technische universität
dortmund

Essays in Finance: Corporate Hedging, Mutual Fund Managers' Behavior, and Cryptocurrency Markets

Dissertation zur Erlangung des akademischen Grades
Doctor rerum politicarum
der Fakultät für Wirtschaftswissenschaften
der Technischen Universität Dortmund

Gerrit Köchling
FEBRUARY 1, 2021

Contents

List of Figures V

List of Tables VII

1 Introduction 1

1.1 Publication Details . . . 5

2 Price Delay and Market Frictions in Cryptocurrency Markets 11

2.1 Introduction . . . 11

2.2 Data and Delay Measures . . . 12

2.3 Empirical Results . . . 13

2.4 Conclusion . . . 15

3 Does the Introduction of Futures Improve the Efficiency of Bitcoin? 17

3.1 Introduction . . . 17

3.2 Data and Methodology . . . 18

3.3 Empirical Results . . . 19

3.4 Conclusion . . . 21

4 Volatility Forecasting Accuracy for Bitcoin 23

4.1 Introduction . . . 23

4.2 Methodology . . . 24

4.3 Data, Empirical Analysis, and Results . . . 25

4.4 Conclusion . . . 31

5 Managerial Behavior in Fund Tournaments - the Impact of TrueSkill 33

5.1 Introduction . . . 33

5.2 Fund Tournaments & Skill . . . 34

5.2.1 The Economics of Tournaments . . . 34

5.2.2 The Impact of Prior Performance through TrueSkill 35
5.2.3 Identifying Skill Based Tendencies in Risk-Shifting 38
5.3 Empirical Results 39
5.3.1 Measuring Performance with TrueSkill 41
5.3.2 Skill Driven Risk-Shifting 41
5.3.3 Robustness Tests 46
5.4 Conclusion 52

6 Do Firms Hedge in Order to Avoid Financial Distress Costs? 53
6.1 Introduction 53
6.2 Modeling Framework 57
6.2.1 Estimation of the FDC Function 57
6.2.2 Implications of an FDC-induced Hedging Equilibrium 59
6.3 Empirical Results 62
6.3.1 Data Description and Methodology 62
6.3.2 Absolute FDC and Hedging 67
6.3.3 Marginal FDC Benefits and Hedging 70
6.3.4 Robustness Checks 72
6.4 Conclusion 78

Appendices 81

A Appendix for Chapter 5 81
A.1 General Tournament Behavior 81
A.2 Tables – Robustness Tests 83

B Appendix for Chapter 6 89
B.1 Estimating the Financial Distress Cost Parameter η from a Capital Structure Equilibrum 89
B.2 Construction of the FDC Variables 91
B.3 Correlation Matrix 95
B.4 Industry Distribution 96

Bibliography 97

List of Figures

2.1 Evolvement of the Average Price Delay over Time 13

4.1 Standard GARCH(1,1) Volatility Forecasts, Volatility Proxies, and Losses 28
4.2 Visualization of one-day-ahead Volatility Forecasts 30

5.1 Schematic Work of TrueSkill as a Factor Graph 37
5.2 Managers per Tournament and Benchmark Related Performance 40
5.3 Correlation of TrueSkill and the Underlying Information Ratio 42
5.4 Comparison of Skill Developments by TrueSkill and ELO 51

B.1 Visualization of the First Optimization Problem 92
B.2 Visualization of the Second Optimization Problem 93
B.3 Contour Plot of the Theoretical Hedge Ratio 93
B.4 3D Plot of the Theoretical Hedge Ratio 94

List of Tables

2.1 Correlations and Descriptive Statistics 14
2.2 Regressions of Price Delay on Market Liquidity 15

3.1 Descriptive Statistics 18
3.2 Results for the Pre- and Post-Futures Periods 21

4.1 Descriptive Statistics 26
4.2 Number of Superior Models 27
4.3 Results of the MCS Procedure 29

5.1 Risk Transitions for Managers of Different Skill Levels 43
5.2 Risk Transitions Based on Extreme Risk-Shifting 45
5.3 Regressions of Risk-Shifting on Different Skill-Levels 50

6.1 Variable Definitions 68
6.2 Descriptive Statistics 69
6.3 Regressions of Hedging Extent on Hedging Incentives including the Absolute Amount of Expected FDC 71
6.4 Regressions of Hedging Extent on Hedging Incentives including the Marginal Benefits of FDC Reduction 73
6.5 Regressions of Hedging Extent on Hedging Incentives for Different Subsamples 75
6.6 Regressions of Alternative Proxies of Hedging Extent on Hedging Incentives 77

A.1 Contingency Tables of Annual Tournaments following Brown et al. (1996) 82
A.2 Risk Transitions for Managers of Different Skill Levels - Active Return 83
A.3 Rank Correlations Based on Different Performance Measures 84
A.4 Risk Transitions for Different Hyperparameters: $\sigma = 12.5$ 85
A.5 Risk Transitions for Different Hyperparameters: $\sigma = 6.25$ 86

A.6 Risk Transitions for Managers of Different Skill Levels - Secondary Benchmarks 87

B.1 Correlation Matrix 95
B.2 Industry Distribution of the Dataset 96

Acknowledgment

I would like to thank Professor Peter N. Posch, my mentor. He gave me the opportunity to write this thesis, gave me academic freedom, and provided me with constant encouragement and guidance. I am also profoundly indebted to my co-authors, Philipp Schmidtke, Janis Müller, Lutz Hahnenstein, and Alexander Swade who have contributed greatly to my personal and professional growth. I am also grateful to the finance research group at TU Dortmund University, with whom I spent an amazing time not only as colleagues but also as friends. Special thanks go to Tobi and Yannick who have been my companions since the beginning of my bachelor's studies.

Finally and with upmost importance, I am sincerely grateful for the unconditional support and love of my parents and my brother. Thank you mum and dad, Klaus, Beate, and Nils.

1 Introduction

A central concept of financial economics is the informational efficiency of financial markets. It describes a market in which the prices of financial assets represent all available information and, consequently, a situation in which investors cannot systematically beat the market on a risk-adjusted basis. The theoretical roots of this concept go back a long way (Bachelier, 1900; Mandelbrot, 1963). Fama (1970) operationalized the efficient market hypothesis forming the basis for several theories, such as asset pricing models that provide a relationship between an asset's required return and its risk.

This dissertation covers research from the fields of corporate finance, asset management, and cryptocurrency markets whose underlying questions can be broadly summarized under the concepts of market efficiency and risk management. In two separate contexts, Chapters 2 and 3 empirically investigate the efficiency of the relatively new market for cryptocurrencies. Assessing the market efficiency is a crucial challenge due to the novelty, concerns about the intrinsic value of cryptocurrencies (cf. Quiggin (2013) among others), and massive public interest in the market. Equally important, Chapter 4 examines the risk, or more precisely, the volatility forecasting capabilities of a broad collection of generalized autoregressive conditional heteroscedasticity (GARCH)-type models (Bollerslev, 1986) for Bitcoin returns. The fifth chapter explores how mutual fund managers deal with risk in a tournament environment.[1] Introducing a new theoretical approach, Chapter 6 uses a proprietary dataset of corporate derivatives usage to provide a fresh perspective on whether firms hedge (bankruptcy) risk.

Market efficiency refers to the state of a market in which prices at any time "fully reflect" all available information (Fama, 1970, 1991). Fama (1970) divides price adjustments into three information subsets: historical prices, public information, and monopolistic access to any information relevant to price formation. Empirical testing of the inability of taking advantage of such information to systematically profit from trading the underlying assets indicates *weak-form*, *semi-strong*, and *strong* market efficiency, respectively.

Starting with Urquhart (2016), the weak-form efficiency has almost exclusively been studied for Bitcoin, whereas only a few papers have focused on cryptocurrencies in general (Brauneis and Mestel, 2018; Wei, 2018). The present dissertation expands this field by concentrating on the average price delay of the cryptocurrency market concerning new information. Using the three price delay measures initially proposed by Hou and Moskowitz (2005), Chapter 2 demonstrates that the price delay of the cryptocurrency market has decreased significantly over the past three years. As the delay measures parsimoniously capture the severity of market frictions that cause a delay of information incorporation into cryptocurrency prices, Chapter 2 concludes that the cryptocurrency market becomes more informational efficient over time. Further tests reveal that this improvement is substantially linked to an increase in market liquidity.

Exemplary for market frictions are short-sale constraints (Saffi and Sigurdsson, 2011). Due to the novelty of crypto assets, they are less regulated than the established equity markets, which likely imposes barriers for institutional investors to access the market due to a lack of infrastructural and regulatory frameworks. Institutional market engagement, in turn, fosters efficiency (Boehmer and Kelley, 2009). Chapter 3 addresses the effect of the launch of Bitcoin futures in December 2017 on Bitcoin's spot-price efficiency. Carrying out multiple empirical tests to quantify various aspects of the return predictability of Bitcoin prices from historical prices, Chapter 3 finds that the return predictability decreases after introducing futures, suggesting an increase in the weak-form informational efficiency of Bitcoin.

The unprecedented development of Bitcoin[2] combined with its association with financing illegal activity (Foley et al., 2019), its highly speculative components (Cheah and Fry, 2015), and its unregulated nature illustrates the importance of understanding the risks associated with a Bitcoin investment. Chapter 4 focuses on out-of-sample one-day-ahead Bitcoin return volatility forecasts of GARCH-type models and builds model confidence sets (MCS) (Hansen et al., 2011) for a statistically sound distinction between models of equivalent performance and underperformance. The findings indicate that smaller MCS (i.e., greater distinction between equal- and underperforming models), are facilitated by a jump-robust volatility proxy based on intra-day returns and asymmetric loss functions. However, the relatively large final sets confront the modeler with numerous statistically equivalent models in terms of forecasting accuracy, suggesting caution when making model recommendations for Bitcoin volatility.

The remainder of the thesis moves away from cryptocurrency markets but maintains a focus on risk. Chapter 5 analyzes the risk-shifting tendencies of mutual fund managers in a tournament environment, first introduced by Brown et al. (1996). In this context, losing managers (i.e., those ranked below the median manager at the midpoint of the year) are incentivized to proactively raise their portfolio risk in the second half of the year to increase their chances of being among the winning managers at year-end, which can result in higher fund inflows and compensation (Sirri and Tufano, 1998; Kempf and Ruenzi, 2008b). Within this framework, Chapter 5 focuses on how prior performance affects this behavior. For this, the Microsoft's TrueSkill algorithm (Microsoft Research, 2005) is employed, which is a skill-based ranking system based on the Bayesian network theory, originally designed for the gaming industry. Our findings suggest a positive correlation of prior performance and risk-shifting in line with the literature emphasizing the "overconfidence" of successful managers (Ammann and Verhofen, 2007; Puetz and Ruenzi, 2011). Furthermore, skilled fund managers seem to hold or increase their risk in the second half of the year, regardless of their relative success in the first half.

The last chapter of this dissertation covers the use of derivatives by corporations to hedge their risk. In a perfect and frictionless market, the use of derivatives to hedge risk should not affect the firm value because shareholders can replicate the firm's chosen capital structure (Modigliani and Miller, 1958). Following this, incentives to hedge risk arise from market imperfections such as tax benefits and financial distress costs (FDC) (Smith and Stulz, 1985), among others. In a Merton (1974) setting, Chapter 6 proposes a new theoretical approach by which ex-ante expected FDC are estimated based on the value of an asset-or-nothing put option on the firm's assets. Chapter 6 further proposes optimal hedge ratios that capture the marginal benefits of a further FDC reduction, trading off the ex-ante expected FDC and expected transaction costs for hedging in an equilibrium setting. For a proprietary dataset of the use of derivatives of 189 German middle-market companies, our approach explains a significant share of the empirically observed cross-sectional variations in hedge ratios.

While the present dissertation adds to a diverse set of literature strands, the following three contributions are most important. First, the work adds to the growing literature on cryptocurrencies. The expansive growth of the cryptocurrency market marks a (possibly) new era of decentralization. Cryptocurrencies impose severe challenges to regulators worldwide, from being absolutely or implicitly banned to being completely legal without any rigorous rules. Hence, a complete understanding of the market is of utmost importance. By examining market efficiency and risk, this dissertation adds to this understanding, which is of interest to cryptocurrency regulators, developers, users, risk managers, and others involved in this emerging asset class. Second, the dissertation adds to the literature studying the influence of behavioral factors on individuals' decision-making, particularly the literature studying the relationship between past performance and future choices of shifting risk. The dissertation extends the empirical work in the area of fund tournaments by highlighting the self-confident behavior of skilled managers in increasing their portfolio risk in the second half of the calendar year. Third, this thesis adds to the literature on corporate hedging by introducing a novel estimation approach of ex-ante expected FDC, closely tied to corporate finance theory. The thesis provides a fresh perspective on whether firms hedge to escape the expense of distress, and it enriches the literature from the perspective of German middle-market companies and a financial intermediary.

1.1 Publication Details

Paper I (Chapter 2):

Price delay and market frictions in cryptocurrency markets

Authors:

Gerrit Köchling, Janis Müller, Peter N. Posch

Abstract:

We study the efficiency of cryptocurrencies by measuring the price's reaction time to unexpected relevant information. We find the average price delay to significantly decrease during the last three years. For the cross-section of 75 cryptocurrencies we find delays to be highly correlated with liquidity.

Publication Details:

Economics Letters 174 (2019), 39–41

https://doi.org/10.1016/j.econlet.2018.10.025

Paper II (Chapter 3):

Does the introduction of futures improve the efficiency of Bitcoin?

Authors:

Gerrit Köchling, Janis Müller, Peter N. Posch

Abstract:

The introduction of futures on Bitcoin eases the access of institutional investors to the market and offers an efficient way to short the cryptocurrency. We investigate the effect of this event on the market's price efficiency and find the Bitcoin market to turn efficient. We conduct commonly used tests for market efficiency and check the robustness of our results by investigating Bitcoin Cash, a hard fork of Bitcoin, where we do not find a change in market's efficiency.

Publication Details:

Finance Research Letters 30 (2019), 367-370

https://doi.org/10.1016/j.frl.2018.11.006

Paper III (Chapter 4):

Volatility forecasting accuracy for Bitcoin

Authors:

Gerrit Köchling, Philipp Schmidtke, Peter N. Posch

Abstract:

We analyze the quality of Bitcoin volatility forecasting of GARCH-type models applying different volatility proxies and loss functions. We construct model confidence sets and find them to be systematically smaller for asymmetric loss functions and a jump robust proxy.

Publication Details:

Economics Letters 191 (2020): 108836

`https://doi.org/10.1016/j.econlet.2019.108836`

Paper IV (Chapter 5):

Managerial behavior in fund tournaments – the impact of TrueSkill

Authors:

Alexander Swade, Gerrit Köchling, Peter N. Posch

Abstract:

Measuring mutual fund managers' skills by Microsoft's TrueSkill algorithm, we find highly skilled managers to behave self-confident resulting in higher risk-taking in the second half of the year compared to less skilled managers. Introducing the TrueSkill algorithm, which is widely used in the e-sports community, to this branch of literature, we can replicate previous findings and theories suggesting overconfidence for mid-years winners.

Publication Details:

Journal of Asset Management (2021)
https://doi.org/10.1057/s41260-020-00198-7

Paper V (Chapter 6):

Do firms hedge in order to avoid financial distress costs?
New empirical evidence using bank data

Authors:

Luth Hahnenstein, Gerrit Köchling, Peter N. Posch

Abstract:

We present a new approach to test the financial distress costs theory of corporate hedging empirically. We estimate the ex ante expected financial distress costs, which serve as a starting point to construct further explanatory variables in an equilibrium setting, as a fraction of the value of an asset-or-nothing put option on the firm's assets. Using single-contract data of the derivatives' use of 189 German middle-market companies that stems from a major bank as well as Basel II default probabilities and historical accounting information, we are able to explain a significant share of the observed cross-sectional differences in hedge ratios. Hence, our analysis adds further support for the financial distress costs theory of corporate hedging from the perspective of a financial intermediary.

Publication Details:

Journal of Business Finance & Accounting (2020)
`https://doi.org/10.1111/jbfa.12489`

2 Price Delay and Market Frictions in Cryptocurrency Markets

The following is based on Köchling et al. (2019b):

Köchling, G., J. Müller, and P. N. Posch (2019b). Price delay and market frictions in cryptocurrency markets. *Economics Letters 174*, 39–41.
https://doi.org/10.1016/j.econlet.2018.10.025

3 Does the Introduction of Futures Improve the Efficiency of Bitcoin?

The following is based on Köchling et al. (2019a):

Köchling, G., J. Müller, and P. N. Posch (2019a). Does the introduction of futures improve the efficiency of Bitcoin? *Finance Research Letters 30*, 367–370.
https://doi.org/10.1016/j.frl.2018.11.006

4 Volatility Forecasting Accuracy for Bitcoin

The following is based on Köchling et al. (2020):

Köchling, G., P. Schmidtke, and P. N. Posch (2020). Volatility forecasting accuracy for Bitcoin. *Economics Letters 191*, 108836.

https://doi.org/10.1016/j.econlet.2019.108836

5 Managerial Behavior in Fund Tournaments - the Impact of TrueSkill

The following is based on Swade et al. (2021).

5.1 Introduction

Fund managers compete for investor's money by signaling their ability to generate risk-adjusted returns (or alpha) to the market. Using Microsoft's TrueSkill to estimate each manager's skill, we study the impact on the portfolio's risk level. We find highly skilled managers to take systematically more risk within one year's tournament compared to less skilled managers. These results are robust regarding different market phases, different years with pronounced risk-shifting incentives, and different empirical approaches.

Our work contributes to the existing literature by introducing Microsoft's TrueSkill algorithm as a new measure and thus regarding the tournament nature of the fund managers as a "game". Building upon Bayesian network theory, TrueSkill identifies and tracks the skills of managers in a competitive setting in which the belief about a manager's skill is estimated on the basis of a manager's past performance relative to all other active managers. Despite broad evidence for the long-term underperformance of active managers against a benchmark (Fama, 1965), individual managers seem to outperform the market in the short-term, resulting in higher fund inflows and compensation (Sirri and Tufano, 1998; Kempf and Ruenzi, 2008b), hence promoting a competitive environment among fund managers.

Second, we extend the empirical work in the area of fund tournaments, which was first introduced by Brown et al. (1996). They analyze the behavior of mutual fund managers within one year and detect a risk-seeking investment style for mid-term losers. Replicating their findings, our results indicate winners increasing their risk suggesting a different trend of individual behavior in tournaments in recent years. We then follow

Kempf et al. (2009) and highlight risk-shifting differences in years driven by incentives (winners are rewarded for their outperformance) and years driven by unemployment risk (losers are facing high chances of having their funds closed due to underperformance). We extend this area of research by detecting certain investment patterns based on the individual skill level of the managers and highlight the correlation between skill and risk-seeking.

The remainder is structured as follows: In Section 5.2, we introduce the fund tournaments' setup and Microsoft's TrueSkill, Section 5.3 contains the empirical analysis, while the final section concludes.

5.2 Fund Tournaments & Skill

5.2.1 The Economics of Tournaments

Research in the fields of managerial tournaments is considered as a subset of the agency theoretic contracting theory, which deals with the disparity between principals' and agents' interests and risk aversions. Bolton et al. (2005) summarize the basic assumptions and implications for multiple scenarios in different areas of economics.

The underlying premise of our analysis is to view the market for portfolio management service as a multi-period decision making. This implies that investors decide in a cyclical pattern which fund service to invest in. One significant aspect of this investment process is the established compensation structure within the fund industry. Fund managers are often compensated based on their funds' assets under management which implies large incentives to generate high fund inflows. Empirical evidence for the positive correlation in a multi-period context of the past performance of the individual fund and new fund inflows has been provided for example by Sirri and Tufano (1998).

This correlation leads to the plain risk adjustment hypothesis in literature of losing managers increasing their risk at mid-term in order to catch up on the leading managers within their peer (cf. Brown et al. (1996)):

$$\frac{\sigma_{2L}}{\sigma_{1L}} > \frac{\sigma_{2W}}{\sigma_{1W}} \tag{5.2.1}$$

where σ_{pL} indicates the risk level of a loser's portfolio in period $p \in \{1, 2\}$ of a two-period annual tournament and σ_{pW} the risk level of a winner's portfolio, respectively. Multiple researchers followed this hypothesis and analyzed various aspects and implications such as different time periods, competition within fund families, the impact of the selected fund segment, among others. Important ideas and results can be found in the works of Chevalier and Ellison (1997), Busse (2001), Deli (2002), Kempf and Ruenzi (2008a), Kempf and Ruenzi (2008b), and Bär et al. (2010). Despite the findings of all these researchers, there are still contrary opinions about the existence of such tournament behavior between managers and especially the exact behavioral aspects for winners and losers, respectively.

5.2.2 The Impact of Prior Performance through TrueSkill

New fund inflows are positively correlated with the standings of the individual fund at the end of the tournament, i.e. the end of the year. Most investors tend to trust in the past performance of a fund and expect it to result in positive returns at or around the benchmark level once the fund claims a top-level within a certain year. Hence, investors update their beliefs about the strength of an individual manager based on past, observed returns, and prior beliefs. In empirical research, this behavior has been modeled for example by Berk and Green (2004), who use a model that includes two key aspects: First, the performance of fund managers is not persistent and, second, investors behave as Bayesians. The first aspect can be interpreted as fund managers are not outperforming a passive benchmark continuously. Second, investors update their belief about the strength of an individual manager based on past, observed returns, and prior beliefs. This leads to the concept of conditional probabilities also known as Bayesian probability where the probability is interpreted as some reasonable expectation based on prior beliefs and knowledge.

The TrueSkill algorithm has been developed by a team from Microsoft Research in 2005 and is used for match-making in various online games ever since. The purpose of this ranking system is to detect and track the skill of individual players despite playing in teams, derive public rankings, and implement a match-making system that allows players of the same skill to play against each other. The general idea behind TrueSkill is to update the presumption about a player's skill based on the observed outcome of a given game. This technique is called *Bayesian inference* as explained for example by

Box and Tiao (2011). TrueSkill characterizes the belief of a manager's skill as Gaussian uniquely described by its mean μ and standard deviation σ (cf. Microsoft Research (2005)). The parameter μ can be interpreted as the average manager's skill belief whilst σ describes the uncertainty about that skill level. The more games a participant plays, the smaller becomes his σ and therefore, the knowledge about a player's skill becomes more precise. Furthermore, his average skill level μ is updated based on the match outcome.

One of the most important advantages of TrueSkill is its adaptivity to any underlying setup of ranking match outcomes. It only needs a clear ranking for each match - whether teams are compared with each other or individuals. We will give a brief overview of the underlying process of TrueSkill in order to derive a basic understanding of its functionality. However, we will not explain every mathematical step and its technical realization within the algorithm but refer to the paper of Herbrich et al. (2006).

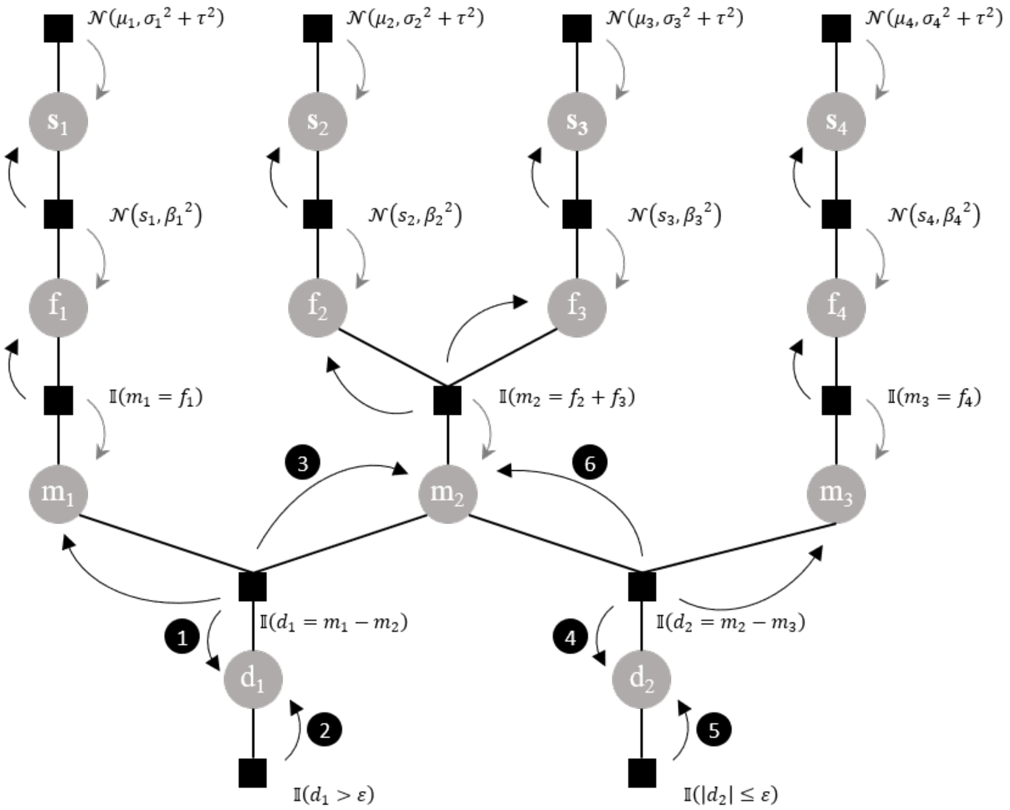
Let k managers with a total of n funds $\{1, ..., n\}$ compete in a match. Each fund is uniquely assigned to a single manager resulting in k disjunct subsets $A_j \subset \{1, ..., n\}$. For each match, the outcome $\mathbf{r} := (r_1, ..., r_k) \in \{1, ..., k\}$ indicates the match specific ranks r_j for each manager j in an ascending order; i.e. $r_j = 1$ is the winner and possible draws are given as $r_i = r_j$. Making use of Bayes' rule, the conditional probability $P(\mathbf{r}|\mathbf{s}, A)$ of the game outcome $\mathbf{r}$ given the individual skills $\mathbf{s} := (s_1, ..., s_n)$ of all participating funds in their manager assignments $A := (A_1, ..., A_k)$ leads to the posterior distribution of

$$p(\mathbf{s}|\mathbf{r}, A) = \frac{P(\mathbf{r}|\mathbf{s}, A)p(\mathbf{s})}{P(\mathbf{r}|A)}. \tag{5.2.2}$$

The prior distribution of the funds' skill $f(\mathbf{s}) := \prod_{i=1}^{n} \mathcal{N}(\mu_i, \sigma_i^2)$ is assumed to be a factorizing Gaussian whilst each fund i has a performance $f_i \sim \mathcal{N}(s_i, \beta_i^2)$ in the match, centered around their individual skill s_i with fixed variance β_i^2. With TrueSkill, the performance m_j of a manager j is defined as the sum of its individual funds' performances indicated by $m_j := \sum_{i \in A_j} f_i$ (cf. Herbrich et al. (2006)). Figure 5.1 shows the exemplary process of TrueSkill as a factor graph. This methodology is used in information technologies to describe complicated 'global' functions consisting of many variables which are most likely derived themselves from various 'local' functions. Those global functions factor as a product of the local functions and can therefore be described in a bipartite graph called factor graph. Further information can be found in

Kschischang et al. (2001).

Figure 5.1: Schematic Work of TrueSkill as a Factor Graph



Notes: Schematic work of TrueSkill illustrated as a factor graph (based on Herbrich et al. (2006)) for the resulting joint distribution $p(\mathbf{s}, \mathbf{f}, \mathbf{,}|\mathbf{r}, A)$ of three managers with a total of four funds and manager 1 winning whilst manager 2 and manager 3 draw ($k = 3$, $A_1 = \{1\}$, $A_2 = \{2, 3\}$, $A_3 = \{4\}$ and the ranking $\mathbf{r} := (1, 2, 2)$). The black boxes represent the factor functions which are used to calculate the local variables - visualized by the light grey circles. The grey arrows indicate the initial calculation of the skill level for all three managers followed by the 'inner iteration circle'. This circle is used to approximate the new skill level of all managers whilst after that, the black arrows indicate the updates of the skill beliefs for each individual fund.

5.2.3 Identifying Skill Based Tendencies in Risk-Shifting

In a first step, we calculate the six-month rolling information ratio as a performance measure of each fund. We use these ratios to create a rating of the funds on a monthly base to feed-forward to the TrueSkill algorithm. At this stage, funds with less than one year of tracking record prior to the start of the tournament year are also included due to the initial calculation of skill levels. Second, the funds included in the annual tournaments compete against each other on a monthly base whereas their skill level - and therefore the skill level of each manager - is calculated by TrueSkill based on the performance rankings. To compare the skill level of different fund managers, we use only each manager's expected average skill level μ once the skill development is calculated. To overcome biases for new managers who have not reached their intentional skill level yet, we only consider managers and therefore funds with at least one year of tracking record. This leads to at least 18 *matches* between all managers and their funds before they are categorized at the end of a tournament's interim period for the first time.

To analyze the skill dependent risk-shifting, we use conditional transition matrices for the best 20% (high skill), the next 60% (medium skill), and the least 20% (low skill) of each year's managers. We follow the work of Ammann and Verhofen (2009) and adapt this transition approach, commonly known from credit default analyses. The transitions are based on the historical volatility of each manager's portfolio, whereas each manager is assigned to a risk tercile:

$$(e_{i1}, e_{i2}) \in \{1, \ldots, 3\}^2, \qquad i = 1, \ldots, 3 \tag{5.2.3}$$

with e_{i1} characterizing the risk tercile of manager i in the interim period and e_{i2} the risk tercile in the second half of the year's tournament. Here, 1 indicates the highest risk tercile and 3 the lowest, respectively. These *migration events* of the same kind are now aggregated in a 3x3 matrix of *migration frequencies* where the generic element

$$c_{jk} = \sum_{i=1}^{3} \mathbf{1}\{(e_{i1}, e_{i2}) = (j, k)\} \tag{5.2.4}$$

is the number of migration events from j to k and $\mathbf{1}\{\ldots\}$ the indicator function. Furthermore, we assume that the observations e_{i2} are the realization of the random variables $\widetilde{e}_{i2}$ with conditional probability distribution

$$p_{jk} = \mathbf{P}\left(\widetilde{e}_{i2} = k \mid \widetilde{e}_{i1} = j\right), \qquad \sum_{k=1}^{3} p_{jk} = 1 \tag{5.2.5}$$

with the probability p_{jk} of the risk level of a manager's portfolio to change from the *j-th* to the *k-th* tercile. Therefore, we use the migration rates as observed:

$$\hat{p}_{jk} = \frac{c_{jk}}{n_j} \tag{5.2.6}$$

with $n_j = \sum_{k=1}^{3} c_{jk}$. To identify any differences between the differently skilled managers, we use a chi-squared test to check for pairwise homogeneity of the transition matrices. The test statistic

$$\chi^2 = \sum_{k=1}^{3} \sum_{s=1}^{2} \frac{\left(c_{jk}(s) - n_j(s)\hat{p}_{jk}^{+}\right)^2}{n_j(s)\hat{p}_{jk}^{+}} \tag{5.2.7}$$

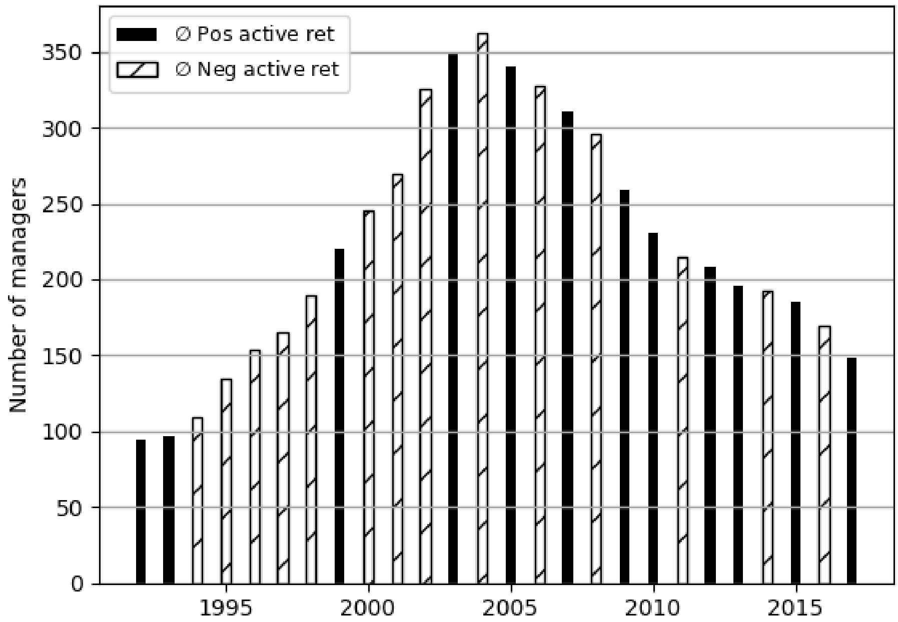
is asymptotically χ^2-distributed with two degrees of freedom. The variable $\hat{p}_{jk}^{+}$ models the estimated probability based on the aggregated data of the two transition matrices and s is the index for the respective sample, e.g. high- and medium-skilled manager.

By the nature of this approach our analyses put emphasis on the whole dynamics of the risk-shifting tendencies of differently skilled fund managers. Transition matrices as employed in this study are, inter alia, widely used in the literature on credit risks (cf. Höse et al. (2009) for details) and in previous studies focusing on prior performance and risk-taking of mutual fund managers (Ammann and Verhofen, 2007, 2009).

5.3 Empirical Results

Our empirical analysis builds on the two databases Morningstar and Bloomberg. Following Brown et al. (1996) and further researchers in their choice of taking growth-oriented US equity funds due to the high interest of financial press and direct investor involvement, we include all funds classified by the Morningstar categories *US OE Large Growth*, *US OE Small Growth* and *US OE Mid-Cap Growth*. We use monthly closing prices by Bloomberg of the categorized funds for the period of 1991 to 2017. This long period allows analyzing the behavior of the managers in various market situations since the selected period combines multiple different aspects such as financial crisis and market phases with a positive long-term trend, e.g. 2009-2017. All funds are listed in US dollar and we clean them for survivorship bias.

Figure 5.2: Managers per Tournament and Benchmark Related Performance



Notes: Black (white) bars indicate a positive (negative) average active return in the respective year.

Furthermore, we tackle the fact that various funds are team-managed and multiple managers handle more than one fund by using a string matching algorithm to identify funds managed by the same managers. We exclude all team-managed funds and match the remaining funds clearly to a single manager. This results in 559 individual managers who hold at least one fund on their own within the given time period.

We include all funds in each year's tournament which have at least one year of tracking record and do not miss any data point in the given period. Also, we use two periods of six months to analyze the risk-shifting, which leads to June being the end of the interim period. Those managers above the average at that point are classified as winners and those below as losers. Managers with two or more funds fulfilling these requirements are considered to hold an equally weighted portfolio of their funds to reduce the impact of pro-active risk-shifting across multiple funds. To calculate benchmark related performance measures, we use the data of the MSCI North America for the same period. An overview of the annual tournaments and the average performance of its participating manager against the benchmark is given in Figure 5.2.

There are several options to measure risk-levels of mutual funds. Examples are the return standard deviation, the tracking-error standard deviation which is the standard deviation of the excess returns of the fund over a benchmark, or the systematic risk a fund takes which is commonly estimated via a market model. However, the latter two are rather uncommon in mutual fund tournament studies. We follow previous studies and measure risk by the annualized standard deviation of the monthly fund returns (Brown et al., 1996; Kempf and Ruenzi, 2008b).

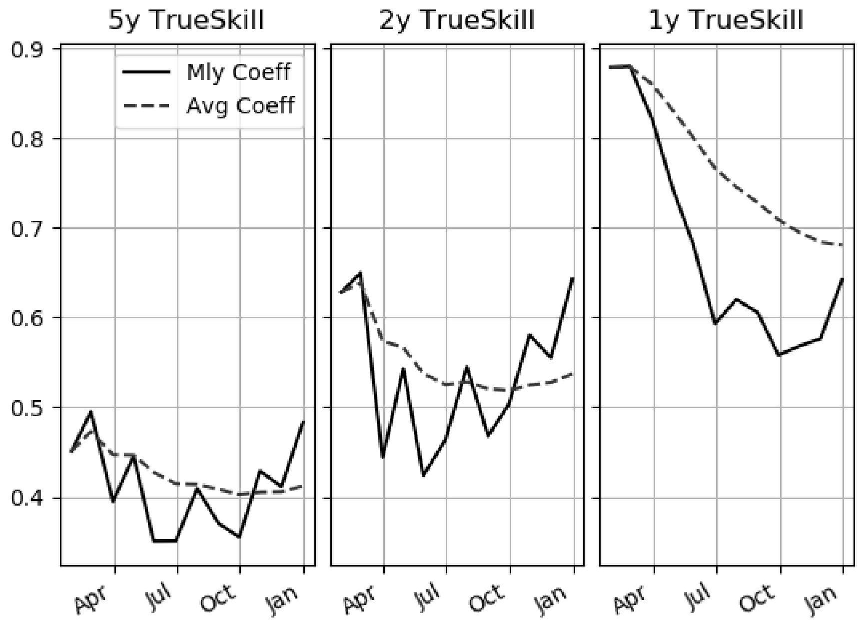
5.3.1 Measuring Performance with TrueSkill

We start our empirical analysis by demonstrating TrueSkill's capability to take prior performance into account. Figure 5.3 shows the development of the Pearson correlation coefficients between the TrueSkill based rankings of all participating funds within the tournament of five, two, and one years and their information ratio rankings. The left panel shows the correlation with TrueSkill levels being calculated for 4 years prior to 2015, the middle one with 1 year prior, and the right one with TrueSkill establishment just starting in 2015. Hence, Figure 5.3 underlines the time dependence of TrueSkill and its adaptation of prior performance while establishing skill levels. Since investors' decisions are often based on behavioral aspects such as prior performance or performance of fund family members (e.g. Sirri and Tufano (1998), Nanda et al. (2004)), TrueSkill is an adequate skill measure due to its capability of incorporating these aspects.

5.3.2 Skill Driven Risk-Shifting

Table 5.1 shows the aggregated risk-shifting tendencies for the whole sample period. It is structured into four panels - the first one is showing the unconditional transition rates based on the risk terciles in the first and second half of the year and the other three panels are showing the transition rates for the different skill levels. Thus, the three skill-based transition matrices are sub-samples of the unconditional case. The χ^2-values are representing the H0-hypotheses of conditional transitions being equal to the unconditional. Panel D shows significant differences to the unconditional case at the 5% and 1% level for winners and losers, respectively. Indeed, the tendencies in

Figure 5.3: Correlation of TrueSkill and the Underlying Information Ratio



Notes: This figure shows the evolution of the Pearson rank correlations between TrueSkill and its underlying performance measure over different time spans for an exemplary year (2015). More precisely, the left (middle, right) figure shows the rank correlation between the TrueSkill rankings estimated over the trailing five (two, one) years and the rankings based solely on the information ratio over the trailing six months to the corresponding month in 2015.

increasing the risk levels are much lower for managers with less skill than for those with high skill.

Table 5.1: Risk Transitions for Managers of Different Skill Levels

Values in %	Winner				Loser			
Risk tercile	high	medium	low	χ^2	high	medium	low	χ^2
				Panel A: Unconditional				
high	62.4	25.7	11.8		61.3	25.0	13.7	
medium	30.0	44.8	25.2		26.6	40.9	32.5	
low	11.1	32.9	56.0		11.2	28.1	60.7	
				Panel B: High Skill				
high	62.5	27.0	10.5		64.8	23.6	11.5	
medium	29.0	47.1	24.0		25.8	43.0	31.1	
low	12.8	31.1	56.2	0.93	12.3	30.4	57.3	2.94
				Panel C: Medium Skill				
high	63.0	24.6	12.3		61.0	24.8	14.3	
medium	31.7	42.6	25.6		27.1	42.7	30.2	
low	11.3	35.0	53.7	2.74	12.2	29.1	58.7	2.08
				Panel D: Low Skill				
high	60.2	28.0	11.8		59.0	27.1	13.8	
medium	25.4	49.2	25.4		25.8	34.3	40.0	
low	8.1	29.1	62.8	7.43**	7.9	24.4	67.8	13.1***

Notes: This table shows the risk-shifting tendencies from the year's first-half tercile to the tercile in the second half of the year for the full aggregated dataset. Panel A represents the whole sample, whilst Panel B to D show the transitions for different skill levels. Each manager is classified as being a winner (loser) if his performance measured by the information ratio lies above (below) the median at the end of the interim period. χ^2-values testing H0-hypotheses of conditional transitions being equal to the unconditional. ***, **, and * indicate significance at the 1%, 5%, and 10% level (two-tailed tests), respectively.

The first observable pattern is the difference in general risk-seeking between winners and losers in general. Whilst winners tend to stay at their initial level or even increase the risk in the second period of the year, losers act the other way around. With transition rates of 30.0, 11.1, and 32.9 for winner compared to rates of 26.6, 11.2, and 28.1 for losers, Panel A demonstrates the risk-seeking behavior of winners. Vice versa rates of risk decreasing by 25.7, 11.8, and 25.2 compared to 25.0, 13.7, and 32.5 complement this pattern. The subsamples given by Panel B to D indicate similar patterns across the different skill levels. Still, a lot of managers stay within their first half risk tercile with transitions up to 62.4. The transitions for remaining managers are highest for the extreme risk terciles of high and low risk.

Looking at the impact of different skill levels for either tournament standing, we find clear tendencies of high-skilled managers increasing their risk more often than those with less skill regardless of their first-half performance. The comparison of Panel B and Panel D shows higher risk increasing rates for skilled managers in both positions. Hence, the risk decreasing rates are always higher for managers with less skill. Additionally, the risk remaining transitions are bigger for high-skilled managers in the highest risk tercile and low-skilled managers in the lowest risk tercile, respectively.

The subsample for high- and medium-skilled managers are also closely related to the unconditional one. The χ^2-test values show no significant differences here. In contrast, the subsample of low-skilled managers differs from the unconditional sample at the 5% level for winners and even at the 1% level for losers. This indicates more controversial behavior for the minority of less-skilled managers, who seem to secure their wins if possible and cut their losses during bad tournaments.

In the next step, we take a closer look at years of extreme risk-shifting. Therefore, we aggregate the five years with the highest risk decreasing by losers and those with the highest risk increasing by losers whilst winners acting vice versa. These periods are classified as years dominated by unemployment risk and years dominated by compensation incentives. Hence, we follow Kempf et al. (2009) in their explanation for different risk-shifting tendencies in special periods. The five compensation incentive dominated years are 1992, 1995, 2006, 2014, and 2017, identified in Table A.1 in Appendix A.1 as those years where the highest RARs are given for mid-year losers. The years dominated by the risk of unemployment are 1993, 2000, 2001, 2004, and 2016; these are the years where losers have extremely low risk adjustment ratios at mid-term.

Table 5.2 highlights the differences between years dominated by compensation incentives (Panel A) and years dominated by unemployment risk (Panel B). Overall, both panels show similar patterns of winners increasing the risk level in the second half as well. Whilst Panel B has no significant difference between skilled and unskilled winners, Panel A emphasizes the overconfidence of managers with higher skill levels, who are

Table 5.2: Risk Transitions Based on Extreme Risk-Shifting

Values in %	Winner			Loser		
Risk tercile	high	medium	low	high	medium	low
		Panel A: Compensation Incentive Dominated				
High Skill						
high	57.5	35.0	7.5	72.0	28.0	0.0
medium	12.5	52.5	35.0	47.8	34.8	17.4
low	10.0	30.0	60.0	8.7	34.8	56.5
Low Skill						
high	43.3	40.0	16.7	47.1	41.2	11.8
medium	26.9	42.3	30.8	25.0	39.3	35.7
low	12.5	16.7	70.8	8.9	17.9	73.2
χ^2		5.17*			12.3***	
		Panel B: Unemployment Risk Dominated				
High Skill						
high	75.9	24.1	0.0	71.2	15.4	13.5
medium	31.0	57.1	11.9	4.0	64.0	32.0
low	0.0	26.4	73.6	0.0	22.2	77.8
Low Skill						
high	77.8	18.5	3.7	67.5	25.0	7.5
medium	25.8	61.3	12.9	18.9	32.4	48.6
low	4.1	26.5	69.4	2.3	22.7	75.0
χ^2		0.79			9.68***	

Notes: This table presents risk transitions for aggregated data of the five years dominated by compensation incentives and unemployment risk, respectively. The selection of the years is based on risk adjustment ratios for each year. χ^2-values representing homogeneity test statistic for transitions of high- and low-skilled managers. ***, **, and * indicate significance at the 1%, 5%, and 10% level (two-tailed tests), respectively.

seeking more risk past the interim period. The difference between skilled and unskilled managers is significant at the 10% level.

More importantly, the skill level of individual managers affects their decision making in a losing scenario. Skilled managers seem to rely on their prior performance and increase their risk level dramatically with transitions of 47.8, 8.7, and 34.8 in years dominated by compensation incentives. Instead of cutting their losses, they attempt to catch up by investing very self-confident. Less skilled managers behave differently and cut their losses. They have decreasing transitions of 41.2, 11.8, and 35.7. Here, the skill level of each manager seems to determine his behavior dramatically. The difference between these types of skills is significant at the 1% level. In years dominated by unemployment, the majority of all managers decrease their risk level in the second half of the year, if they lose. Only very few skilled managers try to increase their risk level at this stage and instead, a few managers with less skill start to gamble for a win. Those few seem to go all in before their funds are closed permanently. The difference between skilled and unskilled managers is again significant at the 1% level.

Ammann and Verhofen (2007) introduce another dynamic Bayesian network approach to analyze the impact of prior performance. They find similar results given as risk-increasing behavior after years of good performance and decreasing risk-taking after bad years. Within their following work, Ammann and Verhofen (2009) even highlight the same patterns of winning managers increasing their risk in the following period and loser acting vice versa. Our findings are in line with their results and even underlining the impact of prior performance - measured as investor's belief about the individual manager's skill.

5.3.3 Robustness Tests

Underlying Performance Measure The most important parameter within the TrueSkill setup seems to be the choice of the underlying performance measure to calculate monthly rankings, which are the start of further skill calculations. We test for the impact of different performance measures by repeating our analysis with monthly active returns of all participating managers. Table A.2 in Appendix A.2 shows very similar results to our previous analysis indicating high-skilled managers to increase their risk most of the time regardless of their performance in the first half of the year. These results underline the high correlation between different performance measures as shown by Eling and Schuhmacher (2007). We calculate the Spearman rank-order correlation coefficients inclusive a two-sided p-value for a hypothesis test with the null hypothesis of non-correlation between the data series for three different measures. Table A.3 in Appendix A.2 outlines the strong and significant correlation between the Sharpe ratio, Information ratio and active return rankings. We conclude that the choice of the underlying performance measure does not affect our initial results significantly.

Skill Thresholds The results could be driven by the choice of quantiles that classify managers into their skill level. In the main specification, we classified the top 20% as highly skilled and the bottom 20% as low-skilled which leaves a 20-60-20 split. Other reasonable splits, e.g. 10-80-10, lead to the same conclusions as we show in untabulated results.

Risk Adjustment Ratio Approach Our next robustness test deals with the general tournament behavior regardless of the individual skill of each manager. Therefore, we replicate the contingency table approach introduced by Brown et al. (1996) based on the risk adjustment ratios. The results presented in Table A.1 in Appendix A.1 are in line with our results of skill-driven investments, indicating a different trend of individual behavior in tournaments in recent years. Winners have higher RARs in most of the years, which is in contrast to earlier findings of Brown et al. (1996). Still, this demonstrates that our findings are in line with previous methodologies.

Hyperparameter of the Prior Distribution In our empirical analysis, we set the initial prior distribution of the fund managers' skills as described in Section 2.2 as $f(\mathbf{s}) := \prod_{i=1}^{n} \mathcal{N}(\mu_i, \sigma_i^2)$ with $\mu_i = 25$ and $\sigma_i = \frac{\mu_i}{3} \approx 8.33$. Please note that the average skill level μ_i is not of much interest in absolute terms since all managers are assumed to start with the same initial skill. Since we do not define a unit to measure the skill other than using the Gaussian's parameters μ_i and σ_i, the relative belief of two fund managers given by their skill distribution is of higher relevance. In that terms, it does not make much difference whether we start with a level of 10, 100, or the standard level of 25[9] as proposed by Herbrich et al. (2006), which originates from TrueSkill's early comparability with the ELO ranking.

To underline the low impact of the initial priors on our results, we vary the relation between μ_i and σ_i, i.e. $\sigma_i \in \{\frac{\mu_i}{2}, \frac{\mu_i}{4}\}$. The results are qualitatively similar to our base case $\sigma_i = \frac{\mu_i}{3}$, see Tables A.4 and A.5 in Appendix A.2.

The neglectable impact of the priors is in line with the theoretical expectation about their impact: With sample size $n \longrightarrow \infty$ the difference between two posteriors based on different Gaussian priors tends towards zero. The same holds for larger prior variances σ_i, as outlined for example by Ley et al. (2017).

Different Benchmark Indexes Within our analysis, we use a risk-adjusted approach to determine the rankings of each manager used for the TrueSkill algorithm. In fact, our measure of choice is the information ratio as a market model adjustment measure where the benchmark is the MSCI North America. Given the different setup of mutual funds and their long-term purposes, e.g. equity-only, long-only, multi-asset, and so on, our chosen benchmark might not be appropriate for every mutual fund in the universe. Nevertheless, we restrict our fund sample to growth-oriented US equity mutual funds as earlier researchers before (Brown et al., 1996; Taylor, 2003; Kempf and Ruenzi, 2008b). The categorization is based on the widely accepted classification by Morningstar, which leads to a quite homogeneous sample. We qualify this putative sample restriction by similar arguments used in earlier research.

However, Morningstar specifies two benchmark indexes for each of its categories. The primary index for all three categories used in this study is the S&P500 which correlates almost perfectly with the MSCI North America. The secondary benchmark index differs for each category.[10] We repeat our analysis benchmarking each fund on its secondary benchmark index and report the results in Table A.6. Overall, the conditional transition matrices differ stronger from the unconditional transition matrix than in our baseline case. In line with our previous findings, we find a tendency that winning managers increase their risk more than losers and that managers classified as low-skilled seem to adjust their risk less than managers classified as high-skilled.

Regression Approach On the basis of the conditional transition matrix approach, our results suggest that the risk-shifting tendencies are significantly different for low- and high-skilled fund managers and, beyond that, that high-skilled managers tend to increase their risk-levels to a higher extent compared to low-skilled managers. We acknowledge that conclusions like these have to be interpreted with caution due to unobservable covariates that might influence the results. To mitigate the effect of omitted variables and provide further empirical evidence for our conclusions, we formulate the following regression model:

$$\Delta\sigma_{i,t} = \beta_1 \text{Rank}_{i,t} \times D^{\text{H}}_{i,t} + \beta_2 \text{Rank}_{i,t} \times D^{\text{L}}_{i,t} + \beta_3 \sigma^{\text{First Half}}_{i,t} + \epsilon_{i,t} \tag{5.3.1}$$

where the dependent variable, $\Delta\sigma_{i,t} = \sigma^{\text{Second Half}}_{i,t} - \sigma^{\text{First Half}}_{i,t}$, is the change in standard deviations of fund i's returns from the first to the second half of the year t. $\text{Rank}_{i,t}$ denotes the rank of the fund manager with respect to all other managers scaled to the interval $[0, 1]$ (1 being best). High respectively low manager skill is denoted by $D^{*}_{i,t}$ with $^* \in \{\text{H,L}\}$. In a further specification, we replace $\text{Rank}_{i,t}$ with dummy variables indicating that a fund manager ranked in the top 20% respectively bottom 20% of all active managers analogous to the main analysis. For all specifications, we include time and fund-company fixed effects. The latter control, for example, for all time-invariant characteristics attributable to a manager's company that may influence the results.

We present the results of four specifications in Table 5.3, two each using either the information ratio or active returns to estimate the managers' skill levels via TrueSkill. All specifications indicate that high-skilled fund managers significantly increase their risk after performing well in the first half of the year. Contrary, we find the opposite signs for any coefficient associated with risk-shifting of less-skilled fund managers. Equality tests reject the null hypotheses $D^{\text{Win}} \times D^{\text{H}} = D^{\text{Win}} \times D^{\text{L}}$ and $D^{\text{Loss}} \times D^{\text{H}} = D^{\text{Loss}} \times D^{\text{L}}$. The explained variation in risk-shifting amounts to $\approx 75\%$, which is a common value in fund tournament studies. Overall, the results support our conclusions drawn from the conditional transition matrix approach and provide further insights on the channels that foster the results.

Comparison to ELO Last, we compare TrueSkill with another popular skill measure - the ELO rating, most known from the world of chess. The ELO ranking system is used in competitive chess as well as various unofficial rankings, e.g. online gaming or football tournaments. It is much simpler in its calculations and therefore not capable to adapt teams playing each other. Figure 5.4 shows the skill development of three random managers of the whole period sample measured by TrueSkill and ELO. Both

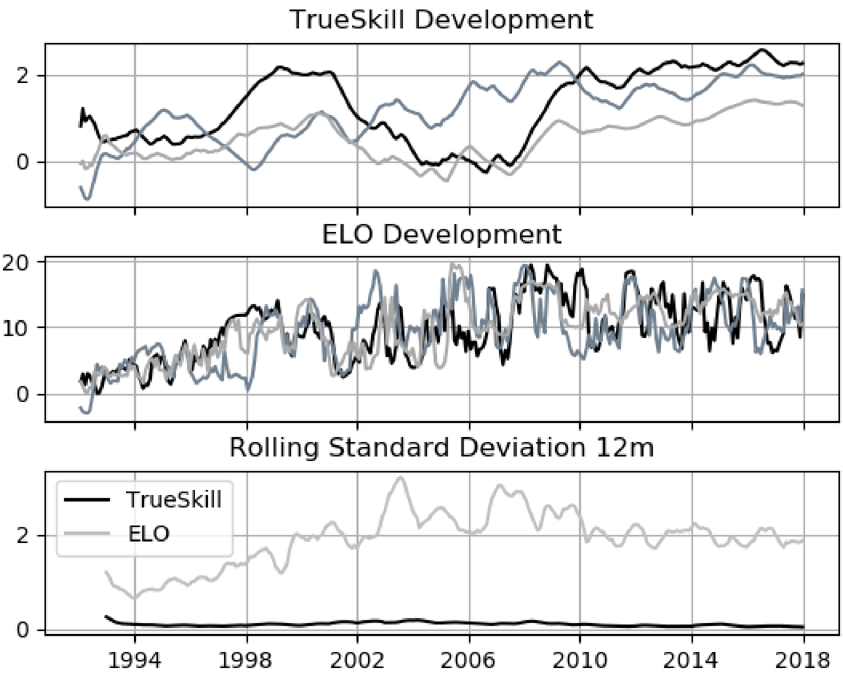
Table 5.3: Regressions of Risk-Shifting on Different Skill-Levels

	Information Ratio		Active Return	
	(1)	(2)	(3)	(4)
Rank × D^{H}	0.005*		0.006*	
	(1.889)		(1.940)	
Rank × D^{L}	−0.003		−0.003	
	(−0.584)		(−0.689)	
D^{Win} × D^{H}		0.003*		0.005**
		(1.747)		(2.060)
D^{Win} × D^{L}		−0.003		−0.003
		(−1.042)		(−0.986)
D^{Loss} × D^{H}		0.003		0.003
		(0.909)		(0.917)
D^{Loss} × D^{L}		−0.004		−0.008***
		(−1.580)		(−2.854)
$\sigma_{\text{First Half}}$	−0.361***	−0.363***	−0.362***	−0.365***
	(−5.116)	(−5.124)	(−5.114)	(−5.143)
Fixed effects	Yes	Yes	Yes	Yes
Observations	5155	5155	5157	5157
Adjusted R^2	0.747	0.747	0.747	0.748

Notes: This table presents results of a regression of fund managers' performance in the first half of the year on their risk-shifting in the second half, conditional on their estimated skill levels (high, low). Rank denotes the rank of the fund manager scaled to the interval $[0, 1]$ (1 being best) and D indicate dummy variables for high or low skill, or for ranking among the top 20% best or worst managers. Robust standard errors are clustered by year. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

ratings are based on monthly matches between all managers participating in a given year's tournament. The skill levels are normalized to make them comparable since the absolute level differs between both systems. Due to our premise of being included in a year's tournament if and only if there is more than one year of tracking record, the managers seem to start with different levels, but in fact, they started all with the same setup, initially. The ELO ratings vary rapidly on a high frequency, whilst the TrueSkill ratings are adjusting themselves much slower and only react to unexpected outcomes.

Figure 5.4: Comparison of Skill Developments by TrueSkill and ELO



Notes: This figure shows the temporal development of skill ratings based on TrueSkill and ELO for three randomly chosen fund managers from our sample. ELO is a method for calculating the relative skill levels, commonly used in chess. The bottom figure compares the rolling standard deviations of the two methods highlighting the stable skill belief estimated via TrueSkill.

The third panel of Figure 5.4 underlines the differences in volatility by representing the rolling standard deviation over 12 months of the normalized ELO and TrueSkill ratings, respectively. Hence, the average TrueSkill standard deviation is at 0.106 and therefore much lower than the one of ELO given as 1.907. A good skill measure should offer low volatility to establish a stable belief about the skill level of an individual manager in the long-term. The time stability of TrueSkill shows its potential to classify managers into skill levels and derive skill-based behavior from it.

Summarizing the results of the robustness checks, our results about the impact of skill are in line with theories in behavioral finance and psychology, showing the overconfidence of outperforming managers in their investment decisions. Taylor and Brown (1988) find evidence of people having unrealistically positive views of themselves which leads to the described self-confidence not only after being among the winners for a couple of competitions and De Bondt and Thaler (1995) detect a positive correlation between high confidence and above average-trading frequencies.

5.4 Conclusion

Our results highlight the self-confident behavior of skilled managers by holding or increasing their portfolio risk in almost every situation compared to those with less skill. Applying the TrueSkill algorithm to display investors' beliefs about the individual skill level of fund managers, we present a way to model the positive correlation of prior performance and new investment decisions.

The impact of good performance in recent years seems to lead to an overconfident investment style of managers, who are shifting their portfolio risk towards the higher tercile of the peer group in the second half of the year. Only a few managers classified with less skill increase their risk in a losing situation. We demonstrate the robustness of our results regarding the choice of the performance measure to rank the managers each month as well as the usability of TrueSkill as an adequate representation of investor's belief about a manager's skill.

6 Do Firms Hedge in Order to Avoid Financial Distress Costs? New Empirical Evidence Using Bank Data

The following is based on Hahnenstein et al. (2020).

6.1 Introduction

From Smith and Stulz (1985) there has been a continuously growing literature dealing with the questions why and how firms should use derivative instruments to reduce the variability in their income cash flows. Economic theories of corporate hedging are based on taxes, agency costs and costs of bankruptcy or – in a wider sense – costs of financial distress (FDC) as the main market imperfections, whose management may result in value increases for the firm‘s stakeholders.[11] Bartram (2000) and Aretz and Bartram (2010) provide a comprehensive overview of rationales for corporate hedging and the empirical literature testing these economic theories which have up to now not been able to yield final conclusions regarding the explanatory power of the three different economic arguments:

- Tax reasons are due to rules that give rise to convexity in the taxation schedule and have been very thoroughly scrutinized for the U.S. tax system (see e.g. Graham and Smith (1999)) but have overall accomplished only weak empirical support.
- Variables used to test whether corporate hedging can lower the agency costs resulting from shareholder-bondholder or shareholder-manager conflicts lead to fairly mixed results with only a small number of proxies (e.g. R&D expenditures) showing the predicted effects.

- There are quite many studies that contribute to the existing empirical evidence with regard to FDC, see e.g. Nance et al. (1993), Mian (1996), Géczy et al. (1997) and Chen and King (2014). Various proxy variables – like e.g. the (long-term) debt ratio, the short-term liquidity ratio and the interest coverage ratio, credit ratings or credit spreads – have been employed as substitutes for the expected FDC, which cannot be directly observed, and could sometimes be identified as statistically significant. However, there is up to now no paper in the hedging literature that tries to estimate FDC, which is the economic explanatory variable according to finance theory, directly on the basis of a structural model (cf. e.g. Glover (2016), who uses a similar approach to analyze the firm's capital structure decision).

In this paper, we provide a fresh perspective on the question if firms hedge in order to avoid ex ante expected FDC. We estimate FDC as a fraction of an asset-or-nothing put option and further introduce a trade-off between FDC and transaction costs to calculate optimal hedge ratios. Using a proprietary dataset stemming from a major German bank comprising OTC derivative deals from 189 German middle-market companies, we find both variables to explain a significant share of the observed cross-sectional differences in hedge ratios based on both nominal and market values. To be more specific, we contribute to the literature in two main aspects:

Firstly, we come up with a novel estimation approach for the ex ante expected FDC as an explanatory variable that is much more closely tied to corporate finance theory than the previous literature. The basic idea is to construct an empirical measure of the differences in ex ante expected FDC that can be directly used as an explanatory variable for the observed cross-sectional differences in samples of companies' derivatives usage. Our estimation approach is based on the Merton (1974) structural model of debtholder default and makes use of the analytical formula for an "asset-or-nothing put option", which allows us to compute FDC as a fraction of the value of total assets.

We are able to show empirically that this measure of firm-specific ex ante FDC is superior to the use of the traditional proxy variables, like e.g. the debt ratio, the interest coverage ratio and the short-term liquidity ratio, whose choice is rather ad hoc and is not based on a solid theoretical underpinning. Moreover, the new explanatory variable lends itself to be further exploited within an equilibrium setting that leads to an additional type of explanatory variables: In order to determine its optimal hedge ratio, each firm trades off its ex ante expected FDC with the expected transaction costs (TC) that serve as a counterweight to prevent the firm from hedging as much as possible. As there are no systematic deviations in the transaction costs for derivatives hedging between firms (except for size issues), the cross-sectional differences between optimal hedge ratios in equilibrium should mainly be driven by differences in the firm-specific, marginal benefit of a further FDC reduction. We calculate both the absolute amount of expected FDC and the optimal hedge ratio for each firm in such an FDC-TC equilibrium and use them as our leading explanatory variables in a couple of linear regression models that build the empirical part of our paper.

Secondly, we enrich the existing knowledge about corporate hedging by testing our explanatory variables on a rich dataset from a major bank providing thus far unavailable information on the firm level. We analyze the usage of over the counter (OTC) interest rate and exchange rate (FX) derivatives in a sample of German middle-market companies on the basis of a proprietary dataset that stems from a major German bank. The credit risk in this market segment is generally non-investment grade so that the proper assessment of the risk of bankruptcy or default is crucial for the banks servicing this segment. From the firms' viewpoint, the threat of financial distress therefore should have a relevant magnitude.

The dataset contains all the existing derivative contracts that these companies had entered into with the bank at fiscal year-ends 2015 and 2014 and it provides us with single-contract level data. Hence, our dataset is different from those used in previous empirical studies in two main respects: On the one hand, our information on the derivative contracts used is far more granular, but on the other hand, the firms might have also entered into OTC derivatives contracts with other banks, which stay hidden from our eyes. As the probability that a firm does derivatives business with more than one bank is supposed to increase with company size, we pay special attention to the size variable as a control variable. Because of the construction of our proprietary dataset, we are able to exploit the bank‘s internal rating data and the resulting regulatory “Basel II” PDs for the firms in the sample as well as the corresponding balance sheet data that are processed as a part of the rating system. Since the previous studies have been fairly restricted in terms of data availability, access to a large set of companies‘ derivative contracts opens up a new perspective on corporate hedging, namely that of a financial intermediary.

While the literature dealing with expected financial distress as an incentive for corporate hedging mostly covers the US market (see again Aretz and Bartram (2010) for an overview), there are only a few studies taking the hedging activities of German firms into account. In an extensive international study, Bartram et al. (2009) analyze 7319 non-financial companies from 50 countries covering over 80% of the overall global market capitalization of non-financial firms. Surprisingly, their empirical findings frequently run counter to the usual theoretical predictions: Regarding the FDC hypothesis, for example, they find derivative users to be larger and more profitable. However, they also find derivative users to have significantly higher leverage and fewer liquid assets, as suggested by the common theory. Carroll et al. (2017) investigate the determinants of derivative usage for non-financials firms from 11 European countries including Germany. They also find leverage to be a significant determinant of overall derivative usage. In line with these findings for European countries, Marsden and Prevost (2005) also find a positive relationship between the probability of financial distress and the use of derivatives for a sample of New Zealand listed companies. In an earlier study, Prevost et al. (2000) compare and contrast risk management practices of firms in New Zealand to those of firms in the considerably larger, more developed US, UK, and German markets. Among other findings, the authors conclude that New Zealand companies have many of the same reasons and objectives for using derivatives as firms in the much larger American and European economies.

Bodnar and Gebhardt (1999) were the first to compare the derivative usage of US and German companies by analyzing two surveys from both countries and matching companies based on size and industry: Their findings suggest that German firms are overall more likely to hedge and that US and German firms partly differ in their primary goal of hedging, their choice of instruments, and by the influence of their market view when taking derivative positions. In a more recent study, Henschel (2006, 2010) finds German SMEs' hedging decisions to be clearly orientated towards the owner-manager and that a direct link between risk management and business planning is seldom found. In an earlier study for Germany, Glaum (2002) surveyed 74 non-financial firms' exchange rate risk management purposes: He finds that highly levered firms rather hedge and do not take bets or use selective risk management in line with the FDC hypothesis. Hence, it seems reasonable to take the analysis of the FDC hypothesis a step further when a new proprietary data source, namely the single-contract files of the derivative use of the corporate middle market clients of a large German bank, is available. As the FDC hypothesis has been studied for other European markets as well (e.g. Judge (2006) finds strong evidence supporting the FDC hypothesis in a sample of 400 UK firms) we produce results that are also quite relevant in an international setting. Furthermore, we do not only contribute to the knowledge about the derivatives usage in the largest economy of the Eurozone, but the modeling approach presented generally allows for a refined analysis of the FDC hypothesis that seems applicable in other countries as well. It could similarly be applied to other national or international datasets whenever they entail a measure for the firm's PD that can be combined with leverage in an exogenous, Merton-style capital structure model. An example of such a potentially fruitful usage in future research would be e.g. the publicly available data from the European high-yield bond markets.

The paper is structured as follows: In Section 2, we introduce our modeling framework and present the theoretical basis for our approach. Section 3 contains the empirical analysis, while the final section concludes.

6.2 Modeling Framework

6.2.1 Estimation of the FDC Function

We consider a capital market with several firms, which are all-equity financed in the beginning. Each firm can choose to issue debt and to enter into derivative contracts. The stochastic future market value of their operating cash flows in t is called V_t and we assume for the sake of analytical tractability that V_t follows a geometric Brownian motion

$$V_t = V_0 e^{\left(\mu_V - \frac{\sigma_V^2}{2}\right)t + \sigma_V W_t}, \tag{6.2.1}$$

where μ_V denotes the drift-term, $\sigma_V > 0$ the volatility and W_t a Wiener-process. Hence, V_t follows for fixed t a lognormal distribution with parameters $\mu = \ln(V_0) + \left(\mu_V - \frac{\sigma_V^2}{2}\right) t \in \mathbb{R}$ and $\sigma = \sigma_V \sqrt{t}$. For reasons of simplicity, we limit this analysis on a one-period setting and denote $V := V_1$ and $\sigma = \sigma_V$. For $V \sim \mathcal{LN}(\mu, \sigma^2)$ the well-known probability density function, which is defined on $]0, \infty[$, is given by

$$f(V, \mu, \sigma) := \frac{1}{\sqrt{2\pi}\sigma V} e^{-\frac{(\ln(V)-\mu)^2}{2\sigma^2}} \tag{6.2.2}$$

and the corresponding cumulative distribution function is given by

$$\mathrm{F}(V, \mu, \sigma) := \int_0^V f(x, \mu, \sigma) dx. \tag{6.2.3}$$

Following Merton (1974), we use a structural model of default. The firm can issue debt in $t = 0$. We denote the total amount, which is payable in $t = 1$ and which comprises both principal and interest, by $D > 0$. Assuming the drift term μ_V, V_0, D and the probability of default are given, the volatility σ can be determined by solving

$$\begin{aligned} \mathrm{PD} &= \Phi\left(-\frac{\ln\left(\frac{V_0}{D}\right) + \mu_V - \frac{1}{2}\sigma^2}{\sigma}\right), \\ \Leftrightarrow \quad \sigma &= \Phi^{-1}(\mathrm{PD}) + \sqrt{\Phi^{-1}(\mathrm{PD})^2 + 2\left(\ln\left(\frac{V_0}{D}\right) + \mu_V\right)} \end{aligned} \tag{6.2.4}$$

where Φ denotes the cumulative distribution function of the standard normal distribution. Equation (6.2.4) provides a way to estimate the volatility of the asset value distribution, which is not a directly observable parameter, when the drift parameter μ_V, the firm's leverage, and an appropriate PD estimate are given.

We use the regulatory ("Basel II") probability of default (PD) of the companies to calculate the volatility parameter. The Basel II PD contains all the available information about the probability of a potentially distressed situation from a debtor's point of view and is a reliable source. We regard the Basel II default definition as an adequate way to distinguish between "bad" states of the world, in which the firm incurs costs of financial distress and those "good" states, where it does not.[12]

FDC arise when a firm is in or close to default. In the literature on corporate finance and corporate hedging, several alternative specifications of FDC functions can be found.[13] Following the mainstream literature on corporate hedging, we model FDC as a percentage portion of future firm value. We denote the FDC parameter, which we will assume to be firm-specific in the empirical study later on, by $\eta \in]0, 1[$ (Brennan and Schwartz, 1978; Leland, 1998; Ross, 1996). Assuming general risk-neutrality, which is rather common (cf. Castanias (1983), Bradley et al. (1984), Kale and Noe (1990) or Kale et al. (1991)) in this type of analysis, the market value of FDC in $t = 0$ emerges as

$$FDC := \int_0^D \eta V f(V,\mu,\sigma)dV = \eta \mathrm{E}_0\left[V \mid V < D\right]. \tag{6.2.5}$$

According to option pricing theory, we can interpret the conditional expected value $\mathrm{E}\left(V \mid V < D\right)$ as the value of an asset-or-nothing put option. Given an underlying $S = V$ and an strike price $K = D$, this binary option has the payoff

$$S \text{ if } S \leq K, \text{ or } 0 \text{ if } S > K. \tag{6.2.6}$$

Following Cox and Rubinstein (1985), its value is given by the first term of the Black-Scholes formula (Black and Scholes, 1973), which equals the unprotected present value of the underlying asset price conditional upon exercising the option. Cf. also Rubinstein and Reiner (1991). Hence, we can rewrite Equation (6.2.5):

$$FDC = \eta V_0 e^{-r_f} \Phi\left(-\frac{\ln\left(\frac{V_0}{D}\right) + r_f + \frac{1}{2}\sigma^2}{\sigma}\right). \tag{6.2.7}$$

With the exception of η, the parameters in (6.2.7) are either directly observable market data or can be calculated from the firm's PD via (6.2.4). We assume η to be a firm-specific parameter that can be inferred from a capital structure equilibrium which is given by a traditional static trade-off model. We introduce this capital structure model in Appendix B.1. For the optimally levered firm η is given by Equation (B.1.5) in Appendix B.1, so that we can estimate the absolute amount of FDC for all firms according to (6.2.7).

6.2.2 Implications of an FDC-induced Hedging Equilibrium

In this subsection, we analyze the testable implications of an equilibrium situation, in which all firms choose their optimal level of volatility considering the effects of a volatility reduction on the present value of their specific FDC.

Hedging is regarded as a means to reduce the volatility σ in the distribution of future asset value V. We assume that all firms have unrestricted access to a set of derivative contracts which are traded in frictionless market. Without any market frictions, the value of any hedging contract is zero at the time when it is written. By assuming an economy of risk-neutral agents, this translates into a zero effect on expected future cash flows. Hence, the effect of hedging on FDC is given by the following first partial derivative from (6.2.7) using the asset-or-nothing put option pricing formula:

$$\frac{\partial FDC}{\partial \sigma} = \eta V_0 e^{-r_f} \phi \left(\frac{\ln\left(\frac{D}{V_0}\right) - r_f - \frac{1}{2}\sigma^2}{\sigma} \right) \left(\frac{\ln\left(\frac{V_0}{D}\right) + r_f}{\sigma^2} - \frac{1}{2} \right) > 0 \tag{6.2.8}$$

if $D < e^{\mu} = V_0 e^{r_f - \frac{1}{2}\sigma^2}$.

Obviously, the FDC function of each firm is strictly increasing in firm value volatility σ_j, if its probability of default PD_j is below at least 50%. Hence, by costlessly reducing σ_j, hedging reduces the ex ante expected FDC and increases firm value in these cases.

Since we assume a capital structure optimum independent of the hedging policy, the change in σ in Equation (6.2.8) stems directly from the use of a derivative instrument on the asset value distribution and shall not be misinterpreted as a change of σ resulting from a shift in leverage or PD that would have an indirect impact via Equation (6.2.4) and that would lead to a different comparative statics result.

What is new in our paper is that we give Equation (6.2.8) a cross-sectional interpretation, which we will state later on as a part of our main Proposition: The marginal benefit of hedging by reducing FDC differs across firms: It depends on the firm's individual FDC parameter η, on its size V_0, on its exogenously given optimal debt ratio D_j/V_j and on the corresponding probability of default PD_j, which enters (6.2.8) via σ_j (see (6.2.4)). Hence, the differences among firms' marginal benefits of FDC hedging can be measured using a set of firm parameters, that are either directly observable or that can otherwise be empirically estimated.

As a counterweight to FDC that prevents firms from transferring 100% of its hedgeable risk to the financial markets, we introduce transaction costs TC into the model, cf. Hahnenstein and Röder (2007) for a hedging model with transaction costs. The transaction cost function we assume is

$$TC = \gamma V_0 \left(\sigma^* - \sigma\right), \tag{6.2.9}$$

where σ^* denotes the optimal firm value volatility after hedging. Thus, the difference $(\sigma^* - \sigma)$ denotes the reduction in volatility that goes along with the optimal hedging policy. The parameter $0 < \gamma < 1$ denotes the marginal transaction costs of hedging, which we assume to be constant across all firms. It can be interpreted as a basis point fee payable for each EUR of the derivative nominal that leads to the intended decrease in the absolute firm value volatility. The optimal (percentage) volatility σ^* that minimizes the sum of FDC and transaction costs is given by the following first-order condition as a unique solution:

$$\frac{\partial FDC}{\partial \sigma} + \frac{\partial TC}{\partial \sigma} \stackrel{!}{=} 0 \Leftrightarrow \frac{\partial FDC}{\partial \sigma} - \gamma V_0 \stackrel{!}{=} 0 \Leftrightarrow \frac{\frac{\partial FDC}{\partial \sigma}}{V_0} \stackrel{!}{=} \gamma \tag{6.2.10}$$

In our empirical study, we use the minimum firm-specific value of $\frac{\partial FDC}{\partial \sigma}$ in our sample ("marginal utility of the marginal hedging company") as a proxy for γ, as this value indicates, at which transaction cost level hedging is still profitable.

The second-order condition for a minimum of total costs is met, which can be easily seen by taking a look at Formula (6.2.7). As the cumulative standard normal distribution function $\phi(x)$ is convex for all x smaller than zero, the sum of FDC and transactions costs is convex in σ as a sum of two convex functions, if

$$\frac{\ln\left(\frac{D}{V_0}\right) - r_f - \frac{1}{2}{\sigma^*}^2}{\sigma^*} < 0 \Leftrightarrow D < V_0 e^{r_f + \frac{1}{2}{\sigma^*}^2}, \tag{6.2.11}$$

which does not imply further restrictions as we already restricted D to be less than $V_0 e^{r_f - \frac{1}{2}\sigma^2} < V_0 e^{r_f + \frac{1}{2}\sigma^2}$ (cf. Appendix B.1). Hence, σ^* indeed minimizes the sum of ex ante expected FDC and transaction costs.

As the parameter σ represents the asset volatility of the unhedged company and as the optimal level of volatility after hedging is given by σ^*, we can now define the firms' optimal hedge ratios in equilibrium as

$$H_j^* := \frac{\sigma_j - \sigma_j^*}{\sigma_j}. \tag{6.2.12}$$

. The optimal hedge ratio of the firm is defined as the optimal volatility reduction that satisfies the first-order condition (6.2.10) as a percentage of the volatility before hedging. We state the results of this section in the following proposition which lays the basis for our discussion of its testable empirical implications later on.

Proposition. *In the hedging equilibrium, each firm $j = 1, ..., n$ chooses its optimal hedge ratio H_j^*, so that the sum of ex ante expected FDC and transaction costs is minimized. For a given set of firm-specific parameters $\left(\frac{D_j^*}{V_{0_j}}, PD_j^*, \eta_j^*\right)$ and a non firm-specific transaction cost parameter γ, there is a unique set of optimal hedge ratios H_j^*. The cross-sectional variation in the firms' hedging behavior can be attributed to differences in the marginal benefits of hedging $\frac{\partial FDC}{\partial \sigma}$, which result from differences in the firm-specific parameters $\left(\frac{D_j^*}{V_{0_j}}, PD_j^*, \eta_j^*\right)$.*

We illustrate the empirical implications of the model - with the help of a numerical example - on the basis of our empirical dataset in Appendix B.2. However, it is already clear that we aim at explaining the cross-sectional differences in the observed hedging behavior in our sample by the differences in H_j^*, which will be our leading explanatory variable (besides the absolute amount of FDC). H_j^* can be interpreted as the optimal relative (percentage) volatility reduction that minimizes FDC and that combines a set of empirically observable company parameters in a theoretically rigid approach.

6.3 Empirical Results

6.3.1 Data Description and Methodology

The dataset is obtained in an anonymized form from a major German bank in line with the rules of banking secrecy. In particular, all company names were erased beforehand. The bank has been in the corporate lending business for decades and is considered systemically relevant for the banking system. Within its internal organization, specialized departments are dedicated to sell all types of derivatives to its corporate clients.

The data contains all the OTC derivative contracts the bank entered with about 500 non-financial, non-public sector counterparties at year-end 2014 and 2015. The dataset includes detailed counterparty information such as legal entity identifier, client group identifier (for client groups consisting of more than one legal entity, i.e. typically one parent company with more than one subsidiary), industry code, current counterparty credit rating and corresponding Basel II PD, the precise product type and both the current fair value and the nominal amount of the contract. The interest rate risk-related product types included in our sample are interest rate swaps, forward deals as well as caps and floors. The currency risk-related products contain FX swaps, cross-currency swaps, and FX options in about 20 currencies. The sample does not include exchange-traded products as these derivatives are not bilateral with the bank being the contractual counterparty.

The so-called Basel II PDs are the bank's internal PD estimates, which are used for both bank internal processes like loan approval and margin calculation, but also for the purpose of calculating regulatory capital requirements. The PD estimation is based on a quantitative logit model, which is calibrated to the actual default time series observed within the banking group by means of maximum likelihood estimation and which has been granted a supervisory permission as an IRBA (internal ratings-based approach) model under the Basel II regulation. See e.g. the overview in Engelmann and Rauhmeier (2006) for this typical type of Basel II rating models.[14] The logit model makes use of the firms' equity/total assets ratios, interest coverage ratios and liquidity ratios, but also employs some other balance sheet and cash flow figures, which constitute the individually transformed input variables and which are then combined within a non-linear function. Hence, the [0;1]-scaled PD function that contains all the balance-sheet data relevant to predict corporate default risk seems to be the natural starting point to estimate the firms' ex ante financial distress costs.

The German market for OTC derivative sales to corporates has been subject to further regulation during the last years (e.g. through the new EU directives EMIR and MiFID II). However, there were no external restrictions that limit the banks‘ contractual freedom and competition between banks has been close. As we are not aware of any particular internal restrictions either (e.g. bank internal rules that would require a certain hedging policy if a downgrade crosses a rating class border or which are related to its lending standards), we are convinced that the observed contracts are the outcome of a primarily demand-driven process of contract conclusions.

We remove counterparties with missing information, natural persons, and public-private partnerships and limit our analysis to non-defaulted firms with an annual turnover between EUR 5 million and EUR 1 billion as the bank uses different risk management and client approaches for very small and large firms. Hence, our typical sample firm is a German middle-market corporate ("Mittelstand") who has its shares not listed on a stock exchange, so that we cannot measure the hedging benefit on shareholders' equity directly like e.g. in Allayannis and Weston (2001). Moreover, most of these firms rely on bank financing and private debt rather than on issuing tradable bonds, which is in line with the observation that they are not externally rated by the international rating agencies and that their financial statements are prepared according to local GAAP and not according to IFRS. Many firms in the sample produce goods for worldwide export, so that they need to manage their FX exposure from future revenues in various foreign currencies, actually more than 20 in the sample. However, unlike the sample firms analyzed by Allayannis et al. (2001) or by Bartram et al. (2010), they usually do not represent truly multinational corporates in the sense that they run production facilities across international subsidiaries and can thereby apply an arsenal of non-financial hedging instruments. Since our sample firms are on average much smaller and since they form a homogeneous group insofar as they have their production facilities mainly concentrated within Germany or countries of the Eurozone, we think that they will not greatly differ in their use of alternative FX risk management tools, like e.g. operational hedging, pass-through or foreign-currency denominated debt. Hence, although we do not have data on these potential other hedging instruments, we think that the derivative use we can observe in the bank data is a very good proxy for the sample firms' overall hedging approach.

In examining the relation between hedging and FDC we estimate the linear regression model

$$y_{i,t} = X_{i,t}\beta + \alpha_i + \gamma_t + \epsilon_{i,t}, \tag{6.3.1}$$

where $y_{i,t}$ is the hedge proxy variable and $X_{i,t}$ the design matrix whose rows correspond to the independent variables. α_i denote the industry fixed effects, γ_t the time fixed effects and $\epsilon_{i,t}$ the error term.

The approach taken is commonly based on linearly regressing a binary variable for the hedger/nonhedger characteristic of the firm on a set of pre-specified explanatory variables. Instead of using a binary regression, other papers (see e.g. Allayannis et al. (2001) and Graham and Rogers (2002)) have used a metric variable for the hedge ratio that is based on mandatory accounting disclosures of derivative use.

We construct three variables as hedge ratio proxies for each firm, namely the sum of all notional values of the derivative contracts divided by (a) its book value of total assets and (b) its total debt. The third hedge ratio proxy (c) is constructed as the sum of all fair values of the derivative contracts divided by the firm's book value of total assets. While we use (a) as our main hedge proxy, we introduce (b) and (c) in the robustness section. A potential disadvantage of aggregating nominal values as a proxy for derivative use arises from neglecting other characteristics of the contracts (for example different maturities, long/short positions, ...). In fact, we are in the lucky position of having access to the detailed single-contract data of all the derivatives the firms have with the particular bank at year-end. But, since we cannot distinguish between differences in the firm's overall open position that underlies the hedging contract at the point in time it was closed, it does not make sense to net between long/short resp. buy/sell positions. Another similar justification for aggregating nominals is given by Carroll et al. (2017), who refer to Hentschel and Kothari (2001): Although one would expect financial firms to hold offsetting positions to run a 'balanced book', non-financial firms have no obvious reason to hold offsetting derivatives positions. So we simply chose to interpret an additional EUR of the aggregated notional amount as an indicator of more hedging activity. Other existing studies suggest using a dummy variable indicating the use of derivatives (e.g. Bartram (2019)) as an alternative measure. Unfortunately, this approach is not applicable in this study since our dataset comprises only companies being involved in hedging activities. However, the use of aggregated nominal values is commonly used in many other recent studies (see e.g. Allayannis et al. (2001); Borokhovich et al. (2004); Gay and Nam (1998); Graham and Rogers (2002); Hentschel and Kothari (2001); Howton and Perfect (1998); Lel (2012)) and we regard it as the best alternative for our dataset.

Due to the nature of our sample, we solely study firms that are involved in hedging activities, which may introduce a self-selection bias. This potential issue could be bypassed by adding firms to the sample which are not involved in hedging activities and using a Tobit regression instead of OLS to account for the introduced zeros in the dependent variable. For example, Guay and Kothari (2003) also report regressions of hedging activity on proxies for hedging incentives based on a sample of firms using derivatives. In untabulated results, their results are similar for a Tobit specification that included non-derivatives users. Besides sample selection biases, Bartram et al. (2011) also discuss other empirical challenges such as endogeneity and omitted variables.

In an attempt to mitigate these concerns, they use a matching method that controls for the differences in the likelihood of using derivatives. By this, they attempt to find "similar" firms, where to the extent possible the "similar" firm differs only in its choice not to use derivatives. Unfortunately, we cannot conduct a comparable analysis using our data, since a large sample of non-derivative users comparable to ours is required to obtain meaningful matches.

The book value of total assets is our main proxy for company size. Besides size, we include profitability, short-term liquidity, interest coverage ratio, and debt ratio as commonly used control variables in our regression model. These variables were included in the bank's datafile and were inter alia used to produce the internal rating valid at year-end, which is also used for the regulatory capital calculation under the Basel II internal ratings-based (IRB) approach. Cf. Table 6.1 for a detailed overview. Descriptive statistics on the dataset, winsorized at 1% and 99%, are shown in Table 6.2.

It is commonly argued that firms with higher debt ratios, lower interest coverage, lower profitability, and less liquidity are more likely to use derivatives. Moreover, bankruptcy costs are typically assumed to be less than proportional to firm size, hence smaller firms should be more likely to hedge (Gruber and Warner, 1977). In that sense, these variables can be interpreted as traditional proxy variables for FDC. Empirical evidence on international datasets, which also include observations from Germany, however, has up to now found only mixed support for these hypotheses (see e.g. again Bartram et al. (2009)). The corresponding part of the correlation matrix for our dataset in Appendix C (see Table B.1 in Appendix B.3) is in line with this literature and supports all of these predictions, since all the correlations with the observed derivative use (variables named Notionals and MV) have the hypothesized signs, albeit some are just above the 10% significance level.

For the variable H, which is the optimal hedge ratio we predict on the basis of the marginal FDC, we obtain highly significant negative correlations with interest coverage, profitability, and short-term liquidity and a positive correlation with leverage, which is plausible, as it indicates that our new explanatory variable H is quite in line with the predictions for the commonly applied traditional proxy variables concerning observed hedge ratios. It should be noted that a similar interpretation of the "correct" sign for the correlation coefficients between the absolute FDC variable and the control variables is not valid. The reason for this is that we estimate the absolute FDC as a fraction of firm value in case of bankruptcy, which by construction leads to a high correlation between firm size and the absolute amount of FDC. Hence, the interpretation of the univariate effects is misleading here.

Our final sample consists of 189 medium-sized firms giving us a representative sample of hedging in the German middle-market corporates ("Mittelstand"). Table B.2 in Appendix B.4 shows the industry distribution of the dataset. Due to the size of the companies and their relationship with the major bank, we are likely observing that the vast majority of the firms' hedging activity is channeled through this bank. Cf. Machauer and Weber (2000) for more insights into the German bank/firm relationship and Harhoff and Körting (1998) find most German small and medium-sized companies to trade with less than two banks. However since we cannot ensure that other hedging activities take place, we consider the hedge ratio as a random variable that asymptotically approaches the real (unobservable) hedge ratio with decreasing firm size. Therefore using company size as a control variable in the empirical analysis is both crucial for us and common in previous studies.

6.3.2 Absolute FDC and Hedging

We begin with testing whether there is a positive relationship between the absolute amount of expected FDC and the observed hedge ratios. To reiterate, the absolute amount of expected FDC is defined as a fraction of an asset-or-nothing put option. Table 6.3 shows the result of the estimated regression model (6.3.1) of the absolute FDC on the scaled sum of notional values of derivative contracts held by each company, considering control variables and both industry and time fixed effects.

Strikingly, the size of a company, measured by the natural logarithm of the book value of total assets, significantly negatively influences the observed hedge ratios. Several explanations come to mind with regard to this finding, especially as it differs from what Graham and Rogers (2002) document. We already mentioned earlier that the probability that a firm engages in derivatives business with more than one bank increases in firm size (Harhoff and Körting, 1998; Ongena and Smith, 2000). Hence, there is an increased probability of missing notional values of derivative contracts for larger companies due to contracts with other banks. Second, one could think of the simple mathematical explanation that, since the observed hedge ratios are scaled by total

Table 6.1: Variable Definitions

Variable	Definition
Dependent variables	
Notionals	Sum of gross notional values of derivative contracts held by the company over book value of total assets.
MV	Sum of absolute fair values of derivative contracts held by the company over book value of total assets.
$\text{Notionals}_{\text{Debt}}$	Sum of gross notional values of derivative contracts held by the company over book value of debt.
Independent variables	
FDC	Expected absolute financial distress costs as constructed in Section 6.2.
H	Theoretical hedge ratio comprising marginal benefits of FDC reduction through hedging as constructed in Section 6.2.
Debt ratio	Book value of liabilities over total assets.
Interest coverage ratio	Operating income over interest expenses.
Profitability	Operating income over sales.
Short-term liquidity	Cash and cash equivalents over book value of liabilities.
Size	The natural logarithm of book value of total assets.

Notes: Table 6.1 shows the definitions of the variables used throughout this study. Independent variables are constructed by balance sheet data used by the bank to obtain the probabilities of default according to its approved regulatory model under the Basel II internal ratings-based approach.

Table 6.2: Descriptive Statistics

Variable	Min	Mean	Max	SD
Dependent variables				
Notionals	0.0025	0.0978	0.7222	0.1202
MV	0.0000	0.0034	0.0276	0.0051
$\text{Notionals}_{\text{Debt}}$	0.0042	0.1540	1.1480	0.1936
Independent variables				
FDC	293.75	10843.04	54822.34	12033.89
H	0.2578	0.4060	0.6020	0.0697
Debt ratio	0.2182	0.6722	0.9680	0.1554
Interest coverage ratio	-5.8189	6.8798	56.9224	10.9794
Profitability	-0.0318	0.0423	0.1750	0.0419
Short-term liquidity	0.0012	0.1392	1.5209	0.2341
Size	15.6570	18.1677	20.1976	1.1577

Notes: Table 6.2 shows the descriptive statistic of the dataset. Notionals respectively $\text{Notionals}_{\text{Debt}}$ is the sum of gross notional values of derivative contracts held by the company over book value of total assets respectively liabilities. MV is the sum of absolute fair values of derivative contracts held by the company over book value of total assets. FDC is the absolute amount of expected financial distress costs and H the theoretical hedge ratio comprising marginal benefits of FDC reduction through hedging as constructed in Section 6.2. Debt ratio is defined as book value of liabilities over total assets. Interest coverage ratio is calculated as operating income over interest expenses and Profitability as operating income over sales. Short-term liquidity denotes cash and cash equivalents over book value of liabilities. Size is measured as the natural logarithm of book value of total assets.

assets, an enlargement of the denominator can lead to lower hedge ratios if they do not increase proportionally.

Besides the size variable, the only other variable with significant explanatory power in both specifications is the absolute amount of FDC. Its coefficient is significantly positive at the 1% confidence level with a magnitude of 2.9008. Including industry and time fixed effects, this value increases to 2.9132. This indicates that German middle-market companies indeed hedge in order to avoid ex ante expected FDC: The higher the absolute FDC, the greater is the incentive to reduce a portion of firm value volatility by using derivatives.

Regarding the remaining control variables, we cannot observe significant links to the dependent variable. This is surprising as these variables are commonly used proxies for hedging incentives such as expected financial distress. However, one evident reason for this is that the FDC variable already explains the fraction of the observed hedge ratio variations rooted in expected FDC. Obviously, our direct estimation approach yields better empirical results than the use of the traditional proxy variables.

Regarding our results, we recognize the issue of endogeneity to which empirical studies of corporate hedging are generally prone (cf. Aretz and Bartram (2010)). Our approach to tackle this challenge is to treat the underlying FDC function as exogenous, insofar as it is designed to measure differences across firms that result from their operating business models when it comes to a situation of financial distress. This FDC function forms the common basis for both the company's hedging and leverage decisions in our modeling approach and is estimated from empirically observable variables.

6.3.3 Marginal FDC Benefits and Hedging

We repeat the previous regression model estimation but replace the absolute amount of FDC with the theoretically optimal hedge ratio H estimated from marginal FDC reduction benefits as an explanatory variable. To reiterate, H results from trading off expected FDC with the transaction costs of hedging these.

H can be interpreted as another perspective on FDC incentives to hedge. While the significantly positive coefficient for FDC in Table 6.3 implies a higher hedging extent for firms facing higher expected FDC, a significantly positive coefficient here would indicate that the cross-sectional differences between the empirical hedge ratios can be

Table 6.3: Regressions of Hedging Extent on Hedging Incentives including the Absolute Amount of Expected FDC

Dependent variable	Notionals	
FDC (in million)	2.9008***	2.9132***
	(3.321)	(3.313)
Debt ratio	0.0485	0.0426
	(0.991)	(0.837)
Interest coverage ratio	0.0002	0.0002
	(0.384)	(0.360)
Profitability	0.0229	0.0190
	(0.104)	(0.086)
Short-term liquidity	−0.0015	0.0060
	(−0.071)	(0.246)
Size	−0.0739***	−0.0742***
	(−5.571)	(−5.625)
Intercept	1.3753***	
	(6.261)	
Fixed Effects	No	Yes
Adj. R^2	0.2458	0.2348
Observations	321	321

Notes: Table 6.3 displays the results of the estimated model $y_{i,t} = X_{i,t}\beta + \alpha_i + \gamma_t + \epsilon_{i,t}$ where $X_{i,t}$ denotes the design matrix whose rows correspond to the independent variables, α_i denote the industry fixed effects, γ_t the time fixed effects, and $\epsilon_{i,t}$ the error terms. Below the coefficients the robust t-statistics are given in parentheses. Notionals is the sum of gross notional values of derivative contracts held by the company over book value of total assets. FDC is the absolute amount of expected financial distress costs as constructed in Section 6.2. Debt ratio is defined as book value of liabilities over total assets. Interest coverage ratio is calculated as operating income over interest expenses and Profitability as operating income over sales. Short-term liquidity denotes cash and cash equivalents over book value of liabilities. Size is measured as the natural logarithm of book value of total assets.
Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

explained by firm-specific, marginal benefits of FDC reduction. Albeit we expect a positive coefficient for the hedge ratio variable H, our expectation about deviations in the magnitude and significance of its coefficient compared to the coefficient of the absolute FDC variable is ambiguous. By construction, H comprises information about both the absolute height of FDC and the marginal benefits of hedging these costs. Hence, we believe that the model estimation will result in a higher regression coefficient for H than FDC. On the other hand, a decrease in the coefficient might indicate a superior role of the absolute expected FDC height in the hedging decision process.

A similar pictures emerges when comparing the results in Table 6.4 to those obtained in the previous regression (cf. Table 6.3). The marginal FDC variable H possesses significant explanatory power in both specifications. The coefficient of H is significantly positive at the 5% confidence level with a magnitude of 0.44 and 0.50 respectively. This finding is in line with our expectations. The economic impact of our results is quite pronounced. A one unit increase in H (FDC) FDC corresponds to a 0.50 (2.91) unit increase in the absolute hedge ratios. Thus companies on average compensate for higher bankruptcy costs by a steep increase in their hedging activities. This magnitude can be explained by the relatively low absolute FDC in our sample as well as the practical implementation costs of higher hedging activity.

6.3.4 Robustness Checks

Extent of Derivative Use and Number of Banking Relationships In the attempt to control for the case that larger firms are more likely to possess derivative contracts whose notional values are not included in the dataset, we gradually downsize the dataset with respect to the companies' size and rerun the conducted analysis. More specifically, we build two subsamples based on dismissing (a) the largest 25% and (b) the largest 50% of the firms. We expect both the coefficients of the FDC variables and their significance to increase. The results are documented in Table 6.5.

In line with the expectation, both the FDC and the H coefficient increase each time a smaller subsample is taken into consideration. While for H the coefficient almost doubled compared to the main specification, the FDC coefficient jumps from a magnitude of 2.9132 to 19.7861 when only considering companies having a size below the median firm size of the sample. However, only the coefficient of H is becoming

Table 6.4: Regressions of Hedging Extent on Hedging Incentives including the Marginal Benefits of FDC Reduction

Dependent variable	Notionals	
H	0.4443**	0.5033**
	(2.222)	(2.361)
Debt ratio	−0.0915	−0.1105*
	(−1.626)	(−1.835)
Interest coverage ratio	0.0001	0.0002
	(0.216)	(0.347)
Profitability	0.1606	0.1734
	(0.702)	(0.753)
Short-term liquidity	−0.0023	0.0080
	(−0.106)	(0.313)
Size	−0.0480***	−0.0484***
	(−7.398)	(−7.343)
Intercept	0.8460***	
	(7.055)	
Fixed Effects	No	Yes
Adj. R^2	0.2470	0.2419
Observations	321	321

Notes: Table 6.4 displays the results of the estimated model $y_{i,t} = X_{i,t}\beta + \alpha_i + \gamma_t + \epsilon_{i,t}$ where $X_{i,t}$ denotes the design matrix whose rows correspond to the independent variables, α_i denote the industry fixed effects, γ_t the time fixed effects, and $\epsilon_{i,t}$ the error terms. Below the coefficients the robust t-statistics are given in parentheses. Notionals is the sum of gross notional values of derivative contracts held by the company over book value of total assets. H is the theoretically optimal hedge ratio estimated from marginal FDC benefits as explained in Section 6.2. Debt ratio is defined as book value of liabilities over total assets. Interest coverage ratio is calculated as operating income over interest expenses and Profitability as operating income over sales. Short-term liquidity denotes cash and cash equivalents over book value of liabilities. Size is measured as the natural logarithm of book value of total assets. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

slightly more significant. The FDC coefficient, on the other hand, is less significant for the two subsamples than for the full sample. We believe that this finding is rooted in the relation between the size of a company and our construction of the expected FDC. Our FDC function is defined as a fraction of firm value (see Formula (6.2.5)) in the case of bankruptcy. By gradually downsizing the sample with respect to company size, we not only control particularly for size, but also for the absolute amount of FDC. Hence, both size and FDC lose some significance following this procedure, whereas H does not.

Different Measures of the Extent of Derivative Use So far, we scaled the sum of notional values of derivative contracts by the book value of total assets for each company. Commonly, the amount of debt is used alternatively for scaling the notional values to construct a measure of the extent of derivative use (Graham and Rogers, 2002). Hence, we replace the dependent variable used in the main analysis by one scaled by debt.

This specification can be interpreted as a measure for hedging per dollar of debt. As the left columns in Table 6.6 show, we obtain similar results to the previously conducted analysis. In this case though, the coefficients of the marginal and absolute FDC variables are significant at 10% and 5% level respectively. Nonetheless, the debt ratio again seems to negatively influence the observed hedge ratios. Graham and Rogers (2002) use the amount of debt as a measure of financial distress and find their results to be robust against this alternative measure of hedging extent. We argue that this specification induces a negative coefficient on the debt ratio because debt is in the denominator of the dependent variable. The correlation matrix B.1 in Appendix B.3 fosters this impression as $\text{Notionals}_{\text{Debt}}$ is the only dependent variable being negatively correlated to the debt ratio.

As a third proxy of a firm's hedging extent, we utilize the fair values of the derivative contracts. They specify the amount that the contract holder would receive or pay to liquidate these contracts and have also been utilized as proxies for derivative use in earlier studies (see for example Berkman and Bradbury (1996); Spanò (2007); Choi et al. (2013)). A serious disadvantage of using fair values compared to notional values as a hedging proxy is their dependence on the price movements of the corresponding underlying. For example, many fair values of derivative contracts are zero at origination, although their hedged notional values might be large. In our sample though, derivative contracts are already held for 2.5 years on average. Thus, we believe that the sum

Table 6.5: Regressions of Hedging Extent on Hedging Incentives for Different Subsamples

Dependent variable	Notionals			
Sample	≤ 75% quantile(Size)		≤ 50% quantile(Size)	
FDC (in million)	5.7843*		19.7861*	
	(1.936)		(1.674)	
H		0.6190**		0.8816**
		(2.545)		(2.527)
Debt ratio	0.0874	−0.1194	0.2053*	−0.0804
	(1.143)	(−1.576)	(1.858)	(−0.724)
Interest coverage ratio	0.0005	0.0005	0.0011	0.0014
	(0.561)	(0.549)	(0.748)	(0.904)
Profitability	−0.0090	0.2228	−0.2073	0.1142
	(−0.035)	(0.837)	(−0.431)	(0.235)
Short-term liquidity	0.0131	0.0002	0.0487	0.0494
	(0.393)	(0.005)	(0.572)	(0.647)
Size	−0.0869***	−0.0634***	−0.1288***	−0.0890***
	(−4.369)	(−6.080)	(−3.557)	(−4.693)
Fixed effects	Yes	Yes	Yes	Yes
Adj. R^2	0.1853	0.2193	0.1312	0.1843
Observations	241	241	161	161

Notes: Table 6.5 displays the results for two subsamples, namely by excluding the 25% respectively 50% largest companies in the sample. The estimated model is $y_{i,t} = X_{i,t}\beta + \alpha_i + \gamma_t + \epsilon_{i,t}$ where $X_{i,t}$ denotes the design matrix whose rows correspond to the independent variables, α_i denote the industry fixed effects, γ_t the time fixed effects, and $\epsilon_{i,t}$ the error terms. Below the coefficients the robust t-statistics are given in parentheses. Notionals is the sum of gross notional values of derivative contracts held by the company over book value of total assets. FDC is the absolute amount of expected financial distress costs and H the theoretical hedge ratio comprising marginal benefits of FDC reduction through hedging as constructed in Section 6.2. Debt ratio is defined as book value of liabilities over total assets. Interest coverage ratio is calculated as operating income over interest expenses and Profitability as operating income over sales. Short-term liquidity denotes cash and cash equivalents over book value of liabilities. Size is measured as the natural logarithm of book value of total assets. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

of the absolute fair values of derivative contracts serves as a suitable alternative to test our hypothesis. The correlation between the constructed hedge proxies based on fair values respectively notional values amounts to 0.642 (cf. Table B.1 in Appendix B.3). Table 6.6 summarizes the results. They are similar to those obtained in the main specifications. Both the coefficient of the marginal and absolute FDC variables are significant at 5% and 1% level respectively supporting our hypothesis that firms hedge in order to avoid FDC.

Table 6.6: Regressions of Alternative Proxies of Hedging Extent on Hedging Incentives

Dependent variable	$\text{Notionals}_{\text{Debt}}$		MV	
FDC (in million)	3.2730**		0.1254***	
	(2.407)		(3.055)	
H		0.5878*		0.0169**
		(1.788)		(2.003)
Debt ratio	−0.1923**	−0.3691***	0.0025	−0.0031
	(−2.124)	(−3.721)	(1.003)	(−1.128)
Interest coverage ratio	−0.0003	−0.0002	0.0000	0.0000
	(−0.269)	(−0.235)	(−1.375)	(−1.298)
Profitability	−0.1110	0.0702	0.0045	0.0095
	(−0.270)	(0.166)	(0.393)	(0.802)
Short-term liquidity	0.0989	0.1016	0.0014	0.0015
	(1.383)	(1.388)	(1.256)	(1.179)
Size	−0.1034***	−0.0743***	−0.0023***	−0.0013***
	(−5.200)	(−7.191)	(−4.300)	(−4.138)
Fixed effects	Yes	Yes	Yes	Yes
Adj. R2	0.2328	0.2376	0.0988	0.0925
Observations	321	321	321	321

Notes: Table 6.6 displays the results for two alternative proxies of hedging extent. The estimated model is $y_{i,t} = X_{i,t}\beta + \alpha_i + \gamma_t + \epsilon_{i,t}$ where $X_{i,t}$ denotes the design matrix whose rows correspond to the independent variables, α_i denote the industry fixed effects, γ_t the time fixed effects, and $\epsilon_{i,t}$ the error terms. Below the coefficients the robust t-statistics are given in parentheses. $\text{Notionals}_{\text{Debt}}$ is the sum of gross notional values of derivative contracts held by the company over book value of liabilities and MV is the sum of absolute fair values of derivative contracts held by the company over book value of total assets. FDC is the absolute amount of expected financial distress costs and H the theoretical hedge ratio comprising marginal benefits of FDC reduction through hedging as constructed in Section 6.2. Debt ratio is defined as book value of liabilities over total assets. Interest coverage ratio is calculated as operating income over interest expenses and Profitability as operating income over sales. Short-term liquidity denotes cash and cash equivalents over book value of liabilities. Size is measured as the natural logarithm of book value of total assets. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

6.4 Conclusion

Exploring if firms hedge in order to avoid ex ante expected FDC, we expand a Merton (1974) framework to estimate FDC as a fraction of an asset-or-nothing put option. Our empirical FDC estimates are based on information about the firms' regulatory "Basel II" PDs, which are available on bank-level, as well as on publicly accessible accounting figures. Assuming that firms choose their debt levels optimally, we determine the firm-specific financial distress cost parameters in a trade-off between FDC and tax savings. The resulting absolute amount of firm-specific FDC is our first novel explanatory variable, which is assumed to be positively correlated with the observed hedging activity. We then introduce a second trade-off between FDC and transaction costs to calculate optimal hedge ratios. We expect these optimal hedge ratios, which result from the marginal FDC benefits in equilibrium and which are our second novel explanatory variable, to be accompanied by higher observed hedge ratios, too.

Testing our model empirically we obtain granular data from a major bank. The dataset contains all OTC derivatives the bank entered with about 189 middle-market counterparties (non-financial, non-public sector) at fiscal year-end 2014/2015. Regressing our FDC variables on the observed hedge ratios we find a significantly positive relation when considering several control variables and fixed effects. Although it is quite probable that most firms in our dataset mainly trade derivatives with only a very small number of banks, we admit that the observed hedge ratios might not cover the full extent of derivative use of the considered companies. Since larger firms are more likely to possess derivative contracts whose notional values are not included in the dataset, we gradually downsize the dataset with respect to the companies' size in the robustness section. In line with our expectations, the magnitude of the coefficients for both FDC variables increases. Furthermore, our results are robust to different constructions of the empirical hedge ratio and different choice of model parameters.

Our contribution is a novel measure of firm-specific ex ante costs of financial distress based on an option-theoretical approach, which we then extend to an equilibrium setting. Moreover, our empirical analysis differs from previously used datasets and enriches the literature by the perspective of a financial intermediary on the corporate hedging decision. We are able to support the hypothesis that firms hedge in order to avoid ex ante expected financial distress costs.

Concerning implications of our findings for corporate policy as well as for banks' derivative sales policies, we think that a quantitative analysis of the FDC impact should become a more explicit part of firms' hedging decisions. For the German middle-market companies we have focused on in this paper, such an analysis should expediently be linked to the annual Basel II rating process, whose main outcome is a forward-looking one-year default probability. In this context, our modeling approach to estimate ex ante expected FDC could be integrated for benchmarking purposes. From a financial intermediate's perspective, such quantitative information should be embraced as a new anchor point for offering customized consulting and marketing activities in financial derivatives.

From a research point of view, currently only very little seems to be known about the role of the sell-side for corporate derivatives use. In order to gain more insight about the policies of the different sell-side market participants and their views on the corporate decision process, more survey work seems necessary in a first step.

The partial equilibrium two-stage estimation approach presented in this paper is applicable in future research projects or the above mentioned quantitative business analyses whenever data about the firms' debt-equity ratio and a corresponding PD proxy variable is available. The PD proxy variable, which we took from our bank dataset as a regulatory Basel II PD, could easily be replaced by mean historical default rates per rating class if a sample of externally rated firms was analyzed. Moreover, such a proxy variable could also be constructed from observed credit spreads, if the firms under analysis have issued bonds, which are traded in a liquid debt market, or if there are even liquid CDS quotes. In order to have a substantial magnitude of FDC in the sample, a natural choice would be the European market for high-yield bond issuers, where both external ratings and credit spreads are available.

A Appendix for Chapter 5

A.1 General Tournament Behavior

To detect general tournament behavior, we follow Brown et al. (1996) by using their contingency table approach: The performance of every manager i is given as the information ratio IR_{iM} against the MSCI North America in the first *6* months of the year to identify mid-term winners and losers as those above or below the median information ratio, respectively. All managers hold an equally weighted portfolio of their funds $j \in \{1, ..., n\}$ included in the tournament with a portfolio return of r_{ik}^{port}.

In order to calculate the information ratio for each fund given as $IR = \frac{active\ premia}{tracking\ error}$, we determine the cumulative return as $RTN_i = \prod_{k=1}^{6} \left(1 + r_{ik}^{port}\right) - 1$, which finally leads to the formula for the information ratio of manager i at the end of June

$$IR_i = \frac{RTN_i - RTN_b}{\sqrt{\frac{1}{6-1} \sum_{k=1}^{6} \left(r_{ik}^{port} - r_{bk}\right)^2}} \tag{A.1.1}$$

The variable RTN_b is the cumulative return of benchmark returns r_{bk} of month $k \in \{1, ..., 6\}$. The risk adjustment ratio (RAR) of manager i for the given tournament year with interim assessment date in June is:

$$RAR_i = \sqrt{\frac{\sum_{k=6+1}^{12} (r_{ik}^{port} - \bar{r}_{i(12-6)})^2}{(12-6)-1}} \div \sqrt{\frac{\sum_{k=1}^{6} (r_{ik}^{port} - \bar{r}_i)^2}{6-1}} \tag{A.1.2}$$

with $\bar{r}_{i(12-6)}$ and $\bar{r}_i$ representing the mean portfolio return of fund manager i before and after the assessment date, respectively. This variable measures the risk adjustments of a given portfolio within the two periods of the year's tournament by comparing the portfolio's volatility in both periods. Thus, we rank the RAR in a similar way as the IR and determine high RAR as those above the median and low RAR as those below the median for the first and second period, respectively.

Table A.1: Contingency Tables of Annual Tournaments following Brown et al. (1996)

Freq. in %		Winner		Loser			
Year	No.[a]	High RAR	Low RAR	High RAR	Low RAR	χ^2-value[b]	p-value
1992	94	19.2	30.9	30.9	19.2	5.1489	0.1612
1993	97	33.0	17.5	17.5	32.0	9.6907	0.0337
1994	109	22.9	27.5	27.5	22.0	1.1284	0.7702
1995	135	20.2	30.6	29.9	19.4	5.8806	0.1176
1996	153	25.8	25.2	24.5	24.5	0.0728	0.9949
1997	165	27.9	22.4	22.4	27.3	1.7636	0.6229
1998	189	26.1	24.5	23.9	25.5	0.2128	0.9755
1999	220	25.0	25.0	25.0	25.0	0.0000	1.0000
2000	245	33.1	17.1	17.1	32.7	24.208	0.0000
2001	269	34.2	16.0	16.0	33.8	34.985	0.0000
2002	325	25.9	24.3	24.3	25.5	0.2552	0.4625
2003	350	27.1	22.9	22.9	27.1	2.5714	0.4625
2004	362	30.4	19.6	19.6	30.4	16.807	0.0008
2005	340	23.0	26.8	27.1	23.0	2.1563	0.5406
2006	328	20.2	30.0	30.0	19.9	12.927	0.0048
2007	311	30.4	20.1	19.7	29.8	12.877	0.0049
2008	296	27.8	22.0	22.4	27.8	3.6983	0.2959
2009	259	24.9	25.7	25.3	24.1	0.1362	0.9872
2010	231	26.0	24.2	24.2	25.5	0.2208	0.9742
2011	215	27.0	23.3	23.3	26.5	1.0558	0.7878
2012	208	27.4	22.6	22.6	27.4	1.9231	0.5885
2013	196	24.5	25.5	25.5	24.5	0.0816	0.9930
2014	193	21.2	29.0	29.0	20.7	4.9896	0.1726
2015	185	31.3	18.9	18.9	30.8	10.957	0.0120
2016	169	33.1	17.2	17.2	32.5	16.633	0.0008
2017	148	21.0	29.1	29.1	21.0	3.8919	0.2734

[a] Number of managers within the given tournament year.
[b] Based on the null hypothesis of every cell receiving 25% of the distribution.

Notes: This table presents the annual contingency tables of risk adjustment ratios (RAR) for the whole dataset covering the years 1992-2017. Managers who perform at the end of the interim period above (below) the median are classified as winners (losers). The same methodology applies to the classification of high (low) RARs.

A.2 Tables – Robustness Tests

Table A.2: Risk Transitions for Managers of Different Skill Levels - Active Return

Values in %	Winner				Loser			
Risk tercile	high	medium	low	χ^2	high	medium	low	χ^2
				Panel A: Unconditional				
high	62.6	25.9	11.5		61.1	24.9	14.0	
medium	31.0	44.7	24.2		25.5	40.9	33.7	
low	12.1	32.2	54.8		10.2	27.9	61.9	
				Panel B: High Skill				
high	64.1	26.4	9.5		66.5	24.1	9.4	
medium	35.5	45.0	19.5		26.9	43.8	29.4	
low	16.2	34.7	49.1	5.96*	14.2	29.1	56.7	7.18**
				Panel C: Medium Skill				
high	61.7	25.2	13.1		59.3	25.3	15.4	
medium	29.4	44.4	26.2		26.1	41.6	32.3	
low	11.1	32.2	56.7	1.92	10.3	29.4	60.3	2.06
				Panel D: Low Skill				
high	63.5	27.6	8.8		61.0	24.5	14.5	
medium	31.0	45.7	23.4		22.2	36.1	41.7	
low	9.7	34.8	55.5	0.64	7.3	22.8	69.9	13.63***

Notes: This table shows the risk-shifting tendencies from the year's first-half tercile to the tercile in the second half of the year for the full aggregated data set. Panel A represents the whole sample, whilst Panel B to D show the transitions for different skill levels. Each manager is classified as being a winner (loser) if his performance measured by the active return lies above (below) the median at the end of the interim period. χ^2-values testing H0-hypotheses of conditional transitions being equal to the unconditional. ***, **, and * indicate significance at the 1%, 5%, and 10% level (two-tailed tests), respectively.

Table A.3: Rank Correlations Based on Different Performance Measures

Performance measures	Sharpe ratio	Active return	Information ratio
Sharpe ratio	1		
Active return	0.983***	1	
Information ratio	0.943***	0.963***	1

Notes: The ranks are calculated over a time period from 1992 to 2017. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Table A.4: Risk Transitions for Different Hyperparameters: $\sigma = 12.5$

Values in %	Winner				Loser			
Risk tercile	high	medium	low	χ^2	high	medium	low	χ^2
				Panel A: Unconditional				
High	62.4	25.7	11.8		61.3	25.0	13.7	
Med	30.0	44.8	25.2		26.6	40.9	32.5	
Low	11.1	32.9	56.0		11.1	28.2	60.7	
				Panel B: High Skill				
High	62.6	26.7	10.8		65.8	23.8	10.4	
Med	29.2	46.6	24.2		26.8	42.5	30.7	
Low	13.0	31.3	55.7	6.35**	13.5	31.8	54.7	0.66
				Panel C: Medium Skill				
High	62.7	25.0	12.3		61.0	25.4	13.6	
Med	32.1	42.7	25.2		27.2	42.9	29.9	
Low	11.5	34.7	53.7	2.75	12.2	29.4	58.3	2.63
				Panel D: Low Skill				
High	61.1	27.4	11.5		57.6	25.3	17.2	
Med	23.9	49.4	26.7		24.8	34.8	40.5	
Low	7.3	29.6	63.1	22.25***	6.8	22.5	70.8	8.58**

Notes: This table shows the risk-shifting tendencies from the year's first-half tercile to the tercile in the second half of the year for the full aggregated data set for a different choice of hyperparameter for the prior distribution of the fund managers' skills, e.g. $\sigma = 12.5$. Panel A represents the whole sample, whilst Panel B to D show the transitions for different skill levels. Each manager is classified as being a winner (loser) if his performance measured by the active return lies above (below) the median at the end of the interim period. χ^2-values testing H0-hypotheses of conditional transitions being equal to the unconditional. ***, **, and * indicate significance at the 1%, 5%, and 10% level (two-tailed tests), respectively.

Table A.5: Risk Transitions for Different Hyperparameters: $\sigma = 6.25$

Values in %	Winner				Loser			
Risk tercile	high	medium	low	χ^2	high	medium	low	χ^2
				Panel A: Unconditional				
High	62.4	25.7	11.8		61.3	25.0	13.7	
Med	30.0	44.8	25.2		26.6	40.9	32.5	
Low	11.1	32.9	56.0		11.1	28.2	60.7	
				Panel B: High Skill				
High	64.7	23.9	11.4		64.1	22.2	13.8	
Med	26.9	46.2	26.9		23.7	41.0	35.3	
Low	11.2	36.2	52.6	4.36	11.8	32.4	55.9	3.42
				Panel C: Medium Skill				
High	61.8	26.3	11.9		60.8	25.9	13.3	
Med	33.1	43.1	23.8		27.0	43.6	29.4	
Low	12.0	32.6	55.3	3.50	11.9	29.6	58.5	1.98
				Panel D: Low Skill				
High	61.8	26.1	12.1		60.5	24.9	14.6	
Med	23.9	48.3	27.8		27.7	33.0	39.4	
Low	8.0	29.3	62.6	16.75***	9.0	22.3	68.8	7.26**

Notes: This table shows the risk-shifting tendencies from the year's first-half tercile to the tercile in the second half of the year for the full aggregated data set for a different choice of hyperparameter for the prior distribution of the fund managers' skills, e.g. $\sigma = 6.25$. Panel A represents the whole sample, whilst Panel B to D show the transitions for different skill levels. Each manager is classified as being a winner (loser) if his performance measured by the active return lies above (below) the median at the end of the interim period. χ^2-values testing H0-hypotheses of conditional transitions being equal to the unconditional. ***, **, and * indicate significance at the 1%, 5%, and 10% level (two-tailed tests), respectively.

Table A.6: Risk Transitions for Managers of Different Skill Levels - Secondary Benchmarks

Values in %	Winner				Loser			
Risk tercile	high	medium	low	χ^2	high	medium	low	χ^2
				Panel A: Unconditional				
High	62.4	25.7	11.8		61.3	25.0	13.7	
Med	30.0	44.8	25.2		26.6	40.9	32.5	
Low	11.1	32.9	56.0		11.1	28.2	60.7	
				Panel B: High Skill				
High	68.7	23.6	7.7		67.5	23.4	9.1	
Med	31.6	43.1	25.4		24.2	38.8	37.1	
Low	16.5	34.6	48.9	8.65**	12.8	31.5	55.7	10.52***
				Panel C: Medium Skill				
High	60.3	25.7	14.0		57.8	27.1	15.1	
Med	29.2	44.7	26.1		28.2	43.1	28.7	
Low	10.8	33.0	56.1	5.78*	10.4	29.2	60.4	1.35
				Panel D: Low Skill				
High	60.9	28.7	10.3		65.0	20.7	14.3	
Med	30.7	46.5	22.8		24.0	36.3	39.8	
Low	6.5	30.8	62.7	9.90***	12.3	22.6	65.1	5.61*

Notes: This table shows the risk-shifting tendencies from the year's first-half tercile to the tercile in the second half of the year for the full aggregated data set for a different choice of benchmarks for the funds in the sample. While in the baseline specification all funds are benchmarked against the MSCI North America, they are now benchmarked against different Russel indexes, see Section 5.3. Panel A represents the whole sample, whilst Panel B to D show the transitions for different skill levels. Each manager is classified as being a winner (loser) if his performance measured by the active return lies above (below) the median at the end of the interim period. χ^2-values testing H0-hypotheses of conditional transitions being equal to the unconditional. ***, **, and * indicate significance at the 1%, 5%, and 10% level (two-tailed tests), respectively.

B Appendix for Chapter 6

B.1 Estimating the Financial Distress Cost Parameter η from a Capital Structure Equilibrum

In order to provide a counterweight to the FDC given by (6.2.7), we introduce a corporate tax function. Interest rates are tax-deductible, which provides an incentive for borrowing at the corporate level by generating a tax shield. Taxable income in $t = 1$ stems from operating earnings (EBIT), which go along with an increase (or decrease) in total assets from V_0 to V. It is reduced by multiplying the nominal interest rate $i > 0$, which is assumed to be constant across all firms for the sake of simplicity, times the debt level that is chosen by the company. The corporate tax rate is denoted as $\tau \in]0, 1[$. The resulting tax shield is only valuable in those future states of the world, where the taxable income is not negative anyway. The whole idea of tax shield modeling is to create an analytically tractable counterweight to financial distress costs for the firms' capital structure decision. It is not meant as an analysis to further explore tax reasons for corporate hedging, which we do not regard as relevant under the German tax system. Cf. Graham and Rogers (2002) for such an analysis for the US. The market value of the tax claim in $t = 0$, which is identical with the expected value of the random cash flow in $t = 1$, emerges as

$$T := \tau \int_{V_0+iD}^{\infty} (V - V_0 - iD) f(V, \mu, \sigma) dV. \tag{B.1.1}$$

The shareholders decide about the optimal debt amount by maximizing the market value of their residual claims in $t = 1$. Since the debtholders are fairly compensated for the default risk, the maximization of shareholder wealth is equivalent to minimizing the sum of the market values of taxes and financial distress costs. This yields the first-order condition

$$\frac{\partial T}{\partial D} + \frac{\partial FDC}{\partial D} \stackrel{!}{=} 0. \tag{B.1.2}$$

Applying the product rule to the derivative of the tax function leads to

$$\frac{\partial T}{\partial D} = -\tau i + \tau i F(V_0 + iD, \mu, \sigma) < 0. \tag{B.1.3}$$

Applying Leibniz‘ rule, the first partial derivative of Equation (6.2.5) with respect to D is given by

$$\frac{\partial FDC}{\partial D} = \eta D f(D, \mu, \sigma) > 0. \tag{B.1.4}$$

When the firm has chosen its unique optimal debt level $D = D^*$ according to the first-order condition (B.1.2), the following condition must hold for the financial distress cost parameter η^*:

$$\begin{aligned} -\frac{\partial T}{\partial D} = \frac{\partial FDC}{\partial D} &\Leftrightarrow \tau i - \tau i F(V_0 + iD^*, \mu, \sigma) = \eta^* D^* f(D^*, \mu, \sigma) \\ &\Leftrightarrow \eta^* = \frac{\tau i - \tau i F(V_0 + iD^*, \mu, \sigma)}{D^* f(D^*, \mu, \sigma)}. \end{aligned} \tag{B.1.5}$$

To ensure the optimal debt level D^* is indeed minimizing the sum between the market values of taxes and financial distress costs, the second order condition needs to be met:

$$\frac{\partial^2 T}{\partial D^2} + \frac{\partial^2 FDC}{\partial D^2} = \tau i^2 f(V_0 + iD, \mu, \sigma) + \eta f(D, \mu, \sigma) + \eta D \frac{\partial}{\partial D} f(D, \mu, \sigma) \stackrel{!}{>} 0. \tag{B.1.6}$$

It is sufficient to take the second part of this Equation into account, as the second derivation of the tax function $\frac{\partial^2 T}{\partial D^2} = \tau i^2 f(V_0 + iD, \mu, \sigma)$ is greater or equal to zero regardless of the chosen debt level D. Simple mathematical operations show for the second derivation of the financial distress costs function that

$$\begin{aligned} \frac{\partial^2 FDC}{\partial D^2} &= \eta f(D, \mu, \sigma) + \eta D \frac{\partial}{\partial D} f(D, \mu, \sigma) \\ &= \frac{\eta}{\sqrt{2\pi}\sigma D} e^{-\frac{(\ln(D)-\mu)^2}{2\sigma^2}} + \eta \left(-\frac{1}{\sqrt{2\pi}\sigma D} e^{-\frac{(\ln(D)-\mu)^2}{2\sigma^2}} - \frac{\ln(D) - \mu}{\sqrt{2\pi}\sigma^3 D} e^{-\frac{(\ln(D)-\mu)^2}{2\sigma^2}} \right) \\ &= \frac{\eta}{\sqrt{2\pi}\sigma^3 D} e^{-\frac{(\ln(D)-\mu)^2}{2\sigma^2}} (\mu - \ln(D)) > 0 \end{aligned} \tag{B.1.7}$$

if $D < e^{\mu} = V_0 e^{r_f - \frac{1}{2}\sigma^2}$. Thus, if D^* is less than the median of the respective lognormal distribution, in other words if the probability of default of the company is less than at least 50%, D^* is indeed a cost minimum. We summarize these intermediate results in a Lemma:

Lemma. *In the exogenous capital structure equilibrium, each firm $j = 1, ..., n$ chooses its optimal debt level D_j^*, so that the sum of ex-ante expected corporate taxes and financial distress costs is minimized. For any given set of firm-specific distribution parameters (μ_j, σ_j) and of non firm-specific parameters for interest and tax rates, there is a unique set of firm-specific financial distress cost parameters η_j^*, which characterizes this capital structure equilibrium.*

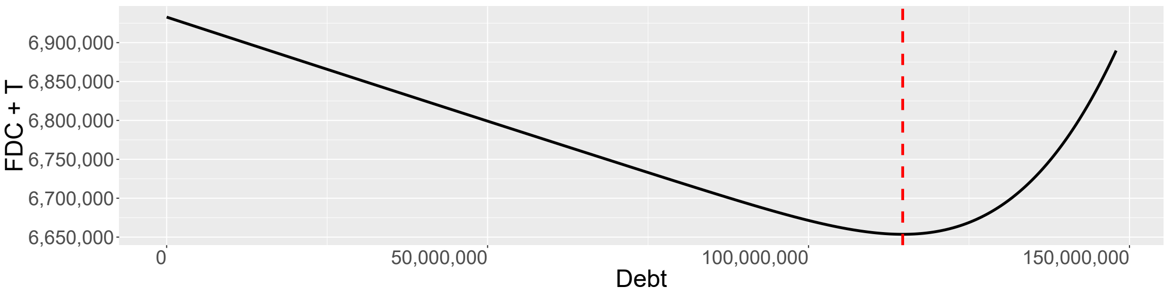
In the empirical part of this study, we set the the total average effective tax rate on company profits to 30% which comprises both federal tax and municipal tax components (BdF, 2016) and the interest rate i to 1.94% for 2014 and to 1.68% for 2015, which were the effective rates for new loans to non-financial firms granted by German banks in December of the respective year according to Beier and Bade (2017).

B.2 Construction of the FDC Variables

We want to motivate the construction process of the FDC variables with some graphical illustrations. Given the empirical book values of debt and total assets of the 189 firms in our sample and their probabilities of default according to the internal ratings-based approach of the bank, we can numerically solve for the firm value volatility following the Merton (1974) framework (cf. Equation (6.2.4)). For example, we pick a random observation from the dataset with book values of debt and totals assets amounting to about EUR 115 million and EUR 228 million respectively, and a probability of default of 0.53%. For this firm one obtains a firm value volatility of about 25.5%.[15] Note that we have set $r_f = 0$ without loss of generality.

We now utilize our FDC model and are able to calculate η_j^* for each firm $j = 1, ...189$ following the closed formula (B.1.5). As shown in Appendix B.1, this setting $\left(D_j^*, \eta_j^*\right)$ is optimal in the sense of trading off expected financial distress costs and tax savings. Figure B.1 visualizes this choice for the exemplary firm mentioned above.

Figure B.1: Visualization of the First Optimization Problem

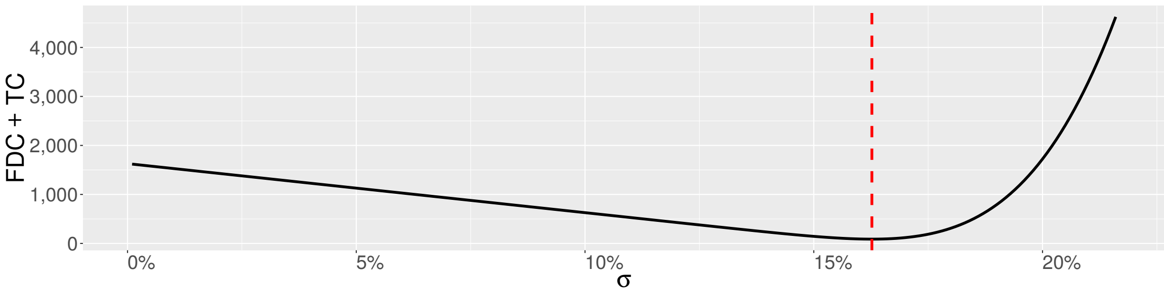


Notes: Visualization of the first optimization problem (see Equation (B.1.2)). The solid black line shows the sum of financial distress costs and taxes in dependence of debt D. The red dotted line shows the optimal amount of debt D*, given the FDC parameter η^*.

Thereupon, we are able to determine the expected FDC determined by multiplying the FDC parameter η^* with the value of the asset-or-nothing put option (cf. Equation (6.2.7)). To prevent firms from fully hedge all of their risk, we introduce transaction costs as described in formula (6.2.9). The marginal transaction costs parameter γ is set to 0.4 basis points, which is the minimum firm-specific value of the derivation of the FDC function (cf. Equation (6.2.7)) with respect to the firm value volatility. By numerically solving Equation (6.2.10), we obtain the optimal firm value volatility σ^* that minimizes the ex-ante expected FDC with respect to transaction costs. For the exemplary firm mentioned at the beginning of this section this optimization is illustrated in Figure B.2.

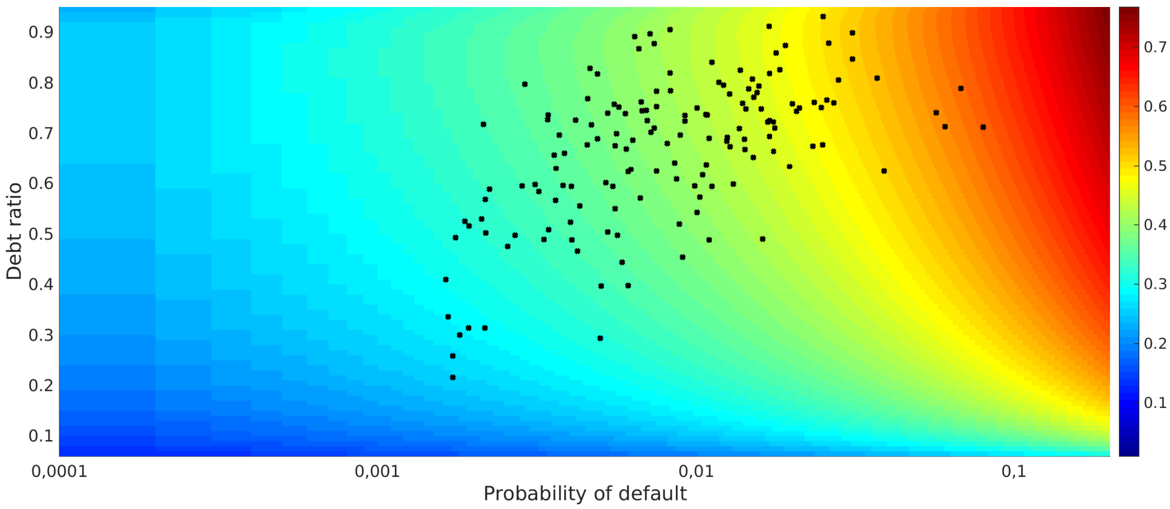
Finally, we are able to determine the theoretically optimal hedge ratio H^* according to Equation (6.2.12) which is driven by the marginal benefits of FDC reduction. Figures B.3 and B.4 show H^* in dependence of the debt ratio and PD. The black points highlight the obtained values H_j^* based on the observations as of 2015 from the dataset.

Figure B.2: Visualization of the Second Optimization Problem



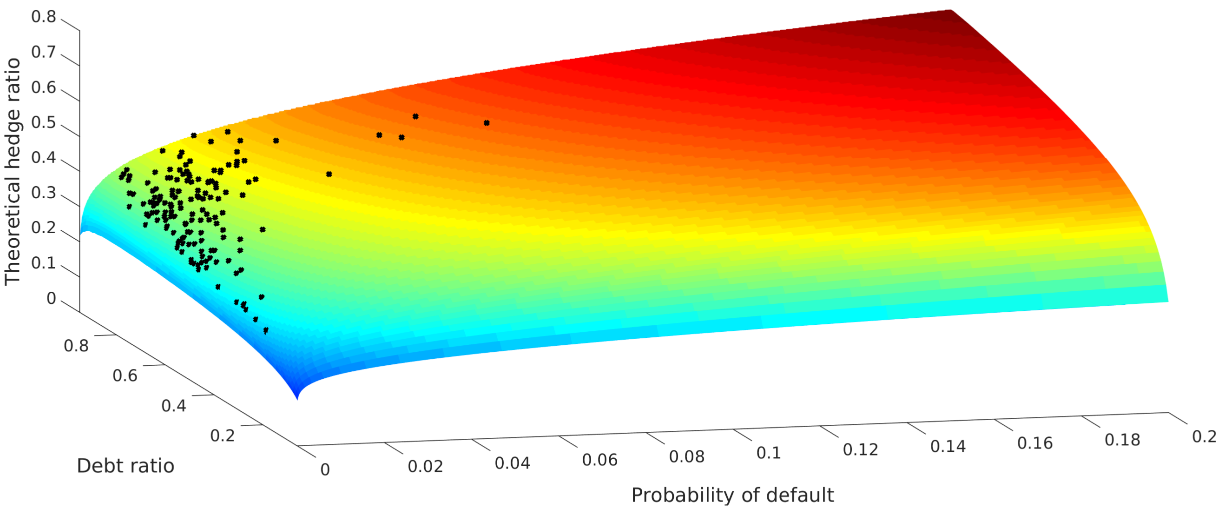
Notes: Visualization of the second optimization problem (see Equation (6.2.10)). The solid black line shows the sum of financial distress costs and transaction costs in dependence of the firm value volatility σ. The red dotted line shows the optimal firm value volatility σ^*.

Figure B.3: Contour Plot of the Theoretical Hedge Ratio



Notes: Contour plot of the theoretical hedge ratio H^* in dependence of the debt ratio $\frac{D}{V}$ and probability of default PD. The black points highlight the obtained values H_j^* based on the observations as of 2015 from the dataset. Note that the x-axis is for the sake of clarity logarithmically scaled.

Figure B.4: 3D Plot of the Theoretical Hedge Ratio



Notes: Theoretical hedge ratio H^* in dependence of the debt ratio $\frac{D}{V}$ and probability of default PD. The black points highlight the obtained values H_j^* based on the observations as of 2015 from the dataset.

B.3 Correlation Matrix

Table B.1: Correlation Matrix

	Notionals	MV	$Notionals_{Debt}$	Debt ratio	Interest coverage ratio	Profitability	Short-term liquidity	Size	FDC
MV	0.642***	1							
	(14.960)								
$Notionals_{Debt}$	0.915***	0.601***	1						
	(40.516)	(13.417)							
Debt ratio	0.082	0.065	-0.145***	1					
	(1.478)	(1.169)	(-2.617)						
Inte. cov. ratio	-0.089	-0.091	0.010	-0.424***	1				
	(-1.590)	(-1.633)	(0.171)	(-8.357)					
Profitability	-0.087	-0.048	-0.039	-0.287***	0.564***	1			
	(-1.556)	(-0.866)	(-0.697)	(-5.348)	(12.205)				
Short-term liqu.	-0.051	-0.022	0.121**	-0.486***	0.499***	0.423***	1		
	(-0.913)	(-0.393)	(2.169)	(-9.927)	(10.281)	(8.331)			
Size	-0.403***	-0.238***	-0.359***	-0.109*	0.146***	-0.016	0.003	1	
	(-7.874)	(-4.378)	(-6.873)	(-1.958)	(2.634)	(-0.289)	(0.047)		
FDC	-0.300***	-0.145***	-0.253***	-0.232***	0.042	0.065	0.019	0.736***	1
	(-5.607)	(-2.616)	(-4.661)	(-4.259)	(0.752)	(1.171)	(0.340)	(19.392)	
H	0.221***	0.190***	0.029	0.653***	-0.487***	-0.469***	-0.457***	-0.147***	-0.113**
	(4.057)	(3.452)	(0.524)	(15.391)	(-9.958)	(-9.491)	(-9.177)	(-2.662)	(-2.035)

Notes: Table B.1 shows the Pearson correlation coefficients of the dependent and independent variables. Below the coefficients the t-statistics are given in parentheses. Notionals respectively $Notionals_{Debt}$ is the sum of gross notional values of derivative contracts held by the company over book value of total assets respectively liabilities. MV is the sum of absolute fair values of derivative contracts held by the company over book value of total assets. Debt ratio is defined as book value of liabilities over total assets. Interest coverage ratio is calculated as operating income over interest expenses and Profitability as operating income over sales. Short-term liquidity denotes cash and cash equivalents over book value of liabilities. Size is measured as the natural logarithm of book value of total assets. FDC is the absolute amount of expected financial distress costs and H the theoretical hedge ratio comprising marginal benefits of FDC reduction through hedging as constructed in Section 6.2.

B.4 Industry Distribution

Table B.2: Industry Distribution of the Dataset

Industry sector	Absolute	Relative (%)
Consumer NonDurables	62	19.31
Consumer Durables	10	3.12
Manufacturing	97	30.22
Oil, Gas, and Coal	0	0.00
Chemicals	12	3.74
Business Equipment	1	0.31
Telephone and Television	0	0.00
Utilities	2	0.62
Wholesale, Retail, and Some Services	102	31.78
Healthcare, Medical Equipment, and Drugs	0	0.00
Money Finance	0	0.00
Other	35	10.90

Notes: Table B.2 shows the industry distribution of the dataset. Originally, firms were classified by the German "WZ2008" code, which we mapped to Fama French 12 industry classes obtained from Kenneth French's homepage using three crosswalks, namely WZ2008 to ISIC Rev. 4, ISIC Rev. 4 to NAICS 2017 and NAICS 2017 to SIC. We checked each mapping to avoid unreasonable mappings.

Bibliography

Allayannis, G., J. Ihrig, and J. P. Weston (2001). Exchange-rate hedging: Financial versus operational strategies. *American Economic Review 91*(2), 391–395.

Allayannis, G. and J. P. Weston (2001). The use of foreign currency derivatives and firm market value. *Review of Financial Studies 14*(1), 243–276.

Alvarez-Ramirez, J., E. Rodriguez, and C. Ibarra-Valdez (2018). Long-range correlations and asymmetry in the Bitcoin market. *Physica A: Statistical Mechanics and its Applications 492*, 948–955.

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets 5*(1), 31–56.

Ammann, M. and M. Verhofen (2007). Prior performance and risk-taking of mutual fund managers: A dynamic bayesian network approach. *Journal of Behavioral Finance 8*(1), 20–34.

Ammann, M. and M. Verhofen (2009). The impact of prior performance on the risk-taking of mutual fund managers. *Annals of Finance 5*(1), 69–90.

Andersen, T. G. and T. Bollerslev (1998). Answering the Skeptics: Yes, Standard Volatility Models do Provide Accurate Forecasts. *International Economic Review 39*(4), 885.

Andersen, T. G., T. Bollerslev, F. X. Diebold, and H. Ebens (2001). The distribution of realized stock return volatility. *Journal of Financial Economics 61*(1), 43–76.

Andersen, T. G., D. Dobrev, and E. Schaumburg (2012). Jump-robust volatility estimation using nearest neighbor truncation. *Journal of Econometrics 169*(1), 75–93.

Aretz, K. and S. M. Bartram (2010). Corporate hedging and shareholder value. *Journal of Financial Research 33*(4), 317–371.

Bachelier, L. (1900). Théorie de la spéculation. In *Annales scientifiques de l'École normale supérieure*, Volume 17, pp. 21–86.

Bär, M., A. Kempf, and S. Ruenzi (2010). Is a team different from the sum of its parts? Evidence from mutual fund managers. *Review of Finance 15*(2), 359–396.

Bariviera, A. F. (2017). The inefficiency of Bitcoin revisited: A dynamic approach. *Economics Letters 161*, 1–4.

Bariviera, A. F., M. J. Basgall, W. Hasperué, and M. Naiouf (2017). Some stylized facts of the Bitcoin market. *Physica A: Statistical Mechanics and its Applications 484*, 82–90.

Barndorff-Nielsen, O. E. and N. Shephard (2002). Econometric Analysis of Realized Volatility and Its Use in Estimating Stochastic Volatility Models. *Journal of the Royal Statistical Society. Series B (Statistical Methodology) 64*(2), 253–280.

Bartels, R. (1982). The rank version of von Neumann's ratio test for randomness. *Journal of the American Statistical Association 77*(377), 40–46.

Bartram, S. M. (2000). Corporate risk management as a lever for shareholder value creation. *Financial Markets, Institutions & Instruments 9*(5), 279–324.

Bartram, S. M. (2019). Corporate hedging and speculation with derivatives. *Journal of Corporate Finance 57*, 9–34.

Bartram, S. M., G. W. Brown, and J. Conrad (2011). The effects of derivatives on firm risk and value. *Journal of Financial and Quantitative Analysis 46*(4), 967–999.

Bartram, S. M., G. W. Brown, and F. R. Fehle (2009). International evidence on financial derivatives usage. *Financial Management 38*(1), 185–206.

Bartram, S. M., G. W. Brown, and B. A. Minton (2010). Resolving the exposure puzzle: The many facets of exchange rate exposure. *Journal of Financial Economics 95*(2), 148–173.

BdF (2016). Die wichtigsten Steuern im internationalen Vergleich 2015. Technical report, Federal Ministry of Finance.

Beier, R. and M. Bade (2017). MFI interest rate statistics Data Report 2017-06. Technical report, Deutsche Bundesbank.

Berk, J. B. and R. C. Green (2004). Mutual fund flows and performance in rational markets. *Journal of Political Economy 112*(6), 1269–1295.

Berkman, H. and M. E. Bradbury (1996). Empirical evidence on the corporate use of derivatives. *Financial Management*, 5–13.

Black, F. and M. Scholes (1973). The pricing of options and corporate liabilities. *Journal of Political Economy 81*(3), 637–654.

Bodnar, G. M. and G. Gebhardt (1999). Derivatives usage in risk management by US and German non-financial firms: A comparative survey. *Journal of International Financial Management & Accounting 10*(3), 153–187.

Boehmer, E. and E. K. Kelley (2009). Institutional investors and the informational efficiency of prices. *Review of Financial Studies 22*(9), 3563–3594.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics 31*(3), 307–327.

Bolton, P., M. Dewatripont, et al. (2005). *Contract theory.*

Borokhovich, K. A., K. R. Brunarski, C. E. Crutchley, and B. J. Simkins (2004). Board composition and corporate use of interest rate derivatives. *Journal of Financial Research 27*(2), 199–216.

Bouri, E., P. Molnár, G. Azzi, D. Roubaud, and L. I. Hagfors (2017). On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier? *Finance Research Letters 20*, 192–198.

Box, G. E. and G. C. Tiao (2011). *Bayesian inference in statistical analysis*, Volume 40. John Wiley & Sons.

Bradley, M., G. A. Jarrell, and E. Kim (1984). On the existence of an optimal capital structure: Theory and evidence. *Journal of Finance 39*(3), 857–878.

Brauneis, A. and R. Mestel (2018). Price discovery of cryptocurrencies: Bitcoin and beyond. *Economics Letters 165*, 58–61.

Brennan, M. J. and E. S. Schwartz (1978). Corporate income taxes, valuation, and the problem of optimal capital structure. *Journal of Business*, 103–114.

Brock, W. A., D. A. Hsieh, and B. D. LeBaron (1991). Nonlinear Dynamics, Chaos, and Instability: Statistical Theory and Economic Evidence.

Brock, W. A., J. A. Scheinkman, W. D. Dechert, and B. LeBaron (1996). A Test for Independence on the Correlation Dimension. *Econometrics Reviews 15*(3), 197–235.

Brown, K. C., W. Harlow, L. T. Starks, et al. (1996). Of Tournaments and Temptations: An Analysis of Managerial Incentives in the Mutual Fund Industry. *Journal of Finance 51*(1), 85–110.

Busse, J. A. (2001). Another look at mutual fund tournaments. *Journal of Financial and Quantitative Analysis 36*(1), 53–73.

Carroll, A., F. O'Brien, and J. Ryan (2017). An examination of European firms' derivatives usage: the importance of model selection. *European Financial Management 23*(4), 648–690.

Castanias, R. (1983). Bankruptcy risk and optimal capital structure. *Journal of Finance 38*(5), 1617–1635.

Charles, A., O. Darné, and J. H. Kim (2011). Small sample properties of alternative tests for martingale difference hypothesis. *Economics Letters 110*(2), 151–154.

Cheah, E.-T. and J. Fry (2015). Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin. *Economics Letters 130*, 32–36.

Chen, J. and T.-H. D. King (2014). Corporate hedging and the cost of debt. *Journal of Corporate Finance 29*, 221–245.

Cheung, A. W. K., E. Roca, and J. J. Su (2015). Crypto-currency bubbles: An application of the Phillips–Shi–Yu (2013) methodology on Mt. Gox bitcoin prices. *Applied Economics 47*(23), 2348–2358.

Chevalier, J. and G. Ellison (1997). Risk taking by mutual funds as a response to incentives. *Journal of Political Economy 105*(6), 1167–1200.

Choi, J. J., C. X. Mao, and A. D. Upadhyay (2013). Corporate risk management under information asymmetry. *Journal of Business Finance & Accounting 40*(1-2), 239–271.

Chu, J., S. Chan, S. Nadarajah, and J. Osterrieder (2017). GARCH Modeling of Cryptocurrencies. *Journal of Risk and Financial Management 10*(17).

Corbet, S., B. Lucey, and L. Yarovaya (2018). Datestamping the Bitcoin and Ethereum bubbles. *Finance Research Letters 26*, 81–88.

Corwin, S. A. and P. Schultz (2012). A simple way to estimate bid-ask spreads from daily high and low prices. *Journal of Finance 67*(2), 719–760.

Cox, J. C. and M. Rubinstein (1985). *Options markets.* Prentice Hall.

De Bondt, W. F. and R. H. Thaler (1995). Financial decision-making in markets and firms: A behavioral perspective. *Handbooks in Operations Research and Management Science 9*, 385–410.

Deli, D. N. (2002). Mutual Fund Advisory Contracts: An Empirical Investigation. *Journal of Finance*, 109–133.

Delignieres, D., S. Ramdani, L. Lemoine, K. Torre, M. Fortes, and G. Ninot (2006). Fractal analyses for 'short' time series: A re-assessment of classical methods. *Journal of Mathematical Psychology 50*(6), 525–544.

Deriche, M. and A. H. Tewfik (1993). Maximum Likelihood Estimation of the Parameters of Discrete Fractionally Differenced Gaussian Noise Process. *IEEE Transactions on Signal Processing 41*(10), 2977–2989.

Diebold, F. X. and R. S. Mariano (1995). Comparing Predicitve accuracy. *Source: Journal of Business & Economic Statistics 13*(3), 253–263.

Durlauf, S. N. (1991). Spectral based testing of the martingale hypothesis. *Journal of Econometrics 50*(3), 355–376.

Dyhrberg, A. H. (2016a). Bitcoin, gold and the dollar - A GARCH volatility analysis. *Finance Research Letters*.

Dyhrberg, A. H. (2016b). Hedging capabilities of bitcoin. Is it the virtual gold? *Finance Research Letters 16*, 139–144.

Eling, M. and F. Schuhmacher (2007). Does the choice of performance measure influence the evaluation of hedge funds? *Journal of Banking & Finance 31*(9), 2632–2647.

Engelmann, B. and R. Rauhmeier (2006). *The Basel II risk parameters: Estimation, validation, and stress testing*. Springer Science & Business Media.

Escanciano, J. C. and I. N. Lobato (2009). An automatic Portmanteau test for serial correlation. *Journal of Econometrics 151*(2), 140–149.

Escanciano, J. C. and C. Velasco (2006). Generalized spectral tests for the martingale difference hypothesis. *Journal of Econometrics 134*(1), 151–185.

Fama, E. F. (1965). The behavior of stock-market prices. *Journal of Business 38*(1), 34–105.

Fama, E. F. (1970). Efficient Capital Markets : A Review of Theory and Empirical. *Journal of Finance 25*(2), 383–417.

Fama, E. F. (1991). Efficient capital markets: II. *Journal of Finance 46*(5), 1575–1617.

Foley, S., J. R. Karlsen, and T. J. Putniņš (2019). Sex, drugs, and bitcoin: How much illegal activity is financed through cryptocurrencies? *Review of Financial Studies 32*(5), 1798–1853.

Gay, G. D. and J. Nam (1998). The underinvestment problem and corporate derivatives use. *Financial Management*, 53–69.

Géczy, C., B. A. Minton, and C. Schrand (1997). Why firms use currency derivatives. *Journal of Finance 52*(4), 1323–1354.

Glaum, M. (2002). The determinants of selective exchange risk management–evidence from German non-financial corporations. *Journal of Applied Corporate Finance 14*(4), 108–121.

Glover, B. (2016). The expected cost of default. *Journal of Financial Economics 119*(2), 284–299.

Graham, J. R. and D. A. Rogers (2002). Do firms hedge in response to tax incentives? *Journal of Finance 57*(2), 815–839.

Graham, J. R. and C. W. Smith (1999). Tax incentives to hedge. *Journal of Finance 54*(6), 2241–2262.

Gruber, M. J. and J. B. Warner (1977). Bankruptcy costs: Some evidence. *Journal of Finance 32*(2), 337–347.

Guay, W. and S. P. Kothari (2003). How much do firms hedge with derivatives? *Journal of Financial Economics 70*(3), 423–461.

Hahnenstein, L., G. Köchling, , and P. N. Posch (2020). Do firms hedge in order to avoid financial distress costs? New empirical evidence using bank data. *Journal of Business Finance & Accounting.*

Hahnenstein, L. and K. Röder (2007). Who hedges more when leverage is endogenous? A testable theory of corporate risk management under general distributional conditions. *Review of Quantitative Finance and Accounting 28*(4), 353–391.

Hansen, P. R. (2005). A test for superior predictive ability. *Journal of Business and Economic Statistics 23*(4), 365–380.

Hansen, P. R., Lunde Asgar, and Nason James M. (2011). The Model Confidence Set. *Econometrica 79*(2), 453–497.

Harhoff, D. and T. Körting (1998). Lending relationships in Germany–Empirical evidence from survey data. *Journal of Banking & Finance 22*(10), 1317–1353.

Henschel, T. (2006). Risk management practices in German SMEs: An empirical investigation. *International Journal of Entrepreneurship and Small Business 3*(5), 554–571.

Henschel, T. (2010). Typology of risk management practices: An empirical investigation into German SMEs. *International Journal of Entrepreneurship and Small Business 9*(3), 264–294.

Hentschel, L. and S. P. Kothari (2001). Are corporations reducing or taking risks with derivatives? *Journal of Financial and Quantitative Analysis 36*(1), 93–118.

Herbrich, R., T. Minka, and T. Graepel (2006). TrueSkill™: A Bayesian skill rating system. In *Proceedings of the 19th International Conference on Neural Information Processing Systems*, pp. 569–576. MIT Press.

Höse, S., S. Huschens, and R. Wania (2009). Rating migrations. In *Applied Quantitative Finance*, pp. 105–123. Springer.

Hou, K. and T. J. Moskowitz (2005). Market Frictions, Price Delay, and the Cross-Section of Expected Returns. *Review of Financial Studies 18*(3), 981–1020.

Howton, S. D. and S. B. Perfect (1998). Currency and interest-rate derivatives use in US firms. *Financial Management*, 111–121.

Hurst, H. E. (1951). Long term storage capacities of reservoirs. *Trans. Am. Soc. Civ. Eng. 116*, 776–808.

Jiang, Y., H. Nie, and W. Ruan (2018). Time-varying long-term memory in Bitcoin market. *Finance Research Letters 25*, 280–284.

Judge, A. (2006). Why and how UK firms hedge. *European Financial Management 12*(3), 407–441.

Kale, J. R. and T. H. Noe (1990). Corporate hedging under personal and corporate taxation. *Managerial and Decision Economics 11*(3), 199–205.

Kale, J. R., T. H. Noe, and G. G. Ramirez (1991). The effect of business risk on corporate capital structure: Theory and evidence. *Journal of Finance 46*(5), 1693–1715.

Katsiampa, P. (2017). Volatility estimation for Bitcoin: A comparison of GARCH models. *Economics Letters 158*, 3–6.

Kempf, A. and S. Ruenzi (2008a). Family matters: rankings within fund families and fund inflows. *Journal of Business Finance & Accounting 35*(1-2), 177–199.

Kempf, A. and S. Ruenzi (2008b). Tournaments in mutual-fund families. *Review of Financial Studies 21*(2), 1013–1036.

Kempf, A., S. Ruenzi, and T. Thiele (2009). Employment risk, compensation incentives, and managerial risk taking: Evidence from the mutual fund industry. *Journal of Financial Economics 92*(1), 92–108.

Khuntia, S. and J. K. Pattanayak (2018). Adaptive market hypothesis and evolving predictability of Bitcoin. *Economics Letters 167*, 26–28.

Kim, J. H. (2009). Automatic variance ratio test under conditional heteroskedasticity. *Finance Research Letters 6*(3), 179–185.

Köchling, G., J. Müller, and P. N. Posch (2019a). Does the introduction of futures improve the efficiency of Bitcoin? *Finance Research Letters 30*, 367–370.

Köchling, G., J. Müller, and P. N. Posch (2019b). Price delay and market frictions in cryptocurrency markets. *Economics Letters 174*, 39–41.

Köchling, G., P. Schmidtke, and P. N. Posch (2020). Volatility forecasting accuracy for Bitcoin. *Economics Letters 191*, 108836.

Kristoufek, L. (2018). On Bitcoin markets (in)efficiency and its evolution. *Physica A 503*(November 2017), 257–262.

Kschischang, F. R., B. J. Frey, and H.-A. Loeliger (2001). Factor graphs and the sum-product algorithm. *IEEE Transactions on Information Theory 47*(2), 498–519.

Lahmiri, S., S. Bekiros, and A. Salvi (2018). Long-range memory, distributional variation and randomness of bitcoin volatility. *Chaos, Solitons and Fractals 107*, 43–48.

Laurent, S., J. V. Rombouts, and F. Violante (2012). On the forecasting accuracy of multivariate GARCH models. *Journal of Applied Econometrics 27*(6), 934–955.

Lel, U. (2012). Currency hedging and corporate governance: A cross-country analysis. *Journal of Corporate Finance 18*(2), 221–237.

Leland, H. E. (1998). Agency costs, risk management, and capital structure. *Journal of Finance 53*(4), 1213–1243.

Lewis, J. B. and D. A. Linzer (2005). Estimating regression models in which the dependent variable is based on estimates. *Political Analysis 13*(4), 345–364.

Ley, C., G. Reinert, Y. Swan, et al. (2017). Distances between nested densities and a measure of the impact of the prior in Bayesian statistics. *The Annals of Applied Probability 27*(1), 216–241.

Ljung, G. and G. Box (1978). On a measure of lack of fit in time-series models. *Biometrika 65*(2), 297.

Machauer, A. and M. Weber (2000). Number of bank relationships: An indicator of competition, borrower quality, or just size? Technical report, CFS Working Paper.

Mandelbrot, B. (1963). The Variation of Certain Speculative Prices. *Journal of Business 36*(4), 394–419.

Marsden, A. and A. K. Prevost (2005). Derivatives use, corporate governance, and legislative change: An empirical analysis of New Zealand listed companies. *Journal of Business Finance & Accounting 32*(1-2), 255–295.

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *Journal of Finance 29*(2), 449–470.

Mian, S. L. (1996). Evidence on corporate hedging policy. *Journal of Financial and Quantitative Analysis 31*(3), 419–439.

Microsoft Research (2005). TrueSkill Ranking System.

Modigliani, F. and M. H. Miller (1958). The cost of capital, corporation finance and the theory of investment. *The American economic review 48*(3), 261–297.

Nadarajah, S. and J. Chu (2017). On the inefficiency of Bitcoin. *Economics Letters 150*, 6–9.

Nance, D. R., C. W. Smith, and C. W. Smithson (1993). On the determinants of corporate hedging. *Journal of Finance 48*(1), 267–284.

Nanda, V., Z. J. Wang, and L. Zheng (2004). Family values and the star phenomenon: Strategies of mutual fund families. *Review of Financial Studies 17*(3), 667–698.

Ongena, S. and D. C. Smith (2000). What determines the number of bank relationships? Cross-country evidence. *Journal of Financial Intermediation 9*(1), 26–56.

Patton, A. J. (2011). Volatility forecast comparison using imperfect volatility proxies. *Journal of Econometrics 160*(1), 246–256.

Pilgram, B. and D. T. Kaplan (1998). A comparison of estimators for 1/f noise. *Physica D 114*, 108–122.

Prevost, A. K., L. C. Rose, and G. Miller (2000). Derivatives usage and financial risk management in large and small economies: A comparative analysis. *Journal of Business Finance & Accounting 27*(5-6), 733–759.

Puetz, A. and S. Ruenzi (2011). Overconfidence among professional investors: Evidence from mutual fund managers. *Journal of Business Finance & Accounting 38*(5-6), 684–712.

Quiggin, J. (2013). The Bitcoin Bubble and a Bad Hypothesis. *The National Interest*.

Ross, M. P. (1996). *Corporate hedging: What, why and how?* Working paper, University of California, Berkeley.

Rubinstein, M. and E. Reiner (1991). Unscrambling the binary code. *Risk Magazine 4*(9), 20.

Saffi, P. A. C. and K. Sigurdsson (2011). Price Efficiency and Short Selling. *Review of Financial Studies 24*(3), 821–852.

Sirri, E. R. and P. Tufano (1998). Costly search and mutual fund flows. *Journal of Finance 53*(5), 1589–1622.

Smith, C. W. and R. M. Stulz (1985). The determinants of firms' hedging policies. *Journal of Financial and Quantitative Analysis 20*(4), 391–405.

Spanò, M. (2007). Managerial ownership and corporate hedging. *Journal of Business Finance & Accounting 34*(7-8), 1245–1280.

Swade, A., G. Köchling, and P. N. Posch (2021). Managerial behavior in fund tournaments—the impact of TrueSkill. *Journal of Asset Management*, 1–14.

Taylor, J. (2003). Risk-taking behavior in mutual fund tournaments. *Journal of Economic Behavior & Organization 50*(3), 373–383.

Taylor, S. E. and J. D. Brown (1988). Illusion and well-being: A social psychological perspective on mental health. *Psychological Bulletin 103*(2), 193.

Tiwari, A. K., R. Jana, D. Das, and D. Roubaud (2018). Informational efficiency of Bitcoin—An extension. *Economics Letters 163*, 106–109.

Troster, V., A. K. Tiwari, M. Shahbaz, and D. N. Macedo (2018). Bitcoin returns and risk: A general GARCH and GAS analysis. *Finance Research Letters*.

Urquhart, A. (2016). The inefficiency of Bitcoin. *Economics Letters 148*, 80–82.

Urquhart, A. (2017). Price clustering in Bitcoin. *Economics Letters 159*, 145–148.

Vidal-Tomás, D. and A. Ibañez (2018). Semi-strong efficiency of Bitcoin. *Finance Research Letters*.

Wald, A. and J. Wolfowitz (1940). On a Test Whether Two Samples are from the Same Population. *The Annals of Mathematical Statistics 11*(2), 147–162.

Wei, W. C. (2018). Liquidity and market efficiency in cryptocurrencies. *Economics Letters 168*, 21–24.

West, K. D. (1996). Asymptotic Inference about Predictive Ability. *Econometrica 64*(5), 1067 – 1084.

White, H. (2000). A Reality Check for Data Snooping. *Econometrica 68*(5), 1097–1126.