisis. Under the assumption that returns have a thin-tailed distribution, the tail distribution can be translated to extreme events over a factor. If the tail of a probability distribution has an extreme value distribution, the log of the probability of tail outcomes is linearly related to the log of the random variable. The proportionality factor is the tail index. See for example Kearns/Pagan (1999). For a more precise explanation see Acharya et al. (2016).

The second part of Δ^i, $\frac{(k-1)(f^i-b^i)}{w_0^i}$ is simply an adjustment term.[13] It is relatively small and will not be considered any further in this study. Thus, Δ^i are essentially the excess costs of financial distress.

In their empirical implementation, Acharya et al. (2016) test the predictive power of their SES measure. They use the past financial crisis as the crisis event and the pre-crisis year as their measurement period.

For the first part of SES, the ex-ante degree of undercapitalization, they use leverage as a proxy. This is feasible because the real *z* is not observable and because leverage and undercapitalization are related to each other. They are related because with higher leverage, a lower fraction of assets is covered by equity capital, and the firm is therefore closer to being undercapitalized (if not already undercapitalized). To avoid using book values as far as possible, the authors use a proxy for market leverage, $\frac{book\ assets-book\ equity+market\ equity}{market\ value\ of\ equity}$. Because data for the market value of assets is not available, they approximate it by subtracting the book value of equity from the book assets and add the market value of equity.

The second term, *MES* , is easily measurable.[14]

The third part of SES, the excess costs of financial distress Δ^i, is left out. They argue that although $E\left[\,DC^i \mid W_1 < zA\,\right]$, the expected costs of financial distress in a crisis, are probably very significant, they would be approximately be zero in non-crisis times and therefore cannot be captured. Overall, they rely only on *MES* and leverage to predict SES.

MES and leverage are measured in the pre-crisis year and tested for their power to predict a bank's systemic expected shortfall. Acharya et al. (2016) find significant explanatory power and conclude that their SES measure (combining MES and leverage) "appear(s) to be able to predict the financial firms with the worst contributions in systemic crises".

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[13] $(f^i - b^i)$ measures the excess returns on bonds and is part of MES as equity can be written as assets less distress costs and outstanding debt. When translating MES to extreme return over *k*, this term would scale up with the same factor. Acharya et al. (2016) state, that this term should actually not scale up, multiplying it by *(k - 1)* thus scales it back (Note: *k* >1).

[14] The scaling factor k is actually irrelevant to finding the correlation between SES and $MES_{5\%}^i$, as k is a constant. Simply using $MES_{5\%}^i$ will thus have the same explanatory power.

In this thesis we will attempt to measure the expected excess costs of financial distress and implement it into the empirical measurement of systemic expected shortfall.

3.2 CoVar

Another similar measure for banks' systemic risk contribution, CoVar, has been proposed by Adrian and Brunnermeier (2016). In contrast to Acharya et al. (2016), the authors suggest a measure based on Value at Risk (VaR) instead of the expected shortfall. Here, the measure of interest is the change in a financial system's VaR when a company is getting in distress. SES and CoVar differ in their measurement methodology. Where Acharya et al. (2016) base their prediction of asset values during a crisis on Extreme Value Theory, Adrian and Brunnermeier (2016) apply quantile regression. This model shows several weaknesses compared to the SES approach. The use of VaR is disadvantageous compared to the use of the expected shortfall, especially in the situation, where the behavior beyond the VaR-quantile is of interest. This is because VaR is only a certain threshold but does not capture the quantity of the losses beyond this threshold and exactly these losses matter in a crisis. Furtermore, Adrian and Brunnermeier (2016) find only a weak correlation between a company's VaR and the change in the system's VaR. Accordingly, this motivates putting the focus on SES rather than on CoVar in this thesis.

4 Estimating expected cost of financial distress

4.1 Literature review

Several studies investigated actual and expected costs of financial distress. One of the most prominent studies is that of Andrade and Kaplan (1998), who determine the costs attributable to financial distress after a firm defaulted. Their sample consists of 31 companies that encountered financial distress after highly-levered transactions and they find that the actual costs of financial distress amount to 10% - 23% of pre-distress firm value. They argue that, consistent with Acharya et al. (2016), expected (ex-ante) costs of financial distress are negligible because the probability of default is usually low.

In contrast to Andrade and Kaplan (1998), Almeida and Philippon (2007) estimate the expected costs of financial distress. For this purpose, they use the ex-post distress costs estimates from Andrade and Kaplan (1998) and weigh them with probabilities of default to obtain estimates for their expected value. As opposed to other studies that rely on historical probabilities of default to calculate expected costs of financial distress, they use observed bond spreads to obtain risk-adjusted default probabilities. This automatically takes risk premia in bad states into account, which other studies ignore. Risk premia are higher in bad states because then the marginal utility of money to investors is higher than in good states (Breitkopf and Elsas, 2012). They find that expected distress costs amount to up to 4.5% of pre-distress firm value for investment grade firms (whereas ignoring risk premia, expected distress costs amount to only 1.4%).

Based on a sample of 175 firm that defaulted in the period between 1997 and 2010, Davidenko, Strebulaev and Zhao (2012) estimate the actual costs of financial distress that arise due to bankruptcy. In contrast to Andrade and Kaplan (1998), they do not only analyze distress costs for highly levered firms, rather they use a more diversified sample. Using an event-study approach, the authors extract the firm’s distress costs from the change in equity and debt prices around the announcement of default. They find that the average distress costs amount to 21.7% of asset values and that they are significantly lower for highly levered firms (20.2%).

Breitkopf and Elsas (2012) estimate expected costs of financial distress for European non-financial firms. They find average expected distress costs of 6.7 % of asset values. The unique feature about their estimation procedure is that they don’t take any ad-hoc values for the estimation of loss given default which is an essential parameter in the estimation of distress costs. Rather, they estimated the parameter from observed market values of equity and spreads of credit default swaps.

We think that distress costs of banks are even higher for the following reason. It seems likely, that banks are over-levered due to deposit insurance and being “too big to fail” (TBTF). The term TBTF usually applies to systemically important banks that require certain regulation while solvent in order to keep them solvent (through a bailout for example) and/or that are subject to special liquidation rules with respect to allocation losses when they are bankrupt, that don’t apply to other companies in the same industry (see Kaufman, 2014). This creates a moral hazard problem for systemically important financial institutions as it gives bank owners incentives to engage in risk shifting and therefore to take on excessive risk. In support to this argument, the leverage ratchet theory (Admati et al., 2013) shows that particularly bank owners have no incentives to de-lever, even if they deviate from their optimal capital structure.

Following the findings in recent literature, we think that distress costs will be significantly different from zero, other than assumed by Acharya et al. (2016). We want to estimate expected costs of financial distress for U.S. bank holding companies and to expand Acharya et al.'s (2016) SES measure. For this purpose, we will use the estimation procedure applied by Breitkopf and Elsas (2012). In the following section, we describe their estimation procedure in more detail.

4.2 The Breitkopf and Elsas (2012) procedure for estimating distress costs

Distress costs can be estimated using the framework of structural models. Based on Merton's (1974) model of corporate debt, Leland (1994) derives a structural model incorporating taxes and distress costs, which is thus grounded on the trade-off theory of capital structure (Myers 1984, Fischer et al. 1989). Leland and Toft (1996) complement this model by including an endogenous default barrier.

Building on the Leland and Toft (1996) model (LT model), Breitkopf and Elsas(2012) developed a framework to directly estimate distress costs from CDS and stock price data instead of using ad-hoc values for model exogenous parameters.

Structural models, like the LT model, can be generalized by the following form:

$$(5)\ firm\ value = \text{ unlevered } asset\ value + PV(tax\ shield) - PV(distress\ costs)$$

As can be seen, the expected costs of financial distress are an explicit component of this model. One central parameter determining distress costs is loss given default (LGD), defined as the ratio of losses to exposure at default (Schuermann 2014). Because this parameter is unknown prior to default, studies such as Almeida and Philippon (2007) have to make assumptions about the size of

LGD. Breitkopf and Elsas (2012) avoid this by using credit default swap (CDS) spreads[15] to find market implied parameter values.

Besides LGD, there are other unknown exogenous parameters in the LT model that must be known in order to obtain estimates for distress costs, such as asset values, asset volatilities, debt maturity (T) and the asset pay-out ratio. Instead of making flat assumptions about their values, Breitkopf and Elsas (2012) derive them from market prices.

In order to obtain market implied estimates for the unknown parameters e.g. LGD, Breitkopf and Elsas (2012) must know firm value components such as the unlevered assets value and asset volatility. To obtain those, Breitkopf and Elsas (2012) use the direct relationship between equity prices (that can be observed), unlevered asset value and asset volatility to obtain the unlevered asset value and the asset volatility. They do this for various combinations of LGD, T and the asset payout ratio. Thus, they obtain a large matrix with different time series of asset values and volatilities and then use observed CDS spreads to search the time series for the combination that corresponds best to the observed CDS spreads.

In this thesis, we will use the same procedure with the only difference that we take the asset payout ratio as given by approximating it through a weighted average of dividends and interest expenses. Reneby et al. (2005) state that the approximation through weighted averages provides reasonable results.

In summary, to obtain market-implied expected costs of financial distress we, in accordance with Breitkopf and Elsas (2012), conduct the following steps:

1. Estimation of the market values of assets and asset volatilities using the Leland and Toft (1996) framework for various combinations of debt maturities and LGDs.
2. Determination of market-implied values for LGD by searching for the optimal parameter combination through calibration with observed CDS spreads on a subindustry-level

[15] Credit default swaps are instruments that provide an insurance against the default of a counterparty. Usually the holder of a bond would buy it as a protection of the bond issuer defaulting (and consequently the bond holder losing his investment). In such a case, the CDS buyer makes periodical payments to the seller of the CDS. The total amount of the payments as a percentage of the notional principal is known as the CDS spread or the premium (Hull, 2012). If the reference entity defaults, the CDS seller must compensate the buyer with the nominal value of the bonds. Naturally, the amount of the premium depends on the likelihood of the firm defaulting.

3. Translation of the estimated LGD parameters to the expected costs of financial distress for each firm.

In the following section, we describe the different steps in more detail.

5 Empirical Design

5.1 Estimating Asset Values and Asset Volatilities

Leland and Toft (1996) derive closed-form solutions for the determination of firm value components. Leland and Toft (1996) extend the Merton (1974) model by including the tax deductibility of interest payments (tax shield) and bankruptcy costs which enables the valuation of corporate securities in the context of the Trade-Off theory.

The foundation of the model is the assumption that a firm has unlevered assets whose value follows a geometric Brownian motion[16]:

$$(6)\ \frac{dV}{V} = [\mu(V,t) - \delta]dt + \sigma dz$$

where μ is the expected rate of return of the unlevered asset value V, and δ is the fraction of assets paid out to equity and debt holders (payout ratio). The firm has a stationary debt structure, which means that the firm continuously replaces maturing debt and with freshly issued coupon bonds (Leland & Toft, 1996). Under these assumptions, Leland and Toft (1996) provide a closed-form solution for the determination of the firm value:

$$(7)\ v(V;V_B) = V + \frac{\tau C}{r}\left[1 - \left(\frac{V}{V_B}\right)^{-x}\right] - \alpha V_B\left(\frac{V}{V_B}\right)^{-x}$$

[16] It is possible to extend the Leland & Toft model and making it more realistic by incorporating a jump diffusion process. Hilberink and Rogers (2002) show in a series of cases the impact of a jump-diffusion process in the Leland and Toft model. The find all maturities, except short ones, the firm value components are similar.

where τ is the tax rate, r is the risk-free interest rate, C is the coupon, α is loss given default. $\left(\frac{V}{V_B}\right)^{-x}$ is the present value of one dollar at the time the firm defaults with x being a discount factor. V are the firm's assets, $\frac{\tau C}{r}\left[1-\left(\frac{V}{V_B}\right)^{-x}\right]$ is the present value of the firm's tax shield, while $\alpha V_B\left(\frac{V}{V_B}\right)^{-x}$ is the present value of the firm's distress costs. V_B is the asset value where the owners of the firm find it optimal to stop servicing the debt (i.e. default). This is shown in the following formula:

$$(8)\ V_B = \frac{\left(\frac{C}{r}\right)\left(\frac{A}{rT}-B\right)-\frac{AP}{rT}-\frac{\tau C x}{r}}{1+\alpha x-(1-\alpha)B}$$

The market value of debt and equity is defined as:

$$(9)\ D(V;V_B,T) = \frac{C}{r} + \left(P-\frac{C}{r}\right)\left(\frac{1-e^{rT}}{rT} - I(t)\right) + ((1-\alpha)V_B - \frac{C}{r})J(T)$$

$$(10)\qquad E(V;V_B,T) = v(V;V_B) - D(V;V_B,T)$$

P is the principal of debt, for explanations of variables A and B in equation (8) and I(T) and J(T) in equation (9), we refer to Leland and Toft (1996).[17]

The problem is, that many of the parameters that determine the firm value in the LT model cannot be directly overserved. Some parameters, such as the market value of equity and the principal of debt, can be observed, while others, for example the default barrier, V_B, are determined within the model by the optimal behavior of the firm owners. Two parameters, the coupons and the asset

[17] Equation (7) and (8) are only valid if the tax shield is not lost prior to default. For the cases where this happens, Leland and Toft (1996) derived closed form solutions as well. They can be found in Appendix A.

payout ratio, can be approximated. Parameters, such as asset value, asset volatility, maturity and loss given default cannot be directly observed.

Duan, Gauthier & Simonato, (2005) use an iterative approach to find asset values and asset volatilities. Unlike the market value of equity (E) for exchange listed companies, the market value of assets is not observable, hence they use the functional relationship that exists between E and the unlevered asset value (V) to find the asset value that is consistent with the observed market value of equity for the firm. This works by inverting the equity function, equation (9), and deriving asset values and volatilities through an iterative approach.

The approach works by making an initial guess on the asset volatility σ_0, which is included in the term x, and generate a time series of 250 asset values that correspond to this volatility and the observed daily equity prices during the time period of 250 days. The resulting asset value time series is used to calculate a new volatility σ_1, which serves as an updated guess on the true annual asset volatility. Then we redo the previous step with σ_1. This procedure is repeated i times until the values for σ for two consecutive iterations converge, i.e. when σ_i deviates from σ_{i-1} by no more than 2%. This yields the annual asset volatility. However, we do not assume that the volatility remains constant throughout the whole year and therefore we transform this volatility into the daily volatility and then assign it to the asset value of day 1. Then we move the observation period forward by one day (day one leaves the time series, and day 251 is added) and repeat the iteration process to obtain the daily volatility for day 2 and continue to do so until we have generated a time series of daily asset values and their corresponding daily volatilities.

We repeat this entire process for all firms with different combinations of time to maturity, T, and loss given default, LGD.

5.2 Determination of Market-Implied Parameter Values and Calibration with CDS Spreads

After obtaining estimates for asset values and volatilities using the iterative approach just described, we have one time series of asset values and asset volatilities per combination of T and LGD. In the next step, we find the optimal parameters for each subindustry through a calibration with CDS spreads.

Reneby, Ericsson and Wang (2005) derive a formula for calculating the theoretical value of credit default swaps and spreads using the stochastic assumptions of the LT model. They split the valuation of the credit default swaps into two parts, the premium paid by the protection buyer and the expected payoff to the buyer if the reference entity defaults.

If a credit default swap involves paying a continuous flow of CDS premiums 'q' until some day between today and expiration, Reneby et al. claim that the value of the CDS is given as:

$$CDS\,(V,t) = (P-(1-\alpha)P) * G(V,t,T^*) - \frac{Q}{r}(1-H(V,t,T^*)-G(V,t,T^*)) \tag{11}$$

The first part of the equation is the value of the bond's principal in case the firm goes bankrupt. The second part is the value of the risk-less infinite cash flow less two terms, $H(V,t,T^*)$ and $G(V,t,T^*)$. $G(V,t,T^*)$ is a dollar-in-default claim if the firm defaults and $H(V,t,T^*)$ is a binary option on the firm not defaulting.

The CDS fee at initiation $t=0$, Q, is chosen in a way that the credit default swap has zero value:

$$Q = r * \;(P-(1-\alpha)P) * \frac{G(V_0,0,T^*)}{(1-H(V_0,0,T^*)-G(V_0,0,T^*))} \tag{12}$$

where alpha is the same LGD as in the Leland and Toft (1996) model. The CDS premium is then defined as:

$$(13) \qquad q = \frac{Q}{P}$$

Equation (12) expresses the CDS fee as a fraction of the bond notional. Reneby et al. (2005) find that the model implied CDS spreads are quite accurate. The whole derivation of the CDS valuation formulas can be found in Appendix B.

In order to obtain the market implied parameters LGD and T, we must first calculate the CDS premiums implied by the LT Model. For this purpose, we use the daily asset values and volatilities found in Step 1 for each combination of LGD and T. We then search for the combinations of LGD and T which results in CDS premiums that are closest to the actually observed CDS premiums. This is achieved via the Root Mean Squared Error (RMSE) function.

Breitkopf and Elsas (2012) use an adapted version of the RMSE for their calibration:

$$(14) \qquad RMSE_j = \sqrt{\sum_{j=1}^{n} \left(\frac{1}{DD_j}\right) * \left(S_{LT_j} - S_{act_j}\right)^2}$$

where n is the number of observations, DD is the distance to default, S_{LT} is the CDS premium implied by the LT model and S_{act} is the observed CDS spread. Because CDS spreads are not available for all companies, we split our sample into sub-industries according to SIC codes. We sum up the bank-individual RMSEs for each sub-industry. This yields the sub-industry's specific RMSE, which we optimize.

The root mean squared error (RMSE) is a goodness of fit measure that, in this context, measures the squared deviations between the calculated and the observed CDS spreads. To find the optimal values, RMSE must be minimized.

As can be seen in the objective function (13), Breitkopf and Elsas (2012) weigh the squared spread difference for each observation with the factor $\frac{1}{DD_j}$, where DD is the distance to default for company j. The distance to default is a measure for the default risk of a company. It measures the difference between the expected asset value and the default barrier in terms of standard deviations, i.e. how many standard deviations the asset value can decline before the company defaults. Breitkopf and Elsas (2012) argue, that CDS spreads show a large variation when default risk is low. This means, when default risk is low, observed spreads can be both, high and low. As credit default swaps act as an insurance against the default of a firm, one would expect CDS spreads to be low in case of a low probability of default. If this is not the case, there must be other factors driving the spreads which are not priced in a theoretical model. Therefore, the model-predicted CDS spreads might be low, although observed spreads are high. This can be seen in the following plot:

Figure 5: Model-implied CDS-spreads vs observed CDS-spreads

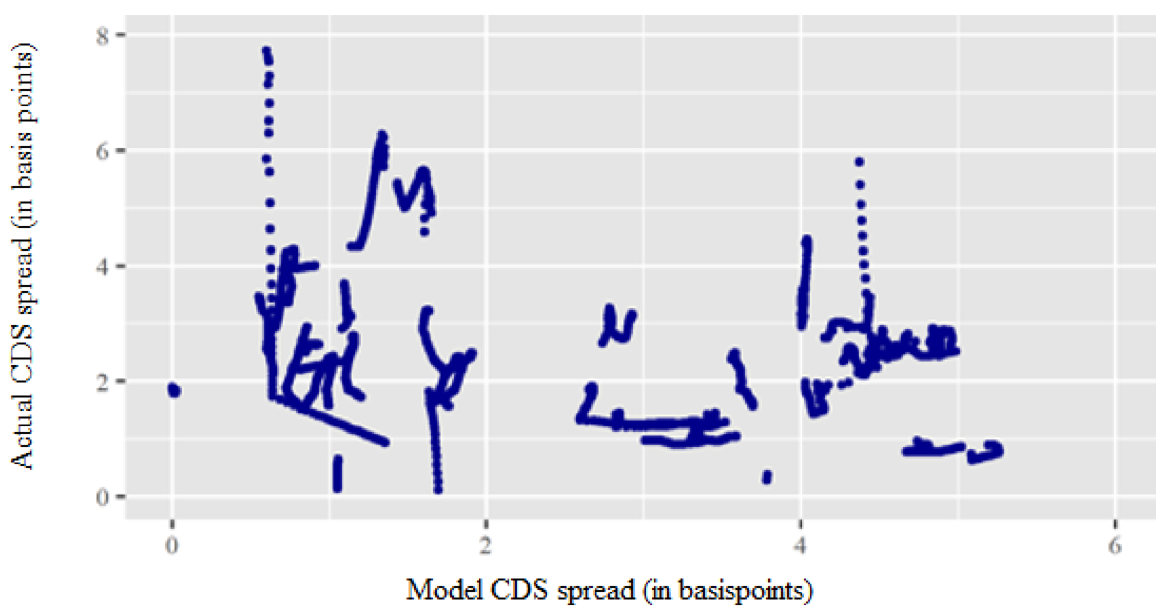


Figure (5) plots observed spreads against model implied spreads. Optimally, if the model described the observed CDS spreads perfectly well, all data points should be on a 45° line. As can be seen, this is not the case. Especially the observed spreads corresponding to low model implied spreads, i.e. to model implied spreads with a low probability of default show large variation. For very low model implied spreads, observed spreads have a range of up to 8 basis points.

Getting back to our optimization problem, $(S_{LT} - S_{act})^2$ can be high, not due to a bad parameter choice of T and LGD but because of the underlying theoretical model which does not describe the observed spreads perfectly well. In this case, these inconsistent observations should be attributed lower weights because the observed and predicted values cannot be perfectly optimized through the right parameter choice. But it is the right parameter choice that our objective function is looking for.

To calculate the distance to default, Breitkopf and Elsas (2012) use a formula derived by Merton (1974), which is defined as:

$$(15) \qquad DD = \frac{\ln\left(\frac{V}{V_B}\right) + (\mu - 0.5 * \sigma^2) * T}{\sigma * \sqrt{T}}$$

where μ is a firm's expected rate of return between time zero and T, V is the unlevered asset value, σ is the asset volatility and V_B is the same default barrier as before. We calculate the expected rate of return μ using the capital asset pricing model (CAPM).

To find the market implied parameters for time to maturity and LGD, we calculate the RMSE for all possible combinations of T and LGD and pick the combination with the lowest RMSE. That means that for each possible combination of the two parameters, we must estimate asset values and asset volatilities. This quickly becomes unfeasible due to the time it takes to compute such time series as described in section 6.2. The firm's asset value and asset volatility for a given day is usually found within 10 iterations (Breitkopf and Elsas, 2012). This implies that it takes approximately 625.000[18] calculations to find V and σ for a one year time series on a daily basis, one company and one single combination of T and LGD. The time this would take for even a small data-set makes it an unfeasible approach within the scope of this thesis.

As applied in Breitkopf and Elsas (2012), a solution to this computational problem is to limit the possible input parameters for T and LGD and to set up a multi-dimensional matrix containing time series of asset values and asset volatilities for a limited amount of combinations of parameters. The different values for T we use for the grid are {3, 5, 7, 9} in years, for LGD we use {10%, 25%, 40%, 55%, 70%}. Breitkopf and Elsas (2012) obtain optimal maturities in their sample between 5.9 and 9.5 years. As banks tend to rely more on short-term funding, we expect to find maturities that minimize the RMSE objective between 3 and 9 years. Based on the findings in other studies (see literature review), we do not expect LGD to exceed 70% and we believe it is at least 10%. From there on, we choose intervals with equal lengths.

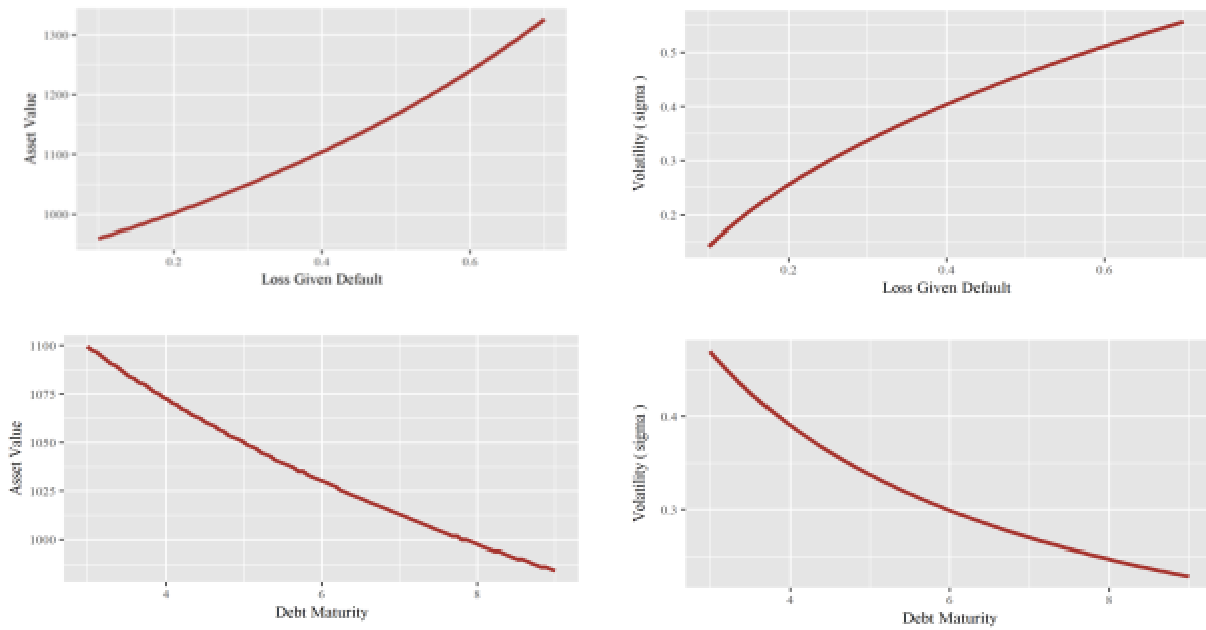
The objective function will search within this matrix for the smallest possible value of RMSE. To enable solutions in between the matrix items, we apply an interpolation scheme. Instead of finding asset values and volatilities for all possible points in between, we interpolate between them to obtain the values. This further reduces computational time. Breitkopf and Elsas (2012) mention, this is reasonable because V and σ are relatively smooth functions of T and LGD. The smaller the distance between the entries in the matrix, the smaller the approximation error due to the interpolation. Thus, we trade off gains in computational time against approximation errors.

We want to test whether it is in fact justified to interpolate between the different values of T and LGD that were mentioned above. We want to see how smooth the functions are for asset value and asset volatility with varying debt maturity and LGD. If the functions are not smooth, then interpolation cannot be justified due to large approximation errors[19]. As shown below in Figure (6), asset values and volatilities within the LT model are very smooth in alpha and debt maturity.

[18] For each asset value and asset volatility, a time series of 250 is used. Assuming there is 250 trading days a year, this would be 250*250*10 = 625.000

[19] To assess this, we assume values for the risk-free rate, the principal of debt, payout ratio and observed equity values as input. When we vary T for asset values, we assume a constant volatility and when we vary T for asset volatility, we assume constant asset values. When varying T, we keep LGD constant, so the only thing that changes are T and the output (asset value or asset volatility). The same goes for when the LGDs are varied for asset values and asset volatilities.

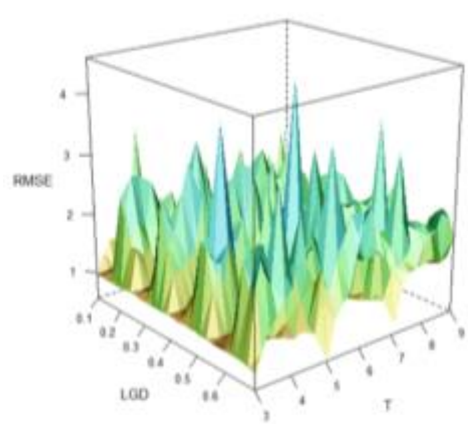
Figure 6: Smoothness Plots



Given this, we think it is justified to interpolate between asset values and asset volatilities.

However, unlike the asset values and asset volatilities, the RSME objective function is not smooth in either LGD or T. To show this, we calculate the RMSE for 900 combinations of LGD and T for the whole sample of our firms, which shows the difficulties of trying to apply linear optimization. This can be seen below:

Figure 7: Surface Plot of the RMSE Function



To work around this problem, Breitkopf and Elsas (2012) use a stochastic global optimization method known as simulated annealing that uses a randomized optimization algorithm. They do this because, as seen in the plot above, the objective function has multiple local minima. This can be imagined with a 3-dimensional surface plot that is searched for the lowest point (minimum) of the RMSE function in a random process until it is approximated to a convenient degree. We calculate the optimal parameters over a 2.5-year period for each subindustry. In our sample, if a sufficiently short sample is chosen, the optimization is likely to find solutions for LGD and T at the endpoints of the grid. This is the reason why we optimize the parameters over the 2.5-year period.

The more iterations the optimization procedure uses, the more precise will the results be but the optimal parameters are varying with each optimization run due to its random nature (Breitkopf & Elsas, 2012). We therefore again need to trade precision against the number of times we want to repeat the procedure. We chose to do 2000 iterations, and repeat these 50 times and take the average of them.

5.3 Translation of loss given default into expected costs of financial distress

After finding market implied values for loss given default (LGD) through the calibration with credit default swap spreads, we can translate LGD to expected costs of financial distress. Leland and Toft (1996) provide the following formula for the expected distress costs of a given firm:

$$DC_j = \alpha V_{B_j} \left(\frac{V_j}{V_{B_j}} \right)^{-x_j} \qquad (16)$$

DC are a firm’s expected costs of financial distress. The subindustry specific LGD is multiplied with the present value of a firm’s asset value when hitting the default barrier. Thus, even though LGD and T are estimated on a subindustry level, we can obtain expected costs of financial distress on firm-level. The further away the asset value is from the default barrier, the lower the expected distress costs. If a firm defaults, the magnitude of the expected distress cost, i.e. the fraction of asset value lost, is solely determined by the LGD.

5.4 Implementation of distress costs into the measure for systemic expected shortfall

After obtaining market implied estimates for a firm's expected costs of financial distress, our goal is to implement them in Acharya et al.'s (2016) measure for the systemic expected shortfall. The term that needs to be estimated is Δ^i. Equation 4 is inserted again for convenience:

$$\Delta^i = \frac{E\left[DC^i \mid W_1 < zA\right] - kE\left[DC^i \mid I_{5\%}\right]}{w_0^i} - \frac{(k-1)(f^i - b^i)}{w_0^i}$$

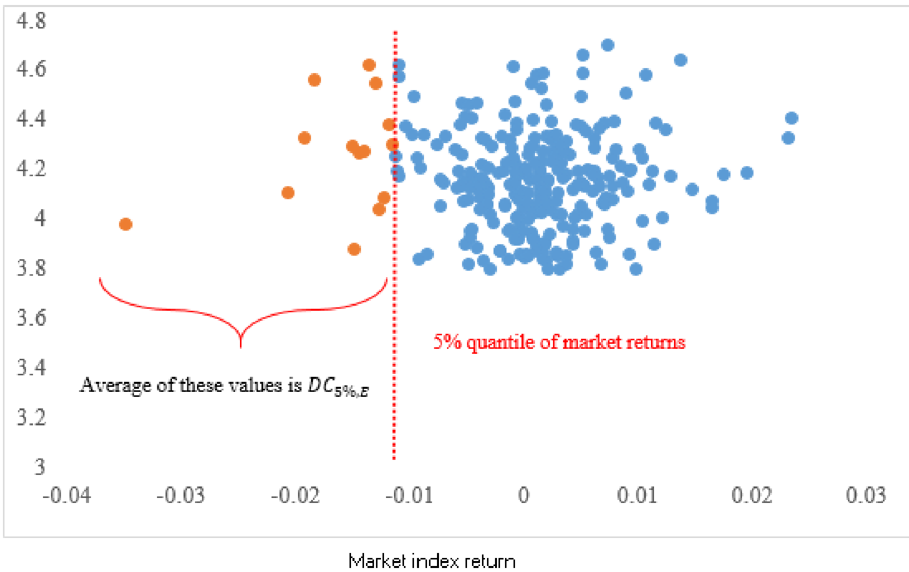
The main part of Δ^i is $\frac{E\left[DC^i | W_1 < zA\right] - kE\left[DC^i | I_{5\%}\right]}{w_0^i}$, which is the difference between the expected costs of financial distress during a crisis and the present value of distress costs measured during the 5% worst market days of a year translated to crisis returns (excess cost of financial distress) as a proportion of equity capital. The expected distress costs during a crisis are not known. Furthermore, we do not know *k*. Therefore, as a proxy of Δ^i we will use the estimated cost of financial distress during the 5% worst market days of a year as a proportion of the firm's equity.

$$(17) \qquad DC^i_{5\%,E} = \left(\frac{1}{\#days} \sum\nolimits_{t:system\ is\ in\ its\ 5\%\ tail} DC^i_t\right) \frac{1}{w_0^i}$$

where DC^i_t are company i's CDS-implied distress costs on day t and w_0^i is firm i's market value of equity on the last day of our sampling period.

To better understand what equation (16) refers to, we plot expected distress costs from the period of June 2006 to June 2007 as a proportion of equity capital against the market return for Fannie Mae.

Figure 8: Illustration of the Calculation of $DC^i_{5\%,E}$



The red data points to the left of the dotted line represent expected distress costs to equity during the 5 % worst market days. By averaging these red data points we obtain $DC^i_{5\%,E}$.

If we assume that the expected costs of financial distress are within a similar range for all companies, the difference of $E\left[DC^i \mid W_1 < zA\right]$ and $E\left[DC^i \mid I_{5\%}\right]$ should explain a firm's systemic expected shortfall to the same extent as just $E\left[DC^i \mid I_{5\%}\right]$ should with a reverse sign. A larger Δ^i implies a larger difference between the distress costs during a crisis and the amount, we would estimate through the multiplication of $E\left[DC^i \mid I_{5\%}\right]$ with k. Therefore, when only implementing $\frac{E\left[DC^i | I_{5\%}\right]}{w_0^i}$ we expect this term to stand in a negative relationship to SES. This can be also shown mathematically. The following formula shows the relationship between SES and the explanatory variables:

$$(18) \qquad \frac{SES^i}{w_0^i} = x_1 + x_2 + \frac{E\left[\mathrm{DC}^i \middle| W_1 < zA\right]}{w_0^i} - \frac{kE\left[\mathrm{DC}^i \middle| I_{5\%}\right]}{w_0^i} - x_3$$

where x_1 is firm i's degree of undercapitalization, x_2 is firm i's marginal expected shortfall during the 5% worst market days and the last three terms are the components of delta with x_3 being the adjustment term, as shown in equations (4) and (5). We can reformulate this equation to:

$$(19) \qquad \frac{SES^i}{w_0^i} - \frac{E\left[\mathrm{DC}^i \middle| W_1 < zA\right]}{w_0^i} = x_1 + x_2 - \frac{kE\left[\mathrm{DC}^i \middle| I_{5\%}\right]}{w_0^i} - x_3$$

The dependent variable is now firm i's systemic expected shortfall less the present value of distress costs during a crisis. Holding $\frac{E\left[\mathrm{DC}^i \middle| W_1 < zA\right]}{w_0^i}$, x_1, x_2 and x_3 constant, the larger $\frac{E\left[\mathrm{DC}^i \middle| I_{5\%}\right]}{w_0^i}$ is, the smaller will the term on the right-hand side of the equation be because of the negative sign. To satisfy the equation, the left-hand side must be smaller, or more negative, as well. Because we hold the expected distress costs during a crisis constant, this is only satisfied if $\frac{SES^i}{w_0^i}$ becomes more negative, i.e. that the systemic expected shortfall increases.

6 Empirical Analysis

6.1 Data

To examine the predictive power of excess costs of financial distress and the extended estimation of Acharya et al.'s (2016) measure for a bank's systemic expected shortfall (SES), our sample period comprises the pre-crisis time between June 2006 and June 2007, which is the same period as the authors use. Our estimators are compared to the realized return during the crisis, which Acharya et al. (2016) compress to the period from July 2007 through December 2008.

Acharya et al. (2016) use a sample of 102 US bank holding companies (BHCs), all U.S. financial companies with a market capitalization above $5 billion as of June 2007. We exclude ten of these 102 companies in our analysis due to lack of data availability[20] and thus obtain a remaining sample of 94 U.S. financial companies.

Table 1 shows the BHCs included in our analysis and their subindustry.

We use two sources for retrieving data. To allow for comparability of our results to those of Acharya et al. (2016), we use the same data as the authors do. To determine the 5% worst days in the sample period, we use the value weighted index from the Center for Research in Security Prices (CRSP). The marginal expected shortfall (*MES*) in the sample period as well as the systemic expected shortfall (SES) during the crisis are based on equity prices from the same data source. Book value of assets and book value of equity used in the calculation of their quasi-leverage measure are retrieved from the CRSP – Compustat merged data base.

[20] The eight companies we excluded are: Compass Bancshares Inc., Lorrilard Inc. (former Loews), T Rowe Price Group, Eaton Vance Corp., Edwards AG Inc., CBOT Holdings Inc., Intercontinental Exchange Inc., NYSE group Inc..

Table 1 Financial Institutions in the Sample according to Sub-Industry

This table presents the names of the financial institutions according to their sub-industry.

Broker-dealer	Depository	Insurance	Non-depository
BEAR STEARNS COMPANIES INC	B B & T CORP	A F LA C INC	ALLTEL CORP
E TRADE FINANCIAL CORP	BANK NEW YORK INC	AETNA INC NEW	AMERICAN CAPITAL STRATEGIES LTD
GOLDMAN SACHS GROUP INC	BANK OF AMERICA CORP	ALLSTATE CORP	AMERICAN EXPRESS CO
LEHMAN BROTHERS HOLDINGS INC	CITIGROUP INC	AMBAC FINANCIAL GROUP INC	AMERIPRISE FINANCIAL INC
MERRILL LYNCH & CO INC	COMERICA INC	AMERICAN INTERNATIONAL GROUP	BLACKROCK INC
MORGAN STANLEY DEAN WITTER & CO	COMMERCE BANCORP INC NJ	AON CORP	C B RICHARD ELLIS GROUP INC
NYMEX HOLDINGS INC	HUDSON CITY BANCORP INC	ASSURANT INC	C I T GROUP INC NEW
SCHWAB CHARLES CORP NEW	HUNTINGTON BANCSHARES INC	BERKLEYWR CORP	CAPITAL ONE FINANCIAL CORP
	JPMORGAN CHASE & CO	BERKSHIRE HATHAWAY INC DEL(A)	CHICAGO MERCANTILE EXCH HLDG INC
	KEYCORP NEW	BERKSHIRE HATHAWAY INC DEL(B)	FEDERAL HOME LOAN MORTGAGE CORP
	M & T BANK CORP	C I G N A CORP	FEDERAL NATIONAL MORTGAGE ASSN
	MARSHALL & ILSLEY CORP	C N A FINANCIAL CORP	FIDELITY NATIONAL INFO SVCS INC
	NATIONAL CITY CORP	CHUBB CORP	FIFTH THIRD BANCORP
	NEW YORK COMMUNITY BANCORP INC	CINCINNATI FINANCIAL CORP	FRANKLIN RESOURCES INC
	NORTHERN TRUST CORP	COUNTRYWIDE FINANCIAL CORP	JANUS CAP GROUP INC
	P N C FINANCIAL SERVICES GRP INC	COVENTRY HEALTH CARE INC	LEGG MASON INC
	PEOPLES UNITED FINANCIAL INC	FIDELITY NATIONAL FINL INC NEW	LEUCADIA NATIONAL CORP
	REGIONS FINANCIAL CORP NEW	GENWORTH FINANCIAL INC	MASTERCARD INC
	SOVEREIGN BANCORP INC	HARTFORD FINANCIAL SVCS GROUP IN	S E I INVESTMENTS COMPANY
	STATE STREET CORP	HEALTH NET INC	S LM CORP
	SUNTRUST BANKS INC	HUMANA INC	T D AMERITRADE HOLDING CORP
	SYNOVUS FINANCIAL CORP	LINCOLN NATIONAL CORP IN	UNION PACIFIC CORP
	U S BANCORP DEL	LOEWS CORP1	
	UNIONBANCAL CORP	M B I A INC	
	WACHOVIA CORP 2ND NEW	MARSH & MCLENNAN COS INC	
	WASHINGTON MUTUAL INC	METLIFE INC	
	WELLS FARGO & CO NEW	PRINCIPAL FINANCIAL GROUP INC	
	WESTERN UNION CO	PROGRESSIVE CORP OH	
	ZIONS BANCORP	PRUDENTIAL FINANCIAL	
		SAFECO CORP	
		TORCHMARK CORP	
		TRAVELERS COMPANIES	
		UNITEDHEALTH GROUP	
		UNUM GROUP	
		WELLPOINT INC	

We use two sources for retrieving data. To allow for comparability of our results to those of Acharya et al. (2016), we use the same data as the authors do. To determine the 5% worst days in the sample period, we use the value weighted index from the Center for Research in Security Prices (CRSP). The marginal expected shortfall (*MES*) in the sample period as well as the systemic expected shortfall (SES) during the crisis are based on equity prices from the same data source. Book value of assets and book value of equity used in the calculation of their quasi-leverage measure are retrieved from the CRSP – Compustat merged data base.

We retrieve total debt values, dividend yields, market capitalizations and the risk-free rate from Thompson-Reuters Datastream for the estimation of the firm value components within the Leland and Toft (1996).

The annual interest rate paid on a bond is the coupon expressed as a percentage of the face value. We approximate coupons by multiplying the principal debt value with the yield of the 'Bank of America Merrill Lynch U.S. Financial Bond Index'. This index tracks the bond yields of major US financial firms. This is done because of limitations of data availability and because of Datastream's definition of interest expenses.

We use the yield on 3-month Treasury bills as the risk-free rate. We approximate dividends by multiplying the dividend yield with the market value of equity. We calculate the asset payout as the sum of dividends and the coupon paid on debt.

The sub-sample used in the CDS calibration is a subset of the 102 firms which have CDS contracts outstanding. Of the 102 firms, 40 have CDS contracts outstanding. Of these 40 institutions, six are classified as Broker-Dealers, six as depositories, eight companies as Non-depositories and 20 as insurance companies[21]. We use credit default swaps with a maturity of 5 years as suggested by Reneby et al. (2005) from MarkIt through CRSP.

[21] We have swapped Charles Schwab as Broker-Dealer and Janus capital group is a non-depository as correctly stated in Appendix A of Acharya et. al (2016)

6.2 Descriptive Statistics

6.2.1 Parameter Estimates

We use the approach described in the previous section to find optimal parameters of loss given default (LGD) and time to maturity (T) for the subindustries: depositories, non-depositories, insurance firms and broker-dealers. The estimated parameters can be seen in the following table:

Table 2: Parameter estimates

This table shows the debt maturity, the loss given default, the RMSE and the number of firm for each sub industry. The sub industries are "Broker-dealers", "Depositories", "Non-depositories" (also called "Other") and "Insurance".

	Debt Maturity	Loss Given Default	RMSE	#Firms
Broker-dealer	4.43	32.74%	0.5928	6
Depositories	4.95	41.39%	0.2389	6
Non-depositories	5.23	39.92%	0.6492	8
Insurance	6.4	37.77%	0.2937	20

Table (2) presents the estimated parameters for time to maturity, loss given default per subgroup, the RMSE obtained in the calibration procedure, and the number of firms within each subgroup. As can be seen, the estimated values for loss given default are in the range of 32% - 42%. Depository institutions show the highest LGD, Broker Dealers the lowest. Time to maturities range from 4 to 7 years. Broker dealers have the liability structure with the shortest time to maturity, while insurance companies have the longest.

The values we obtained for loss given default are higher than seen in previous literature. In particular Andrade and Kaplan (1998) find maximum LGD's of 23% (they call it ex-post distress costs, but this is equivalent to loss given default) and many other studies, as Almeida and Philippon (2007) and Elkhami, Erricson and Pearson (2009) rely on these LGD values to estimate expected distress costs. The average debt-to-assets ratio in Andrade and Kaplan (1998) is 0.95. The same ratio in our sample is much lower. Davidenko, Strebulaev and Zhao (2012) find that the actual costs of default are lower for highly-levered firms, which would explain why our LGD estimates are higher. This argument also applies to the CDS-implied LGD estimates of Breitkopf and Elsas (2012). They find LGD values ranging from 32.75% to 75.25% in their sample on European Non-financial companies, which most likely have a lower debt-to-assets ratio. Our estimates are in the lower-end of this range.

Our RMSE values are also at the lower end compared to Breitkopf and Elsas (2012). The RMSE estimates vary from 0.2937 to 0.6492 whereas in Breitkopf and Elsas they vary from 0.2 to 1.2.

We can think of two reasons why our estimates diverge from estimates obtained by Breitkopf and Elsas (2012). First, our estimates are obtained on a sub-industry level, whereas Breitkopf and Elsas (2012) obtain them on an industry level. Homogeneity is likely to reduce the RMSE as firms within one subindustry are likely to have more similar debt maturities and losses given default than firms within a whole industry. Secondly, our calibration period is half as long as that Breitkopf and Elsas (2012). Shortening the calibration period also reduces RMSE.

Our CDS-implied time to maturity of debt is smaller than the findings of Breitkopf and Elsas (2012). The values they found for T range from 5.9 to 9.5 years. In our sample, only insurance companies have a maturity structure which is covered by this range. It is intuitive that our obtained values for T are smaller, as banks rely more on short term financing than companies in other industries do.

6.2.2 Expected Costs of Financial Distress

We translate the sub-industry specific parameters to expected distress costs, tax shield and the unlevered asset value for all companies in our sample.

To get a feeling for the size of expected distress costs, we show summary statistics for distress costs in proportion to asset value in the table below. Although our variable of interest is the ratio of expected distress costs to equity capital, the relation to asset value is more intuitive considering the meaning for the company. Furthermore, this ratio can be compared to values of expected distress costs found in other studies.

Table 3: Summary Statistics for Tax Shield, Expected Distress Costs and Unlevered Asset Value

This table presents the descriptive statistics of tax shield, distress costs and asset value for 94 U.S. financial firms. Tax shield and distress costs are shown as a proportion of unlevered asset value.

	Min	5% Quantile	Median	Mean	95% Quantile	Max
Distress costs	0.00	0.00%	1.87%	5.11%	19.85%	27.47%
Tax Shield	0.00	0.71%	5.92%	6.21%	13.19%	16.33%
Unl. asset value ($million)	4,188	5,685	24,840	103,396	605,397	1,000,395

Table (3) shows summary statistics of expected costs of financial distress as a percentage of asset value for our sample of 94 US bank holding companies for the period from June 2006 through June 2007. The average value for the expected distress costs is 5.11%, the median is 1.8%. The distribution is therefore skewed, with very high values pushing the average up. Five percent of all distress costs are above 19.85%. To get a better picture of this variable, we plot the distribution as shown in Figure (9)

Figure 9: Distribution of $DC^{i}_{5\%,V}$

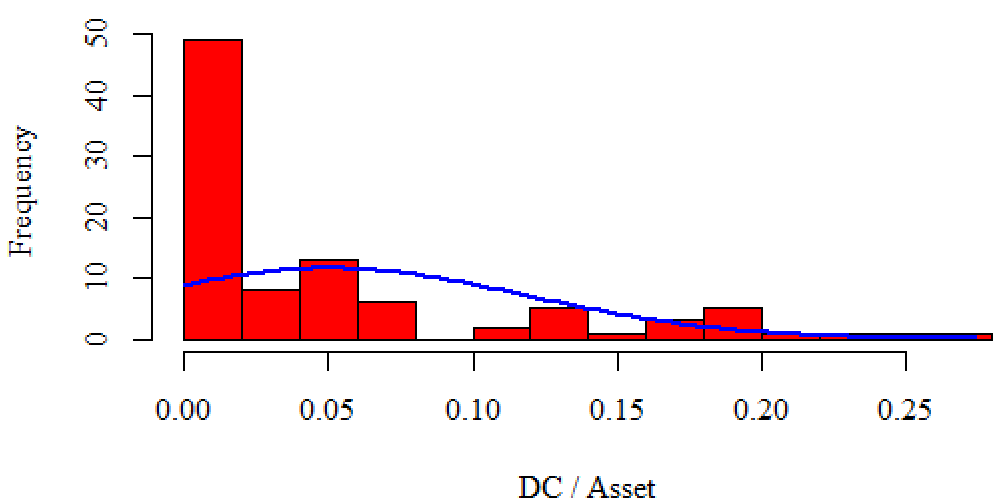


Figure (9) shows the distribution of expected distress costs as a proportion of unlevered asset value for the 94 companies in our sample. As can be seen there are many banks that have very small expected distress costs with values slightly above zero. Most banks have expected distress costs in the range of 0% to approximately 8%. However, the as can be seen in the graph there are some companies with expected distress costs that exceed this range.

The five companies with the highest distress costs are the Federal National Mortgage Association (Fannie Mae, 27.47%), the Federal Home Loan Mortgage Association (Freddie Mac, 25.42%), CIT group (22.18%), Bear Stearns (20.47%) and Lehman Brothers (20.00%). This result is remarkable because all five companies either went bankrupt or had to be bailed out during the crisis. Fannie Mae and Freddie Mac were taken over by the US government in 2008, Bear Stearns has been taken over by JPMorgan Chase, Lehman Brother collapsed in 2008 and CIT group filed for bankruptcy in 2009 (Acharya et al., 2016). T-Rowe, Eaton Vance, N Y S E and Intercontinental Exchange have the lowest ratios of expected distress costs to unlevered asset value, around 0% for all companies. T Rowe had no liquidity problems, they were even able to hire more employees during the crises (T Rowe, Financial Report 2008).

Acharya et al. (2016) do not scale a bank's expected costs of financial distress with the unlevered asset value, rather they use a bank's market capitalization to account for firm size. The following table shows summary statistics for the costs of financial distress as a percentage of market capitalization measured in the period from June 2006 through June 2007.

Table 4: Summary Statistics of Expected Distress Costs to Market Capitalization

This table presents the descriptive statistics of distress costs to market capitalization and the market capitalization of 94 firms. The market capitalization is in $ millions.

	Min	**5% Quantile**	**Median**	**Mean**	**95% Quantile**	**Max**
DC to Market cap	0.00	0.00	0.03	0.31	1.59	4.87

Table (4) presents the summary statistics for our sample of 94 US financial firms. On average, BHC's costs of financial distress exceed market capitalization by two times (2.98). The median is much lower than the average with a value of 0.57. 50% of the companies in the sample exceed the median by to a large extent.

Table 5: Five Firms with the Largest $DC^{i}_{5\%,E}$

This table presents the names of the five firms with the largest $DC^{i}_{5\%,E}$

Firm	$DC^{i}_{5\%,E}$
Freddie Mac	4.68
Fannie Mae	4.25
Freddie Mac	4.68
Bear Stearns	2.45
Lehman Brothers	1.95

Table (5) shows the average expected distress costs during the 5% worst market days in the pre-crisis year as a proportion of market capitalization as of end of June 2007. Freddie Mac and Fannie Mae show the largest ratios with values of 4.68 and 4.25 respectively. These numbers mean, that the present value of financial distress costs exceed equity value nearly five times. On the third place is the Bear Stearns which also has been bailed out in 2008, on the fourth place is Lehman Brothers, a bank that has been acquired by Bank of America during the financial crisis.

6.2.3 Expected Costs of Financial Distress during the 5% Worst Market Days

We turn now to the measure that we take as a proxy for a bank's excess costs of financial distress namely the expected costs of financial distress when the market is in its 5% quantile in our sample period as a percentage of market capitalization. We furthermore extend the analysis to the other explanatory variables of SES, namely *MES* and leverage. *MES*, as outlined in section 3 is a bank's marginal expected shortfall when the market is in its 5% worst days of a year. To calculate this term, Acharya et al. (2016) use the following formula:

$$MES^{i}_{5\%} = \frac{1}{\#days} \sum_{t: system\ is\ in\ its\ 5\%\ tail} R^{i}_{t} \qquad (20)$$

As can be seen in equation (17), *MES* is the weighted average of the returns during the 5% worst market day. Because market value of assets and debt is usually not available in databanks, Acharya et al. (2016) approximate market-valued leverage (LVG) through the following term:

$$(21) \qquad LVG^i = \frac{quasi-market\ value\ of\ assets^i}{market\ value\ of\ equity^i} = \frac{book\ assets^i - book\ equity^i + market\ equity^i}{market\ value\ of\ equity^i}$$

We estimate *MES* in the pre-crisis year and *LVG* as of June 2007 for the companies in our sample.

The following table summarizes the estimates of $DC^i_{5\%,E}$ for the 94 firms in our sample. Besides the summary statistics on $DC^i_{5\%,E}$, we show summary statistics for the empirical measures of *MES* and excess ex-ante leverage of a bank.

Table 6: Descriptive Statistics

This table presents the descriptive statistics for *MES*, *LVG* and $DC^i_{5\%,E}$. Panel A shows the minimum and the maximum, the mean and the median and the 5%, 95% quantile respectively. Panel B provides a t-test, with t-stastics, p-value and a 95% confidence interval for $DC^i_{5\%,E}$.

Panel A

	Min	5% Quantile	Median	Mean	95% Quantile	Max
$DC^i_{5\%,E}$	*0.00*	0.00	0.03	0.32	1.68	4.68
MES	0.39	0.88	1.47	1.63	2.82	3.36
LVG	1.01	1.12	4.52	5.24	13.89	25.62

Panel B	T-statistics	P-value	95% Confidence Interval
$DC^i_{5\%,E}$	4.03	0.00	0.16 - 0.47

Panel A presents summary statistics for $DC^i_{5\%,E}$, *MES* and *LVG*, the three explanatory variables of systemic expected shortfall. Panel B shows the t-values and p-values of the statistical test whether the average $DC^i_{5\%,E}$ is statistically different from zero.

The mean value of $DC^i_{5\%,E}$ is 0.32 for the 94 companies. With a value of 0.03, the median is very low compared to the mean value. As already observed in the section above, the distribution of $DC^i_{5\%,E}$ is skewed. 50% of the companies have very high $DC^i_{5\%,E}$ in relation to the remaining 50% in the sample as it pulls up the average. 5% of companies have values above 1.68. This is extremely high when compared to the average value as it is 500% above it.

Acharya et al. (2016) argued, that $DC^{i}_{5\%,E}$ is on average around zero. The results of the significance test in Panel B show that this value is actually significantly different from zero. The p-value is zero, the average value is highly significant. This finding confirms our assumption as outlined in section (4).

Figure 10: Distribution of DC/equity

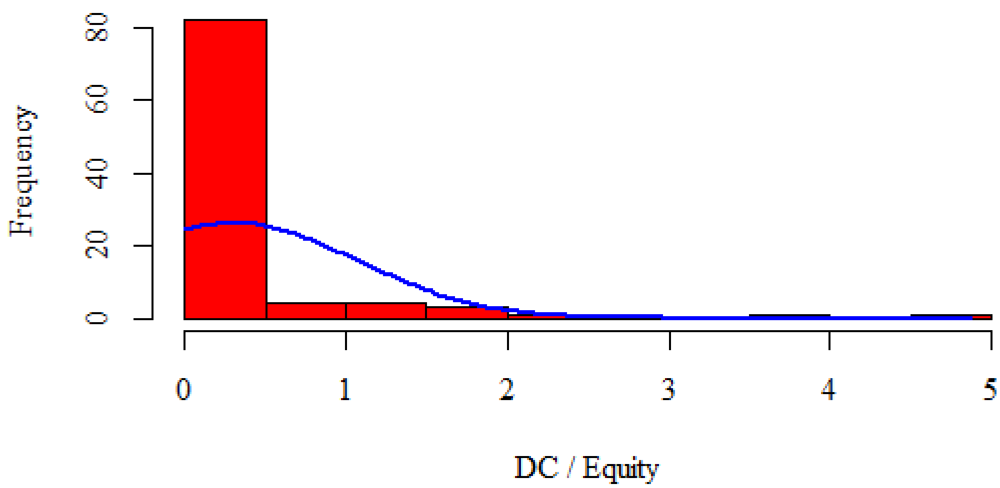


Figure 10 shows a graphical presentation of the distribution of $DC^{i}_{5\%,E}$. The values are heavily concentrated around zero with a few firms above one.

To test the cross-sectional explanatory power of the three variables on a financial company's systemic expected shortfall, Acharya et al. (2016) use different approaches. They identify three measures that are related to systemic shortfall. The three measures are: (i) a firm's equity returns during the financial crisis, where they define the crisis as the period between July 2007 and December 2008 (realized SES), (ii) the SCAP capital shortfall and (iii) credit default swaps during the crisis. They use these measures, which are basically ex-post measures of shortfalls during a crisis and regress them on *MES* and *LVG*, measured ex-ante to test the predictive power.

We extend their analysis of measures (i) and (ii) with $DC^{i}_{5\%,E}$ and test, whether this measure can explain capital shortfalls during the crisis. Before we turn to the results, we will first take a look at the measures that we later use to test the explanatory power of $DC^{i}_{5\%,E}$. These are realized SES and SCAP shortfalls.

6.3 Realized Equity Returns during the Crisis

The first term Acharya et al. (2016) use to test the predictive power of their SES measure is a firm's realized equity return from July 2007 till December 2008. As the authors, we refer to this term as realized SES. Using realized SES as a measure of a bank's contribution to systemic risk, Acharya et al. (2016) indirectly assume that a financial firm's contribution to systemic risk is proportional to a firm's equity performance during the crisis. In Table t we show company specific values for realized *SES*, *MES*, *LVG*, $DC^i_{5\%,E}$. Furthermore the table includes two columns called Rank A and Rank DC which we explain as follows.

Acharya et al. (2016) generate a scale, which ranks companies according to both *MES*, and *LVG*, They do this because, according to their model, it is not only one of the two variables that explains realized *SES*, but both variables together. The ranking comes from a cross sectional regression of realized *SES* on *MES*, the quasi leverage ratio *LVG* and industry specific dummies as shown in equation (21).

$$\text{(22)} \qquad Realized\ SES^i = \beta_0 + \beta_{MES} MES^i_{5\%} + \beta_{LVG} LVG^i + \beta_O Other^i + \beta_I Insurance^i + \beta_{BD} Broker - dealer^i + u^i$$

The dummies Other, Insurance and Broker-dealer are added to the regression to take into account sub-industry specific variation in equity returns. The regression yields the coefficients on the variables β_{MES} and β_{LVG}. These are then multiplied with the respective values for *MES* and *LVG* for each company, which gives $Rank_A$.

Our rank, $Rank_{DC}$ works in the same way, we just add the new variable $DC^i_{5\%}$ to the regressors, as in equation (22):

$$\text{(23)} \qquad Realized\ SES^i = \beta_0 + \beta_{MES} MES^i_{5\%} + \beta_{LVG} LVG^i + \beta_{DC} DC^i_{5\%,E} + \beta_O Other^i + \beta_I Insurance^i + \beta_{BD} Broker - dealer^i + u^i$$

The following table presents the company specific input values for our empirical tests.

Table 7: Systemic risk ranking of financial firms during June 2006 to June 2007

CompName	RealizesSES	MES	QuasiLVG	$Rank_A$	TA	ME	DC/Equity	$Rank_{DC}$
Bear Stearns Companies Inc	-93.28	3.15	25.62	1	423.30	16.66	2.45	1
Federal Home Loan Mortgage Corp	-98.75	1.36	21.00	2	821.67	40.16	4.68	2
Federal National Mortgage Assn	-98.78	2.25	14.00	3	857.80	63.57	4.26	3
Lehman Brothers Holdings Inc	-99.82	2.83	15.83	4	605.86	39.51	1.95	4
C I T Group Inc New	-91.08	2.45	8.45	8	85.16	10.52	1.77	5
Ameriprise Financial Inc	-62.41	2.68	7.72	7	108.13	14.95	0.00	6
Merrill Lynch & Co Inc	-85.21	2.64	15.32	5	1076.32	72.56	1.65	7
Countrywide Financial Corp	-87.46	2.09	10.39	6	216.82	21.57	1.40	8
Morgan Stanley Dean Witter & Co	-76.21	2.72	14.14	9	1199.99	88.40	1.08	9
Metlife Inc	-44.06	1.52	11.85	10	552.56	47.82	0.01	10
Hartford Financial Svcs Grp Inc	-82.02	1.46	11.48	11	345.65	31.19	0.00	11
Principal Financial Group Inc	-59.75	1.71	10.15	12	150.76	15.61	0.00	12
Lincoln National Corp	-72.08	1.59	10.15	13	187.65	19.21	0.02	13
Prudential Financial Inc	-67.16	1.43	10.75	14	461.81	45.02	0.08	14
Goldman Sachs Group Inc	-60.59	2.64	11.25	15	943.20	88.54	1.29	15
C B Richard Ellis Group Inc	-88.16	2.84	1.55	24	5.95	8.35	0.03	16
E Trade Financial Corp	-94.79	3.29	7.24	21	62.98	9.39	0.22	17
Jpmorgan Chase & Co	-31.48	1.93	9.09	17	1458.04	165.51	0.44	18
T D Ameritrade Holding Corp	-28.75	2.43	2.40	26	18.53	11.92	0.01	19
Genworth Financial Inc	-91.43	1.59	7.62	18	111.94	14.96	0.04	20
Sovereign Bancorp Inc	-85.77	1.95	8.34	20	82.74	10.11	0.39	21
M B I A Inc	-93.34	1.84	5.47	25	43.15	8.14	0.96	22
Washington Mutual Inc	-99.61	1.80	8.67	23	312.22	37.63	0.51	23
Citigroup Inc	-85.86	1.66	9.25	22	2220.87	253.70	0.60	24
American Capital Strategies Ltd	-91.08	2.15	1.73	34	12.15	7.75	0.09	25
Janus Cap Group Inc	-71.12	2.23	1.34	36	3.76	5.16	0.01	26
Legg Mason Inc	-76.98	2.19	1.25	40	10.08	12.97	0.01	27
Franklin Resources Inc	-51.23	2.20	1.08	41	9.62	33.07	0.00	28
Unumprovident Corp	-27.21	1.46	5.99	27	52.07	8.95	0.02	29
Fifth Third Bancorp	-77.61	1.29	5.33	30	101.39	21.30	0.12	30
S L M Corp	-84.54	0.92	6.40	33	132.80	23.69	1.27	31
State Street Corp	-41.07	2.12	5.54	28	112.27	23.01	0.04	32
Capital One Financial Corp	-57.90	1.28	4.70	38	145.94	32.60	0.65	33
Berkley W R Corp	-3.57	1.95	3.07	31	16.63	6.32	0.00	34
S E I Investments Company	-45.61	2.00	1.08	52	1.12	5.69	0.00	35
National City Corp	-94.28	1.48	7.70	29	140.64	19.18	0.22	36
Blackrock Inc	-12.07	1.83	1.60	55	21.99	18.18	0.00	37
Bank Of America Corp	-68.05	1.44	7.46	32	1534.36	216.96	0.48	38
American Express Co	-69.00	1.56	2.70	53	134.37	72.66	0.07	39
Leucadia National Corp	-43.54	1.80	1.28	61	6.38	7.63	0.00	40
Comerica Inc	-63.00	1.55	6.77	35	58.57	9.27	0.15	41
Wachovia Corp 2nd New	-88.34	1.31	7.64	37	719.92	98.06	0.34	42
Loews Corp	-44.08	1.63	3.28	45	79.54	27.38	0.00	43
C I G N A Corp	-67.69	1.54	3.50	46	41.53	15.03	0.00	44
Bank New York Inc	-29.05	1.90	4.64	47	126.33	31.43	0.07	45
Keycorp New	-73.09	1.31	7.41	39	94.08	13.47	0.16	46

Table 7 ctd.

CompName	RealizesSES	*MES*	QuasiLVG	$Rank_A$	TA	ME	DC/Equity	$Rank_{DC}$
C N A Financial Corp	-64.73	1.22	4.92	43	60.74	12.95	0.00	47
Union Pacific Corp	-15.14	1.58	1.70	66	37.30	31.03	0.00	48
Commerce Bancorp Inc	-4.42	1.26	7.40	42	48.18	7.08	0.00	49
Huntington Bancshares Inc	-62.50	1.27	7.23	44	36.42	5.35	0.22	50
Northern Trust Corp	-16.84	1.75	4.92	50	59.61	14.14	0.03	51
Fidelity National Info Svcs Inc	-46.19	1.54	1.42	75	7.80	10.45	0.02	52
Allstate Corp	-43.63	1.10	4.72	54	160.54	37.36	0.00	53
Unionbancal Corp	29.14	1.22	6.88	51	53.17	8.25	0.06	54
Hudson City Bancorp Inc	35.63	1.26	6.39	57	39.69	6.50	0.63	55
Assurant Inc	-47.98	1.18	4.08	59	25.77	7.13	0.00	56
M & T Bank Corp	-43.46	1.49	5.47	58	57.87	11.57	0.13	57
Ambac Financial Group Inc	-98.47	1.45	2.69	64	21.06	8.89	0.04	58
Chicago Mercantile Exch Hldg Inc	-59.88	1.47	1.19	80	5.30	18.64	0.00	59
St Paul Travelers Cos Inc	-12.32	1.26	3.54	63	115.36	35.52	0.00	60
American International Group Inc	-97.70	0.71	6.12	56	1033.87	181.67	0.07	61
Aetna Inc New	-42.17	1.45	2.58	65	49.57	25.31	0.01	62
B B & T Corp	-26.22	1.30	6.15	60	127.58	22.43	0.13	63
Safeco Corp	13.56	1.42	2.51	68	13.97	6.61	0.00	64
Chubb Corp	-2.25	1.36	2.74	67	51.73	21.74	0.00	65
Regions Financial Corp New	-73.55	1.27	6.06	62	137.62	23.33	0.13	66
Progressive Corp Oh	-31.52	1.51	1.89	74	21.07	17.42	0.00	67
Mastercard Inc	-13.49	1.27	1.21	85	5.61	13.23	0.00	68
Humana Inc	-38.79	1.40	1.97	76	13.33	10.24	0.01	69
Wells Fargo & Co New	-10.88	1.34	5.17	71	539.87	118.08	0.12	70
Suntrust Banks Inc	-62.60	1.08	6.35	69	180.31	30.58	0.04	71
P N C Financial Services Grp Inc	-27.35	1.24	5.50	72	125.65	24.69	0.13	72
Western Union Co	-30.84	2.10	1.34	84	5.33	16.09	0.01	73
Torchmark Corp	-32.18	1.15	2.85	77	15.10	6.40	0.00	74
Aon Corp	9.48	1.20	2.55	79	24.79	12.51	0.00	75
Zions Bancorporation	-66.42	1.02	6.26	73	48.69	8.31	0.12	76
Cincinnati Financial Corp	-28.29	1.17	2.53	81	18.26	7.46	0.00	77
Marshall & Ilsley Corp	-60.34	1.20	5.20	78	58.30	12.34	0.11	78
Alltel Corp	5.98	1.08	1.25	89	1 7.44	23.23	0.09	79
Schwab Charles Corp New	-15.95	2.57	2.71	88	49.00	25.69	0.00	80
New York Community Bancorp Inc	-23.11	0.92	5.81	82	29.62	5.33	0.43	81
Aflac Inc	-8.52	0.85	3.07	86	60.11	25.14	0.00	82
Fidelity National Title Gp Inc	-16.80	1.09	1.73	87	7.37	5.25	0.01	83
Health Net Inc	-79.37	1.04	1.47	92	4.73	5.93	0.00	84
Synovus Financial Corp	-36.53	1.12	3.92	90	33.22	10.04	0.00	85
Coventry Health Care Inc	-74.19	0.99	1.39	95	6.41	9.01	0.00	86
Marsh & Mclennan Cos Inc	-17.94	0.92	1.67	94	17.19	17.15	0.01	87
Berkshire Hathaway Inc Del B	-10.85	0.39	4.12	91	269.05	49.29	0.08	88
U S Bancorp Del	-17.56	0.88	4.55	93	222.53	57.29	0.12	89
Wellpoint Inc	-47.22	0.88	1.60	96	54.19	48.99	0.00	90
Nymex Holdings Inc	-34.46	2.47	1.23	99	3.53	11.57	0.00	91
Peoples Bank Bridgeport	5.77	1.16	2.75	97	13.82	5.33	0.00	92
Unitedhealth Group Inc	-47.94	0.72	1.47	98	53.15	68.53	0.00	93
Berkshire Hathaway Inc Del	-11.76	0.41	2.29	91	269.05	119.00	0.00	94

Rank correlation: 0.98

Table (7) presents realized SES, MES, LVG , $Rank_A$, total book value of assets as of June 2006, market equity of June 2006, $DC^i_{5\%,E}$, $Rank_{DC}$ for the 94 companies in our sample. It is an extension of Appendix C in Acharya et al. (2016) with our estimated variables of interest $DC^i_{5\%,E}$, and our rank, $Rank_{DC}$.

The values are sorted according to $Rank_{DC}$. Both ranking scales provide very similar evaluations, they have a correlation of 0.98 which means they are close to being perfectly correlated. The ten companies ranked 1-10 in $Rank_A$ are the same as the companies on the first ten positions of $Rank_{DC}$, but in a slightly different order. In both measures, Bear Stearns, the Federal Home Loan Mortgage Association (Freddie Mac) and Federal National Mortgage Association (Fannie Mae) are ranked first, second and third. Acharya et al. (2016) already noticed, Bear Stearns, ranked first, has the highest quasi leverage ratio (*LVG*) as of June 2007 and third highest marginal expected shortfall during the 5% worst market days (*MES*). It was one of the first failing firms in the financial crisis. The authors furthermore notice, Freddie Mac and Fannie Mae, although ranked second and third, do not have a very high value for *MES* but a comparatively high leverage ratio (they also were under the failing companies during the crisis). They conclude, that it is not only *MES* on a stand-alone basis that explains bad future performance, but rather a combination of *MES* and *LVG* (note that the authors did not account for distress costs in their empirical study). Freddie Mac, ranked second in both ranking scales, also has the second largest *LVG* (21) and a *MES* of 1.36.

However, Fannie Mae, on the third place, has only the 6^{th} highest leverage and 17^{th} highest *MES*. Fannie Mae, just like Freddie Mac, had financial difficulties during the crisis and had to be bailed out. Being ranked third therefore seems plausible, but cannot be explained by highest leverage or *MES* values. In turn, Fannie Mae had the second largest ratio of distress costs during the 5% worst market days to equity. This explains the high position in the ranking scales.

As already mentioned, the correlation between the two ranks is very high. If the rankings are so similar, one could ask whether the incorporation of distress costs adds much value. Possibly, the ranking does not change much when incorporating $DC_{5\%,E}$ but the example with Fannie Mae shows, that it might still explain some of the scaling. Looking at the three companies ranked third, all of them are also ranked 1-3 in terms of $DC_{5\%,E}$ with ratios of 2.45, 4.68 and 4.25 respectively.

Another company, CIT Group, is ranked 7th in $Rank_A$ and 6th in $Rank_{DC}$. $Rank_A$ does not consider distress costs, CIT Group's quasi-leverage is only 14th largest with a value of 9.25 and its *MES* is 13th largest with a value of 2.45%. Still the firm is ranked in the Top 10, which, when looking at the highly negative realized SES, is not surprising. CIT also received financial support from the government. When looking at $DC_{5\%,E}$, CIT Group has the third largest value. As is the case for Fannie Mae, the large proportion of distress costs is one possible explanation for the high ranking of CIT group.

These numbers suggest, that it might be indeed the combination of three variables, *MES*, *LVG* and $DC_{5\%,E}$, that together explain bad crisis performance. Especially looking at Fannie Mae and CIT group highlights the potential relevance of including $DC_{5\%,E}$.

The similarity of the rankings suggests, that $DC_{5\%,E}$ has a high correlation with at least one of the other two explanatory variables. In the following we show the correlation matrix for realized SES, *MES*, *LVG* and $DC_{5\%,E}$.

Table 8: Correlation Matrix

This table shows the correlation between measures of systemic risk and realized SES. Included in the table are *LVG*, *MES* and $DC_{5\%,E}$

	Realized SES	*MES*	*LVG*	$DC_{5\%,E}$
Realized SES	1.00	-0.31	-0.47	-0.41
MES		1.00	0.24	0.33
LVG			1.00	0.73
DC				1.00

When taking a quick look at the correlation matrix in Table 8, we observe that the variable that has the highest correlation with realized SES is leverage. *MES* has the lowest correlation with realized SES. Leverage and $DC_{5\%,E}$ have a relatively high correlation coefficient of 0.73. This might explain the similarities between $Rank_A$ and $Rank_{DC}$.

6.4 Capital Shortfalls assessed in SCAP

As the second assessment of systemic risk, Acharya et al. (2016) examine the explanatory power of their SES measure on the 2009 performed SCAP regulatory stress test. The authors claim, that the regulators' profound analysis of bank data in a hypothetical stress scenario relates to their SES measure and that "regulators are essentially computing systemic risk".

Table 9 presents SCAP results as of April 2009 and the three explanatory variables of the theoretical measure for a bank's capital shortfall due to systemic risk for 18 banks that participated in the test[22]. MES is measured from April 2008 through March 2009, quasi-leverage LVG is measured as of the first quarter of 2009. $DC_{5\%,E}$ is measured between April 2008 and March 2009. Table 9 presents the correlation matrix between different systemic risk variables both from the SCAP and from Acharya.

Table 9: SCAP Panel

Bank Name	**SCAP Shortfall**	**Tier1**	**Tier comm**	**Scap / Tier1**	**Scap / tier1comm**	MES	LVG	$DC_{5\%,E}$
Regions Financial Corp New	2.5	12.1	7.6	20.66%	32.89%	14.8	44.4	3.33
Bank of America Corp	33.9	173.2	75	19.57%	45.20%	15.1	50.4	94.42
Wells Fargo & Co New	13.7	86.4	34	15.86%	40.29%	10.6	20.6	30.32
Keycorp New	1.8	11.6	6	15.52%	30.00%	15.4	24.4	2.94
Suntrust Banks Inc	2.2	17.6	9.4	12.50%	23.40%	12.9	39.9	4.42
Fifth Third Bancorp	1.1	11.9	4.9	9.24%	22.45%	14.4	67.2	2.38
Citigroup Inc	5.5	118.8	23	4.63%	23.91%	15	127	91.35
Morgan Stanley Dean Witter & Co	1.8	47.2	18	3.81%	10.00%	15.2	25.4	29.88
P N C Financial Services Grp Inc	0.6	24.1	12	2.49%	5.00%	10.6	21.6	5.74
American Express Co	0	10.1	10	0.00%	0.00%	9.75	7.8	8.86
B B & T Corp	0	13.4	7.8	0.00%	0.00%	9.57	14.8	3.74
Bank New York Inc	0	15.4	11	0.00%	0.00%	11.1	6.46	2.31
Capital One Financial Corp	0	16.8	12	0.00%	0.00%	10.5	33.1	17.53
Goldman Sachs Group Inc	0	55.9	34	0.00%	0.00%	9.97	18.9	39.80
Jpmorgan Chase & Co	0	136.2	87	0.00%	0.00%	10.5	20.4	77.79
Metlife Inc	0	30.1	28	0.00%	0.00%	10.3	26.1	1.81
State Street Corp	0	14.1	11	0.00%	0.00%	14.8	10.8	3.98
U S Bancorp Del	0	24.4	12	0.00%	0.00%	8.54	10.5	9.99

[22] Note that one financial company that participated in the SCAP has been left out in this sample. This company is General Motors Acceptance Corporation (GMAC), which had a SCAP shortfall of $11.5 billion.

As we mentioned in section 5.3 ten banks failed the test. This can be seen in the table. The banks that have SCAP shortfalls above zero, are those banks that failed the test. We now look at the correlations between the shortfall measures and the three explanatory variables.

Table 10: SCAP Correlation Matrix

	Scap / Tier1	**Scap / tier1comm**	***MES***	***LVG***	$\boldsymbol{DC_{5\%,E}}$
Scap / Tier1	1.00	0.95	0.59	0.32	0.14
Scap / Tier1comm		1.00	0.62	0.48	0.32
MES			1.00	0.54	0.21
LVG				1.00	0.52
$DC_{5\%,E}$					1.00

The correlations between LVG and the SCAP shortfall ratios, as well as the correlations between $DC_{5\%,E}$ and the SCAP shortfall ratios are lower than the correlations between each of the two variables with realized SES, as can be seen in Table 10. The correlations between $DC_{5\%,E}$ and the two SCAP shortfall ratios are rather weak with 0.14 and 0.32 respectively. In contrast, MES has a relatively high correlation with SCAP/Tier 1 capital (0.59) and with SCAP/Tier 1 common equity (0.62).

We note that the correlations between MES, LVG and $DC_{5\%,E}$ are different than in Table 8. The reason is that the sample is much smaller, it includes only 18 companies in contrast to the 94 companies in the full sample. Furthermore, the measurement period is different.

7 Results

7.1 Regressing Realized SES on Expected Distress Cost to Equity

We now present results for the regression of the realized equity returns during the crisis measured between July 2007 and December 2008 (realized SES) on MES, LVG and $DC_{5\%,E}$ for the 94 U.S. financial companies with a market capitalization above $5 billion as of June 2007. We regress realized SES on each variable in isolation and on different combinations with only two of them, i.e. on MES and LVG, on MES an $DC_{5\%,E}$ and on LVG and $DC_{5\%,E}$. Each regression furthermore contains sub-industry specific dummies. The full regression, i.e. including all three explanatory variables plus the dummies has the following form:

$$\text{(1) } Realized\ SES^i = \beta_0 + \beta_{MES} MES^i_{5\%} + \beta_{LVG} LVG^i + \beta_{DC} DC^i_{5\%,E} + \beta_O Other + \beta_I Insurance^i + \beta_{BD} Broker^i - dealers^i + u^i$$

We have seen in the previous section that for some BHCs, $DC_{5\%,E}$ seems to explain realized SES. The BHCs with the highest ratios also experience large declines in equity returns during the crisis. However, we have also seen that more than 50% of the companies have very low ratios. Still, we expect $DC_{5\%,E}$ to explain realized SES to some extent.

Table (11) summarizes the results of the cross-sectional OLS regression with Newey-West estimated error terms of the returns during the crisis on the explanatory variables MES, LVG and $DC_{5\%}$. Adjusted R-squared values are taken from simple OLS-regressions.

Table 11: Regression Results

This table contains the results of the cross-sectional regression analysis of individual BHC stocks returns (Realized SES) in the period 01-07-2007 to 31-12-2008 on systemic risk measures in the period from 01-06-2006 to 29-06-2007. The dummies "Other", Insurance" and "Broker-dealers" are sub-industry specific dummies. Model (i) to (iii) include only one of the explanatory variables, whereas model (v) and (vi) combines $DC_{5\%,E}$ with *LVG* and *MES*. Lastly, model (vii) combines all three independent variables.

***, **, * indicates significance at the 1, 5 and 10 % level, respectively. Error terms are NeweyWest.

Models	(i)		(ii)		(iii)		(iv)		(v)		(vi)		(vii)	
Intercept	-0.12		-0.19	**	-0.54	***	0.02		-0.11		-0.20	**	0.01	
MES	-0.22	***					-0.16	***	-0.21	***			-0.17	**
LVG			-0.04	***			-0.04	***			-0.04	***	-0.03	***
DC					-0.17	***			-0.15	***	0.00		-0.02	
Other	-0.06		-0.23	**	0.18	*	-0.16		0.04		-0.19	**	-0.11	
Insurance	-0.05		-0.08		0.14		-0.10		-0.08		-0.09		-0.11	
Broker-dealers	0.03		-0.06		0.04		0.14	*	0.23		0.00		0.20	*
Adj. R2	0.10		0.24		0.18		0.27		0.20		0.22		0.26	
AIC	56.87		40.96		48.87		38.19		48.27		45.08		42.08	
Nobs	94		94		94		94		94		94		94	

The estimated coefficients of the regression as shown in regression equation (1) are shown in model (vii). This is the regression of realized SES on all three theoretically motivated explanatory variables of a firm's contribution to systemic risk: the marginal risk contribution (*MES)*, its quasi-leverage (LVG) and distress costs when the market is in its 5% tail as a percentage of equity capital ($DC_{5\%,E}$).

As can be seen, all coefficients are negative. This means that the higher *MES*, LVG or $DC_{5\%,E}$, the more negative are realized equity returns on average. However, in model (vii) the coefficient on $DC_{5\%,E}, \beta_{DC}$, is not significantly different from zero. In contrast, the coefficients on *MES* and *LVG* are.

In turn, β_{DC} is significant in regression models (iii) and (v), that is in all models where we leave out quasi leverage. As can be seen in Table 7, the correlation between $DC_{5\%,E}$ and LVG is quite high with a value of 0.73. This indicates, that quasi-leverage explains a large part of the variation in realized SES that is also explained by β_{DC}. The adjusted R-squared is comparatively low, when excluding *MES* and LVG. In regression model (vii), it has a value of 0.26, whereas the value is only 0.18 when regressing on $DC_{5\%,E}$ alone, 0.2 when regressing on $DC_{5\%,E}$ and MES and 0.22 when regressing realized SES on $DC_{5\%,E}$ and LVG.

In all presented regressions, the estimated coefficients on leverage and MES are highly significant. Model (iv) shows the coefficients with MES, LVG and the subindustry specific dummies as the regressors, as in Acharya et al. (2016) thus leaving out $DC_{5\%,E}$ [23]. As can be seen by comparing column (iv) with column (vii), β_{MES} and β_{LVG} do not change much when including $DC_{5\%,E}$. Leaving out one explanatory variable in a regression model usually results in biased coefficients if the omitted variable is correlated with one of the regressors or when it has a significant effect on the dependent variable. Therefore, as we have seen that $DC_{5\%,E}$ and LVG have a high correlation, it seems likely that $DC_{5\%,E}$ does not have explanatory power.

When comparing adjusted R-squared values of models (iv) and (vii), they are slightly lower when including $DC_{5\%,E}$. This indicates that this model does not explain realized SES better than model (iv). This further indicates that our proxy measure for Acharya et al.'s excess costs of financial distress does not add any value to the empirical measure of SES.

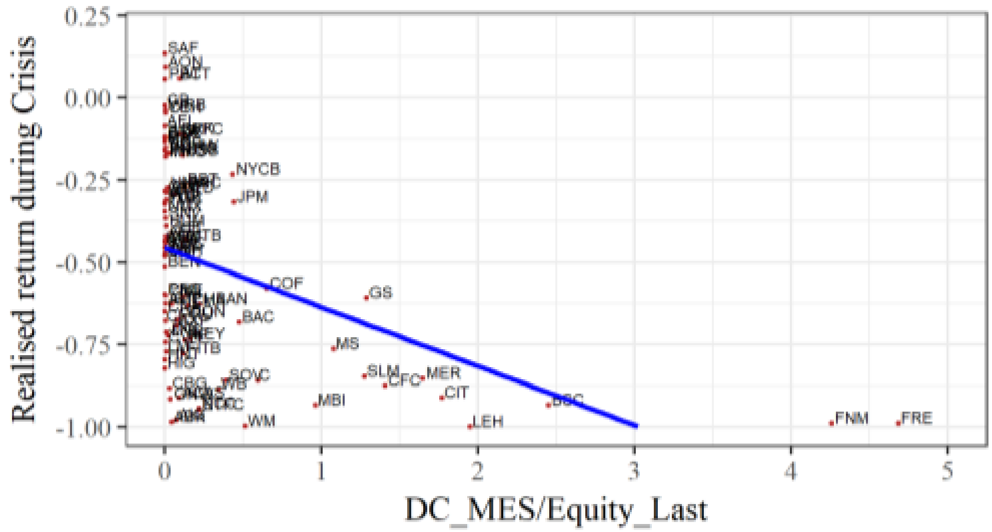
We furthermore compute the Akaike Information Critereon (AIC), which is a measure for a model's goodness of fit. It enables comparison between models (Stock & Watson, 2012). The smaller AIC, the better is the model. In our regressions, AIC increases when including our estimator for distress costs.

This finding is surprising because $DC_{5\%,E}$ has the theoretical justification for being one component of a bank's systemic expected shortfall. Furthermore, the companies with the highest values of $DC_{5\%,E}$ experienced large declines in equity values during the crisis.

We further investigate the relationship between equity returns during July 2007 and December 2008 and a firm's expected distress costs during the 5% worst market days in the pre-crisis year to equity capital ($DC_{5\%,E}$). Therefore, we plot the two variables against each other.

[23] Note that the estimated coefficients are slightly different from the estimates in Acharya et al. (2016) due to reduced sample and because of the small differences in some of the values

Figure 11: Relationship between Realizes SES and $DC_{5\%,E}$



At a first glance, our proxy for excess distress costs, does not seem to be indicative for equity returns during the crisis.

For firms with a high ratio of distress costs during the 5% worst market days to market equity as of end-June, the relationship seems to hold. For example, Fannie Mae and Freddie Mac show the highest ratio and are among the firms with the most negative realized crisis returns. Bear Stearns, CIT and Merrill Lynch have slightly lower but still high values of $DC_{5\%,E}$ and experience large, but less severe stock price declines.

However, when looking at companies with low $DC_{5\%,E}$, there does not seem to be a relationship. For these firms we see both, very negative but also positive values for realized SES. It seems as some of the companies that experience the largest stock price declines during the crisis have very small expected distress costs in the pre-crisis year. One example for these companies is the insurance company, American International Group (AIG). This company has $DC_{5\%,E}$ of 0.07 but realized equity returns of -97.7% between July 2007 and December 2008. This company had to be bailed out by receiving financial support from the Federal Reserve and the U.S. government of $170 billion (see Mishkin, 2011, pp.54).

We already noticed from Table 7, that a large part of the 94 financial institutions in our sample have low $DC_{5\%,E}$. Particularly, we noticed that 50% of the ratios are below 0.03. Furthermore, we noticed, that the correlation between realized SES and $DC_{5\%,E}$ is -0.41 (see Table 8).

It might be possible that $DC_{5\%,E}$ only indicates a firm's systemic risk contribution if the ratio is particularly high. With other words, the ratio might have a significant predictive power for realized SES if it is above a certain threshold, otherwise not. When looking at Figure 9 it might be possible that this threshold is the median value of $DC_{5\%,E}$, which is 0.03.

To test whether this is the case, we make a second set of regressions, where we exclude all companies with $DC_{5\%,E}$below the median. The regressions have the same form as before that can be extracted from regression equation (1) just for a reduced sample of 47 financial firms.

Table 12: Stock returns, risk of banks and systemic risk contribution, above median

This table contains the results of the cross-sectional regression analysis of individual BHC stocks returns (Realized SES) in the period 01-07-2007 to 31-12-2008 on systemic risk measures in the period from 01-06-2006 to 29-06-2007 for BHCs above the median of $DC_{5\%,E}$ (median = 0.03). The dummies "Other", "Insurance" and "Broker-dealers" are sub-industry specific dummies. Model (i), (ii) and (iv) are the original regressions as in Acharya et al (2016). Model (iii) has $DC_{5\%,E}$ as the sole explanatory variable, whereas model (v) and (vi) combines $DC_{5\%,E}$ with LVG and MES. Lastly, model (vii) combines all three independent variables.

***, **, * indicates significance at the 1, 5 and 10 % level, respectively. Error terms are NeweyWest.

Models	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)
Intercept	-0.11	-0.31***	-0.45***	0.02	-0.11	-0.27***	0.07
MES	-0.26**			-0.24**	-0.24**		-0.24**
LVG		-0.03**		-0.02***		-0.03**	-0.03**
DC			-0.09**		-0.07**	0.03	0.05
Other	-0.20*	-0.27**	-0.18	-0.20**	-0.13	-0.31**	-0.25**
Insurance	-0.32***	-0.30***	-0.29***	-0.32***	-0.31***	-0.31**	-0.33***
Broker-dealers	0.00	-0.16	-0.27***	0.16	0.06	-0.15	0.18
Adj. R2	0.24	0.21	0.18	0.29	0.26	0.20	0.28
AIC	29.42	31.35	33.27	27.17	29.22	33.24	29.91
Nobs	47	47	47	47	47	47	47

Table (12) shows regression results for the regression of realized SES on different combinations of MES, LVG and $DC_{5\%,E}$ for all companies with $DC_{5\%,E}$ above the median 0.03. The results are very similar to those of the full sample regression in Table (11). As before, $\beta_{DC\ above\ median}$ is only significant when excluding LVG from the set of regressors.

We can see in regression model (vii) that when regressing all theoretical components of systemic expected shortfall and the sub-industry specific dummies, $\beta_{DC\ above\ median}$ is also not significant but the coefficients on *MES* and *LVG* are.

Adjusted R-squared values slightly increase compared to the full-sample regressions in Table 11. This increase is very small, e.g. from 0.26 to 0.28 in models (vii). Therefore, we conclude that separating the sample into two subgroups and analyzing the relationship for companies with $DC_{5\%,E}$ above median does not add further value. $DC_{5\%,E}$ does not seem to explain realized crisis returns.

7.2 Regression on SCAP results

To further investigate the predictive power of expected distress costs during the 5% worst market days to equity as a theoretical measure for systemic risk, we now turn to the 2009 SCAP results as an approximation for the systemic shortfall.

As before, we vary the composition of the regressors by considering all possible combinations of *MES*, *LVG* and $DC_{5\%,E}$. In accordance with Acharya et al. (2016), we do not include sub-industry specific dummies.

The full regression, i.e. including all three explanatory variables plus the dummies now takes the following form:

$$(1)\ \frac{SCAP\ shortfalls^i}{regulatory\ capital^i} = \beta_0 + \beta_{MES} MES_{5\%}^i + \beta_{LVG} LVG^i + \beta_{DC} DC_{5\%,E}^i + u^i$$

Thus, we replicate the regressions in Acharya et al. (2016) with SCAP shortfall as a percentage of Tier 1 capital (Panel A) and Tier 1 common equity (Panel B) and extend their analysis with our variable, $DC_{5\%,E}$. The regression results can be viewed in Table 13.

Table 13: Regression on SCAP shortfalls:

Panel A contains the results of the cross-sectional regression with the dependent variable being SCAP shortfall/Tier1. In **Panel B** the dependent variable is SCAP shortfall/Tier1comm. Systemic risk measures are from the period from 01-04-2008 to 31-03-2009. *LVG* is as of first quarter 2009. The dummies "Other", "Insurance" and "Broker-dealers" are sub-industry specific dummies. Model (i), (ii) and (iv) are the original regressions as in Acharya (2016). Model (iii) has $DC_{5\%,E}$ as the sole explanatory variable, whereas model (v) and (vi) combines $DC_{5\%,E}$ with *LVG* and *MES*. Lastly, model (vii) combines all three independent variables.

***, **, * indicates significance at the 1, 5 and 10 % level, respectively. Error terms are NeweyWest.

Panel A: Dependent variable is SCAP shortfall/Tier1

Models	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
Intercept	-16.71 **	3.14	4.98 **	-16.77 **	-16.68 **	3.18	-16.88 **
MES	1.85 ***			1.86 **	1.84 ***		1.87 **
LVG		0.08		0.00		0.09	0.00
DC			0.03		0.00	-0.01	0.01
Adj. R2	0.31	0.04	0,00	0.27	0.27	0.00	0.22
AIC	121.21	127.18	128.70	123.21	123.20	129.16	125.20
No. Obs	18	18	18	18	18	18	18

Panel B: Dependent variable is SCAP shortfall/Tier1comm

Models	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
Intercept	-36.17 ***	4.40	9.05	-30.82 **	-35.20 ***	4.12	-32.20 **
MES	4.04 ***			3.29 **	3.76 ***		3.38 **
LVG		0.27 **		0.12		0.24 *	0.07
DC			0.16		0.10	0.05	0.07
Adj. R2	0.34	0.18	0.05	0.33	0.34	0.14	0.30
AIC	147.42	151.22	154.00	148.46	148.28	153.06	150.0
No. Obs	18	18	18	18	18	18	18

As can be seen in regression models (i) – (vii), the coefficient on $DC_{5\%,E}$ is not significantly different from zero in any of the regression models. We notice, that the only significant coefficient is β_{MES}. This coefficient is significant in all regression models. In Panel A, when regressing SCAP shortfall as a percentage of Tier 1 capital, *MES* is the only variable that has explanatory power.

The coefficient on *MES* seems to be robust vis-à-vis the composition of the explanatory variables, as it does not change much when adding more explanatory variables. For example, in regression (vii), the estimated coefficient has a value of 1.87, meaning that an increase in *MES* of 0.1, the SCAP/Tier1 ratio increases by 1.87. The fact that the coefficient is approximately constant means that LVG and $DC_{5\%,E}$ are either uncorrelated with *MES* (which is not the case) and/or that they really have no explanatory power.

Adjusted R-squared values are very low, in Panel A even close to zero, when not including *MES* to the set of regressors. The largest values for the adjusted R-squared, 0.27, are obtained in regressions (iv) and (v), when regressing SCAP results on *MES* and either LVG or $DC_{5\%,E}$. When regressing on the full set of explanatory variables in Panel A, R-squared drops to 0.22.

The regression results in Panel B are very similar with the difference that LVG has significant explanatory power on a stand-alone basis (ii) or when additionally including $DC_{5\%,E}$ (vi), but not in conjunction with *MES*.

As in the previous regressions, our variable $DC_{5\%,E}$ does not seem to add any value to explaining SCAP shortfalls. However, in contrast to the previous regressions, LVG does not seem to add any value either. This is surprising because, as shown in Table (11), β_{LVG} seemed to be a very important factor in explaining realized SES. Under the assumption, that aggregated SCAP shortfalls do illustrate systemic risk, as argued by Acharya et al. (2016), it is surprising that the coefficient on LVG is not statistically significant.

One disadvantage of regressing SCAP shortfalls is the small sample size. The sample only contains 18 companies. For cross-sectional OLS regressions, a small sample size is problematic because the sample standard deviation becomes very large. This does not necessarily change the coefficient estimates, but it does change the statistical significance (see Wooldrige, 2009).

It is also possible, that SCAP shortfalls are not a good measure to take as a proxy for systemic expected shortfall. We argued in section 2.3 that the assumption that the individual default risks of banks add up to systemic risk is flawed. Therefore, SCAP shortfalls/Regulatory Capital is not necessarily the right approximation for a company's systemic expected shortfall.

However, according to Acharya et al. (2016), a bank's overall risk has two components, the individual risk and the systemic risk contribution. Thereby, SES is just an additional component besides a financial firm's individual default risk (ES). Thus, what SCAP shortfall measures is exactly the individual risk and not the contribution to systemic risk, SES.

7.3 Regressing Realized SES on Expected Distress Costs to Asset Value

We have seen in the previous section that expected distress costs during the 5% worst market days as a proportion of equity capital do statistically not explain crisis returns when including leverage as an explanatory variable. Although this is the theoretically motivated proxy measure, this measure might not be the right scaling factor for firm size to use when being interested in the pure effect of distress costs.

What is of interest in the model is the effect of expected costs of financial distress on a bank's systemic risk contribution. But the absolute amount of expected distress costs is not of much use because larger firms will naturally have larger distress costs, although in both cases maybe only 20% of assets will be lost in case of a default due to financial distress, no matter what. Therefore, it is reasonable to account for firm size by scaling expected distress costs by a number that determines firm size.

As we are only interested in accounting for firm size, the scaling factor should only contain information about size. However, using equity capital contains information about a company's leverage.

To understand why, consider a simple example that stands in context with the Trade-Off theory. Firm X must decide how to finance the assets worth 100. In this example, Firm X has two options. Either it uses only equity capital, or it takes on debt worth 10 and finances the rest with equity capital. In the first option, if fully equity financed, the firm value is 100. Logically, equity is worth 100 as well and debt is worth 0.

100 is therefore the value of unlevered assets, equity, and the value of the whole firm.

In the second option, Firm X would raise debt with a face value of 10. In this example, unlevered assets are still worth 100 but through tax benefits of debt and the present value of distress costs, the firm value changes. In our example, firm value increases to 101.5, equity value decreases to 91.1 and the market value of debt is 10.4.

The two cases are outlined in the following table:

Table 14: Example

	Option 1	Option 2
Firm Value	100	101.5
Unlevered Assets V	100	100
Equity value	100	91.1
Debt value	0	10.4

In our case, the capital structures of the companies in the sample are already set. Still, when scaling by equity capital, the capital structure will be reflected in the ratio. If all companies in the sample had the proportions of debt and equity capital, scaling by equity capital would be reasonable. However, scaling by equity does not only control for firm size, but also for leverage.

This is possibly also the explanation why we found the coefficient on $DC_{5\%}$ insignificant when adding leverage as an explanatory variable, but significant when regressing without leverage. This is because, as just outlined, $DC_{5\%,E}$ captures the same cross-sectional variation as does leverage.

To counter this problem, we change the proxy measure of a bank's excess costs of financial distress. We are still interested in scaling expected distress costs during the 5% worst market days by firm size. For this purpose, we scale the expected distress costs with the unlevered asset value. The unlevered asset value, or V as in the Leland and Toft (1996) framework is the firm value if the company was 100% equity financed.

Our new proxy measure for a bank's excess costs of financial distress now takes the following form:

$$(24) \qquad DC^{i}_{5\%,V} = \left(\frac{1}{\#days} \sum_{t:system\ is\ in\ its\ 5\%\ tail} DC^{i}_{t}\right) \frac{1}{V^{i}_{0}}$$

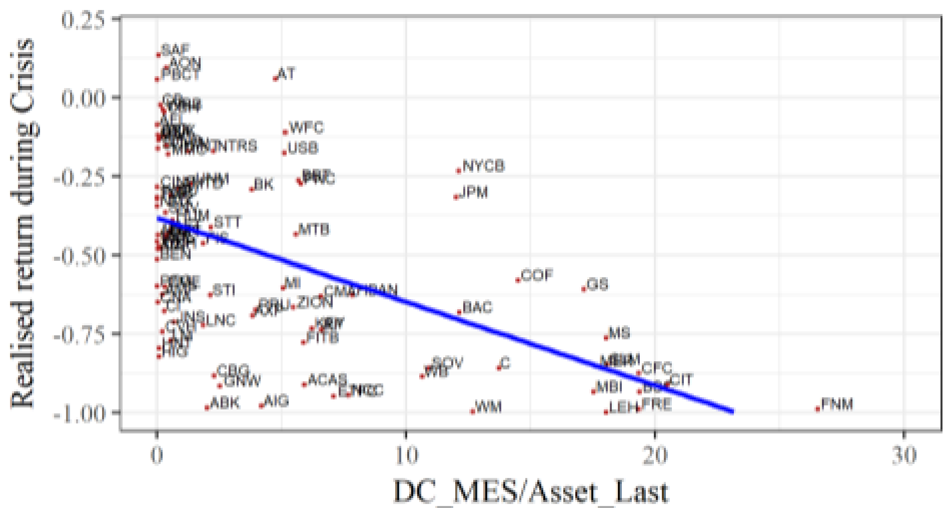
where V^{i}_{0} is bank i's unlevered asset value as of end of June 2007. To test, whether our new proxy measure for excess costs of financial distress does a better job in describing realized equity returns during the crisis, we repeat the previous regression of realized equity returns during July 2007 –

December 2008 on the three theoretical components of systemic expected shortfall *MES*, *LVG* and $DC^i_{5\%,V}$ for the 94 bank-holding companies in our sample. The new regression equation has the following form:

$$(25) \qquad Realized\ SES^i = \beta_0 + \beta_{MES} MES^i_{5\%} + \beta_{LVG} LVG^i + \beta_{DC,V} DC^i_{5\%,V} + \beta_O Other^i + \beta_I Insurance^i + \beta_{BD} Broker - dealers^i + u_i$$

Before showing the regression results, we plot $DC^i_{5\%,V}$ against realized equity return during the crises. This plot can be seen in Figure (12).

Figure 12: Relationship between Realized SES and $DC^i_{5\%,V}$



At a first glance, $DC^i_{5\%,V}$ seem to explain realized SES much better than the previous measure, distress costs during the 5% worst market days as a proportion of market value of equity as of June 2007. Figure (12) shows that a higher value of $DC^i_{5\%,V}$ measured in the pre-crisis year has better explanatory power for more negative equity returns during the crisis. For example, the graph illustrates that Freddie Mac, Fannie Mae, Lehman Brothers, CIT are among the firms with the highest proportion of distress costs and also among the firms with the most negative equity returns. Furthermore, none of the firms with the lowest realized returns during the crisis have their distress costs to equity in the lowest spectrum.

To get a clearer picture of the relationship between realized SES and $DC^{i}_{5\%,V}$, we look at the estimated coefficients that result from estimating the parameters in equation (24). As in the previous regressions, we look at different combinations of the regressors. Table (16) presents the results.

Table 15: Stock returns, DC scaled by assets as a systemic risk contribution variable

This table contains the results of the cross-sectional regression analysis of individual BHC's stocks returns (Realized SES) in the period 01-07-2007 to 31-12-2008 on systemic risk measures in the period from 01-06-2006 to 29-06-2007. The dummies "Other", "Insurance" and "Broker-dealers" are sub-industry specific dummies. Model (i), (ii) and (iv) are the original regressions as. Model (iii) has $DC^{i}_{5\%,V}$ as the sole explanatory variable, whereas model (v) and (vi) combines $DC^{i}_{5\%,V}$ with *LVG* and *MES*. Lastly, model (vii) combines all three independent variables.

***, **, * indicates significance at the 1, 5 and 10 % level, respectively. Error terms are NeweyWest.

Models	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)
Intercept	-0.12	-0.19***	-0.26***	0.02	0.01	-0.19***	0.03
MES	-0.22***			-0.16**	-0.19***		-0.17**
LVG		-0.04***		-0.04***		-0.02**	-0.02**
DC			-0.03***		-0.03***	-0.02***	-0.02***
Other	-0.06	-0.23***	-0.17**	-0.16**	-0.08	-0.21***	-0.13*
Insurance	-0.05	-0.08	-0.14*	-0.10	-0.16**	-0.13	-0.15*
Broker-dealer	0.03	-0.06	-0.12	0.14	0.14	-0.05	0.16
Adj. R2	0.10	0.24	0.24	0.27	0.29	0.27	0.31
AIC	56.87	40.96	41.41	38.19	35.97	38.04	34.25
No. Obs	94	94	94	94	94	94	94

In contrast to previous results, the estimated coefficient on our proxy for a bank's excess costs of financial distress is always highly significant on at least a 1% confidence level. The coefficient on $DC^{i}_{5\%,V}$ is still negative in all regression models, as before. The larger the fraction of expected distress costs during the 5% worst market days to unlevered asset value, the lower the observed equity returns during the crisis. The coefficient on $DC^{i}_{5\%,V}$ is -0.02.

Beyond that, β_{MES} and β_{LVG} are also statistically significant in all models (i) to (vii). This result is in line with the theoretical measure for the systemic expected shortfall.

In addition to $\beta_{DC,V}$, the coefficients on *MES* and *LVG* are also negative, as in the previous regressions. This corresponds to our expectations of the relationship between the variables and realized SES.

When comparing regression model (vii) that is the regression output of realized SES on all three components of the theoretical SES measure with regression (v) that leaves out $DC^{i}_{5\%,V}$ (as in Acharya et al., 2016), we observe that adjusted R-squared increases from 0.27 to 0.31. Furthermore, model (vii) has the highest value for adjusted R-squared of all models.

When comparing the adjusted R-squared values of regression models (vii) in Table 11 where we regress on $DC_{5\%,E}$, the R-squared values here are also higher. We conclude that of all regressions conducted so far, this is the one that fits realized equity returns during the crisis best. The standard error for distress costs to assets is much smaller than the corresponding one for distress costs to equity (0.0053 against 0.0457). This might be the reason why distress costs to assets are statistically significant and distress costs to equity are not.

When further comparing the coefficient on $DC^{i}_{5\%,V}$ from regression (vii) to the coefficient on $DC_{5\%,E}$ from regression mode (vii) in Table 11, we find that the coefficients have the same value in both regressions, namely -0.02. Holding the denominator (unlevered asset value or market value of equity) constant, both variables therefore have the same effect on realized SES. However, the difference is that the coefficient on $DC_{5\%,E}$ is not statistically significant. We therefore address the question, whether the variables are economically significant. Wooldridge (2012) argues that statistical significance depends exclusively on the size of the T-Statistics whereas economic significance is determined by size and sign of the coefficient estimates.

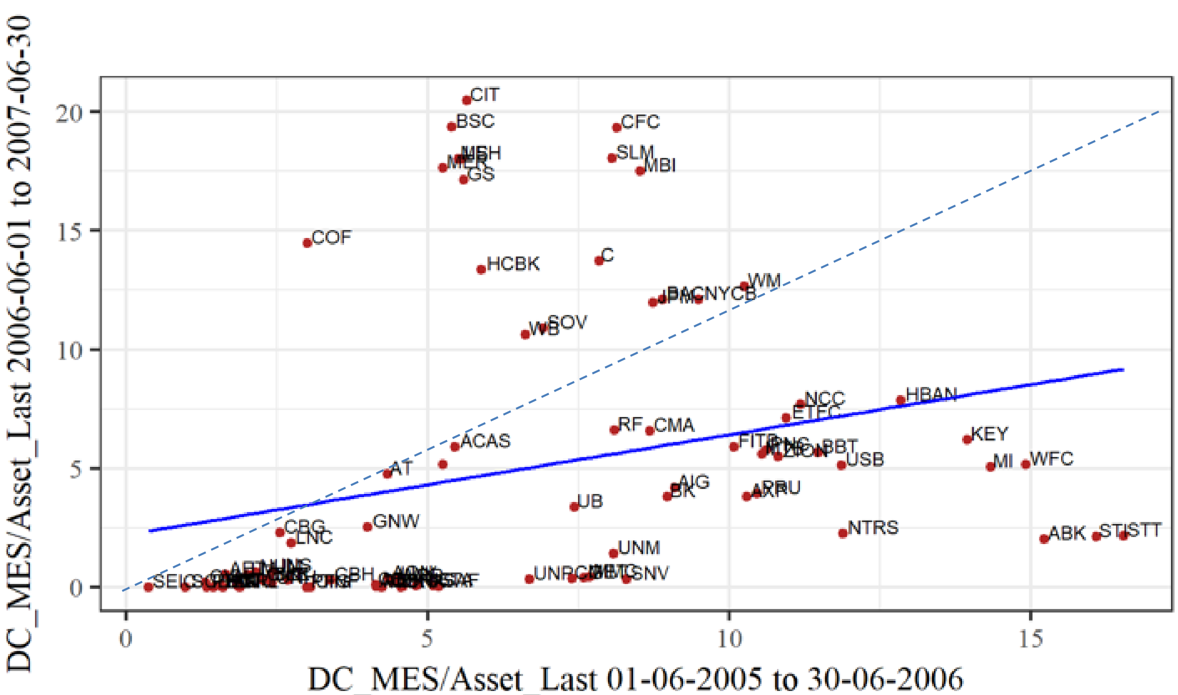
Given the coefficients, we are also interested in how much of an increase in the variable is required to produce a 1%-decrease in predicted SES. We find that it would require an increase of 0.61 in distress costs to equity to produce a 1%-decrease in predicted *SES*. This increase can come in the form of an increase in distress costs or a decrease in market value of equity. For distress costs to assets this would correspond to a 0.61% increase in distress costs to assets.

7.4 Robustness check

In the previous section, we assessed the predictive power of distress costs/assets to indicate a systemic short-fall in equity capital. We now want to test, how much time in advance SES has predictive power. As Acharya et al. (2016) state, if there was significant time-series variation in distress costs to assets, the optimal taxation policy of the regulator would be much harder to implement. Therefore, it is in our interest to see how early $DC^{i}_{5\%,V}$ can explain the cross section of realized equity returns during the financial crises.

For this purpose, we plot $DC^{i}_{5\%,V}$ measured between June 2005 to 30th of June 2006 against $DC^{i}_{5\%,V}$ from the period of June 2006 to 30th of June 2007 for our sample of U.S. BHC's. The resulting plot can be seen in Figure 13.

Figure 13: Stability of $DC^{i}_{5\%,V}$ Over Time



The plot shows distress costs during the 5% worst market days as a proportion of assets seem to be highly related between the two one-year periods. This relationship seems to hold especially for firms that have very high distress costs relative to assets (above 10 % of assets) but also for firms with distress costs close to zero.

Acharya et al. (2016) find that the explanatory power of *MES* declines the longer the time difference between sample time and crisis (Acharya et al, 2016, pp 27). Regarding expected distress costs, we have mixed expectations as some firms change from having relatively low distress costs to high and vice versa.

To test the explanatory power of the SES measure in the year before the prior-crisis year, we compute combinations of *MES*, *LVG* and $DC^{i}_{5\%,V}$ for 1st of June 2005 to 30th of June 2006 and make a cross-sectional regression with equity returns during the crisis (realized SES) on the three variables. We then do the same again just with combinations of *MES*, *LVG* and $DC^{i}_{5\%,V}$ in the period from 03-01-2005 to 03-01-2006. The regression outputs can be seen in Table 17.

Table 16: Regression Results

This table contains the results of the cross-sectional regression analysis of individual BHC stocks returns (Realized SES) in the period 01-07-2007 to 31-12-2008. The dummies "Other", "Insurance" and "Broker-dealers" are sub-industry specific dummies. Model (i), (ii) (iiI)and (iv) are *MES*, *LVG* and $DC^{i}_{5\%,z\,V}$Model (v) to (viii) *MES*, *LVG* and $DC^{i}_{5\%,V}$are different combination in the period from 03-01-2005 to 03-01-2006.

***, **, * indicates significance at the 1, 5 and 10 % level, respectively. Error terms are NeweyWest.

	June 2005 – June 2006								January 2005 – January 2006							
Models	(i)		(ii)		(iii)		(iv)		(v)		(vi)		(vii)		(viii)	
Intercept	-0.02		0.01		0.01		0.17		-0.22	***	0.26	*	-0.07		-0.10	
MES	-0.15		-0.15	*			-0.16	*	0.07		0.18				0.07	
LVG	-0.04	***			-0.04	***	-0.04	***	-0.04	***			-0.04	***	-0.03	***
DC			-0.03	**	-0.40	**	-0.02	**			-0.02	**	-0.02		-0.02	
Other	-0.27	**	-0.27	**	0.10	***	-0.37	***	-0.31	***	-0.30	**	-0.34	***	-0.36	***
Insurance	-0.08		-0.18	*	-0.18		-0.19	*	-0.06		-0.11		-0.12		-0.12	
Broker-dealer	0.11		-0.27	*	-0.18		0.00		-0.11		-0.50	***	-0.17		-0.21	
Adj. R2	0.20		0.12		0.22		0.23		0.17		0.10		0.19		0.18	
AIC	44.87		52.32		42.57		42.13		45.54		51.83		43.58		45.24	
No. Obs	85		85		85		85		85		85		85		85	

We observe several things from Table 17. First, in accordance with the observations of Acharya et al. (2016), when regressing realized SES on *MES* and *LVG*, we see that *MES* does not have explanatory power. Regressing on all SES components in the period from June 2005 to June 2006 as seen in regression (iv), all components are highly significant. Combining all three components gives the highest adjusted R-squared, this model has the highest overall explanatory power. In (vi), adjusted R-squared is at least 1% larger than in the alternative regressions for the same period.

Second, we see that all coefficients have a negative sign for the period from June 2005 to June 2006. The economic interpretation of this is simple. It implies that lower equity returns during a crisis are related to a higher marginal expected shortfall, higher quasi-leverage ratio and to a higher proportion of distress costs. This is consistent with our previous findings.

It is not surprising, that the expected costs of financial distress as a proportion of assets do explain crisis returns, even when measured two years prior to the crisis. As we have seen in Figure 13, expected distress costs seem to be relatively stable.

In the period from January 2005 to January 2006 we observe that the coefficient on distress costs to assets is no longer significant for the full model (viii). It still has the same sign and the same magnitude and thus the same economic significance. MES is not significant in any model in this period which is not surprising because returns in the past are less and less correlated with future returns. Acharya goes on and tries different weighting schemes on *MES*. We will not do something similar here as we are not working with returns. We also notice that the adjusted R-squared drops and AIC increases, which indicates less explanatory power of the model. Despite that, *LVG* still retains certain characteristics that gives it explanatory power for realized SES well ahead in time. We conclude that $DC^{i}_{5\%,V}$ is just as robust and stabile, if not more, than *MES* is. This is natural as expected costs of financial distress do not change much in the short run. On a longer time horizon, it is more likely that $DC^{i}_{5\%,V}$ changes as the capital structure of the BHC change.

To summarize, we find that the expected cost of financial distress to equity does not explain returns during the crisis nor has it any explanatory power in explaining the outcome of the 2009 SCAP stress test. This is even though it is the closest measure to the theoretical measure proposed by Archarya et al. (2016). We argue that distress costs to equity might be a bad scaling factor when accounting for firm size as it seems like it explains the same cross sectional variation as leverage does. We further find that when changing the scaling to unlevered asset value, distress costs have significant explanatory power even when accounted for leverage.

8 Discussion

8.1 Implications to Practice

The predictive power we found for distress costs regarding systemic expected shortfall suggests potential implications in banking regulation and stress testing.

Supervisory institutions constantly work on the enhancement of prevailing banking regulation. Most currently, Basel III foresees for example the gradual implementation of a minimum leverage ratio. This regulatory leverage ratio imposes banks to hold a minimum of 3% Tier 1 common equity capital of total 'on and off' balance sheet assets. We have seen that leverage ratio has a significant relationship with crisis returns, in this context it is reasonable to impose a minimum standard because banks do not have incentives to hold the economically optimal leverage. The intention behind a leverage ratio is good. However, it is, as other regulatory capital ratios, based on book values and therefore sensitive to the same shortfalls as book-ratios in general.

Expected distress costs, however, are more difficult to regulate because, in contrast to leverage, they are much more difficult to estimate ex-ante.

The results show that market based measures can indicate capital shortfalls in a crisis. In this context, *MES*, leverage and distress costs could be implemented in the current stress testing procedures.

Based on *MES* and on historical correlations between a bank's market equity and the market index, Acharya et al. (2014) develop an alternative stress test called the V-lab stress test. The V-lab stress tests basically measures the decline in a firm's equity prices after a large decline in stock price indices (which is the stress scenario). They use *MES* to compute a risk weight (V-lab risk weight), which they use to weigh total assets with.

The higher the risk weight, the more risky is the bank ex-ante. In the stress tests, the stressed equity capital needs to exceed a fraction of the "market risk-weighted" assets.

The V-lab stress test has the advantage that, in contrast to the current regulatory stress tests, it relies on publicly available data and is very easy to implement. Including expected distress costs in the V-lab stress test could possibly provide more precise estimates of the shortfalls in a crisis. For example, expected distress costs could be added to the amount of assets that are weighted with the V-lab risk weight.

However, as Acharya et al. (2014) state, the V-lab stress test should not replace current regulatory stress tests as they provide valuable information through the disclosure of bank data and results for regulators and the market. The V-lab (or similar) stress tests should rather be used as a complementary.

8.2 Limitations

Our analysis is limited to a sample of 94 US. Bank holding companies. In order to make a more general statement about the relationships between crisis performance and *MES*, *LVG* and expected distress costs, it might be necessary to extend the sample and to apply the same approach to other countries.

Furthermore, the estimation procedure used to obtain market-implied estimated for expected costs of financial distress is only valid in connection with the assumptions underlying the Leland and Toft (1996) framework. This model is not necessarily the right model for estimating firm value components. The model captures important features of the Trade-Off theory but it also misses out on other ideas. For example, as Breitkopf and Elsas (2012) state, one of the missing features is that is does not incorporate Jensen's disciplining effect of debt.

The calibration procedure we applied as proposed by Breitkopf and Elsas (2012) is both very time-consuming and requires a large amount of data. Therefore, we derived only one average parameter of T and LGD each over a period of 2,5 years for each subindustry. This implies the assumption that these parameters are constant over those 2,5 years. However, the asset and debt composition of a financial institution is most likely not constant for such a long time period. Consequently, LGD and T change over time. Thus, using smaller time frames for the estimation of theses parameters will result in more precise estimates and results.

Furthermore, we approximated the asset payout ratio by a weighted average of interest expenses and dividends. One could hence argue that we are missing out on potential payouts that could influence the calibration procedure.

9 Conclusion

Current regulation and supervisory stress tests aim at ensuring systemic stability and to prevent another crisis. Their current procedure has several weaknesses, most importantly that they do not account for systemic risk. Acharya et al. (2016) developed a theoretical measure of a bank's contribution to systemic risk (SES) that has three components: the marginal expected shortfall (*MES*), leverage and excess distress costs. In their empirical implementation, the authors leave out the estimation of excess distress costs.

In this thesis, we developed an empirical measure for a bank's excess costs of financial distress that we can use to extend the empirical measure for systemic expected shortfall (SES). We obtain market-implied values for expected distress costs using an estimation procedure proposed by Breitkopf and Elsas (2012). Their estimation procedure uses the relationships between corporate securities in the structural model framework of Leland and Toft (1996) and publicly available stock price and CDS data.

We find that on average, the expected costs of financial distress are in fact significantly different from zero in non-crisis times. Furthermore, we find that the ratio of expected distress costs to equity capital, the firm size scaling factor proposed by Acharya et al. (2016), does explain crisis returns on a stand-alone basis, but not in conjunction with leverage. We further find that when changing the scaling factor from equity capital to unlevered asset value, the term is highly significant.

We consider several robustness checks where we examine how much in advance crisis returns can be predicted. Like leverage, the expected distress costs explain crisis returns even if measured two years before the crisis. However, when going further back, the explanatory power disappears.

Therefore, distress costs could be used to extend alternative stress tests such as the V-Lab stress test.

10 List of Literature

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11 Appendix

11.1 Appendix A – The solution of the Leland and Toft model

The Value of the firm when the tax shield is lost prior to bankruptcy ($V_B \leq V_T$), where V_T defines that asset value at which the tax shield is lost and is calculated as: $V_T = \frac{C}{\delta}$. There is two scenarios besides the one described in the main body of the theses, where the tax shield at bankruptcy ($V_T \leq V_B < V$). One where the tax shield is already lost $V_B < V \leq V_T$ and one where it is not lost yet, but if the assets value drops it is lost before bankruptcy. This can be summarized using the following equations:

$$v(V;V_B) = \begin{cases} V + \frac{\tau C}{r}\left[1 - \left(\frac{V}{V_B}\right)^{-x}\right] - \alpha V_B \left(\frac{V}{V_B}\right)^{-x}, & V_T \leq V_B < V \\ V + \frac{\tau C}{r}\frac{x}{x+1}\frac{1}{V_T}V - \frac{\tau C}{r}\frac{x}{x+1}\frac{V_B^{x+1}}{V_T}V^{-x} - \alpha V_B \left(\frac{V}{V_B}\right)^{-x}, & V_B < V \leq V_T \\ V + \frac{\tau C}{r} - \frac{\tau C}{r}\frac{x}{x+1}\frac{1}{V_T}\left(V_B^{x+1} + \frac{V_T^{x+1}}{x}\right)V^{-x} - \alpha V_B \left(\frac{V}{V_B}\right)^{-x}, & V_B < V_T < V \end{cases}$$

The asset value for where it is optimal to declare bankruptcy for the firm owners, also depend upon whether the tax shield is lost before bankruptcy. The LT model has two cases, one where it is the tax shield is lost at bankruptcy, which can be found in the main body of the text. If the tax shield is lost before bankruptcy $V_B \leq V_T$ this will influence the optimal default decision by the firm owners. This can be summarized through the following equations:

$$V_B = \begin{cases} \dfrac{\left(\frac{C}{r}\right)\left(\frac{A}{rT} - B\right) - \frac{AP}{rT} - \frac{\tau C x}{r}}{1 + \alpha x - (1-\alpha)B}, & V_T < V_B, \\ \dfrac{\left(\frac{C}{r}\right)\left(\frac{A}{rT} - B\right) - \frac{AP}{rT} - \frac{\tau C x}{r}}{1 + x\left(\frac{\tau C}{r V_T} + \alpha\right) - (1-\alpha)B}, & V_B \leq V_T, \end{cases}$$

The auxiliary quantities in the model is defined as

$$a = \frac{r - \delta - \frac{1}{2}\sigma^2}{\sigma^2}$$

$$z = \frac{\sqrt{(a\sigma^2)^2 + 2r\sigma^2}}{\sigma^2}$$

$$x = a + z$$

$$A = 2ae^{-rT}N\left(a\sigma\sqrt{T}\right) - 2zN\left(z\sigma\sqrt{T}\right) - \frac{2}{\sigma\sqrt{T}}n\left(z\sigma\sqrt{T}\right) + \frac{2e^{-rT}}{\sigma\sqrt{T}}n\left(a\sigma\sqrt{T}\right) + (z - a)$$

$$B = -\left(2z + \frac{2}{z\sigma^2 T}\right)N\left(z\sigma\sqrt{T}\right) - \frac{2}{\sigma\sqrt{T}}n\left(z\sigma\sqrt{T}\right) + (z - a) + \frac{1}{z\sigma^2 T}$$

$$\mathrm{I(T)} = \frac{1}{rT}\left(G(T) - e^{-rT}F(T)\right)$$

$$\mathrm{J(T)} = \frac{1}{\mathrm{z}\sigma\sqrt{T}}(-\left(\frac{\mathrm{V}}{\mathrm{V_B}}\right)^{-\mathrm{a}+\mathrm{z}} \mathrm{N}(\mathrm{q}_1(\mathrm{T})) * \mathrm{q}_1(\mathrm{T}) + \left(\frac{\mathrm{V}}{\mathrm{V_B}}\right)^{-\mathrm{a}-\mathrm{z}} \mathrm{N}(\mathrm{q}_2(\mathrm{T})) * \mathrm{q}_2(\mathrm{T}))$$

where $F(T), G(T), q_1, q_2, h_2, h_1$ *and* b is defined as:

$$F(t) = N\left(h_1(t)\right) + \left(\frac{V}{V_B}\right)^{-2a} N(h_2(t)$$

$$G(t) = \left(\frac{V}{V_B}\right)^{-a+z} N\left(q_1(t)\right) + \left(\frac{V}{V_B}\right)^{-a-z} N\left(q_2(t)\right)$$

$$b = \ln\left(\frac{V}{V_B}\right)$$

$$h_1(t) = \frac{(-b - a\alpha^2 t)}{\sigma\sqrt{t}}$$

$$h_2(t) = \frac{(-b + a\alpha^2 t)}{\sigma\sqrt{t}}$$

$$q_1(t) = \frac{(-b - z\alpha^2 t)}{\sigma\sqrt{t}}$$

$$q_2(t) = \frac{(-b + z\alpha^2 t)}{\sigma\sqrt{t}}$$

11.2 Appendix B – Reneby, Ericsson and Wang bond valuation formulae

Using proposition 1 in Reneby, Ericsson and Wang, the value of a coupon bond with M coupons paid out times $\{t_i : i = 1 \dots M\}$ is:

$$CB(V,t) = \sum_{i}^{M-1} c * H(V,t;t_i)$$
$$= (c+P) * H(V,t;T)$$
$$= \psi P * G(V,t;T)$$

For the Credit default swap spread:

First we define $G(V,t)$ as a dollar-in-default claim:

$$G(V,t) = \left(\frac{V}{V_B}\right)^{-\theta}$$

where

$$\theta = \frac{\sqrt{(h^B)^2 + 2r} + h^B}{\sigma}$$

And

$$h^B = \frac{r - \delta - \alpha - 0.5\sigma^2}{\sigma}$$

Then we can define a dollar-in-default claim with maturity $G(V,t,T)$ as the value of a claim paying off \$1 in default if it occurs before T. We can define the binary option as $H(V,t,T^*)$ as the claim of paying off \$1 at T if default has not occurred before T.

To do so, the probabilities of the "survival event" (T $\nleq \boldsymbol{T}$) at t are estimates using lemma 1 (see Reneby et Al., 2005 for further details) under the probability measures $Q^m: m = \{B, G\}$ are

$$Q^m(\mathrm{T} \nleq \boldsymbol{T}) = \Phi\left(k^m\left(\frac{V}{V_B}\right)\right) - \left(\frac{V}{V_B}\right)^{-\frac{2}{\sigma}h^m} \Phi\left(k^m\left(\frac{V_B}{V}\right)\right)$$

where

$$k^m(x) = \frac{\ln(x)}{\sigma\sqrt{T-t}} + h^m\sqrt{T-t}$$

$$h^G = h^B - \theta * \sigma = -\sqrt{(h^B)^2 + 2r}$$

where $\Phi(k)$ denotes the cumulative standard normal distribution function.

Then we can define the price of the binary option as:

$$H(V,t,T^*) = e^{-r(T-t)} * Q^B$$

And the price of a dollar in default claim with maturity T:

$$G(V,t,T) = G(V,t) * (1 - Q^G)$$

11.3 Appendix C – derivations of MES and tau

Before explaining the derivation of the optimal tax and MES, we will state the banks incentives and the setting in the economic model.

The economy has N financial Firms, indexed by i = 1, ..N and 2 periods, t = 0, 1. Each bank decide how much x_j^i to invest in each available asset j = 1, ..J, acquiring total assets:

$$a^i = \sum_{j=1}^{J} x_j^i \qquad (1)$$

Which can be financed with debt or equity. Initial endowment $\overline{w}_0^i$ and equity capital w_0^i and the bank can raise debt b^i which imply the following budget constrant:

$$w_0^i + b^i = a^i \qquad (2)$$

At time t=1 asset j pays of r_j^i per dollar invested for bank i.

The total income for bank i at time t = 1 is then $y^i = \hat{y}^i - \varphi^i$

where φ^i is the cost of financial distress and $\hat{y}^i$ is pre-distress income:

$$\hat{y}^i = \sum_{j=1}^{J} x_j^i r_j^i \qquad (3)$$

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

$$\varphi^i = \Phi(\hat{y}^i, f^i) \qquad (4)$$

α^i is the fraction of the debt that is implicitly or explicitly guaranteed by the government. The face value is set so that the debt holders break even:

$$b^i = \alpha^i f^i + \left(1 - \alpha^i\right) E[\min(f^i, y^i)] \qquad (5)$$

The net worth of the bank at time 1 is then

$$w_i^i = \hat{y}^i - \varphi^i - f^i \qquad (6)$$

The bank is then optimizing:

$$\max_{w_0^i, b^i, \{x_j^i\}_j} \text{c} * (\overline{w}_0 - w_0^i - \tau_0) + E[u(1_{[w_1^i > 0]} \text{x } w_1^i)] \qquad (7)$$

Under the constraints of equation (2) to (6).

The optimal tax policy of the regulator has two terms. The tax is dependent on expected shortfall of the firm and the systemic expected shortfall of the firm. His main problem is finding the optimal policy that proctects the ecnomy the best from systemic risk and makes the debt insurance program efficient. In the model, banks chose their leverage and allocate their assets and then pay taxes. So the optimal tax policy is dependent on the choices the banks makes.

Derivation of proposition 1

The regulators problem in equation (1) in the main body of the theses is derived in the following manner.

Using the definition of tau *i* in equation (14), the bank's problem is:

$$\max_{w_0^i, b^i, \{x_j^i\}_j} \text{c} * (\overline{w}_0 - w_0^i - \tau_0) + E[u(1_{[w_1^i > 0]} \text{x } w_1^i)] - \alpha^i g * pr(w_1^i < 0) ES^i$$

$$-e * pr(w_1 < zA) SES^i$$

The first two terms represents the sum of utilities of the bank *i* which the banks optimizes. The third part represents the expected cost of the debt insurance program and the fourth part represents the cost of the externality of financial cost that the bank places on the economy.

Using equation (12) and (13), this becomes

$$\max_{w_0^i, b^i, \{x_j^i\}_j} \text{c} * (\overline{w}_0 - w_0^i - \tau_0) + E[u(1_{[w_1^i > 0]} \text{x } w_1^i)]$$

$$+E[\alpha^i g 1_{1_{[w_1^i < 0]}} w_1^i + e 1_{[w_1 < zA]} \text{ x } w_1^i]$$

The set of programmes for i = 1,…,N is equivalent to the planners program and the budget constrain can be adjusted with tau_ 0

Derivation of proposition 2

Derivation of proposition 2, equity value satisfies: $w_1^i - w_0^i = \sum_{j=1}^{J} r_j^i\, x_j^i - \varphi^i - f^i - w_0^i$. This allows Acharya et al to write:

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

In the expectations we have $E\left[-\, r_j^i \mid I_{5\%}\right] = \beta_{i,j} \frac{\zeta}{\zeta - 1} \bar{\varepsilon}_m^{\%}$ and therefore $E\left[-\, r_j^i \mid w_1^i < zA\right] = kE\left[-\, r_j^i \mid I_{5\%}\right]$. Using the definition of SES the Authors write:

$$1 + \frac{SES^i}{w_0} = \frac{za^i}{w_0^i} - E\left[\frac{w_1^i}{w_0^i} - 1 \middle| w_1^i < zA\right]$$

$$= \frac{za^i}{w_0^i} + \frac{x_j^i}{w_0^i} \sum_{j=1}^{J} E\left[-\, r_j^i \middle| w_1^i < zA\right] + \frac{E\left[\varphi^i \middle| w_1^i < zA\right]}{w_0^i} + \frac{f^i - b^i}{w_0^i}$$

Hence under the powerlaw assumption:

$$1 + \frac{SES^i}{w_0} - k * MES^i = \frac{za^i}{w_0^i} + \frac{E\left[\varphi^i \middle| w_1 < zA\right] - E\left[\varphi^i \middle| I_{5\%}\right]}{w_0} + (1 - k)\frac{f^i - b^i}{w_0^i}$$

11.4 Appendix D – R-code

Assetgrid Data sorting code

```
rm(list = ls()) #remove everything
setwd("C:/Users/…") #Set working directory
install.packages("lubridate") #install packages
library(readxl)
library(lubridate)

#First we make a function that insert columns specific places in a matrix/dataframe.
append_col <- function(x, cols, after=length(x)) {
  x <- as.data.frame(x)
  if (is.character(after)) {
    ind <- which(colnames(x) == after)
    if (any(is.null(ind))) stop(after, "not found in colnames(x)\n")
  } else if (is.numeric(after)) {
    ind <- after
  }
  stopifnot(all(ind <= ncol(x)))
  cbind(x, cols)[, append(1:ncol(x), ncol(x) + 1:length(cols), after=ind)] }

#Load data
df1 <- as.data.frame(read.csv('Brokerdealerdata.csv', header=TRUE, stringsAsFactors=FALSE))
df2 <- as.data.frame(read.csv('Depositorydata.csv', header=TRUE, stringsAsFactors=FALSE))
df3 <- as.data.frame(read.csv('Otherdata.csv', header=TRUE, stringsAsFactors=FALSE))
df4 <- as.data.frame(read.csv('Insurancedata.csv', header=TRUE, stringsAsFactors=FALSE))
df1 <- df1[-1,]
df2 <- df2[-1,]
df3 <- df3[-1,]
df4 <- df4[-1,]
df <- cbind(df1,df2[,4:21],df3[,4:27],df4[,4:63]) #Cbind every dataset together
```

```
debt <- grepl("TOTAL.DEBT", colnames(df)) #which columns contains debt values.
debt <- which(debt == "TRUE") #only true
#adjusting total debt to same millions like equity
for (i in 1:length(debt)){
  df[,(debt[i])] <- ifelse(!is.na( df[,(debt[i])]), as.numeric( df[,(debt[i])])/1000, 0)
  df[,(debt[i]+1)] <- ifelse(!is.na( df[,(debt[i]+1)]), as.numeric( df[,(debt[i]+1)])/100, 0)  }

#adjusting iboxx and risk free to percentages
df[,2]<-as.numeric(df[,2])/100
df[,3]<-as.numeric(df[,3])/100

#calculating coupons
for (i in length(debt):1){
  y <- debt[i]
  df <- append_col(df, 0,y)  }
Coupons <- grepl("cols", colnames(df))
Coupons <- which(Coupons == "TRUE")
#calculating coupons
for (i in 1:length(Coupons)){
  df[,(Coupons[i])] <- as.numeric(df[,(Coupons[i]-1)])*as.numeric(df[,3])  }

#calculating pay out rations
DY <- grepl("DIVIDEND.YIELD", colnames(df))
DY <- which(DY == "TRUE")
for (i in 1:length(DY)){ #length(debt)
  C <- ifelse(!is.na( df[,(DY[i]-1)]),  df[,(DY[i]-1)], 0)
  dy <- ifelse(!is.na( df[,(DY[i])]),  df[,(DY[i])], 0)
  MV <- ifelse(!is.na( df[,(DY[i]-3)]),  df[,(DY[i]-3)], 0)
  P <- ifelse(!is.na( df[,(DY[i]-2)]),  df[,(DY[i]-2)], 0)
  delta <- (as.numeric(C)+as.numeric(dy)*as.numeric(MV))/(as.numeric(P)+as.numeric(MV))

  df[,(DY[i])] <- delta }
```

```
#naming everything
names <-  grepl("col", colnames(df))
names <- which(names == "TRUE")
colnames(df)[names] <- "C"
DY <- grepl("DIVIDEND.YIELD", colnames(df))
DY <- which(DY == "TRUE")
colnames(df)[DY] <- "delta"
#Fixing dates
dates <- as.numeric(df[,1])
df[,1] <- as.Date(dates, origin="1899-12-30")
#Write file
write.csv(df, "Data_sort.csv", row.names = FALSE)
```

 # CDS Data sorting code

```
#This sorting procedure is repeated for each sub-industry
rm(list = ls())
sort <- as.data.frame(read.csv('Data_sort.csv', header=TRUE, stringsAsFactors=FALSE))
dates <- sort[,1]
#Load CDS data
#df1 <- as.data.frame(read.csv('Brokerdealer_CDS.csv', header=TRUE, stringsAsFactors=FALSE))
#df1 <- as.data.frame(read.csv('Depository_CDS.csv', header=TRUE, stringsAsFactors=FALSE))
#df1 <- as.data.frame(read.csv('Other_CDS.csv', header=TRUE, stringsAsFactors=FALSE))
df1 <- as.data.frame(read.csv('Insurance_CDS.csv', header=TRUE, stringsAsFactors=FALSE))
redcode <- df1[!duplicated(df1[,1]),1]
Names <- df1[!duplicated(df1[,1]),6]
names <- df1[!duplicated(df1[,6]),6]  #firm names
df <- as.data.frame(matrix(0,nrow <- length(dates),ncol <- (length(names))+1))
df[,1] <- dates
#The date format is really awkward and needs to be fixed as R cannot recognize it as dates.
colnames(df)[2:(length(names)+1)] <- names[1:length(names)] #give names to columns
```

```
old <- df1[,2]
n <- 5
step1 <- paste(substr(old, 1, n-1), "/", substr(old, n, nchar(old)), sep = "")
n <- 8
step2 <- paste(substr(step1, 1, n-1), "/", substr(step1, n, nchar(step1)), sep = "")
dates2 <- as.Date(step2)
dates3 <- strftime(dates2,"%m/%d/%Y")
df1[,2] <- dates3

#Assigning names to out put matrix and filling in  CDS spread data
for ( i in 1:length(names)){
   col <- which(colnames(df)==names[i])
  for ( j in 1:dim(df)[1]){
   rows <- which(names[i] == df1[,6])
  row <- which(df1[rows,2] == df[j,1])
  rows[row]
  if(length(row)==0){next}
   df1[which(names[i] == df1[row,6]),8]
  df[j,col] <- df1[rows[row],8]  }  }

#Making sure that every column sits like the balance sheet data
sequencer <- seq(4, length(sort),4)
colnames(sort)[ sequencer]
df_final <- as.data.frame(matrix(0,nrow <- length(dates),ncol <- (length(names))+1))
colnames(df_final)[2:(length(names)+1)] <- colnames(sort)[kk[21:40]]

#Broker-Dealer
df_final <- df
#Other
df_final[,1]<-df[,1]
df_final[,2]<-df[,8]
df_final[,3]<-df[,4]
df_final[,4]<-df[,6]
```

```
df_final[,5]<-df[,3]
df_final[,6]<-df[,2]
df_final[,7]<-df[,5]
df_final[,6]<-df[,9]
df_final[,9]<-df[,7]
#Depository
df_final[,1]<-df[,1]
df_final[,2]<-df[,5]
df_final[,3]<-df[,3]
df_final[,4]<-df[,6]
df_final[,5]<-df[,2]
df_final[,6]<-df[,5]
df_final[,7]<-df[,7]

#Insurance
df_final[,1]<-df[,1]
df_final[,2]<-df[,10]
df_final[,3]<-df[,6]
df_final[,4]<-df[,12]
df_final[,5]<-df[,2]
df_final[,6]<-df[,5]
df_final[,7]<-df[,16]
df_final[,8]<-df[,17]
df_final[,9]<-df[,15]
df_final[,10]<-df[,3]
df_final[,11]<-df[,11]
df_final[,12]<-df[,20]
df_final[,13]<-df[,9]
df_final[,14]<-df[,21]
df_final[,15]<-df[,18]
df_final[,16]<-df[,8]
df_final[,17]<-df[,14]
df_final[,18]<-df[,19]
```

```
df_final[,19]<-df[,4]
df_final[,20]<-df[,7]
df_final[,21]<-df[,13]

#write.csv(df_final, "Brokerdealer_CDS_sort.csv", row.names = FALSE)
#write.csv(df_final, "Depository_CDS_sort.csv", row.names = FALSE)
#write.csv(df_final, "Other_CDS_sort.csv", row.names = FALSE)
#write.csv(df_final, "Insurance_CDS_sort.csv", row.names = FALSE)

setwd("C:/Users/heinr/Dropbox/My Theses/Estimating Distress costs/Params/CDS")
#cbind
df1 <- as.data.frame(read.csv('Brokerdealer_CDS_sort.csv', header=TRUE, stringsAsFactors=FALSE))
df2 <- as.data.frame(read.csv('Depository_CDS_sort.csv', header=TRUE, stringsAsFactors=FALSE))
df3 <- as.data.frame(read.csv('Other_CDS_sort.csv', header=TRUE, stringsAsFactors=FALSE))
df4 <- as.data.frame(read.csv('Insurance_CDS_sort.csv', header=TRUE, stringsAsFactors=FALSE))
df <- cbind(df1,df2[,2:dim(df2)[2]],df3[,2:dim(df3)[2]],df4[,2:dim(df4)[2]]) #Cbind every dataset together
#Final CDS file
write.csv(df, "CDS_sort.csv", row.names = FALSE)
```

Leland and Toft functions

```
PV <- function(V,V_B,r,delta,sigma) {
# Present value of $1 with infinite horizon at first passage
 V_B[V_B<=0] <- 0
ifelse(V_B > V, V <- V_B, V <- V )
ratio <- V/V_B
sigma2 <- sigma^2
a <- (r - delta - 0.5*sigma2)/sigma2
z <- sqrt((a*sigma2)^2 + 2*r*sigma2)/sigma2
x <- a + z
pv <- (ratio)^(-x)
return(pv) }
```

```
barrierEq11 <- function(t,C,P,alpha,r,delta,sigma,tau){
 #Equation 11
sigma2 <- sigma^2
a <- (r - delta - 0.5*sigma2)/sigma2
z <- sqrt((a*sigma2)^2 + 2*r*sigma2)/sigma2
V_T <- C/delta
x <- a + z
ert <- exp(-r*t)

A <- 2*a*ert* pnorm(a*sigma*sqrt(t)) - 2 * z * pnorm(z*sigma*sqrt(t)) -
   (2/(sigma*sqrt(t))) * dnorm(z*sigma*sqrt(t)) + (2*ert)/(sigma*sqrt(t)) * dnorm(a*sigma*sqrt(t)) +
   (z - a)

B <- -(2*z + 2/(z*sigma2*t)) * pnorm(z*sigma*sqrt(t)) - 2/(sigma*sqrt(t)) * dnorm(z*sigma*sqrt(t)) +
   (z - a) + 1/(z*sigma2*t)

numerator = (C/r)*(A/(r*t)-B) - A*P/(r*t) - tau*C*x/r
denom = 1 + alpha*x - (1-alpha)*B
V_B = numerator/denom
return(V_B)   }

barrierB1 <- function(t,C,P,alpha,r,delta,sigma,tau){
  #V_B from appendix (B1)
  sigma2 <- sigma^2
  a <- (r - delta - 0.5*sigma2)/sigma2
  z <- sqrt((a*sigma2)^2 + 2*r*sigma2)/sigma2
  V_T <- C/delta
  x <- a + z

  ert <- exp(-r*t)
  A <- 2*a*ert* pnorm(a*sigma*sqrt(t)) - 2 * z * pnorm(z*sigma*sqrt(t)) -
   (2/(sigma*sqrt(t))) * dnorm(z*sigma*sqrt(t)) + (2*ert)/(sigma*sqrt(t)) * dnorm(a*sigma*sqrt(t)) +
```

```
  (z - a)

 B <- -(2*z + 2/(z*sigma2*t)) * pnorm(z*sigma*sqrt(t)) - 2/(sigma*sqrt(t)) * dnorm(z*sigma*sqrt(t)) +
  (z - a) + 1/(z*sigma2*t)

 numerator <- (((C / r) * (A / (r * t) - B)) - ((A * P) / (r * t)))
 denom <- (1 + x * (((tau * C) / (r * V_T)) + alpha) - (1 - alpha) * B)
 V_B <- numerator/denom
 return(V_B)   }
```

optimbarrier <- function(t,C,P,alpha,r,delta,sigma,tau, V){

```
 #optimal default barrier
 V_B <- barrierEq11(t,C,P,alpha,r,delta,sigma,tau)
 V_T = C/delta
ifelse(V_T > V_B, V_B <- barrierB1(t,C,P,alpha,r,delta,sigma,tau), V_B <- barrierEq11(t,C,P,alpha,r,delta,sigma,tau) )
return(V_B)   }
```

firmeq8 <- function(t,C,P,alpha,r,delta,sigma,tau, V, V_B){

```
 sigma2 <- sigma^2
 a <- (r - delta - 0.5*sigma2)/sigma2
 z <- sqrt((a*sigma2)^2 + 2*r*sigma2)/sigma2
 V_T <- C/delta
 pv <- PV(V,V_B,r,delta,sigma)
 x <- a + z
 TS <- (tau*C)/r*(1-pv) #Tax shield
 BC <- alpha*pmin(V_B,V)*pv #Distress costs
 v <- V + TS - BC
return(v)}
```

firmB1 <- function(t,C,P,alpha,r,delta,sigma,tau, V, V_B){

```
#Firm value equation found in Appendix B of Leland and Toft
 sigma2 <- sigma^2
 a <- (r - delta - 0.5*sigma2)/sigma2
```

```
  z <- sqrt((a*sigma2)^2 + 2*r*sigma2)/sigma2
  x <- a + z
  V_T <- C/delta

  A1 <- ((tau*C)/r)*(x/(x+1))*1/V_T
  A2 <- -((tau*C)/r)*(x/(x+1))*(((V_B)^(x+1))/V_T)
  B2 <- -((tau*C)/r)*(x/(x+1))*(1/V_T)*((V_B^(x+1)+(1/x)*(V_T^(x+1))))
  pv <- PV(V,V_B,r,delta,sigma)
  ifelse(V_T > V, TS <- V*A1+A2*(V)^(-x),TS <- ((tau*C)/r)+B2*(V^(-x))) #Tax shield
  BC <- alpha*pmin(V_B,V)*pv #Distress costs
  v <- V + TS - BC
return(v)}
```

marketdebt <- function(t,C,P,alpha,r,delta,sigma,tau, V, V_B){

```
  #Market value of debt
  sigma2 <- sigma^2
  a <- (r - delta - 0.5*sigma2)/sigma2
  z <- sqrt((a*sigma2)^2 + 2*r*sigma2)/sigma2
  x <- a + z
  V_B[V_B<=0] <- 0.00001
  ifelse(V_B > V, V <- V_B, V <- V )
   ratio <- V/V_B
  ratio[is.na(ratio)] <- 1
  b = log(ratio)
  q_1 <- as.numeric(-b - z * (sigma2) * t) / (sigma * sqrt(t))
  q_2 <- as.numeric(-b + z * (sigma2) * t) / (sigma * sqrt(t))
  h_1 <- as.numeric(-b - a * (sigma2) * t) / (sigma * sqrt(t))
  h_2 <- as.numeric(-b + a * (sigma2) * t) / (sigma * sqrt(t))
  Ft <- pnorm(h_1) + (V / V_B) ^ (-2 * a) * pnorm(h_2)
  Gt <- (V / V_B) ^ (-a + z) * pnorm(q_1) +(V / V_B) ^ (-a - z) * pnorm(q_2)
  It <- (1 / (r* t)) * (Gt - exp(-r * t) * Ft)
  Jt <- (1 / (z * sigma * sqrt(t))) * ((-(V / V_B) ^ (-a + z) * pnorm(q_1) * q_1+ (V / V_B) ^ (-a - z) * pnorm(q_2) *
q_2))
  marketdebt = C/r  + (P-C /r) *
```

```
   (((1 - exp(-r * t)) / (t * r))  - It) + ((1 - alpha) * pmin(V_B,V) - C / r) * Jt
  return(marketdebt)   }
```

optimFirm <- function(t,C,P,alpha,r,delta,sigma,tau, V, V_B){

```
  V_T = C/delta #Coupons / asset pay out ratio
  ifelse(V_T > V_B, v <- firmB1(t,C,P,alpha,r,delta,sigma,tau, V, V_B), v <- firmeq8(t,C,P,alpha,r,delta,sigma,tau,
V, V_B)  )
  return(v)  }
```

equity <- function(t,C,P,alpha,r,delta,sigma,tau, V, V_B){

```
#Equity pricing function from Leland and Toft
  D <- marketdebt(t,C,P,alpha,r,delta,sigma,tau, V, V_B)
  v <- optimFirm(t,C,P,alpha,r,delta,sigma,tau, V, V_B)
  e <- v-D
  return(e) }
```

CDSvalue <- function(t, C, P, alpha, r, delta, sigma, tau, V, V_B){

```
#Calc the CDS value from Reneby and Wang
  V_B[V_B<=0] <- 0.00001
  ifelse(V_B > V, V <- V_B, V <- V )
  ratio <- V/V_B
  ratio[is.na(ratio)]<-1
  sigma2 = sigma^2
  Psi <- 1-alpha
  HB <- (r-delta - alpha-0.5*sigma2)/sigma
  HG <- -sqrt((HB ^ 2) + 2 * r)
  theta <- (sqrt(((HB) ^ 2) + 2 * r) + HB) / (sigma)
  gat <- ((V / V_B) ^ (-theta))
  Y1<- log(ratio)/(sigma*sqrt(t)) + HB*sqrt(t)
  Y2<- log(ratio)/(sigma*sqrt(t)) + HG*sqrt(t)
  Y3<- log(1/ratio)/(sigma*sqrt(t)) + HB*sqrt(t)
  Y4<- log(1/ratio)/(sigma*sqrt(t)) + HG*sqrt(t)
```

```
  QB <- pnorm(Y1)-((ratio)^(-(2/sigma)*HB))*pnorm(Y3)
  QG <- pnorm(Y2)-((ratio)^(-(2/sigma)*HG))*pnorm(Y4)
  Hfunc <- exp(-r*t)* QB           #Down and out binary option
  Gfunc <- gat*(1-QG)              #Dollar in default claim with maturity t
    nom <- (r*(P-Psi*P)*Gfunc)
  denom <- (1 - Hfunc - Gfunc)
  Q <- nom/denom
  Q <- ifelse(is.nan(Q), 1,  Q )
  return(Q) }
```

```
CDSspread <- function(t, C, P, alpha, r, delta, sigma, tau, V, V_B){
#Calc. the implied CDS spread from LT model
 V_B[V_B<=0] <- 0
  ifelse(V_B > V, V <- V_B, V <- V )
  Q <- CDSvalue (t, C, P, alpha, r, delta, sigma, tau, V, V_B)
  Spread <- Q/P/100
  return(Spread) }
```

```
Volatility <- function(X){
#Calculates the volatility of a time series of 250 observations
vlogreturn <- c()  #calculate log return
  vlogreturn <- log(X[(2:length(X))]/X[1:(length(X)-1)])
  #mean <- mean(vlogreturn)
  #sigma <- sqrt(sum((vlogreturn-mean)^2))
  sigma <-  sd(vlogreturn, na.rm = TRUE)*sqrt(250)
return(sigma)}
```

```
impliedAsset <- function(t,C,P,alpha,r,delta,sigma,tau, target){
  #Implies the asset value from the target (observed) equity value
  ifelse(is.na(C) | is.na(target) | is.na(P),Ubound <- NA, Ubound <-(target+P)*2)
  Lbound <- rep(0,length(Ubound))
  V <- (Ubound+Lbound)
```

```
  repeat{
    if(any(is.na(Ubound))){break}
    V_B <- optimbarrier(t,C,P, alpha, r, delta,sigma, tau,V)
    e <- equity(t,C,P,alpha,r,delta,sigma,tau, V, V_B)
    cond <- abs(target - e)
    cond2 <- ifelse(cond < 10, "YES", "NO")
    ifelse(e[cond2 == "NO"] > target[cond2 == "NO"], Ubound[cond2 == "NO"] <- (Ubound[cond2 == "NO"]+Lbound[cond2 == "NO"])/2, Lbound[cond2 == "NO"] <- (Ubound[cond2 == "NO"]+Lbound[cond2 == "NO"])/2)
    V[cond2 == "NO"] <- Ubound[cond2 == "NO"]+Lbound[cond2 == "NO"]
    if(all(Ubound[cond2 == "NO"]==Lbound[cond2 == "NO"])){break}
    if(all(cond2 == "YES")){break}  }
  ifelse(is.na(Ubound),V <-NA, V<-V)
  return(V)  }
```

impliedVol <- function(t,C,P,alpha,r,delta,tau, target, V){

```
#only for assessing smoothness
V_target <- target + P
high = 2
low = 0
  repeat{
    if((high - low)<0.0001){break}
    sigma <- (high+low)/2
    V <- impliedAsset(t,C,P,alpha,r,delta,sigma,tau, target)
    if(V<V_target ){high <-(high+low)/2
    }else{low  <-(high+low)/2     }   }
  sigma <- (high+low)/2
  return(sigma) }
```

Assessing the smoothness of Leland and Toft functions

```
#This code is repeated first for LGD then for Debt maturity
tau <- 0.25
```

```
r <- 0.025
delta <- 0.07
P <- 750
C <- P*0.05
target <- (1000-P)
t <- 5
alpha <- 0.3
vttm <- seq(3,9,((9-3)/100))
valpha <- seq(0.1,0.70,(0.7-0.1)/100)
y1 <- c()
y2 <- c()
for (j in 1:101){
t <- vttm[j]
#alpha <- valpha[j]
y1[j] <-  impliedAsset(t,C,P,alpha,r,delta,0.25,tau, target)
y2[j] <- impliedVol(t,C,P,alpha,r,delta,tau, target, (P+target))  }
X <- vttm #for assessing debt maturity
#X <- valpha #for assessing LGD
library (ggplot2)
Z <- as.data.frame(cbind(X,y1,y2))
g<-ggplot(Z, aes(X,y2))+geom_line(color="firebrick",size=1.25)+
  theme(plot.background = element_rect(fill = 'white'))+
  theme(panel.background = element_rect(fill = 'grey90'))

# for assessing LGD
#g<-g+labs(x="Loss Given Default", y=expression(paste("Volatility ( ", "sigma", " )")),
# title="Figure 6: Asset Volatility in LGD ")+
#  theme(text=element_text(family = "Times New Roman",size = 10))
#g<-g+labs(x="Loss Given Default", y="Asset Value",title="Figure 5: Asset Volatility in LGD ")+
#  theme(text=element_text(family = "Times New Roman",size = 10))

# for assessing debt maturity
g<-g+labs(x="Debt Maturity", y=expression(paste("Volatility ( ", "sigma", " )")),
```

```
title="Figure 8: Asset volatility in debt maturity")+
  theme(text=element_text(family = "Times New Roman",size = 10))
g<-g+labs(x="Debt Maturity", y="Asset Value",title="Figure 7: Asset value in debt maturity ")+
  theme(text=element_text(family = "Times New Roman",size = 10))
#g <- g+xlim(c(2.9,9.1))#+ ylim(c(0.25,0.45))
#g <- g+xlim(c(0.099,0.711))#+ ylim(c(0.25,0.45))
g
ggsave("whateverplotwehave.png", width = 5, height = 3)
```

 # Producing grids containing LGD and T

```
rm(list=ls())
setwd("C:/Users/… ") #set working directory to where balance sheet data are
library(doParallel)
library(foreach)
#run all Leland and Toft functions again so that they are loaded, then load data
df <- read.csv('Data_sort.csv', header=TRUE, stringsAsFactors=FALSE)
df <- as.data.frame(df)
df <- df[complete.cases(df[,2]),]
cols <- grepl("TOTAL.DEBT", colnames(df))
cols <- which(cols == "TRUE")
hh <- seq(1,length(cols)*2,2)
results <- array(data = NA, dim = c(5,4,(dim(df)[1]-783),length(cols)*2))  #5 x LGD, 5 x ttm, cols of dataset, rows of
#dataset
vres <- vector(length=250)
valpha <- c(0.10, 0.25, 0.40, 0.55, 0.70 ) #five LGDs
vttm <- c(3, 5, 7, 9) #four maturities
tau <- 0.25 #Tax rate

for (X in 1:5){ #Loop around LGD
alpha <- valpha[X]
for (Y in 1:4){ #Loop around debt maturity
t <- vttm[Y]
```

```
for (u in 1:length(cols)){
w <- as.numeric(cols[u])
no_cores <- detectCores()
cl <- makeCluster(no_cores)
registerDoParallel(cl)
matrix = foreach(d = 784:1695, .combine=rbind) %dopar% {
c(d,d)
sigma = 0.05 #Assign some value to sigma #1695
Newsigma = 0.5 #This is the scripts first guess of asset volatility.
repeat {
   if(abs(sum(sigma-Newsigma))<0.02){break}
    sigma = Newsigma
   for(j in ((d-250):d)){
   target <- df[j,(w-1)]
   r <- df[j,2]
   C <- df[j,(w+1)]
   delta <- df[j,(w+2)]
   P <- df[j,(w)]
   vres[j-d+250] <- impliedAsset(t, C, P, alpha, r, delta, sigma, tau, target)  }
   Newsigma <- Volatility(vres)
   if(is.na(Newsigma)){break}
   if(Newsigma<0.04){break} }
return(c(vres[250],sigma))
}#for loop with d
results[X,Y,, hh[u]] <-  matrix[,1] #Asset
results[X,Y,,(hh[u]+1)] <-  matrix[,2]#Volatility
stopCluster(cl)
registerDoSEQ()
}#Firms
save(results, file = "GridParameter.RData", envir = .GlobalEnv) # Save results continuously
}#ttm
}#alpha
```

Root square mean error functions

#This function enables interpolation

If we don't know how the LT functions behave, then we cannot do this

```
contfunction <- function(pars, Firm){
#Firm is column number that the Firm is sitting in
#  pars <- c(0.8, 1)
alpha  <- pars[1]
t  <- pars[2]
#alpha weights
  if( alpha > 0.1 && alpha <= 0.25){
    y1 = (alpha-0.1)/(0.25-0.1) #weight on 0.25 alpha array / weight on upper array / on x +1
    y2 = 1-y1 #weight on 0.1 alpha array / weight on upper array / on x
    x1 = 1   }
  if( alpha > 0.25 && alpha <= 0.4){
    y1 = (alpha-0.25)/(0.4-0.25)
    y2 = 1-y1
    x1 = 2  }
  if( alpha > 0.4 && alpha <= 0.55){
    y1 = (alpha-0.4)/(0.55-0.4)
    y2 = 1-y1
    x1 = 3  }
  if( alpha > 0.55 && alpha <= 0.7){
    y1 = (alpha-0.55)/(0.7-0.55)
    y2 = 1-y1
    x1 = 4  }
  if( alpha > 0.7){
    y1 = 1
    y2 = 1-y1
    x1 = 4  }
  if( alpha <= 0.1 ){
    y1 = 0
    y2 = 1-y1
```

```
    x1 = 1}
if( t > 3 && t <= 5){
    y21 = (t-3)/(5-3) #weight on 5 time array / weight on upper array / on z +1
    y22 = 1-y21
    z1 = 1  }
  if( t > 5 && t <= 7){
    y21 = (t-5)/(7-5)
    y22 = 1-y21
    z1 = 2  }
  if( t > 7 && t <= 9){
    y21 = (t-7)/(9-7)
    y22 = 1-y21
    z1 = 3  }
  if( t > 9 ){
    y21 = 1
    y22 = 1-y21
    z1 = 3  }
  if( t <= 3 ){
    y21 = 0
    y22 = 1-y21
    z1 = 1  }
#Simple vector calculations in R
  #1-4 time-to-maturity
  V1 = results[x1,z1,,Firm]*y22
  V2 = results[x1,(z1+1),,Firm]*y21
  V3 = results[(x1+1),z1,,Firm]*y22
  V4 = results[(x1+1),(z1+1),,Firm]*y21
  #5-6 alpha
  V5 = (V1+V2)*y2
  V6 = (V3+V4)*y1
  #result – output vector
  V_final = V5+V6
return(V_final) }
```

```
RMSE1 <- function(pars){
#This function shows how it is done for broker-dealers. One can easily modify it for other industries.
# We have RMSE2, RMSE3 and RMSE4, i.e. one for each industry, only one is shown.
alpha <- pars[1]
t <- pars[2]
tau = 0.25
ifelse(alpha < 0.1, alpha <- 0.1, alpha <- alpha)
ifelse(alpha > 0.7, alpha <- 0.7, alpha <- alpha)
ifelse(t < 3, t <- 3, t <- t)
ifelse(t > 9, t <- 9, t <- t)
input <- seq(1,80,2)
library(lubridate)
CDSt <- 5
RMSE <- c()
for (i in 1:6){ #vary per industry 7-13 = depositors, 14-20 = non-depositors, 21-40 = insurance
Firm <- i
startdate <- which(df2$Name == "06/01/2006")
cols1 <- grepl("TOTAL.DEBT", colnames(df2))
cols1 <- which(cols1 == "TRUE")
debtcol <- cols1[Firm] # need to define "cols" again
P <- df2[startdate:(dim(df2)[1]),debtcol] #Also need new df
C <- df2[startdate:(dim(df2)[1]),(debtcol+1)]
r <- df2[startdate:(dim(df2)[1]),2]
delta <- df2[startdate:(dim(df2)[1]),(debtcol+2)]
S_act <- df1[startdate:(dim(df1)[1]),Firm +1]
Stock <- contfunction(pars, input[Firm])
Stock <- Stock[(length(Stock)-length(P)-250):(length(Stock)-length(P))]
ret <- Stock[2:251]/Stock[1:250]-1
startSP500 <- which(SP500$Name == "06/01/2006")
MKT <- as.numeric(SP500[(startSP500-250):startSP500,3])
MKTret <- MKT[2:251]/MKT [1:250]-1
rf <- df2[(startdate-250):(startdate -1),2]
```

```
ExMKTret <- MKTret - rf
Exret <- ret#-rf #NEEEDS TO CHANGE for julia regress
Beta <- lm(Exret ~ ExMKTret -1 )
Assetbeta <- Beta$coefficients
rm (Stock,ret,  MKT , MKTret, Beta )
MKTret <- as.numeric(SP500[(startSP500:dim(SP500)[1]),3])
MKTret <- MKTret[1:(length(MKTret)-1)]/MKTret[2:(length(MKTret))]-1
NewMKTret <- as.numeric(SP500[(startSP500-1):(dim(SP500)[1]),3])
MKTret <- NewMKTret[2:length(NewMKTret)]/NewMKTret[1:(length(NewMKTret)-1)]-1
mu <- r+as.numeric(Assetbeta)*(MKTret-r)
V <- contfunction(pars, input[Firm])
V <- V[(length(V)-length(P)+1):912]
sigma <- contfunction(pars,(input[Firm]+1))
sigma <- sigma[(length(sigma)-length(P)+1):912]
V_B <-  optimbarrier(CDSt,C,P,alpha,r,delta,sigma,tau, V) #Default barrier
S_LT <- CDSspread(CDSt, C, P, alpha, r, delta, sigma, tau, V, V_B) #LT CDS spread
sigma2 <- sigma*sigma
dates <- as.Date(df1[startdate:(dim(df1)[1]),1], "%m/%d/%Y" )
DD <- (log(V/pmin(V_B,V))+((mu-0.5*(sigma2))*t))/(sigma*sqrt(t)) #mu = rf+Assetbeta*(rm -rf)
vS_LT <- c()
vS_act <- c()
vS_DD <- c()
d = 4
end <- ifelse(d < 4, 1, d-4)
for (d in 1:length(V)){
  if (is.na(S_act[d])){next}
  vS_act[d] <- ifelse(wday(dates[d], label=TRUE) == "Fri", mean(S_act[d:end], na.rm = TRUE), NA) #S_act
  vS_LT[d] <- ifelse(wday(dates[d], label=TRUE) == "Fri", mean(S_LT[d:end], na.rm = TRUE), NA) #S_LT
  vS_DD[d] <- ifelse(wday(dates[d], label=TRUE) == "Fri",mean(DD[d:end], na.rm = TRUE), NA) #DD

  vS_LT[d] <- ifelse(is.na(vS_act[d]) | is.na(vS_DD[d]) |vS_act[d] < 0.0001, NA, vS_LT[d] )# #Only S_Lt when S_act
and DD is present
  vS_DD[d] <- ifelse(is.na(vS_act[d]) |vS_act[d] < 0.0001, NA, vS_DD[d] ) #Only DD when S_act is present
  vS_act[d] <- ifelse(is.na(vS_DD[d])|vS_act[d] < 0.0001 , NA, vS_act[d] ) #Only S_act when DD is present }
```

```
vS_act <- vS_act[!is.na(vS_act)]
vS_LT <- vS_LT[!is.na(vS_LT)]
vS_DD <- vS_DD[!is.na(vS_DD)]
RMSE1 <- vS_LT - vS_act
RMSE2 <- RMSE1 ^2
RMSE3 <- RMSE2/abs(vS_DD)
RMSE4 <- sum(RMSE3)
RMSE5 <- sqrt(RMSE4)
RMSE[i] <- RMSE5 }
RMSE <- sum(RMSE, na.rm = TRUE)
 return(RMSE)  }
##
#produce RSME surface plot
f.name <- "Figure 9: RMSE function"
x1 <- seq(0.1, 0.7, length = 30)
x2 <- seq(3, 9, length = 30)
X <- as.matrix(expand.grid(x1, x2))
colnames(X) <- c("LGD", "T")
library(doParallel)
library(foreach)
no_cores <- detectCores()
cl <- makeCluster(no_cores)
registerDoParallel(cl)
matrix = foreach(d = 1:900, .combine=rbind) %dopar% {
  c(d)
pars <- c(X[d,1],X[d,2])
res <-  RMSE1(pars) #change i to 1:40
return(c(res))
}
stopCluster(cl)
registerDoSEQ()
y <- matrix
```

```
# put X and y values in a data.frame for plotting
df <- data.frame(X, y)
# plot the function
library(lattice) # use the lattice package
wireframe(y ~ LGD * T # y, x1, and x2 axes to plot
    , data = df # data.frame with values to plot
    , main = f.name # name the plot
    , shade = TRUE # make it pretty
    , scales = list(arrows = FALSE) # include axis ticks
    , screen = list(z = -50, x = -70) # view position   )
```

Optimization procedure

```
#This code find the optimal T and LGD from the produced grids and CDS data.
rm(list=ls())
#optimization procedure!
setwd("C:/Users/… ")
library(readxl)
load("C:/Users/heinr/…/GridParameter_final.RData") #load grids
df1 <-  as.data.frame(read.csv('CDS_sort.csv', header=TRUE, stringsAsFactors=FALSE))
df2 <-  as.data.frame(read.csv('Data_sort.csv', header=TRUE, stringsAsFactors=FALSE))
SP500 <- as.data.frame( read_excel('Market.xlsx'))
SP500 <- SP500[-1,]
dates2 <- as.Date(as.numeric(SP500[,1]), origin = "1899-12-30")
SP500[,1] <- strftime(dates2,"%m/%d/%Y")
params_new <- matrix(data = NA, ncol = 3, nrow = 4)
colnames(params_new) <- c("time-to-maturity","LGD","RMSE")
rownames(params_new) <- c("BrokerDealer","Depository", "Non-depository", "Insurance")
library(doParallel)
library(foreach)
#use simulated annealing for each industry to find optimal values. Maxit is number of iterations. As R does 2 guesses
#per iteration, this corresponds to 2000 guesses. We compute 50 LGDs and Ts per subindustry and take the average.
for (n in 1:4){
  if(n==1){
```

```
  no_cores <- detectCores()
  cl <- makeCluster(no_cores)
  registerDoParallel(cl)
    matrix1 = foreach(d = 1:50, .combine=rbind) %dopar% {
    c(d,d)
    params <- optim(p = c(0.7,5.5), fn = RMSE1, method = "SANN", control = list(maxit = 1000))
    alpha <- params$par[1]
    t <- params$par[2]
    ifelse(alpha < 0.1, alpha <- 0.1, alpha <- alpha)
    ifelse(alpha > 0.7, alpha <- 0.7, alpha <- alpha)
    ifelse(t < 3, t <- 3, t <- t)
    ifelse(t > 9, t <- 9, t <- t)
    return(c(alpha,t))}
  stopCluster(cl)
  registerDoSEQ()
  alpha <- mean(matrix1[,1])
  t <- mean(matrix1[,2])
  params_new[n,2] <- round(alpha,4)
  params_new[n,1] <- round(t,4)
  write.csv(params_new, "params_new.csv", row.names = FALSE) }

if(n==2){
  no_cores <- detectCores()
  cl <- makeCluster(no_cores)
  registerDoParallel(cl)
  matrix2 = foreach(d = 1:50, .combine=rbind) %dopar% {
    c(d,d)
    params <- optim(p = c(0.40,5), fn = RMSE2, method = "SANN", control = list(maxit = 1000))
    alpha <- params$par[1]
    t <- params$par[2]
    ifelse(alpha < 0.1, alpha <- 0.1, alpha <- alpha)
    ifelse(alpha > 0.7, alpha <- 0.7, alpha <- alpha)
    ifelse(t < 3, t <- 3, t <- t)
```

```
    ifelse(t > 9, t <- 9, t <- t)
    return(c(alpha,t))}
  stopCluster(cl)
  registerDoSEQ()
  alpha <- mean(matrix2[,1])
  t <- mean(matrix2[,2])
  params_new[n,2] <- round(alpha,4)
  params_new[n,1] <- round(t,4)
  write.csv(params_new, "params_new.csv", row.names = FALSE)  }
if(n==3){
  no_cores <- detectCores()
  cl <- makeCluster(no_cores)
  registerDoParallel(cl)
  matrix3 = foreach(d = 1:50, .combine=rbind) %dopar% {
    c(d,d)
    params <- optim(p = c(0.40,5), fn = RMSE3, method = "SANN", control = list(maxit = 1000))
    alpha <- params$par[1]
    t <- params$par[2]
    ifelse(alpha < 0.1, alpha <- 0.1, alpha <- alpha)
    ifelse(alpha > 0.7, alpha <- 0.7, alpha <- alpha)
    ifelse(t < 3, t <- 3, t <- t)
    ifelse(t > 9, t <- 9, t <- t)
    return(c(alpha,t))}
  stopCluster(cl)
  registerDoSEQ()
  alpha <- mean(matrix3[,1])
  t <- mean(matrix3[,2])
  params_new[n,2] <- round(alpha,4)
  params_new[n,1] <- round(t,4)
  write.csv(params_new, "params_new.csv", row.names = FALSE)  }
if(n==4){
  no_cores <- detectCores()
  cl <- makeCluster(no_cores)
```

```
  registerDoParallel(cl)
  matrix4 = foreach(d = 1:50, .combine=rbind) %dopar% {
   c(d,d)
   params <- optim(p = c(0.40,5), fn = RMSE4, method = "SANN", control = list(maxit = 1000))
   alpha <- params$par[1]
   t <- params$par[2]
   ifelse(alpha < 0.1, alpha <- 0.1, alpha <- alpha)
   ifelse(alpha > 0.7, alpha <- 0.7, alpha <- alpha)
   ifelse(t < 3, t <- 3, t <- t)
   ifelse(t > 9, t <- 9, t <- t)
   return(c(alpha,t))}
  stopCluster(cl)
  registerDoSEQ()
  alpha <- mean(matrix4[,1])
  t <- mean(matrix4[,2])
  params_new[n,2] <- round(alpha,4)
  params_new[n,1] <- round(t,4)
  write.csv(params_new, "params_new.csv", row.names = FALSE)  } }
```

 # Estimate distress costs

```
#Estimate Asset value, distress costs and tax shield for all firms
rm(list=ls())
setwd("C:/Users…/Params/Opti")
params <- read.csv("Params_Final.csv") #load T and LGD
setwd("C:/Users/all balalnce sheet date ") #Values for all firms with industry LGD and T
library(doParallel)
library(foreach)
#load data
df <- read.csv("Final_sort.csv",header=TRUE, stringsAsFactors=FALSE)
df <- as.data.frame(df)

df <- df[complete.cases(df[,2]),]
cols <- grepl("TOTAL.DEBT", colnames(df))
```

```
cols <- which(cols == "TRUE")
End <- which(df[,1] == "2007-06-29")
Start <- which(df[,1] == "2004-06-01")
dates <- df[(Start:End),1]
hh <- as.integer(seq(1,length(cols)*3,3))
Estimates <- as.data.frame(matrix(data = NA, nrow = End-Start+1, ncol = length(cols)*3)) #make data frame for our
#output
colnames(Estimates)[hh] <- colnames(df)[(cols-1)]
cols <- grepl("MARKET", colnames(Estimates))
cols <- which(cols == "TRUE")
colnames(Estimates)[cols+1] <- "Distress cost"
colnames(Estimates)[cols+2] <- "Tax shield"
#Needed for procedure
cols <- grepl("TOTAL.DEBT", colnames(df))
cols <- which(cols == "TRUE")
vres <- vector(length=250)
tau <- 0.25 #Tax rate


#Go on and calculate it
for (u in 1: length(cols) { #
w <- as.numeric(cols[u])
if(u <= 10){
  alpha <- params[1,2]
  t <- params[1,1] }
if(u > 10 && u <=39){
  alpha <- params[2,2]
  t <- params[2,1] }
if(u > 39 && u<=65){
  alpha <- params[3,2]
  t <- params[3,1] }
if(u > 65){
  alpha <- params[4,2]
  t <- params[4,1] }
no_cores <- detectCores()
```

```
cl <- makeCluster(no_cores)

registerDoParallel(cl)

matrix = foreach(d = Start:End, .combine=rbind) %dopar% {

c(d,d,d)

sigma = 0.05 #Assigne some value to sigma

Newsigma = 1 #This is the scripts first guess of asset volatilty. A larger number is preferable otherwise the code may abort.

repeat {

    if(is.na(df[d,(w)]) | any(is.na(df[d:(d-250),(w-1)]))){break}

    if(any(df[(d:(d-250)),(w)] < 0.01)){break}

    if(abs(sum(sigma-Newsigma))<0.02){break}

    sigma = Newsigma

    for(j in ((d-250):d)){

    target <- df[j,(w-1)]

    r <- df[j,2]

    C <- df[j,(w+1)]

    delta <- df[j,(w+2)]

    P <- df[j,(w)]

    vres[j-d+250] <- impliedAsset(t, C, P, alpha, r, delta, sigma, tau, target)  }

    Newsigma <- Volatility(vres)

    if(is.na(Newsigma)){break}

    if(Newsigma<0.04){break}}

if(is.na(df[d,(w-1)]) | is.na(df[d,(w)]) | (df[d,(w)]) < 0.01 | any(df[(d:(d-250)),(w)] < 0.01)){

  V <- "NA"

  DC <- "NA"

  TS <- "NA"  }

else{

  r <- df[d,2]

  C <- df[d,(w+1)]

  delta <- df[d,(w+2)]

  P <- df[d,(w)]

  V <- vres[250]

  V_B <- optimbarrier(t,C,P, alpha, r, delta, sigma, tau, V)

  DC <- alpha*pmin(V_B,V)* PV(V, V_B, r, delta, sigma )
```

```
  v <- optimFirm(t,C,P,alpha,r,delta,sigma,tau, V, V_B)
  TS <- v-V+DC }
return (c(V,TS, DC))
}#for loop with d
stopCluster(cl)
registerDoSEQ()
Estimates[,(hh[u])] <- matrix[,1]
Estimates[,(hh[u]+1)] <- matrix[,2]
Estimates[,(hh[u]+2)] <- matrix[,3]
write.csv(Estimates, "Distresscost_Finalversion.csv")
}#Firms
Matrix <- cbind(dates,Estimates)
write.csv(Matrix, "Distresscost_Finalversion2.csv")
```

MES, LVG and Distress costs to asset/Equity, distress costs changes

```
#This code calculates MES, LVG, Distress costs to asset and distress to equity.
rm(list=ls())
setwd("C:/Users/…/AcharyaReplication/MeasuringSystemicRisk/Data new")
install.packages("readxl")
library(readxl)
wrdsTCKR <- read.table("codelist.txt", header = FALSE)
bookdatawrds <- read_excel("Compustat book data.xlsx", col_names = TRUE)
stockdatawrds <- read_excel("CRSP StockReturns.xlsx", col_names = TRUE)
Mktdata <- read_excel("CRSP Market Index.xlsx", col_names = TRUE)
CompListAcharya <- read_excel("Company list Acharya et al..xlsx", col_names = TRUE)
Mktdiscrete <- as.matrix(as.numeric(unlist(Mktdata[,4])))       #Output returns are discretely compounded
Mktdate <- as.matrix(as.Date(unlist(Mktdata[,9]),origin = "1899-12-30"))
#create Market vector logreturns
Mktidx <- as.matrix(Mktdata[,5])
Mktlog <- as.matrix(log(Mktidx[2:nrow(Mktidx),]/Mktidx[1:(nrow(Mktidx)-1),]))
# Date Logret DiscrRet
Mktret <- cbind(Mktdate[2:nrow(Mktdate),], Mktlog, Mktdiscrete[2:nrow(Mktdiscrete)])
#Bookdata ticker
```

CompNames <- bookdatawrds[,9]

#Report, Ticker, Total Assets, Book Equity, Comp Names bookdatawords[,13] contains calendar quarter, [,14] fiscal

Bookdata <- cbind(bookdatawrds[,14], bookdatawrds[,9], bookdatawrds[,15], bookdatawrds[,16], bookdatawrds[,11])

#Stock price data(stocks) Date, Ticker, Stockprice, MCAP, Comp Names, Permno, discr.Ret

Stockprice <- as.matrix(stockdatawrds[,5])

Mcap <- as.matrix(Stockprice*stockdatawrds[,6])/1000 #/1000 damit gleiche Einheit wie bookdata

StockDate <- as.matrix(as.Date(unlist(stockdatawrds[,11]), origin = "1899-12-30"))

stocks <- cbind(StockDate,stockdatawrds[,3], Stockprice, Mcap, stockdatawrds[,4], stockdatawrds[,1], stockdatawrds[,7])

stocks[which(stocks[,6]==83443),5] <- "BERKSHIRE HATHAWAY INC DEL B"

stocks[which(stocks[,6]==89303),5] <- "LORRILARD INC"

Check if Data is right

Bookcheck <- which(Bookdata[,1]=='2007Q2')

Bookcheck <- Bookdata[Bookcheck,]

Equitycheck <- which(stocks[,1]==as.numeric(as.Date("2007-06-29")))

Equitycheck <- stocks[Equitycheck,]

Acharyalist <- CompListAcharya[,2:6]

match with “Acharyalist”

wo <- as.matrix(match(unlist(Acharyalist[,2]), Bookcheck[,2]))

Bookmatched <- Bookcheck[wo,]

Bookmatched[which(is.na(wo)),] <- tail(Bookdata[which(Bookdata[,2]==as.character(Acharyalist[which(is.na(wo)),2])),],1)#-----------eventuell funtioniert das Einfuegen nicht mit mehreren NA's

Matched <- cbind(Bookmatched, Acharyalist)

wo1 <- as.matrix(match(Equitycheck[,6], Matched[,9])) #match Equity und Buchdaten nach [,2] ist Ticker, [,5] ist company name

Bookcheckmatched <- Matched[wo1,]

```
# PERIOD BookTicker TotalAssets BookEquity Name PERMNO Date, Ticker, Stockprice, MCAP, Comp Names,
#Permno, discr.Ret, SIC

Totalcheck <- cbind(Bookcheckmatched[,1:5], Bookcheckmatched[,9], Equitycheck, Bookcheckmatched[,10])

Totalcheck <- as.matrix(Totalcheck[complete.cases(Totalcheck),])

TotalcheckMcap <- as.matrix(as.numeric(Totalcheck[,10]))


QuasiLvgcheck <- as.matrix((as.numeric(Totalcheck[,3])-
as.numeric(Totalcheck[,4])+TotalcheckMcap)/TotalcheckMcap)

QuasiLvgcheck <- cbind(Totalcheck[,11], QuasiLvgcheck)


#Period BookTicker Permno Companyname TotalAssets, BookEquity, MarketEquity, Quasilvg, SIC

TotalcheckEnd <- cbind(Totalcheck[,1],Totalcheck[,2], Totalcheck[,6], Totalcheck[,5],
Totalcheck[,3],Totalcheck[,4],Totalcheck[,10], QuasiLvgcheck[,2], Totalcheck[,14])


CompaniesSample <- as.matrix(unique(CompNames, FALSE))

CompTckr <- bookdatawrds[,9]

UniqueTckr <- as.matrix(unique(CompTckr, FALSE))


MktRetPreCrisis <- Mktret[Mktret[,1]>=as.numeric(as.Date("2006-06-01")) & Mktret[,1]<
as.numeric(as.Date("2007-07-01")),]  #Ret im passenden Zeitfenster

FiveperworstMkt <- subset(MktRetPreCrisis, MktRetPreCrisis[,2] < quantile(MktRetPreCrisis[,2],0.05))


#---------------- #Example ICE --------------------------------------------------------------------

BearStocks <- which(stocks[,2]=="ICE")

BearStocks <- as.matrix(stocks[BearStocks,])

# BearStocks <- cbind(as.numeric(BearStocks[,1]), BearStocks[,2], as.numeric(BearStocks[,3]))

BeardiscRet <- as.matrix(as.numeric(BearStocks[,7]))

# Date Price

BearStocks <- cbind(as.numeric(BearStocks[,1]), as.numeric(BearStocks[,3])) ## matrix does not function well when
#the vector contrains strings

BearlogRet <- as.matrix(log(BearStocks[2:nrow(BearStocks),2] / BearStocks[1:(nrow(BearStocks)-1),2]))

BearlogRetDiv <- log(BeardiscRet+1)

# Date Price logRet discRet

BearStocks <- cbind(BearStocks, BearlogRetDiv, BeardiscRet)
```

```
BearRealizedSES <- BearStocks[BearStocks[,1]>=as.numeric(as.Date("2007-07-02")) & BearStocks[,1]<=as.numeric(as.Date("2008-12-31")), ]

BearRealizedSES <- BearRealizedSES[complete.cases(BearRealizedSES),]

BearRealizedSES <- as.numeric(exp(sum(BearRealizedSES[,3]))-1)


BearBook <- which(Bookdata[,2]=='ICE')

BearBook <- Bookdata[BearBook,]


BearStockMkt <- as.matrix(match(BearStocks[,1], FiveperworstMkt[,1]))

BearStockMkt2 <- as.matrix(match(FiveperworstMkt[,1], BearStocks[,1]))

BearStockMkt <- as.matrix(BearStockMkt[!is.na(BearStockMkt)])

BearStockMkt2 <- as.matrix(BearStockMkt2[!is.na(BearStockMkt2)])

BearStocks <- BearStocks[BearStockMkt2,]  #kann zu BearStocks ueberschrieben werden, falls jetzt richtiges Ergebnis

BearMkt <- FiveperworstMkt[BearStockMkt,]

# Date Price logRet discRet logMkt

FiveperworstBearRet <- as.matrix(cbind(BearStocks, BearMkt[,2]))

MESBear = mean(FiveperworstBearRet[,4]) # Ergebnis evtl falsch weil log returns? Ja, richtig mit discrete returns


##-----------------------------------------------------------------------------------------------------------------------

#matching with the permno identifier

CompSampleStocks <- as.matrix(as.numeric(unique(stocks[,6], FALSE)))

xxx <- read_excel("Company list Acharya et al..xlsx", col_names = TRUE)

Permno <- as.matrix(xxx[,5])

Permnomatch <- as.matrix(match(CompSampleStocks[,1], Permno))   #Die Variablen aus CompSampleStocks, wo sind sie in Permno

Permnomatch2 <- as.matrix(match(Permno, CompSampleStocks[,1]))

Permnomatch <- as.matrix(which(is.na(Permnomatch)))

Permnomatch <- as.matrix(CompSampleStocks[Permnomatch,])    # Permnos of CompanySampleStocks which are not in the Acharya list

Permnomatch2 <- as.matrix(which(is.na(Permnomatch2)))

Permnomatch2 <- as.matrix(xxx[Permnomatch2,])

#93150 is CIT group,  -> Everything checks out


#---- MES Table-----------------------------------------------------------------------------------------------------
```

```
#Ticker CompName MES RealizedSES
MES = matrix(0, nrow = nrow(CompSampleStocks),5)
#RealizedSES = CompName RealizedSES
RealizedSes = matrix(0, nrow = nrow(CompSampleStocks),2)
AvgLoss <- matrix(0, nrow = nrow(CompSampleStocks),2)
Versuch <- matrix(0, nrow = 30, 1)

for(i in 1:102){
   #Date, Ticker, Stockprice, MCAP, CompNames, Permno, discr.Ret, changeMCAP, Logrets
  UniqueCompStocks <- which(stocks[,6]==CompSampleStocks[i,1])
  UniqueCompStocks <- stocks[UniqueCompStocks,]
  UniquePrice <- as.matrix(as.numeric(UniqueCompStocks[,3]))
  UniquediscRet <- as.matrix(as.numeric(UniqueCompStocks[,7]))
  UniqueCompLog <- as.matrix(log(UniquediscRet+1))
  UniqueChangeMCAP <- as.matrix(as.numeric(UniqueCompStocks[2:nrow(UniqueCompStocks),4]) - as.numeric(UniqueCompStocks[1:nrow(UniqueCompStocks)-1,4]))
  UniqueCompStocks <- as.matrix(cbind(UniqueCompStocks, rbind(0, UniqueChangeMCAP),UniqueCompLog))
   #Determine Realizes SES
  UniqueRealizedSES <- UniqueCompStocks[UniqueCompStocks[,1]>=as.numeric(as.Date("2007-07-02"))& UniqueCompStocks[,1]<=as.numeric(as.Date("2008-12-31")),]
  UniqueRealizedSES <- as.numeric(UniqueRealizedSES[complete.cases(UniqueRealizedSES),9])
  UniqueRealizedSES <- as.numeric(exp(sum(UniqueRealizedSES))-1)

   UniquematchMkt <- as.matrix(match(UniqueCompStocks[,1], FiveperworstMkt[,1]))
  UniquematchMkt2 <- as.matrix(match(FiveperworstMkt[,1], UniqueCompStocks[,1]))
  UniquematchMkt <- as.matrix(UniquematchMkt[!is.na(UniquematchMkt)])
  UniquematchMkt2 <- as.matrix(UniquematchMkt2[!is.na(UniquematchMkt2)])
   UniqueCompStocks <- UniqueCompStocks[UniquematchMkt2,]
  UniqueMkt <- FiveperworstMkt[UniquematchMkt,]

  FiveperworstTotal <- as.matrix(cbind(as.numeric(UniqueCompStocks[,7]),as.numeric(UniqueCompStocks[,8]), UniqueMkt[,2]))

  #MES[i,] <- UniqueCompStocks[3,]    nur fuer test
```

```
  #Permno CompName MES RealizedSES AvgLoss
 MES[i,] <- cbind(UniqueCompStocks[1,6], UniqueCompStocks[1,5], mean(FiveperworstTotal[,1]), UniqueRealizedSES, mean(FiveperworstTotal[,2]) )
 RealizedSes[i,] <- cbind(UniqueCompStocks[1,5],UniqueRealizedSES)
 AvgLoss[i,] <- cbind(UniqueCompStocks[1,5], mean(FiveperworstTotal[,2]))
  #Versuch <- cbind(Versuch, FiveperworstTotal[,8])
} #End of MES loop


#Avg Contribution
AvgContribution <- cbind(AvgLoss[,1],matrix(0, nrow = nrow(AvgLoss),1))
AvgContribution2 <- as.matrix(as.numeric(AvgLoss[,2]))
bb <- as.matrix(AvgContribution2[!is.nan(AvgContribution2),1])
bb <- as.matrix(sum(bb[,1]))
for (i in 1:nrow(AvgContribution2)){
 AvgContribution[i,2] <- ifelse(is.nan(AvgContribution2[i,1]), NaN, AvgContribution2[i,1]/bb) }


colnames(MES) <- c("Permno", "CompName", "MES", "RealizedSES", "AvgLoss")
colnames(AvgContribution) <- c("CompName", "AvgContribution")
colnames(TotalcheckEnd) <- c("Period", "BookTckr", "Permno", "CompName", "TotalAssets", "BookEquity", "MarketEquity", "QuasiLVG", "SIC")


MES <- cbind(MES, AvgContribution)
AppendixB <- match(MES[,1], TotalcheckEnd[,3])
AppendixB <- TotalcheckEnd[AppendixB,]
AppendixB <- cbind(AppendixB, MES)
AppendixB <- AppendixB[complete.cases(AppendixB),]


SICCodes <- as.numeric(AppendixB[,9])


DummyBroker <- as.matrix(as.numeric(SICCodes==6211))
#colnames(DummyBroker) <- c("DummyBroker")
DummyInsurance <- as.matrix(as.numeric(SICCodes==63 | SICCodes==64))
#colnames(DummyInsurance) <- c("DummyInsurance")
DummyOther <- as.matrix(as.numeric(SICCodes==61| SICCodes==62| SICCodes==65| SICCodes==67))
```

```
#colnames(DummyOther) <- c("DummyOther")

#AppendixB <- cbind(AppendixB, DummyBroker, DummyInsurance, DummyOther)

FittedRealizedSES <- as.matrix(0.02 + 0.15*as.numeric(AppendixB[,12])*100 - 0.04*as.numeric(AppendixB[,8]) - 0.1145*DummyOther - 0.1017*DummyInsurance + 0.16*DummyBroker)

FittedRealizedSES <- cbind(AppendixB[,4], FittedRealizedSES)

#colnames(FittedRealizedSES) <- c("CompName", "FittedSES")

FittedRank <- as.matrix(FittedRealizedSES[order(as.numeric(FittedRealizedSES[,2])),])

FittedRank <- cbind(FittedRank, 1:nrow(FittedRank))

colnames(FittedRank) <- c("CompName", "FittedSES", "FittedRank")

gg <- as.matrix(match(AppendixB[,4], FittedRank[,1]))

FittedRank <- FittedRank[gg,]

AppendixB <- cbind(AppendixB, FittedRank[,3])

AppendixB <- cbind(AppendixB[,11],AppendixB[,9], round(as.numeric(AppendixB[,13])*100,2), round(as.numeric(AppendixB[,12])*-100,2), AppendixB[,14], AppendixB[,16], round(as.numeric(AppendixB[,8]),2), AppendixB[,17], AppendixB[,5], AppendixB[,7])

AppendixBsorted <- AppendixB[order(as.numeric(AppendixB[,4]),decreasing = TRUE),]

colnames(AppendixBsorted) <- c("CompName","Sic", "RealizesSES", "MES", "AvgLoss", "AvgContribution", "QuasiLVG", "Rank", "TA", "ME")


#AppendixBsorted contains the original MES and LVG analysis of Acharya et al (2016).

#Now we add distress costs


##----------------------------------Distress costs-----------------------------------------------------------------

CalResults <- read_excel("Calibration results excel.xlsx",  col_names = TRUE, na = "NA") #short sample that is #needed to do the regressions

CalResults2 <- read.csv("Distresscost_Finalversion2.csv", row.names = 1) #This longer sample is needed to do #robustness check

reducer1 <- which( CalResults2[,1] == "2005-01-03") #"2005-01-03" or 2005-06-01

reducer2 <- which( CalResults2[,1] == "2006-01-03") #"2006-01-03" or 2006-06-29

CalResults2 <- CalResults2 [reducer1:reducer2,]

CalResultsNoDate <- CalResults[,3:ncol(CalResults)] #For other period

DCDate <- as.matrix(as.Date(unlist(CalResults[,2]),origin = "1899-12-30"))#changed for new period

n <- as.numeric(ncol(CalResultsNoDate)/3)

options(scipen=999) # to get rid of scientific notation


#For original period
```

```
V <- data.matrix(CalResultsNoDate[,seq(1,ncol(CalResultsNoDate),3) ]) #Unlevered asset value
TS <- CalResultsNoDate[,seq(3,ncol(CalResultsNoDate),3) ] #Tax shield
DCabs <- data.matrix(CalResultsNoDate[,seq(2,ncol(CalResultsNoDate),3) ]) #Raw distress costs
DC <-  DCabs/V
namer <- seq(2, 301, 3) #For naming the long sample with correct labels
CompNames <- as.matrix(colnames(V))
##-----------------------------------------------
#For robustness analysis these values are used
colnames(CalResults2)[namer] <- CompNames #Assigning right values for my little sample
V <- data.matrix(CalResults2[,seq(2,ncol(CalResults2),3) ]) #Unlevered asset value
TS <- data.matrix(CalResults2[,seq(4,ncol(CalResults2),3) ])#Tax shield
DCabs <- data.matrix(CalResults2[,seq(3,ncol(CalResults2),3) ]) #Raw distress costs
DC <-  DCabs/V
DCDate <- as.matrix(as.Date(unlist(CalResults2[,1]),origin = "1899-12-30"))#changed for new period
##-----------------------------------------------

DCmitDate <- as.matrix(cbind(DCDate, DC)) #fixing dates
colnames(DCmitDate) <- c("Date",CompNames) #naming column with dates
AvDC <- as.matrix(colMeans(DC, na.rm = TRUE)) #Average DC/unlevered asset value
rownames(AvDC)<- CompNames #naming Distress cost
highestDC <- round(subset(AvDC, AvDC[,1] > quantile(AvDC[,1], 0.95, na.rm = TRUE)),4) #Fix it
colnames(highestDC) <- "Distress Cost / Asset"
quantile(AvDC,0.95,na.rm = TRUE )
quantile(AvDC,0.05,na.rm = TRUE )
mean(AvDC,na.rm = TRUE )
median(AvDC,na.rm = TRUE )
min(AvDC,na.rm = TRUE )
max(AvDC,na.rm = TRUE )

#--------------------------------------------------- Makes distributional plots---------------------------
#do it for one and thereafter change to other variable of interest
x <- AvDC
h<-hist(x, breaks=10, col="red", xlab="DC / Equity",
```

```
    main="Figure 11: Histogram of DC/Equity distribution", family = "Times New Roman")
xfit<-seq(min(x,na.rm = TRUE),max(x,na.rm = TRUE),length=100)
yfit<-dnorm(xfit,mean=mean(x,na.rm = TRUE),sd=sd(x,na.rm = TRUE))
yfit <- yfit*diff(h$mids[1:2])*length(x)
lines(xfit, yfit, col="blue", lwd=2)#+  theme(text=element_text(family = "Times New Roman",size = 10))
setwd("C:/Users/heinr/Dropbox/My Theses/Estimating Distress costs/Smoothplots")
ggsave("Figure10.png", width = 5, height = 3) #Save it

#-------------Merging with Acharya-----------------------------------------------------

matchMkt2DC <- as.matrix(match(FiveperworstMkt[,1], DCmitDate[,1])) #Matching
matchMkt2DC <- as.matrix(matchMkt2DC[!is.na(matchMkt2DC)])#Matching
DCMES <- DCmitDate[matchMkt2DC,]
AvDCMES <- as.matrix(colMeans(DCMES[,2:ncol(DCMES)])) #Final MES for Distress costs
rownames(AvDCMES)<- CompNames
highestDCMES <- subset(AvDCMES, AvDCMES[,1] > quantile(AvDC[,1], 0.95, na.rm=TRUE))
lowestDCMES <- subset(AvDCMES, AvDCMES[,1] < quantile(AvDC[,1], 0.05, na.rm=TRUE))



#-------------Match with Equity Acharya------------------------------------------------
StocksCols <- matrix(0, nrow = nrow(DCmitDate),n)
DCmitDateName <- rbind(cbind("Date", t(CompNames)), DCmitDate)
for(i in 1:n){
  #Date, Ticker, Stockprice, MCAP, CompNames, Permno, discr.Ret, changeMCAP, Logrets
  UniqueCompStocksDC <- which(stocks[,5]==CompNames[i,1])
  PermnoDCmatch <- unique(stocks[UniqueCompStocksDC,6])
   UniqueCompStocksDC_new <- which(stocks[,6]==PermnoDCmatch)
  UniqueCompStocksDC <- stocks[UniqueCompStocksDC_new,]

  UniqueMCAP <- as.matrix(as.numeric(UniqueCompStocksDC[,4]))
   MatchStockDC <- as.matrix(match(DCmitDate[,1], UniqueCompStocksDC[,1]))
  UniqueMCAP <- UniqueMCAP[MatchStockDC,]
   StocksCols[,i] <- UniqueMCAP   }
```

```
colnames(StocksCols) <- CompNames


##------------------------MES distress with last day Equity-----------------------------

#colnames(DC_corr) <- CompNames #282 last day, but changes with dataset (i.e. for robustness)

DCraw <- DCabs #stockcols = ME, both numbers are in millions

DCrawDate <- as.matrix(cbind(DCDate, DCraw))

colnames(DCrawDate) <- c("Date",CompNames)

DCrawtoMES <- DCrawDate[matchMkt2DC,] #MES calculatation

AvDCrawMES <- as.matrix(colMeans(DCrawtoMES[,2:ncol(DCrawtoMES)], na.rm = TRUE)) #taking average of 5% worst market days

AvDCMEStolastME <- AvDCrawMES/StocksCols[282,]

highestDCraw <- subset(AvDCMEStolastME, AvDCMEStolastME[,1] > quantile(AvDCMEStolastME[,1], 0.95,na.rm = TRUE))

t.test(AvDCMEStolastME)


##------------------------DC MEs to last V-----------------------------

#282 last day, but changes with dataset (i.e. for robustness)

DCV <- as.matrix(cbind(DCDate, DCabs))

colnames(DCV)[2:ncol(DCV)] <- CompNames

DCV_MESday <- DCV[matchMkt2DC,]

DC_MES <- as.matrix(colMeans(DCV_MESday[,2:ncol(DCV_MESday)],na.rm = TRUE))

DCMEStolastV <- as.matrix(DC_MES/V[282,]*100)

t.test(DCMEStolastV, na.rm=TRUE)


##------------------------DC MES return-----------------------------

matchMkt3DC <- as.matrix(match(FiveperworstMkt[,1], DCmitDate[2:282,1])) #Matching

matchMkt3DC <- as.matrix(matchMkt3DC[!is.na(matchMkt3DC)])#Matching

w1 <- DCabs[2:dim(DCabs)[1],]

w0 <- DCabs[1:(dim(DCabs)[1]-1),]

DCreturn <- as.matrix(w1)/as.matrix(w0)-1

colnames(DCreturn)<- CompNames

DCrettoMES <- cbind(DCtoMCAPmitDate[2:282,1], DCreturn)

DCretMES <- DCrettoMES[matchMkt3DC,]

DCretMES_f <- as.matrix(colMeans(DCretMES[,2:ncol(DCretMES)],na.rm = TRUE))*100
```

```
t.test(DCretMES_f)

#-------------Attach to Appendix B----------------------------
matchwithB <- as.matrix(match(AppendixB[,1],CompNames[,1])) #firms match firms
CompNamesApB <- as.matrix(CompNames[matchwithB,])
AvDCMEStolastMEapB <- as.matrix(AvDCMEStolastME[matchwithB,])#
AvDCMEStolastVapB <- as.matrix(DCMEStolastV[matchwithB,])
DCretMES_fapB <- as.matrix(DCretMES_f[matchwithB,])

AvDCtoMCAPMESApB <- cbind(CompNamesApB, AvDCMEStolastMEapB, AvDCMEStolastVapB, DCretMES_fapB)
AppendixBExtended <- cbind(AppendixB, AvDCtoMCAPMESApB ) #average DC to market of , #average DC MES to asset value
colnames(AppendixBExtended) <- c("CompName","Sic", "RealizesSES", "MES", "AvgLoss",
                         "AvgContribution", "QuasiLVG", "Rank","TA",
                         "ME", "CompName",  "DC / ME_last", "DC/Asset_last", "return DC MES")

#-----------------------Do statistics of estimators---------------------------------------------------
Q = 10 #this is is distress cost to last equity for example
median(as.numeric(AppendixBExtended[,Q]), na.rm = TRUE)
mean(as.numeric(AppendixBExtended[,Q]), na.rm = TRUE)
min(as.numeric(AppendixBExtended[,Q]), na.rm = TRUE)
max(as.numeric(AppendixBExtended[,Q]), na.rm = TRUE)
quantile(as.numeric(AppendixBExtended[,Q]), 0.05, na.rm=TRUE)
quantile(as.numeric(AppendixBExtended[,Q]), 0.95, na.rm=TRUE)

#--------------------------------reduce sample to rid of NA ----------------------------------
AppendixBExtended[which(AppendixBExtended[,13] == "NaN"),13] = NA
AppendixBExtended[which(AppendixBExtended[,13] == "-Inf"),13] = NA
reducer1 <- which(is.na(AppendixBExtended[,13]))
AppendixBExtended_short <- AppendixBExtended[-reducer1,]
colnames(AppendixBExtended_short) <- c("CompName","Sic", "RealizesSES", "MES", "AvgLoss",
                         "AvgContribution", "QuasiLVG", "Rank","TA",
                         "ME", "CompName",  "DC / ME_last", "DC/Asset_last", "return DC MES")
```

```
#--------------------------perform regressions-----------------------------------------------------------

library(sandwich)

library(lmtest)

SICCodes <- as.numeric(AppendixBExtended_short [,2])

DummyBroker <- as.matrix(as.numeric(SICCodes==6211))

DummyInsurance <- as.matrix(as.numeric(SICCodes==63 | SICCodes==64))

DummyOther <- as.matrix(as.numeric(SICCodes==61| SICCodes==62| SICCodes==65| SICCodes==67))


#This is for Distress costs to Equity which situates in column 11, distress costs to asset in 12 and Distress cost returns
in #column 13

X <- cbind(as.numeric(AppendixBExtended_short [,4]),

           as.numeric(AppendixBExtended_short [,7]),

           as.numeric(AppendixBExtended_short [,11]),

     DummyOther, DummyInsurance, DummyBroker )

colnames(X)<-c("MES", "LVG","DC","Dummy other", "Dummy Insurance", "Dummy Broker")

 y <- as.matrix(as.numeric(splash2[,3])/100)

model <- lm(y ~ X)

AIC(model)

summary(model)

coeftest(model, vcov=NeweyWest(model, prewhite=FALSE))


#Fitted rank – Calculate the Model predicted SES


ModelSES <- model$coefficients[1]+as.numeric(AppendixBExtended_short [,4])*

  model$coefficients[2]+

  as.numeric(AppendixBExtended_short [,7])*model$coefficients[3]+

  as.numeric(AppendixBExtended_short [,11])*model$coefficients[4]+

  DummyOther*model$coefficients[5]+

  DummyInsurance*model$coefficients[6]+DummyBroker*model$coefficients[7]


AppendixBExtended_short <- cbind(AppendixBExtended_short,ModelSES)

#Then inserting in excel to make it nice and order it
```

SCAP and SCAP regressions

```
#This section calculates distress costs to equity and to assets performs analyzes of SCAP panel
rm(list=ls())
setwd("C:/Users/heinr/…/AcharyaReplication/MeasuringSystemicRisk/Data new")
install.packages("readxl")
library(readxl)

wrdsTCKR <- read.table("codelist.txt", header = FALSE) #original data
bookdatawrds <- read_excel("Compustat book data.xlsx", col_names = TRUE) #original data
stockdatawrds <- read_excel("CRSP StockReturns.xlsx", col_names = TRUE) #original data
Mktdata <- read_excel("CRSP Market Index.xlsx", col_names = TRUE) #original data
CompListAcharya <- read_excel("Company list Acharya et al..xlsx", col_names = TRUE) #original data
Mktdiscrete <- as.matrix(as.numeric(unlist(Mktdata[,4])))    #Output returns are discretely compounded
Mktdate <- as.matrix(as.Date(unlist(Mktdata[,9]),origin = "1899-12-30"))
#create Market vector logreturns
Mktidx <- as.matrix(Mktdata[,5])    # Mktidx <- as.matrix(Mktidx[!is.na(Mktidx)]) ----> nicht notwendig, da keine na's
Mktlog <- as.matrix(log(Mktidx[2:nrow(Mktidx),]/Mktidx[1:(nrow(Mktidx)-1),]))
# Date Logret DiscrRet
Mktret <- cbind(Mktdate[2:nrow(Mktdate),], Mktlog, Mktdiscrete[2:nrow(Mktdiscrete)])

CompNames <- bookdatawrds[,9]
Bookdata <- cbind(bookdatawrds[,14], bookdatawrds[,9], bookdatawrds[,15], bookdatawrds[,16], bookdatawrds[,11])

#Stock price data(stocks)    Date, Ticker, Stockprice, MCAP, Comp Names, Permno, discr.Ret
Stockprice <- as.matrix(stockdatawrds[,5])
Mcap <- as.matrix(Stockprice*stockdatawrds[,6])/1000    #/1000 damit gleiche Einheit wie bookdata
StockDate <- as.matrix(as.Date(unlist(stockdatawrds[,11]), origin = "1899-12-30"))
stocks <- cbind(StockDate,stockdatawrds[,3], Stockprice, Mcap, stockdatawrds[,4], stockdatawrds[,1], stockdatawrds[,7])

stocks[which(stocks[,6]==83443),5] <- "BERKSHIRE HATHAWAY INC DEL B"
stocks[which(stocks[,6]==89303),5] <- "LORRILARD INC"
```

```
Bookcheck <- which(Bookdata[,1]=='2007Q2')

Bookcheck <- Bookdata[Bookcheck,]

Equitycheck <- which(stocks[,1]==as.numeric(as.Date("2007-06-29")))

Equitycheck <- stocks[Equitycheck,]

Acharyalist <- CompListAcharya[,2:6]

# match mit Acharyalist

wo <- as.matrix(match(unlist(Acharyalist[,2]), Bookcheck[,2]))

Bookmatched <- Bookcheck[wo,]

Bookmatched[which(is.na(wo)),] <- tail(Bookdata[which(Bookdata[,2]==as.character(Acharyalist[which(is.na(wo)),2])),],1)#-----------eventuell funtioniert das Einfuegen nicht mit mehreren NA's

Matched <- cbind(Bookmatched, Acharyalist)


wo1 <- as.matrix(match(Equitycheck[,6], Matched[,9]))    #match Equity und Buchdaten nach [,2] ist Ticker, [,5] ist company name

Bookcheckmatched <- Matched[wo1,]

# PERIOD BookTicker TotalAssets BookEquity Name PERMNO Date, Ticker, Stockprice, MCAP, Comp Names, Permno, discr.Ret, SIC

Totalcheck <- cbind(Bookcheckmatched[,1:5], Bookcheckmatched[,9], Equitycheck, Bookcheckmatched[,10])

Totalcheck <- as.matrix(Totalcheck[complete.cases(Totalcheck),])

TotalcheckMcap <- as.matrix(as.numeric(Totalcheck[,10]))

QuasiLvgcheck <- as.matrix((as.numeric(Totalcheck[,3])-as.numeric(Totalcheck[,4])+TotalcheckMcap)/TotalcheckMcap)

QuasiLvgcheck <- cbind(Totalcheck[,11], QuasiLvgcheck)

#Period BookTicker Permno Companyname TotalAssets, BookEquity, MarketEquity, Quasilvg, SIC

TotalcheckEnd <- cbind(Totalcheck[,1],Totalcheck[,2], Totalcheck[,6], Totalcheck[,5], Totalcheck[,3],Totalcheck[,4],Totalcheck[,10], QuasiLvgcheck[,2], Totalcheck[,14])

CompaniesSample <- as.matrix(unique(CompNames, FALSE))

CompTckr <- bookdatawrds[,9]

UniqueTckr <- as.matrix(unique(CompTckr, FALSE))

MktRetPreCrisis <- Mktret[Mktret[,1]>=as.numeric(as.Date("2008-04-01")) & Mktret[,1]< as.numeric(as.Date("2009-03-31")),]  #Ret im passenden Zeitfenster

FiveperworstMkt <- subset(MktRetPreCrisis, MktRetPreCrisis[,2] < quantile(MktRetPreCrisis[,2],0.05))

####### Permnomatch nur notwendig um zu checken welche Firmen fehlen

CompSampleStocks <- as.matrix(as.numeric(unique(stocks[,6], FALSE)))
```

```
xxx <- read_excel("Company list Acharya et al..xlsx", col_names = TRUE)

Permno <- as.matrix(xxx[,5])

Permnomatch <- as.matrix(match(CompSampleStocks[,1], Permno))   #Die Variablen aus CompSampleStocks, wo sind sie in Permno

Permnomatch2 <- as.matrix(match(Permno, CompSampleStocks[,1]))

Permnomatch <- as.matrix(which(is.na(Permnomatch)))

Permnomatch <- as.matrix(CompSampleStocks[Permnomatch,])    # Permnos of CompanySampleStocks which are not in the Acharya list

Permnomatch2 <- as.matrix(which(is.na(Permnomatch2)))

Permnomatch2 <- as.matrix(xxx[Permnomatch2,])

#---- MES Table-----------------------------------------------------------------------------------------------------------

setwd("C:/Users/heinr/Dropbox/My Theses/FUCKSCAP")

SCAP <- read_excel("SCAPalicious.xlsx", col_names = TRUE)

namo <- as.matrix(SCAP[,1])

namo[9] <- "P N C FINANCIAL SERVICES GRP INC"

namo[11] <- "B B & T CORP"

#Ticker CompName MES RealizedSES

MES = matrix(0, nrow = 18, 5)


for(i in 1:18){

  print(i)

  #Date, Ticker, Stockprice, MCAP, CompNames, Permno, discr.Ret, changeMCAP, Logrets

  UniqueCompStocks <- grepl(namo[i], stocks[,5] )

  PermnoDCmatch <- unique(stocks[UniqueCompStocks,6])

  UniqueCompStocks <- which(stocks[,6]==PermnoDCmatch)

  UniqueCompStocks <- stocks[UniqueCompStocks,]

  UniquePrice <- as.matrix(as.numeric(UniqueCompStocks[,3]))

  UniquediscRet <- as.matrix(as.numeric(UniqueCompStocks[,7]))

  UniqueCompLog <- as.matrix(log(UniquediscRet+1))

  UniqueChangeMCAP <- as.matrix(as.numeric(UniqueCompStocks[2:nrow(UniqueCompStocks),4]) - as.numeric(UniqueCompStocks[1:nrow(UniqueCompStocks)-1,4]))

  UniqueCompStocks <- as.matrix(cbind(UniqueCompStocks, rbind(0, UniqueChangeMCAP),UniqueCompLog))


  #Determine Realizes SES
```

```
  UniqueRealizedSES <- UniqueCompStocks[UniqueCompStocks[,1]>=as.numeric(as.Date("2007-07-02"))& UniqueCompStocks[,1]<=as.numeric(as.Date("2008-12-31")),]

  UniqueRealizedSES <- as.numeric(UniqueRealizedSES[complete.cases(UniqueRealizedSES),9])

  UniqueRealizedSES <- as.numeric(exp(sum(UniqueRealizedSES))-1)

  UniquematchMkt <- as.matrix(match(UniqueCompStocks[,1], FiveperworstMkt[,1]))

  UniquematchMkt2 <- as.matrix(match(FiveperworstMkt[,1], UniqueCompStocks[,1]))

  UniquematchMkt <- as.matrix(UniquematchMkt[!is.na(UniquematchMkt)])

  UniquematchMkt2 <- as.matrix(UniquematchMkt2[!is.na(UniquematchMkt2)])

  UniqueCompStocks <- UniqueCompStocks[UniquematchMkt2,]

  UniqueMkt <- FiveperworstMkt[UniquematchMkt,]

  FiveperworstTotal <- as.matrix(cbind(as.numeric(UniqueCompStocks[,7]),as.numeric(UniqueCompStocks[,8]), UniqueMkt[,2]))

  #Permno CompName MES RealizedSES AvgLoss

  MES[i,] <- cbind(UniqueCompStocks[1,6], UniqueCompStocks[1,5], mean(FiveperworstTotal[,1]), UniqueRealizedSES, mean(FiveperworstTotal[,2]) )

  #Versuch <- cbind(Versuch, FiveperworstTotal[,8]) }

colnames(MES) <- c("Permno", "CompName", "MES", "RealizedSES", "AvgLoss")


#----------------------------------- Including distress costs--------------------------------------

setwd("C:/Users/…/SCAP ") #set working directory directory containing SCAP and distress costs

SCAP <- read_excel("SCAPalicious.xlsx", col_names = TRUE)

df <- read_excel("Distresscostsresults.xlsx",  col_names = TRUE)

DCnodates <- df[,2:55]

SCAP <- read_excel("SCAPalicious.xlsx", col_names = TRUE)

MktRetPreCrisis <- Mktret[Mktret[,1]>=as.numeric(as.Date("2008-04-01")) & Mktret[,1]< as.numeric(as.Date("2009-03-31")),]  #Ret im passenden Zeitfenster

FiveperworstMkt <- subset(MktRetPreCrisis, MktRetPreCrisis[,2] < quantile(MktRetPreCrisis[,2],0.05))

critdays <- as.Date(unlist(FiveperworstMkt[,1]),origin = "1970-01-01")

V <- data.matrix(DCnodates[,seq(1,length(DCnodates ),3)])

TS <- data.matrix(DCnodates[,seq(3,length(DCnodates ),3)])

DCabs <- data.matrix(DCnodates[,seq(2,length(DCnodates ),3)])

DCmitdate <- cbind(as.numeric(as.Date(unlist(df[,1]),origin = "1899-12-30")),DCabs)

CompNames <- as.matrix(colnames(V))

StocksCols <- matrix(data = 0, nrow = dim(DCmitdate)[1],ncol = 18)
```

```
for(i in 1:18){
  #Date, Ticker, Stockprice, MCAP, CompNames, Permno, discr.Ret, changeMCAP, Logrets
  UniqueCompStocksDC <- which(stocks[,5]==CompNames[i,1])
  PermnoDCmatch <- unique(stocks[UniqueCompStocksDC,6])

  UniqueCompStocksDC_new <- which(stocks[,6]==PermnoDCmatch)
  UniqueCompStocksDC <- stocks[UniqueCompStocksDC_new,]
  UniqueMCAP <- as.matrix(as.numeric(UniqueCompStocksDC[,4]))
  #UniqueCompStocks <- as.matrix(cbind(UniqueCompStocks, rbind(0, UniqueChangeMCAP),UniqueCompLog))
  MatchStockDC <- as.matrix(match(DCmitdate[,1], UniqueCompStocksDC[,1]))
  UniqueMCAP <- UniqueMCAP[MatchStockDC,]
  StocksCols[,i] <- UniqueMCAP }
criticaldays <- as.numeric(critdays)
matchMkt2DC <- as.matrix(match(FiveperworstMkt[,1], DCmitdate[,1]))
matchMkt2DC <- as.matrix(matchMkt2DC[!is.na(matchMkt2DC)])



#----------------------DC SCAP to LAST ME/V--------------------------------
DCraw <- DCabs #stockcols = ME, both numbers are in millions
AvDCraw <- as.matrix(colMeans(DCraw, na.rm = TRUE)) #taking average of vector of ratios
#rownames(AvDCtoMCAP)<- CompNames
#highestDCraw <- subset(AvDCtoMCAP, AvDCtoMCAP[,1] > quantile(AvDCtoMCAP[,1], 0.95,na.rm = TRUE))
#fix that
DCrawDate <- as.matrix(cbind(DCmitdate[,1], DCraw))
colnames(DCrawDate) <- c("Date",CompNames)
DCrawtoMES <- DCrawDate[matchMkt2DC,] #MES calculatation
AvDCrawMES <- as.matrix(colMeans(DCrawtoMES[,2:ncol(DCrawtoMES )], na.rm= TRUE)) #taking average of
5% worst market days
AvDCMEStolastME <- AvDCrawMES/StocksCols[261]
AvDCMEStolastV <- AvDCrawMES/V[261]
#Attaching SICC
kk <- c()
names <- as.matrix(TotalcheckEnd[,4])
for ( i in 1:18){
```

```
kk[i] <- which( SCAP[i,1] == names )
}
SICCCODES <- as.matrix(TotalcheckEnd[kk,c(4,9)])
AppendixC <- cbind(SCAP,AvDCMEStolastME,AvDCMEStolastV, SICCCODES)
colnames(AppendixC)[11:12] <- c("Names", " SICCCODES ")

#---------------------------------------------
#Regressions, with different estimators
library(sandwich)
library(lmtest)
SICCodes <- as.numeric(as.matrix(AppendixC[,12]))
DummyBroker <- as.matrix(as.numeric(SICCodes==6211))
DummyInsurance <- as.matrix(as.numeric(SICCodes==63 | SICCodes==64))
DummyOther <- as.matrix(as.numeric(SICCodes==61| SICCodes==62| SICCodes==65| SICCodes==67))
Dummyprob <- as.numeric(as.matrix(AppendixC[,5]))<=0
Dummyprob <- ifelse(Dummyprob == FALSE, 1, 0)
#our extensions
X <- cbind(as.numeric(AppendixC[,7]), as.numeric(AppendixC[,8]) ,as.numeric(AppendixC[,10]))#, Dummyprob)#,as.numeric(ProbineAPP[,8]))
#7 = MES, 8 = LVG, 10 = DC to equity, 11 = DC to asset
y <- as.matrix(as.numeric(AppendixC[,6])*100) #SCAP/TIER1 <- 5, SCAP/TIER1comm <- 6
options(scipen=999)
model <- lm(y ~ X)
AIC(model)
summary(model)
coeftest(model, vcov=NeweyWest(model, prewhite=FALSE))
#-----------------------------------------------------------------------------------
```

Robustness – graphs and tables

```
#Graphing
#We made files containing distress costs to equity, MES and LVG for different time intervals
options(scipen=999) #Get rid of scientific
splash1 <- read.csv("20052006v2.csv", row.names= 1) #june 2005 to june 2006
```

```
# splash1 <- read.csv("20052006.csv", row.names= 1) #January 2005 to January 2005

splash2 <- read.csv("20062007.csv", row.names= 1) #Original

splash2 <- splash2[,-c(5,6,11)] #Removing contribution numbers and an column that contain firms names (which is
#already in there)

splash1<-splash1[-28,]

splash1<-splash1[-86,]#86 with others


jj <- c()

for (j in 1:length(splash1[,1])){

print(j)

jj[j] <- which(as.character(splash1[j,1]) == as.character(splash2[,1]))   }

splash2 <- splash2[jj,]

newdf <- cbind(as.matrix(splash1[,1]),as.matrix(splash1[,13]),as.matrix(splash2[,1]),

              as.matrix(splash2[,13]))

x <- as.numeric(newdf[,2])

y <- as.numeric(newdf[,4])

Name <- as.vector(newdf[,1])

ticker <- c()

for (i in 1:81){

  print(i)

  kk <- which(stocks[,5] == Name[i])

  kk <- kk[length(kk)]

  ticker[i] <- unique(stockdatawrds[kk,3])

}#end loop


ticker <- as.matrix(ticker)

rmv <- which(ticker == "character(0)")

ticker[rmv] <- ""

mm <- as.data.frame(cbind(Name, ticker))

library(ggplot2)

#install.packages("extrafont")

library(extrafont)

font_import()

loadfonts(device = "win")
```

```
fonts()

Z <- as.data.frame(cbind(x,y)) #make data in data frame to use ggplot

#Make plot

g<-ggplot(data = Z, aes(y <- Z[,2], x = Z[,1], color= "DC_MES/Asset_last"))+
  geom_point(color="firebrick",size=1)

g <- g+geom_text(aes(label=as.character(ticker)),hjust=-0.1, vjust=0, size = 2, color = "black")

#( ", "in %", " )")

g<-g+labs(x=expression(paste("DC_MES/Asset_Last 03-01-2005 to 03-01-2006" )), y="DC_MES/Asset_Last 2006-06-01 to 2007-06-30",
          title="Figure 14: Stability of DC_MES /Asset_Last over time")+
  theme_bw()+
  theme(text=element_text(family = "Times New Roman",size = 10))

g <- g+stat_smooth(method="lm", se=FALSE, color = "blue", size = 0.5)

g # show plot
```