Four Essays on the Relation between Distress Risk and Equity Returns

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1. Introduction

The objective of this document is to summarize the research context of the work I have done in the last three years as research associate and PhD student at the University of Bremen. The document presents main ideas and methodologies that have guided and accompanied me along the way. The central question of the thesis is whether firm distress risk explains stock returns. This question is important because it has been suspected that distress risk might reconcile a growing evidence on patterns in returns, which are otherwise hard to explain, with conventional economic theory.

The main motivation for the thesis is that research on the cross-section of stocks seems to be in a state of “chaos” (Cochrane 2011, p. 1058). Harvey et al. (2015) survey the literature and document hundreds of variables that have been proposed to explain average stock returns. Most of these variables are firm characteristics. The main concerns of this empirical literature are to either propose new proxies for risk or to even challenge the conventional risk-return relation in general. But the abundance of papers and variables leaves us in a state of confusion. First, how many independent firm characteristics determine expected returns? Firm characteristics are correlated with each other and the countless attempts to associate different characteristics with returns amount to an unprecedented data mining. There is a need to condense the set of explanatory variables. Second, why do common firm characteristics explain expected returns? This is the deeper economic question. Firm characteristics are a particularly nasty type of variable because they rarely give rise to straightforward interpretations. Explaining why common characteristics are related to returns will often amount to mere speculation because many characteristics are highly ambiguous. The goal of my thesis is to unambiguously define firm distress risk as a characteristic in order to assess whether it can explain patterns in returns with regard to other common characteristics. Distress risk is a popular explanation for several characteristics (Fama & French 1995, 1996). The thesis assesses whether distress risk can answer the two questions posed above by investigating its ability to explain patterns in returns. This task is important because it could help to reconcile empirical evidence on asset pricing “anomalies” with conventional risk-based explanations.

The theory is straightforward. The Consumption-Based Capital Asset Pricing Model (CCAPM), the most general absolute asset pricing model, states that investors worry about consumption risk. The Intertemporal Capital Asset Pricing Model (ICAPM) is nested in this framework and it is the workhorse for modern empirical research. The theory is based on the premise that investors
dislike assets which do badly when they are otherwise desperate. Assets that co-
vary positively with their “hunger” must compensate them with higher returns.
For instance, a stock which does badly in a recession, when investors are likely
to be simultaneously adversely affected by other shocks, is regarded as unattrac-
tive and should only be considered by investors if it offers higher average returns.
Hence, the empirical literature, which is now charged with data-mining, should
indeed be looking at state variable risk \cite{Cochrane2007}. Fama & French \cite{Fama1995, Fama1996}
argue that distress risk is an ICAPM state variable and suggest that firm
distress risk proxies for the risk associated with this state variable. Investors who
have outside labor income should dislike owning the stock of high distress risk
firms because the stock of these firms is expected to do badly just when the odds
of loosing jobs increase. Distress risk is a plausible ICAPM state variable because
this description should characterize the average investor.

The actual empirical work is presented in four papers in the annex of this document
and the main empirical findings are briefly summarized in section 4. Specifically,
the research has produced three results: First, evidence from event studies suggests
that the above sketched relation between distress risk and stock returns exists.
Investors discount the value of distressed firms and are especially reluctant to
finance distressed firms in times of aggregate contraction. Stock market reactions
to rating events are more pronounced in times of aggregate contraction, there
is a flight to safety in the stock market. This phenomenon appears to be highly
persistent. The European Central Bank (ECB) has recently tried to counter it with
a battery of unconventional monetary policy measures, but my evidence shows that
these programs are rather unsuccessful in stimulating the propensity of investors
to finance distressed firms. Second, models to measure default risk at the firm level
are evaluated in a new and unique database on corporate defaults in the German
stock market. This is a rather technical issue that bears clear recommendations
for practical implementations in risk management. Third, the high accuracy risk
scores of these models are used to assess the relation between distress risk and
long-run average stock returns. The results remain inconclusive in this case, but
they suggest a few general insights for future research. In spite of all efforts to
reduce the ambiguity of distress risk as a firm characteristic (by defining it as a
powerful forecaster of defaults), viewing distress risk as a firm characteristic, which
is common in the empirical literature \cite{Campbell2008, Dichev1998, Griffin2002}, is potentially misleading. Pure default risk affects only a small
proportion of firms to a significant extent. Stock investors should therefore be able
to diversify it away.

The theoretical context presented in this document is very powerful and com-
prehensive. Some of the world’s most renowned researchers have looked into the
questions I ask in this thesis. To that end, I do regard my empirical work as small steps towards a better understanding of the relationship between equity returns and distress risk. Specifically, I believe they contribute in two significant ways to the existing literature. First, they are to a considerable extent to be regarded as out-of-sample tests. The vast majority of empirical research in finance is based on US data and models, which are commonly used in research and practice, have rarely been put to a test in other samples. This is troublesome because there are important differences between the US financial system and, say, the German market. The latter is clearly defined as a bank-based system where equity ownership is low, attitudes toward financial risk are different and so on. By looking specifically at markets other than the US, I try to account for these factors in assessing how well the findings and models from the US can be transferred to other markets. As a consequence, a big challenge of my work has been to collect relevant data. Data on US financial markets are now so easily accessible through modern research databases, it does not take programming skills at all to generate highly sophisticated samples. By contrast, all of the data I have worked with required combining several sources and a lot of very cumbersome manual work has been done to generate informative samples. I regard this as the second contribution of my thesis. In the light of an intense research activity and competition between researchers in our field, the uniqueness of data is a distinguishing feature of my work.

The structure of this document is as follows: Section 2 discusses the main theoretical ideas behind the research. Section 3 is devoted to explaining the methodological framework. It contains a review of several popular models to forecast corporate defaults and an up-to-date discussion of methods in empirical asset pricing. The four research papers I have written are presented in section 4. Section 5 concludes. The appendix contains information on collaboration with peers, the four papers, a declaration of authorship and my curriculum vitae.

2. Theory and Motivation

Any analysis should start off with some intuition. Over the last years, I have repeatedly discussed my research with people from diverse backgrounds. The typical intuitive answer reads: “Distressed equity should yield higher returns. You would demand a premium as a debt investor in a distressed firm, equity investors should be compensated similarly!” Behind this statement is the idea that debt and equity are priced in a similar fashion.
The upper panel shows a histogram of daily excess returns on the MSCI EMU index in percentages. The lower panel shows a histogram of a CDS spread index constructed from the French, German, Italian and Spanish cross-section of CDS spreads in basis points. Further details on the data are provided in the fourth research paper in appendix B.

Figure 1: Distribution of excess equity returns and CDS spreads

Indeed, some empirical research suggests there are several common risk factors in returns on stocks and bonds (Fama & French, 1993; Schaefer & Strebulaev, 2008). However, Fama & French (1993) find bond market factors alone can explain very little of the cross-sectional variation of equity returns. Before opening up another dimension (the cross-section), we should ask whether the intuition is visible in the time series. Figure 1 illustrates the different characters of equity and debt-related securities as plots of the distributions of excess returns on the MSCI European Monetary Union (EMU) index and a Credit Default Swaps (CDS) spread index for the EMU.

Equity returns, displayed in the upper panel of figure 1, are much more symmetrically distributed than credit spreads. A characteristic feature of the distribution of credit-related securities is a right skew: a large fraction of firms has rather low credit spreads and, at most times, the credit market mirrors exactly this. It appears that equities fluctuate permanently in both directions reflecting a potentially

\footnote{See, for instance, table 8a in Fama & French (1993).}
large number of (risk) factors affecting the prospects of firms. Sometimes there are good news, sometimes things look rather bleak. On average, things appear to be just fine and equity investors receive slightly positive excess returns. Equity investors have to endure much and this is their reward. Credit spreads are strictly larger than zero. Hence, debt investors receive a compensation for something that is always there. The risk is not a constant, but there is no pronounced tendency for things to cancel out. This is the nature of credit risk and this thesis investigates whether such risk can be found in equity returns.

In the following, I turn to some theoretical foundations by summarizing models that are now frequently used to price stocks. The goal is to discuss why distress risk might play a role in these models.

2.1. Asset Pricing Theory: From the Consumption Model to the ICAPM

Conventional asset pricing models are based on solid theoretical foundations. For instance, Markowitz (1952) portfolio theory and a neoclassical equilibrium framework gave rise to the Sharpe (1964) and Lintner (1965) Capital Asset Pricing Model (CAPM) - a model taught in undergraduate finance courses. Therefore, it is not introduced here. The empirical failures of the CAPM are legendary and too numerous to summarize here. After all, the one factor CAPM has frequently been criticized for not being able to explain why different stocks earn vastly different returns on average. Consequently, subsequent empirical work, pretty much under the aegis of Fama & French (1992), has found many other unexplained patterns in the cross-section of equities. Subrahmanyam (2010) offers a literature review. In general, this body of research can be regarded as an extensive explorative data analysis without clear theoretical foundations. Explaining the empirical findings, i.e. linking them back to a theory, is mighty difficult. The crux of the asset pricing research of the last decades appears to be that going from the theory to the data has not yielded fully convincing empirical results, whereas the road from the data to the theory is equally long and thorny.

2.1.1. The Consumption Capital Asset Pricing Model

In light of this experience, it is very helpful to evaluate what the most general asset pricing models, which are far more generic than the single factor CAPM, suggest we should find in the data. The Rubinstein (1976), Breeden & Litzenberger (1978)
and Breeden (1979) CCAPM is the most general absolute asset pricing model, which nests all other common models as special cases (Cochrane 2005, Chp. 1-4). Absolute asset pricing models price assets given fundamental sources of risk, whereas relative asset pricing models price one security given others. The goal of this thesis is to assess whether distress risk is a fundamental source of risk in equity returns. Thus, it is important to understand what the ancestor of all absolute pricing models, the CCAPM, postulates. This model is much more parsimonious with regard to assumptions than the textbook CAPM. All it takes to derive this model is to assume investors maximize lifetime utility, can trade securities at no transaction costs and are not credit-constrained. According to the CCAPM asset prices \( p \) depend on the choice between saving and consumption \( c \) and are through a stochastic discount factor \( m \) linked to consumption growth. The fundamental CCAPM asset pricing function is stated in (1):

\[
p_t = E_t[m_{t+1} \times x_{t+1}]
\]

with \( m_{t+1} = \psi \times \frac{u'(c_{t+1})}{u'(c_t)} \),

\( x_{t+1} = p_{t+1} + d_{t+1} \).

The stochastic discount factor \( m \) depends on subjective impatience \( \psi \) and the marginal utility of today’s and tomorrow’s consumption \( u'(c) \). \( x_{t+1} \) is the absolute profit consisting of tomorrow’s price and dividends. Conventionally, such a functional form is simply called a \( p = E[m \times x] \) model. Often, it is convenient to think about this model in terms of returns instead of prices. Because the asset return is given as \( R_{t+1} = \frac{x_{t+1}}{p_t} \), (1) is also frequently stated as

\[
1 = E[m \times R].
\]

The elegance of this simple structure lies in the way it enables us to straightforwardly derive many very general insights from it. In the following, time subscripts have been dropped for notational simplicity if they are not necessary. Let \( R = (1 + r) \) denote the rate of return. The pricing kernel (1) can be rearranged to represent the risk-free rate \( r^f \). Because there is no uncertainty about \( R^f = (1 + r^f) \), it can be represented as \( R^f = \frac{1}{E[m]} \). Furthermore, multiplying out inside the expectation parameter in (1) yields:

\[2^\text{Proof: Consider the return on an individual security } i:\]

\[1 = E[m \times R_i]\]
\[ p = E[m] \times E[x] + Cov[m, x]. \]  

(3)

Substituting \( E[m] \) with \( \frac{1}{\bar{r}} \) establishes a direct relation between prices and consumption risk:

\[ p = \frac{E[x]}{Rf} + Cov[m, x]. \]  

(4)

The first term on the right-hand side of (4) is the present value of the payoffs. The second term is a risk surcharge. The most important implication of the CCAPM is that investors dislike assets that are expected to lose value when consumption growth is low. To see this more clearly, we can write out the stochastic discount factor using (1) in (4) to obtain

\[ p = \frac{E[x]}{Rf} + \frac{Cov[\psi \times u'(c_{t+1}), x]}{u'(c_t)}. \]  

(5)

Investors discount prices of assets which are negatively correlated with marginal utility of consumption. Conventional economic theory suggests \( u'(c) \) is decreasing in \( c \). Therefore, marginal utility of consumption is especially high when consumption is low, for instance during a recession. Prices of assets whose payoff \( x \) is low in such states are discounted according to (5) to incentivize risk averse investors to buy these assets in spite of the negative correlation. In other words, investors require premiums for holding assets that are expected to generate negative payoffs when they are hit by negative consumption shocks. Being an absolute asset pricing model, the CCAPM establishes a positive relation between returns and the most fundamental risk among all risks in economics: consumption risk.

This model is comprehensive and concise, there are hardly good economic arguments against the way it establishes a relation between fundamental macroeconomic risk and asset prices. However, the empirical evidence is not very supportive. To test it, one needs data on aggregate consumption, which comes with many

\[ 1 = E[m] \times E[(1 + r_i)] \times Cov[m \times (1 + r_i)]. \]

Provided that asset \( i \) is risk-free, \( Cov[m \times (1 + r_i)] = 0 \). Hence:

\[ Rf = \frac{1}{E[m]}. \]
measurement issues and is, at best, available in monthly frequency (Breeden et al. 1989). Empirically, the seminal test of the CCAPM by Mehra & Prescott (1985) has given rise to the equity premium puzzle. A few further rearrangements establish a direct testable relation between asset price risk and consumption risk. Multiplying out inside the expectations parameter in (2) for a given asset $i$ yields

$$1 = E[m] \times E[R_i] + \rho_{m,R_i} \times \sigma_{R_i} \times \sigma_m. \quad (6)$$

This expression delivers the so-called Hansen & Jagannathan (1991) bound, which establishes bounds on the levels of returns given levels of risk:

$$E[R_i] = \frac{1}{E[m]} - \rho_{m,R_i} \times \sigma_{R_i} \times \frac{\sigma_m}{E[m]} \quad \Leftrightarrow \quad E[R_i] = R_f - \rho_{m,R_i} \times \sigma_{R_i} \times \frac{\sigma_m}{E[m]} \quad (7)$$

According to (7), risk-free securities earn the risk-free rate, securities with a positive correlation coefficient $\rho_{m,R_i}$ are positively correlated with the discount factor and thus, due to the conventional assumptions regarding marginal utility (see (5)), negatively correlated with consumption. Such assets are a hedge for consumption risk, they have high payoffs when consumption is low, and yield lower returns than the risk-free rate. Typically, such assets are just as hard to find as negative correlations in real financial markets. Finally, securities that are negatively correlated with the discount factor are the most risky assets from the perspective of a consumer. Consequently, they must reward investors with higher returns. Correlation coefficients like $\rho_{m,R_i}$ cannot exceed 1 in absolute terms. Hence, (7) can be rearranged to

$$\left| \frac{E[R_i] - R_f}{\sigma_R} \right| \leq \frac{\sigma_m}{E[m]}. \quad (8)$$

The left-hand side of (8) is the well-known Sharpe (1964) ratio. It cannot exceed the right-hand side due to the constraint on the correlation coefficient. The expressions (7) and (8) relate the excess return on any security $i$ to the volatility of the

3 A huge body of literature is devoted to measuring and explaining consumption growth. Work by some of the most renowned finance researchers on this topic underlines how important this matter is for asset pricing (Campbell 1991, Cochrane 1991, Thaler 1990).
discount factor and the correlation of the asset with the discount factor. Moreover, assuming a constant relative risk aversion utility function \( u(c) = \frac{c^{1-\theta}}{1-\theta} \) in (1) with \( u'(c) = c^{-\theta} \) and risk aversion \( \theta \) allows for a representation of the right-hand side of (8) as

\[
\left| \frac{E[R_i] - R_f}{\sigma_R} \right| \leq \frac{\sigma_m}{E[m]} \approx \theta \times \sigma(\Delta ln(c)).
\] (9)

As stated before, investors require a larger compensation for asset price risk when consumption risk \( \sigma(\Delta ln(c)) \) or risk aversion is large. The infamous equity premium puzzle is buried in these expressions. Mehra & Prescott (1985) report the long-run historical average return on US equities as \( r = 0.0698 \) with a standard deviation of \( \sigma_R = 0.1654 \) and the risk-free rate over the same time period (1889-1976) is given as \( r_f = 0.0080 \). These values yield a Sharpe ratio of 0.3736. According to (9), this is to be put in the context of risk aversion and consumption growth volatility. Mehra & Prescott (1985) find that the volatility of consumption growth is only 0.0357 and this would require a risk aversion coefficient of \( \theta \approx 10.5 \). But such a level of risk aversion is completely at odds with the data. A large strand of literature summarized by Mehra & Prescott (1985) suggests the coefficient should be well below 1. Hence, observed equity premiums are too large to be consistent with the CCAPM (equity premium puzzle). The equity premium puzzle has inspired a vast body of research that has been summarized by Kocherlakota (1996). In spite of these efforts, it continues to be regarded as a puzzle.

This thesis aims to contribute to explaining the cross-section of equity returns. Expression (7) suggests the CCAPM could do this in principle. Several authors have examined the ability of the model to explain cross-sectional return differences. Empirical work on the CCAPM proceeds as follows. As a first step, the \( 1 = E[m, R] \) structure is explicitly written down assuming a specific utility function and then linearized to obtain an empirically tractable specification. Assuming a constant relative risk aversion utility function, Mankiw & Shapiro (1986) derive

\[ \text{Reference} \]

\[ \text{Reference} \]

\[ \text{Reference} \]

\[ \text{Reference} \]
\[ r_i = r^f + (E[r^m] - r^f) \times \frac{\text{Cov}(r_i, c_{t+1})}{\sigma_c} \]  

which gives rise to straightforward estimation techniques. In analogy to the familiar \textbf{CAPM}, the normalized covariance on the right-hand side of (10) is the asset’s consumption beta. The results presented by Mankiw & Shapiro (1986) suggest consumption betas contain much less information on stock returns than the conventional \textbf{CAPM}. Similar results have been obtained by Cochrane (1996) and Lettau & Ludvigson (2001). Even though there is little to criticize in the way the \textbf{CCAPM} establishes a relation between consumption risk and asset prices from a theoretical perspective, the empirical results are not (yet) fully supportive of this model.

\subsection*{2.1.2. The Intertemporal Capital Asset Pricing Model}

For these reasons, the empirical literature has turned to alternative models relating expected returns to generic state variables. A special case of the \textbf{CCAPM} is the Merton (1973) \textbf{ICAPM} which is more suitable for empirical work. In deriving the \textbf{ICAPM}, it is assumed that consumers do not only optimize with respect to current and future consumption but also with respect to certain time variant state variables that characterize future investment opportunities. If investment opportunities depending on state variables vary over time, an asset’s exposure to the state variable will determine its average return.

What might these state variables be? Following the \textbf{CAPM} and \textbf{CCAPM} logic an obvious state variable is wealth.\footnote{The consumer optimization problem underlying all asset pricing models can be formulated in terms of wealth instead of consumption because wealth, savings and consumption are related to each other through budget constraints.} In the \textbf{CAPM} and the \textbf{ICAPM} wealth as a state variable is typically approximated by the market portfolio, i.e. the return on a portfolio of all risky assets in the economy. Apart from this rather intuitive insight, there might be a plethora of further state variables \(z\), so linearization of the \textbf{ICAPM} including these state variables as part of the consumer optimization problem yields specifications like

\[ E[r_i] - r^f = \beta^m_i \times (r^m - r^f) + \sum \beta^z_i \times \mu^z, \]  

where \(r^m\) is the return on the market portfolio, \(\mu^z\) are the prices of state variable...
risk and $\beta$ coefficients represent the sensitivities to these risk factors. Expressions like (11) are nested in the CCAPM framework. All it takes in addition to (10) is to assume that consumption wealth risk can be reasonably approximated by the return on the market portfolio. Moreover, the simple CAPM is nested in the CCAPM because it contains the assumption that no additional state variable and just consumption wealth risk approximated by the market portfolio is relevant for the consumer optimization problem. The ICAPM and the CAPM are just approaches to substitute consumption out of the discount factor (Cochrane 2005, Chp. 9).

It is evident that (11) alone has the potential to spark the enthusiasm of empirical researchers. On the surface, it might appear to provide the empirical researcher with a “fishing license” (Fama 1991), according to which relating arbitrary exogenous variables to asset returns would be justified on the grounds of the ICAPM. However, the standards for an ICAPM state variable are higher. It is important to recall that we are dealing with state variables which are of special hedging concern to investors (Merton 1973). For instance, a recession might be a state of concern for investors. When investors care about their wealth in recessionary states and dislike assets which worsen their situation in such times, they drive up current prices for assets which are expected to provide a safe haven in recessions and drive down prices of assets which are expected to collapse in such times. Consequently, the former asset (the recession hedge) should yield a lower average return, whereas the latter asset (the risky asset) should yield a higher average return. This example illustrates that a variable can only be a state variable in (11) if it forecasts aggregate macroeconomic activity (Cochrane 2005, Maio & Santa-Clara 2012, Boons 2016). This restriction is the ultimate safeguard against an interpretation of the ICAPM as a fishing license for new factors.\footnote{This restriction is very often ignored in the literature. Strictly speaking, it is even ignored by Fama & French themselves.}

The discussion about ICAPM state variables is the origin of the debate about the relation between distress risk and equity returns. Fama & French (1996) conjecture distress risk is a state variable because, for most investors, human capital (labor income) is an important asset, too. Investors, who are employed in industries with high distress risk should avoid holding the stocks of these firms because a negative shock to these firms would reduce both the value of their human capital and the value of their financial assets. Fama & French (1996), who have suggested this explanation for the value factor, directly connect to the CCAPM and ICAPM theory with this line of argumentation.
2.2. Empirical Asset Pricing: Factor Models and their Failures

The Fama-French distress proposition is an important motivation for the empirical work in this thesis. However, it is helpful to look at what empirical asset pricing models based on the theory presented above have accomplished so far before elaborating on the empirical relationship between distress risk and equity returns further. As will become apparent later, assessing the relation between distress risk and equity returns can be regarded as a key battleground in modern finance.

Fama & French (1992, 1993) proposed the Fama & French-3-factor-model (FFM) in a time when the inability of the single factor CAPM to explain returns and patterns of returns with respect to size and book-to-market ratios became widely accepted empirical facts. The factors Small-Minus-Big (SMB) and High-Minus-Low (HML) are supposed to summarize these common pattern in stock returns. The empirical FFM is defined as

$$E[r_i - f^1] = \alpha_i + \beta^{nm}_i \times (r^m - r^f) + \beta^{SMB}_i \times SMB + \beta^{HML}_i \times HML,$$

where zero pricing errors imply $\alpha = 0$. Overall, the work of Fama & French manifested in the FFM and a wide variety of articles, can be associated with two goals. The first goal, the main concern brought forward in Fama & French (1992, 1993, 2012), is to show how well empirical asset pricing models, especially the FFM explain the cross-section of stock returns. The first goal is, for the most part, a statistical exercise. The second goal, which is most clearly formulated in Fama & French (1996) and Fama (1996) but visible in all other papers, too, is to link the size (SMB) and value (HML) factors to state variables of special hedging concern. Without this claim, there is not much that seems to connect (12) with the CCAPM and ICAPM theory discussed above and the FFM may even appear ad-hoc. Therefore, the second goal is about the economic content of the FFM.

The empirical strengths and weaknesses of the FFM are now very well known. The model has made its way into the textbooks and is now standardly used in practical applications like corporate valuation or the evaluation of portfolio managers. Nevertheless, there is a vast body of literature on the empirical failures of the model. Apart from size and value effects, researchers have detected many other patterns in stock returns. The “anomalies-literature” is too extensive to summarize here, selective summaries are provided by Richardson et al. (2010) and Schwert (2003). The most popular “anomaly” in this regard is the Jegadeesh & Titman (1993) momentum effect. Momentum cannot be explained by the FFM and has given rise
to the momentum factor Winner-Minus-Loser (WML) (Carhart 1997). Moreover, an astonishingly large number of further “anomalies” has caused researchers to propose new factors. In a thorough review of the literature, Harvey et al. (2015) find 313 articles published in top academic journals or presented at top conferences that propose 316 different factors for multifactor models. Cochrane (2005, 2011) calls this phenomenon a “factor zoo”. Obviously, the empirical methodology of Fama & French has sparked a debate, which has made some things much less clear. A growing strand of the methodological literature expresses skepticism with regard to the enormous number of patterns that have been detected in stock returns. Concerns about data-snooping, correctly sized test statistics and publication bias are obvious. Accounting for these issues is expected to reduce the number of “anomalies” and factors in the future (Harvey et al. 2015, Lewellen et al. 2010, McLean & Pontiff 2016).

An important motivation for this thesis is the controversial debate about the economics behind the FFM. This debate is centered on the question whether the FFM risk factors SMB and HML are compensation for systematic risk in the economy. As explained above, Fama & French are the main proponents of the risk hypothesis. However, they acknowledge their work remains somewhat incomplete as they conclude that their results “do not cleanly identify the two consumption-investment state variables of special hedging concern to investors that would provide a neat interpretation of our results in terms of Merton’s (1973) ICAPM” (Fama & French 1996, p.82). Roughly a decade later, the risk camp in finance has presented some interesting new evidence in favor of risk-based explanations for the FFM factors. Hahn & Lee (2006) show changes in the default and term spreads explain size and value premiums in the US stock market. Petkova (2006) proposes a factor model based on shocks to the dividend yield, term and default spreads as well as the short rate. She shows that these variables are correlated with SMB and HML. Moreover, her model based on macroeconomic shocks has superior explanatory ability than the FFM. These results support the notion of the FFM as an ICAPM. More recently, the literature has acknowledged the restriction on empirical work related to the ICAPM explained in section 2.1.2: state variable candidates must forecast macroeconomic activity. Maio & Santa-Clara (2012) and Boons (2016) demonstrate the ability of several macroeconomic variables to do so is consistently priced in the cross-section of stocks. According to these results, which are based on the condition that the ICAPM is no “fishing license”, there is no “factor zoo” but ample evidence for risk-based explanations.

On the other side of the fence is behavioral finance. Advocates for behavioral
explanations oppose the assumption of rational agents, which is essential for the CCAPM and its nested models. Instead, they claim the patterns in stock returns reflect investor over- and underreaction or mispricing in short. De Bondt & Thaler (1987) argue seasonal patterns in stock returns can be explained by under- and overreaction. Lakonishok et al. (1994) find that investors tend to naively extrapolate past earnings growth into the future and thereby underestimate the true value of firms with high book-to-market ratios. According to this argumentation, incompetent investors drive up prices of growth firms and drive down prices of value firms creating a value effect in stock returns. In a seminal paper, Daniel & Titman (1997) demonstrate stock returns covary simply because they share certain characteristics and not because they load on risk factors as stated in the models summarized above. From the perspective of the risk camp, this evidence is disturbing as anything beyond behavioral explanations for these results in hard to conceive. The results brought forward by behavioral finance, Shiller (2003) provides a literature summary, put the use of multifactor models like (12) into question.

Where do we stand now? Capital market theory, most notably the CCAPM, establishes a distinct relation between risk and returns. Ultimately, there should be only one risk that explains returns: consumption risk. Empirical models, like the FFM are supposed to be clever tricks to replace consumption risk with easy to measure firm characteristics. However, the empirical procedures have opened the floodgates for many different characteristics that are associated with failures of the models. These errors are manifested in a vast “anomalies” literature. After all, such errors must not be lethal, as all models are wrong, but some are useful (Box & Draper 1987). However, effectively, we are now dealing with a highly multidimensional problem. There is a plethora of characteristics and we still know relatively little about the economics behind them. The big problem is, the relation between risk and returns, which was established by theory, seems to be evaporating in the data. Are common characteristics proxies for risk? If so, what kind of risk do they measure? Answering these questions is necessary in order to find out whether models like the FFM are variants of the ICAPM/CCAPM.

2.3. Distress Risk - A Missing Link?

Fama & French (1993, 1995, 1996) conjecture distress risk is a state variable in the ICAPM and the SMB and HML factors are proxies for this state variable. Distress risk has four properties that render it an appealing state variable candidate:
1. Distress risk fluctuates over the business cycle. Figure 2 illustrates this statement using data on corporate defaults in the German stock market, which are used in two of the empirical research papers of this thesis. Defaults peak during the two recessions in 2003 and 2009. Hence, default risk might very well be regarded as a recession state variable (Cochrane 2007).

2. The average investor should be exposed to distress risk regardless of her asset market exposure. Fama & French (1996) make exactly this point. When investors have labor income in the private sector, their wealth will be adversely affected by default risk in low states, for example due to layoffs. This could create correlation between consumption risk and asset price risk that CCAPM/ICAPM investors dislike.

3. Estimating distress risk is less error prone than measuring consumption growth. Admittedly, the former is not exactly trivial. One of the research papers of this thesis deals with bankruptcy forecasting models and section 3 explains several default risk indicators in detail. However, distress risk measures rely on audited accounting and stock market data, not on surveys, which researchers need to conduct in order to gauge consumption volatility (Breeden et al. 1989, Campbell 1991, Cochrane 1991). The quality of data in modern financial databases, like Thomson Reuters Datastream, is by no means perfect, but it should be much better than the quality of data which can be reached when questioning a representative sample of households. Moreover, distress risk estimates are available in higher frequency, whereas consumption volatility data is typically low-frequency data.

4. Distress risk can be stated as a firm characteristic. In fact, it is most intuitive to specify distress risk as a firm attribute, perhaps as a probability of default (PD) (see section 3 for further details). This gives rise to straightforward interpretations and well-known methods in finance. Furthermore, it allows us to connect to a large body of research. Several characteristics that are known to be correlated with stock returns are associated with distress risk. For instance, small firms are much more likely to default on debt payments. Various default risk models use firm size as a predictor and underline that it is negatively related to risk (Campbell et al. 2008, Ohlson 1980, Shumway 2001). Book-to-market ratios have likewise been found to be associated with default risk. Campbell et al. (2008) and Ding et al. (2012) show value firms are more likely to default than growth firms.


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11 The third spike in 2013 is due to a large wave of defaults in the solar cells industry.
Figure 2: Corporate Defaults in the German Stock Market

suggest it as a risk-based explanation for the FFM factors. The big question is whether distress risk is a missing link reconciling multifactor models with a CCAPM/ICAPM interpretation. Obviously, the question at hand is important enough to determine the future of empirical asset pricing and therefore too big and controversial to answer in a PhD thesis. This is why I have chosen to present this thesis as a collection of four research papers which provide empirical evidence on several important aspects of this question.

The first paper assesses how equity markets respond to news about distress risk over the business cycle in the short-run. Credit ratings are used as a measure of distress risk and business cycle identification algorithms are applied to classify recessions in a large international sample. The remaining three papers look into the long-run relationship between distress risk and equity returns. A growing strand of the US literature is devoted to this topic. The research presented in this thesis aims at providing out-of-sample evidence by looking at German and European data. This undertaking has made it necessary to evaluate several alternative measures of distress risk. Credit ratings are not available for large cross-sections of firms, except for the Compustat US-file. Therefore, the second paper is concerned with performance tests of several distress risk models. Together with two co-authors, I assess how well the models forecast defaults in the German

capita market. This is a crucial part of the methodology for the subsequent papers because it addresses the measurement error problem discussed above. Further details on distress risk measures are also explained in the next section. The distress risk know-how developed in this work has been used in the third paper to conduct a series of asset pricing tests. Together with two co-authors, I assess the relation between distress risk and equity returns and examine whether distress risk can explain size, value and momentum effects in the German stock market. The fourth and final paper deals with recent developments in monetary policy. Unconventional monetary policy aims at reducing funding costs for distressed firms. To be effective, the monetary policy must pass through a transmission mechanism in equity and credit markets. I check whether the transmission mechanism of monetary policy in the EMU works as expected. I show how stocks and CDS of firms in the EMU respond to monetary policy shocks and assess how this response depends on distress risk. Basically, this paper presents another perspective on the cyclical relationship between distress risk and equity returns and points out some difference between equity and credit markets.

3. Methodology

This section discusses how firm distress risk should be estimated. Various measures have been proposed, I present the most common ones. Reducing measurement errors and obtaining a precise estimate for distress risk is crucial in order to isolate distress risk from other effects in asset returns. This issue is discussed in detail in the second research paper, which contains a quantitative analysis of the forecasting performance of models discussed in this section. The material below is based on an extensive review of the literature that I have conducted when I began the work on the thesis. It is supposed to clarify how distress risk is measured in the literature and also in risk management practice.

3.1. Measuring Distress Risk

We are looking for a distress risk firm characteristic in order to use this information in asset pricing tests. What is the meaning of “distress”? Distress is not equivalent to default. However, both are closely related to each other; defaults are typically preceded by a phase of distress. As such, distress is typically defined as a period where cash flow is not sufficient to cover the current obligations of the firm (Andrade & Kaplan 1998; Asquith et al. 1994; Whitaker 1999; Wruck 1990). Yet,
the following section will show that low profitability and insufficient debt coverage are typical predictors of corporate defaults. In a similar vein, Pindado et al. (2008) find that default- and distress risk are not entirely different since models forecasting distress apply largely the same predictors as their default risk counterparts. After all, the work in this thesis needs to identify firms which are in distress and these are firms with elevated default risk. In accordance with the existing strand of the literature on distress risk and equity returns, I use the terms distress risk and default risk interchangeably in the following.\[3\]

In this manner, the thesis can build on a large strand of the forecasting literature that is summarized in the following. Default risk models can be classified in two categories: structural and reduced form models. The former are derived from asset pricing theories and the latter are data-driven approaches. In practice, estimating distress risk is often outsourced to rating agencies providing opinions on credit risk. In principle, credit ratings are offered to investors free of charge. From an investor’s perspective, they may appear as a parsimonious and efficient solution to the problem. Therefore, the review of the literature below begins with a discussion of credit ratings.

3.1.1. Credit Ratings

Ratings are supposed to deliver information and alleviate the agency problem in financial markets. Furthermore, they serve as a device to transmit regulatory standards into the practice of portfolio management. John Moody invented the credit rating in 1909 in order to facilitate lending in the emerging railroad bond market. Prior to the ascent of ratings, information on creditworthiness was flowing through informal channels with heavy dependence on insiders, such as journalists and bankers (Sylla 2002). Ratings were primarily meant to provide publicly accessible information on credit risk. Ratings became an institutional feature of the capital market when the US regulators incorporated ratings into their policies in the 1930s. In 1986, ratings became even more important in regulation as the Investment Company Act limited the possibility of portfolio managers to invest in securities with ratings below certain thresholds. These developments have created the so-called “investment grade threshold”: ratings BBB- and higher are called investment grade ratings.

Ratings are opinions of the rating agency on the credit risk associated with an

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issuer or an issue. Rating agencies are usually anxious to clarify that ratings, which are published on an ordinal scale, offer no direct link to a PD (Standard & Poor’s 2011). Moreover, rating agencies claim they apply a “through-the-cycle” methodology in order to identify a long-run trend in credit risk. This approach is unfavorable in risk management because it lowers the accuracy of PDs (Altman & Rijken 2006). Agencies argue investors, who use ratings as basis for transaction decisions in portfolio management, require some degree of rating stability (Moody’s 2006, Standard & Poor’s 2008).

In spite of these limitations, information on the likelihood of an issuer to default is arguably the most sought-after information contained in a rating. One method to uncover the link is given by the rating transition matrix. The transition matrix published by Moody’s (2008) tells us that an issuer with an Aaa rating, on average, experiences a downgrade to Aa within one year with a probability of 7.74% and goes into default with a probability of virtually zero. The PD increases as the rating decreases, so that, on average, an issuer with a rating of Caa, well below the investment-grade cut-off, shows a likelihood of 12% to default within a year. The transition matrix is merely a descriptive statistic of the rating history and thus inherently backward-looking. Nickell et al. (2000) analyze the stability of the transition matrix through time. They find that the above stated probabilities vary considerably in time, especially through the business cycle. To sum up, extracting PDs from credit ratings is laden with some conceptual difficulties and feasible only based on a very large and reliable rating history database.

With regard to the ability of credit ratings to differentiate defaulters from survivors, recent work by Hilscher & Wilson (2016) shows ratings are easily outperformed by reduced form default risk models. However, they still appear to contain important information on the long-run component of default risk. In accordance with these results, Löffler (2013) finds ratings predict the long run trend in default risk. In addition, there is an ever-growing literature on the information content of rating changes for capital markets. These studies generally find that rating changes contain little information for equity and fixed-income markets (Hand et al. 1992, Holthausen & Leftwich 1986, Norden & Weber 2004). Typically, asset prices show strong reactions weeks before downgrades, no reactions in the aftermath of downgrades and no reactions to upgrades in general. The first research paper of this thesis assesses how markets react to news about distress risk conveyed by rating changes. This article adds to the literature by suggesting that the market reaction to rating changes should depend on the business cycle. In accordance with the

\[14\text{In addition to this conceptual issue, the issuer-pay model and the competition in the ratings market may impair the ability of credit ratings to provide reliable information on default risk (Bolton et al. 2012).}\]
idea of distress risk as an ICAPM state variable, the reactions are shown to be significantly stronger (weaker) during recessions (expansions). Further details are provided in section 4.

3.1.2. Structural and Reduced Form Default Risk Models

The findings in the literature summarized above cast some doubts on the use of credit ratings as indicators for distress. Furthermore, a large history of credit ratings for the cross-section of German and European firms, which is used to provide out-of-sample evidence on the relation between distress risk and equity returns, is not available. Economies in the EMU are commonly regarded as bank-based economies. Many firms in these economies are simply not rated because their creditors are banks which handle credit risk with proprietary models. This is why I spent considerable time with the development and testing of default risk models. The results of this work are presented in the second research paper.

The quantitative analysis in this article was preceded by a thorough review of the related literature. Forecasting corporate defaults has been an active field of research since the 1960s, so there was no need to start from scratch.

There are two classes of default risk models. Structural models are based on valuation theories and infer PDs from security prices. The most well-known model in this class is the Merton (1974) Distance-to-Default (DD), which can be used to estimate PDs based on stock prices. Moreover, there are approaches to infer PDs from CDS and bond spreads (Bharath & Shumway 2008, Giesecke et al. 2010). Reduced form accounting models are atheoretical and data-driven approaches. Work in this areas has been pioneered by Beaver (1966) and Altman (1968), who tried to identify the most relevant accounting information for the prediction of bankruptcies.

I have reviewed all accessible articles devoted to forecasting default with structural and reduced form accounting models. The literature has predominantly applied two different methodological frameworks to estimate distress risk with reduced form accounting models: linear discriminant analysis and several forms of binary response regressions (logit and probit regressions), including survival models. Therefore, the review is restricted to articles applying these methods. The Cox (1955) model, the most popular model in survival analysis, is computationally equivalent to multiperiod logit models (Shumway 2001). The label survival analysis is more well known in medical research or engineering and has made its way into economics from these areas.

Furthermore, neural networks have been used to forecast defaults. The bulk of this research...
lists all articles which have been reviewed.
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Table 1: Review of forecasting studies

This table lists all accessible articles which are concerned with forecasting defaults. Column 2 lists their sources for default dates. Columns 3-6 provide further information on their sample. The last column indicates the methodology applied in an article. DD refers to the Merton (1974) model. LDA is linear discriminant analysis. SA refers to survival analysis. Logit and probit models are binary response regressions.
The oldest article listed in table 1, Beaver (1966), dates back to the 1960s and the latest one, Hilscher & Wilson (2016), has only been published recently. There has been a continuous research interest in the field, yet the overall number of articles (53) is not nearly as large as the “anomalies” literature summarized by Harvey et al. (2015). One explanation for this finding is that default data are not as standardly available as stock prices and balance sheet items in commercial databases. In fact, the articles surveyed usually combine information gathered from several databases and compiling the data frequently involves cumbersome manual work. Defaults are rare events and several older studies listed in table 1 rely on very few defaults which makes their results less reliable. In spite of these difficulties, a general finding emerging from this literature is that defaults are predictable with high accuracy up to one year ahead. There is not a single study that concludes otherwise. Hence, measuring distress risk as an unambiguous firm characteristic seems to be possible.\(^{17}\)

### 3.1.3. Reduced form accounting models

Pioneered by the work of Altman (1968), early reduced form accounting models were developed using linear discriminant analysis. Ohlson (1980) showed this technique unrealistically assumes equal covariance matrices of predictors across defaulters and survivors. He recommended logit regressions as a superior method and the literature has largely stucked with it since then. Furthermore, the literature summary shows there are only few studies which develop or test default risk models in markets other than the US. Table 1 contains no article recommending a certain procedure with regard to the German or other EMU member stock markets. In light of the significant institutional differences between the US and the EMU, it is not appropriate to adapt a model proposed by the US literature without prior out-of-sample tests. I found such a test was in order before work on the pricing of default risk in the German equity market could be undertaken.

Screening the literature for the most promising techniques is the first step. With regard to reduced form accounting models this boils down to a variable selection problem. There is no significant methodological debate in this field, most articles apply some form of binary response regression. The papers listed in table 1 differ with respect to what they feed into the models rather than with regard to how

\(^{17}\)Comparing the forecasting performance of specific models discussed in the articles listed in table 1 is difficult because the procedures and metrics used to assess model performance differ. A detailed discussion of modern performance metrics is provided in the second research paper (see appendix B).
parameters are estimated. Table 2 shows the most powerful combination of exogenous variables applied by several important articles that are explicitly devoted to forecasting defaults. Only articles published in top academic journals or presented at important conferences are included.

There are five categories of variables which are in various ways considered to be relevant in reduced form accounting models. Information on profitability, leverage and liquidity are part of almost any model. Following Ohlson (1980), most studies use net income to total assets as a proxy for profitability. Leverage is commonly modeled as the total liabilities to total assets ratio. Confirming the conjecture about a relation between size and distress discussed in section 2, size also enters many models. Another common category is liquidity, whereas debt coverage is completely missing in modern models. Since Shumway (2001), market based variables reflecting valuation play an important role in reduced form accounting models. However, the book-to-market ratio, the characteristic associated with the value effect, is only by a few studies found to be a significant predictor.

Table 2 illustrates that the most common models in the literature do not differ dramatically from each other. Out-of-sample tests of all models are therefore not likely to yield very interesting results. The second research paper presented in this thesis has evaluated the out-of-sample performance of two models whose exogenous variables are not overlapping substantially. Specifically, it considers the Altman (1968) Z-Score, which can be regarded as ancestor of reduced from accounting models. Nevertheless it is still frequently applied in different areas of empirical research, including empirical asset pricing (Dichev 1998, Griffin & Lemmon 2002). Moreover, the paper tests the failure score (F-Score) proposed by Campbell et al. (2008). This model is now regarded as state-of-the-art in reduced form accounting models (Bauer & Agarwal 2014, Ding et al. 2012, Hilscher & Wilson 2016). The structure of these two models is explained in detail in the second research paper.

### 3.1.4. Distance to Default

In addition, the second research paper assesses how the structural Merton (1974) DD fares as a predictor of corporate defaults. Merton assumes the Modigliani & Miller (1958) theorem holds. Consequently, a firm’s equity is a residual claim and can be regarded as a European call option on the firm’s assets $V_A$ with a strike price equal to the book value of the firm’s liabilities $D$. Intuitively speaking, equity holders can pay out creditors and then keep the rest of the firm value when the call matures after $T$ years. Firms default when their asset value hits the debt value. This renders the call option worthless. Solving for the probability that equity has
This table presents the variable selection of important forecasting studies in the literature. Only important studies which are explicitly devoted to forecasting defaults of public firms are included. The variables of the model showing the strongest out-of-sample performance have been selected.

Table 2: Independent variables in reduced form accounting models

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29
no value yields

\[
\text{Merton-PD} = N\left(-\frac{\ln\left(\frac{V_{A,t}}{D_t}\right) + (\mu - 0.5 \times \sigma_A^2)}{\sigma_A \times \sqrt{T}}\right),
\]

(13)

where \(\sigma_A\) and \(\mu\) denote asset volatility and growth, respectively and \(N(\ldots)\) is the cumulative normal distribution. The fraction inside the brackets is the distance-to-default, a leverage ratio scaled by asset volatility indicating how far away the firm is from the default point. A lower value indicates higher risk. Inserting the negative of this fraction into the normal distribution yields a PD \(^{18}\).

Obviously, this is a methodologically clean and elegant way to obtain information on default risk. Moreover, it has the advantage that no information on corporate defaults are needed to compute the statistic. The DD has been frequently applied in empirical asset pricing research (Vassalou & Xing 2004; Garlappi & Yan 2011; Ferreira Filipe et al. 2014). However, the forecasting literature summarized in table 1 has voiced some concern as to whether the DD contains reliable information on future defaults. Several studies, for instance Agarwal & Taffler (2008), Bharath & Shumway (2008), Campbell et al. (2008), Wu et al. (2010) and Xu (2013), demonstrate reduced form accounting models outperform the DD with regard to the ability to discriminate between defaulters and survivors. Moreover, several papers show the assumption of the normal distribution leads to severely downward-biased PDs in (13) (Hillegeist et al. 2004; Eom et al. 2004). Still, the performance of the Merton (1974) DD as a forecaster of defaults against common reduced form accounting models has never been comprehensively evaluated in the German stock market. The second empirical paper of this thesis closes this research gap.

### 3.1.5. Bond and CDS Spreads

For the sake of completeness, it should be further mentioned that another strand of the literature deals with extracting default risk information from credit-related securities instead of equities. A discussion of bond and CDS pricing is obviously beyond the scope of this thesis, but using default risk information in the prices of such securities deserves a few comments, especially since regulators have actively advocated the use of this kind of information in risk management (EBA 2014, p. 23).

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\(^{18}\)Further details on the estimation of (13) are provided in the second research paper.
Compared with the CDS market, the corporate bond market has a much longer history. Chan-Lau (2006) provides a brief introduction on default risk implied by bond prices. The expected payoff $B$ of a zero-bond with a face value of one unit maturing in one period is given as

$$B = \frac{(1 - PD) + PD \times RR}{1 + r}, \quad (14)$$

where $RR$ is the recovery rate in case of default and $r$ is the risk-free rate. Under the assumption that bonds are priced by risk-neutral agents, the implied $PD$ can be easily solved from (14). Along the lines of Fons (1987), this framework can be extended in a straightforward way to coupon bonds with any maturity.

How informative are bond spreads about defaults? The evidence is extremely sparse. The findings of Giesecke et al. (2010) suggest bond spreads are not informative about defaults. A large proportion of bond spreads is driven by factors that are unrelated to credit quality, such as interest rate, tax and liquidity risk (Driessen 2004, Huang & Huang 2012). From an empirical perspective, an important factor hampering the use of bond spreads in PD models is the vast heterogeneity of issue-specific clauses in the bond market. Bharath & Shumway (2008) state their database is seriously reduced after the elimination of bonds with special features. After all, they are left with 58 defaults. Hence, their finding that bond spreads contain useful information in predicting defaults comes with a caveat. Furthermore, it is noteworthy that Giesecke et al. (2010) who search for defaults in the U.S. bond market from 1866-2008 in a cumbersome manual cross-database analysis are able to identify only 143 defaults. In practice, it seems impossible to use bond spreads as a basis for PD forecasts for these reasons.

Compared with the corporate bond market, the CDS market is smaller but more standardized and thus easier to handle in empirical work. There is a clear theoretical link between bond yields and CDS spreads that is best illustrated by an arbitrage argument. On the one hand, consider a fixed-rate corporate bond with maturity $N$ and a yield-to-maturity $y$. Furthermore, assume that the $N$ year CDS spread for the same reference entity is defined as $s$. As above, $r$ is the $N$ year risk-free rate. Ignoring restrictions on short selling, counterparty risk, tax and liquidity premia, no arbitrage implies that the pay-off from a portfolio of the corporate bond and a long position in the CDS should be equal to a long position in the risk-free bond. This intuition is formalized in (15):

$$(y - s) - r = 0. \quad (15)$$
If the left-hand side of the parity (15) is larger (smaller) than zero, it will be profitable to assume a long (short) position in the corporate bond and the CDS while assuming a short (long) position in the risk-free bond. Even though the hypothetical CDS used in this no-arbitrage argument also ignore some real world contractual features of CDS, such as the so-called “cheapest-to-deliver” option, Hull et al. (2012) find the relationship postulated in (15) holds well empirically.\footnote{Hull et al. (2012) find the relationship postulated in (15) holds well empirically.}

The CDS spread $s$ is an insurance premium and it implies a PD. Following Chan-Lau (2006), I assume the perspective of a protection seller in the CDS market. Given the same hypothetical zero-bond assumed in (14), her expected loss $L$ is just the mirror image of the bondholder’s expected pay-off:

$$L = PD \times (1 - RR),$$

where the PD and the recovery rate are deemed to be independent. Under the assumptions underlying the relationship (15), the CDS spread $s$ for the zero-bond is given as the discounted expected loss (16):

$$s = \frac{PD \times (1 - RR)}{1 + r}.$$  

Thus, the PD can be recovered from (17) if the recovery rate, the risk-free rate and the spread are given. The CDS pricing theory pioneered by Hull & White (2000) paves the way to obtain a more sophisticated framework with multiple coupon periods that enables us to solve for the PD if we observe the CDS spread. In essence, the spread $s$, which is the market price of default risk, will equalize the expected discounted pay-offs from protection sellers and buyers. It is quite difficult to implement this model for empirical purposes. Berndt & Obreja (2010) show the approximation (18)

$$PD = 4 \times log\left(1 + \frac{s}{4 \times RR}\right)$$  

suffices, if the arbitrage argument made explicit in (15) holds and CDS coupons are paid on a quarterly basis, as it is now standard in the market.\footnote{Berndt & Obreja (2010) find a common factor in European CDS spreads is highly correlated with catastrophe risk, i.e. the risk of an economic event which will lead to a simultaneous}
extracted from bond spreads, (18) yields a risk neutral probability. To illustrate the implications of using such risk neutral measures for default forecasts, consider the following case study of four European industrial firms. On the left axis, figure 3 depicts the physical Merton-PD, which has been computed using (13) at the beginning of every month between 2008-2015. Furthermore, the right axis in figure 3 shows the risk neutral probabilities implied by the 1-year senior unsecured CDS spread given by (18).

These figures show time series plots of PDs implied by the Merton (1974) model and CDS. The Merton model has been computed at the beginning of every month from 03/2008 to 05/2015 using one year of historically observable daily equity returns and balance sheet data. The latter has been lagged by six months to account for the publication bias. A PD has been extracted from CDS spreads using the approximation (18). All data has been downloaded from Datastream.

Figure 3: Case Study - Physical vs. Risk Neutral Probabilities

CDS implied PDs are at many times a multiple of physical PDs. Hence, market participants in the CDS market are not risk neutral but risk averse. In fact, CDS implied PDs can exceed one in extreme situations, for instance when there default of several blue chip companies.
are rumours about bankruptcy, which was the case at the end of 2009 for HeidelbergCement. Moreover, such situations seem to cause large disturbance in CDS spreads even after the physical PDs have returned to uncritical levels. These results underline that CDS should not be used for default forecasts (Jarrow 2012). Strictly speaking, (18) does not yield a probability but a pricing measure. The same applies to bond spreads. A conclusive study of the forecasting power of CDS implied PDs does not exist. Another practical reason for this is that the CDS market is very small and defaults are very rare.\footnote{A history of credit events dealt with in the CDS market is available on the website \url{http://www.creditfixings.com}. There were 10 worldwide corporate credit events in 2008 and 6 in 2016.} The fourth research paper presented in section 4 analyzes the entire cross-section of French, German, Italian and Spanish CDS. The number of firms with existing contracts is only 108. Moreover, the efficiency of the CDS market remains a debated issue. Recent research suggests the CDS market is characterized by imperfect competition, market frictions (Gündüz et al. 2012) and illiquidity (Junge & Trolle 2013). Up until now, CDS appear to be useless for default forecasts, as well.

So far, the section has been a wrap-up of the main ideas behind distress risk models. The goal was to discuss the reliability of several approaches to measure distress risk. On the one hand, there is a variety of reduced form accounting models and, on the other hand, there is the Merton (1974) model. A final conclusion as to how well these approaches measure default risk is the main concern of the second research paper and deferred to the summary of the empirical results in section 4. Moreover, it has been explained that approaches based on bond and CDS spreads are no viable alternative for the problem at hand. In theory and practice, there is a much stronger and well-known consensus about methods to cope with market risk than with credit risk. Dealing with market risk is now a standard subject in undergraduate and postgraduate finance courses, credit risk is typically barely touched in university courses. Bohn (2011), who provides one of the few textbooks on credit risk, suggests the lack of data as a main explanation for this phenomenon. Estimating and testing models requires data that are generally unavailable to the public and require a lot of manual work. Rating agencies have a clear advantage in this regard because they have been building large proprietary databases for a long time. Storing the data in a safe and secret place keeps them in business, but it basically prevents external reviews of the performance of ratings as risk measures. What credit ratings really achieve as forecasters remains largely unclear in the literature. This opens up the debate about the use of structural and reduced form accounting models in empirical research. There is only one way to make sure these models provide precise estimates of distress risk, namely a quantitative evaluation of their forecasting performance. The results for such an analysis are summarized
3.2. Empirical Asset Pricing Methods

Armed with knowledge about distress risk models, the remainder of this section turns to asset pricing methods. It explains how the distress risk characteristic can be used to assess the relationship between distress risk and equity returns. In general, there are two perspectives of interest in this regard: a) how do equity markets react when information about distress risk is disclosed in the short-run and b) what are the implications of distress risk for equity returns in the long-run. There is an established methodology for both perspectives that has been summarized by major textbooks. Hence, the methodological discussion in this document is relatively brief.

3.2.1. Assessing Market Reactions with Event Studies

Assessing the reactions of stock prices to news about firm distress risk can be regarded as a test of the short-run CAPM mechanics: Do investors discount the prices of distressed firms or is distress irrelevant for equity investors? The first research paper is directly devoted to answering this question. Moreover, the fourth paper deals with a similar topic as it addresses the equity and CDS market reactions of credit-constrained firms to monetary policy shocks.

Early tests of the Efficient Market Hypothesis (EMH) focused on the ability of the stock market to filter and process information. Fama et al. (1969) proposed the traditional event study methodology as a framework to test the EMH. Since then, the research focus has shifted to more subtle questions and the event study framework has been applied to address various other issues, including the impact of regulatory changes or assessing damages in legal proceedings. In short, the event study framework can be used to gauge the effects of economic events on the value of firms (MacKinlay 1997). In the context of this thesis, the events of interest are related to distress. Credit ratings are interesting in this regard because their publications mark distinct events. The large body of research on the stock market reaction to rating changes has already been mentioned above. The basic structure of an event study is depicted in figure 4.

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22See, for example, Cochrane (2005).
The estimation window spans a time period before the event of interest in which the parameters of asset pricing models are estimated. The models are supposed to capture expected returns. For instance, one might assume the FFM is an adequate description of expected returns and use the estimation window to estimate a stock’s loadings on the market, size and value factors, respectively. The estimation window is separated from the calculation window because parameter estimation is based on the assumption that the stock price of interest evolves normally throughout the estimation window and is not affected by the event of interest. In figure 4, the demarcation of the event window from the calculation window is indicated by the time subscripts \( l \) and \( k \). There is no rule as to how many days the estimation window should span, but the number must be sufficient to guarantee the feasibility of regression procedures. As a next step, the required parameters are used to compute fitted values as a proxy for expected returns in the calculation window, which may contain \( 2 \times j + 1 \) ticks centered around the event day denoted as \( t \) in figure 4. The variable of interest in the calculation window are the residuals of the asset pricing models which are obtained by subtracting the fitted values from the actually observed returns. These residuals are called abnormal returns (AR). Moreover, cumulating AR yields an abnormal holding period return called cumulative abnormal return (CAR). The conventional null hypothesis is \( CAR = 0 \).

A battery of hypothesis tests has been proposed. The power of these event-studies tests suffers from a few methodological problems. Return variances increase around the event day, \( CAR \) tend to be highly autocorrelated and the whole procedure is very sensitive to outliers (Brown & Warner 1985). Recently, the methodology has been enhanced by new powerful nonparametric tests (Kolari & Pynnonen 2011).

If firm distress risk is indeed a state variable in the ICAPM, tests should reject the null when markets learn about distress risk. Specifically, they should discount the value of a firm when default risk increases and respond with increasing prices to news about decreasing distress risk. These are the mechanics required to generate a premium for distressed firms. Furthermore, since state variables reflect macroeconomic activity, there should be a significant dependence of the reaction on the business cycle. We would expect the discount to distressed firms to be especially large when the economy is in a recession because recessions are typically
accompanied by high agency costs of lending and tight credit markets. A firm suffering from a downgrade in such a setting should be more affected than a firm downgraded in a booming economy. This is precisely what the first research paper summarized in section 4 tests.

3.2.2. Approaches to Assess Long-Run Relationships

The short-run event-study is limited to analyze reactions, the calculation window depicted in figure 4 spans a few weeks at the most. Obviously, a look at the long-run relationship is necessary to gauge whether distress risk explains patterns in equity returns. From a methodological point of view, this requires something like a multivariate panel regression of several characteristics $C$ for each firm $i$, including distress risk, on long-run returns $r$ (Cochrane 2011):

$$r_{i,t+1} = a + b'C_{i,t} + \epsilon_{i,t+1}. \quad (19)$$

Almost any research sample in finance consists of repeated observations of a cross-section, i.e. empirical research in finance is mainly based on panel data. Still, real panel regressions like (19) are relatively uncommon in empirical asset pricing (Cochrane 2011, Freyberger et al. 2016). One can only speculate about the reasons, perhaps one reason is that tests of the EMH became important in the 1960s, when panel data analysis was still in its infancy. A whole subbranch of econometrics devoted to the problem stated in (19) has evolved in asset pricing. Below I discuss portfolio sorts and Fama & MacBeth (1973) regressions, two methods which have been applied in the thesis as ways to test long-run relationships. These are still the most commonly used methods. Obviously, there is not really anything new about them, but the vast body of literature on “anomalies” summarized by Harvey et al. (2015) (see section 2) has given rise to a new debate about inference in finance, which I add to the short methodological discussion here.

Portfolio sorts appeared in the late 1970s. Basu (1977) was a very early adopter. The technique is appealing to intuition because it mirrors the actual experience of an investor ranking firms according to some firm characteristic and then forming portfolios based on this ranking. The long run performance of such investment strategies are used to infer the relationship between the characteristic and returns. Usually, the final tests are based on long-short portfolios which assume a long (short) position in the top- (bottom-) ranked firms. Apart from its intuition, this method has two compelling advantages. First, the sorts itself are nonparametric
(though, admittedly, standard regression tests of the long-short portfolios are typically parametric). Second, sorts can be used to detect non-linear relationships. Many theories suggest a non-linear relation between characteristics and returns (Garlappi et al. 2006, Garlappi & Yan 2011), a linear regression will fail in these instances. On the other hand, portfolio sorts have several downsides. Cochrane (2011) emphasizes they are simply not able to deal with the multidimensionality characterizing modern asset pricing. Double-sorts are still feasible, in some instances maybe even triple-sorts, but sorting can get us nowhere near to controlling for the plethora of characteristics that has been proposed in the literature. Furthermore, Lo & MacKinlay (1999) point out that sorting on a variable showing in-sample correlation with returns gives rise to a data-snooping bias. Following in the same vein, Berk (2000) shows sorts affect the variance structure in the panel: sorting a cross-section on a characteristic that is known to be correlated with returns yields portfolio returns with high variance between the portfolios but, compared to the full-sample, lower within variance. Reducing the within variance of portfolios or test assets can artificially swamp the explanatory power of asset pricing models. Lastly, a researcher applying portfolio sorts has to question the assumptions underlying the technique: Are the assets in a portfolio really liquid and are short-sales feasible? Are the extreme portfolios, which are used to compute long-short strategy returns, especially affected by these limitations? These issues are to a lesser degree a problem when using US data since data quality generally is, in this case, less of an issue and control variables for liquidity are available. However, my personal research experience prompts me to express more doubts when the sample consists of European stocks and the variable of interest (distress) is per se associated with extreme return behavior.

Portfolio sorts treat the cross-section and time series dimensions separately, sorts address the cross-section and regressions address the time series. Cochrane (2011) argues this is effectively equivalent to nonparametric cross-sectional regressions with histogram weights. After all, sorts might be not that different from true panel data models like (19). The connection between panel data analysis and the two-pass Fama & MacBeth (1973) regressions is even more straightforward. This approach can be used to assess whether a certain factor or characteristic is priced in the cross-section. When the variable of interest is a factor, the procedure begins with an estimation of factor loadings, for instance an estimation of CAPM betas for each asset. Thereafter, the factor loadings or characteristics, which do not need to be estimated beforehand, are regressed in the cross-section at each point in time on returns. That is, Fama & MacBeth (1973) regressions are a series of \( t \) cross-sectional regressions similar to (19), just without the time dimension, resulting in \( t \) estimates of cross-sectional coefficients and standard errors or \( t \)-values. The most obvious thing to do next in order to obtain an estimate for
the long-run relation between the exogenous variable and expected returns is to average the coefficient estimates and \( t \)-values. After all, Fama & MacBeth (1973) regressions are also related to panel data methods like (19). Cochrane (2005) discusses circumstances under which the two-pass procedure outlined above is equivalent to a pooled Ordinary Least Squares (OLS) regression.

A common assumption underlying regression frameworks like (19) and the Fama & MacBeth (1973) cross-sectional regressions is that the error terms \( \epsilon \) are independent and identically distributed. More recently, two important concerns about the standard errors in finance have been voiced by Cameron et al. (2006), Petersen (2008) and Gow et al. (2010). The first concern refers to cross-sectionally correlated error terms. Whenever some unobservable factor affects returns contemporaneously, the assumption \( \text{Cov}(\epsilon_{i,t}, \epsilon_{j,t}) \) is violated in each cross-sectional regression and standard errors are subject to a time effect. Second, returns might be autocorrelated in time, i.e. \( \text{Cov}(\epsilon_{i,t}, \epsilon_{i,t+s}) \) for \( s \neq 0 \) does not hold, which is called a firm effect. These effects may cause standard errors to be severely downward-biased. According to the literature survey of Petersen (2008), 42% of research papers in finance did not adjust standard errors for these problems which is likely to render their results incorrect. Cameron et al. (2006) have proposed to compute errors clustered on firm and time in order to deal with these issues. Petersen (2008) as well as Gow et al. (2010) present simulation evidence underlining the importance of these adjustments in finance. The former recommend to compute several standard errors in procedures like Fama & MacBeth (1973) regressions or the general framework (19). Conventional errors should be shown alongside of firm-level, time-level and two-way clustered errors.

To recap, methods in empirical asset pricing have been living a life of their own until the end of the last decade. Portfolio sorts and Fama & MacBeth (1973) regressions are both in some way related to a generic panel regression framework like (19), but they tend to deal with variation in the cross-section and in the time series in separate steps. Portfolio sorts are nonparametric and able to deal with nonlinearity, but Fama & MacBeth (1973) regressions are better suited to deal with multidimensional problems. Important recent methodological contributions

\(^{23}\)When the exogenous variable in the cross-sectional regressions are estimated factor loadings, a correction of the standard problems for the errors-in-variables problem according to Shanken (1992) is recommendable.

\(^{24}\)The conventional OLS variance estimator is \( V = s^2 \times (X'X)^{-1} \), where \( s^2 = \frac{1}{N-K} \times \sum_{i=1}^{N} \epsilon_i \) and \( N, K \) denote the numbers of observations and parameters, respectively. With one-way clustering the variance estimator is \( V_{\text{clustered}} = (X'X)^{-1} \times \sum_{i=1}^{N_c} u_j' \times u_j \times (X'X)^{-1} \), where \( N_c \) denotes the number of clusters (e.g. firms/years) and \( u \) is \( \sum \epsilon_i \times x_i \) in each cluster. See Cameron et al. (2006) for further details and the variance estimator in the case of two-way clustering.
are beginning to acknowledge the panel structure of finance data more directly and Cochrane (2011) recommends uniting time series and cross-sections in true panel data models for future research. Empirical research in this thesis follows this recommendation and applies portfolio sorts, Fama & MacBeth (1973) regressions as well as panel data models in a more narrow definition.

4. Empirical Results

The research papers, which have been written over the course of the last three years, speak for themselves. They represent the actual work I have done. This section offers a short summary of their main results and tries to contextualize them. Summaries are necessarily a reduction and rarely as good as the originals. Instead of just condensing and rephrasing material from the papers, I try to provide some additional material that has not made it into the final versions of the papers (mainly to save space) and discuss the significance of the results for the research context outlined in this document.

4.1. The Relevance of Credit Ratings over the Business Cycle

If distress risk is priced in the equity market, the value of stocks should decline when investors learn about increasing risk. But when and how do they get this information? Section 3 explains that credit ratings are probably not the best forecasters of default, but their use is widespread and in some cases mandatory from a regulatory perspective. By and large, they are to be regarded as facilitators and distributors of distress risk news.

As such, we expect that equity investors react in some way to credit rating changes. Specifically, we expect that downgrades, indicating an increase in distress risk, tend to reduce the value of equity. Following a substantial downgrade, equity investors should stand a lower chance of extracting rents from the firm due to the higher risk of bankruptcy and the absolute priority rule. The flipside of this, an upgrade, should give rise to increasing equity returns. The first objective of the first research paper is to test these relations in an event study of rating changes. The paper adds to the literature as it is based on a very large international database including rating events from all three major rating agencies. Moreover, it does not only investigate rating changes but also other more nuanced information released by rating agencies (rating outlooks and watchlist events). Figure 5 illustrates the
This figure shows the evolution of CAR associated with rating events at time zero. CAR have been computed based on the CAPM and averaged in a 91 day calculation window to obtain the series shown in the plot. “Out.” denotes rating outlooks and “Watch.” denotes inclusions of firms in an agency watchlist in order to review the current rating.

Figure 5: Reaction of stock prices to rating changes

As expected, the paper finds that all events which are associated with increasing distress risk give rise to negative equity returns. The strongest reaction occurs after downgrades. Positive news about a firm’s creditworthiness give rise to comparably low stock market reactions. The different reactions to positive and negative events are likely to mirror risk aversion. All in all, these results confirm that investors discount the value of distressed firms. So far, these results are straightforward and not overly exciting. In fact, they seem merely mechanical and have already been documented in the empirical literature (Hand et al. 1992, Holthausen & Leftwich 1986, Norden & Weber 2004).

The papers extends the conventional rating event study analysis by investigating empirical findings.
the dependence of market reactions on different phases of the business cycle. Several theoretical considerations suggest market reactions to rating events are more pronounced in recessions and lower during expansions. The paper discusses the theory of the agency costs of lending (Bernanke et al. 1996, Tirole 2006) on the one hand and the dynamics of competition in the ratings market on the other hand (Bolton et al. 2012). The former postulates that the adverse selection problem and moral hazard, distinguishing a good from a bad firm, becomes much more severe in recessions when the overall success rate of investment projects is lower. According to this theory, investors find it less attractive to finance distressed firms during economic downturns. This is exactly the same argumentation as the Fama & French (1995, 1996) case for distress risk as an ICAPM state variable. Therefore, the second contribution of the paper can also be regarded as an attempt to assess whether the short-run reaction of stocks to news about distress is consistent with the Fama & French distress risk story.

The evidence does indeed support this view. Bernanke et al. (1996) document a flight to quality in several debt markets during recessions. The first research paper finds equity investors behave similarly. During economic downturns, investors sell-off stocks of downgraded firms to a stronger degree than during expansions or neutral business cycle phases. This effect is especially pronounced in the speculative grade segment. Furthermore, the paper shows there are hardly any reactions to rating changes in the investment grade segment, which is characterized by very low PDs. The investment grade definition seems to indicate a threshold below which there is significant distress risk. Stocks of firms rated below the threshold display strong cyclical reactions that are fully consistent with the notion of a distress risk state variable. Stocks of firms with investment grade rating, firms whose PDs are de-facto null, are not affected by news about distress risk. Of course, this evidence tells us nothing about long-run distress risk premia but only that the short-term reactions are fully consistent with such premia. Without the evidence, there would be no need to look into the long-run. Moreover, the evidence also tells us where to look, namely at firms with significant PDs.

4.2. The Performance of Default Risk Models in the German Stock Market

A long-term analysis requires a reliable model to measure PDs. An important aim of the thesis is to provide out-of-sample evidence on the relation between distress risk and stock returns by looking at the German stock market. While the literature review in section 3 underlines several models might be able to deliver this
information, the performance of such models has never been tested in the German stock market. Therefore, the second article aims at evaluating the performance of these models in the German stock market. In particular, the paper considers the Altman (1968) Z-Score, Campbell et al. (2008) F-Score and Merton (1974) DD. The goal is to obtain a firm characteristic which provides reliable information on default risk and can be used in empirical asset pricing research. As argued in section 2 testing the ability of models to forecast defaults is a crucial preliminary step in order to reduce measurement errors and arbitrariness in firm characteristics.

In contrast to the other research papers presented in this thesis, developing and testing default risk models is more of a technical issue. In particular, such undertakings involve three challenges. First, the procedures require reliable data on corporate defaults. Considerable time was spent on attempts to automatically retrieve such information from commercial databases. In the end, these sources were found to be highly unreliable. They appear to list several incorrect dates, sometimes pre- or backdating defaults by more than a year, and miss a large number of defaults. Therefore, very cumbersome manual searches have been conducted to retrieve information on the final state of all firms which have left the German stock market since 1990. In this fashion, 181 default events could be unambiguously defined as dates of firms filing for default with German courts. The search procedure has yielded a binary variable, which is equal to one at this instant and zero otherwise.

The second challenge is estimating model parameters using this data. The explained data structure suggests binary response models for this task. All three common models, logit, probit and complementary-log-log links, have been considered in the article. Moreover, for both the research question at hand and the practical use of default risk models, it is critical to obtain forward-looking out-of-sample risk measures. Specifically, parameter estimates should only be based on information which investors could use in real time. The paper adapts a “walk-forward” estimation strategy with repeated estimation periods explained by Sobehart et al. (2000) to ensure investors could have used the models considered in reality. This results in true out-of-sample risk scores and PDs which are in the third and final step tested with regard to their ability to forecast defaults.

A powerful model should have two different traits: First, it should reliably classify default risk. As explained in section 3 not all models require this step. Specifically, the Altman (1968) Z-Score and the Merton (1974) DD do not require a re-estimation of parameters, but their forecasting performance may improve when this is done (Grice & Ingram 2001, Bharath & Shumway 2008). The paper compares the original specifications of the Z-Score and DD with new recalibrated version which are called Z-Score (recal.) and DD (recal.), respectively.
defaulters and survivors by providing a ranking of risk. This is called discriminatory power. A model with high discriminatory power generates low type-1, classifying a defaulter as survivor, and type-2, classifying a solid firm as defaulting, error rates. The paper uses receiver-operating-characteristics (ROC) analysis as a technique to test discriminatory power. Second, a model should also provide accurate PDs and explain the variation of the default rate across the sample. For any subset of firms in a sample, the average model PD of that subset should be close to the actual empirical default rate in the subset. If this is given, the model is called well-calibrated. While discriminatory power refers to the ordinal ranking of risk, calibration addresses the metric PDs that the model implies. Both properties are illustrated in figure 6 below.

The four plots illustrate the performance of default risk models. The model PDs have been sorted into deciles, decile 10 contains the 10% of observations with the highest default risk. The diamonds indicate the true empirical default rate in a decile, the connected circles indicate the mean PD per decile as estimated by each model.

Figure 6: The Performance of Default Risk Models
Both discriminatory ability (ranking) and calibration are visualized in the plots. For each model, observations have been sorted into deciles. The first decile contains the 10% of observations with the lowest PDs and so on. Discriminatory ability is visible when a model shows monotonously increasing true default rates, the diamonds in the figure, from decile 1 to 10. Only few (if any) defaults should occur in low risk deciles and most defaults, ideally all of them, should occur in decile 10. Though not all models show the desired monotonous increase, the figure underlines default rates are elevated in the higher risk deciles. In other words, all four models display some discriminatory ability. The F-Score shown in the bottom right panel of figure displays the best discriminatory power according to the analysis conducted in the paper. A well-calibrated model has mean decile PDs, the circles in the figure, which are close to the true empirical decile PDs (the diamonds). We can see models differ tremendously in this regard. The Merton 1974 model produces severely downward-biased PDs, all of them are close to zero. The top left panel shows the recalibrated version of the DD. Recalibrating DD with binary response regressions reduces the downward bias, but it does not completely eliminate it. The recalibrated Z-Score does also show a tendency to produce downward-biased PDs. F-Score is once more the best performing model.

What are the lessons learned from all this? Figure underlines that F-Score wins the model horse race. Additional results in the paper confirm defaults in the German stock market are well predictable. It is reasonable to assume investors are well aware of this fact. Comparable results have been presented by the related literature on default risk models summarized in section and similar models are applied in corporate banking. Consequently, the long-run analysis on the relation between distress risk and stock returns applies the F-Score to measure market expectations of default risk. The paper on market reactions to rating changes has found that in the investment grade segment are close to zero. The patterns in figure confirm that a large share of firms is virtually not at risk. This is consistent with the notion that distress risk is probably irrelevant for investors in these firms.

26Deciles 2-7 in the top left panel of figure are empty because the Merton 1974 model produces many zero PDs. Further details are provided in the second paper.
4.3. The Relation between Distress Risk and Returns in the German Stock Market

Does distress risk measured by the F-Score explain average stock returns? The third article asks two different questions: Are investors rewarded a premium for holding the equity of distressed firms? Are common characteristics-effects, like value and momentum effects, in fact distress effects? Answering these questions sheds light on whether distress risk is an ICAPM state variable that explains common patterns in returns. Being able to show this is true would be an important step towards reconciling the conflicting empirical evidence on the explanatory ability of a plethora of characteristics (the “factor zoo”) with conventional risk based ICAPM/CCAPM explanations.

The previous findings have pointed to nonlinearities in the relationship between distress risk and returns. Therefore, it is natural to start the analysis with portfolio sorts. Semi-annual excess returns on F-Score sorted portfolios are presented in panel A of table 3.

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27Brueckner (2013) and Artmann et al. (2012) show these effects are present in the German stock market, whereas there is no evidence for a size effect.

28This is table 4 in the third research paper.
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### High risk

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### Panel B: Carhart [1997]-Four-Factor-Model (CFM) Regression Coefficients

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### Panel C: Portfolio Characteristics

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<td>0.04</td>
<td>0.04</td>
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<td>0.02</td>
<td>-0.01</td>
</tr>
</tbody>
</table>

Firms are sorted according to their F-Scores at the beginning of every January and July between 2001-2015. The first portfolio contains all firms with the 10% of lowest F-Scores and so on. Portfolios are held for six months. Panel A shows value-weighted semi-annual excess returns and alpha coefficients for the CAPM, FFM as well as the CFM. Panel B shows the estimated regression coefficients of the CFM. T-Values are stated in parentheses. Panel C shows several portfolio characteristics. BTM is book-to-market equity, RoA is return on assets.

Table 3: Returns on Distress Risk Equity Portfolios
Unfortunately, the results remain inconclusive. Excess returns on portfolios 5-9 are negative, but only portfolio 9 shows large negative returns which are, on average, statistically different from zero. Average excess returns on the high risk portfolio are positive but statistically not different from zero. The alpha coefficients of common risk factor models are economically insignificant. Interpreting firms in portfolio 1 as safe and firms in portfolio 10 as distressed is in line with the previous findings. The first paper has shown the equity market reacts to news about distress when PDs are significantly different from zero (in the speculative grade segment). The second paper illustrates firms in portfolio 10 are at risk, whereas firms in other portfolio are rather not distressed (see figure 6). The 10-1 portfolio, which is long (short) distressed (safe) firms, yields an average return that is statistically not different from zero. According to this test, there is no distress risk effect.

Can any further conclusions be drawn from the data? In particular, does the roughly V-shaped pattern of portfolio returns tell us anything? One might argue the decay in returns after portfolio 4 indicates firms are gradually becoming distressed, whereas firms in portfolio 10 are already dead. This argumentation is based on the differences between distress and default (Wruck 1990). It suggests a negative relation between distress (risk) and returns but no relation between default (risk) and returns. However, not all firms in portfolio 10 default, the average portfolio F-Score, which is shown in panel C of table 3, translates into an annual PD of roughly 3.2%. We know the F-Score produces PDs which are close to the true default rates. Hence, the most plausible interpretation for firms in portfolio 10 is that they are truly distressed; some default but most survive. Moreover, the portfolio 9 -5.2 mean F-Score translates into a mean annual PD of only 1%. Is this already a concern for investors? Lastly, the implied mean annual PDs on all other portfolios are only a few basis points. Can we really say firms in portfolio 7 are more distressed than firms in portfolio 6 or do other factors explain the differences in excess returns? There is hardly anything that supports the former.

More persuasive is the idea that the excess returns in table 3 are explained by other, unobserved variables. Panel C points to strong patterns with regard to size, book-to-market equity and momentum, three good old friends. Apparently, distress risk alone is not able to provide convincing explanations for returns. The rest of the paper is devoted to assessing whether it can still at least partially explain patterns in returns with regard to these well-known characteristics. It cannot. Like Artmann et al. (2012), I find evidence for significant value and momentum effects in returns. Empirically, F-Scores are correlated with these characteristics, they enter F-Score as exogenous variables (see table 2). In spite of the correlation, there is

29Applying the logit transformation to the F-Scores in panel C of table 3 yields a semi-annual PD.
no evidence for a causal link between distress risk and size, value and momentum effects. After all, distress risk appears to contribute nothing to explaining stock returns. The excess returns in table 3 are probably explained by correlation of F-Scores with other characteristics, but the idea of a distress risk characteristic bringing order into the mess of characteristics-effects seems wrong.

Will there never be order in the cross-section of stocks? Should we perhaps even abandon the Fama & French (1995, 1996) distress story? A final verdict is deferred to section 5. At this point, it is worth recalling that common characteristics like size, book-to-market equity and momentum have a “catch all” nature. They are most likely collections of several different economic effects, which may very well amplify or cancel each other out. In spite of all efforts to reduce measurement error and arbitrariness, a distress characteristic like the F-Score may ultimately suffer from similar drawbacks. After all, default risk models are also only combinations of accounting and market information. In the end, it comes down to the question of what investors consider to be important. Is a slightly elevated F-Score (or any other default risk score) a considerable signal for distress risk or is the negative momentum (small size / high book-to-market ratio) that enters its computation a more important signal for something else? In most cases, it is unclear to what extent characteristics capture the macroeconomic processes which are decisive for the CCAPM/ICAPM mechanics. Firm characteristics have only in rare cases straightforward interpretations. We should probably not use them so extensively as explanatory variables for returns. Cochrane (2007) suggests to focus on the actual macroeconomic process instead. Following in this vein, instead of defining an elevated book-to-market ratio (or about any other characteristic) as an indicator for distress, we should perhaps ask which firms are especially exposed to tightening lending standards or try to identify industries in decline. Approaches like these are more straightforward because they acknowledge the concept of systematic risk more directly than conventional firm characteristics. Further recommendations for future research based on this thought are provided in section 5.

4.4. The Reaction of European Stocks to Unconventional Monetary Policy

At first sight, the fourth research paper may seem to be only remotely connected to the research context outlined in this document. The paper assesses the response of stocks and CDS to unconventional monetary policy shocks. The link to the overall context of the thesis is buried in the transmission mechanism of monetary policy. The related empirical literature has found that the credit channel is the
most important one among several of such transmission channels (Mishkin 1996, Bernanke & Gertler 1995, Ciccarelli et al. 2015).

Credit channels suggest expansionary monetary policy can reduce the agency problem in financial markets. The theory of cyclical agency costs and its effect on the propensity of investors to finance risky firms has already been discussed above. Bernanke et al. (1996) document a flight to safety in several credit markets and the first research paper suggests a similar effect takes place in the equity market. Monetary policy might counter these effects with expansionary actions. Specifically, central banks could be able to improve the balance sheets of credit-constrained firms as they commit to purchasing assets in several credit (and equity) markets. Increasing bond (equity) prices will lower risk premia and ease funding conditions for these firms. Asset purchase programs are commonly called unconventional monetary policy. Recently, they have gained popularity among several major central banks. The fourth research paper asks whether credit channels are operative and central banks can indeed counter the flight to safety, which has been documented in the first research paper. Specifically, the paper investigates the reactions of stocks and CDS in the entire cross-section of French, German, Italian and Spanish firms in order to provide another perspective on the relation between distress risk and stock returns. It shifts the focus from the long-run back to the short-run. The previous results suggest that, given the methodological framework at hand, more interesting economic conclusions can be drawn from this perspective. This has been the main motivation for the paper in the overall research context.

Like the first article, this paper makes use of the event study methodology. In contrast to firm specific rating events, the events of interest in this case are market-wide monetary shocks. Since all firms are at the same time affected by them, it is not sensible to apply the Fama et al. (1969) event study methodology outlined in section 3. Instead, the article applies several different methods to extract monetary policy shocks from interest rates (Kuttner 2001, Rogers et al. 2014) and uses these shocks as exogenous variables in time-series and panel regressions. The main research hypotheses test the effectiveness of the credit channel. In detail, they state that unconventional monetary policy shocks give rise to stronger increases (decreases) in stock prices (CDS spreads) when firms are distressed. According to the data, the opposite is true. It appears that firms with low distress risk show the strongest increases (decreases) in stock prices (CDS spreads) suggesting that unconventional monetary policy cannot counter the flight to safety. Investors do not regard these programs as beneficial for distressed firms.

Once more, the evidence underlines that the flight to safety is a powerful concept in financial markets. Not even central banks seem to be able to dissolve it. It is
worth recalling that this phenomenon is fully consistent with the idea of distress risk as an ICAPM state variable. Hence, in line with the findings of the first paper, the fourth paper shows the economic distress risk story is visible in the short-run. Moreover, the paper points to a surprising short-run relation between interest rates and stock returns. Since the beginnings of the EMU, the response of the stock market to conventional interest rate shocks induced by ECB actions has had the same sign as the shock. A main rate decrease of the ECB has, on average, given rise to negative and not positive stock market reactions. These additional results, which stand in harsh contrast to economic intuition, cast doubts on the overall effectiveness of monetary policy in the EMU. Furthermore, this finding shows the potential of the current era of zero-interest rates to twist things up. Who thought a prolonged period of below zero interest rates would be possible ten years ago?

How do common empirical models fare with negative interest rates? We should routinely control for these unparalleled developments in empirical research.

5. Conclusion

The overriding goal of the thesis has been to assess whether firm distress risk can reconcile the empirical literature with conventional risk-based CCAPM/ICAPM explanations for stocks returns. The theory says risk averse investors should discount the value of firms because they dislike asset price risk that is correlated with consumption risk. Distress risk does plausibly create this correlation, for instance, when investors depend on labor income. Consequently, the average equity investor should be more reluctant to finance distressed firms than safe firms and she should be especially reluctant to do so when the economy is in a recession. The evidence points to strong cyclical relations between distress risk and stock returns in the short-run. Specifically, investors have a higher propensity to sell off stocks from issuers in the speculative grade rating segment after downgrades when the economy is in a recession. The motives behind this flight to safety appear to be strong. The ECB has recently found it necessary to counter these tendencies with a battery of unconventional monetary policy measures which are supposed to ease funding conditions for distressed firms. However, all this does not seem to affect the behavior of investors. All in all, the CCAPM/ICAPM mechanics are clearly visible in the short-run.

Does the discount on distressed firms give rise to a premium? Can distress risk also explain long-run average returns? Sadly, the results remain inconclusive in this regard. I have spent a lot of time and effort on developing and testing models to measure default risk in order to associate the information provided by these
models with long-run average stock returns. Default risk models are powerful in forecasting corporate defaults. They are an exciting topic on their own and of tremendous importance in practice. However, they seem to bear little consequences for the stock market. Conventional asset pricing tests suggest the relation between default risk scores and excess stock returns is insignificant in the German stock market. Moreover, distress risk cannot provide convincing explanations for other patterns in returns (value and momentum effects).

Why do we see strong reactions of stocks to news about distress in the short-run but no relation between distress risk and long-run average returns? There are two explanations for this. First of all, detecting short run reactions is, by nature, easier than establishing long-run relationships. Numerous factors influence stock returns over the course of a few months, whereas isolating effects in windows spanning a few days is less difficult. Second, conventional theory tells us systematic risk matters in the long-run. Default risk can be measured with very high accuracy, but it is likely that investors can diversify it away. Though corporate defaults follow a procyclical trend, the overall default rate does rarely exceed 4%. Even in such a worst case scenario, an investor who holds the market portfolio will not incur extreme losses from defaults. Losses will only be substantial if the value of all other surviving firms deteriorates, as well.

This brings us to the question whether the definition of distress that has been used in this thesis, the default event, nests this kind of distress risk. Defaults are perhaps too extreme and rare to pose a risk for the average firm. A different way to look at distress risk would be to identify situations when firms are not profitable enough to cover their obligations. Such definitions have already been used to investigate other issues (Andrade & Kaplan 1998, Whitaker 1999). I have experimented with models forecasting early distress instead of defaults, as well. By and large, the results were inconclusive, too. Altering the definition of distress in this fashion reduces the skew in the distribution of risk scores. More firms will be at risk. However, to what extent is the resulting risk a distress risk and to what extent is it a common profitability risk? The relation between stock returns and the latter is, of course, trivial. The crux is that an informative risk characteristic (one that forecasts default) will always follow a skewed distribution with few firms at risk and many that remain totally unaffected. Defining a distress risk characteristic based on a less extreme definition runs into the danger of being ambiguous, which leads us back to where the empirical literature currently stands.

I conclude that measuring distress risk as a firm characteristic is inappropriate in asset pricing. Interesting alternatives for future research can be found in macroeconomics. For example, the results presented by Hahn & Lee (2006) and Petkova.
suggest that the default spread, the difference between risk-free and corporate bonds, is correlated with the Fama & French risk factors in the US. Similarly, Boons (2016) finds the default spread forecasts credit crunches and exposure to this variable is priced in the cross-section of US stocks. In general, macroeconomics opens up natural ways to look at what we call systematic risk in finance. We should recall the main reason for separating empirical finance from macroeconomics was that macroeconomic data are typically low-frequency data and less convenient than return data in research. Alas, high availability of (stock) return data has lead to an unprecedented data-mining which is making it harder than ever to understand what explains average stock returns. Firm characteristics do not seem to take us anywhere. Macroeconomic time series are now much longer than they were when research on the cross-section of stocks began and a larger variety of data has become available. Cochrane (2007) says understanding the macroeconomic risk that drives asset prices is the trunk of the tree. I agree and suggest that future research should reinforce efforts to explain patterns in the cross-section of stock returns with macroeconomic distress risk.

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Appendices

A. Collaboration with Peers

Three of the four research papers presented in the following annex have been written together with two co-authors. The fourth paper is authored solely by myself. This annex provides detailed information on the collaboration with peers in order to acknowledge the contributions of two persons, my supervisor Prof. Dr. Thorsten Poddig and former colleague Dr. Christian Fieberg, to the work presented in this thesis. I am grateful for their help.

The first paper, “The Relevance of Credit Ratings over the Business Cycle”, is based on data that have been collected by Dr. Fieberg. He has also provided some codes for the computation of AR. I have developed the story and hypotheses based on the macroeconomic theory. Moreover, I have written all code for hypothesis tests, regressions, plots and tables. The paper has been rewritten a number of times. All drafts have been written by myself. Prof. Poddig has gone through the text several times and has made valuable recommendations. He has made detailed suggestions with regard to shortening the final draft in order to publish the paper in the Journal of Risk Finance. The paper has been published in this Journal in December 2015.

The second paper, “Forecasting Corporate Defaults in the German Stock Market”, is based on data that have been hand-collected by myself. The theory and methodology have been developed by myself after a very thorough review of the literature. Code and text have been written entirely by myself. Prof. Poddig has made valuable suggestions with respect to the methodology. Moreover, he has gone to great lengths to improve the readability of the paper. Dr. Fieberg has contributed several suggestions and comments. I have presented the paper at the conference ”Reporting, Investor Relations, Capital Markets – Challenges and Opportunities in Financial Communication” at HHL Leipzig in November 2016. The paper has been submitted to the Journal of Risk and is currently under review.

The third paper, “Another Look at the Relation between Distress Risk and Equity Returns - Evidence From Germany” has been written in close collaboration with Prof. Poddig. He has made extensive contributions to the methodology of the paper. I have collected all data. Code and text have been written by myself. Prof. Poddig and I have discussed the results, which remain to some degree inconclusive, for a long time. The interpretations in the paper are a result from these discussions.
Dr. Fieberg has contributed several comments during the early phase of research. I have presented the paper at the 2016 HVB PhD student seminar in Münster. The paper shall soon be submitted to a suitable journal.

B. Research Papers

B.1. Paper I: The Relevance of Credit Ratings over the Business Cycle

The article “The Relevance of Credit Ratings over the Business Cycle” has been published in The Journal of Risk Finance and is not included in this version of the dissertation to avoid any copyright infringement.

B.2. Paper II: Forecasting Corporate Defaults in the German Stock Market

The article “Forecasting Corporate Defaults in the German Stock Markets” will be published in The Journal of Risk and is not included in this version of the dissertation to avoid any copyright infringement.

B.3. Paper III: Another Look at the Relation between Distress Risk and Equity Returns - Evidence From Germany
We assess the empirical relation between default risk and equity returns in the German stock market in order to provide out-of-sample evidence for the growing strand of literature which investigates whether distress risk a) explains stock returns and b) offers explanations for size, value or momentum effects in equity returns. At the core of this literature, which has come to unsettling and inconclusive results, is a fundamental discussion about the nature of risk factors in multifactor models like the Fama & French 3-Factor Model: are there really straightforward economic explanations (such as distress risk) for these factors? The empirical results for the German stock market lend support to the notion that distress risk itself is an idiosyncratic risk in the equity market. Even though characteristics like size, book-to-market-equity and momentum are intimately related to distress risk, the latter offers no explanation at all for the significant value and momentum effects in the German stock market.

1. Introduction

Researchers have identified way too many patterns in average stock returns. Since Fama & French (1992, 1993, 1996), the list of firm characteristics that supposedly explain returns has become endless. The ever growing literature on the cross-section of stocks and firm characteristics surveyed by Harvey et al. (2015) leaves
us in an uncomfortable place: which characteristics-related effects are real, which are artifacts due to data-mining? How should we deal with the multidimensionality, how many independent characteristics are there (Cochrane 2011)? And finally: how can we make sense of it all? Are there really straightforward economic explanations for common characteristics-related effects? This article is devoted to shed further light on the last two aspects. We assess the empirical relation between stock returns and distress risk in order to investigate whether firm distress risk, a popular explanation (Fama & French 1995, 1996), is behind size, value and momentum effects in the German stock market.

Assessing the ability of distress risk to explain equity returns touches one of the most intensely debated issues in finance. Now the most commonly used empirical asset pricing models are multifactor models like the Fama & French (1993)-3-factor-model (FFM) and the Carhart (1997)-Four-Factor-Model (CFM). These models are widespread in empirical research and practice, notwithstanding that it remains largely unclear what kind of risk their factors actually represent. Advocates of rational pricing theories claim that these factors are systematic risk and have suggested that distress risk is the fundamental explanation behind the factors (Fama & French 1995, 1996). However, a growing strand of the empirical literature finds it extremely difficult to establish a clear-cut relation between distress risk and equity returns.¹ This paper is motivated by the contradictory results of this literature that call for out-of-sample evidence. The German stock market, which differs from the US market, for instance due to Germany being characterized as a bank-based economy, is interesting in this regard for two reasons. First, the German stock market has not been researched as intensively as the US market. Second, there is evidence for significant value and momentum effects but not much support for risk factor models like the FFM or CFM. Several authors find that these models fail to explain returns in the cross-section of German stocks (Artmann, Finter, Kempf, Koch & Theissen 2012, Artmann, Finter & Kempf 2012, Brueckner 2013, Fieberg et al. 2016). While these articles show that there are indeed value and momentum effects in the German stock market, they find that risk factors based on these effects provide no good explanations for returns. The empirical analysis sheds light on whether firm distress risk explains pattern in returns in the cross-section of German stocks.

The empirical analysis provides ex-post and ex-ante perspectives on distress risk.

¹Several papers find that distress risk increases equity returns (Anginer & Yildizhan 2014, Vassalou & Xing 2004, Friewald et al. 2014). However, a growing body of literature reports evidence in favor of a distress risk puzzle, i.e. a negative relation between distress risk and equity returns (Campbell et al. 2008, Dichev 1998, Griffin & Lemmon 2002, Ding et al. 2012, Ferreira Filipe et al. 2014).
We add to the literature by conducting an ex post control firm analysis. Comparing the long-run Buy-and-Hold Abnormal Returns (BHAR) of defaulters against firms with similar characteristics that stay alive shows significant underperformance of the former up to one year before the default event. Prior to that, future defaulters seem to outperform survivors but the return differences are statistically insignificant. Furthermore, we use the default risk models that have been tested in the German stock market by Mertens et al. (2016) for portfolio sorts and Fama & MacBeth (1973) regressions. The F-Score model proposed by Campbell et al. (2008) and recalibrated for the German market by Mertens et al. (2016) serves as base model in the article. We choose this model because it is known to outperform other models in forecasting corporate defaults. Hence, using this model, reduces measurement error and, in general, the arbitrariness of other common characteristics associated with distress risk. Only a small fraction of firms is affected by distress risk, which is by nature an extreme risk. Overall, we find that this risk can be characterized as idiosyncratic in the stock market. Though average returns on F-Score sorted portfolios exhibit a pattern that is similar to the findings of the US-literature (Campbell et al. 2008, Dichev 1998, Griffin & Lemmon 2002), this finding does not pass standard asset pricing tests in the German stock market. Moreover, while distress risk has straightforward relations to characteristics like size, book-to-market-equity (BTM) and momentum, we do not find that it offers convincing explanations for the significant value and momentum effects in the German market.

We perform several robustness checks, most notably by excluding small firms and defaulters. Dropping small firms and defaulters from the sample reduces distress risk substantially but yields stronger evidence for a negative relationship between firm distress risk and stock returns. However, in such settings, models forecasting defaults mainly reflect correlation with momentum and value and not actual distress risk. Overall, the cross-section of German stocks contains relatively more distressed firms than the cross-section of US stocks studies by Campbell et al. (2008). Perhaps the negative relation between distress risk and returns detected by Campbell et al. and others is driven by the low levels of risk and reflects such correlation rather than causality.

The rest of this paper is structured as follows. We explain the appeal of distress risk as an explanatory variable in empirical asset pricing models and summarize the related literature in section 2. Section 3 describes the methodology, in particular the ex post control firm analysis, portfolio sorts and Fama & MacBeth (1973) regressions. The sample is introduced in section 4. Results are presented in section 5. Section 6 discusses the robustness of our results to the variation of various parameters and section 7 concludes.
2. Theory and Hypothesis Development

A stunning data mining has been going in research on the cross-section of stocks. Harvey et al. (2015) survey hundreds of articles in search for variables that have been found to be significantly related to returns. In total, they find 316 different variables. It appears that associating firm $i$’s characteristics $C$ with the excess returns on its stock $r^e$ is one of the most popular sports in economics:

$$r^e_{i,t+1} = \alpha_i + b' \times C_{i,t}. \tag{1}$$

Overall, applying frameworks like (1) has tended to make matters in asset pricing much less clear. Most importantly, the extensive research is calling the way factor models translate (risk) factors into returns into question.

Empirical asset pricing models are themselves commonly based on firm characteristics. The most popular examples are the FFM and the CFM. Fama & French (1992, 1993) have proposed the former in the light of an overwhelming evidence on the failure of the single-factor Capital Asset Pricing Model (CAPM) to explain patterns in returns with regard to firm size (Banz 1981) and BTM (Rosenberg et al. 1985). The FFM was built on the premise that return differences between small and big firms, the Small-Minus-Big (SMB) factor, as well as growth and value firms, the High-Minus-Low (HML) factor, are systematic risk (Fama & French 1995, 1996). Furthermore, Jegadeesh & Titman (1993) show that firm momentum is associated with patterns in returns that are unexplained by the CAPM and the FFM. Consequently, Carhart (1997) proposed to amend the FFM by a a momentum factor constructed from return differences between past winners and loser, the Winner-Minus-Loser (WML) factor. The model including this factor is called the CFM. More recently, Fama & French (2015) suggest to construct additional factors based on investment expenditure and profitability, yet two more firm characteristics.

The papers briefly summarized above certainly play in their own league. Though dealing with four or five characteristics might be complicated enough, this is nowhere near where the empirical literature summarized by Harvey et al. (2015) and Richardson et al. (2010), who provide another review, currently stands. Apparently, there is an ever growing evidence on failures of empirical asset pricing models and new significant characteristics. The cross-section is in a mess. There is an urgent need for cleanup efforts. Cochrane (2011) demands that future research must reduce the “zoo” of anomalies. Which characteristics do explain returns and
which are subsumed by others?

In this article, we investigate whether firm distress risk imposes structure on common characteristics in the German stock market. Below we discuss why distress risk has been brought forward in the related literature as a superimposed risk behind several characteristics. Risk factor models like the FFM do not pass standard tests in the full cross-section of German stocks, but there is strong evidence for significant characteristics-effects, in particular value and momentum effects (Artmann, Finter, Kempf, Koch & Theissen 2012, Artmann, Finter & Kempf 2012, Brueckner 2013, Fieberg et al. 2016). In this regard, the situation seems to be similar to the US. On the other hand, the German data set has not yet been so extensively mined for explanatory variables. This enables us to present interesting out-of-sample evidence on the relation between distress risk and equity returns.

2.1. The Case for Distress Risk

The problem with common characteristics is twofold. First, in many cases there is little theory behind them. The size effect is a good example. There are potentially many reasons why small firms earn, on average, larger returns than big firms (liquidity, bankruptcy risk, opaqueness, to name a few), but Banz (1981) bluntly acknowledges that his discovery of the size effect itself has no theoretical foundations at all. Second, common characteristics are highly ambiguous and if they are a measure for some kind of risk, they are probably subject to measurement errors. Penman et al. (2007) interpret leverage as a proxy for financial risk and find a seemingly puzzling negative relation between leverage and stock returns. However, by intuition this finding must by no means be a puzzle. Sorting firms by leverage will typically show that relatively safe firms apply more leverage and risky firms are constrained in the debt market (George & Hwang 2010). Thinking carefully about what one should do with characteristics and making sure that the characteristics are really an adequate measure for the subject at hand is essential to prevent further chaos in the cross-section.

There are several theoretical arguments for the ability of distress risk to explain patterns in stock returns. Corporate balance sheets mirror business cycle dynamics (Bernanke et al. 1996) and default rates fluctuate pro-cyclically. Following in this vein, Fama & French (1995, 1996) argue that investors, who have outside labor income, should dislike firms with high distress risk. Following basic Intertemporal Capital Asset Pricing Model (ICAPM) (Merton 1973) logic, these firms must, on average, earn larger returns. Consequently, distress risk has been associated
with many different characteristics. Fama & French regard distress risk as an explanation for the value effect. There are also strong arguments for relations of size and momentum with distress risk. Small firms and past losers have much higher default risk (Agarwal & Taffler 2008a, Campbell et al. 2008, Mertens et al. 2016). Hence, distress risk is probably mechanically related to size and momentum. Therefore, it seems plausible that size and momentum effects could be explained by a distress effect. Avramov et al. (2007), who use credit ratings as proxy for distress, find that momentum effects are driven by past losers with low credit ratings. Similar results are presented by Agarwal & Taffler (2008b).

The theoretical case for distress risk is compelling. An important question remains how the concept of distress risk outlined above should be defined in order to be an accurate measure of risk that is useful in empirical research. Firm distress can be defined as a temporary state in which a firm cannot honor its commitments (Asquith et al. 1994, Andrade & Kaplan 1998, Whitaker 1999). This state may lead to default, which is terminal. Though distress and default are not the same (Wruck 1990), the related empirical literature summarized below is centered on the default event. This article follows this literature in treating distress and default risk as if they were one and the same thing. From now on, we use the terms distress risk and default risk interchangeably. We discuss the consequences of this assumption as we present the results. Forecasting corporate defaults (measuring default risk) has a long tradition in finance. Substantial progress has been made in this area since the early work of Altman (1968). Modern default risk models can be regarded as very powerful. Mertens et al. (2016) test several of them in the German stock market and confirm the good performance of the failure score proposed by Campbell et al. (2008). We adapt this model, which is in detail introduced in section 3, as a characteristic for default risk in this article. In doing so, we can substantially reduce the measurement problem. Moreover, we can use this measure in generic frameworks like (1) and make our research directly comparable to the related literature.

A strand of the empirical literature has looked at the relation between equity returns and firm distress risk in the US. This literature has applied different default risk models to measure distress risk at the firm level and then used this information to form distress risk portfolios. The results are summarized in table 1.

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2Distress risk and default risk are probably similar to each other. Pindado et al. (2008) propose empirical models to forecast distress (not default) and find that the variables that are used to forecast distress are the same as variables that are commonly used to forecast defaults.
<table>
<thead>
<tr>
<th>Authors</th>
<th>Default Risk Model</th>
<th>Relationship with Default Risk</th>
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<tr>
<td></td>
<td>Return</td>
<td>Beta</td>
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<tr>
<td>Dichev (1998)</td>
<td>Z-Score, O-Score</td>
<td>-</td>
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<tr>
<td>Griffin &amp; Lemmon (2002)</td>
<td>Z-Score, O-Score</td>
<td>-</td>
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<tr>
<td>Vassalou &amp; Xing (2004)</td>
<td>DD</td>
<td>+</td>
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<tr>
<td>Agarwal &amp; Taffler (2008b)</td>
<td>Z-Score</td>
<td>-</td>
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<tr>
<td>Campbell et al. (2008)</td>
<td>F-Score</td>
<td>-</td>
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<td>Avramov et al. (2009)</td>
<td>Ratings</td>
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<tr>
<td>Breig &amp; Elsas (2009)</td>
<td>DD</td>
<td>-</td>
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<tr>
<td>Garlappi &amp; Yan (2011)</td>
<td>DD</td>
<td>+/-</td>
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<tr>
<td>Ding et al. (2012)</td>
<td>F-Score</td>
<td>-</td>
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<tr>
<td>Frewald et al. (2014)</td>
<td>CDS</td>
<td>+</td>
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<tr>
<td>Anginer &amp; Yildizhan (2014)</td>
<td>Bond Spreads</td>
<td>+</td>
</tr>
<tr>
<td>Ferreira Filipe et al. (2014)</td>
<td>DD</td>
<td>-</td>
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This table summarizes the related literature. Column two indicates the models applied to measure distress risk. Columns three to six indicate the relationship with returns, beta, size and BTM. A + (-) indicates a positive (negative) relationship. +/- indicates an ambiguous relationship. Fields are left blank when the relationship does not become clear in a paper.

Table 1: Literature Summary
The articles apply a battery of models, including the Altman (1968) Z-Score, Ohlson (1980) O-Score, Merton (1974) Distance-to-Default (DD), credit spreads or ratings, as models to measure default risk. Only few articles evaluate how well these approaches actually forecast defaults (Campbell et al. 2008, Vassalou & Xing 2004). As such, the strand of the literature is a good example for the body of research on the cross-section of stocks. The results are inconclusive. Several studies document a negative relation between firm specific distress risk and equity returns (Dichev 1998, Griffin & Lemmon 2002, Campbell et al. 2008, Avramov et al. 2009, Ding et al. 2012, Ferreira Filipe et al. 2014). These authors conclude that this finding contradicts our intuition about the relationship between risk and return in general and have called it the distress risk puzzle. They conclude that anything beyond behavioral explanations for these findings is hard to conceive. However, some authors also report a positive relation between distress risk and equity returns (Anginer & Yildizhan 2014, Friewald et al. 2014, Vassalou & Xing 2004). Moreover, the related literature shows strong relations of distress risk with size and BTM (columns five and six of table 1). Distressed firms tend to be small value firms. These findings are completely in line with the intuition proposed by Fama & French (1993).

By and large, the empirical results remain inconclusive: is there a distress effect in the equity market? If so, can this effect reduce the multidimensionality in the cross-section and explain size value as well as momentum effects? There is need for out-of-sample evidence.

2.2. Research Hypotheses

We present such evidence by repeating the analyses that have been conducted in the U.S. literature in the German capital market. The goal is to assess the basic relation between firm distress risk and equity returns. We use a realistic forecasting model developed by Mertens et al. (2016) to model the market expectations for distress risk and use this information for portfolio sorts and Fama & MacBeth (1973) regressions. Our first hypothesis states that equity investors are compensated for bearing distress risk.

3Breig & Elsas (2009) present some results on the relationship between distress risk and equity returns in the German stock market. This working paper differs from this article as its empirical analysis is based on several test assets and not the entire cross-section of German equities. Their work is based on the premise that distress risk is systematic, so they begin with the construction of risk factors. We take a more agnostic stance on the matter and assess whether there is a distress effect in the cross-section.
H1 Returns on high distress risk firms are larger than returns on low distress risk firms.

Support for H1 would be given by outperformance of the high distress risk portfolio versus the low distress risk portfolio as well as significance of distress risk in Fama & MacBeth (1973) regressions. If H1 is rejected, there can be no superimposed distress risk factor. Nevertheless, distress risk might still be a part of the explanation for size, value and momentum effects. After all, they are catch-all effects that might still partly be related to distress risk. This is what our second set of research hypotheses postulates:

H2 Distress risk explains the size effect: When we control for distress risk, size effects disappear.

H3 Distress risk explains the value effect: When we control for distress risk, value effects disappear.

H4 Distress risk explains the momentum effect: When we control for distress risk, momentum effects disappear.

The hypothesis H2-H4 refer to a common problem in statistics: does an additional control variable (distress risk) affect the significance of the other explanatory variables (size, BTM, momentum)? A careful regression analysis is in order. The methodology is explained in the following.

3. Methodology

We look at the empirical relationship between distress risk and equity returns from two perspectives. An ex post analysis is supposed to shed light on the long run BHAR of investments in bankrupt firms. We expect them to underperform in the years preceding their failure as market participants anticipate their default. To find preliminary evidence for H1, we need to detect positive outperformance of bankrupt firms in the years before their decline. We make use of a control firm analysis to measure long run BHAR of bankrupt firms. The ex ante analysis follows the methodology of the literature listed in table 1 and performs portfolio sorts based on a distress risk model, which has been developed and tested using the same dataset as we will use in this paper. The ex ante portfolio sort approach allows us to derive a realistic relationship between distress risk and expected equity returns. Moreover, Fama & MacBeth (1973) regressions deliver further insight
with regard to the interrelations between firm specific distress risk, size, value and momentum effects (H2-H4).

3.1. Ex Post Control Firm Analysis

Barber & Lyon (1997) recommend the control firm analysis to detect long run abnormal performance. In simulation studies they find that test statistics suffer from new listing, rebalancing and skewness bias, when comparing the firms of interest with proxies for a market portfolio. Their results demonstrate that these problems do not arise when the firms of interest are matched with similar firms. They detect similarity based on size and book-to-market equity. Following this recommendation, we match each bankrupt firm in our sample at the beginning of its records with a similar firm. We deem a firm to be a qualified control firm if it has never entered insolvency proceedings and was neither acquired or delisted from the market for any other reason. Moreover, we require the control firm to be in the same industry. Finally, we apply two criteria to numerically determine similarity: Control firms must have a similar size and a similar BTM. To operationalize this, we z-transform the size and BTM of all eligible firms at the instant of the defaulter first entering the sample. In other words, we z-transform size and BTM in the cross-section consisting of the defaulter and eligible control firms on the first trading day of the defaulter. Then, we compute the Euclidean distance between each qualified control firm and the respective study firm. We select the firm with the minimum distance as the control firm. Following this procedure we can find appropriate control firms in our sample without problems. We do allow a control firm to serve as a control for multiple bankrupt firms. This is necessary in order to find suitable control firms in small industry groups. However, we do not obtain control firms that serve as a control for many different bankrupt firms.\(^4\)

Given an appropriate control firm \(j\), we compute the yearly BHAR for every bankrupt firm \(i\) according to (2):

\[
BHAR_{i,\tau} = \sum_{t=\tau-250}^{t=\tau} r_{i,t} - \sum_{t=\tau-250}^{t=\tau} r_{j,t},
\]

where we apply (2) to the log returns \(r\) for values of \(\tau\) equal to the date of the bankruptcy event and 1-7 years before the bankruptcy event. Hence, we compute

\(^4\)Restricting firms to act as controls for several bankrupt firms does not affect the results.
yearly BHAR for up to eight years before the event given that the history of a bankrupt firm is long enough. This procedure yields a $8 \times n_D$ matrix with BHAR, where $n_D$ denotes the number of defaulters in the sample. Based on this data, we formally test whether bankrupt firms out- or underperform control firms at any point in time. As is expected and evident in the data, BHAR are non normally distributed in the cross-section, they are highly skewed, especially for small values of $\tau$. Thus, we conduct a nonparametric hypothesis test. Specifically, we use the Wilcoxon Signed-Rank test to determine whether the cross-sectional BHAR differ significantly from zero. It is expected that bankrupt firms will underperform the year prior to bankruptcy ($\tau = 0$). To find preliminary evidence for H1, we should detect significantly positive BHAR in the time span long before bankruptcy ($\tau > 2$). This ex post view on default risk is very helpful as it yields results that are intuitively interpretable. Such an analysis has not been conducted in the related literature. Moreover, the ex post analysis does not require a model to estimate distress risk and is therefore to a lesser degree affected by model risk and the joint hypothesis problem (Lo & MacKinlay 1999).

### 3.2. Ex Ante Analysis

However, the parsimonious ex post analysis has three shortcomings and can thus only provide preliminary evidence. First, by considering only defaulters and survivors, this procedure reduces firm specific distress risk to a dichotomy. The analysis provides no insight about the full spectrum of default risk and its relationship with returns. Second, as it relies on the knowledge of future information, it is not a feasible investment strategy and fails to account for the expectations of investors. This aspect seems to be especially important with regard to distress risk. The credit risk literature has developed models that are relatively successful in forecasting defaults, especially if the forecasting horizon does not exceed one year (Bharath & Shumway 2008, Bauer & Agarwal 2014, Mertens et al. 2016, Tian et al. 2015). Not accounting for the predictability of defaults will distort the results. Third, the control firm analysis restricts us from forming portfolios, whereas this is necessary to gauge systematic effects.\(^5\)

To address these issues, we follow the literature listed in table 1 and perform portfolio sorts based on a distress risk model. Specifically, we use a re-calibrated variant of Campbell’s (2008) failure score (F-Score). The F-Score model contains

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\(^5\)Given a sufficient number of firm that default simultaneously, we would be able to conduct an ex-post analysis based on portfolios. The number of defaulters in our sample is too small for such an analysis.
the following exogenous variables for the prediction of defaults:

- NIMTA: net income / market value of total assets
- TLMTA: total assets / market value of total assets
- CASHMTA: cash / market value of total assets
- SIGMA: standard deviation of stock returns
- EXRETA AVG: excess stock return over CDAX
- PRC: log price truncated above log(15) EUR
- RSIZE: relative market capitalization
- MB: market equity / book equity

The exogenous variables listed above include proxies for size (RSIZE), value (MB) and momentum (EXRETA AVG). Hence, the F-Score may be regarded as a super-characteristic that has been calibrated to forecast defaults. Mertens et al. (2016) have tested the F-Score model in the German stock market and provide further computational details (see their section 3.1). They show that this model dominates other known distress risk models in terms of forecasting accuracy in the German market. We use the same data as Mertens et al. (2016) in this article. Hence, it is appropriate to choose this model as our base model for distress risk. We check the robustness of our results with regard to alternative distress risk models in section 6.

Mertens et al. (2016) re-estimate the F-Score at the beginning of every calendar year using a rolling out-of-sample (“walk-forward”) re-estimation procedure (Sobehart et al. 2000).\footnote{Again, we acknowledge that the F-Score might be restrictive as it focuses on the default event and not on the state of distress. While Mertens et al. (2016) show that the model is a reliable predictor of defaults, we cannot test to what extent firms with elevated F-Scores are distressed. However, it is well known that defaults rarely happen out of the blue. The strong performance of forecasters like the F-Score illustrate that firms probably undergo a period of distress before they default. Therefore, we believe that using the F-Score as a proxy for distress and default risk is reasonable.} In principle, a more frequent re-estimation is desirable in this paper because this would enable us to consider market expectations timely. However, the balance sheet indicators listed above are only available in annual frequency. Frequent re-estimations might reduce the default risk forecast to a selection of negative momentum firms. To strike a balance between a timely con-
sideration of expectations and measuring fundamental default risk, we re-estimate the F-Score model in January and July based on semi-annual data and form ten portfolios based on the obtained default risk scores. A higher score implies a higher probability of default. Portfolio one contains the firms with the lowest distress risk, portfolio ten contains the firms with the highest distress risk. For each portfolio, we compute value-weighted and equal-weighted returns as well as the average portfolio characteristics. Moreover, we also compute the returns on the 10-1 portfolio, which shorts low distress risk stocks and assumes a long position in high distress risk stocks. To control for the established risk factors, we compute standard asset pricing models for each portfolio. We apply the CAPM, the Fama & French (1993)-3-factor-model (FFM) and the Carhart (1997)-Four-Factor-Model (CFM).

The ultimate test for the relation between firm specific distress risk and equity returns is based on the 10-1 portfolios. Significantly positive 10-1 returns and alpha coefficients point to a positive distress effect as implied by H1. Insignificant 10-1 returns and alpha coefficients suggest that firm specific distress risk is an idiosyncratic risk in the German equity market. Apart from the standard t-tests, we also perform the Gibbons-Ross-Shanken (GRS) test proposed by Gibbons et al. (1989) as well as the monotonicity test proposed by Patton & Timmermann (2010). The former tests the null that the alpha coefficients in the asset pricing models are jointly equal to zero. The latter tests the null that the mean expected returns of the ten distress risk portfolios exhibit a non-monotonic pattern.

The remaining research hypotheses (H2-H4) are devoted to assessing whether distress risk can explain size, value and momentum effects. As argued in section 2, there might be a complex nexus between these effects. This setup calls for a very careful regression analysis. We perform Fama & MacBeth (1973) regressions as specified in (3)

\[
 r_{i,t+1} = \lambda_0^{t+1} + \text{SIZE}_{i,t} \times \lambda_S^{t+1} + \text{BTM}_{i,t} \times \lambda_V^{t+1} + \text{MOM}_{i,t} \times \lambda_M^{t+1} + F\text{-SCORE}_{i,t} \times \lambda_D^{t+1} + \epsilon_{i,t+1},
\]

(3)

where \( r \) denotes the excess return of firm \( i \) at time \( t \). To maintain consistency, we

\[\text{Mertens et al. (2016) present results on the forecasting performance of the F-Score based on yearly re-estimations, but they conduct robustness checks using semi-annual re-estimations. The F-Score outperforms all other models in this case too. The risk scores used in this article can be translated into six-months-ahead probability of default (PDs). We sort portfolios based on scores because sometimes the distribution of probabilities is highly skewed and this can be a problem for sorting algorithms.}\]
estimate (3) at the beginning of every January and July and aggregate the returns to semi-annual returns. The different time subscripts for returns and characteristics indicate that the re-estimation at the beginning of January is a regression of the characteristics size, BTM, momentum (MOM) and F-Score observed at the beginning of January on the returns observed at the end of June. We estimate several variants of (3). Based on the results that have been presented in the related literature (Artmann, Finter & Kempf 2012, Fieberg et al. 2016, Schrimpf et al. 2007), we expect that a version without F-Score as a control for distress risk shows significant value and momentum effects ($\lambda^V, \lambda^M > 0$). With F-Score as a control for distress risk, a significant coefficient $\lambda^D$ would be evidence for a distress effect (H1). We can judge to what extent distress risk explains the other effects by comparing how significances and magnitudes of the other coefficients change once we control for distress risk (H2-H4).\textsuperscript{8}

A new methodological debate about statistical inference in asset pricing and corporate finance is quickly gaining importance the research community. The debate centers on how standard errors should be computed (Cameron et al. 2006, Gow et al. 2010, Petersen 2008) and how we should deal with the data-snooping bias inherent in modern empirical research (Harvey et al. 2015).

The Fama & MacBeth (1973) procedure uses the time-series of coefficients to estimate standard errors.\textsuperscript{9} Two issues inherent in (3) might cause problems with regard to statistical inference. First, the residuals might be correlated across different firms, $\text{Cov}[\epsilon_{i,t}, \epsilon_{j,t}] \neq 0$ where $i \neq j$, which is called a firm effect. A firm effect is present, when a certain firm is individually affected by some factor that is not explicitly modeled. Second, the residuals might be correlated across time period, $\text{Cov}[\epsilon_{i,t}, \epsilon_{i,t-s}] \neq 0$ where $s \neq 0$, which is called a time effect. A time effect is given when forces that are not modeled as a control variable affect returns at the same time. In general, it is very hard to preclude both effects in finance. This is why Cameron et al. (2006) have proposed clustered standard errors. Standard errors can be clustered on time, firm or both to account for the correlation structures discussed above. Petersen (2008) and Gow et al. (2010) show that unclustered standard errors can lead to grossly wrong conclusions when the correlation structured describe above are in fact present. However, clustering is no universal remedy. In settings without correlated errors the conventional variance estimator is, of course, the right choice. Moreover, clustered errors can be wrong

\textsuperscript{8}In section 4 we show that the empirical correlations between the right-hand-side variables of (3) do not point to serious multicollinearity issues. We find that orthogonalization does not affect the results.

\textsuperscript{9}When factor loadings instead of characteristics are the regressors, the errors should be adjusted for the errors-in-variables problem as suggested by Shanken (1992).
when the number of clusters (number of firms or time periods) is low. We choose to be very careful and report a variety of standard errors for the coefficients. First, we compute the conventional Fama & MacBeth (1973) t-value based on the distribution of the estimated coefficients. Moreover, t-values with standard errors clustered on firm and time are reported. Lastly, we also compute a t-value based on two-way clustered errors.\textsuperscript{10} Clustering has been implemented using the functions provided by Cameron et al. (2006) and Gow et al. (2010). In accordance with these authors, we use critical values from the t-distribution with $G - 1$ degrees of freedom, $G$ being the smallest number of clusters (firms or time periods) along either dimension.

In addition to that, Harvey et al. (2015) conclude that after the extensive data mining that has taken place in the literature, even if standard errors are in fact correct, the hurdle rate for a conventional t-value should be larger than 2.0. To account for the looming data-snooping bias, every new paper makes things worse in this regard, they use a multiple testing framework to evaluate the results of previous research and derive new, more reliable cut-off values for future research.\textsuperscript{11} Harvey et al. (2015) argue that a newly discovered variable should have a t-value above 3.0. This hurdle rate should increase in the future with the number of additional research papers mining the data. One might argue that the hurdle rate should be lower when the sample is not the most actively researched US cross-section of stocks. Albeit, even though it might be less popular, research on, say, the cross-section of German equities, is still the same sport and the data-snooping concern does not completely go away. Hence, careful research should at least express some doubts when the t-values of new factors do not exceed 3.0.

We are convinced that, in spite of these complications, a panel regression like (3) is the right methodology to isolate distress risk from other effects in equity returns because it enables us to address the multidimensionality of the problem (Cochrane 2011). Moreover, in this case statistical inference has very well-researched properties. Nevertheless, we acknowledge that there are alternative methodologies. First, there is the technique of double sorts that can be helpful to assess the joint effect of two different variables on returns. In general, sorts are a nonparametric

\textsuperscript{10}The conventional ordinary least squares (OLS) variance estimator is $V = s^2 \times (X'X)^{-1}$, where $s^2 = \frac{1}{N - K} \times \sum_{i=1}^{N} e_i$, and $N, K$ denote the numbers of observations and parameters, respectively. With one-way clustering the variance estimator is $V_{\text{clustered}} = (X'X)^{-1} \times \sum_{j=1}^{N_c} u_j' \times u_j \times (X'X)^{-1}$, where $N_c$ denotes the number of clusters (e.g. firms/years) and $u$ is $\sum e_i \times x_i$ in each cluster. See Cameron et al. (2006) for further details and the variance estimator in the case of two-way clustering.

\textsuperscript{11}Multiple testing is an area in statistics that is devoted to addressing data-mining biases. In general, the techniques in this area adjust the p-values using the number of hypothesis that have been tested before.

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method. When a relation is non-linear, sorts can help to gain a better visual evaluation. Since a characteristic feature of default risk is that risk indicators exhibit highly skewed distributions, many firms are virtually not at risk, whereas few firms have a high risk of defaulting (Bohn 2011, Mertens et al. 2016), such a method might have its merits, too. Therefore, we consider double sorts in appendix A. In general, sorts are limited in jointly considering several control variables. The cross-section of German equities is rather small, anything beyond double sorts is not appropriate. Daniel & Titman (1997), Daniel et al. (1997) propose an alternative sort technique based on characteristics-adjusted returns, which might fare better in detecting a relationship between distress risk and equity returns net of characteristics-effects. Such an analysis is presented in appendix B.

4. Data and Descriptive Statistics

We obtain all non-financial firms that have equity listed in Frankfurt, the main stock exchange in Germany, from the Thomson Reuters Datastream database. Specifically, we select all non-financial active and dead firms available between 1990 to 2015. We include only securities that Datastream labels as “primary listings”. Equity prices and total return indices are provided with daily frequency. Worldscope balance sheet and profitability data, which are also provided by Datastream, is only available with an annual frequency. These data items are lagged by six months to account for the publication lag. Moreover, individual stock returns and balance sheet items are winsorized at the 1% level.\textsuperscript{12} We define the CDAX index as a proxy for the market portfolio and use the yield to maturity on 1-year German Bunds as proxy for the risk-free rate. Datastream data is known to contain some flaws. We follow the recommendations made by Ince & Porter (2006) and Brueckner (2013) to clean the data. SMB, HML and WML factors have been obtained from Prof. Stehle’s Website.\textsuperscript{13}

For our analysis it is crucial to know when and for which reasons a firm has left the stock market. Most importantly, we need information about defaults to estimate the F-Score model. Unfortunately, this information is not available on Datastream. We use the data on defaults in the German market collected by Mertens et al.\textsuperscript{12}

\textsuperscript{12}Mertens et al. (2016) find that winsorization at alternative levels or refraining from winsorization does not affect the performance of default risk models. Similarly, we do not find that our empirical results are affected by this choice.

\textsuperscript{13}The link to the website is https://www.wiwi.hu-berlin.de/de/professuren/bwl/bb/data. We find that using self-constructed risk factors or the factors provided by Artmann, Finter, Kempf, Koch & Theissen (2012) does not affect our results.
(2016) to determine the exact exit date of all defaulters. Consequently, we set a firm to missing on the day after it has filed for default with a German court. We set other inactive firms that have not defaulted to missing whenever prices have been stale for a year. Moreover, we exclude firms that have been penny stocks for 95% of their lifetime. In particular this should address the most extreme cases of investor fraud that have happened in the German stock market over the course of the years. Besides that, we do not exclude penny stock observations per se. In this regard, our dataset differs from the data used in other empirical work on the German market. Brueckner et al. (2012) remove firms as soon as their share price is below 1 EUR. Artmann, Finter, Kempf, Koch & Theissen (2012) do not really describe how they deal with small prices. Obviously, there are arguments for a strict immediate exclusion of penny stocks (Brueckner et al. 2012). However, small prices and a small market capitalization are natural attendant circumstances of distress and failure. Erasing firms as soon as their share price drops below a certain threshold would imply erasing a lot of high distress risk firms and therefore bias our results.\textsuperscript{14} We conduct several robustness checks to see if very small firms are driving our results.

An introduction to the past and the present of the German stock market is provided by Stehle & Schmidt (2015). This market has a few features that make it interesting for research on the pricing of distress risk. First, the German stock market experienced a massive increase of listed firms in the years before the dot-com bubble burst. This is visible in column two of table 2, which presents the numbers of active and defaulted firms in our sample.\textsuperscript{15} In the late 1990s, the boom of tech-stocks was fueled by Deutsche Boerse AG, the German exchange, with the introduction of a new segment for internet start-ups, the so called “New Market” (Neuer Markt). The idea was to create a market segment similar to NASDAQ with laxer listing standards. After the stock market crash of 2001, a large number of these firms experienced distress and many failed spectacularly. This is illustrated in columns three and four of table 2. This episode has severely damaged the reputation of the German stock market as well as the German equity culture. Before this first default wave, defaults were quasi unheard of in the German stock market. The low number of defaults prior to 2001 restricts us from estimating the F-Score before January 2001. Unfortunately, this leads to a loss of information, in particular on the rise of the New Market. There are two further spikes in the annual default rate in 2009 and in 2013, which are due to the financial crisis and

\textsuperscript{14}Moreover, Brueckner et al. (2012) limit their analysis to firms listed in the top market segment of the Frankfurt stock exchange. This is not possible in a study on failure, as defaults in this segment are extremely rare.

\textsuperscript{15}This table is identical to table 1 in Mertens et al. (2016), who use the same sample to test the performance of default risk models.
a large number of defaults in the German solar cells industry, respectively. Hence, the dynamics of default in our dataset are to some degree similar and to some degree different from the existing research on the pricing of distress risk in the U.S. market. Moreover, Germany is also the textbook example of a bank-based economy. These aspects illustrate that the German stock market can provide interesting out-of-sample evidence on the empirical relation between distress risk and equity returns.
<table>
<thead>
<tr>
<th>Year</th>
<th>Active Firms</th>
<th>Defaulted Firms</th>
<th>Default Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>1991</td>
<td>313</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1992</td>
<td>324</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1993</td>
<td>328</td>
<td>1</td>
<td>0.3</td>
</tr>
<tr>
<td>1994</td>
<td>333</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1995</td>
<td>343</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1996</td>
<td>362</td>
<td>2</td>
<td>0.55</td>
</tr>
<tr>
<td>1997</td>
<td>368</td>
<td>2</td>
<td>0.54</td>
</tr>
<tr>
<td>1998</td>
<td>383</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1999</td>
<td>441</td>
<td>1</td>
<td>0.23</td>
</tr>
<tr>
<td>2000</td>
<td>577</td>
<td>3</td>
<td>0.52</td>
</tr>
<tr>
<td>2001</td>
<td>702</td>
<td>17</td>
<td>2.42</td>
</tr>
<tr>
<td>2002</td>
<td>691</td>
<td>28</td>
<td>4.05</td>
</tr>
<tr>
<td>2003</td>
<td>623</td>
<td>7</td>
<td>1.12</td>
</tr>
<tr>
<td>2004</td>
<td>585</td>
<td>8</td>
<td>1.37</td>
</tr>
<tr>
<td>2005</td>
<td>568</td>
<td>7</td>
<td>1.23</td>
</tr>
<tr>
<td>2006</td>
<td>566</td>
<td>8</td>
<td>1.41</td>
</tr>
<tr>
<td>2007</td>
<td>628</td>
<td>4</td>
<td>0.64</td>
</tr>
<tr>
<td>2008</td>
<td>658</td>
<td>9</td>
<td>1.37</td>
</tr>
<tr>
<td>2009</td>
<td>645</td>
<td>22</td>
<td>3.41</td>
</tr>
<tr>
<td>2010</td>
<td>607</td>
<td>11</td>
<td>1.81</td>
</tr>
<tr>
<td>2011</td>
<td>597</td>
<td>7</td>
<td>1.17</td>
</tr>
<tr>
<td>2012</td>
<td>596</td>
<td>10</td>
<td>1.68</td>
</tr>
<tr>
<td>2013</td>
<td>562</td>
<td>20</td>
<td>3.56</td>
</tr>
<tr>
<td>2014</td>
<td>533</td>
<td>7</td>
<td>1.31</td>
</tr>
<tr>
<td>2015</td>
<td>512</td>
<td>7</td>
<td>1.37</td>
</tr>
<tr>
<td>Full sample</td>
<td>1023</td>
<td>181</td>
<td>17.69</td>
</tr>
<tr>
<td>Yearly average</td>
<td>505</td>
<td>6.96</td>
<td>1</td>
</tr>
</tbody>
</table>

This table presents the total number of active firms in every year as well as the number of defaulters per year. The default rate is the %-share of defaulters in all active firms per year. The full sample default rate is the %-share of defaulters in all firms. Yearly averages are obtained by averaging all yearly observations in the table.

Table 2: Sample Statistics: Total number of firms and number of defaulted firms
We obtain out-of-sample F-Score distress risk score based on this data. Summary statistics for these scores and the other firm characteristics of interest are presented in panel A of table 3.

### Panel A: Summary Statistics

<table>
<thead>
<tr>
<th></th>
<th>Beta</th>
<th>Size</th>
<th>BTM</th>
<th>Momentum</th>
<th>F-Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.48</td>
<td>11.27</td>
<td>0.82</td>
<td>-5.21</td>
<td>-7.11</td>
</tr>
<tr>
<td>StdErr</td>
<td>0.6</td>
<td>44.16</td>
<td>0.71</td>
<td>52.96</td>
<td>1.87</td>
</tr>
<tr>
<td>P25</td>
<td>0.07</td>
<td>0.18</td>
<td>0.38</td>
<td>-27.53</td>
<td>-8.32</td>
</tr>
<tr>
<td>Median</td>
<td>0.43</td>
<td>0.6</td>
<td>0.63</td>
<td>1.39</td>
<td>-7.45</td>
</tr>
<tr>
<td>P75</td>
<td>0.84</td>
<td>2.76</td>
<td>1</td>
<td>24.14</td>
<td>-6.11</td>
</tr>
</tbody>
</table>

### Panel B: Correlations

<table>
<thead>
<tr>
<th></th>
<th>Beta</th>
<th>Size</th>
<th>BTM</th>
<th>Momentum</th>
<th>F-Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beta</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Size</td>
<td>0.06</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BTM</td>
<td>-0.06</td>
<td>-0.1</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Momentum</td>
<td>0.04</td>
<td>0.05</td>
<td>-0.27</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>F-Score</td>
<td>0.1</td>
<td>-0.14</td>
<td>0.12</td>
<td>-0.38</td>
<td>1</td>
</tr>
</tbody>
</table>

This table presents summary statistics (panel A) and correlation coefficients (panel B) for several firm characteristics. P25 and P75 denote the 25- and 75-percentile values, respectively. Size is reported in terms of 100 mn. Euros and momentum is reported in terms of percentage points. The stock returns and balance sheet items have been winsorized at the 1% level.

Table 3: Summary statistics and correlations

Compared with the related literature, the average firm in our sample is slightly smaller, has a higher BTM and much lower momentum. These differences can be explained by our somewhat different sampling procedure and the shortened sample period. As we cannot estimate the F-Score before 2001, we loose the bull phase of the early nineties. Hence, we begin the analysis just before the collapse of the so-called New Economy and do not delete many of the small firms entering the market during this period. In this respect, it is also notable that the distribution of firm size is heavily skewed towards small firms.\(^16\)

As expected, the average F-Score implies a probability of default of roughly zero and the distribution appears to the skewed to the right.\(^17\) Correlation coefficients are shown in panel B of table 3. In

\(^{16}\)This observation is similar to the descriptive statistics presented by Fieberg et al. (2016). An equal-weighted index of all active firms in the sample yields a negative total return over the entire sample period. Stehle & Schmidt (2015) provide further information on the effects of the rise and fall of the “Neuer Markt” segment on the total market capitalization of the German stock market (see their figure 1) .

\(^{17}\)The probability of default can be obtained by applying the logit transformation to the scores.
general, correlations appear to be low. The correlations of size, book-to-market equity and momentum with the F-Score are all intuitive and marginally significant. Alternative default risk models (see section 6) show very similar correlations.

5. Empirical Results

Table 4 shows the results of the control firm analysis. At the instance of the default event ($\tau = 0$, 0-250 days before bankruptcy) and one year prior to the default event ($\tau = 1,251-500$ days before bankruptcy), we observe large negative BHAR. Based on the Wilcoxon Signed-Rank test, these results are highly significant. They do not come as a surprise. Markets anticipate the default event, the death of the firm in its current form, as firms go through a period of distress. BHAR that are observed for the more distant past of the firm are all positive, statistically they are either insignificant or just marginally significant. One might wonder whether these results are still economically significant. After all, the control firm analysis does not yield fully conclusive results. The signs for the periods 2-7 are all in accordance with H1, but the total number of defaults in the sample is perhaps still too low to draw conclusions out of this.

<table>
<thead>
<tr>
<th>$\tau$</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>BHAR (%)</td>
<td>-44.6</td>
<td>-29.75</td>
<td>19.19</td>
<td>17.56</td>
<td>5.68</td>
<td>8.32</td>
<td>6.62</td>
<td>8.51</td>
</tr>
<tr>
<td>P-Val</td>
<td>0</td>
<td>0</td>
<td>0.0767</td>
<td>0.547</td>
<td>0.2262</td>
<td>0.1114</td>
<td>0.2382</td>
<td>0.2216</td>
</tr>
</tbody>
</table>

This table presents the mean yearly BHAR that have been computed based on a control firm analysis. The returns have been winsorized at the 0.01 and 0.99 percentile. Yearly BHAR have been computed at the instances of the default event ($\tau = 0$),...,seven years before the default event ($\tau = 7$).

Table 4: Control Firm Analysis: BHAR

The evidence of strong underperformance of future defaulters up to two years before default implies that markets process existing information about the bad condition of these firms relatively early. This is consistent with the evidence that default risk models based on market and accounting information are relatively successful in forecasting defaults up to one year in advance (Bauer & Agarwal 2014, Hilscher & Wilson 2016, Mertens et al. 2016).

As a next step, we perform semi-annual out-of-sample re-estimations of the F-Score in January and July and sort portfolios on the obtained scores. The results for the ten distress risk portfolios are shown in table 5.
<table>
<thead>
<tr>
<th>Portfolios</th>
<th>Low risk</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>High risk</th>
<th>10</th>
<th>10-1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Excess return (%)</td>
<td>7.66</td>
<td>3.85</td>
<td>1.73</td>
<td>2.05</td>
<td>-3.34</td>
<td>-0.68</td>
<td>-3.63</td>
<td>-3.58</td>
<td>-23.62</td>
<td>2.12</td>
<td>-3.23</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CAPM α (%)</td>
<td>0.06</td>
<td>0.03</td>
<td>0.01</td>
<td>0.01</td>
<td>-0.03</td>
<td>-0.01</td>
<td>-0.05</td>
<td>-0.04</td>
<td>-0.21</td>
<td>0.02</td>
<td>-0.04</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FFM α (%)</td>
<td>0.06</td>
<td>0.03</td>
<td>0.01</td>
<td>0.02</td>
<td>-0.03</td>
<td>-0.01</td>
<td>-0.04</td>
<td>-0.04</td>
<td>-0.22</td>
<td>0.02</td>
<td>-0.04</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CFM α (%)</td>
<td>0.03</td>
<td>0.02</td>
<td>0.01</td>
<td>0.02</td>
<td>-0.02</td>
<td>-0.03</td>
<td>-0.03</td>
<td>-0.19</td>
<td>0.04</td>
<td>0.01</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Beta</td>
<td>0.47</td>
<td>0.35</td>
<td>0.48</td>
<td>0.68</td>
<td>0.77</td>
<td>0.72</td>
<td>0.94</td>
<td>0.85</td>
<td>0.91</td>
<td>0.81</td>
<td>0.33</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SMB</td>
<td>-0.12</td>
<td>-0.19</td>
<td>-0.22</td>
<td>-0.32</td>
<td>-0.28</td>
<td>-0.15</td>
<td>-0.16</td>
<td>-0.04</td>
<td>0.03</td>
<td>0.4</td>
<td>0.37</td>
<td>0.52</td>
<td></td>
</tr>
<tr>
<td>HML</td>
<td>0.03</td>
<td>-0.09</td>
<td>-0.1</td>
<td>-0.11</td>
<td>-0.15</td>
<td>-0.16</td>
<td>-0.23</td>
<td>-0.12</td>
<td>-0.16</td>
<td>-0.19</td>
<td>-0.25</td>
<td></td>
<td></td>
</tr>
<tr>
<td>WML</td>
<td>0.53</td>
<td>0.1</td>
<td>-0.02</td>
<td>-0.14</td>
<td>-0.11</td>
<td>-0.24</td>
<td>-0.19</td>
<td>-0.13</td>
<td>-0.39</td>
<td>-0.38</td>
<td>-0.98</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Panel B: CFM Regression Coefficients

<table>
<thead>
<tr>
<th>Panel C: Portfolio Characteristics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean F-Score</td>
</tr>
<tr>
<td>Mean Size (100 M EUR)</td>
</tr>
<tr>
<td>Mean BTM</td>
</tr>
<tr>
<td>Mean Leverage</td>
</tr>
<tr>
<td>Mean Momentum</td>
</tr>
<tr>
<td>Mean RoA</td>
</tr>
</tbody>
</table>

This table shows the results for portfolio sorts on F-Scores. Each January and July we re-estimate F-Scores in the panel of all active firms and then sort these firms into ten portfolios according to their F-Scores. We hold these portfolios for six months. Panel A shows value-weighted semi-annual excess returns and alpha coefficients for the CAPM, FFM as well as the CFM. Panel B shows the estimated regression coefficients of the CFM. T-Values are stated in parentheses. Panel C shows several characteristics of these portfolios.

Table 5: Returns on Distress Risk Equity Portfolios
Value-weighted excess returns in panel A of table 5 begin to decay after portfolio 1, become negative after portfolio 4 and increase after portfolio 9. Perhaps this v-shaped pattern reflects the different states of firms: firms in portfolio 1-4 are safe, firms in portfolios 5-9 are in decline and firms in portfolios 10 are already in severe distress or in recovery. At first glance, this pattern seems to confirm the distress risk puzzle that has been documented in the US-literature (see table 1). However, Campbell et al. (2008) and Dichev (1998) find that returns decline monotonically in distress risk. Moreover, in the German stock market, the sort on distress risk does not yield significant alpha coefficients - only some are statistically significant and all of them are far from being economically significant. The 10-1 portfolio, which is long high distress risk and short low distress risk stocks, yields a semi annual excess return that is statistically not different from zero. In neither of the applied asset pricing models does this strategy deliver an alpha coefficient that we would regard as economically and statistically significant. Unsurprisingly, the GRS and monotonicity tests both fail to reject the null.

Panel B of table 5 shows the coefficients of the CFM. In general, higher distress risk implies higher market factors, but betas drop after portfolio 9. The same pattern has been presented by Garlappi & Yan (2011), who argue that highly distressed firms are to a lesser extent exposed to systematic risk as the value of equity converges to a recovery value. The high betas and low returns on portfolios 5-9 mark a failure of the CAPM. However, only portfolio nine shows significant alphas. The firms in this portfolio appear to be deeply distressed, yet continue to be in decline. Loadings on the remaining factors are hard to interpret and do not give rise to straightforward conclusions. As it is rather unclear what factor models like the CFM really achieve in the German capital market, we refrain from further interpretations.

Does table 5 tell us anything? From a statistical point of view, the results remain inconclusive. Based on the 10-1 excess returns, we should conclude that the data tell us nothing. One might nevertheless argue that the decline in excess returns from portfolios 1 to 9 is evidence for a distress risk puzzle. We are skeptical for two reasons: First, the results point towards strong interfering value and momentum effects. The portfolio characteristics in panel C of table 5 show suggestive trends with respect to BTM, momentum and other characteristics. Low distress risk firms are growth and past winner firms, high distress risk firms are value and past loser firms. The pattern of excess returns is likely to be explained by these effects. The results of the Fama & MacBeth (1973) regressions below shed further light on this. Second, distress risk naturally is an extreme risk. It is to a much stronger degree a binary risk than other kinds of risk in financial markets. The -8.07 mean F-Score of portfolio 4 translates into a holding period PD of roughly 3 basis points and
the portfolio 5 mean F-Score of -7.72 implies a PD of 4 basis points. Are such PD levels a concern to investors? In fact, the only portfolio with a significant mean PD appears to be portfolio 10. Its -3.4 mean F-Score implies a holding period PD of 3.2%. By way of comparison, the 5.2 mean F-Score of portfolio 9 translates into a PD of only 50 basis points.\textsuperscript{18} After all, these aspects illustrate that explaining excess returns on portfolios 1-9 with distress risk is probably not sensible because distress risk in these portfolios should be irrelevant to investors. Therefore, we believe that the analysis should focus on the extreme portfolios.\textsuperscript{19}

Additional results reveal that returns on all portfolios are left skewed, indicating that several extreme values in the left tail of the distributions influence the results. For the high F-Score portfolios this does not come as a surprise. We expect distressed stocks to show highly negative returns. However, the left-skew in the distribution is also existing in low F-Score portfolios, so the “Neuer Market” downturn appears to affect our results in general to a larger extent than the related literature.\textsuperscript{20} We discuss the robustness of our findings, in particular the distress risk effect, to a more rigorous exclusion of small firms in section 6. Furthermore, we find that standard deviations are increasing from portfolio 1 to 10. Portfolio 10 exhibits the highest annualized volatility, roughly 53% - more than twice as high as the volatility of portfolio 1.\textsuperscript{21} In sum, the returns on highly distressed firms fluctuate strongly. Due to the high volatility, we cannot detect that they differ from zero. The results presented in table 5 point to strong relations between distress risk with size, value and momentum effects, however. To investigate the potential nexus between distress risk, size, BTM and momentum (H2-H4), we run Fama & MacBeth (1973) regressions. The results are presented in table 6.

\textsuperscript{18}Campbell et al. (2008) report similar probabilities. To put this into perspective, Moody’s credit rating transition matrices show that annual default rates above 2% characterize the speculative grade segment (Moody’s 2008).

\textsuperscript{19}The results presented by Mertens et al. (2016) support this view as they show that the ex ante expected number of defaults in the highest F-Score decile (Portfolio 10) is very close to the ex post realized number of defaults. Defaults in low risk portfolios are rare. See their table 4.

\textsuperscript{20}Apart from distress and default, the IPO effect (Ritter 1991) may have caused underperformance of “Neuer Markt” stocks.

\textsuperscript{21}These results are available upon request.
This table presents the results of Fama-MacBeth regressions (3). The dependent variables are the cross-sections of semi-annual excess stock returns between 2001-2015. In panel A the independent variables are firm size, BTM and momentum. In panel B the independent variables are firm size, BTM, momentum and F-Score. The presented coefficients are the time-series means of the values that have been estimated in the repeated cross-sections. We report conventional T-Statistics and several T-Statistics based on clustered standard errors. The reported coefficients of determination are the time series averages of the adjusted $R^2$ from the cross-sectional regressions. The RMSE are computed as the square root of the mean squared residuals. We compute a RMSE for each cross-sectional regression and report the average for all regressions in the table.

Table 6: Fama-MacBeth Regression Results

<table>
<thead>
<tr>
<th>Panel A: size, BTM and momentum</th>
<th>$\lambda^0$</th>
<th>$\lambda^S$</th>
<th>$\lambda^V$</th>
<th>$\lambda^M$</th>
<th>$R^2$</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coefficients</td>
<td>-4.89</td>
<td>0.01</td>
<td>4.57</td>
<td>8.24</td>
<td>0.05</td>
<td>29.96</td>
</tr>
<tr>
<td>T-Stat.</td>
<td>-1.65</td>
<td>0.92</td>
<td>2.86</td>
<td>4.67</td>
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<td></td>
</tr>
<tr>
<td>T-Stat. firm-clustered</td>
<td>-13.08</td>
<td>2.34</td>
<td>10.22</td>
<td>17.27</td>
<td></td>
<td></td>
</tr>
<tr>
<td>T-Stat. time-clustered</td>
<td>-2.52</td>
<td>1.65</td>
<td>6.61</td>
<td>2.74</td>
<td></td>
<td></td>
</tr>
<tr>
<td>T-Stat. two-way-clustered</td>
<td>-2.5</td>
<td>1.64</td>
<td>6</td>
<td>2.75</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: size, BTM, momentum and distress risk</th>
<th>$\lambda^0$</th>
<th>$\lambda^S$</th>
<th>$\lambda^V$</th>
<th>$\lambda^M$</th>
<th>$\lambda^D$</th>
<th>$R^2$</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coefficients</td>
<td>-18.06</td>
<td>0</td>
<td>4.96</td>
<td>5.8</td>
<td>-1.67</td>
<td>0.07</td>
<td>29.66</td>
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<tr>
<td>T-Stat.</td>
<td>-2.21</td>
<td>0.36</td>
<td>4.31</td>
<td>3.98</td>
<td>-2.06</td>
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<tr>
<td>T-Stat. firm-clustered</td>
<td>-7.37</td>
<td>1.75</td>
<td>10.29</td>
<td>15.46</td>
<td>-2.98</td>
<td></td>
<td></td>
</tr>
<tr>
<td>T-Stat. time-clustered</td>
<td>-2.44</td>
<td>1.12</td>
<td>6.71</td>
<td>2.43</td>
<td>-1.22</td>
<td></td>
<td></td>
</tr>
<tr>
<td>T-Stat. two-way-clustered</td>
<td>-2.43</td>
<td>1.12</td>
<td>6.09</td>
<td>2.43</td>
<td>-1.21</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Panel A shows estimation results for a reduced model without distress risk. The independent variables are firm size, BTM and momentum. In accordance with Artmann, Finter, Kempf, Koch & Theissen (2012), Artmann, Finter & Kempf (2012), Glaser & Weber (2003) and Fieberg et al. (2016), we find evidence for priced value and momentum effects but no evidence for a priced size effect in the cross-section of German equities. Value and momentum effects are statistically significant regardless of the way standard errors are computed. Clustering tends to decrease standard errors. Clustered errors have asymptotic properties, a small number of clusters is usually a problem. Firm-level clustering is innocuous in this regard because the number of clusters is well above 900. Time-clustering is a borderline case, since we have only 29 semi-annual observations at hand. Moreover, lower clustered errors result from negative intracluster correlation (Cameron et al. 2006), possibly hinting towards a misspecified model. The results in table 6 show that firm-level clustering has the largest effect on standard errors in this regard. Therefore, negative intra-firm correlation is responsible for the decrease in standard errors.

Panel B shows the estimation results for the model including F-Score. Distress risk enters with a negative sign. Note that an increasing F-Score indicates higher default risk, so the negative coefficient mirrors the patterns of excess returns on F-Score-sorted portfolios in table 5. The Fama & MacBeth (1973) t-value are slightly above the conventional critical value but, according to Harvey et al. (2015), in the area where we should be skeptical. Standard errors clustered on firm point towards a statistically significant coefficient. However, due to the issues explained above, we should neither be fully convinced by them. Time and two-way clustering renders the relationship insignificant. All in all, we certainly do not find any evidence for a positive relationship between distress risk and equity returns (H1). The point estimate do rather point towards a distress risk puzzle but are still in the area of doubt with regard to their statistical significance. Moreover, controlling for distress risk has no effects on the economic and statistical significance of size and value effects. The momentum coefficient decreases after controlling for distress risk and the corresponding standard errors increase slightly, but distress does not wipe out the momentum effect. Hence, the results do neither support H2, H3 and H4.

The coefficients of determination presented in table 6 are typical for an analysis based on an entire cross-section of firms. Because adjusted $R^2$ values alone are not very helpful to judge the performance of alternative models, we also compute a root mean squared error (RMSE) as an indicator for how far off the models are with their predictions. Following the Fama & MacBeth (1973) idea, the values presented in the tables are the time series averages of the cross-sectional RMSE.
Both models in table 6 show similarly large RMSE, indicating that they provide rather poor explanations for excess returns.

So far, the empirical evidence does not support any of the four research hypotheses. However, there might be more convincing evidence when looking at different time lags. For instance, even though momentum is obviously not explainable through the contemporaneous estimate of distress risk, it might be that markets look in the past and continue reactions to past levels of distress. Alternatively, markets might look further into the future and preclude future distress that cannot be estimated with the F-Score model. Note that the former, a reaction to past distress, is inconsistent with the conventional understanding of rational and forward-looking financial markets, whereas the latter implies that investors can forecast distress with higher accuracy than the model developed by Mertens et al. (2016). To investigate these issues, we adapt a technique proposed by Fama & French (1995). At the beginning of every year, we sort firms into 10 portfolios according to size, book-to-market equity and momentum. For each portfolio we record the average F-Score for the time period starting five years before the sort and ending five years after the sort. Thus, we obtain the evolution of distress risk over an eleven-year period for each sort. Averages of these series over all sorts are presented in figure 1. The vertical axes show the probabilities of default implied by the F-Score model to foster interpretation.\textsuperscript{22}

\textsuperscript{22}Neither repeating the sorts at the beginning of every January and July nor changing the window around the sort affects the results.
At the beginning of every year in the sample we sort firms in 10 portfolios on size (the upper panel of the figure), BTM (the middle panel) or momentum (the bottom panel). The instant of this sort is labeled as 0 on the horizontal axes. We track the evolution of distress risk for each firm starting five years before and ending five years after the sort. We record the cross-sectional averages for these 11 values each year. Hence, we obtain $t \times 11$ matrices with cross-sectional averages for each year $t$. The plots illustrate the time-series averages of these matrices. Specifically, they show the top and bottom portfolios for each characteristic. The distress risk patterns illustrate whether a certain characteristic indicates high levels of distress in the past or future.
The distress risk history for big and small firms is depicted in the upper panel of figure 1. Smalls firms are associated with higher risk across the entire eleven-year window considered. Small firms are most likely to default when they are sorted into the small firm portfolio (point zero on the horizontal axis) and big firms are always associated with low levels of distress risk. These results do not suggest that size effects are due to past or future distress. The middle panel of figure 1 shows the evolution of distress risk for portfolios sorted on BTM. We find that distress risk in both the extreme value and extreme growth portfolios is very low and shows no specific pattern. Figure 1 underlines that value stock are not distressed per se. The lower panel of figure 1 shows the distress risk history of past winner and loser firms. The spike (drop) in distress risk for losers (winners) at the instant of the sort mirrors the mechanical relation between distress risk and momentum. Otherwise there is no evidence for patterns in distress risk associated with positive or negative momentum.

6. Robustness Checks

Research on the cross-section of equities allows the researcher many degrees of freedom. The most important choices we have made are the sample construction, in particular the handling of very small firms, and the choice of distress risk model. We consider the results for alternative choices in this section.

First, we repeat the single sort on F-Scores excluding all firms whose market capitalization is over their entire life below 500 Mio. EUR. A firm with such a market capitalization can be regarded as an average small cap in Germany. In this manner, we exclude most of the firms which have been listed in the “Neuer Markt” (Stehle & Schmidt 2015). Strictly speaking, restricting the cross-section in this fashion would require us to abandon the F-Score model proposed by Mertens et al. (2016). To be exactly accurate, we would need to re-estimate the risk models based on the smaller cross-section. However, then we would loose several defaults and would have to shorten the sample period even further. Therefore, we decide to stick with the old F-Score model and assume that investors derive their information about distress risk from the large cross-section but invest only in a smaller cross-section. Restricting the cross-section in this fashion increases the correlation of the F-Score with BTM and momentum. Therefore, the independent information provided by the F-Score is likely to be lower in this setting. The results are presented in table 7.

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23Moreover, this procedure induces a survivorship bias.
This table shows the results for portfolio sorts on F-Scores excluding firms with market capitalization is always below 500 Mio. EUR. Each January and July we re-estimate F-Scores in the panel of all active firms (the entire cross-section) and then sort these firms into ten portfolios according to their F-Scores, whereas we exclude firms whose market capitalization is below 500 mio. EUR for their entire lifetime. We hold these portfolios for six months. Panel A shows value-weighted semi-annual excess returns and alpha coefficients for the CAPM, FFM as well as the CFM. Panel B shows the estimated regression coefficients of the CFM. T-Values are stated in parentheses. Panel C shows several characteristics of these portfolios.

Table 7: Returns of Distress Risk Equity Portfolios excluding very small firms
In the cross-section of large firms we find a negative distress effect, similar to the literature summarized in table 1. Excess returns in table 7 exhibit the same pattern as in the full cross-section. Most notably, average returns on portfolio 10 are larger than returns on portfolio 9. The 10-1 returns are statistically and economically significant. However, the 10-1 CAPM, FFM and CFM alphas remain tiny and economically insignificant. Apparently, the single factor CAPM suffices to explain the lion’s share of the return difference between portfolios 10 and 1. Furthermore, the GRS and monotonicity tests still fail to reject their null hypotheses. A look at the portfolio characteristics confirms that default risk has dropped in the highest distress risk portfolios. In portfolio 10, the average F-Score of -3.69 translates into a holding period default risk of 2.4%, which is substantially lower than the value of 3.2% observed in table 5. Hence, firms in portfolio 10 in table 7 are not as acutely distressed as firms in table 5. Repeating the Fama & MacBeth (1973) regressions in the cross-section of large firms yields the results presented in table 8.
This table presents the results of Fama-MacBeth regressions (3). The dependent variables are the cross-sections of semi-annual excess stock returns between 2001-2015. Firms whose market capitalization never exceeds 500 mn. EUR are excluded. In panel A the independent variables are firm size, BTM and momentum. In panel B the independent variables are firm size, BTM, momentum and F-Score. The presented coefficients are the time-series means of the values which have been estimated in the repeated cross-sections. We report conventional T-Statistics and several T-Statistics based on clustered standard errors. The reported coefficients of determination are the time series averages of the adjusted $R^2$ from the cross-sectional regressions. The RMSE are computed as the square root of the mean squared residuals. We compute a RMSE for each cross-sectional regression and report the average for all regressions in the table.

Table 8: Fama-MacBeth Regression Results excluding very small firms
Excluding small firms does not alter the results presented in panel A of table 6. In table 8 we continue to find significant value and momentum effects and no size effects. In analogy to the single sort in table 7, we find evidence for a negative distress effect in panel B of table 8. Hence, the significance of the F-Score coefficient $\lambda^D$ rests on big firms, which are much less likely to be distressed, than small firms. Taken together, these results may confirm the “distress risk puzzle” presented by Campbell et al. (2008), Dichev (1998) and Griffin & Lemmon (2002). Nevertheless, doubts are warranted with regard to the lower levels of distress in the cross-section of large firms. Is the F-Score really an indicator for distress risk or is it something else? The statistical and economical significance of value and momentum effects remains unaffected when we control for distress risk. Hence, there continues to be no evidence for H2 and H3. We find that controlling for distress risk has slightly stronger effects on the coefficients and standard errors for momentum. As mentioned above, the correlation between F-Score and momentum in the cross-section of large firms is higher than the full-sample value shown in table 3. This probably mirrors the fact that large firms are much less likely to default and F-Score values of these firms are to a stronger extent driven by pure momentum instead of fundamentally decreasing credit quality. Therefore, we do not interpret the interplay between $\lambda^M$ and $\lambda^D$ as strong evidence for H4. Even though there is certainly correlation between momentum and distress risk, there is no evidence that distress risk can explain the momentum effect. We should question whether there is any distress risk in this case.\(^{24}\)

The regression model (3) appears to perform slightly better when small firms are excluded. The RMSE lower in this setting. Still, they are large and point towards model misspecification. Therefore, we conduct another experiment and drop all defaulters from the sample. That is, we assume defaulters had never existed and repeat all analyses based on the cross-section of survivors and firms which left the market for other reasons. This procedure may shed additional light on the differences between distress and default. Maybe default is too extreme as an event and completely predictable for investors so that the results are purely mechanical (because investors know that firms will default). Sorting all non-defaulting firms on F-Score will eliminate this concern as the sample default risk will be artificially restricted to zero in this setting. The results are presented in table 9.

\(^{24}\)Appendix A confirms view by presenting the results from double-sorts.
This table shows the results for portfolio sorts on F-Scores excluding firms which end up defaulting. EUR. Each January and July we re-estimate F-Scores in the panel of all active firms (the entire cross-section) and then sort these firms into ten portfolios according to their F-Scores, whereas we exclude firms that end up defaulting. We hold these portfolios for six months. Panel A shows value-weighted semi-annual excess returns and alpha coefficients for the CAPM, FFM as well as the CFM. T-Values are stated in parentheses. Panel B shows the estimated regression coefficients of the CFM. Panel C shows several characteristics of these portfolios.

### Table 9: Returns of Distress Risk Equity Portfolios excluding Defaulters

<table>
<thead>
<tr>
<th>Portfolios</th>
<th>Low risk</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th>High risk</th>
<th></th>
<th></th>
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<td>9</td>
<td>10</td>
<td>10-1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Excess return (%)</td>
<td>8.53</td>
<td>3.68</td>
<td>2.82</td>
<td>2.26</td>
<td>-0.98</td>
<td>0.56</td>
<td>-3.51</td>
<td>0.08</td>
<td>-15.11</td>
<td>1.52</td>
<td>-7.57</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CAPM α (%)</td>
<td>0.06</td>
<td>0.03</td>
<td>0.02</td>
<td>0.02</td>
<td>-0.01</td>
<td>0</td>
<td>-0.04</td>
<td>-0.01</td>
<td>-0.13</td>
<td>0.01</td>
<td>-0.07</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>FFM α (%)</td>
<td>(2.92)</td>
<td>(1.93)</td>
<td>(1.46)</td>
<td>(0.92)</td>
<td>-0.86</td>
<td>-0.22</td>
<td>-1.26</td>
<td>-0.28</td>
<td>-2.9</td>
<td>(0.14)</td>
<td>-1.26</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CFM α (%)</td>
<td>(2.91)</td>
<td>(2.28)</td>
<td>(1.69)</td>
<td>(1.23)</td>
<td>-0.52</td>
<td>(0.18)</td>
<td>-0.02</td>
<td>-0.19</td>
<td>-2.89</td>
<td>(0.09)</td>
<td>-1.32</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean F-Score</td>
<td>-9.52</td>
<td>-8.78</td>
<td>-8.45</td>
<td>-8.16</td>
<td>-7.85</td>
<td>-7.48</td>
<td>-7.01</td>
<td>-6.39</td>
<td>-5.53</td>
<td>-3.76</td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Mean Size (100 M EUR)</td>
<td>20.9</td>
<td>34.13</td>
<td>31.3</td>
<td>20.43</td>
<td>17.14</td>
<td>15.13</td>
<td>10.91</td>
<td>11.03</td>
<td>5.28</td>
<td>0.84</td>
<td></td>
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<tr>
<td>Mean BTM</td>
<td>0.95</td>
<td>0.95</td>
<td>0.64</td>
<td>0.66</td>
<td>0.77</td>
<td>0.99</td>
<td>1.1</td>
<td>0.87</td>
<td>2.03</td>
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<tr>
<td>Mean Momentum</td>
<td>0.18</td>
<td>0.16</td>
<td>0.12</td>
<td>0.09</td>
<td>0.06</td>
<td>0.03</td>
<td>-0.03</td>
<td>-0.19</td>
<td>-0.42</td>
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<tr>
<td>Mean Leverage</td>
<td>0.39</td>
<td>0.47</td>
<td>0.49</td>
<td>0.48</td>
<td>0.49</td>
<td>0.49</td>
<td>0.51</td>
<td>0.59</td>
<td>1.18</td>
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<td></td>
<td></td>
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</tr>
<tr>
<td>Mean RoA</td>
<td>0.18</td>
<td>0.04</td>
<td>0.04</td>
<td>0.03</td>
<td>0</td>
<td>-0.03</td>
<td>-0.06</td>
<td>-0.13</td>
<td>-0.31</td>
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</tbody>
</table>
Excluding defaulters leads to more frequent sign changes of excess returns on high distress risk portfolios. Excluding the risk of default gives rise to a completely idiosyncratic relation between distress risk and default. All other results remain unchanged. Controlling for defaulters with a dummy variable is equivalent to repeating the Fama & MacBeth (1973) regressions in the cross-sections of non-defaulting firms. The results are presented in table 10.

<table>
<thead>
<tr>
<th>Coefficients</th>
<th>$\lambda_0$</th>
<th>$\lambda_S$</th>
<th>$\lambda_M$</th>
<th>$\lambda_D$</th>
<th>Def.</th>
<th>$R^2$</th>
<th>RMSE</th>
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<td>0.06</td>
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<td>3.87</td>
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<td>T-Stat. firm-clustered</td>
<td>-5.51</td>
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<td>-1.6</td>
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<tr>
<td>T-Stat. time-clustered</td>
<td>-1.85</td>
<td>0.72</td>
<td>6.77</td>
<td>2.42</td>
<td>-0.67</td>
<td>-4.88</td>
<td></td>
</tr>
<tr>
<td>T-Stat. two-way-clustered</td>
<td>-1.85</td>
<td>0.72</td>
<td>6.14</td>
<td>2.42</td>
<td>-0.66</td>
<td>-4.96</td>
<td></td>
</tr>
</tbody>
</table>

This table presents the results of Fama-MacBeth regressions (3). The dependent variables are the cross-sections of semi-annual excess stock returns between 2001-2015. The independent variables are firm size, BTM, momentum, F-Score and a dummy for firms that end up defaulting. The presented coefficients are the time-series means of the values which have been estimated in the repeated cross-sections. We report conventional T-Statistics and several T-Statistics based on clustered standard errors. The reported coefficients of determination are the time series averages of the adjusted $R^2$ from the cross-sectional regressions. The RMSE are computed as the square root of the mean squared residuals. We compute a RMSE for each cross-sectional regression and report the average for all regressions in the table.

Table 10: Fama-MacBeth Regression Results excluding Defaulters

As expected, the dummy enters as highly significant with a large negative sign. The distress risk coefficient $\lambda_D$ remains negative but turns out to be statistically insignificant. All other coefficients are not affected. These additional results illustrate that neither defaults nor default risk explains the value and momentum effects in the German stock market.

Lastly, we consider alternative distress risk models for the portfolio sorts. Specifically, we repeat the sorts using all models tested by Mertens et al. (2016). The additional models are variants of the Altman (1968) Z-Score and the Merton (1974) DD. We consider both models in their original versions and one version of each model which has been calibrated to our data as shown by Mertens et al. (2016). In general, these models are informative about defaults but considerably worse forecasters than the F-Score. Therefore, we do not attach great importance to these results, which we summarize below without presenting additional tables.

Sorts on the Merton (1974) DD and the recalibrated version computed by Mertens et al. (2016) yield statistically significant negative 10-1 portfolio returns. In both
cases, we also find statistically significant alpha coefficients, but they are tiny (≈ 30 basis points per annum) and economically insignificant. The results for the two versions of the Z-Score computed by Mertens et al. (2016), including both the original Altman (1968) model and a new version with re-estimated coefficients, neither point towards a clear relationship between distress risk and equity returns. Sorts based on Altman’s model show a positive but statistically insignificant 10-1 portfolio return and sorts based on the model with re-estimated coefficients show a negative but economically insignificant relationship. Using the original versions of the Merton (1974) DD and the Altman (1968) Z-Score does allow us to extend the sample period and start the analysis in the year 1991. However, the results do not change at all in the extended sample period.

Lastly, we also repeat the Fama & MacBeth (1973) regressions with the alternative distress risk models. As in single-sorts, both versions of DD are negatively related to excess returns but only weakly significant when considering conventional standard errors. However, controlling for DD does not affect the significant value and momentum effects. Altman’s Z-Score remains insignificant and the version with re-estimated coefficients is marginally significant with a negative sign. Controlling for these models does neither affect the other effects. All in all, we find that changing the distress risk model changes the numbers and has very slight effects on statistical significance, but the economic impact is null. There continues to be no convincing evidence for the research hypotheses.

7. Conclusion and Discussion

Sorting firms on F-Scores points to a non-linear relationship between distress risk and equity returns. Average excess returns decay and become highly negative with increasing risk, but returns in the highest risk portfolio are extremely volatile and indistinguishable from zero. We argue that inference should focus on the extreme portfolios because most firms are not affected by distress risk at all. Arbitrage strategies of long positions in distressed firms and short positions in safe firms do not deliver significant returns. F-Score enters with a negative sign when we fit a linear model by means of Fama & MacBeth (1973) regressions. The regression coefficient reflects the non-linear relationship uncovered by the sorts, but the F-Score coefficient is only borderline significant. Several robustness checks, especially excluding small firms and defaulters, cast further doubt on the significance. After all, we interpret our results as consistent with the view that distress risk is an idiosyncratic risk in the German equity market.
Moreover, in line with the related literature, we find significant priced value and momentum effects in the cross-section of German equities but no evidence for a size effect (Artmann, Finter, Kempf, Koch & Theissen 2012, Artmann, Finter & Kempf 2012, Glaser & Weber 2003, Fieberg et al. 2016). It is often speculated that distress risk could explain these phenomena. Our results show that this is not the case. Value and momentum effects continue to exist when we control for distress risk and the size effect continues to be absent. Even though there are certainly mechanical relations between the characteristics size, BTM and momentum on the one hand and distress risk on the other hand, there is no evidence for a distress risk explanation behind size, value and momentum effects.

At first glance, our results confirm the US-literature that has, for the most part, discovered a negative relation between distress risk and equity returns (Dichev 1998, Griffin & Lemmon 2002, Campbell et al. 2008, Avramov et al. 2009, Ding et al. 2012, Ferreira Filipe et al. 2014). However, in the German stock market this finding does not pass standard asset pricing tests. We refrain from calling the negative relation between F-Score and stock returns a distress risk puzzle for two reasons. First, as noted above, statistical significance is not there. Long-short distress risk strategies yield insignificant alphas and the coefficients in Fama & MacBeth (1973) regressions are no more than borderline significant. Second, the pattern of excess returns with regard to F-Score is driven by firms with very low distress/default risk. Except for the extreme F-Score portfolio, average portfolio PDs are below 1% per annum. Hence, the vast majority of firms should probably not be associated with distress risk at all. The results presented by Campbell et al. (2008) and other US-authors show this tendency as well. The F-Score (and other default risk models) are powerful forecasters of corporate defaults, but most firms are simply not at risk. Do markets perceive a slightly elevated risk score as a sign for increased distress risk, even though implied default risk is virtually zero? We find it more convincing that other omitted variables explain the alleged negative relationship between firm distress risk and stock returns.

The results presented in this article may be affected by several limitations. The most grave limitation should be the short sample-period. Due to a low number of corporate defaults prior to 2001 we cannot start our analysis before this year. In effect, this leaves us with only two business cycles and this might be not enough to assess long-run systematic effects on returns. Moreover, the quality of the data that is available for the German stock market is significantly lower than the US data (Brueckner 2013, Ince & Porter 2006). This problem might be aggravated in our particular study because firms in distress should be especially likely to “cook the books” or delay disclosure of important information. In addition to that, we find that a common characteristics-based model does not provide convincing
explanations for the entire cross-section of German stocks. The differences between ex-ante expected returns and ex-post realized returns are staggeringly large and the standard errors of regression coefficients clustered on firm exhibit behavior that is associated with model misspecification. Even though there are patterns with regard to size and momentum in German stock returns, these patterns do not suffice to build powerful empirical pricing models. Hence, our study may lack adequate control variables. Obviously, developing more powerful empirical asset pricing models for the cross-section of German equities warrants further research.

Finally, we think that two very general findings, which call for further research, emerge from the empirical literature on distress risk and equity returns, including this article:

First, we believe that looking at the relation between distress risk and stock returns using a firm characteristic as a proxy for risk is inappropriate. Like the related literature, this article has used a default risk characteristic to measure distress risk. Effectively, such measures are supercharacteristics. They combine many other variables that are known to be related to patterns in returns and are calibrated to be very reliable forecasters of defaults. Consequently, they should be meaningful to investors whenever they indicate a significant PD. However, in most cases (roughly 90% of observations in this paper), they indicate that PDs are close to zero. In other words, distress risk is a binary risk. It is mostly completely absent and only in few cases relevant. Default risk is a highly specific characteristic that is very useful in (credit) risk management but not in asset pricing. Characteristics like BTM and momentum are highly general “catch-all” characteristics. There continues to be an urgent need of risk-based explanations for effects related to size, value and momentum. However, singling out anything like firm default risk is probably not going to lead us anywhere.

Second, we suggest that future research on risk factors in the stock market should adapt a different definition of distress instead. Even though our data show that corporate defaults occur in waves, we are convinced that this definition does not capture systematic effects but risk that equity investors can easily diversify away. Even several joint defaults of firms in a diversified portfolio will not evoke unusually large returns. Hence, firm distress risk is probably not systematic in the equity market. A definition of distress risk as a firm’s exposure to the macroeconomic credit cycle instead of firm-specific default risk should be much better suited to capture the undiversifiable risk of tightening credit markets. We assume that such a definition of distress, which is not a conventional firm characteristic, is more promising in future asset pricing research (Hahn & Lee 2006, Petkova 2006).
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Appendices

A. Double sorts

We double-sort stocks, first on F-Score and then on size, BTM or momentum. Due to the relatively small number of stocks in the German capital market, we sort firms into five portfolios along the first dimension and then sort them into three distress risk portfolios. Hence, each double sort yields $5 \times 3$ portfolios.²⁵ We compute 5-1 distress risk as well as 3-1 size, value and momentum portfolios for each double-sort. If size, value or momentum effects are due to distress risk, they should not be very pronounced if distress risk is very low. Mertens et al. (2016) report that distress risk scores are highly skewed, indicating that many firms are not at risk. If

²⁵Sorting firms into $5 \times 5$ portfolios does alter the results, but we fear that hypothesis tests become less powerful.
distress risk is behind size, value or momentum effects, we should not observe these effects when distress risk is irrelevant. Hence, insignificant (significant) size, value and momentum effects in the low (high) distress risk portfolio support H2-H4.

Some words of caution are due before we present the results: Double sorts are much less effective in dealing with the multidimensionality of empirical asset pricing. Based on the previous results, we know that we should at least control for BTM and momentum when double-sorting firms on distress risk and, for instance, size. Double-sorting is equivalent to controlling for two variables only. Furthermore, unfortunately, we cannot control for liquidity in this full-sample analysis. Double-sorting may produce several extreme portfolios. For example, the small firm with high F-Score is likely to consist of thinly traded stocks. Whether these issues are tradeable or whether prices on Datastream are reliable at all is debatable. Single-sorted portfolios contain a large number of stocks (≈ 55 per portfolio). Double sorts consist of slightly less stocks (≈ 39 per portfolio) and the procedure tends to group more extreme firms in the same portfolio. These caveats should be kept in mind when interpreting the excess returns on double-sorted portfolios presented in table 11.
This table shows the results of conditional double sorts. At first, all assets are sorted into five distress risk portfolios. Then, each of these portfolios is sorted into three size (panel A), BTM (panel B) and momentum (panel C) portfolios. The table presents the obtained value-weighted excess returns corresponding to a holding period of six months. The 5-1 portfolios are long high distress risk and short low distress risk stocks. The 3-1 portfolios are long big, value or past winner stocks and they are short small, growth or past loser stocks. T-values are stated in parentheses.

Table 11: Returns on Size, BTM and Momentum Portfolios across Distress Risk Portfolios
Returns on distress risk and size double-sorted portfolios presented in panel A of table 11 suggest that returns decrease monotonously in size. Nevertheless, there is no size effect in the full sample. Thus, the significance of the size effects in the five distress risk portfolios must reflect correlation of distress with other characteristics. Distressed firms outperform low distress risk firms in the size portfolios 1 but underperform in the size portfolios 3.

Results of the double sort with BTM are presented in panel B of table 11. Value stocks outperform growth stocks in all distress risk portfolios. The the value premium tends to increase with distress risk but is also significant in the low risk portfolio. Moreover, the value premium in the high distress risk portfolio seems very large. This is probably a sample-specific relict of the Dot-Com bubble. Most of the internet start-ups that entered the market between 1999-2002 (see table 2) were growth stocks and underperformed dramatically after their IPOs. Furthermore, the liquidity caveat needs to be taken into account with regard to the extreme growth and distress risk portfolios, as well. Distress risk can, at best, explain a part of the value effect. There is no convincing evidence for H3.

Lastly, panel C of table 11 shows the results for the double sort with momentum. Contrary to the hypothesis H4 and the results presented by the related literature (Avramov et al. 2007, Garlappi & Yan 2011), the momentum effect appears to be driven by low and not high distress risk firms. These findings underline that distress risk cannot explain momentum in the German stock market.

Double sorts are helpful to visualize patterns in data. They do not contradict our previous results, but, for the reasons discussed above, we remain skeptical with regard to their ability to detect significant relationships. We believe that the regression analysis in the paper is better suited to deal with the multidimensionality.

B. Characteristics-adjusted Returns

Following Daniel & Titman (1997) and Daniel et al. (1997) we implement an alternative way to control for size, value and momentum effects when assessing the relation between distress risk and equity returns. Previously, we have controlled for the Fama & French (1993) and Carhart (1997) risk factors as we have sorted firms on distress risk (see table 5). The relevance of these risk factors is, however, intensely debated in the German equity market (Artmann, Finter, Kempf, Koch & Theissen 2012, Artmann, Finter & Kempf 2012). Fieberg et al. (2016) are
able to replicate results presented by Daniel & Titman (1997), who show that characteristics and not risk factors determine expected returns in US data, in the German stock market. This is why we have chosen to control for characteristics and not factors in the Fama & MacBeth (1973) regressions. In single sorts we have not controlled for characteristics at all and in the double sorts we have only controlled for one single characteristic at a time.

To adjust stock returns for characteristics we proceed as follows. At the beginning of every January and July, when we sort portfolios on F-Score, all firms are independently sorted on size, value and momentum as characteristics. We choose three portfolios for each characteristic. These sorts yield 27 portfolios for each size/value/momentum combination. Daniel & Titman (1997) and Daniel et al. (1997) suggest to treat these portfolios as benchmark portfolios. Hence, one of these 27 portfolios can be assigned to each stock as a benchmark portfolio. Given the relatively small cross-section of firms, 541 firms are active on average between 2001-2015, 27 should be about the maximum number of portfolios that can be formed ensuring that diversification effects unfold. We set a benchmark portfolio return to missing whenever the number of stocks in it is lower than three. This does not happen often. Nevertheless, we lose some observations due to this constraint. The characteristics-adjusted return of every single stock is its return minus the its benchmark portfolio return. We repeat the single sort on F-Score, see table 5 for the previous results, with characteristics-adjusted returns. The results, which are presented in table 12, show whether returns net of characteristics-effects show any relation to distress risk.
### Panel A: Portfolio Returns and Alphas

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<th>Portfolio</th>
<th>Low risk</th>
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<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
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<th>8</th>
<th>9</th>
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<tr>
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### Panel B: CFM Regression Coefficients

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### Panel C: Portfolio Characteristics

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<tr>
<th>Portfolio</th>
<th>Mean F-Score</th>
<th>Mean Size (100 M EUR)</th>
<th>Mean BTM</th>
<th>Mean Momentum</th>
<th>Mean Leverage</th>
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</tr>
<tr>
<td>CFM α (%)</td>
<td>-8.07</td>
<td>20.84</td>
<td>0.73</td>
<td>0.18</td>
<td>0.06</td>
<td></td>
</tr>
<tr>
<td>(3.26)</td>
<td>(5.12)</td>
<td>(3.26)</td>
<td>(5.12)</td>
<td>(3.26)</td>
<td>(5.12)</td>
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This table shows the results for portfolio sorts on F-Scores. Each January and July we re-estimate F-Scores in the panel of all active firms and then sort these firms into ten portfolios according to their F-Scores. We hold these portfolios for six months. The returns considered in this table are characteristics-adjusted returns net of size, value and momentum effects. Panel A shows excess returns and alpha coefficients for the CAPM, FFM as well as the CFM. Panel B shows the estimated regression coefficients of the CFM. Panel C shows several characteristics of these portfolios.
In short, the results presented in panel A of table 12 do not lead to different conclusions. The relation between distress risk and characteristics-adjusted equity returns remains roughly inverse-tent-shaped and 10-1 alphas are insignificant. The cross-section considered in the sort is identical to the previous single sort in section 5, yet the characteristics in panel C of table 12 differ slightly from the corresponding values in table 5. These differences result from the loss of observations due to the benchmark portfolio formation procedure outlined above. Unfortunately, information on several high distress risk firms is lost. The high risk decile portfolio F-Score is only -4.07 (PD ≈ 1.7%), whereas the value is -3.4 (PD ≈ 3.2%) in table 5. Even the exclusion of several small firms has not caused a similar loss of information (see table 7). Distressed firms appear to be in extreme size/value/momentum portfolios, not many other firms share these attributes.

We can reduce this loss of information by forming benchmark portfolios based on two instead of three characteristics. We summarize these additional results without presenting the tables. Adjusting for size and BTM only (not adjusting for momentum) as well as adjusting for BTM and momentum (not adjusting for size) delivers qualitatively similar results. Adjusting for size and momentum (not adjusting for BTM) is the only way to lift the distress risk scores up to the previous, unadjusted levels. Hence, distressed firms appear to be members of extreme value portfolios. Still, the size and momentum adjusted returns show no significant pattern with regard to distress risk.
B.4. Paper IV: The Reaction of Equity and Credit Markets to Unconventional Monetary Policy - Are the Markets Buying it?
The Reactions of Equity and Credit Markets to Unconventional Monetary Policy - Are the Markets Buying it?

Richard L. Mertens*

March 24, 2017

The reaction of asset markets to the announcement of monetary policy measures is regarded as crucial for the transmission mechanism of monetary policy. I test whether the cross-sections of European equities and CDS show responses to monetary shocks which are in accordance with the goals behind the ECB policies. In particular, I assess whether credit constrained firms show stronger reactions than firms which are unlikely to be credit constrained. The balance sheet channel of monetary policy states that unconventional monetary policy lifts credit constraints. I obtain some unsettling results: Market reactions to conventional short rate changes are completely at odds with economic theory, but reactions to unconventional measures are in line with theory. Moreover, the reactions in the cross-section contradict the story of the balance sheet channel.

1. Introduction

Asset markets can be a bottleneck for the transmission mechanism of monetary policy. As emphasized by modern monetary theory (Woodford 2003), the desired

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economic effects are unlikely to ensue if financial markets are not fully convinced of the central bank’s goals. If monetary policy is credible, investors will take actions as they learn about monetary news and thereby initiate the transmission mechanism. Otherwise, if markets do not react accordingly, the long-run economic effects of monetary policy are likely to be withheld. The reactions of financial markets to monetary news are especially important for the effectiveness of unconventional monetary policy (UMP) (outright asset purchase programs). In this article, I assess whether equity and Credit Default Swaps (CDS) markets show reactions which are consistent with the intentions behind the UMP of the European Central Bank (ECB). Specifically, I apply an event study approach based on the full cross-section of German, French, Italian and Spanish equities as well as CDS. This large database enables me to assess whether the market reactions are consistent with the balance sheet channel of monetary policy. This theory asserts that monetary policy can lift credit constraints and is regarded as the most important transmission channel of monetary policy (Bernanke & Gertler 1995).

A relatively large body of literature assesses asset market responses to monetary policy actions. Diverse methodologies have been used. The macroeconomic literature predominantly uses vector autoregression models to isolate shocks and assess how these shocks affect asset prices and other macroeconomic time series (Boivin et al. 2010, Chatziantoniou et al. 2013, Ehrmann 2000, Kontonikas & Kostakis 2013). In contrast to this article, which focuses on the immediate response of equity and CDS markets, this methodology is primarily useful to assess the persistence of monetary policy shocks. A larger strand of the finance literature uses time series regressions to estimate the short-run response of asset prices to monetary policy actions. This methodology is also called the event study approach. The first contributions in this area were attempts to identify news which could explain the variance of stock market index returns (Cook & Hahn 1989, Cutler et al. 1988, McQueen & Roley 1993, Pearce & Roley 1983). Following the seminal contribution of Kuttner (2001), more recent work has focused on the estimation of asset price responses to unexpected monetary policy shocks. Continuing in the same vein, my paper is closely related to the work of Bernanke & Kuttner (2005), Bredin et al. (2009), Ehrmann & Fratzscher (2004), Basistha & Kurov (2008) and Gregoriou et al. (2009), who explain the heterogeneous reactions of equity market sectors to unexpected monetary shocks using both time series and cross-sectional regressions. This strand of the literature is growing as central banks worldwide have adapted a broader range of instruments (UMP). More recently, Rogers et al. (2014) and Fratzscher et al. (2014) assess asset market index reactions to UMP announcements of several central banks. Haitsma et al. (2015) assess the reaction of the EuroStoxx 50 index stocks to the announcement of UMP measures. My analysis differs from the existing studies as this is, to my best knowledge, the first
article assessing the reaction of a large cross-section of European equities and CDS to UMP actions.¹

For a number of reasons this approach is superior to the use of benchmark indices. First, it is questionable whether a certain index is a reliable benchmark for the entire market. Second, the use of an entire cross-section enables the researcher to link the reaction of stocks and CDS to the announcement of UMP back to individual firm characteristics. The panel data structure enables me to estimate whether the reactions of credit constrained firms are larger than the reactions of firms without binding credit constraints. Basistha & Kurov (2008) and Haitsma et al. (2015), who use the event study approach to test the existence of such a credit channel, use indices and only a few, very large firms. It is difficult to draw inference from such a sample as credit constraints are typically much more severe among very small firms, which are present in my sample.

The evidence shows the transmission mechanism of CMP is probably damaged in the European Monetary Union (EMU). Conventional interest rate changes appear to evoke equity market reactions with the same sign. However, UMP does indeed evoke increasing equity returns and decreasing CDS spreads. These results confirm the evidence presented by Haitsma et al. (2015) and Rogers et al. (2014). Moreover, I find that stocks and CDS of banks react significantly stronger than firms in other industries. Lastly, I show that large firms, which are unlikely to be credit constrained, show the strongest positive equity returns after the announcement of UMP. This finding stands in contrast to the balance sheet channel and the results presented by Haitsma et al. (2015). In the CDS market, firms which are more likely to be credit constrained show stronger contractions of credit spreads. However, this result is driven by large firms, too. The market capitalization of firms with available CDS is, on average, roughly ten times larger than the market capitalization of firms in the cross-section of equities. Very large firms are not likely to be severely credit-constrained. Moreover, using portfolio sorts, I present some further evidence for a long-run trend in outperformance of low-default risk firms, which are highly unlikely to be credit constrained, versus high default risk firms in the EMU. In spite of the efforts of the ECB, the balance sheet channel does not appear to be operative.

The paper proceeds as follows. Section 2 describes the history of the ECB’s UMP

¹Yet another strand of the literature has moved on to analyze the effects of Conventional Monetary Policy (CMP) on the cross-section of equity returns using the long-run event study methodology (Jensen & Mercer 2002, Maio 2013, Thorbecke 1997). These articles are primarily attempts to gauge relations between the well known risk factors Small-Minus-Big (SMB) and High-Minus-Low (HML) with monetary conditions in the cross-section of US equities.
measures and summarizes the related literature. I deduct my research hypotheses from the officially communicated goals of the programs and the literature’s stance on the transmission mechanism of UMP. The methodology is explained in section 3. I present the sample with several descriptive statistics in section 4. Empirical results follow in section 5 and the robustness of results is discussed in section 6. The article closes with a summary and discussion in section 7.

2. Unconventional Monetary Policy

Interest rates $i$ are decomposed of a risk-free short rate $r$ and several risk premia $\theta$, for instance premia for maturity, illiquidity and default risk:

$$i = r + \theta.$$  (1)

When central banks aim to ease funding conditions, they must try to either decrease $r$, $\theta$ or perhaps even both parameters simultaneously. Conventional Monetary Policy (CMP) is about setting the short run interest $r$ rate at which commercial banks can borrow funds from and deposit funds at the central bank. For decades, monetary policy has been based on rules, like for instance the famous Taylor rules, which provide guidelines regarding the level of short-run benchmark rates (Taylor 1993). From its foundation until the end of the 2000s, the ECB has also followed such an understanding of monetary policy. Alas, CMP measures are no longer sensible when interest rates are at the zero lower bound ($r \approx 0$). The zero lower bound, which characterizes the interest rate environment of the years following the financial crisis of the years 2008/2009, describes the idea that interest rates cannot be lower than 0% because agents in the economy could always hold zero interest cash. Hence, as soon as interest rates are close to zero, conventional interest rate targeting is not any longer an option (Eggertsson & Woodford 2003, Hamilton & Wu 2012). Because the economic crisis following the financial crisis after the year 2008 turned out to be one of the severest crises in economic history, many central banks, including the Bank of England (BoE), Bank of Japan (BoJ) and the Federal Reserve System (FED) were eager to provide further stimulus to their economies. Thus, they had to turn to UMP measures, which aim to decrease the risk premia $\theta$ in (1).
2.1. The Monetary Policy of the ECB since 2008

Even though the ECB has approached the zero-lower-bound later than the FED, which had effectively arrived at levels close to zero in 2008, it had, like other major central banks, begun to adopt UMP already after the first signs of the global financial crisis in 2007/2008. Apart from conventional rate cuts, the ECB had adapted a first set of UMP measures, which was officially called “Enhanced Credit Support”. This package included measures directed at coping with the growing tensions in interbank money markets. A detailed overview is provided by Giannone et al. (2011). As means to provide long-term funding to troubled banks, these measures can be regarded as attempts to reduce term, liquidity and default risk premia in money markets. Furthermore, they were rather short-term actions directed at preventing further panic and wholesale bank-runs. However, in spite of these efforts, the economic crisis in the EMU deepened further and the recovery after the recession has been unusually weak. The severity of this crisis has led the ECB to extend its UMP toolkit to several outright asset purchase programs, which are chronologically listed in table 1.
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</thead>
<tbody>
<tr>
<td>CBPP1</td>
<td>5-7-2009</td>
<td>7-2-2009</td>
<td>6-30-2010</td>
<td>Covered Bonds</td>
<td>60</td>
<td>AA</td>
<td>unlimited</td>
<td>500 mio.</td>
</tr>
<tr>
<td>SMP</td>
<td>5-10-2010</td>
<td>5-10-2010</td>
<td>9-6-2012</td>
<td>Government Bonds</td>
<td>unlimited</td>
<td>unlimited</td>
<td>unlimited</td>
<td>unlimited</td>
</tr>
<tr>
<td>CBPP2</td>
<td>10-6-2011</td>
<td>11-3-2011</td>
<td>10-31-2012</td>
<td>Covered Bonds</td>
<td>40</td>
<td>BBB-</td>
<td>≤ 10.5Y</td>
<td>300 mio.</td>
</tr>
<tr>
<td>ABSPF</td>
<td>9-4-2014</td>
<td>10-20-2014</td>
<td>11-21-2014</td>
<td>Covered Bonds</td>
<td>unlimited</td>
<td>BBB-</td>
<td>unlimited</td>
<td>unlimited</td>
</tr>
<tr>
<td>EAPP</td>
<td>1-22-2015</td>
<td>3-09-2015</td>
<td>3-31-2016</td>
<td>Government Bonds</td>
<td>60 p.m.</td>
<td>BBB-</td>
<td>2Y-30Y</td>
<td>unlimited</td>
</tr>
<tr>
<td>Modified EAPP</td>
<td>3-10-2016</td>
<td>4-1-2016</td>
<td>3-31-2017</td>
<td>Government Bonds</td>
<td>80 p.m.</td>
<td>BBB-</td>
<td>2Y-30Y</td>
<td>unlimited</td>
</tr>
<tr>
<td>CSPP</td>
<td>6-8-2016</td>
<td>3-31-2017</td>
<td>3-31-2017</td>
<td>Corporate Bonds</td>
<td></td>
<td>BBB-</td>
<td>6M-30Y</td>
<td>unlimited</td>
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</tbody>
</table>

This table lists all outright asset purchase programs conducted by the ECB. The column states the days of announcement. Except for Securities Markets Programme (SMP), all programs were announced during the regular Governing Council press conferences. The abbreviation “p.m.” in the volume column indicates purchases are carried out per month. The details listed in this table have been collected using the formal decisions, which have been published in the Official Journal of the European Union.

Table 1: ECB Asset Purchase Programs
These eight programs, which stand out as the main areas of the ECB’s UMP, are directed at different markets. As visible in table 1, they have become more aggressive with regard to volumes and restrictions in time. Most importantly, they all share one overriding goal: easing funding conditions for financial and non-financial corporations.2

2.2. The Transmission Mechanism of UMP

How can UMP contribute to this goal? According to Mishkin (1996), the transmission mechanism of monetary policy consists of three different types of channels. First, the textbook interest rate channel assumes that expansionary monetary policy reduces real interest rates and thereby increases aggregate investment goods demand. The literature is rather skeptical about the viability of the demand-effect, as empirical research has found it difficult to establish a link between short run real interest rates and the cost of capital (Bernanke & Gertler 1995). The second channel is called the asset price channel. An increasing money base might boost the demand for equities. Through Tobin’s q (Tobin 1969), firms would find it attractive to issue new equity to buy more investment goods.

The third type of channels are credit channels.3 The two most important credit channels, the balance sheet and bank lending channels, are illustrated in figure 1. The lower branch of figure 1 depicts the bank lending channel. Through provisions of extended funding or outright asset purchases, UMP can increase liquidity in the banking sector in order to bolster bank lending. The beginning of UMP in the EMU, the “Enhanced Credit Support” package, was obviously targeting the bank lending channel. Moreover, several of the purchase programs listed in table 1 are directed at assets which are to a large extent concentrated in the banking sector. Several papers have investigated how monetary shocks propagate through the banks. By and large, empirical results regarding the significance of the lending channel have been mixed. While several studies confirm that monetary policy affects the ability of banks to provide loans, the effects do not appear to be large enough to explain a substantial share of the variation of aggregate lending (Angeloni et al. 2003, Ashcraft 2006). More recently, Gambacorta & Marques-Ibanez (2011) show that the bank lending channel gained importance during the financial crisis. The other credit channel is the balance sheet channel, which is depicted in the upper branch of figure 1. UMP, especially the purchase programs listed in

2This conclusion is carved out in greater detail and with references to the official ECB communication in appendix A.
3A formal discussion of the credit channels is offered by Tirole (2006, Chp. 13).
table 1, increases asset prices and decreases risk premia. The rise in asset prices improves the balance sheets of firms and thereby increases the net worth of firms (for instance through increasing collateral value). This should, in turn, lessen adverse selection and moral hazard problems. These issues are commonly regarded as the main impediments to lending during economic crises (Bernanke & Gertler 1995, Bernanke et al. 1996, 1999). Ciccarelli et al. (2015) find that the balance sheet channel is an important part of the transmission channel of monetary policy in Europe and the U.S..

Figure 1: The credit channel

In general, the literature on the transmission channels suggest that UMP must propagate through assets markets to achieve the desired macroeconomic effects. Thus, the market reaction to the announcements of UMP is likely to be crucial for its overall success. A new strand of the literature highlighting the importance of expectations for the transmission mechanism of monetary policy lends further support to this view. According to Woodford’s influential handbook, “not only do

4A similar conclusion is drawn by Joyce et al. (2012), who summarize the transmission mechanism of Gilt-purchases by the BoE.
expectations about policy matter but, at least under current conditions, very little else matters” (Woodford 2003, p.15). The importance of setting credible goals for monetary policy, adapting a systematic decision framework and communicating decisions in a convincing manner is now commonly acknowledged. In recent years, “expectation management” or “forward guidance” appears to be of special concern to the ECB and other central banks (Braun 2015).

2.3. Research Hypotheses

My research hypotheses address the importance of such expectations. Successful monetary policy requires the market’s faith. When asset markets find the goals of the central bank not credible, the transmission mechanism of UMP cannot operate as desired. The first obvious question to ask in this regard is whether the announcement of UMP, starting after the financial crisis and including the programs listed in table 1, has evoked any specific market reaction at all. These are my first research hypotheses $H_{1a}$ and $H_{1b}$:

$H_{1a}$ Announcements of UMP measures of the ECB gave rise to positive equity market reactions.

$H_{1b}$ Announcements of UMP measures of the ECB gave rise to contracting CDS spreads.

Details on the measurement of UMP news are provided in the following section. Evidence in favor of $H_{1a}$ and $H_{1b}$ would support the view that the market assumes the ECB’s programs are going to have positive effects. As argued above, this can be seen as a prerequisite for the functionality of transmission mechanisms.

Moreover, using cross-sectional firm level data enables me to test more detailed hypotheses with regard to the specific goals of the programs. EMU member states are regarded as bank-based economies and monetary policy directly affects banks. However, UMP announcements might be perceived as good or bad news for the banking sector by investors. First, all purchase programs listed in table 1, except for the Corporate Sector Purchase Programme (CSPP), are directed at assets which are concentrated in the banking sector. As far as UMP enables banks to get rid of unwanted assets at favorable prices - this is the story of the bank lending channel -, these measures should be regarded as positive news for banks. On the other hand, Borio et al. (2015) show long periods of low interest rates and flat yield curves depress bank profitability. Thus, UMP announcements could also be regarded as negative for the banking industry in the long-run. In either way, banks
should be the first firms to be affected. Therefore, I follow Ricci (2015) as well as Yin et al. (2010) and test the reactions of bank equities as $H2a$. Moreover, I add to the literature and test the reactions of bank CDS as $H2b$.

$H2a$ Stocks of banks show larger positive return reactions than stocks of non-financial firms around the announcement of UMP measures.

$H2b$ CDS of banks show larger contractions than CDS of non-financial firms around the announcement of UMP measures.

Lastly, the ECB vigorously claims its UMP measures, especially the outright asset purchase programs, are conducted to ease the funding conditions of non-financial firms. The balance sheet channel implies that non-financial firms facing high costs of debt benefit from these programs as credit constraints become less binding. If markets are convinced of this strategy, high default risk firms should show stronger equity return reactions and starker contractions of CDS spreads than low default risk firms. This idea is summarized in the third set of research hypotheses $H3a$ and $H3b$:

$H3a$ Stocks of non-financial firms with high default risk show stronger positive reactions than stocks of non-financial firms with low default risk around the announcement of UMP measures.

$H3b$ CDS of non-financial firms with high default risk show stronger contractions than CDS of non-financial firms with low default risk around the announcement of UMP measures.

Several papers (Ehrmann & Fratzscher 2004, Basistha & Kurov 2008, Haitsma et al. 2015) have investigated the reaction of firms which are supposedly credit constrained to monetary policy shocks, but these contributions have two major shortcomings. First, they are based on a cross-section of very large firms (S&P 500 or EuroStoxx50 index members) which are unlikely to be severely credit constrained. Second, they measure credit constraints using industry membership or simple balance sheet indicators. In this article, I test the balance sheet channel using the full cross-section of German, French, Italian and Spanish firms and identify credit constraints with a model which has a proven track record to forecast corporate defaults. Hence, this article is based on a more informative sample and is to a lesser degree affected by measurement errors. The set of control variables

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5A large macroeconomic literature suggests that the credit quality of firms is an important determinant of economic activity. See Bernanke & Gertler (1989) and Bernanke et al. (1996) for two seminal contributions.
used to identify high default risk firms is explained in the following sections. Taken together, \( H_{1a} - H_{3b} \) are tests of the market’s immediate perception of the UMP measures.\(^6\)

### 3. Methodology

The analysis proceeds in three steps to test these hypotheses. At first, I discuss how monetary policy shocks (both conventional and unconventional) can be identified. As a next step, I use these shocks to estimate equity and CDS market responses with time series regressions. Finally, I turn to the cross-section of equities and CDS and apply panel regressions. These methods are frequently used to assess the short-run responses of asset prices to monetary policy.

#### 3.1. Monetary Policy Shocks

Monetary policy decisions are made by the ECB Governing Council, which used to conduct monthly meetings from 2002-2014 and switched to a less frequent meeting schedule in 2015. I construct my sample as a combination of several data items, which are introduced in detail in the next section, recorded at the day of every Governing Council meeting \( t \). Exception were the Governing Council decisions to decrease rates in October 2008 (jointly with other central banks) and the decision to implement SMP in September 2010 at the height of the European debt crisis (see table 1). I include these off-schedule dates into the analysis as Governing Council meeting days.\(^7\)

The Governing Council decisions on UMP are of special interest in this article. According to the efficient market hypothesis (Fama 1970), markets should react to news, whereas monetary policy actions are often-at least partly- anticipated. Therefore, it is necessary to develop reasonable proxies for unexpected monetary policy shocks. This applies to both CMP and UMP. While in this article the focus lies on the latter, I choose to include CMP actions into the analysis for two reasons.

\(^6\)Obviously, it is still too early to judge the long-run economic effects of the ECB’s UMP.

\(^7\)It is debatable whether the famous “whatever-it-takes” speech by ECB president Mario Draghi in 2012 should likewise be included as a date in the analysis. I choose not to because the speech was held at an industry meeting and did certainly not formally announce monetary policy measures. While, in general, speeches of ECB staff might be informative for financial markets, it is difficult to distinguish interesting public appearances from statements which are not that important for the markets on that respective day.
First, it is possible that both CMP and UMP actions are taken simultaneously. An example could be a small shock to short-term interest rates through forward-guidance and rumors about asset purchases when the economy is already at the zero-lower-bound. Hence, CMP shocks are an important control variable when assessing the asset market response to UMP announcements. Second, the empirical methodology for CMP reaction studies can be regarded as established, whereas UMP reaction studies are just beginning to emerge. The existing CMP studies provide a reasonable starting point for a new UMP analysis with the additional possibility to re-assess prior findings regarding CMP reactions. Below I begin with the identification of CMP shocks and then turn to the identification of UMP shocks.

Cook & Hahn (1989) proposed to identify CMP shocks as the difference of the central bank’s main policy rate \( \Delta i_t = i_t - i_{t-1} \). In this context, we are dealing with the ECB’s main refinancing rate. Obviously, this approach fails to account for market expectations. A rate cut of 25 basis points (bps) could be good news for equity markets, when investors were actually expecting a rate increase or no change at all. Conversely, it might be bad news for equity markets, when investors were in fact expecting an even larger increase.

Kuttner (2001) decomposes interest rate changes into expected and unexpected shocks and presents evidence which is consistent with the theory of efficient markets. I apply the Kuttner (2001) decomposition, which has become standard in the related literature, with a slight modification proposed by Gregoriou et al. (2009), who assess the UK stock market reaction to monetary policy announcements by the BoE.\(^8\) Interest rate futures are used to extract the surprise component of CMP actions. In particular, I use the 3-month EURIBOR future contract. The EURIBOR is a highly liquid EMU benchmark rate and conceptionally equivalent to the 3-month LIBOR contract used by Gregoriou et al. (2009). Bernoth & Hagen (2004) show that the 3-month EURIBOR is a reliable predictor of the ECB policy rates. Thus, the EURIBOR future is a good proxy for the market’s expectations about future interest rates.\(^9\) Hence, I define the unexpected CMP interest rate shock \( \Delta i^u_t \) on every Governing Council meeting \( t \) as

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\(^8\)The Kuttner (2001) decomposition makes use of futures contracts for the federal funds rate, the main conventional policy target rate of the FED. Such futures contracts do not exist in the UK and the EMU, which is why the modification by Gregoriou et al. (2009) is necessary. The same approach is adapted by Haitsma et al. (2015).

\(^9\)Though the use of futures as forecasters of future spot rates is standard in the literature, one might in general question that futures contain market expectations. I consider alternative shocks, which are independent from futures markets, in appendix B. The results presented in the following are not affected.
\[ \Delta i_t^u = f_t - f_{t-1}, \]  
\[ (2) \]

where \( f_t \) is the implied future rate (100 minus the future price) observed at the end of the meeting day and \( f_{t-1} \) is the rate observed at the end of the day before the meeting. Given the unexpected CMP shock, the expected short rate shock is stated in (3):

\[ \Delta i_t^e = \Delta i_t - \Delta i_t^u, \]  
\[ (3) \]

whereas \( \Delta i_t \) denotes the total change of the EURIBOR short rate from the end of the day before the meeting until the end of the meeting day. The shocks captured by (2) and (3) are defined by changes of the short rate, they are primarily induced by CMP. As argued in section 2, UMP comes into play, when such measures are, due to the zero-lower-bound, no longer applicable. Like CMP actions, UMP actions are likely to be at least partly expected by investors. To identify the surprise element of UMP announcements, one needs to identify financial instruments which are immediately affected by such decisions. Rogers et al. (2014) and Haitsma et al. (2015) argue that the changes in spreads between long-term Italian and German government bonds are a reliable proxy for unexpected UMP shocks \( \tau^u \). Formally, these are defined as

\[ \tau^u = \begin{cases} 0 & \text{for } 01/01/2002 - 12/31/2007 \\ (i_{t}^{10,IT} - i_{t}^{10,GER}) - (i_{t-1}^{10,IT} - i_{t-1}^{10,GER}) & \text{otherwise}, \end{cases} \]  
\[ (4) \]

where \( i_t^{10,IT} \) are yields on 10-year Italian Government bonds recorded at the end of the trading day for every Governing Council meeting day \( t \). As argued in section 2, long-term bonds are in the focus of the ECB’s UMP. (4) captures changes in different risk premia (term premia, default premia, liquidity premia), which are at the core of the programs listed in table 1. Consequently, increases (decreases) in (4) are associated with restrictive (accommodative) UMP shocks. Following Haitsma et al. (2015), I set \( \tau = 0 \) before the outbreak of the financial crisis. Hence, I assume ECB actions did not affect the spread (4) before 2008. I discuss this assumption in several robustness checks.
3.2. Time Series Regressions

The unexpected monetary policy shocks discussed above are used in several time series regressions to test the hypotheses $H_{1a}$ and $H_{1b}$. In the beginning, I estimate the Cook & Hahn (1989) model using all ECB Governing Council meeting days $t$:

$$r_t = \alpha^{EQT} + \beta^{EQT} \times \Delta i_t + \rho^{EQT} \times \tau_t + \epsilon_t \quad (5)$$
$$s_t = \alpha^{CDS} + \beta^{CDS} \times \Delta i_t + \rho^{CDS} \times \tau_t + \epsilon_t \quad (6)$$

where $\Delta i_t$ is the change of the ECB main rate and $\tau_t$ is the UMP shock as defined in (4). Without this variable (5) is identical to equation one in Cook & Hahn (1989), who apply it to bond rates. I estimate this specification for daily log equity market returns $r_t$ and CDS market spread changes $s_t$ using Ordinary Least Squares (OLS). The $s_t$ are changes of a CDS index constructed as the time series of cross-sectional mean CDS spreads in the sample.\(^{10}\) Economic theory implies a negative response to conventional interest rate changes for equities ($\beta^{EQT} < 0$) and a positive response for CDS spread changes ($\beta^{CDS} > 0$). Moreover, the first research hypotheses $H_{1a}$ and $H_{1b}$ suggest increasing (decreasing) equity prices (CDS spreads) as a response to accommodative UMP shocks. Thus, support for the hypotheses requires $\rho^{EQT} < 0$ and $\rho^{CDS} > 0$.

To consider market expectations, I turn to regressions in the style of Kuttner (2001), Bernanke & Kuttner (2005) and Haitsma et al. (2015). The market responses as a function of expected and unexpected CMP shocks as well as UMP shocks are shown in specifications (7) and (8):

$$r_t = \alpha^{EQT} + \psi^{EQT} \times \Delta i_t^e + \gamma^{EQT} \times \Delta i_t^u + \rho^{EQT} \times \tau_t + \epsilon_t \quad (7)$$
$$s_t = \alpha^{CDS} + \psi^{CDS} \times \Delta i_t^e + \gamma^{CDS} \times \Delta i_t^u + \rho^{CDS} \times \tau_t + \epsilon_t \quad (8)$$

When markets are informationally efficient, we should observe no reactions to expected interest rate shocks ($\gamma^{EQT} = \gamma^{CDS} = 0$). Reactions to unexpected interest rate shocks should be negative for equities ($\psi^{EQT} < 0$) and positive for

\(^{10}\) There is no established full CDS market index. The Markit iTraxx Index is highly liquid but contains only investment grade issuers. Even though speculative grade reference entities are rare in the CDS market, they might be present in my sample. It is a standard procedure in the literature to use self-constructed equal-weighted CDS indices (Hull et al. 2004, Norden & Weber 2004)
CDS ($\psi_{CDS} > 0$). As above, the coefficients of interest are the UMP response coefficients $\rho$ with an implied negative (positive) equity (CDS) market reaction.

The residuals $\epsilon_t$ in (5)-(8) capture factors other than monetary policy events affecting equity returns and CDS spreads at Governing Council meeting days. Whenever one uses OLS to estimate these equations, one assumes these factors are orthogonal to changes in the main rate and UMP actions. This assumption might be problematic for two reasons. First, the causality might run into the other direction, whereas equity and/or CDS market developments cause monetary policy actions. However, this problem is not acute in this article, as I use daily equity returns and CDS spread changes. In this case endogeneity of $\Delta i_t$ or $\tau_u$ due to reverse causality would require central bank action caused by intraday equity and CDS market developments. Bernanke & Kuttner (2005) argue this is highly unlikely. Another look at the transcripts of press conferences after ECB Governing Council meetings assures that not a single decision has been justified with recent developments in capital markets. Neither are there any immediate actions after major events such as the Dot-Com Crisis in 2002 or the Lehman Brothers default in 2008. The reverse causality problem becomes more acute whenever one tries to explain the development of asset prices with monetary policy actions over a longer horizon.

The second problem might be an omitted variables bias. Asset prices on the one hand and monetary policy on the other hand might respond to some unobserved variable, for instance macroeconomic news. Again, this problem is alleviated through the use of daily equity returns and CDS spread changes because same day responses of monetary policy to news are highly unlikely. Rigobon & Sack (2004) have developed a Generalized Method of Moments (GMM) approach to estimate asset price responses to monetary policy actions, which relies on a much weaker set of assumptions than conventional OLS. They show consistency of OLS requires - in the limit - that the variances of monetary policy shocks are infinitely large relative to other shocks on the days of ECB Governing Council meetings. Put differently, it is required that the news about monetary policy dominate all other news when announced. Rigobon & Sack (2004) themselves fail to formally reject the consistency of OLS using daily equity market data. Thus, I choose to follow the mainstream literature which sticks with this strict but not unreasonable assumption and use OLS to estimate (5)-(8).\footnotemark

3.3. Cross-Sectional Analysis

As a next step in the analysis, I apply the time series regressions discussed above in the cross-section of equities and CDS by re-estimating the regressions (5)-(8) for every firm in the sample. The second set of research hypotheses $H2a - H2b$ states that the reactions to UMP should be larger for banks than for non-financial corporations because banks are immediately affected in the transmission mechanism of monetary policy. To test this conjecture, I apply the Wilcoxon rank-sum test to the $\rho$ coefficients in the subsample of banks versus the subsample of non-financial corporations (excluding insurers and other financial services firms). If banks have statistically lower $\rho^{EQT}$ and larger $\rho^{CDS}$ coefficients, we can conclude $H2a$ and $H2b$ are valid.

The last set of research hypotheses ($H3a$ and $H3b$) is about credit-constrained non-financial firms and the balance sheet channel. A firm’s default risk provides information about binding credit constraints, agency costs of lending and costs of debt capital. Moreover, there are reliable models for the estimation of default risk. Therefore, I use firm specific default risk to test $H3a$ and $H3b$. Frameworks for the measurement of default risk for financial firms differ substantially from the measurement of default risk for non-financial firms. Hence, I drop financial firms from the sample at this point. Alongside other variables, I use the Merton (1974) Distance-to-Default (DD), which is stated in (9), as a control variable for default risk.

$$DD_t = \frac{\ln\left(\frac{V_A}{D_t}\right) + (\mu - 0.5 \times \sigma^2_A)}{\sigma_A \times \sqrt{T}}$$  \hspace{1cm} (9)

The DD is a leverage ratio scaled by asset volatility $\sigma_A$. Due to the residual claim character of equity, it can be regarded as a call option on the market value of the firm’s assets $V_A$, with a strike price equal to the book value of the firm’s debt $D$ due in $T$ years. I set $T = 1$. Moreover, I follow the conventional assumptions in the literature and compute $D$ as the sum of total short term debt and one-half times the sum of long term debt (Vassalou & Xing 2004). The physical version of the DD uses $\mu$, which is the growth rate of $V_A$, as drift and $\sigma_A$ is the corresponding standard deviation. In general, the market value of assets $V_A$ is unobservable. However, daily values for $V_A$ are required to estimate $\sigma_A$ and $\mu$ with precision. Vassalou & Xing (2004) have developed an iterative procedure to estimate daily $V_A$ given low frequency book values of assets and daily equity data. I apply this
procedure to compute the DD, which has become a standard in the literature.\footnote{See among others Pires et al. (2013), Valta (2016), Xu & Zhang (2008)} The estimation of the DD proceeds as follows and is repeated on every trading day before an ECB Governing Council meeting. Daily equity prices and the number of shares outstanding are used to compute one year of daily values for the firm’s market capitalization $V_E$. One year of implied daily asset values $V_A$ are backed out using the Black & Scholes (1973) formula (10):

$$V_E = V_A \times N(d_1) - D \times \exp(-r \times T) \times N(d_2)$$

$$d_1 = \frac{\ln\left(\frac{V_A}{D}\right) + (r + 0.5 \times \sigma_A^2) \times T}{\sigma_A \times \sqrt{T}}$$

$$d_2 = d_1 - \sigma_A \times \sqrt{T}.$$ 

Using the Black & Scholes (1973) framework is complicated by the fact that an initial estimate of $\sigma_A$ is required to solve (10). The iterative procedure overcomes this problem by using scaled equity volatility $\sigma_A = \sigma_E \times \frac{V_E}{V_E + D}$ as a first guess, whereas I use a history of one year of equity returns to compute equity volatility $\sigma_E$. This guess yields a first estimate of daily $V_A$ and an updated value for $\sigma_A$, which is once more used to start a new iteration. The procedure is continued until the $\sigma_A$ values converge, whereas convergence requires a difference between the last two estimates which is smaller than $10E^{-4}$. The daily $V_A$ of the last iteration are used to determine the final estimates for $\sigma_A$ and $\mu$, the mean log growth rate of assets. Merton (1974) assumes that firms default when their asset value intersects with their debt value. DD states the distance to this default point in terms of standard deviations. The lower a firm’s DD, the higher its default risk.

The empirical literature on default risk finds that the DD is informative about default risk but not a sufficient statistic to forecast defaults (Bharath & Shumway 2008, Campbell et al. 2008, Hillegeist et al. 2004). In practical applications (credit risk management), reduced form default risk models in the spirit of Altman (1968) are more frequently used. Therefore, several balance sheet and profitability indicators are employed as alternative proxies for default risk. Reduced from default risk models commonly use information about profitability, leverage, liquidity and valuation to forecast corporate defaults (Bauer & Agarwal 2014, Campbell et al. 2008, Tian et al. 2015). Following Campbell et al. (2008), who have developed the current state of the art model, I compute the following indicators:

\footnote{See among others Pires et al. (2013), Valta (2016), Xu & Zhang (2008)}
- NIMTA: EBITDA divided by the market value of total assets
- TLMTA: total liabilities divided by the market value of total assets,

where the market value of total assets is approximated as the market value of equity plus the book value of total debt. These variables account for the fact that firms with low profitability and high leverage are more likely to default.\(^{13}\) To exploit cross-sectional as well as time series heterogeneity, I estimate the asset price reaction to monetary policy announcements using a panel data model. Specifically, I estimate the following two specifications for equity excess returns and CDS spread changes:

\[
\begin{align*}
    r_{i,t} &= a_{EQT}^{EQT} + b_{EQT}^{EQT} \times X_t + c_{1}^{EQT} \times DD_{i,t} + c_{2}^{EQT} \times (EAS_t \times DD_{i,t}) + d_{EQT}^{EQT} \times V_{i,t} + e_{i,t} \\
    s_{i,t} &= a_{CDS}^{CDS} + b_{CDS}^{CDS} \times X_t + c_{1}^{CDS} \times DD_{i,t} + c_{2}^{CDS} \times (EAS_t \times DD_{i,t}) + d_{CDS}^{CDS} \times V_{i,t} + e_{i,t}.
\end{align*}
\]

(11) \hspace{1cm} (12)

The specifications above include firm fixed effects in \(a_i\). I cluster standard errors at the firm level to account for firm dependence (Cameron et al. 2006, Petersen 2008).\(^{14}\) \(X_t\) is a matrix containing the monetary policy shocks \(\Delta u_t\), \(\Delta e_t\) and \(\tau_t\) as explained in section 3.1. \(DD_{i,t}\), the firm-specific DD, appears twice in (11)-(12). The interaction between DD and the \(EAS\) dummy, which is set equal to one at the dates of the announcement of the six purchase programs listed in table 1, is of special interest with regard to the hypotheses \(H_{3a}\) and \(H_{3b}\). When equity investors expect these programs to ease funding conditions, we should observe larger equity returns for firms with lower DD (higher default risk). Hence, we expect \(c_{2}^{EQT} < 0\) under \(H_{3a}\). Conversely, the interaction term is expected to be positive under \(H_{3b}\) in the CDS market (\(c_{2}^{CDS} > 0\)). The matrix \(V_{i,t}\) contains additional firm specific control variables. In addition to NIMTA and TLMTA, I also control for systematic risk using the Capital Asset Pricing Model (CAPM) BETA. BETA is estimated using daily excess stock returns observed in the time frame -250 to -1 day before each Governing Council meeting. To account for other characteristics, which are known to possess explanatory power for cross-sectional equity returns, I present separate estimation results including controls for the firm’s market-to-book equity ratio (MB) and momentum (MOM). The latter is constructed along the lines of

\(^{13}\) Including other typical balance sheet indicators does not affect the results.

\(^{14}\) I find that clustering standard errors both at the firm and time level (two-way clustering) using the algorithm provided by Cameron et al. (2006) does not affect the results.
Jegadeesh & Titman (1993) by using the cumulative return over the last twelve months before every Governing Council meeting day, whereas the last month in this window is skipped to avoid the short-term reversal effect. Moreover, I also add a control for a firm’s market capitalization relative to the full sample market capitalization at each point in time (RSIZE). Lastly, I control for country risk and other macroeconomic risk by adding the yield on the 10 year government bond of each firm’s market (GOV).

4. Data and Descriptive Statistics

The sample consists of firms listed in Frankfurt, Paris, Milan and Madrid (Mercado Continuado). Equity prices, total return indices and Worldscope balance sheet and profitability data have been downloaded from Thomson Reuters Datastream. All active and dead firms available between 01/01/2002 and 06/30/2016 on Datastream are included in the sample, whereas firms without Worldscope balance sheet data have been dropped. Datastream data contain some well known errors. I have carefully followed the procedures proposed by Ince & Porter (2006) and Brueckner (2013) to clean the Datastream files. In particular, firms are labeled as inactive and deleted them from the sample after their prices have been stale for three months. Moreover, nano caps with market capitalizations below 20 million Euros have been deleted. I select the MSCI EMU Index as a proxy for the market portfolio and use the EURIBOR as a proxy for the risk-free rate. All of these data items have been obtained from Datastream, as well.

Datastream also provides CDS spreads. However, matching the Datastream CDS sample with the equity of the underlyings is not straightforward. As the European CDS market is rather small, I have conducted a manual matching procedure using the “related securities” field of Datastream. In detail, I follow Berndt & Obreja (2010) and select the 5-year contracts with modified-modified restructuring clause for senior unsecured Euro denominated debt. Discussions with credit derivatives traders confirm that this type of contract is the most liquid CDS contract in the European market. As proposed by Norden & Weber (2004), I choose the daily mid spread as indicator for the costs of protection. The same filters which are used to clean equity data are also applied to the CDS spreads. Lastly, yields on 10-year government bonds from Datastream have been added to the sample. In particular, I have selected German Bunds, French Obligations Assimilables du Trésor (OAT) as well as Italian and Spanish government bonds.

Figure 2 displays the evolution of excess returns on the MSCI EMU (solid line,
left axis) and the equal-weighted CDS index (dotted line, right axis) in an event window beginning ten days before and ending ten days after the announcement of the six asset purchase programs listed in Table 1. This graphical evidence underlines that the asset purchase programs, which are commonly regarded as the most significant UMP measures of the ECB, have indeed moved financial markets. In most cases, the expected market reactions, i.e. increasing equity prices and decreasing CDS spreads, following the event days, which are denoted by the vertical lines in Figure 2, are visible. However, we cannot take this as hard evidence supporting H1a and H1b because we do not control for expectations in this simple setting.  

Cumulative excess returns of the MSCI EMU in %-points (solid line, left axis) and an equal-weighted CDS index in bps (dotted line, right axis) are plotted beginning ten days before the announcement of asset purchase programs and ending ten days after the announcement.

Figure 2: Equity and CDS market reactions around asset purchase program announcement days

Table 2 presents descriptive statistics on the number of firms in the sample. Panel A shows the number of listed firms per industry. The French subsample is the

\^15 An analysis with event windows is explained in in appendix C.
largest with regard to market capitalization and more firms are listed in Paris than in Frankfurt. In total, there are 76 banks in the sample. This number is sufficient to conduct hypothesis tests for $H2a$. Table 2 also lists other financial firms, which might be more directly affected by unconventional monetary policy. For example, insurers are likely to be negatively affected by these policies because their ability to generate interest income is severely impaired when interest rates are very low. For this reason I exclude these firms as I test $H2$. The largest group of firms are non-financial companies. This group is divided into several further sectors, which are not listed in table 2 to save space.

<table>
<thead>
<tr>
<th></th>
<th>Banks</th>
<th>Insurers</th>
<th>Other Financial</th>
<th>Non-Financial</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A: Listed Firms</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Germany</td>
<td>12</td>
<td>13</td>
<td>85</td>
<td>685</td>
<td>795</td>
</tr>
<tr>
<td>France</td>
<td>19</td>
<td>8</td>
<td>80</td>
<td>748</td>
<td>855</td>
</tr>
<tr>
<td>Italy</td>
<td>27</td>
<td>12</td>
<td>31</td>
<td>264</td>
<td>334</td>
</tr>
<tr>
<td>Spain</td>
<td>18</td>
<td>2</td>
<td>7</td>
<td>145</td>
<td>172</td>
</tr>
<tr>
<td>Total</td>
<td>76</td>
<td>35</td>
<td>203</td>
<td>1842</td>
<td>2156</td>
</tr>
<tr>
<td>Panel B: Firms with available CDS</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Germany</td>
<td>2</td>
<td>3</td>
<td>0</td>
<td>26</td>
<td>31</td>
</tr>
<tr>
<td>France</td>
<td>4</td>
<td>2</td>
<td>3</td>
<td>37</td>
<td>46</td>
</tr>
<tr>
<td>Italy</td>
<td>7</td>
<td>1</td>
<td>1</td>
<td>10</td>
<td>19</td>
</tr>
<tr>
<td>Spain</td>
<td>6</td>
<td>0</td>
<td>0</td>
<td>7</td>
<td>13</td>
</tr>
<tr>
<td>Total</td>
<td>19</td>
<td>6</td>
<td>4</td>
<td>80</td>
<td>109</td>
</tr>
</tbody>
</table>

The upper panel shows the number of firms in the equity market across different sectors. The corresponding numbers for firms with available CDS spreads are listed in the lower panel.

Table 2: Sample Statistics

Panel B of table 2 lists firms with available CDS spreads. In total, there are only 109 firms. Berndt & Obreja (2010) study the entire cross-section of European CDS (17 countries including the UK). Their sample of 150 firms for the time period 2004-2008 is only slightly larger. Once more, my discussions with credit derivative traders confirm that the sample size is realistic for the European market. As there are 19 banks and 80 non-financial corporations with available CDS spreads, I can also conduct reasonable hypothesis tests for $H2b$ and $H3b$. 

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5. Empirical Results

I begin the empirical analysis with a look at equity and CDS market movements on ECB Governing Council meeting days. Table 3 shows the mean excess return on the MSCI EMU index and the mean change of the CDS index with the corresponding standard deviations. Market movements are generally larger when actions have been taken and the six UMP asset purchase program announcements discussed in section 2, (column 4 of table 3) evoke especially strong reactions. When no actions have been taken, equity returns and CDS spread changes are close to zero.

<table>
<thead>
<tr>
<th></th>
<th>Conventional Action</th>
<th>No Action</th>
<th>Purchase Program</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSCI</td>
<td>-0.827</td>
<td>-0.0191</td>
<td>2.085</td>
</tr>
<tr>
<td></td>
<td>(3.068)</td>
<td>(1.476)</td>
<td>(3.603)</td>
</tr>
<tr>
<td>CDS</td>
<td>0.718</td>
<td>-0.0623</td>
<td>-10.11</td>
</tr>
<tr>
<td></td>
<td>(3.869)</td>
<td>(3.847)</td>
<td>(10.96)</td>
</tr>
</tbody>
</table>

This table presents the time series means of excess returns (in %) on the MSCI Europe and CDS spread changes (in bps) on days of ECB Governing Council meetings. Standard errors are reported in parentheses. Conventional actions correspond to days when the ECB main rate has been changed. The third column reports means for days of meetings without any policy changes. The last column reports means for days with announcements of UMP measures. In particular, these are the six purchase program announcements listed in table 1. Three purchase programs (CBPP1,CBPP3/ABSPP,M-EAPP) were announced simultaneously with conventional rate cuts. These three days are counted as purchase program announcement days in this table.

Table 3: Summary Statistics: Market Reactions and Monetary Policy

It is noteworthy that markets have, on average, responded to conventional actions with negative excess equity returns and increasing CDS spreads. In appendix C I show that this picture does not change when event windows instead of daily reactions are considered. In total, the ECB has increased rates at 11 meetings, decreased rates at 18 meetings and left rates unchanged after 137 meetings. Even though rate decreases out number rate increases in column two of table 3, markets did not respond as expected on average. The most likely explanation for this finding is the sample period, which contains the severe and ongoing crisis since 2008. UMP actions did however evoke the expected market reactions. A closer look at every single one of the six UMP announcement days reveals equity markets have responded to the announcement of SMP with the strongest excess returns (+8.60%), whereas the equity market closed at -1.43% in excess of the risk free rate after the
announcement of the Modified Expanded Asset Purchase Programme (EAPP). CDS market reactions have been negative after the announcement of every single UMP measure. As a next step, I assess the average market reactions to monetary policy shocks in the more elaborated time series regression frameworks. Estimation results for the Cook & Hahn (1989) specifications (5)-(6) and the regressions proposed by Kuttner (2001) (7)-(8) are presented in table 4.
This table presents the estimation results for time series regressions. There are three different specifications for excess returns on the MSCI Europe and two different specifications for CDS spread changes. The first column of each panel corresponds to the regression models (5)-(6). The remaining columns report the results for the regressions (7)-(8). Robust standard errors are reported in parentheses below the estimation results. \( \Delta i \) denotes the change of the ECB main refinancing rate. \( \tau^u \) is the UMP shock. \( \Delta i^e \) and \( \Delta i^u \) denote expected and unexpected CMP shocks, respectively. The term \( CRIS \times \ldots \) indicates an interaction with a crisis dummy, which is set equal to one in the time period 2008-2016.

<table>
<thead>
<tr>
<th></th>
<th>MSCI (5)</th>
<th>MSCI (7)</th>
<th>MSCI (7)</th>
<th>CDS (6)</th>
<th>CDS (8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \Delta i )</td>
<td>0.024</td>
<td>0.000</td>
<td>0.000</td>
<td>-0.010</td>
<td>0.02645</td>
</tr>
<tr>
<td></td>
<td>(0.01463)</td>
<td>(0.01905)</td>
<td>(0.01842)</td>
<td></td>
<td>(0.06258)</td>
</tr>
<tr>
<td>( \tau^u )</td>
<td>-0.092***</td>
<td>-0.098***</td>
<td>-0.096***</td>
<td>0.31***</td>
<td>0.31***</td>
</tr>
<tr>
<td></td>
<td>(0.01916)</td>
<td>(0.01905)</td>
<td>(0.01842)</td>
<td></td>
<td>(0.06623)</td>
</tr>
<tr>
<td>( \Delta i^e )</td>
<td>0.25</td>
<td>0.30**</td>
<td></td>
<td>-0.11</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.1434)</td>
<td>(0.09912)</td>
<td></td>
<td>(0.2416)</td>
<td></td>
</tr>
<tr>
<td>( \Delta i^u )</td>
<td>0.30*</td>
<td>0.44***</td>
<td></td>
<td>-0.081</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.1488)</td>
<td>(0.09667)</td>
<td></td>
<td>(0.2658)</td>
<td></td>
</tr>
<tr>
<td>( CRIS \times \Delta i^e )</td>
<td></td>
<td>-0.090</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.2479)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( CRIS \times \Delta i^u )</td>
<td></td>
<td>-0.21</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.2556)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-0.045</td>
<td>-0.061</td>
<td>-0.080</td>
<td>-0.40</td>
<td>-0.39</td>
</tr>
<tr>
<td></td>
<td>(0.1055)</td>
<td>(0.1120)</td>
<td>(0.1108)</td>
<td>(0.3238)</td>
<td>(0.3386)</td>
</tr>
<tr>
<td>Observations</td>
<td>165</td>
<td>166</td>
<td>166</td>
<td>98</td>
<td>98</td>
</tr>
<tr>
<td>Adjusted ( R^2 )</td>
<td>0.293</td>
<td>0.305</td>
<td>0.318</td>
<td>0.572</td>
<td>0.569</td>
</tr>
</tbody>
</table>

Table 4: Time Series Regression Results
The first columns in the MSCI and CDS panels report estimation results for the Cook & Hahn (1989) regressions, which I have augmented with the UMP shock. Robust standard errors are reported in parentheses below the coefficients. Contrary to the economic intuition, point estimates for the change of the ECB main refinancing rate are positive for equity markets and negative for CDS markets, albeit not statistically significant. The more elaborated models (7) and (8) provide even stronger support for this finding, as equity markets show significant positive responses to both expected (Δ\(\iota^e\)) and unexpected (Δ\(\iota^u\)) monetary policy shocks. The coefficients are positive but insignificant for the CDS market. This finding warrants further discussion. Apparently, investors have regarded interest rate decreases as bad news for the equity market. Bredin et al. (2009) run a similar regression on the returns of the DAX Index and several German industry indices over the time period 1989-2004. In general, their coefficients also exhibit a positive sign but are insignificant. They conclude equity markets are ambivalent to the actions of the ECB. My results are even stronger, the coefficients in table 4 are, at least at the 10% level, significant for the equity markets. These results underline that the transmission mechanism of CMP was not operating as expected during the sample period.

Gregoriou et al. (2009) report similar evidence for the UK. I follow these authors and investigate the time stability of the coefficients with an interaction term. It is possible that the market reaction changes as the interest rates approach the zero lower bound. The variable \(CRIS\) shown in column 4 of table 4 is a dummy set equal to one at the first meeting in 2008 and keeps this value until the end of the sample period. The interactions should show whether a specific crisis effect drives the result. It turns out that this is not the case. Coefficients without the interaction remain largely unchanged and the interacted coefficients are indistinguishable from zero.\(^\text{16}\) Taken together, these results imply that financial markets did not perceive accommodative CMP decisions in the sample period as positive news.

The coefficients on the UMP shock variable (\(\tau^u\)) describe the market reactions to the announcements of UMP. The coefficients are always negative and significant for the equity market and positive at statistically significant levels for the CDS market. Holding interest rate shocks constant, a 25 bps reduction of \(\tau^u\) yields an average equity excess return of 2.45% \((-25 \times -0.098\) and decreases CDS spreads by 7.75 bps \((-25 \times 0.31\) on average. Hence, these results are evidence for \(H1a\) and \(H1b\). In general, the models presented in table 4 explain a substantial share of the variation of excess equity returns and CDS spreads on ECB Governing Council meeting days. The adjusted \(R^2\) coefficients are around 30% for the equity market.

\(^\text{16}\)Due to limited data availability, I cannot estimate the specification with interactions for the CDS market.
market models and even close to 50% for the CDS market models. When I adapt
a more narrow definition of UMP and set \( \tau_u = 0 \) on all but the six purchase
program announcement days (see table 1) I obtain qualitatively similar results but
substantially lower coefficients of determination. These results reflect that UMP
is not limited to outright asset purchase programs. Other changes of the assumed
start date of UMP do neither alter the picture presented here. These results are
available upon request.\(^\text{17}\)

As a next step, I turn to the entire cross-section of equities and CDS. To gather
preliminary information about heterogeneous reactions, I estimate the specifications (7) and (8) for every stock and CDS in the cross-section. The box plots
in figure 3 illustrate the cross-sectional distributions of the response coefficients.
Panel A of figure 3 shows the response of excess stock returns and CDS spread
changes to unexpected interest rate shocks \( \Delta i^u \). While the reaction of equities is
close to zero for the vast majorities of firms, there are quite a lot of outliers visible
in the box plot. Likewise, the box plot shows a median response of CDS, which
is close to zero. Outliers are not prevalent in the case of CDS, but we have to
keep in mind that there are only 109 firms with available CDS spreads. Panel B of
figure 3 shows the response coefficients for UMP shocks \( \tau_u \). As conjectured in the
hypotheses \( H2a, H2b, H3a \) and \( H3b \), I find that the reactions to these events are
quite heterogeneous in equity and credit markets. Consistent with the index re-
gression results presented in table 4, the box plots show average negative (positive)
responses of equity excess returns (CDS spread changes) to changes in \( \tau_u \).

\(^{17}\)The regressions are re-estimated with market reactions measured in event windows in ap-
pendix C. The results are qualitatively similar, but the coefficients of determination drops
considerably with increasing window sizes. The bottom line of these additional results is that
monetary policy does not suffice to explain the movements of equity and credit markets over
several days surrounding Governing Council meetings.
These box plots show the cross-sectional distributions of the response coefficients from the regression models (7)-(8). The upper panel shows the response to unexpected CMP shocks $\Delta i^u$. The lower panel shows the response to UMP shocks $\tau^u$.

Figure 3: Cross-Sectional Distribution of Response Coefficient
According to \(H2a\) and \(H2b\), we expect the strongest market reactions in the banking sector. Average UMP response coefficients by markets and sectors are presented in table 5. As visible in the last rows of panels A and B, banks show the strongest responses in both equity and credit markets. The Wilcoxon rank-sum test rejects the null of equal coefficients for banks and non-financial corporations at the 1\% level. Hence, I find that stocks and CDS spreads of banks react stronger to UMP announcements than securities of non-financial firms. Moreover, the negative (positive) reactions observed for bank stocks (CDS) underline markets perceive UMP as beneficial for banks and do not focus on the averse effects of these policies on bank profitability. This result is in line with the equity index evidence presented by Haitsma et al. (2015). In general, \(H2a\) is valid in the German, French and Italian subsamples. In the Spanish subsample, I find that stocks of insurers react even stronger to UMP shocks.\(^{18}\) Bank CDS react stronger than CDS of firms in other industries across all subsamples. Thus, \(H2b\) is valid in all subsamples.

\(^{18}\)As visible in panel A of table 5, markets perceive accommodative UMP shocks as bad news for German insurers. This finding reflects the re-investment problem German insurers face in particular within their life insurance business lines.
This table presents the mean response coefficients to announcements of UMP measures. Panel A shows the cross-sectional means of $\rho^{EQT}$ in (7). Panel B shows the cross-sectional means of $\rho^{CDS}$ in (8). Standard errors are reported in parentheses. Cells with less than 3 observations have been left blank.

Table 5: Response Coefficients in the Cross-Section
The remainder of this paper is devoted to explaining the cross-sectional heterogeneity of stock and CDS market reactions on Governing Council meeting days further. The last set of research hypotheses $H_3a$ and $H_3b$ implies stronger market reactions for high default risk firms. Results for the panel regression models (11)-(12) are presented in table 6. Only equity returns and CDS spreads of non-financial firms have been used in the estimation. The coefficients of the monetary shocks and constants are omitted to save space. The left panel presents the results for equities. The first specification includes a reduced set of control variables. On average, stocks of firms with low default risk (high DD) have shown larger return on days of ECB Governing Council meetings. Moreover, also the interaction of DD with the dummy variable $EAS$, which is set equal to one on each announcement day of the six purchase programs listed in table 1, is positive and highly significant. Not stocks of high default risk firms, but stocks of low risk firms respond with stronger positive returns to the announcements of purchase programs. This stands in harsh contrast to the balance sheet channel and $H_3a$.

Moreover, the results show that equities with high CAPM BETA yield lower returns on Governing Council Meeting days. Jensen & Mercer (2002) find BETA and returns are positively related in times of expansive monetary policy and negatively related in times of restrictive monetary policy. Among others, Pettengill et al. (1995) find a conditional relationship between BETA and expected returns, which is positive in up and negative in down market phases. However, the sample period used here is one of exceptionally expansive monetary policy and an overall positive market performance. Above all, the negative relation between BETA and equity returns on Governing Council Meeting days, which is very stable across different subsamples, implies the equity market does not respond as suggested by capital market theory. The within $R^2$ of the first specification for equities is only 1.8% and increases considerably if controls for the market-to-book equity ratio (MB) and momentum (MOM) are added. Haitsma et al. (2015) and Kontonikas & Kostakis (2013) show that loser stocks react more strongly to monetary policy actions. I cannot confirm this as both interactions of MOM with the monetary policy shocks and interactions of winner/loser dummies with the shocks are insignificant. Moreover, I run a separate panel regression of the lagged monetary policy shocks on momentum returns to assess whether monetary policy shocks explain a substantial share of the variation of momentum. I find that this is not the case.\footnote{These additional results are available upon request.} There are momentum effects in the sample, but they are not explained by monetary policy.

Even though DD as a control for default risk is not significant once I control for

\footnote{These additional results are available upon request.}
momentum, it retains its positive sign. Hence, I cannot find any evidence for a positive reaction of high default risk stocks to announcements of UMP (H3a). Instead, I find weak evidence for a stronger reaction of low default risk firms. This finding is new and contrasts the prior findings of Haitsma et al. (2015) who argue that UMP in the Eurozone has - through a balance channel of monetary policy - evoked strong positive equity returns of highly leveraged firms. Again, it is important to bear in mind that the paper by Haitsma et al. (2015) is based on a sample which consists of the Euro Stoxx 50 firms. In contrast to my sample, their sample is limited to several large firms which are not very likely to be credit constrained.

20Ehrmann & Fratzscher (2004) find stocks of U.S. firms with poor credit ratings are affected significantly more by CMP. Similarly, Basistha & Kurov (2008) show that the response of credit constrained firms to monetary policy shocks is larger than the response on firms, which are not constrained.
<table>
<thead>
<tr>
<th></th>
<th>Equities (11)</th>
<th>Equities (11)</th>
<th>CDS (12)</th>
<th>CDS (12)</th>
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<tr>
<td>DD</td>
<td>0.000000017***</td>
<td>0.000000014***</td>
<td>0.00095***</td>
<td>0.00094***</td>
</tr>
<tr>
<td></td>
<td>(2.4e-09)</td>
<td>(2.8e-09)</td>
<td>(0.0016)</td>
<td>(0.00017)</td>
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<td>EAS × DD</td>
<td>0.23***</td>
<td>0.078</td>
<td>0.70***</td>
<td>0.71***</td>
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<td>(0.050)</td>
<td>(0.044)</td>
<td>(0.13)</td>
<td>(0.12)</td>
</tr>
<tr>
<td>EAS</td>
<td>-1.88***</td>
<td>2.60***</td>
<td>-6.36***</td>
<td>-6.54***</td>
</tr>
<tr>
<td></td>
<td>(0.52)</td>
<td>(0.49)</td>
<td>(1.14)</td>
<td>(1.10)</td>
</tr>
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<td>CRISIS</td>
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<td>0</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>(0.37)</td>
<td>(0.36)</td>
<td>(.)</td>
<td>(.)</td>
</tr>
<tr>
<td>GOV</td>
<td>0.88***</td>
<td>1.27***</td>
<td>0.16</td>
<td>0.18</td>
</tr>
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<td></td>
<td>(0.16)</td>
<td>(0.11)</td>
<td>(0.10)</td>
<td>(0.10)</td>
</tr>
<tr>
<td>BETA</td>
<td>-4.15***</td>
<td>-3.38***</td>
<td>-1.05*</td>
<td>-0.98*</td>
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<td></td>
<td>(0.61)</td>
<td>(0.46)</td>
<td>(0.49)</td>
<td>(0.44)</td>
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<tr>
<td>RSIZE</td>
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<td>0.050</td>
<td>-0.086**</td>
<td>-0.075**</td>
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<td></td>
<td>(0.044)</td>
<td>(0.037)</td>
<td>(0.026)</td>
<td>(0.023)</td>
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<tr>
<td>NIMTA</td>
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<td>0.0022***</td>
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<td></td>
<td>(0.0016)</td>
<td>(0.0058)</td>
<td>(0.019)</td>
<td>(0.019)</td>
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<td>TLMTA</td>
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<td>-0.011***</td>
<td>-0.0015</td>
<td>-0.0014</td>
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<tr>
<td></td>
<td>(0.0050)</td>
<td>(0.0031)</td>
<td>(0.0015)</td>
<td>(0.0013)</td>
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<tr>
<td>MB</td>
<td>0.34***</td>
<td></td>
<td>0.16**</td>
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<tr>
<td></td>
<td>(0.043)</td>
<td></td>
<td>(0.054)</td>
<td></td>
</tr>
<tr>
<td>MOM</td>
<td>17.2***</td>
<td></td>
<td>-0.62</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.51)</td>
<td></td>
<td>(0.33)</td>
<td></td>
</tr>
<tr>
<td>Firm Fixed Effets</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Monetary Controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
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<td>Observations</td>
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<td>172642</td>
<td>7378</td>
<td>7373</td>
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<tr>
<td>Adjusted $R^2$</td>
<td>0.018</td>
<td>0.131</td>
<td>0.182</td>
<td>0.183</td>
</tr>
</tbody>
</table>

This table presents the panel regression results for models (11) and (12). The dependent variables are equity excess returns (in %) and CDS spread changes (in bps.) observed at the end of every Governing council meeting day. DD is the firm specific distance-to-default. EAS is a dummy, which is equal to one on the six announcement events listed in table 1. The monetary shocks represented by (3) and (4) have been included in the estimation but are not displayed to save space. The same applies to firm fixed effects. Standard errors are clustered at the firm level. Two-way clustering at the firm and time level does not affect the results.

Table 6: Panel Regressions
The right panel of table 6 shows the results for the cross-section of CDS spread changes. In general, less control variables enter the CDS specifications at conventional significance levels. As implied by \( H3b \), I find a positive and highly significant relation between DD interacted with the dummy for the purchase programs and spread changes. Holding everything else constant, firms with larger DD (low default risk firms) show larger CDS increases. Conversely, high default risk firms show larger CDS contractions. Hence, the reaction of the credit market is in line with the balance sheet channel.

6. Robustness Checks

All in all, the results show that CDS of large firms react in accordance with the intentions behind the UMP purchase programs, whereas the larger cross-section of equities shows an opposite pattern suggesting stock investors are not convinced that credit constrained firms will benefit. The average market capitalization of a firm with available CDS spreads is close to 20 bn. EUR, whereas the full sample average market capitalization is approximately 2 bn. EUR. Thus, small firms might drive the results. When I restrict the cross-section of equities to firms with available CDS spreads and re-estimate (11), I do indeed obtain a negative, yet insignificant coefficient on the interaction \( EAS \times DD \). However, restricting the cross-section to firms with available CDS leads to a loss of information on credit constrained firms. When I re-estimate (11) once more using all firm observations with a market capitalization above 1 bn. EUR, I obtain a weakly significant positive coefficient on the \( EAS \times DD \) interaction and otherwise results similar to the results presented in table 6.\(^{21}\) The bottom line of these additional regression results, which are available upon request, is equity of very large firms responds to the announcement of UMP with strong positive stock returns. Apparently, markets believe these firms will profit from UMP, whereas markets do not believe in an actual balance sheet channel.

To provide a different perspective on the reaction of high and low default risk firms to UMP, I mimic an arbitrage trading strategy assuming a long position in high DD and a short position in low DD firms. On the day before every ECB Governing council meeting, I sort all firms into ten deciles according to their DD. I assume investors can buy and sell the highest and lowest deciles at the closing price on these days and then hold these portfolio until the day before the next Governing Council meeting. The arbitrage portfolio returns are computed as the top decile

\(^{21}\)A firm with market capitalization above 1 bn. EUR can be regarded as a large small cap stock.
value-weighted portfolio return minus the bottom decile value-weighted portfolio return. The cumulative “10-1” returns are plotted in figure 4. The arbitrage strategy shows a dramatic outperformance against the MSCI EMU index since the end of the financial crisis and the beginning of the adoption of UMP by the ECB. Apparently, firms which are to a lesser degree affected by credit constraints have quite persistently outperformed firms which are likely to be credit constrained. A further inspection shows that the main driver of this outperformance is indeed the underperformance of firms with low DD. Explaining the existence of this trend in detail is beyond the scope of this paper.\textsuperscript{22} Nevertheless, these results provide a context for the previous results. The performance of the arbitrage strategy mirrors a market environment which is bullish for low risk and bearish for high risk firms. Apparently, the asset purchase programs, which are highlighted in figure 4, have not affected this trend. The ECB has not managed to alter the expectations of market participants in this regard. Instead of a balance sheet channel, this results points to a worsening environment for small, credit constrained firms.

\textsuperscript{22}Among others Vassalou & Xing (2004) and Campbell et al. (2008) provide results on the long-run relationship between default risk and equity returns.
The solid line shows the cumulative returns of a trading strategy which is long firms with high DD and short firms with low DD. The dotted line shows the cumulative total return of the MSCI EMU index. The shaded areas mark the announcement of the asset purchase programs listed in table 1.

Figure 4: DD Arbitrage Trading Strategy
I conduct another robustness check by sorting the 80 non-financial firms with available CDS into five portfolios before every Governing Council meeting and compute returns of an arbitrage strategy which is long the equity of the bottom quintile of CDS and short the equity of the top quintile of CDS. Conceptually, this is equivalent to going long high DD and short low DD firms. The CDS arbitrage strategy shows the same outperformance of low risk firms in the time period 2008-2016. These results are available upon request.

7. Summary and Discussion

The results presented in this paper cast some doubt on the effectiveness of monetary policy in the EMU. Between January 2002 and June 2016 conventional main rate decreases have, on average, evoked negative equity returns. However, the ECB unconventional monetary policy has, since 2008, lead to positive equity market and negative CDS market reactions on the announcement days. Bank equities and CDS show the strongest reactions. These findings are in accordance with the literature (Fratzscher et al. 2014, Haitsma et al. 2015, Rogers et al. 2014).

In contrast with previous findings in the literature, I show that the announcement of UMP measures, in particular asset purchase programs, did not evoke a stronger stock market reaction among credit constrained firms, which is implied by the balance sheet channel of monetary policy. In the CDS market, I do indeed find that contracts written on firms, which are more likely to be credit constrained, contract stronger than contracts written on firms with low likelihood of credit constraints. However, the market capitalization of firms with active CDS is roughly ten times as large as the average market capitalization in the entire cross-section of equities and credit constraints are expected to be more severe among small firms. Using the entire cross-section of equities, I find that large firms, which are not likely to be constrained, show the strongest equity returns. Consequently, financial markets regard asset purchase programs as beneficial for large, safe firms and not for small, credit constrained firms.

These results must not necessarily mean that UMP will be completely fruitless in the long run. The measures might slowly pass through a bank lending channel before aggregate lending to non-financial firms increases. However, the asset market channels, in particular the balance sheet channel, seem to be the more important part of the transmission mechanism of UMP (Joyce et al. 2012). This part crucially depends on asset market reactions and the results presented here suggest that the qualitative goals of the ECB’s actions, easing conditions for credit

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Assessing asset price responses to monetary policy actions remains an interesting topic in finance and macroeconomics. This article assesses how markets react to the announcement of new unconventional measures, whereas shocks are measured using spot and future rates. In light of the relentless efforts of central bankers to achieve forward-guidance there might be a variety of additional, more subtle measures central banks undertake to shape expectations, however. For instance, it is likely that the impact of monetary policy on markets is to an even greater extent determined by the wording of the ECB president when communicating the Governing Council decisions at the official press conferences. Loughran (2011) provide a finance dictionary which can be used to classify the tone of financial reports. In this vein, the methodology of textual analysis is likely to offer interesting ways to alternatively measure monetary policy shocks. Even a complete evaluation of a central bank’s communication including press releases and other public statements seems now viable.

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## Appendices

### A. The ECB’s Asset Purchase Programs

This appendix contains a summary of the ECB’s asset purchase programs. I outline the background of these programs and carve out their most important goals with references to the official ECB communication.

Joyce et al. (2012) propose to distinguish between two different types of UMP measures. On the one hand, qualitative easing programs are asset purchases which are supposed to ease funding conditions for commercial banks and non-financial corporations but lead to relatively small or even no increase of the central bank’s balance sheet. Below, I argue that the ECB’s attempts to revive the European covered bond and Asset Backed Securities (ABS) markets can be regarded as qualitative easing. These programs are attempts to reduce default risk and liquidity premia. Another example for such a policy in the USA would be the so-called “Operation Twist”, a balance sheet neutral portfolio turnover, which involves selling short-term and buying long-term government bonds. Clearly, this program was an attempt to reduce maturity premia. On the other hand, quantitative easing programs are purchase programs conducted in large and highly liquid market segments. Normally, such programs involve - but are not limited to - outright purchases of government bonds. Moreover, these programs lead to large increases of the central bank’s balance sheet. While qualitative measures aim to precisely reduce selected risk premia, quantitative measures are to be regarded as a universal weapon.

23The FED QE1 also included mortgage backed securities.
When central banks opt for outright purchases of securities in the capital market, they set five parameters to define their programs. First, they have to decide on the asset classes to be bought. This is the most significant decision because the choice of asset class will inevitably restrict the choices regarding the other parameters. Second, they can choose the volume of securities to be bought. Relative to the chosen asset class market size, this parameter should define the impact of their program. With the choice of the remaining three parameters, the central bank can fine-tune the program to reduce specific premia. The program can be designed to buy specific maturities, specific rating grades and impose restrictions regarding liquidity, for instance by setting a minimum issuance size for eligible securities. The ECB has varied all these parameters in their purchase programs, which are summarized in chronological order in table 1.

The ECB embarked on outright asset purchases with the announcement of its first Covered Bond Purchase Programme (CBPP) in May 2009. At that time, the covered bond market, which is important for the funding of European banks, was disrupted due to the ongoing crisis of trust following the financial crisis. Consequently, CBPP1 was announced as a program designed to “(a) promoting the ongoing decline in money market term rates and (b) easing funding conditions for credit institutions and enterprises.” (ECB 2009, p. 1). The evolution of the ECB’s balance sheet compared with the FED’s balance sheet is shown in the upper panel of figure 5. CBPP1 had a rather modest volume of 40 bn. EUR (relative to an ECB balance sheet volume of approximately 1.9 trillion EUR at that time) and was terminated by the end of June 2010. Some evidence regarding the effectiveness of CBPP1 has been presented by ECB staff. Beirne et al. (2011) claim that the program has, on average, dampened covered bond yields by approximately 12 bps, but they present only very weak evidence on positive spillovers to corporate bonds issued by non-financial firms.

A first purchase programme for government bonds, the Securities Markets Programme (SMP), was installed at the height of the European Debt crisis in 2012. Similar to the early “Enhanced Credit Support” package, SMP was meant to address a “malfunctioning” of financial markets (ECB 2010) and decrease credit spreads in the EMU. As such, this interventionist program differs from the other measures listed in table 1, which are more directed towards long-term strategic goals, especially easing funding conditions for non-financial corporations. Even though purchases under SMP were unrestricted with regard to ratings, maturities and volume, the total amount of purchased securities was rather low compared to purchases of government bond by other central banks.\(^{24}\) Moreover, the purchases

\(^{24}\) At its peak, the volume totaled 210 billion Euros (see the website https://www.bundesbank.de/Redaktion/EN/Glossareintraege/S/security_markets_programme.html).
were sterilized to prevent effects on the money supply.

A second covered bond programme, CBPP2, was implemented to achieve the same goals as the first programme in 2011 (ECB 2011). As visible in table 1, CBPP2 was more aggressive with regard to credit risk and liquidity but came with a lower target volume (40 bn. EUR). While the disruption in the covered bond market had been resolved after the turmoil in 2009, the CBPP programs apparently had not very sustainable effects on funding conditions for non-financial enterprises. The January 2012 bank lending survey, a survey conducted on a quarterly basis by the ECB, reported tightening instead of loosening credit conditions in the EMU (BLS 2012). The lower panel of figure 5 illustrates that credit to non-financial firms was in aggregate contracting at that time.

![Figure 5: Central bank balance sheets and aggregate credit to non-financial corporations in the EMU](image)

The upper panel shows the evolution of the ECB and FED balance sheets in EUR and USD, respectively. All values have been rebased to unity as of January 2002. The lower panel shows the evolution of log credit to non-financial corporations in million EUR as reported by commercial banks in the EMU. The data items have been downloaded from the ECB and FED websites.

**Figure 5:** Central bank balance sheets and aggregate credit to non-financial corporations in the EMU
A third CBPP was announced in September 2014. CBPP3 marks a further escalation in the ECB’s UMP because it involves purchases of covered bonds with unlimited volume and without restrictions on maturities and liquidity (ECB 2014a). Still, as shown in the upper panel of figure 5, the increases of the ECB’s balance sheet due to this program were negligible. Hence, CBPP3 belongs still to the category of qualitative easing. To move the scope of policy measures more towards lending to the real economy, an ABS Purchase Programme (ABSPP) was announced jointly with CBPP3 in September 2014. The ECB’s intentions behind this program were, according to the official communication, to revive the ABS market which had dried up after the financial crisis (ECB 2014b). The size of the European ABS market is small and very few non-financial corporations do actively use ABS as a means of internal finance (Altomonte & Bussoli 2014). However, ABS can enable banks, which are, due to capital requirements, not able to lend, to free up space in their balance sheets in order to provide new loans. The ECB accounts for the limitations of purchases in this market with a maximum of freedom regarding the program’s parameters. Table 1 shows there are no limits regarding volume, maturities or issuance size. ABS may be purchased in the primary as well as the secondary markets and tranches may include senior and guaranteed mezzanine tranches but no equity tranches (ECB 2014b). Until this point, the ECB had avoided balance sheet increases and focused on qualitative easing. According to the upper panel of figure 5, the balance sheet even decreased between 2012 and 2015. Moreover, the lower panel of figure 5 underlines that, ex post, the programs did not have effects on aggregate lending.

Against this backdrop, the ECB moved on to quantitative easing measures in January 2015, when the Expanded Asset Purchase Programme (EAPP) was announced. The objectives behind EAPP are very similar to the goals behind the qualitative easing measures described above: depressed yields on government bonds should ease funding conditions for non-financial corporations and households to foster aggregate investment (ECB 2015). EAPP is supposed to achieve this with monthly purchases of EMU government bonds across a broad range of maturities (2-30 years) in the secondary market. Initially, the program was announced to last for 12 months, but during the announcement the ECB Governing Council underlined that they would be willing to prolong the program if considered necessary. Apart from government bonds, also bonds issued from government agencies and debt securities issued by supranational European Union (EU) institutions may be purchased under EAPP.25 This program is certainly a milestone in the history of monetary policy in the EMU. However, in an international context, it is no

novelty, as other major central banks have conducted very similar programs years before the announcement of EAPP.\textsuperscript{26} The ECB introduced two slight modifications to EAPP in November 2015. These changes are not listed as a separate row in table 1 because the main parameters of EAPP remained unchanged. First, the modifications included purchases of bonds issued by regional governments, such as for example German Bundesländer. Second, the maturity of the entire program was extended to at least March 2017. This did not come as a surprise, since the Governing Council had been very explicit about their willingness to prolong the program during the first official announcement of EAPP in January 2015 and in the official wording of the program (ECB 2015). Consequently, I do not consider these changes as a separate purchase program event in the following empirical analysis. A larger overhaul of the program was announced in March 2016, when the ECB increased the volume of the asset purchases (ECB 2016\textsuperscript{b}). Moreover, this overhaul introduced an additional layer with the introduction of a dedicated corporate bond program called CSPP, which is explicitly limited to non-financial firms (ECB 2016\textsuperscript{a}). The modified EAPP and CSPP are in combination limited to 80 bn. EUR per month.

In effect, the ECB’s history with UMP marks a clear escalation from highly targeted programs aimed at specific risk premia (qualitative easing) to actions with a focus on volume in highly liquid markets. The upper panel of figure 5 illustrates the trend-breaking effect of the EAPP announcement on the ECB balance sheet in January 2015.

B. Alternative Construction of Interest Rate Shocks

As suggested by Kuttner (2001), I construct monetary policy shocks using interest rate futures in section 3 (see (2) and (3)). This procedure assumes futures markets contain expectations of market participants (Fisher 1930, Hicks 1946). Admittedly, one can argue that this story is simply untrue. Indeed, the mechanics of cash-and-carry arbitrage suggest that nothing beyond storage and financing costs determine the relationship between spot and futures markets. In spite of this compelling argumentation, the empirical forecasting literature has clearly found that futures rates forecast spot rates (Cole et al. 1991, Hafer et al. 1992, Patel & Zeckhauser 1987). If one were to reject the informativeness of futures rates for current spot rates, there would be two

\textsuperscript{26}See Rogers et al. (2014) for a summary of the UMP measures of the BoE, BoJ and FED.

alternative ways to gauge the market’s expectations regarding future spot rates. First, one might assume traders make naive forecasts and use the last observed spot rate as a forecast. This possibility has been explicitly considered in the article through modeling the monetary policy shock as $\Delta i$, along the lines of Cook & Hahn (1989).

Alternatively, traders might forecast futures rates using an $AR(p)$ model with lag length $p$. We assume that traders fit an $ARIMA(1,0,0)$ model to the entire available history before every Governing Council meeting in order to forecast the short rate. Subtracting this forecast from the actually observed spot rate at the end of the meeting day yields an alternative unexpected interest rate shock, which we call $\Delta i_{u,AR}$. As in (3), the expected interest rate shock is then given as $\Delta i_{e,AR} = \Delta i_{t} - \Delta i_{u,AR}$. Re-estimating (7) and (8) with these shocks yields the results shown in table 7.

<table>
<thead>
<tr>
<th></th>
<th>MSCI</th>
<th>CDS</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta e,AR$</td>
<td>-0.60</td>
<td>28.6</td>
</tr>
<tr>
<td></td>
<td>(1.6885)</td>
<td>(26.989)</td>
</tr>
<tr>
<td>$\Delta u,AR$</td>
<td>0.25</td>
<td>-0.13</td>
</tr>
<tr>
<td></td>
<td>(0.1543)</td>
<td>(0.2127)</td>
</tr>
<tr>
<td>$\tau_u$</td>
<td>-0.095***</td>
<td>0.31***</td>
</tr>
<tr>
<td></td>
<td>(0.01828)</td>
<td>(0.06553)</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.098</td>
<td>-0.0085</td>
</tr>
<tr>
<td></td>
<td>(0.1493)</td>
<td>(0.4408)</td>
</tr>
<tr>
<td>Observations</td>
<td>164</td>
<td>98</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.290</td>
<td>0.573</td>
</tr>
</tbody>
</table>

This table presents the estimation results for time series regressions (7)-(8) with alternative $AR(1)$ interest rate shocks.

Table 7: Time Series Regression Results - AR(1) shocks

These results do not lead to different conclusions. We find that the $AR(1)$ shocks are insignificant in equity and CDS markets. The conventional unexpected shocks computed using futures markets enters the equity market specification (7) with a positive sign as weakly significant in table 4. It is of similar magnitude and insignificant in this case. The unconventional shocks continue to be highly significant and assume the expected signs.
C. Event Windows

So far, I have assumed that monetary policy actions hit equity and CDS markets on the days of Governing Council meetings. Though I have accounted for expectations in the computation of monetary shocks, it might still be that market reactions change when we consider event windows instead of instantaneous, daily market reactions. In this appendix, I test market reactions using four event windows around the Governing Council meeting days denoted as 10 days before to 10 days after a meeting (-10:10), 5 days before to 5 days after a meeting (-5:5), 1 day before to 1 day after a meeting (-1:1) and the meeting day to one day after the meeting (0:1). Note that large reactions in the aftermath of a meeting contradict our understanding of informationally efficient markets. Table 8 replicates table 3 using these windows. For the sake of completeness, I have also listed the daily reactions (denoted as window 0:0), which are identical to the numbers presented in table 3 in section 5.
<table>
<thead>
<tr>
<th>Event Window</th>
<th>Conventional Action</th>
<th>No Action</th>
<th>Purchase Program</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A: Equities</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>-10:10</td>
<td>0.37</td>
<td>-0.21</td>
<td>4.63</td>
</tr>
<tr>
<td></td>
<td>(7.9)</td>
<td>(5.74)</td>
<td>(8.13)</td>
</tr>
<tr>
<td>-5:5</td>
<td>-1.52</td>
<td>0.13</td>
<td>2.59</td>
</tr>
<tr>
<td></td>
<td>(5.49)</td>
<td>(4.14)</td>
<td>(4.8)</td>
</tr>
<tr>
<td>-1:1</td>
<td>-0.85</td>
<td>0.13</td>
<td>3.87</td>
</tr>
<tr>
<td></td>
<td>(3.22)</td>
<td>(2.45)</td>
<td>(1.99)</td>
</tr>
<tr>
<td>0:1</td>
<td>-0.96</td>
<td>0.05</td>
<td>3.25</td>
</tr>
<tr>
<td></td>
<td>(2.81)</td>
<td>(2.13)</td>
<td>(2.51)</td>
</tr>
<tr>
<td>0:0</td>
<td>-0.71</td>
<td>-0.02</td>
<td>2.09</td>
</tr>
<tr>
<td></td>
<td>(2.46)</td>
<td>(1.37)</td>
<td>(3.6)</td>
</tr>
<tr>
<td>Panel B: CDS</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>-10:10</td>
<td>5.39</td>
<td>1.22</td>
<td>-8.04</td>
</tr>
<tr>
<td></td>
<td>(35.42)</td>
<td>(21.4)</td>
<td>(30.18)</td>
</tr>
<tr>
<td>-5:5</td>
<td>3.97</td>
<td>-0.06</td>
<td>-7.32</td>
</tr>
<tr>
<td></td>
<td>(17.75)</td>
<td>(16.57)</td>
<td>(16.37)</td>
</tr>
<tr>
<td>-1:1</td>
<td>2.99</td>
<td>-0.04</td>
<td>-13.03</td>
</tr>
<tr>
<td></td>
<td>(9.58)</td>
<td>(8.84)</td>
<td>(7.34)</td>
</tr>
<tr>
<td>0:1</td>
<td>2.44</td>
<td>0.04</td>
<td>-12.94</td>
</tr>
<tr>
<td></td>
<td>(8.2)</td>
<td>(7.1)</td>
<td>(9.49)</td>
</tr>
<tr>
<td>0:0</td>
<td>0.72</td>
<td>-0.06</td>
<td>-10.11</td>
</tr>
<tr>
<td></td>
<td>(3.87)</td>
<td>(3.85)</td>
<td>(10.96)</td>
</tr>
</tbody>
</table>

This tables presents cumulative excess returns on the MSCI EMU (in %) over several event windows in panel A. For instance, window -10:10 denotes the window starting 10 days before and ending 10 days after a Governing council meeting. Spread changes on the CDS market (in bps.) over the same windows are presented in panel B. Standard errors are presented in parentheses. The last rows in panels A and B present the market reactions on the days of Governing council meetings. These numbers are identical to the numbers presented in table 3.

Table 8: Market Reactions in Event Windows
First of all, we find that windows spanning more days are associated with larger standard errors. Many different factors, not only monetary policy, affect equity returns (panel A of table 8) and CDS spreads (panel B) when we increase the time span over which reactions are measured. Otherwise, there are no suggestive changes in signs regarding market reactions to CMP or UMP actions. To assess whether the time series regression models (7)-(8) are able to capture the variation of equity excess returns and CDS spread changes measured over the event windows, I re-estimate the specifications below. Table 9 shows the results for (7) when the dependent variable, the excess returns on the MSCI EMU, is the cumulative sum of returns over the windows explained above.

<table>
<thead>
<tr>
<th>MSCI (Event Windows)</th>
<th>-10:10</th>
<th>-5:5</th>
<th>-1:1</th>
<th>0:1</th>
<th>0:0</th>
</tr>
</thead>
<tbody>
<tr>
<td>Δ(i^e)</td>
<td>-0.52</td>
<td>-0.20</td>
<td>0.50***</td>
<td>0.34**</td>
<td>0.25</td>
</tr>
<tr>
<td>(0.5345)</td>
<td>(0.4386)</td>
<td>(0.1243)</td>
<td>(0.1253)</td>
<td>(0.1434)</td>
<td></td>
</tr>
<tr>
<td>Δ(i^u)</td>
<td>-0.42</td>
<td>-0.041</td>
<td>0.55***</td>
<td>0.39**</td>
<td>0.30*</td>
</tr>
<tr>
<td>(0.5425)</td>
<td>(0.4242)</td>
<td>(0.1420)</td>
<td>(0.1357)</td>
<td>(0.1488)</td>
<td></td>
</tr>
<tr>
<td>τ(u)</td>
<td>-0.070</td>
<td>-0.091</td>
<td>-0.12***</td>
<td>-0.099***</td>
<td>-0.098***</td>
</tr>
<tr>
<td>(0.07454)</td>
<td>(0.05629)</td>
<td>(0.02950)</td>
<td>(0.02682)</td>
<td>(0.01905)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-0.23</td>
<td>-0.23</td>
<td>0.11</td>
<td>0.000070</td>
<td>-0.061</td>
</tr>
<tr>
<td>(0.5129)</td>
<td>(0.3589)</td>
<td>(0.1859)</td>
<td>(0.1676)</td>
<td>(0.1120)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>165</td>
<td>165</td>
<td>166</td>
<td>166</td>
<td>166</td>
</tr>
<tr>
<td>Adjusted (R^2)</td>
<td>0.012</td>
<td>0.048</td>
<td>0.214</td>
<td>0.179</td>
<td>0.305</td>
</tr>
</tbody>
</table>

This table presents the estimation results for the time series model (7), whereas the dependent variable, which is the excess return on the MSCI EMU index, is measured over several event windows. For instance, window -10:10 denotes the window starting 10 days before and ending 10 days after a Governing council meeting. The last column repeats the results which have been presented in table 4 in section 5, where the dependent variable is just the daily excess return recorded on a Governing Council meeting day. Robust standard errors are reported in parentheses.

Table 9: Time Series Regression Results for Equities - Event Windows

The last column of the table repeats the estimation results presented in table 4. Again, I do not find any suggestive sign changes. The coefficients assume the same signs as in table 4 when I measure returns over the two or three-days windows. The event windows looking into the more distant past and future deliver regression coefficients which are insignificant altogether. A look at the adjusted \(R^2\)
coefficients underlines that the regression models are not suited to explain equity excess returns over long horizons, the specification with daily reactions, which has been presented in section 5, is by far the most convincing one in terms of $R^2$. I take these additional results as support for the procedure undertaken in the article. There is not much information in equity returns measured over a period of days surrounding Governing Council meeting days, which we can explain with monetary policy actions. The results which arise when I measure CDS market reactions over the event windows do neither give rise to different conclusions. They are presented in table 10 below.

<table>
<thead>
<tr>
<th>CDS (Event Windows)</th>
<th>-10:10</th>
<th>-5:5</th>
<th>-1:1</th>
<th>0:1</th>
<th>0:0</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta \tau^e$</td>
<td>0.41</td>
<td>0.79</td>
<td>-0.55</td>
<td>-0.13</td>
<td>-0.11</td>
</tr>
<tr>
<td></td>
<td>(3.0855)</td>
<td>(2.0056)</td>
<td>(0.8049)</td>
<td>(0.6669)</td>
<td>(0.2416)</td>
</tr>
<tr>
<td>$\Delta \tau^u$</td>
<td>-0.28</td>
<td>0.49</td>
<td>-0.64</td>
<td>-0.17</td>
<td>-0.081</td>
</tr>
<tr>
<td></td>
<td>(3.1874)</td>
<td>(2.0863)</td>
<td>(0.8319)</td>
<td>(0.6965)</td>
<td>(0.2658)</td>
</tr>
<tr>
<td>$\tau^u$</td>
<td>0.30</td>
<td>0.25</td>
<td>0.42***</td>
<td>0.41***</td>
<td>0.31***</td>
</tr>
<tr>
<td></td>
<td>(0.3078)</td>
<td>(0.2264)</td>
<td>(0.1077)</td>
<td>(0.08535)</td>
<td>(0.06258)</td>
</tr>
<tr>
<td>Constant</td>
<td>1.69</td>
<td>0.50</td>
<td>-0.21</td>
<td>-0.14</td>
<td>-0.39</td>
</tr>
<tr>
<td></td>
<td>(2.4353)</td>
<td>(1.7798)</td>
<td>(0.8360)</td>
<td>(0.6579)</td>
<td>(0.3386)</td>
</tr>
<tr>
<td>Observations</td>
<td>98</td>
<td>98</td>
<td>98</td>
<td>98</td>
<td>98</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.013</td>
<td>0.015</td>
<td>0.287</td>
<td>0.382</td>
<td>0.569</td>
</tr>
</tbody>
</table>

This table presents the estimation results for the time series model (8), whereas the dependent variable, which is the change of the CDS index, is measured over several event windows. For instance, window -10:10 denotes the window starting 10 days before and ending 10 days after a Governing council meeting. The last column repeats the results which have been presented in table 4 in section 5, where the dependent variable is just the daily excess return recorded on a Governing Council meeting day. Robust standard errors are reported in parentheses.

Table 10: Time Series Regression Results for CDS - Event Windows

In analogy to the equity market results, I find that there are no sign changes and the results which arise when CDS spread reactions are measured over a longer time span are completely insignificant. Moreover, the results exhibit the same downward trend in $R^2$: the ability to explain market reactions with monetary policy becomes very limited as the event window increases. Taken together, these results support the way monetary policy shocks have been measured in the related
literature (Rogers et al. 2014, Haitsma et al. 2015) and this article.
Declaration of Authorship

I hereby certify that the thesis I am submitting is entirely my own original work except where otherwise indicated. Any use of the work of other authors has been properly acknowledged and cited. I agree to make an electronic copy available to the examiners should it be necessary to check for plagiarism.


______________________________   ________________________________
City/Date                                      Richard Lennart Mertens