Essays on Portfolio- and Bank-Management

Wissenschaftliche Arbeit zur Erlangung des Grades
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Vorwort

Es gibt viele Menschen, denen ich zum Dank verpflichtet bin. Die sich anschließende Liste erhebt nicht den Anspruch auf Vollständigkeit.

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Non-technical Summary

This cumulative dissertation is a collection of three independent research papers, all of which have been presented on conferences with refereed programs, and are under review of international journals. The papers were written during October 2007 to September 2011 at the University of Konstanz. Two papers are on trading strategies and portfolio optimization, respectively. The paper *Does Portfolio Optimization Pay?* analyzes static portfolio policies and demonstrates by simulations that a simple approximation of the optimal portfolio performs very well compared to the optimal portfolio. The paper *Mechanically Evaluated Company News* analyses the impact of company news on the financial market and the profitability of dynamic portfolio strategies based on company news. The third paper, *Leverage, Profitability and Risk of Banks*, is motivated by the regulatory reforms in the aftermath of the financial crisis. It relates risk and profitability of banks to the leverage ratio. In the following three paragraphs, I briefly describe the methodologies and the main results of each paper.

Chapter 1, *Does Portfolio Optimization Pay?*, is joint work with Günter Franke. The structure of the optimal, risky portfolio of a rational investor with hyperbolic absolute risk aversion is entirely governed by the exponent in her utility function. Hence, the optimal portfolio is described by two decisions, the structure of the risky portfolio and the wealth allocated to the risky portfolio and to the risk-free asset, respectively. This is known as two-fund-separation. We show that a simple approximation of the optimal portfolio reduces the certainty equivalent only to a very small extent, if there are no approximate arbitrage opportunities in the market. Without loss of generality, let us consider constant relative risk aversion. All investors have the same initial endowment. Then, we use the structure of the optimal risky portfolio of an investor with low relative risk aversion ϕ as an approximation for the structure of the optimal risky portfolio of investors with higher relative risk aversion γ, $\gamma \geq \phi$. Therefore, the structure of the approximate risky portfolio is the same for all investors, even though the exponents in the utility functions might differ. To approximate the optimal allocation of capital to the risky portfolio, we scale the risky portfolio of the ϕ-investor by the ratio of relative risk aversions, i.e. ϕ/γ. Overall, the certainty equivalent is almost insensitive if we replace the optimal portfolio by the approximation. Hence, we extend the two-fund-separation heuristically. Furthermore, the approximation portfolio might be more robust to changes in the return distribution and to parameter uncertainty than the optimal portfolio. These results have important implications for the fund and asset management industry. Even though the customers of an asset management company might differ with respect to their exponent in the utility function, it might be sufficient for the asset management company to offer only one risky fund. This might reduce costs significantly. Also in markets with strong parameter uncertainty, exact portfolio optimization does not appear to pay.

In Chapter 2, *Mechanically Evaluated Company News*, I shed light on the question how investors respond to information on corporations. I consider 62 companies listed in the S&P500 with liquid stock option and credit derivative markets. The information flow about these companies is measured by Reuters company news. This hand-collected dataset is mechanically analyzed with the 'General Inquirer' dictionary considering the word categories 'positive', 'negative', 'strong' and 'weak'. Given a company, a news story is reduced to a numerical value, called sentiment. The variation in the sentiment among company news within one trading day is called disagreement. I estimate a vector autoregressive model to relate sentiment and disagreement to the financial market, i.e. stock return, option implied volatility, stock and option trading volume and the CDS spread. The model is estimated company-specifically and also jointly for all companies. In both settings, the estimated relationships between news and the financial market are consistent with market microstructure models where investors observe public signals and interpret them individually, i.e. strong positive and negative sentiment and high disagreement are associated with high trading volume. I further find that stock returns and CDS spreads are correlated with sentiment and disagreement. Moreover, stock markets appear to be not fully efficient with respect to information in news articles. Sentiment and disagreement predict stock returns at the following day. The economic relevance of this pattern is tested with trading strategies. Simple, dynamic trading strategies that invest in a stock given 'good' company news, and short-sell the stock given 'bad' news are comparable to approximate arbitrage opportunities even in the presence of realistic transaction costs.

In Chapter 3, *Leverage, Profitability and Risk of Banks*, I analyze market prices and balance sheets of European and U.S. banks. This analysis is motivated by the financial crisis and the ensuing regulatory reforms, especially the implementation of an upper limit on the non-risk weighted leverage ratio in Europe. Since the non-risk weighted capital structure of U.S. banks was already capped, different relationships between profitability, risk and the leverage ratio for U.S. and European banks might allow predicting effects of an upper limit on the leverage ratio for European banks. First, I investigate the speed of adjustment in the leverage ratio and find that it is faster for U.S. banks than for European banks. Compared to the literature on industrial corporations, U.S. banks have a significantly higher speed of adjustment. The adjustment speed of European banks is similar to that of industrial corporations. The restriction on the capital structure might force U.S. banks to adjust their capital structure faster. Second, I find that profitability and risk-adjusted profitability of banks is, on average, maximized for some interior leverage ratio, i.e. profitability and risk-adjusted profitability increase with the leverage ratio up to critical thresholds and then declines. This finding is robust and, for European banks, the decrease in profitability appears to be very strong if the leverage ratio exceeds the threshold. CDS spreads of European banks indicate that the decrease in profitability and risk-adjusted profitability is predominantly caused by a strong increase in expected default frequencies. However, the CDS spreads of U.S. banks appear to be not related to leverage. This might be due to the upper cap on the leverage ratio in the United States. The findings of this analysis are important for bank owners and the regulator. If the owners of a bank maximize profitability, high and low leverage ratios might not be optimal. Also, since CDS spreads might be positively correlated with systemic risk, an upper limit on the non-risk weighted leverage ratio might be an efficient tool for the regulator to restrict systemic risk.

Nichttechnische Zusammenfassung

Die vorliegende Dissertation besteht aus drei unabhängigen Forschungsarbeiten, die alle auf begutachteten Konferenzen vorgetragen wurden, und die sich im Begutachtungsprozess bei internationalen Fachzeitschriften befinden. Die Arbeiten entstanden zwischen Oktober 2007 und September 2011 an der Universität Konstanz. Das erste Papier, *Does Portfolio Optimization Pay?*, untersucht anhand von Simulationen eine einfache Approximation des optimalen Portfolios eines Investors mit hyperbolischer absoluter Risikoaversion, das zweite Papier, *Mechanically Evaluated Company News*, testet unter anderem dynamische Handelsstrategien, die auf der Analyse von Unternehmensnachrichten basieren. Im dritten Papier, *Leverage, Profitability and Risk of Banks*, untersuche ich den Zusammenhang von Risiko, Profitabilität und dem Verschuldungsgrad bei amerikanischen und europäischen Banken. Im Folgenden beschreibe ich kurz das Vorgehen in den Papieren und deren wichtigsten Ergebnisse.

Kapitel 1, *Does Portfolio Optimization Pay?*, ist gemeinsam mit Günter Franke verfasst. Die Struktur des optimalen, riskanten Portfolios eines rationalen Investors mit hyperbolischer absoluter Risikoaversion wird vom Exponenten in der Nutzenfunktion bestimmt. Das optimale Portfolio kann folglich durch zwei Entscheidungen beschrieben werden, der Struktur des riskanten Portfolios und der Aufteilung des Vermögens zwischen dem riskanten Portfolio und der risikofreien Anlage. Dieses Prinzip wird Zwei-Fonds-Separation genannt. Für Märkte ohne approximative Arbitrage entwickeln wir eine einfache Approximation für das optimale Portfolio, die nur einen unbedeutenden Rückgang im Sicherheitsäquivalent des Investors verursacht. Ohne Beschränkung der Allgemeinheit betrachten wir den Fall konstanter relativer Risikoaversion. Alle Investoren haben die gleiche Anfangsausstattung. Wir nehmen die Struktur des optimalen Portfolios eines Investors mit niedriger konstanter relativer Risikoaversion, ϕ, als Approximation für die Struktur des optimalen, riskanten Portfolios von Investoren mit höherer relativer Risikoaversion, γ, $\gamma \geq \phi$. Die Approximation der optimalen Struktur ist somit unabhängig von der Nutzenfunktion des Investors. Um die Größe des optimalen, riskanten Portfolio zu approximieren, skalieren wir das optimale riskante Portfolio des ϕ-Investors mit dem Quotienten der relativen Risikoaversionen, d.h. ϕ/γ. Das Sicherheitsäquivalent des γ-Investors bleibt fast unverändert, falls das optimale Portfolio durch die Approximation ersetzt wird. Dieses Resultat erweitert die Zwei-Fonds-Separation heuristisch. Ferner ist die Approximation robust gegen Änderungen der Wahrscheinlichkeitsverteilung der Renditen und gegen Parameterunsicherheit. Diese Resultate haben weitreichende Implikationen für das praktische Portfolio- und Fondsmanagement. Ein Fondsmanager mit Kunden, die sich bezüglich ihrer Risikoaversion unterscheiden, benötigt keinen individuellen riskanten Fonds für jeden Investor. Dies kann die Kosten für das Fondsmanagement signifikant reduzieren. Des Weiteren lohnt sich in Märkten mit hoher Unsicherheit bezüglich der Verteilung der Renditen eine exakte Portfolio Optimierung oft nicht.

In Kapitel 2, *Mechanically Evaluated Company News*, untersuche ich den Einfluss von Unternehmensnachrichten auf den Finanzmarkt. Ich betrachte 62 Unternehmen aus dem S&P500, die einen liquiden Options- und CDS Markt haben. Meine selbst erstellte Datenbank mit Unternehmensnachrichten von Reuters wird mit dem 'General Inquirer' Lexikon ausgewertet. Die Wortkategorien 'positiv', 'negativ', 'stark' und 'schwach' werden benutzt, um durch Nachrichten das Sentiment für ein Unternehmen zu messen. Die Variation des Sentiments von Unternehmensnachrichten an einem Handelstag bezeichne ich als Disagreement. Der Einfluss von Sentiment und Disagreement auf den Finanzmarkt wird mittels eines vektor-autoregressiven Modells ermittelt. Dieses Modell wird sowohl für jedes Unternehmen einzeln, als auch für alle Unternehmen gemeinsam geschätzt. Beide Vorgehensweisen zeigen, dass Sentiment und Disagreement stark mit Aktienrenditen, der Volatilität, Handelsvolumen in Aktien und Optionen, und dem CDS Spread, korreliert sind. Die Ergebnisse bestätigen Modelle zur Marktstruktur und zur Informationsverarbeitung von Investoren, in welchen Investoren öffentliche Signale beobachten und diese individuell interpretieren. Eine weitere Beobachtung ist, dass die Finanzmärkte nicht vollständig effizient erscheinen. Sentiment und Disagreement prognostizieren Aktienrenditen am folgenden Handelstag. Die ökonomische Relevanz dieser Beobachtung wird mit einfachen, dynamischen Handelsstrategien getestet. Aktien werden gekauft, nachdem positive Nachrichten publiziert wurden, und werden leerverkauft, wenn negative Nachrichten publiziert wurden. Die Renditen solcher Strategien sind vergleichbar zu denen bei approximativer Arbitrage, selbst unter Berücksichtigung von Transaktionskosten.

In Kapitel 3, *Leverage, Profitability and Risk of Banks*, analysiere ich Markt- und Bilanzdaten von amerikanischen und europäischen Banken. Die Untersuchung ist unter anderem durch die Finanzmarktkrise und die angekündigten Änderungen in der Bankregulierung in Europa, speziell der Beschränkung des nicht risiko-gewichteten Verschuldungsgrads, motiviert. Da der Verschuldungsgrad von U.S. Banken bereits einer Obergrenze unterliegt, ermöglicht ein Vergleich der Ergebnisse für U.S. und europäische Banken mögliche Konsequenzen einer Obergrenze für europäische Banken abzuschätzen. Als erstes bestimme ich die Anpassungsgeschwindigkeit des Verschuldungsgrads. Europäische Banken adjustieren den Verschuldungsgrad langsamer als amerikanische Banken. Verglichen mit Ergebnissen aus der Literatur über Industrieunternehmen ist die Geschwindigkeit der Adjustierung von amerikanischen Banken deutlich höher, die von europäischen Banken ist auf ähnlichem Niveau. Des Weiteren steigt die (risikoangepasste) Profitabilität zunächst mit dem Verschuldungsgrad bis zu einem kritischen Wert und fällt danach. Dieser Zusammenhang ist robust und für europäische Banken stark ausgeprägt. Eine Analyse der CDS Spreads belegt, dass europäische Banken mit hohem Verschuldungsgrad auch einen hohen CDS Spread haben. Dies deutet an, dass der schnelle Rückgang der Profitabilität, falls der Verschuldungsgrad eine gewisse Grenze überschreitet, aus steigenden Ausfallwahrscheinlichkeiten resultiert, die nicht durch Steuervorteile kompensiert werden. Dieser Zusammenhang wird nicht für amerikanische Banken gefunden und kann mit den Unterschieden in der Regulierung begründet werden. Die Resultate der Studie sind wichtig für die Gesellschafter einer Bank und für den Regulator. Falls die Gesellschafter die Rendite maximieren, ist der Verschuldungsgrad eine wichtige Determinante, und ein hoher und niedriger Verschuldungsgrad nicht optimal. Da CDS Spreads positiv mit systemischem Risiko korrelieren, kann eine Obergrenze für den Verschuldungsgrad das systemische Risiko senken.

Chapter 1

Does Portfolio Optimization Pay?[1]

Abstract: All HARA-utility investors with the same exponent invest in a single risky fund and the risk-free asset. In a continuous time-model stock proportions are proportional to the inverse local relative risk aversion of the investor ($1/\gamma$-rule). This paper analyzes the conditions under which the optimal buy and hold-portfolio of a HARA-investor can be approximated by the optimal portfolio of an investor with some low level of constant relative risk aversion using the $1/\gamma$-rule. It turns out that the approximation works very well in markets without approximate arbitrage opportunities. In markets with high equity premiums this approximation may be of low quality.

1.1 Introduction

Over the last decades a sophisticated theory of decision making under risk, based on the expected utility paradigm, has been developed. Following the seminal papers by Arrow (1974), Pratt (1964), Rothschild and Stiglitz (1970), Diamond and Stiglitz (1974), many papers showed how optimal decisions depend on the utility function. In finance, portfolio choice is perhaps the most important application of expected utility theory.

This paper argues that portfolio optimization often does not pay. It shows that in a large variety of market settings an investor with a HARA (hyperbolic absolute

[1]joint work with Günter Franke

risk aversion) - utility function may simply buy a given risky fund and the risk-free asset without noticeable effects on her expected utility. Our approach builds on two seminal papers. Cass and Stiglitz (1970) proved two fund-separation for any HARA-function given the exponent ϕ. We argue that, in the absence of approximate arbitrage opportunities, the same risky fund may be used by investors with higher exponents. To determine the proportion of wealth invested in the risky fund we build on Merton (1971). He showed that in a continuous-time model with i.i.d. asset returns the optimal instantaneous stock proportions of an investor are proportional to $1/\gamma$ with γ being the local relative risk aversion of the agent. We use the $1/\gamma$-rule as a rule of thumb for portfolio choice in our finite period setting. Instead of continuously adjusting the investment in the risky fund we assume a buy and hold-policy to restrain transaction costs. To analyze the quality of this simple portfolio policy, we derive the optimal portfolio for some HARA-investor with exponent ϕ and for another HARA-investor with a higher exponent γ and check how well the γ-optimal portfolio is approximated by the ϕ-optimal portfolio.

We measure the approximation quality by the approximation loss. This is defined as the relative increase in initial endowment required for the approximation portfolio to generate the same certainty equivalent as the optimal portfolio. If, for example, an initial endowment of 100 \$ is invested in the optimal portfolio and the approximation loss is 5%, then the investor needs to invest 105 \$ in the approximation portfolio to equalize the certainty equivalents of both portfolios.

The main findings of the paper can be summarized as follows. For a given market setting the approximation loss depends not only on γ and ϕ, but also on the elasticity of the pricing kernel, θ. To illustrate, assume a stock market such that the elasticity of the pricing kernel with respect to the market return is a constant θ. Investors buy/sell stocks and borrow/lend at the risk-free rate. According to the $1/\gamma$-rule, the γ-investor buys the optimal stock portfolio of the ϕ-investor, multiplied by γ/ϕ, without changing its structure. If $\gamma < \phi$, then the γ-investor invests more in stocks than the ϕ-investor. Hence the γ-investor may have to borrow at the risk-free rate. But then she may end up with negative terminal wealth which is infeasible. Hence, we require $\gamma \geq \phi$. We find a very small approximation loss for $\gamma \geq \phi \geq \theta$. Then the $1/\gamma$ -rule works very well. But we find possibly high approximation losses for $\theta \geq \gamma \geq \phi$ and for $\gamma \geq \theta \geq \phi$. Whenever the elasticity of the pricing kernel, θ, is much higher than ϕ, the ϕ-investor will be very aggressive in her risk taking. Her portfolio implies a high approximation loss for an investor whose relative risk aversion γ is clearly higher than ϕ. The γ-investor would be more conservative in her risk taking than the $1/\gamma$-rule suggests. Therefore this rule does a poor job. A market setting with a high pricing kernel elasticity implies a high equity premium, it also provides approximate arbitrage opportunities as defined by Bernardo and Ledoit (2000). If, however, γ is very large, then the γ-investor takes a very small risk anyway so that the approximation loss is rather small. Hence, the $1/\gamma$-rule works quite well when the equity premium is rather small, but it may be seriously misleading in case of a high equity premium.

Fortunately the problem of a high equity premium can be resolved by replacing the market return by a transformed market return with a low pricing kernel elasticity. Also, if the pricing kernel elasticity of the market return is not constant, a transformed market return with low constant pricing kernel elasticity can easily be derived. This transformed market return can be viewed as the payoff of a special exchange traded fund (ETF). Then the approximation portfolio invests in this ETF and the risk-free asset. The approximation loss is quite small then for a wide range of HARA-investors. This result also holds under parameter uncertainty. Thus, the approximation may be viewed as a generalization of the two-fund separation of Cass and Stiglitz (1970).

The practical relevance of our findings is easily illustrated. A portfolio manager has many different customers investing in different risky funds and the risk-free asset. Their preferences may be characterized by increasing, constant or declining relative risk aversion (RRA) and can be approximated by a HARA-function. The portfolio manager proceeds as follows. First, she derives the optimal portfolio for some low constant RRA ϕ. Second, she allocates the customer's initial endowment to the same portfolio and the risk-free asset, using the $1/\gamma$-rule for the risky investment and putting the rest in the risk-free asset. Hence, the allocations for different customers only differ by the amount invested in that risky portfolio and the amount invested risk-free. Also, if an investor manages her portfolio herself, she might not bother about the precise optimization of the risky fund, but use the same fund as other HARA-investors.

Our analysis refers to static portfolio choice. We do not address dynamic portfolio strategies, which may try to exploit predictability of asset returns. As a caveat, our results should not be applied to risk management, which focuses on tail risks. Our results are based on the certainty equivalent of portfolio payoffs covering the full distribution of payoffs.

The rest of the paper is organized as follows. Section 2 gives a literature review.

Section 3 and 4 describe the general approximation approach and the measurement of the approximation quality. Section 5 analyzes the approximation quality in a perfect market with a continuous state space and long investment horizons. In section 6, we consider a market with very few states. Section 7 concludes.

1.2 Literature Review

There is an extensive literature on portfolio choice. Hakansson (1970) derives the optimal portfolio for a HARA-investor in a complete market. Regarding dynamic strategies, Merton (1971) was one of the first to look into these strategies in a continuous time model. Later on, Karatzas et al. (1986) provide a rigorous mathematical treatment of these strategies. They pay attention, in particular, to non-negativity constraints for consumption. Viceira (2001) discusses dynamic strategies in the presence of uncertain labor income. He uses an approximation approach to derive a simplified strategy which, however, deviates very little in terms of the certainty equivalent from the optimal strategy. Other papers, for example, Balduzzi and Lynch (1999), Brandt et al. (2005), look for optimal strategies in the case of asset return predictability, Chacko and Viceira (2005) analyze the impact of stochastic volatility in incomplete markets. Brandt et al. (2009) derive optimal portfolios using stock characteristics like the firm's capitalization and book-to-market ratio.

Black and Littermann (1992) show that the optimal portfolio for a (μ, σ)-investor reacts very sensitively to changes in asset return parameters. Yet, the Sharpe-ratio may vary only little. Then an intensive discussion on shrinkage-models started. Recently, DeMiguel, Garlappi and Uppal (2009) compare several portfolio strategies to the simple $1/n$ strategy that gives equal weight to all risky investments. Using the certainty equivalent return for an investor with a quadratic utility function, the Sharpe-ratio and the turnover volume of each strategy, they find that no strategy consistently outperforms the $1/n$ strategy. In a related paper, DeMiguel, Garlappi, Nogales and Uppal (2009) solve for minimum-variance-portfolios under additional constraints. They find that a partial minimum-variance portfolio calibrated by optimizing the portfolio return in the previous period performs best out-of-sample. Jacobs, Müller and Weber (2009) compare various asset allocation strategies including stocks, bonds and commodities and find that a broad class of asset allocation strategies with fixed weights for the asset classes performs out-of-sample equally well in terms of the Sharpe-ratio as long as strong diversification is maintained. Hodder, Jackwerth and Kolokolova (2009) find that portfolios based on second order stochastic dominance perform best out-of-sample. Our approximation results will be shown to hold also under parameter uncertainty.

1.3 The Approximation Approach

To explain our approximation approach, first derive the optimal portfolio of a HARA-investor. We consider a market with n risky assets and one risk-free asset. The gross return of asset i is denoted R_i for $i \in \{1, \ldots, n\}$. We denote the vector $(R_1, \ldots, R_n)'$ by $\mathbf{R}$. The gross risk-free rate is R_f. An investor with initial endowment W_0 maximizes her expected utility of payoff V, given by

$$V := V(\alpha, W_0) = (W_0 - \alpha'\mathbf{1})R_f + \alpha\mathbf{R} = W_0 R_f + \alpha\mathbf{r},$$

where α_i denotes the dollar-amount invested in asset i, $\alpha = (\alpha_1, \ldots, \alpha_n)$, and $\mathbf{1}$ is the n-dimensional vector consisting only of ones. $r_i = R_i - R_f$ denotes the random excess return of asset i and $\mathbf{r} = (r_1, \ldots, r_n)'$. The investor has a utility function with hyperbolic absolute risk aversion

$$u(V) = \frac{\gamma}{1-\gamma}\left(\frac{\eta + V}{\gamma}\right)^{1-\gamma}, \tag{1.1}$$

where the parameters η and γ assure that u is increasing and concave in V. Moreover, $0 < \gamma < \infty$ indicates decreasing absolute risk aversion. For $\gamma = 1$, we obtain log-utility. The well-known first order condition for this optimization problem is

$$\mathbb{E}\left[r_i\left(\frac{\eta + W_0 R_f + \alpha^+\mathbf{r}}{\gamma}\right)^{-\gamma}\right] = 0,\ \forall i \in \{1, \ldots, n\}. \tag{1.2}$$

The optimal solution is denoted α^+.

Our approximation approach consists of the following three steps. First, we transform the decision problem to an equivalent problem under constant RRA. Define $\tilde{W}_0 = \frac{\eta}{R_f} + W_0$ as the enlarged initial endowment. Then after substituting $\tilde{W}_0$ in (1.2), this condition remains the same, but the investor is constant relative risk averse. Second, we restrict the enlarged initial endowment to the artificial initial endowment γ/R_f. This leaves the structure of the optimal portfolio unchanged. Without loss of generality, we multiply the first order condition (1.2) by $(\tilde{W}_0 R_f/\gamma)^{\gamma}$. This gives

$$\mathbb{E}\left[r_i\left(1 + \frac{\hat{\alpha}^+\mathbf{r}}{\gamma}\right)^{-\gamma}\right] = 0,\ \forall i \in \{1, \ldots, n\}. \tag{1.3}$$

The terminal wealth implied by (1.3) is

$$\hat{V}^{+} = V\left(\hat{\alpha}^{+}, \frac{\gamma}{R_f}\right) = \gamma + \hat{\alpha}^{+}\mathbf{r} > 0. \tag{1.4}$$

Positivity follows from $u'(\hat{V}^{+}) \to \infty$ for $\hat{V}^{+} \to 0$.

The solution of the optimization problem for an investor with enlarged initial endowment $\tilde{W}_0$ is proportional to that with artificial endowment $\frac{\gamma}{R_f}$: $V^{+} = \hat{V}^{+}\tilde{W}_0 R_f/\gamma$ with $\alpha^{+} = \hat{\alpha}^{+}\frac{\tilde{W}_0 R_f}{\gamma} = \hat{\alpha}^{+}\frac{\eta + W_0 R_f}{\gamma}$.

Third, we define some low level of constant relative aversion ϕ to approximate the optimal portfolio. We approximate the solution of equation (1.3), $\hat{\alpha}^{+}$, by $\hat{\alpha}^{-}$, the solution of

$$\mathbb{E}\left[r_i\left(1 + \frac{\hat{\alpha}^{-}\mathbf{r}}{\phi}\right)^{-\phi}\right] = 0,\ \forall i \in \{1, \ldots, n\}. \tag{1.5}$$

The terminal wealth implied by (1.5) is $\phi + \hat{\alpha}^{-}\mathbf{r} > 0$, given the artificial endowment ϕ/R_f. To make up for the difference in artificial initial endowment in our approximation, the difference, $\gamma/R_f - \phi/R_f$, is simply invested in the risk-free asset adding $\gamma - \phi$ to the terminal wealth $\phi + \hat{\alpha}^{-}\mathbf{r}$,

$$\hat{V}^{-} = \phi + \hat{\alpha}^{-}\mathbf{r} + (\gamma - \phi) = \gamma + \hat{\alpha}^{-}\mathbf{r}. \tag{1.6}$$

Since $\phi + \hat{\alpha}^{-}r > 0$, $\hat{V}^{-}$ is also positive for $\gamma \geq \phi$.

Comparing $\hat{\alpha}^{+}$ and $\hat{\alpha}^{-}$ reveals two effects, a structure effect and a volume effect. The structure of α is defined by $\alpha_1 : \alpha_2 : \alpha_3 : \ldots : \alpha_n$. This structure changes with the level of RRA used for optimization. This structure change is denoted the structure effect. The volume is defined as the amount of money invested in all risky assets together. Hence the volume equals $\sum_{i=1}^{n} \alpha_i$. This volume also changes when RRA ϕ replaces RRA γ. The volume change is denoted the volume effect.

The $1/\gamma$-rule suggests that the stock proportions are inversely proportional to the investor's local relative risk aversion.

$$\frac{\hat{\alpha}^{+}}{\frac{\gamma}{R_f}} \sim \frac{1}{\gamma} \qquad \text{or} \qquad \hat{\alpha}^{+} \sim \frac{1}{R_f}.$$

Similarly,

$$\frac{\hat{\alpha}^{-}}{\frac{\phi}{R_f}} \sim \frac{1}{\phi} \qquad \text{or} \qquad \hat{\alpha}^{-} \sim \frac{1}{R_f}.$$

Hence if the $1/\gamma$-rule is absolutely correct, $\hat{\alpha}^+ = \hat{\alpha}^-$. As a consequence, the volume and the structure effect would disappear. Doubling γ doubles the artificial initial endowment and the relative risk aversion so that the $1/\gamma$-rule implies unchanged risky investments. Therefore, one benchmark for evaluating the quality of our approximation approach is a zero volume effect and a zero structure effect.

The approximation (1.6) assures $\hat{V}^- > 0$ for $\gamma \geq \phi$. For $\gamma < \phi$, the investor would borrow $(\phi - \gamma)/R_f$ at the risk-free rate. Then, $\hat{V}^-$ might turn negative since $\phi + \hat{\alpha}^- \mathbf{r}$ can be very close to zero. $\hat{V}^- < 0$ would be infeasible and is ruled out if $\gamma \geq \phi$. Therefore our approximation requires $\gamma \geq \phi$. This will be assumed in the following.[2]

1.4 The Approximation Quality

1.4.1 The General Argument

Whether portfolio optimization pays depends on the approximation quality. First, we present some arguments which support our conjecture of a strong approximation quality. Comparing (1.4) and (1.6) gives the difference between the optimal and the approximation portfolio payoff, $\hat{V}^+ - \hat{V}^- = (\hat{\alpha}^+ - \hat{\alpha}^-)\,\mathbf{r}$. Hence we expect a good approximation if the vectors $\hat{\alpha}^+$ and $\hat{\alpha}^-$ are similar. Essential for this is that both utility functions display similar patterns of absolute risk aversion in the range of relevant terminal wealth. The utility functions

$$\frac{\gamma}{1-\gamma}\left(\frac{\gamma + \alpha\mathbf{r}}{\gamma}\right)^{1-\gamma} \text{ and } \frac{\phi}{1-\phi}\left(\frac{\phi + \alpha\mathbf{r}}{\phi}\right)^{1-\phi}$$

give absolute risk aversion functions

$$\frac{1}{1 + \alpha\mathbf{r}/\gamma} \text{ and } \frac{1}{1 + \alpha\mathbf{r}/\phi}.$$

Hence, if the portfolio excess return αr is zero, both utility functions display absolute risk aversion of 1. As long as the portfolio excess return does not differ much from 0, absolute risk aversion is similar for both functions implying similar portfolio choice. Figure 1.1 illustrates the absolute risk aversion functions for different levels of γ. The smaller is γ, the steeper the curve is. For exponential utility, the curve is horizontal at a level of 1. The similarity of the absolute risk aversion patterns suggests small volume and structure effects.

[2] In the appendix, we briefly describe an alternative approximation based on the exponential utility function.

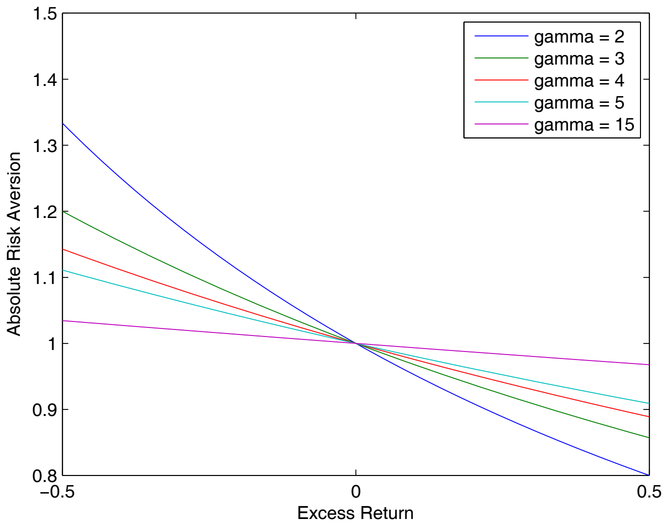

Figure 1.1: The absolute risk aversion of the HARA-function with endowment γ/R_f declines in the portfolio excess return. For increasing γ the difference between the absolute risk aversion of the HARA-function and that of the exponential utility function, being 1 everywhere, decreases.

The first order conditions (1.3) and (1.5) allow us to derive more precisely market settings of high approximation quality. Let $u^i(\cdot)$ denote the i-th derivative of the utility function. Then a Taylor series for the first derivative of the utility function around an excess return of zero yields

$$u'(\hat{\alpha}^+\mathbf{r}) = \sum_{i=0}^{\infty} \frac{u^{(i+1)}(0)}{i!} (\hat{\alpha}^+\mathbf{r})^i \tag{1.7}$$

so that

$$\left(1 + \frac{\hat{\alpha}^+\mathbf{r}}{\gamma}\right)^{-\gamma} = 1 + \sum_{i=1}^{\infty} (-1)^i \frac{(\hat{\alpha}^+\mathbf{r})^i}{i!} \prod_{j=0}^{i-1} \left(\frac{j}{\gamma} + 1\right). \tag{1.8}$$

Hence, the first order condition (1.3), multiplied by $\hat{\alpha}_i^+$ and summed over i, yields

$$\begin{aligned} \mathbb{E}\left[\hat{\alpha}^+\mathbf{r}\left(1 + \sum_{i=1}^{\infty} (-1)^i \frac{(\hat{\alpha}^+\mathbf{r})^i}{i!} \prod_{j=0}^{i-1} \left(\frac{j}{\gamma} + 1\right)\right)\right] &= 0 \\ \Leftrightarrow \quad \mathbb{E}[\hat{\alpha}^+\mathbf{r}] + \sum_{i=1}^{\infty} (-1)^i \frac{\mathbb{E}[(\hat{\alpha}^+\mathbf{r})^{i+1}]}{i!} \prod_{j=0}^{i-1} \left(\frac{j}{\gamma} + 1\right) &= 0. \end{aligned}$$

Denoting the i-th non-centered moment of the optimal portfolio excess return by m_i

and rearranging the last equation, the previous equation can be rewritten as

$$\frac{m_1}{m_2} + \frac{1}{2}\frac{m_3}{m_2}\left(\frac{1}{\gamma}+1\right) - \frac{1}{6}\frac{m_4}{m_2}\left(\frac{2}{\gamma}+1\right)\left(\frac{1}{\gamma}+1\right) + \ldots = 1. \tag{1.9}$$

From the first order condition (1.5) we have

$$\frac{n_1}{n_2} + \frac{1}{2}\frac{n_3}{n_2}\left(\frac{1}{\phi}+1\right) - \frac{1}{6}\frac{n_4}{n_2}\left(\frac{2}{\phi}+1\right)\left(\frac{1}{\phi}+1\right) + \ldots = 1, \tag{1.10}$$

where n_i is the i-th non-centered moment of $\hat{\alpha}^{-}\mathbf{r}$. Absolute portfolio excess returns below 1 imply $|\alpha\mathbf{r}|^{i+1} < |\alpha\mathbf{r}|^{i}$. Then it follows for the non-centered moments: $|m_{i+2}| \ll |m_i|,\ i \geq 2$. Also, $|m_3| \ll m_2$. Therefore, we may neglect the terms $m_i,\ i \geq 5$, in the Taylor series and focus on the first four moments. The same is true for n_i.

Whenever the excess return distributions of the optimal and the approximation portfolio have non-centered third and fourth moments close to zero, both first order conditions are very similar implying a very good approximation quality[3]. Otherwise, equations (1.9) and (1.10) indicate that the approximated return distribution derived from (1.10) attaches too much weight to the skewness and the kurtosis relative to (1.9) for $\gamma > \phi$. Hence, we expect the approximated return distribution to have fatter tails, but less skewness than the optimal return distribution. This follows because a HARA-investor with declining absolute risk aversion likes positive skewness, but dislikes kurtosis.

We summarize our findings in the following lemma:

Lemma 1 *Let $\gamma \geq \phi$. The approximation is of high quality even for large differences between ϕ and γ if the non-centered moments of the optimal and of the approximation portfolio excess return decline fast, i.e. if $m_{i+2} \ll m_i,\ i \geq 2,\ m_3 \ll m_2$ and $n_{i+2} \ll n_i,\ i \geq 2,\ n_3 \ll n_2$.*

1.4.2 The Approximation Loss

We measure the economic impact of the approximation by the approximation loss. Compare the certainty equivalent of the optimal portfolio α^{+} and that of the approximation portfolio α^{-}. In both cases, the certainty equivalent is based on the

[3]For small portfolio risk, $m_i \to 0$ for $i > 2$. Then the optimal portfolio satisfies $m_1/m_2 \to 1$ rendering γ irrelevant. This is the case in a continuous time model with i.i.d. returns. Then the volume and the structure effect disappear.

investor's HARA-function (1.1). For that utility function, given a portfolio α, the certainty equivalent, CE, is defined by

$$\begin{aligned}\left(\frac{\eta+CE}{\gamma}\right)^{1-\gamma} &= \mathbb{E}\left[\frac{(\eta/R_f+W_0)R_f+\alpha\mathbf{r}}{\gamma}\right]^{1-\gamma} \\ &= \left(\tilde{W}_0\frac{R_f}{\gamma}\right)^{1-\gamma}\mathbb{E}\left[1+\frac{\hat{\alpha}\mathbf{r}}{\gamma}\right]^{1-\gamma} = \left(\frac{ce}{\gamma}\right)^{1-\gamma}. \qquad (1.11)\end{aligned}$$

Expected utility is the same for an investor with utility function (1.1) and endowment W_0 and an investor with constant relative risk aversion and enlarged initial endowment $\tilde{W}_0 = \eta/R_f + W_0$. Therefore, we consider the enlarged certainty equivalent $ce = \eta + CE$. Define ε as the ratio of the enlarged certainty equivalent, ce^+, of the optimal portfolio $\alpha^+ = \hat{\alpha}^+\tilde{W}_0R_f/\gamma$, and the enlarged certainty equivalent, ce^-, of the approximated optimal portfolio $\alpha^- = \hat{\alpha}^-\tilde{W}_0R_f/\gamma$. Then

$$\varepsilon = \frac{ce^+}{ce^-} = \left(\frac{\mathbb{E}\left[\left(\frac{(\eta/R_f+W_0)R_f+\alpha^+\mathbf{r}}{\gamma}\right)^{1-\gamma}\right]}{\mathbb{E}\left[\left(\frac{(\eta/R_f+W_0)R_f+\alpha^-\mathbf{r}}{\gamma}\right)^{1-\gamma}\right]}\right)^{1/(1-\gamma)} = \left(\frac{\mathbb{E}\left[\left(1+\frac{\hat{\alpha}^+\mathbf{r}}{\gamma}\right)^{1-\gamma}\right]}{\mathbb{E}\left[\left(1+\frac{\hat{\alpha}^-\mathbf{r}}{\gamma}\right)^{1-\gamma}\right]}\right)^{1/(1-\gamma)}. \qquad (1.12)$$

Hence, ε is the same for the enlarged initial endowment $\eta/R_f + W_0$ and the artificial initial endowment γ/R_f. This is stated in:

Lemma 2 *For a given market setting, the certainty equivalent ratio ε depends on the exponent γ, but not on the initial endowment nor on the parameter η.*

The lower boundary of ε is one, since the optimal portfolio $\hat{\alpha}^+$ yields the highest possible certainty equivalent. For a HARA-investor there exists a second interpretation of ε. $k = (\varepsilon - 1) \geq 0$ is the relative increase in the enlarged initial endowment $\tilde{W}_0$, that is required for the approximation portfolio to generate the same expected utility as the optimal portfolio generates with initial endowment $\tilde{W}_0$. To see that $\varepsilon = 1 + k$, note

$$\left(\frac{\tilde{W}_0R_f}{\gamma}\right)^{1-\gamma}\mathbb{E}\left[\left(1+\frac{\hat{\alpha}^+\mathbf{r}}{\gamma}\right)^{1-\gamma}\right] = \left(\frac{(1+k)\tilde{W}_0R_f}{\gamma}\right)^{1-\gamma}\mathbb{E}\left[\left(1+\frac{\hat{\alpha}^-\mathbf{r}}{\gamma}\right)^{1-\gamma}\right].$$

Rearranging yields

$$1+k = \left(\frac{\mathbb{E}\left[\left(1+\frac{\hat{\alpha}^+\mathbf{r}}{\gamma}\right)^{1-\gamma}\right]}{\mathbb{E}\left[\left(1+\frac{\hat{\alpha}^-\mathbf{r}}{\gamma}\right)^{1-\gamma}\right]}\right)^{1/(1-\gamma)} = \frac{ce^+}{ce^-} = \varepsilon.$$

We call k the approximation loss. If $k = 0.02$, for example, then the investor needs to invest additionally 2% of his enlarged initial endowment in the approximation portfolio to achieve the same expected utility as her optimal portfolio does.

For $\gamma = \phi$, the approximation loss is 0, by definition. If we increase γ, the approximation loss will be positive. But it does not increase monotonically. Instead, for $\gamma \to \infty$, $k \to 0$ again. For $\gamma \to \infty$, the investor's utility is exponential and the artificial initial endowment tends to infinity. The exponential utility investor buys a risky portfolio independently of her initial endowment. Given an infinite artificial initial endowment, this risky portfolio turns out to be irrelevant for the optimal payoff $\hat{V}^+$. The same is true for the approximated payoff $\hat{V}^-$. Hence, both certainty equivalents converge for $\gamma \to \infty$ so that $k \to 0$.

In the following, we illustrate the approximation loss k by looking, first, at a complete market with a continuous state space and different distributions of the market return. Thereafter, we consider a discrete state space with few states only.

1.5 Approximation in a Continuous State Space

1.5.1 Demand Functions for State-Contingent Claims

Characterization of Demand Functions

We start from a perfect market with a continuous state space. First, assume a complete market. Then state-contingent claims for all possible states $s \in \mathcal{S}$ exist. Hakansson (1970) was the first to investigate investment and consumption strategies of HARA investors in a complete market. Consider an investor with constant relative risk aversion γ and artificial initial endowment γ/R_f. The investor's demand for state-contingent claims, $\hat{\alpha} = (\hat{\alpha}_s)_{s\in\mathcal{S}}$, is optimized

$$\max_{\hat{\alpha}} \mathbb{E}\left[\frac{\gamma}{1-\gamma}\left(\frac{\gamma+\hat{\alpha}}{\gamma}\right)^{1-\gamma}\right] \; s.t. \; \mathbb{E}[\pi V] = \gamma/R_f, \tag{1.13}$$

where $\pi = (\pi_s)_{s\in\mathcal{S}}$ denotes the pricing kernel and $\hat{\alpha}_s$ is the demand for claims with payoff one in state s and zero otherwise. Differentiating the corresponding Lagrangian with respect to α_s gives the well-known optimality condition for each state

$$\left(\frac{\gamma+\hat{\alpha}_s}{\gamma}\right)^{-\gamma} = \lambda\pi_s, \; s \in \mathcal{S}. \tag{1.14}$$

First, we assume that the pricing kernel is a power function of the market portfolio return

$$\pi_s = \frac{1}{R_f} \frac{R_{M,s}^{-\theta}}{\mathbb{E}[R_M^{-\theta}]}, \tag{1.15}$$

where $R_{M,s}$ denotes the gross market return in state s and θ is the constant relative risk aversion of the market, i.e. the constant elasticity of the pricing kernel. Hence, we assume a pricing kernel as implied by the Black-Scholes setting.

Replacing π_s by (1.15) and solving (1.14) for $\hat{V}_s^+ = \gamma + \alpha_s$ yields for finite γ

$$V_s^+ = R_{M,s}^{\theta/\gamma} \exp\{a(\gamma)\}. \tag{1.16}$$

$a(\gamma)$ depends on the investor's relative risk aversion and is determined by the budget constraint: $\mathbb{E}[R_M^{\theta/\gamma} \exp\{a(\gamma)\}\pi] = \frac{\gamma}{R_f}$. We have

$$\exp\{a(\gamma)\} = \gamma \frac{\mathbb{E}[R_M^{-\theta}]}{\mathbb{E}\left[R_M^{-\theta+\theta/\gamma}\right]} = \frac{\gamma}{\mathbb{E}^Q\left[R_M^{\theta/\gamma}\right]}, \tag{1.17}$$

with $\mathbb{E}^Q[\cdot]$ being the expectation operator under the risk neutral probability measure using the pricing kernel $\pi(R_M)$.

The optimal terminal wealth, $\hat{V}^+$, is approximated by $\hat{V}^-$. For $\gamma \geq \phi$, $\hat{V}^-$ is the optimal terminal wealth of an investor with CRRA ϕ and artificial endowment ϕ/R_f, supplemented by the risk-free payoff $(\gamma - \phi)$,

$$\hat{V}_s^- = R_{M,s}^{\theta/\phi} \exp\{a(\phi)\} + (\gamma - \phi). \tag{1.18}$$

How does $(\hat{V}_s^+ - \hat{V}_s^-)$ depend on $(\gamma - \phi)$ for $\gamma > \phi$? The functions $\hat{V}^+(R_M)$ and $\hat{V}^-(R_M)$ intersect twice, given a sufficiently large domain of R_M. Both functions have to intersect at least once to rule out arbitrage opportunities. For $R_M \to 0$, $\hat{V}^- \to \gamma - \phi > \hat{V}^+ \to 0$. Also $\hat{V}^- > \hat{V}^+$ for $R_M \to \infty$ (this follows from $\theta/\gamma < \theta/\phi$). Since $\hat{V}^+(R_M)$ is more concave than $\hat{V}^-(R_M)$, both functions intersect twice. The demand for state contingent claims is overestimated by the approximation in the bad states and in the good states and underestimated in between, as Figure 1.2 illustrates. This range-dependent over-/underestimation of the optimal demand characterizes the structure effect.

Consider the special case $\phi = \theta$. This implies that $\hat{V}^-$ is linear in R_M and, hence, $\exp\{a(\theta)\} = \theta/\mathbb{E}^Q[R_M] = \theta/R_f$. Then (1.18) yields

$$\hat{V}_s^- = \frac{\theta}{R_f} R_{M,s} + \gamma - \theta,\ \gamma \geq \theta. \tag{1.19}$$

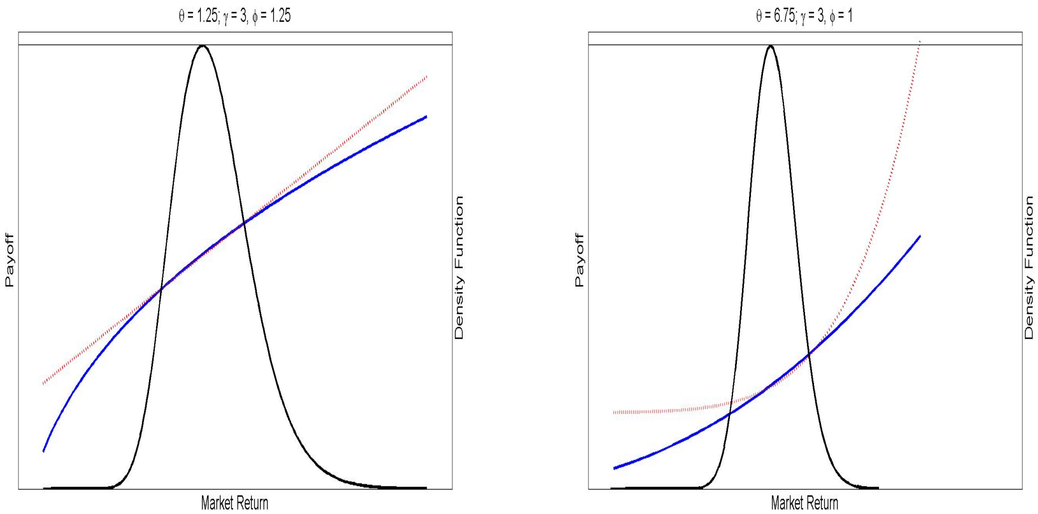

Figure 1.2: **Left:** The figure shows the optimal demand for state contingent claims (blue solid curve) and the approximation demand (red dotted line) for $\gamma = 3 \geq \phi = \theta = 1.25$. In addition, on a different scale the graph shows the probability density of the market return. **Right:** $\gamma = 3$, $\theta = 6.75$ and $\phi = 1$. This implies a strongly convex approximation demand function while the optimal demand function is only moderately convex.

The approximation portfolio policy is very simple. The investor invests θ/R_f in the market portfolio and $(\gamma - \theta)/R_f$ in the risk-free asset.

Approximation Quality and Shape of the Probability Distribution

Next, we illustrate the effect of the shape of the market return distribution on the approximation quality. A change in the probability distribution of R_M implies an adjustment in the intersection point(s) of $\hat{V}^+(R_M)$ and $\hat{V}^-(R_M)$. This adjustment tends to stabilize the approximation quality. To characterize the adjustment, we state the following Lemma:

Lemma 3 *Assume $\gamma > \phi$. Let p be a changing parameter of the market return distribution and $R_M^j = R_M^j(p), j \in \{l, u\}$, denote the lower respectively upper market return where $\hat{V}^+(R_M|p)$ and $\hat{V}^-(R_M|p)$ intersect. Then, holding $\mathbb{E}^Q[R_M] = R_f$ and*

θ constant, $\frac{\partial \ln R_M^j}{\partial p}$ is given by

$$\frac{\partial \ln R_M^j}{\partial p} \frac{\theta}{\phi} \frac{1}{\gamma} \left[\hat{V}^+(R_M^j) - \gamma \right] = \left[\frac{\partial a(\gamma)}{\partial p} - \frac{\partial a(\phi)}{\partial p} \right] \frac{\hat{V}^+(R_M^j)}{(\gamma - \phi)} + \frac{\partial a(\phi)}{\partial p}, \tag{1.20}$$

with

$$\gamma \frac{\partial a(\gamma)}{\partial p} = -\int_0^\infty \hat{V}^+(R_M) \frac{\partial F^Q(R_M)}{\partial p} \tag{1.21}$$

and

$$\phi \frac{\partial a(\phi)}{\partial p} = -\int_0^\infty \hat{V}^-(R_M) \frac{\partial F^Q(R_M)}{\partial p}. \tag{1.22}$$

$F^Q(R_M)$ is the cumulative probability distribution of R_M under the risk-neutral measure.

The proof of this lemma is given in the appendix. The lemma relates changes in the risk-neutral probability distribution of the market return to changes in the intersection points of $\hat{V}^+(R_M)$ and $\hat{V}^-(R_M)$. For simplicity, assume $\theta = \phi$. Then $\exp\{a(\phi)\} = \phi/R_f$ so that $\partial a(\phi)/\partial p = 0$. Then, by (1.20), since $\hat{V}^+ > 0$ and $\hat{V}^+(R_M^l) - \gamma < 0$, $\hat{V}^+(R_M^u) - \gamma > 0$, a marginal change in the underlying probability distribution function of R_M (1) either lowers R_M^l and raises R_M^u or (2) raises R_M^l and lowers R_M^u, or (3) leaves both unchanged.

For illustration, consider a mean preserving spread in the market return, such that $\mathbb{E}^Q[R_M] = R_f$ stays the same. Lemma 1 suggests that the approximation loss increases. However, Lemma 3 implies that an increase in the volatility lowers R^l and increases R^u. To see this, subtract $\phi \frac{\partial a(\phi)}{\partial p} = 0$ from equation (1.21),

$$\gamma \frac{\partial a(\gamma)}{\partial p} = \int_0^\infty \left[\hat{V}^-(R_M) - \hat{V}^+(R_M) \right] \frac{\partial F^Q(R_M)}{\partial p}.$$

Increasing the volatility reallocates probability mass from the center to the tails, so that the integral is positive. Then, by (1.20), $\frac{\ln R_M^l}{\partial p} < 0$ and $\frac{\ln R_M^u}{\partial p} > 0$. This reduces the claim difference $(\hat{V}^+ - \hat{V}^-)$ in the tails and raises it in the center so that the approximation quality is stabilized.

Alternatively, consider a reduction in the skewness of the market return distribution. It is not clear whether the intersection points are spreading. Relocating probability mass from the right to the left tail of the market return distribution would lower $\mathbb{E}^Q[R_M]$ and, therefore, is infeasible. In order to keep $\mathbb{E}^Q[R_M] = R_f$ unchanged, the probability mass needs to go up in some range of R_M with $R_M > R_f$. Therefore, $a(\gamma)$ can change in either direction, stabilizing the approximation quality.

1.5.2 Simulation Results for $\gamma \geq \phi = \theta$

Normal Distribution

Now we illustrate the approximation loss numerically for various probability distributions of R_M and various time horizons. The investor buys state-contingent claims due at the time horizon. She does not readjust the portfolio over time. First assume that $\ln R_M$ is normally distributed with mean μ and variance σ^2. Then $\ln \mathbb{E}[R_M] = \mu + \frac{\sigma^2}{2}$ so that the annual Sharpe-ratio is

$$\frac{\mathbb{E}[R_M] - R_f}{\sigma(R_M)} = \left[1 - \exp\left\{r_f - \left(\mu + \frac{\sigma^2}{2}\right)\right\}\right] \left(\exp\{\sigma^2\} - 1\right)^{-1/2}.$$

The elasticity of the pricing kernel is $\theta = \frac{\mu + \sigma^2/2 - r_f}{\sigma^2}$, the certainty equivalent of $\hat{V}^+$ has a closed form representation

$$ce(\hat{V}^+) = \gamma \exp\left\{\frac{1}{2}\frac{\sigma^2\theta^2}{\gamma}\right\}.$$

For $\gamma \geq \phi$, the approximation portfolio is given by (1.19). To compute its certainty equivalent, we have to rely on numerical integration techniques.

Consider the case $\phi = \theta$. To calibrate our analysis to observable market returns, we first use an annual expected logarithmic market return $\mu = 6\%$, an annual market volatility $\sigma = 25\%$ and an instantaneous risk-free rate $r_f = 3\%$. This implies a pricing kernel elasticity of $\theta = 0.98$, an annual equity premium of 6.51% and an annual Sharpe-ratio of 23.4%. We consider investors with constant relative risk aversion in the range $[0.98; 8]$, an investment horizon between three month and 5 years and assume an i.i.d. market return. Hence, the expected logarithmic market return for t years is $\mu_t = t\mu$ and the standard deviation of the t-year logarithmic market return is $\sigma_t = \sqrt{t}\sigma$.

Figure 1.3 shows the approximation loss. For $\gamma = 0.98$, the approximation portfolio equals the optimal portfolio so that there is no approximation loss. For $\gamma > \phi = \theta$, the approximation loss increases with a longer investment horizon because the market return distribution becomes wider implying higher risk. Yet, the approximation quality still remains very good. The highest approximation loss in Figure 1.3, left, is about 0.3% for an investor with γ about 3 and an investment horizon of 5 years, or, about 0.06% per year. In other words, the investor would need to raise her initial endowment by 0.3% to make up for the approximation loss. This suggests that portfolio optimization does not pay.

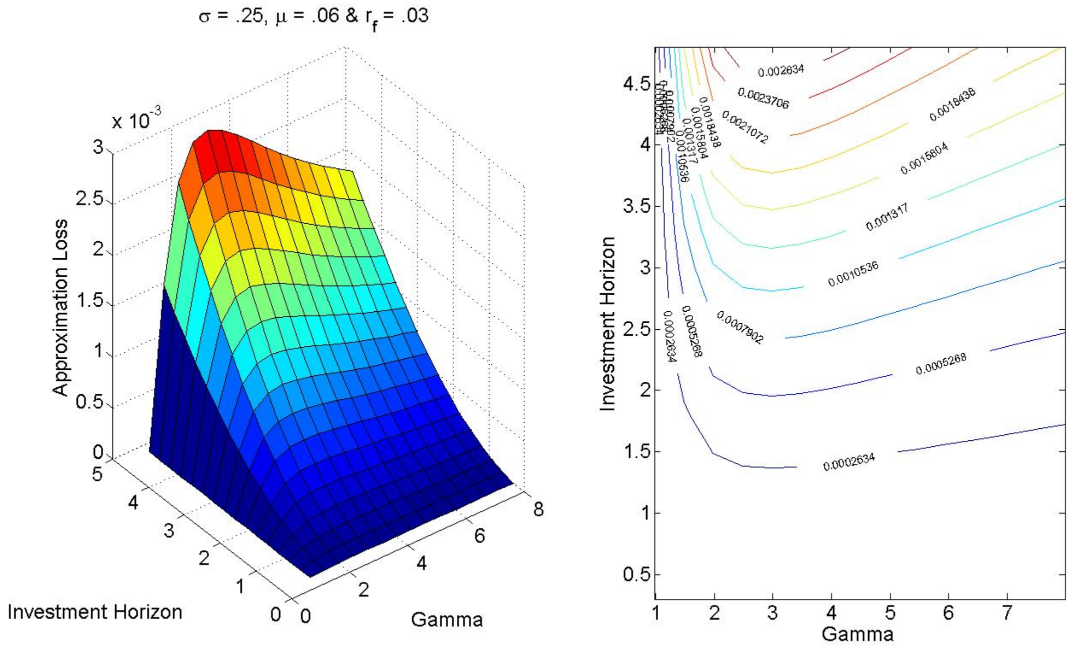

Figure 1.3: **Left:** The surface shows the approximation loss for $\gamma \in [0.98; 8]$, $\phi = \theta = 0.98$ and an investment horizon between 3 months and 5 years. For this setting, the highest loss in certainty equivalent is obtained for γ between 3 and 4 and an investment of five years. The investor would have lost about 0.3% of the optimal certainty equivalent or 0.06% per year. **Right:** Each isoquant shows the combination of γ and investment horizon with the same approximation loss k depicted in the curve.

The impact of γ and the investment horizon can also be seen in Figure 1.3, right, which depicts isoquants of the approximation loss, i.e. combinations of γ and investment horizon yielding the same loss. For an investment horizon of 2.5 years, for example, the loss always remains below 0.08%. For all horizons the loss has a maximum at some γ between 2 and 4 and then monotonically declines to zero with increasing γ.

To illustrate the relation between the approximation loss and the chosen parameters, let $\mu = 0.075$ and $\sigma = 0.15$, retaining $r_f = 3\%$. Then the Sharpe-ratio is 36.3% and the elasticity of the pricing kernel is 2.5. Let $\gamma \in (2.5; 15)$. In this scenario the highest approximation loss is 0.1% for an investment horizon of 5 years and γ about 8.

Next, consider a somewhat extreme case with $\mu = 0.08$, $\sigma = 0.10$ and $r_f = 3\%$. This yields a Sharpe-ratio of 53.4% and a pricing kernel elasticity of 5.5. Let $\gamma \in (5.5; 20)$. Then the highest approximation loss is 0.04% for an investment horizon of 5 years and γ about 17.

The results indicate that the highest approximation loss is inversely related to the pricing kernel elasticity respectively the Sharpe-ratio, provided $\gamma \geq \phi = \theta$. This is not surprising because a higher pricing kernel elasticity has only small effects on the shape of the $\hat{V}^+(R_M)$- and $\hat{V}^-(R_M)$-curves, but is associated with a strong decline in $\sigma(R_M)$ so that the moments m_j and n_j, $j > 1$, of the portfolio excess return decline (Lemma 1). Thus, the approximation works quite well.

Symmetric, Fat-tailed Distributions

Next, we analyze fat-tailed distributions. Consider a t-distribution to account for excess kurtosis (fat tails) in logarithmic market returns. The density for a t-year investment period is given by

$$f(\ln R_{M,t}|\mu_t, \sigma_{\nu,t}, \nu_t) = \frac{\Gamma\left(\frac{\nu_t+1}{2}\right)}{\sigma_{\nu,t}\sqrt{\nu_t \pi}\,\Gamma\left(\frac{\nu_t}{2}\right)} \left(1 + \frac{\left(\frac{\ln R_{M,t}-\mu_t}{\sigma_{\nu,t}}\right)^2}{\nu_t}\right)^{-(\nu_t+1)/2}, \tag{1.23}$$

where $\sigma_{\nu,t} = \sigma_t(\nu_t/(\nu_t - 2))^{-1/2}$. The mean of the distribution is $\mu_t = t\mu$, the standard deviation is $\sigma_t = \sqrt{t}\sigma$ and the excess kurtosis is $\frac{6}{\nu_t-4}$ for $\nu_t > 4$. Empirical studies, for example Corrado and Su (1997), report a kurtosis of about 12 for the monthly logarithmic returns of the S&P 500 between 1986 and 1995. Assuming i.i.d. returns, this translates into an annual kurtosis $\kappa_1 = 3.75$. Independent increments imply $\kappa_t = 3 + \frac{(\kappa_1-3)}{t}$ for t-years. For robustness, we stress the calculation of the approximation loss with an annual kurtosis of 4.5. This gives the simple rule for ν_t: $\nu_t = 4t + 4$. Using the initial parameter values, $\mu = 0.06$ and $\sigma = 0.25$, we derive the Sharpe-ratio and the approximation loss for t-distributed logarithmic market returns. The Sharpe-ratio is 23%. The approximation loss is shown in Figure 1.4, left. We assume $\phi = \theta = \frac{\mu - r + \frac{1}{2}\sigma^2}{\sigma^2} = 0.98$. The fat tails raise the approximation loss, as predicted by Lemma 1. However, the approximation loss is still remarkably low, even for an investment horizon of five years. For $\gamma = 3$ and a five year horizon, the highest approximation loss is about 0.35%, i.e. about 0.07% per year.

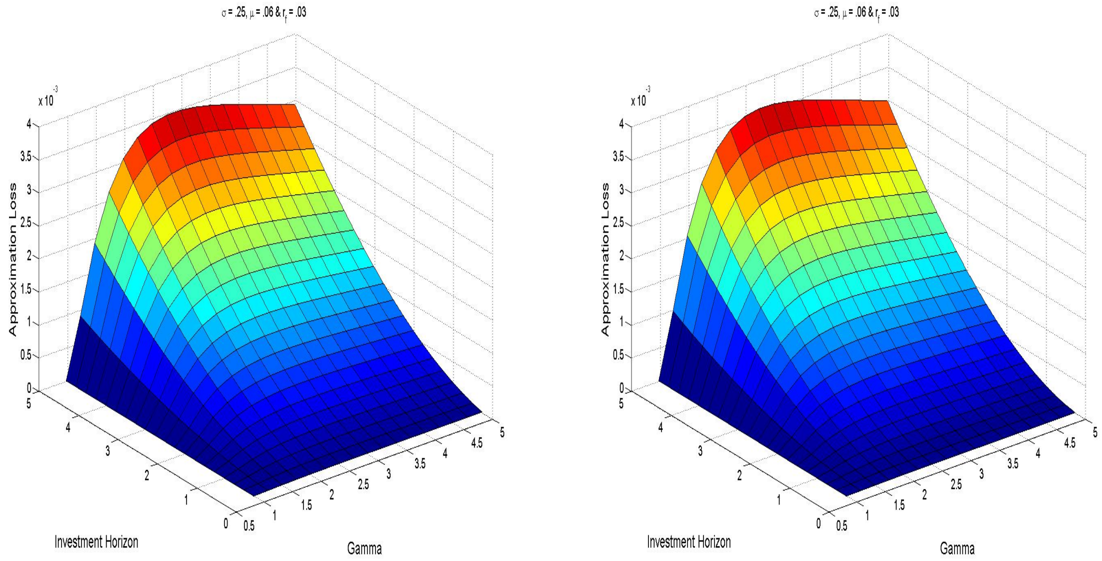

Figure 1.4: The surface shows the approximation loss for $\gamma \in [0.98; 8]$, $\phi = \theta = 0.98$ and an investment horizon between 3 months and 5 years. **Left:** The logarithmic market return is t-distributed. We assume independent and identically distributed increments, hence, $\mu_t = 0.06t, \sigma_t = 0.25\sqrt{t}$ and $\nu_t = 4t + 4$. For $\gamma \approx 3$ and an investment horizon of five years, the highest approximation loss is about 0.4%. **Right:** The logarithmic market return is left-skewed, fat tailed distributed with independent and identically distributed increments.

Left-skewed, Fat-tailed Distributions

As a final example of a complete market we consider a distribution with fat tails and negative skewness. Since 1987 stock returns up to one year are mostly skewed to the left. This is also true for stock index returns. For the simulation we use the skewed, fat tailed normal distribution to model the logarithmic market return. The density function is given by

$$f(\ln R_{M,t}|\lambda_t, \omega_t, \xi_t) = \left(\frac{2}{\sigma_t}\right) n\left(\frac{\ln R_{M,t} - \lambda_t}{\omega_t}\right) \mathcal{N}\left(\xi_t \left(\frac{\ln R_{M,t} - \lambda_t}{\omega_t}\right)\right), \tag{1.24}$$

where $n(\cdot)$ is the density of the standard normal distribution and $\mathcal{N}(\cdot)$ is the standard normal distribution function. The mean is given by $\mu_t = \lambda_t + \omega_t \delta_t \sqrt{2/\pi}$, the standard deviation is $\sigma_t = \omega_t \sqrt{1 - 2\delta_t^2/\pi}$, where $\delta_t = \xi_t / \sqrt{1 + \xi_t^2}$ [4]. Corrado and Su (1997) find that the monthly logarithmic stock returns of the S&P 500 are skewed to the

[4] The skewness is $sk_t = \frac{4-\pi}{2} \frac{\left(\delta_t \sqrt{2/\pi}\right)^3}{(1-2\delta_t^2/\pi)^{3/2}}$ and the excess kurtosis is $2(\pi - 3)\frac{\left(\delta_t \sqrt{2/\pi}\right)^4}{(1-2\delta_t^2/\pi)^2}$.

left at -1.67. Assuming i.i.d. returns, this translates to an annual skewness of about -0.5[5]. We stress this number and use an annual skewness of -0.6 together with an annual excess kurtosis of 0.4426. For each investment horizon, we choose the parameters λ_t, ω_t and ξ_t such that $\mu_t = 0.06t, \sigma_t = 0.25\sqrt{t}$, $sk_t = -0.6/\sqrt{t}$ and the excess kurtosis over t years is $(3.4426 - 3)/t$. This yields a somewhat higher annual Sharpe-ratio of 24.6%. The approximation loss is shown in Figure 1.4, right, for $\gamma \geq \phi = \theta$, and $t \in [0.3; 5]$. The highest loss is about 0.36% for $\gamma = 3$ and 5 years. Figure 1.4, left, and Figure 1.4, right, indicate very similar loss levels. Skewness and excess kurtosis do not affect the approximation loss substantially. This is driven also by the adjustment of the intersection points of the optimal and the approximate demand functions to the shape of the probability distribution. Hence the approximation works well also for skewed, leptokurtic distributions, given $\gamma \geq \phi = \theta$. The costs of a sophisticated portfolio optimization are likely to exceed its benefits.

1.5.3 Simulation Results for $\gamma \geq \phi \neq \theta$

So far the simulations were based on $\gamma \geq \phi = \theta$. If the pricing kernel elasticity is lowered, then the smaller equity premium induces investors to take less risk. This is true for the optimal and for the approximation portfolio. Hence the approximation loss should decline with a smaller θ. Since the last section shows that the approximation loss is rather insensitive to skewness and leptokurtosis, we use again the lognormal distribution with $\sigma = 0.25$ and $\mu + \frac{\sigma^2}{2} - r_f = \theta\sigma^2$ to simulate the impact of θ on the approximation loss. Figure 1.5 shows the approximation loss for an investment horizon of one year and different combinations of γ and θ. In Figure 1.5, left, $\phi = 1$, in Figure 1.5, right, $\phi = 2$. Both figures clearly show that the approximation loss monotonically grows with θ, holding γ and ϕ constant. Hence, if $\theta < \phi$, the approximation loss is smaller than that for $\theta = \phi$. Therefore, the approximation works even better for $\theta < \phi$, as expected.

Conversely, the approximation loss strongly increases with the pricing kernel elasticity, given $\theta \gg \phi$. For $\phi = 1$, the highest approximation loss in Figure 1.5, left, is about 1.1% for the highest $\theta = 11$ and $\gamma \approx 5$. For $\phi = 2$ (Figure 1.5, right), it is about 0.16% for $\theta = 11$ and $\gamma \approx 6.5$. These findings nicely illustrate the approxi-

[5]Independent increments imply $sk_t = sk_1/\sqrt{t}$, where sk_1 denotes the skewness for one year and sk_t is the skewness for t-years.

mate arbitrage-story of Bernado and Ledoit (2000). They show that a market with very high pricing kernel elasticity offers approximate arbitrage opportunities. An investor with low relative risk aversion would then take very much risk through a strongly convex demand function for state-contingent claims, see Figure 1.2, right. Claims in states of high market returns are very cheap, they almost offer a free lunch to investors with low relative risk aversion. Therefore these investors buy a large number of these claims. Investors with $\gamma \geq \theta$ benefit much less from this effect because they buy a linear or a concave demand function. This implies a high approximation loss as long as γ is not very high.

Clearly, the approximation loss is smaller for a higher ϕ. This is due to the fact that an investor with higher ϕ would take less risk and, thus, benefit less from the approximate arbitrage opportunity. The effect on the approximation loss can be seen by comparing Figures 1.5, left, and 1.5, right.

Summarizing, the approximation does a very good job when the approximation is based on a linear or concave demand function ($\phi \geq \theta$). But it does a poor job when the approximation is based (1) on a strongly convex demand function ($\theta \gg \phi$), (2) the investor's optimal demand function is much less convex ($\gamma \gg \phi$) and (3) γ is not so high that risk taking becomes negligible.

1.5.4 Non-Constant Elasticity of the Pricing Kernel

So far we assumed constant elasticity of the pricing kernel for the market return. Ait-Sahalia and Lo (2000), Jackwerth (2000), Rosenberg and Engle (2002), Bliss and Panigirtzoglou (2004), Barone-Adesi, Engle and Mancini (2008) estimate the elasticity of the pricing kernel using prices of options on the S&P 500 and the FTSE 100. They conclude that the pricing kernel elasticity is declining, perhaps with a local maximum in between.

If the pricing kernel of the market portfolio does not have constant elasticity, we derive a transformed market portfolio such that its pricing kernel has low constant elasticity. Then, instead of the market portfolio, we use this transformed market portfolio for the approximation. Assume that the elasticity $\nu(R_M) = -\partial \ln \pi(R_M)/\partial \ln R_M$ is positive and non-constant. Let $R_{TM} := g(R_M) := \exp\left\{\frac{1}{\tilde{\theta}}\int_{\varepsilon}^{R_M} \nu(R_M^0) d\ln R_M^0\right\}$, where $\tilde{\theta}$ is a small, positive constant. ε is a positive lower bound of R_M. g is invertible and yields a pricing kernel $\tilde{\pi}$ of constant elasticity $\tilde{\theta}$ with respect to R_{TM}. This follows since

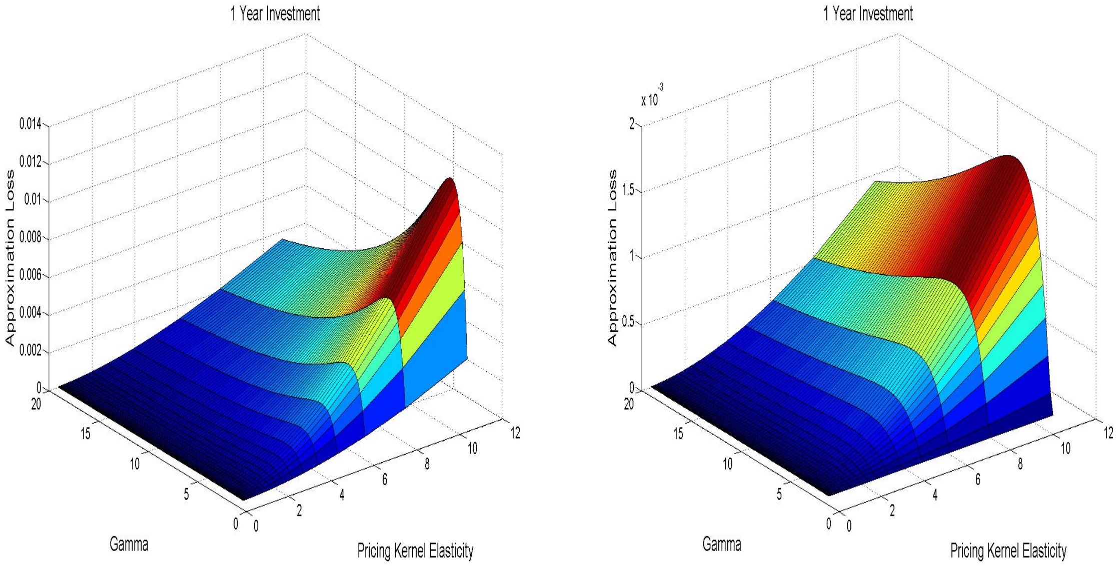

Figure 1.5: **Left:** The approximation loss for an investment horizon of one year as a function of θ and γ, assuming a lognormal market return with $\sigma = 0.25$. $r_f = 0.03$ and $\phi = 1$. $\gamma \in [\phi; 20]$, $\theta \in [0.44; 11]$. **Right:** The approximation loss for the same setting as in Figure 1.5, left, but with $\phi = 2$.

$$\begin{aligned} -\ln \pi(R_M) + \ln \pi(\varepsilon) &= \int_{\varepsilon}^{R_M} \nu(R_M^0) d \ln R_M^0 \\ &= \tilde{\theta} \ln g(R_M) \\ &= \tilde{\theta} \ln R_{TM} \\ &= -\ln \tilde{\pi}(R_{TM}) + \ln \pi(\varepsilon). \end{aligned} \tag{1.25}$$

The per unit-probability price for a claim contingent on R_{TM}, $\tilde{\pi}(R_{TM})$, equals $\pi(R_M)$, the price for a claim contingent on $R_M = g^{-1}(R_{TM})$. By definition, R_{TM} is a one-to-one transformation of the market return so that constant elasticity $\tilde{\theta}$ of the new pricing kernel $\tilde{\pi}(R_{TM})$ is assured. This is true regardless of the sign of $\nu'(R_M)$. Moreover, the level of the constant pricing kernel elasticity of the transformed market return can be chosen freely. Therefore, we can always create an exchange traded fund (ETF) on the market return with return R_{TM} and low constant elasticity $\tilde{\theta}$ of its pricing kernel. This ETF is a suitable candidate for the approximation portfolio so that

$$\hat{V}^{-}(R_{TM}) = \frac{\tilde{\theta}}{R_f} R_{TM} + (\gamma - \tilde{\theta}); \qquad \gamma \geq \tilde{\theta}.$$

This approximation assures a low approximation loss.

1.5.5 Incomplete Markets

So far we considered complete markets. In an incomplete market, the pricing kernel is no longer unique. Suppose, first, that a pricing kernel on the market with low constant elasticity is feasible. For this case the preceding analysis has shown that buying the market portfolio and the risk-free asset provides a very good approximation to the optimal portfolio for a large variety of settings. Actually, in an incomplete market the approximation quality is even better. This follows because incompleteness does not affect the availability of the market portfolio and, hence, the approximation portfolio, but the optimal portfolio in a complete market may not be available. This reduces the approximation loss.

Second, suppose that a pricing kernel with low constant elasticity is not feasible. Then we can use an ETF. If both, the ETF and the portfolio which would be optimal in a complete market, cannot be replicated exactly in an incomplete market, then the approximation loss might go up or down. But, given a large number of available risky assets, the difference between a complete and an incomplete market should be small.

1.5.6 Extension to Parameter Uncertainty

So far all parameters are assumed to be known precisely. The discussion on parameter uncertainty focuses on the probability with which one portfolio is preferable to another one in the presence of parameter uncertainty. As discussed before, several papers conclude that, given a set of well-diversified portfolio strategies, no strategy significantly outperforms the other strategies. To address this issue, consider the following setting. Initially the investor buys a portfolio of state-contingent claims based on the a priori probability distribution of the market return. The pricing kernel is consistent with the a priori distribution. In the spirit of the papers on parameter uncertainty, we derive the a priori probability that ex post, i.e. given the a posteriori distribution, the ex ante optimal portfolio is still preferred to the approximation portfolio. Let $\mathcal{I}$ denote the parameter vector of the a posteriori distribution of the market return. Hence, we check

$$\mathcal{P} = \text{Prob}\left[\, \mathcal{I} \;\middle|\; ce(\hat{V}^{+}|\mathcal{I}) \geq ce(\hat{V}^{-}|\mathcal{I}) \,\right], \tag{1.26}$$

where $ce(\hat{V}|\mathcal{I})$ is the certainty equivalent of portfolio payoff $\hat{V}$, given the a posteriori distribution $\mathcal{I}$.

To illustrate, assume that each a posteriori distribution of the market return is log normal, $n(\ln R_M|\mathcal{I})$. Then the a priori probability density of R_M is given by $\int n(\ln R_M|\mathcal{I})dF(\mathcal{I})$, with $F(\mathcal{I})$ being the cumulative probability distribution of $\mathcal{I}$. We use a symmetric truncated normal distribution for $\mathcal{I} = [\mathbb{E}[R_M], \sigma(R_M)]$ with bounds $[0.8955; 1.2955]$ for $\mathbb{E}[R_M]$ and $[0.1782; 0.3782]$ for $\sigma(R_M)$. We assume that $\mathbb{E}[R_M]$ and $\sigma(R_M)$ are uncorrelated and that the standard deviation of both parameters is 0.1. This yields an a priori probability distribution of R_M with simulated expected market return of 1.0974 and standard deviation of 0.2942. This distribution is not log normal. Given the a priori distribution, we derive $\exp\{a(\gamma)\}$ by simulation and obtain the optimal demand $\hat{V}^+(R_M)$. The linear demand function $\hat{V}^-(R_M)$ is based on $\phi = \theta = 1$ and is independent of the distribution. Figure 1.6 plots the certainty equivalent difference, $ce(\hat{V}^+|\mathcal{I}) - ce(\hat{V}^-|\mathcal{I})$, for a time horizon of 1 year and for $\gamma = 3$, $\gamma = 8$ and $\gamma = 50$. Also, the plot illustrates the $\mathcal{I}$-range for which this difference is positive, i.e. it is above the black zero hyper-plane. The a priori probability of this range is $\mathcal{P} \approx 0.75$ for all γ-values. Hence, the optimal portfolio does not outperform the approximation portfolio at any conventional significance level. Therefore, the regret probability $(1 - \mathcal{P})$ of not having chosen the approximation portfolio is substantial.

This finding is not surprising because the approximation portfolio payoff is linear in the market return while the optimal payoff is concave. The certainty equivalent of the linear payoff is less sensitive to parameter variations than that of the concave payoff. Since, a priori, the certainty equivalent of the optimal portfolio exceeds that of the approximation portfolio only by a small percentage, we can only expect a high probability $\mathcal{P}$ if the a posteriori certainty equivalent of the optimal portfolio is as stable as that of the approximation portfolio with respect to parameter variations. But as illustrated in Figure 1.6, this is not true. Therefore the investor faces a rather high regret probability $(1 - \mathcal{P})$. This may be viewed as another argument for choosing the simple approximation portfolio instead of the complicated optimal portfolio.

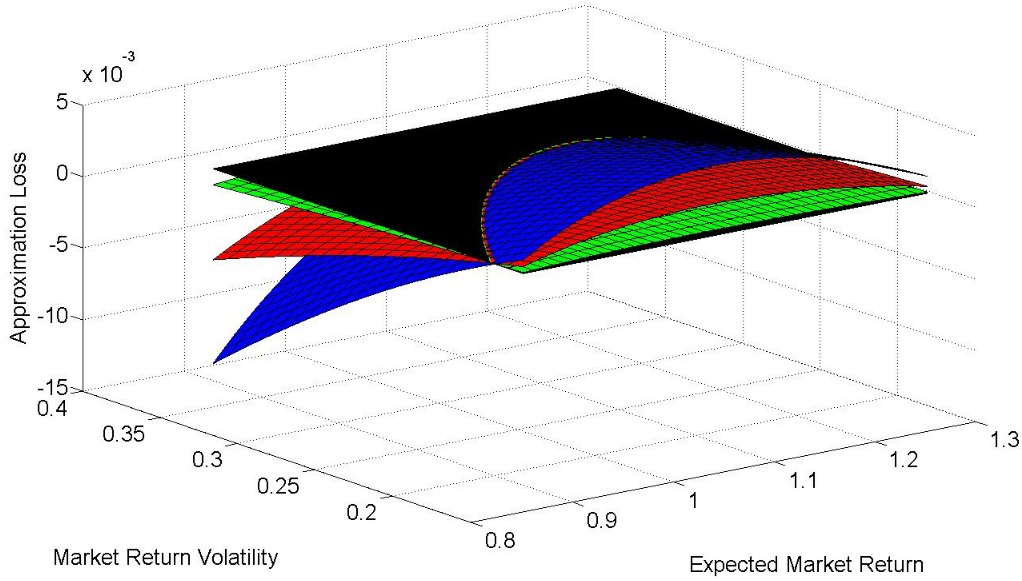

Figure 1.6: The plot shows the a posteriori-approximation loss assuming parameter uncertainty. The expected market return and the market volatility are a posteriori-realizations of truncated, normally distributed random variables. The blue (red) [green] surface shows the loss assuming $\gamma = 3$ ($\gamma = 8$) [$\gamma = 50$], the black hyper-plane marks zero everywhere.

1.6 Approximation in a Discrete State Space

In a continuous state space the probability mass of the optimal and the approximation portfolio payoff may be concentrated around the zero excess payoff inducing a strong approximation quality. This quality might be weaker for portfolio returns with more probability mass in the tails. Lemma 1, however, suggests that the approximation loss is similar in a continuous and a discrete state space whenever the non-central moments are similar. To find out about these effects, we now analyze the approximation quality in a discrete state space with few states.

As an example, consider a bank which only invests in loans. The loan market is arbitrage free. Loans either are fully paid or go into default paying a non-random recovery amount. If the bank can invest in many different loans, it can achieve strong portfolio diversification. Then the loan portfolio payoff can be approximated quite well by a continuous unimodal probability distribution. This suggests again a high approximation quality in the absence of approximate arbitrage opportunities.

Distribution	$\gamma = 2$ R	L	$\gamma = 3$ R	L	$\gamma = 10$ R	L
$\hat{\alpha}^+$	4.7813	1.8519	4.3083	1.8830	3.7183	1.9187
$(\hat{\alpha}^+ - \hat{\alpha}^-)$	-1.6290	0.1158	-2.1020	0.1469	-2.6920	0.1826
k	0.0038	0.0002	0.0048	0.0002	0.0028	0.0001

Table 1.1: It shows the optimal investment in the risky asset for $\gamma = 2, 3$ and 10 and the volume effect $(\hat{\alpha}^+ - \hat{\alpha}^-)$. The approximated investment based on $\phi = 1$ is $\hat{\alpha}^- = 6.4103$ for R and $\hat{\alpha}^- = 1.9677$ for L. k is the approximation loss. R (L) denotes the probability distribution skewed to the right (left).

Critical might be cases in which the number of loans is small. In the following, we present examples with one and two loans.

1.6.1 One Risky Asset

In the case of only one risky asset, there is no structure effect. Yet, the volume effect $(\hat{\alpha}^+ - \hat{\alpha}^-)$ remains and determines the approximation loss. A volume effect would not exist if the $1/\gamma$-rule would work perfectly. $\hat{\alpha}^+ = \hat{\alpha}(\gamma)$ and $\hat{\alpha}^- = \hat{\alpha}(\phi)$ denote the optimal and the approximate amount invested in the single risky asset, derived from the first order conditions (1.3) respectively (1.5).

We analyze a negatively and a positively skewed binomial distribution. Both distributions have the same expected return of 10.5% and standard deviation of 30%, so that the Sharpe-ratio is the same. The risk-free rate is 3%. Let u (d) be the gross return in the up-state (down-state). p is the up-state probability for the distribution R skewed to the right and also the down-state probability for the distribution L skewed to the left. For example, let $p = 0.25$, $u_R = 1.42$ and $d_R = 1$, $u_L = 1.21$ and $d_L = 0.79$. Hence the distribution R has a skewness of 0.191, while distribution L has a skewness of -0.165. The approximated investment in the risky asset is the optimal investment using $\phi = 1$. The optimal investment, the volume effect and the approximation loss are shown in Table 1.1 for an investor with constant relative risk aversion $\gamma = 2$, $\gamma = 3$ and $\gamma = 10$.

The volume effect is negative (positive) for the positively (negatively) skewed return distribution. The volume effect relative to the optimal investment in the risky asset is rather large (small) for the positively (negatively) skewed distribution. Yet, the approximation loss is rather small in all cases. It is larger for the positively skewed distribution, and declines with increasing γ for high values of γ.

The intuition for the sign of the volume effect can be derived from Figure 1.1. The optimal volume depends on the absolute risk aversion levels in the down-state and the up-state. Given $\gamma > \phi$, the absolute risk aversion is higher [smaller] for the utility function with parameter ϕ than for that with parameter γ in the down-state [up-state].

For the positively skewed distribution the absolute difference in risk aversion is much higher in the up-state than in the down-state. Therefore we expect a negative volume effect, $\hat{\alpha}^+ < \hat{\alpha}^-$. For a negatively skewed distribution we expect a positive volume effect. This is confirmed in Table 1.1. For a symmetric distribution, the absolute difference in risk aversion is about the same in the down- and in the up-state. Therefore $\hat{\alpha}^+(\gamma) \approx \hat{\alpha}^-(\phi)$ implying a very small volume effect.

There is an easy way to understand the strong volume effect for the positively skewed distribution. For a binomial distribution, the first order condition yields

$$p_u r_u \left(1 + \frac{\hat{\alpha}^+ r_u}{\gamma}\right)^{-\gamma} = (1 - p_u)|r_d| \left(1 + \frac{\hat{\alpha}^+ r_d}{\gamma}\right)^{-\gamma}$$

$$\Leftrightarrow \frac{p_u r_u}{(1 - p_u)|r_d|} = \left(\frac{\gamma + \hat{\alpha}^+ r_u}{\gamma + \hat{\alpha}^+ r_d}\right)^{\gamma}. \tag{1.27}$$

The left hand side of (1.27) denotes the gain/loss- ratio of Bernado and Ledoit (2000). The higher it is, the closer is an approximate arbitrage opportunity. For the positively (negatively) skewed distribution the gain/loss- ratio is 4.33 (2.25). Hence, the positively skewed distribution is much closer to approximate arbitrage. An investor with low relative risk aversion benefits more from approximate arbitrage than an investor with higher risk aversion by choosing a more aggressive portfolio. This explains for $\phi = 1$ the high value of $\hat{\alpha}^- = 6.41$, the strong negative volume effect and the relatively high approximation loss.

As argued by Bernado and Ledoit, a high elasticity of the pricing kernel indicates an approximate arbitrage opportunity[6]. The pricing kernel elasticity is 4.18 (1.90)

[6] Consider the Arrow-Debreu prices in this complete market setting. For a binomial return there always exists a pricing kernel with constant elasticity. The two Arrow-Debreu prices are

$$\pi_u = \frac{1}{R_f} \frac{p_u R_u^{-\theta}}{\mathbb{E}[R^{-\theta}]} \text{ and } \pi_d = \frac{1}{R_f} \frac{(1 - p_u) R_d^{-\theta}}{\mathbb{E}[R^{-\theta}]}.$$

for the positively (negatively) skewed distribution. Hence, the higher elasticity for the positively skewed distribution also motivates a higher approximation loss.

1.6.2 Two Risky Assets with Dependent Returns

Next, consider two risky loans with correlated binomial returns. In this case there exist only 4 states of nature. If there are two loans with different expected returns and perfectly negatively correlated returns, then there exists an arbitrage opportunity. If the returns are strongly negatively correlated, then there exists an approximate arbitrage opportunity. Hence, investors with low relative risk aversion will take very large positions in the risky assets which should raise the approximation loss.

For illustration, let the marginal distribution of each risky asset have a binomial distribution with equal probability for both outcomes, the up-state and the down-state. The gross return of asset 1 is $R_1 = (1.2; 0.925)$ and of asset 2 is $R_2 = (1.3; 0.85)$, respectively. The risk-free rate is 3%. This implies an expected excess return of 3.25% for asset 1 and 4.5% for asset 2. The standard deviation is 13.75% for the first asset and 22.5% for the second asset. Holding the marginal distributions for both asset returns constant, we change the return correlation by the following procedure. Let $P_{s,t} := \text{Prob}(R_1 = s, R_2 = t)$ denote the probability that asset 1 is in the s-state and asset 2 is in the t-state, $s, t \in \{\text{up, down}\}$. Then, the joint probability is

$$[P_{s,t}]_{s,t\in\{\text{up, down}\}} = \begin{pmatrix} 0.5 - x & x \\ x & 0.5 - x \end{pmatrix},$$

with $x \in [0; 0.5]$. Reducing $P_{\text{up, up}}$ and $P_{\text{down, down}}$ by x and adding x to $P_{\text{down, up}}$ and $P_{\text{up, down}}$, decreases the correlation without affecting the marginal distributions.

The approximation portfolio is based on $\phi = 0.98$. For relative risk aversion $\gamma \in [0.98; 8]$ and for a return correlation between -0.8 and 0.8, Figure 1.7, left, shows the approximation loss. It is very low for correlations above -0.5, but increases strongly for lower correlations. Given negatively correlated assets, the investor can buy a

The ratio $\frac{\pi_u}{\pi_d}$ can be used to solve for the pricing kernel elasticity θ,

$$\theta = \frac{\ln\left(\text{gain-loss-ratio}\right)}{\ln\left(\frac{R_u}{R_d}\right)}.$$

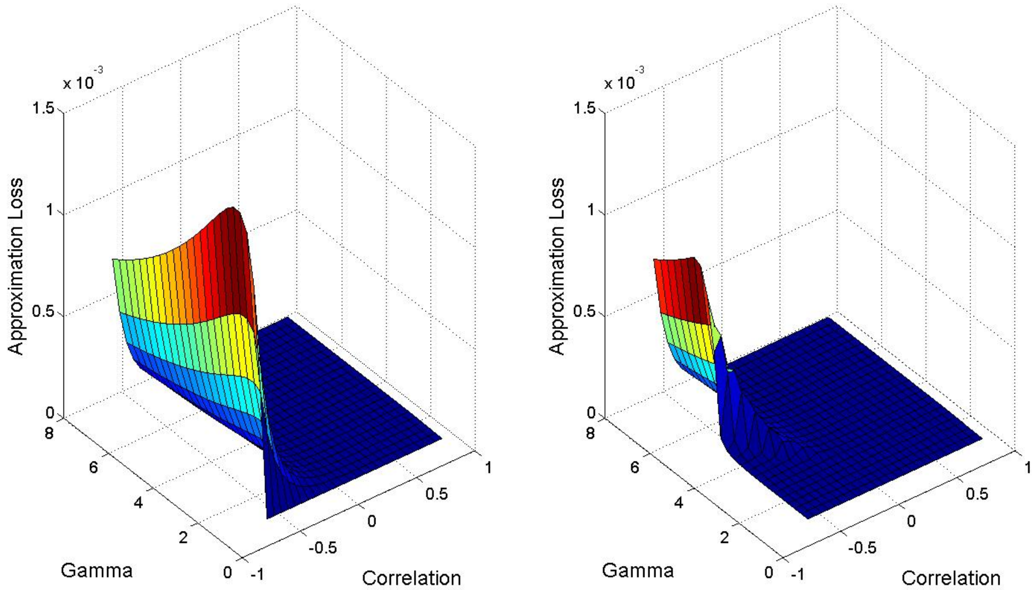

Figure 1.7: $\gamma > \phi = 0.98$, correlation of binomial returns between -0.8 and 0.8. **Left:** The figures show the approximation loss in a market with two binomial assets for different return correlations and γs. The expected excess return for asset 1 is 3.25% and 4.5% for asset 2. The volatility is 13.75% and 22.5%, respectively. **Right:** The figure shows the approximation loss for the same market setting with borrowing being prohibited.

hedged portfolio with long positions in both assets and earn a high portfolio return with little downside potential. Consider the case with correlation -0.6 and $\gamma = 2.5$. The optimal portfolio invests about 3.57$ of the initial endowment in asset 1 and about 2.06$ in asset 2. This gives an expected excess return of the optimal portfolio of 8.61% and a standard deviation of 17.64%. The approximation portfolio invests 3.02$ in asset 1 and 1.70$ in asset 2 implying an approximation loss of about 0.15%. The volume effect is $(3.57 + 2.06) - (3.02 + 1.70) = 0.91$$, it is quite strong. The structure effect $\frac{3.57}{2.06} - \frac{3.02}{1.70} = -0.04$ is, however, very weak. For higher correlations, the approximation quality is excellent.

Figure 1.8 shows the volume and the structure effect. The volume effect is quite strong for strongly negative correlation, while the structure effect is always quite modest. This indicates that the approximation quality is impaired primarily by the volume effect.

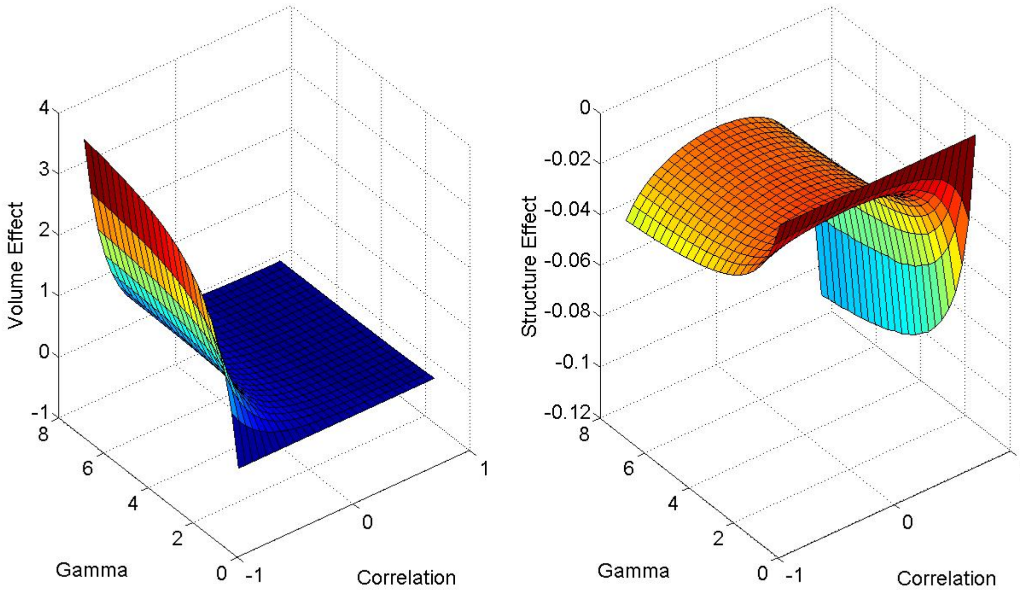

Figure 1.8: **Left:** The volume effect for a market with two binomial assets as in Figure 1.7. Only for strongly negative asset correlation there is a substantial volume effect. **Right:** The structure effect is remarkably small.

The example shows that the approximation loss is substantial whenever the asset correlation supports an approximate arbitrage. Then the investor with low RRA ϕ takes large positions in both risky assets and borrows a lot. If we exclude short selling, then approximate arbitrage opportunities cannot be used extensively so that the approximation loss is much smaller. This is illustrated in Figure 1.7, right. Compared to Figure 1.7, left, the restriction lowers the approximation loss strongly in the area $[-0.8, -0.4] \times [0.98, 4]$, where the first dimension is the asset correlation and the second the relative risk aversion γ.

1.6.3 The $1/n$ Policy

Finally, we compare our approximation to the $1/n$ policy. According to DeMiguel, Garlappi and Uppal (2009), the risky fund can be composed according to the $1/n$ rule without much of an effect given parameter uncertainty. We ignore this uncertainty. The investor only decides how much money to allocate to the risk-free asset. Hence

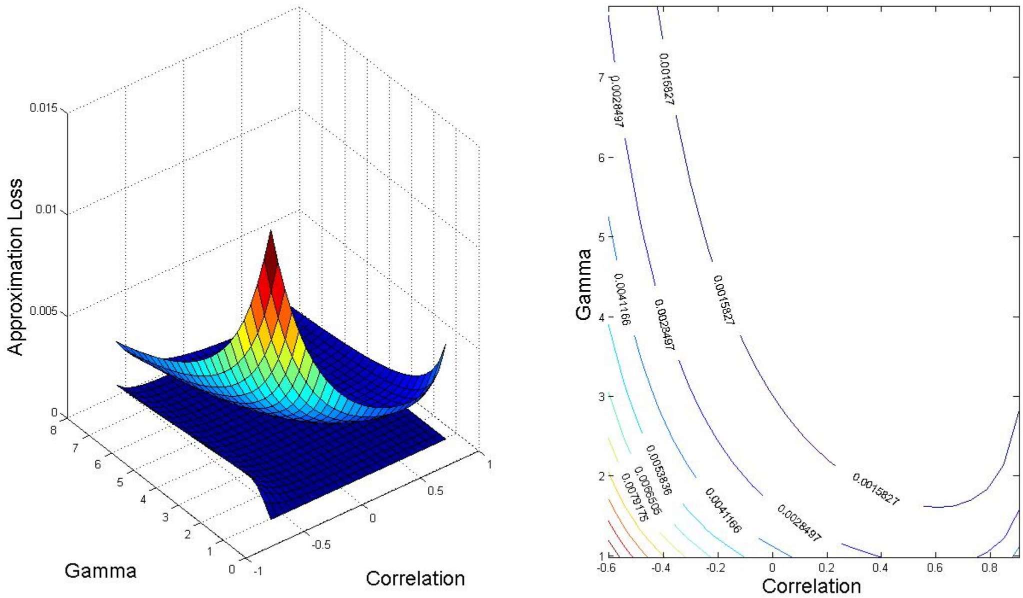

Figure 1.9: $\gamma > \phi = 0.98$, correlation between -0.8 and 0.8. **Left:** The upper surface depicts the approximation loss for the $1/n$ strategy in a market with two binomially distributed assets. The lower surface gives the approximation loss for our approximation strategy, see Figure 1.7, left. The $1/n$ strategy is clearly outperformed by our approximation approach for many combinations of asset correlation and relative risk aversion. **Right:** Combinations of relative risk aversions and correlations with (almost) equal approximation quality for the $1/n$ strategy.

the portfolio problem is

$$\max_{\hat{\alpha}} \mathbb{E}\left[\left(1 + \frac{\hat{\alpha}'\mathbf{r}}{\gamma}\right)^{1-\gamma}\right] \; s.t. \; \hat{\alpha}_1 = \ldots = \hat{\alpha}_n.$$

We measure the loss of the $1/n$ portfolio approach against the unrestricted optimal portfolio. Figure 1.9 shows the approximation loss for the $1/n$-policy for the market setting in which both loans have the same parameters as in Figure 1.7, and the corresponding isoquants. For comparison, it also shows the approximation loss for our approximation strategy (lower surface). The figure indicates large approximation losses in the range of up to 1.5%. Therefore, the structure of the $1/n$-portfolio clearly differs from that of the optimal portfolio. This finding does not invalidate that of DeMiguel, Garlappi and Uppal (2009), which is driven by uncertainty about the parameters of the multivariate return distribution.

1.7 Conclusion

Sophisticated portfolio optimization is unlikely to pay in a large variety of settings. We constrain our analysis to HARA-investors with declining absolute risk aversion and ask whether the parameters of the utility function really matter for optimal investment decisions. The paper shows that the optimal portfolio can be approximated without noticeable harm by the portfolio which is optimal for some HARA-investor with lower relative risk aversion, if approximate arbitrage opportunities do not exist. If these opportunities exist and the approximation portfolio takes high risk while the optimal portfolio does not, then the approximation leads to high approximation losses. Whenever the pricing kernel of the market return displays constant elasticity, an investor with higher relative risk aversion may simply buy the market portfolio and the risk-free asset without noticeable harm. Otherwise, the investor may buy a transformed market portfolio with low constant elasticity of the pricing kernel. Critical for a strong approximation quality is that the investor's relative risk aversion is higher than that used for the approximation and that approximate arbitrage opportunities do not exist.

Our findings generalize the two fund-separation of Cass and Stiglitz such that differences in the structures of optimal risky funds, driven by different levels of relative risk aversion, matter little in the absence of approximate arbitrage opportunities.

If there exists uncertainty about the parameters of the asset returns, then our examples demonstrate that the approximation portfolio turns out to be better than the optimal portfolio with a substantial probability. This also supports the use of a simple approximation portfolio. Further research might analyze the approximation quality in market settings in which investors use dynamic trading strategies to benefit from stock return predictability. Also the set of utility functions should be widened beyond HARA.

1.8 Appendix

1.8.1 Alternative Approximation Approach

An alternative approximation approach is based on the optimal portfolio of an investor with constant absolute risk aversion of 1 and artificial initial endowment γ/R_f. For this investor, the first order condition is

$$\mathbb{E}\left[r_i \exp\{-\hat{\alpha}'\mathbf{r}\}\right] = 0,\ \forall i \in \{1, \ldots, n\}, \tag{1.28}$$

irrespective of her initial endowment. We make use of $(1 + x/p)^p \rightarrow \exp\{x\}$ for $p \rightarrow \infty$ to connect the first order condition (1.3) of an investor with artificial initial endowment γ/R_f and constant relative risk aversion to the first order condition of an investor with constant absolute risk aversion of 1, i.e.

$$\mathbb{E}\left[r_i \left(1 + \frac{\hat{\alpha}'\mathbf{r}}{\gamma}\right)^{-\gamma}\right] \stackrel{\gamma\to\infty}{\longrightarrow} \mathbb{E}[r_i \exp\{-\hat{\alpha}'\mathbf{r}\}],\ \forall i \in \{1, \ldots, n\}. \tag{1.29}$$

Hence, the solution of (1.28) might be used as an alternative approximation for $\hat{\alpha}^+$, the solution of (1.3). However, this approach does not rule out negative terminal values of the approximate optimal portfolio, which is infeasible for HARA utility functions. To see this, consider a complete market with market return R_M and a pricing kernel with constant elasticity θ. In general, the optimal portfolio payoff is implicitly given by

$$\frac{\partial \ln V}{\partial \ln R_M} = \frac{\theta}{RRA(V)},$$

where $RRA(V)$ denotes the relative risk aversion. For the exponential utility investor, this yields the demand function $V_s^- = \theta \ln R_{M,s} + b$, where b is determined by the budget constraint $\mathbb{E}[V^-\pi] = \gamma/R_f$, hence $b = \gamma - \theta\frac{\mathbb{E}[R_M^{-\theta}\ln R_M]}{\mathbb{E}[R_M^{-\theta}]}$. Now consider normally distributed logarithmic market returns, i.e. $\ln R_M \sim \mathcal{N}(\mu, \sigma^2)$. This yields the explicit demand function

$$V_s^- = \gamma + \theta \ln R_{M,s} - \theta(\mu - \theta\sigma^2),$$

which is not positive for all market returns. More precisely, the probability that the portfolio payoff is negative is $\mathcal{N}(-\theta\sigma - \gamma/(\theta\sigma))$, with $\mathcal{N}$ being the standard normal distribution function. Therefore, this approach is not discussed.

1.8.2 Proof of Lemma 3

At an intersection point, $\hat{V}^+(R_M^j) = \hat{V}^-(R_M^j)$. Then, we have at an intersection with $R = R_M^j$,

$$\frac{\partial \hat{V}^+(R)}{\partial p} = \frac{\partial \hat{V}^-(R)}{\partial p}$$

$$\Leftrightarrow \frac{\theta}{\gamma}\exp\{a(\gamma)\}R^{(\theta/\gamma)-1}\frac{\partial R}{\partial p} + \frac{\partial a(\gamma)}{\partial p}\hat{V}^+(R)$$
$$= \frac{\theta}{\phi}\exp\{a(\phi)\}R^{(\theta/\phi-1)}\frac{\partial R}{\partial p} + \frac{\partial a(\phi)}{\partial p}\left[\hat{V}^-(R) - (\gamma - \phi)\right]$$

Since $\hat{V}^+(R) = \hat{V}^-(R)$, we have

$$\frac{\theta}{\gamma}\hat{V}^+(R)\frac{\partial \ln R}{\partial p} + \frac{\partial a(\gamma)}{\partial p}\hat{V}^+(R) = \left[\frac{\theta}{\phi}\frac{\partial \ln R}{\partial p} + \frac{\partial a(\phi)}{\partial p}\right][\hat{V}^+(R) - (\gamma - \phi)]$$

$$\Leftrightarrow \frac{\partial \ln R}{\partial p}\frac{\theta}{\phi}\frac{1}{\gamma}(\gamma - \phi)[\hat{V}^+(R) - \gamma] = \left[\frac{\partial a(\gamma)}{\partial p} - \frac{\partial a(\phi)}{\partial p}\right]\hat{V}^+(R) + \frac{\partial a(\phi)}{\partial p}(\gamma - \phi).$$

Dividing by $(\gamma - \phi)$ yields equation (1.20). Equations (1.21) and (1.22) follow from differentiating the budget constraint with respect to p.

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Chapter 2

Mechanically Evaluated Company News and their Impact on Stock and Credit Markets

Abstract: I analyze company news from Reuters with the 'General Inquirer' and relate measures of positive sentiment, negative sentiment and disagreement to abnormal stock returns, stock and option trading volume, the volatility spread and the CDS spread. I test hypotheses derived from market microstructure models. Consistent with these models, sentiment and disagreement are strongly related to trading volume. Moreover, sentiment and disagreement might be used to predict stock returns, trading volume and volatility. Trading strategies based on positive and negative sentiment are profitable if the transaction costs are moderate, indicating that stock markets are not fully efficient.

2.1 Introduction

Investors read daily newspapers, internet articles, watch TV news and listen to the radio. The information obtained might affect their trading decision and, hence, market prices, trading volume and volatility. Barber and Odean (2008) show that the number of news releases by Dow Jones News Service is related to the trading behavior of individual investors. Engelberg and Parsons (2011) find a causal relationship between financial news articles in local newspapers and the trading volume of local retail investors. However, news have many dimensions. The number of relevant news articles for a company is a very restrictive measure and ignores much information that might be important for financial markets, e.g. the sentiment. Tetlock (2007) and Groß-Klußmann and Hautsch (2011) find that the sentiment of news articles predicts daily index returns, and intraday liquidity and volatility, respectively. The sentiment of chat-room postings, which could contain news as well, may have predictive power for financial markets too, see Antweiler and Frank (2004), Das, Matinez-Jeres and Tufano (2005) and Das and Chen (2007). I build on these studies and construct a flexible content analysis algorithm to measure sentiment and disagreement, analyzing company news from Reuters.

Reuters company news usually describe and interpret a wide range of facts and events which might be relevant for companies. The author's interpretation and her word choice may provide valuable information for financial markets. The author's view might account for the economic environment, the firm's industry position, the management quality and much more aspects which are rather hard to measure quantitatively. If the author concludes that some fact is positive news for a company, she will use friendly and positive words to write the news story. If the facts are considered as negative, alarmed and sad words will probably characterize the news story. Of course, the quality of the author's comments depends on her background. This makes the analysis of chat-room postings and their impact on the market difficult, since everybody can post her opinion, rumors or lies without reputation damage. Reuters company news are more credible, which makes their analysis interesting. Another advantage of Reuters company news is that they allow studying the impact of heterogeneous events (e.g. earnings and dividends announcements, analyst recommendations, et cetera) on financial markets simultaneously.

I use the 'General Inquirer' to measure the sentiment of a news story with respect to a company and disagreement among news stories mechanically. The 'General Inquirer' assigns words to word categories. The word categories 'positive' and 'negative' are used to measure positive and negative sentiment of news stories. Also, I use the word categories 'strong' and 'weak' to measure the uncertainty of a news story. I test whether positive sentiment, negative sentiment and disagreement of Reuters company news articles impact financial markets. My dataset consists of information on 62 large U.S. companies listed at the NYSE or the Nasdaq with liquid stock option and CDS markets for the time period June 01, 2007 to December 31, 2010.

First, I investigate the co-movement of sentiment and disagreement with abnormal stock return derived from the three factor Fama-French model, stock and option trading volume, the volatility spread and the CDS spread using daily data. This analysis allows to test implications given by market microstructure models where investors interpret public signals individually. Sentiment approximates the intensity of public signals and disagreement approximates the degree of difference of opinion. My results are consistent with these models.

Second, I show that sentiment and disagreement have predictive power for (abnormal) stock returns, stock trading volume and the volatility spread. Positive sentiment is frequently followed by positive (abnormal) returns and disagreement tends to lower (abnormal) returns on the following day. The volatility spread increases after negative sentiment and disagreement. Stock trading volume is significantly higher after news with positive sentiment, but disagreement tends to reduce stock trading volume at the following day. The latter finding is surprising and might be due to an immediate execution of orders scheduled to the following day, given inconsistent news articles. Then, trading volume might be low during the subsequent day.

Finally, I test the economic relevance of positive and negative sentiment by analyzing trading strategies based on sentiment. Even though I consider realistic transaction costs of 10 bps per round-trip, the trading strategies are comparable to approximate arbitrage opportunities, indicating that the stock market is not fully efficient. For transaction costs of 20 bps, the trading strategies are, on average, still profitable, but bear a substantial loss potential. The strategies cannot compensate for transaction costs of 30 bps and more.

The contribution of this paper is manyfold. (1) I consider a large number of companies with liquid stock and derivative markets and analyze the relationship between news articles and (abnormal) stock returns, stock and option trading volume, the volatility spread and the CDS spread company individually. Hence, I do not aggregate returns, etc., at the same day across companies. This distinguishes this study from Tetlock (2007), who considers index returns, and from Das et al. (2005), who analyze four representative companies individually. (2) I analyze a comprehensive and hand-collected dataset of news stories, downloaded from the homepage of Reuters with a flexible procedure. I extend Groß-Klußman and Hautsch (2011), who relate pre-calculated dummy variables for positive and negative sentiment to the stock market, by introducing a continuous sentiment score. (3) Reuters company news are highly credible. This distinguishes this analysis from Antweiler and Frank

(2004) and Das and Chen (2007), who study chat-room postings. Das et al. (2005) analyze chat-room postings, too, claiming that these postings disseminate public information. My analysis might contribute to those study, since it analyzes news articles which might be closer to public information and, hence, less noisy. (4) To my best knowledge, this study is the first that analyzes the relationship between the CDS spread and sentiment and disagreement, respectively, of general news articles.

The rest of the paper is organized as follows. Section 2 gives a literature review. Section 3 derives testable hypotheses from market microstructure models. Thereafter, I explain how market activity is measured. I describe my hand-collected news database in section 4. Section 5 describes the content analysis and defines measures for sentiment and disagreement. Thereafter, I relate these measures to the market variables and develop trading strategies based on sentiment. Section 8 concludes and gives an outlook for further research.

2.2 Related Literature

Several papers investigate the relationship between a company's publicity and the stock market. Publicity often refers to the number of newspaper articles on the company. In an early study, Mitchell and Mulherin (1994) relate the number of news releases by Dow Jones & Company to the absolute value of the market return, the absolute value of firm-specific return and the trading volume. By controlling for macroeconomic announcements and weekday effects, the study documents a significant relationship between news activity and market activity. Barber and Odean (2008) define attention-grabbing stocks as stocks with high abnormal trading volume, extreme returns or news coverage. They show that individual investors are more likely to purchase attention-grabbing stocks than other stocks. Engelberg and Parsons (2011) address the causality between news articles and investors' behavior. They identify articles on earnings announcement in local newspapers. Local news coverage predicts trading volume of local investors and gives strong support to a causal relationship from news coverage to trading. Fang and Peress (2009) study the cross-section of stock returns. They find that stocks with media coverage, measured by the number of articles on the company in the four major U.S. newspapers (New York Times, USA Today, Wall Street Journal, Washington Post), underperform stocks without media coverage.

Of course, the number of news per day ignores the content of the news article.

Tetlock (2007) identifies weak or negative words in the daily article ‘Abreast of the Market’ in the Wall Street Journal with a content analysis algorithm, the ‘General Inquirer’. He finds that the number of negative or weak words predicts the return of the Dow Jones Industrial Average on the following day. This effect is offset within the subsequent five days and disappears after one week. Groß-Klußmann and Hautsch (2011) show that the sentiment of news articles and their relevance for companies listed at the LSE predict high frequency returns, volatility and liquidity. The sentiment of a news article is calculated by Reuters and can take on only the values +1, 0 and -1. The relevance of the news story determines the sensitivity of the market with respect to the news article. Tetlock et al. (2008) show that print news can predict fundamental value as well as market value. However, trading strategies based on these forecasts generate profits only if transaction costs are excluded. Carretta et al. (2010) study the Italian stock market and its reaction to corporate governance news. News stories are analyzed with respect to content and tone, revealing that the content of news on profitable corporations is important to explain stock returns.

Several studies use a more general definition of news and consider chat-room postings as news. However, this kind of information is presumably more noisy and, hence, less credible than regular news articles. Antweiler and Frank (2004) relate measures for bullishness and disagreement in chat-room postings and chat-room activity to market activity. Their main finding is that chat-room postings predict realized volatility and trading volume, given high frequency data. Das et al. (2005) analyze chat-room postings for four representative companies with different size and find a contemporaneous relationship between the sentiment of investors’ conversations and market returns, but no predictive power. This motivates their conclusion that investors first trade and then talk. Das and Chen (2007) apply a wide spectrum of text analysis algorithms to chat-rooms postings and develop measures for sentiment and disagreement. Relating these measures to the stock market return of the corresponding company also shows that investors’ sentiment is related to market activity. Tumarkin and Whitelaw (2001) analyze chat-room postings, too. However, their findings on the interdependence between market observations and posted news are inconclusive.

By using a narrow definition of news, the number of articles might reduce significantly and a mechanical content analysis might not be necessary. Brooks, Patel and Su (2003) analyze stock responses to rare, negative surprises like the Exxon Valdes catastrophe, plane crashes or the sudden death of a CEO. They find that stocks respond with a delay to fully unanticipated news, but overreact, see also Brounen and Derwall (2010), who study the impact of terrorist attacks and earthquakes, respectively. Yu (2011) uses the dispersion in analyst forecasts to measure disagreement. A portfolio of stocks with high disagreement underperforms compared to a portfolio with low disagreement. Boyd, Hu and Jagannathan (2005) do not focus on firm specific news, they analyze unemployment reports and find that stock markets respond to unemployment news conditional on the state of the economy.

Not only stock prices seem to respond to textual information, there is evidence that the prices of credit derivatives and fixed income securities do so as well. Norden (2008) studies the relationship between credit default swap spreads and rating announcements, see also Hull, Predrescu and White (2004), finding that the market anticipates rating reviews and downgrades. The number of bank lenders determines the degree of anticipation, indicating that information spills over from the major lenders to the market. Hess et al. (2008) study the impact of macroeconomic news on commodity future price indices. The index return responds to news about the inflation rate or real activity only in a recession. Hautsch and Hess (2002) analyze the U.S. employment report's impact on T-bond futures returns. Besides of liquidity patterns, the study documents asymmetries in the T-bond future price reaction to positive and negative news. Coval and Shumway (2001) propose a very remarkable measure of information arrival, the ambient noise in the CBOT trading pit. This measure predicts returns, liquidity and the customer order flow of the 30 year U.S. treasury bond for several minutes.

2.3 Market Reactions

2.3.1 Hypotheses

The efficient market hypothesis says that market prices adjust immediately to public information. I test this hypothesis. Hence

> ***Hypothesis 1:*** Market prices adjust immediately to public information (i.e. sentiment and disagreement) leaving no predictive power for public company news.

The next hypotheses relate stock and option trading volume and volatility to news. Assuming homogeneous beliefs, the absence of private information and homogeneous preferences, investors do not trade if new information becomes public, starting at an equilibrium, see Milgrom and Stokey (1982). However, this is inconsistent with the empirical studies cited before. Harris and Raviv (1993) and Kandel and Pearson (1995) drop the assumption of homogeneous beliefs. They assume that investors observe noisy, public signals and update their beliefs consistently with their individual interpretation. Different levels of confidence with respect to the noisy, public signal across investors (difference of opinion) might cause heterogeneous changes in the demand for risky assets and, hence, trading. Furthermore, Cao and Ou-Yang (2009) extend this framework and show that public signals and heterogeneous priors may also cause trading in stock options. Banerjee and Kremer (2010) relate a time-varying magnitude of difference of opinion to trading volume and price volatility and find that "[...] periods of major disagreement are periods of higher volume and also of higher absolute price changes" (Journal of Finance 65, p. 1271). The latter might be a measure of return volatility.

Company news might be closely related to public signals. They are usually unscheduled and fundamental. Therefore, I approximate the intensity of public company signals by the sentiment of relevant news article. The degree of differences of opinion is approximated by the variation in the sentiment of relevant news articles within a trading day, hereafter called disagreement. Hence

> ***Hypothesis 2:*** Trading volume of stocks and options increases with positive sentiment and negative sentiment.
>
> ***Hypothesis 3:*** An increase in disagreement raises trading volume of stocks and options.
>
> ***Hypothesis 4:*** The stock return volatility increases with disagreement.

According to Hong and Stone (2007), heterogeneous priors of investors are one explanation why disagreement affects the stock market. Others are limited attention and gradual information flow. These explanations have similar implications on the relationship between the stock market and disagreement.

Another strand of literature explains trading by information asymmetries across investors. Tetlock (2010) analyzes market data around company announcements and finds pattern which are consistent with information asymmetries. Blume, Easley and O'Hara (1994) show theoretically that trading volume might contain valuable information to determine the precision of noisy, private information and might be useful for stock pricing, see also Suominen (2001). Sarwar (2005) and Kyriacou and Sarno (1999) study option trading volume and market volatility. Both studies find a strong predictive power of option trading volume for volatility and vice versa. Adjusting hedged portfolios to changes in volatility might explain why volatility predicts option trading volume. Also, investors with private information might exploit their informational advantage aggressively with options and use the leverage effect or bet on volatility via derivatives. Hence, option trading volume might predict volatility. By analyzing the ratio of traded put and call options, Pan and Poteshman (2006) find that stocks with low ratios significantly outperform stocks with high ratios. Again, this indicates that informed traders use derivates to realize their informational advantage. These studies show that one has to control for the implicit information such as historical returns, volatility and trading volume, to measure the role of news accurately.

Besides of returns, stock and option trading volume and volatility, I include the CDS spread of a company in the analysis for two reasons: (1) Structure models for credit derivatives, such as Merton (1974), imply that the equity market and the credit market are closely linked. Cremers et al. (2006) and Zhang, Zhou and Zhu (2009) document a close relationship between credit markets and equity markets. Hence, I control for information spillovers from debt to equity markets and vice versa. (2) I test if the CDS spread is related to the degree of difference of opinion and to public signals. Since equity volatility and the unobservable asset volatility in structure models are positively related, the CDS spread might also respond to a change in difference of opinion, given that the equity volatility reacts and that markets are efficient. Therefore

Hypothesis 5: The CDS spread increases with disagreement.

Furthermore, the volatility spread and the CDS spread represent market prices of traded derivatives. Predictability might indicate low market efficiency and would contradict Hypothesis 1.

2.3.2 Measures of Market Reactions

The daily close-to-close excess stock return of company i at day t, denoted $r_{i,t}$, might be used as a measure for the stock market's response to news releases. More appropriate and in line with many other studies is the abnormal stock return, measured by the residuum in the three factor Fama-French model (hereafter FF model / factors / residuum), see Fama and French (1993). The residual measures the stock price movements that are not due to common market risk factors, but might be due to firm-specific risk factors and news, respectively. The FF factors and the risk-free interest rate are downloaded from the homepage of Kenneth French see `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html`, the dividend adjusted stock prices are downloaded from Thomson Reuters Datastream. I estimate

$$r_{i,t} = \alpha_i + \beta_{i,\text{Market}} X_{\text{Market},t} + \beta_{\text{SMB},i} X_{\text{SMB},t} + \beta_{\text{HML},i} X_{\text{HML},t} + \varepsilon_{i,t}, \qquad (2.1)$$

where $\beta_{i,\cdot}$ denotes the factor loading of the corresponding factor $X_{\cdot,t}$ (Market, **S**mall **M**inus **B**ig market capitalization, **H**igh **M**inus **L**ow book to market ratio). The estimated residuum is defined by $\hat{\varepsilon}_{i,t} := r_{i,t} - \hat{r}_{i,t}$, where $\hat{r}_{i,t}$ is the explained stock return.[1]

I measure the stock trading volume by the daily turnover volume, divided by the average turnover volume in the preceding 3 months. This measure is denoted $T_{i,t}$. To address the study of Sarwar (2005) and Kyriacou and Sarno (1999), and to test the model of Cao and Ou-Yang (2009), I also include the cumulated option trading volume of all outstanding options on stock i at day t, divided by its 3-month moving average. This measure is denoted $O_{i,t}$. The time series of trading volumes are provided by Thomson Reuters Datastream. I use the 3-month volatility spread, defined by

$$V_{i,t} = IV_{i,t} - RV_{i,t},$$

to measure the investors expectations on volatility relative to realized volatility. $IV_{i,t}$ is the at-the-money implied volatility of 3-month constant maturity options, calculated by Thomson Reuters Datastream. According to Martens and van Dijk (2007), the 3-month realized volatility is well approximated by

$$RV_{i,t} = \sqrt{\frac{1}{2} \sum_{s=t-60}^{t} [(\ln H_{i,s} - \ln L_{i,s})^2 - (2 \ln 2 - 1)(\ln R_{i,s})^2]},$$

where $H_{i,s}$ is the highest intraday stock price within day s and $L_{i,s}$ is the lowest

[1] $\hat{\varepsilon}$ is estimated in-sample. $\hat{\varepsilon}_{i,t}$ is not adjusted for momentum since momentum might be useful to explain trading volume or volatility in the regression analysis. Furthermore, the regression models account for autocorrelation in returns.

intraday stock price. $R_{i,s}$ is the close-to-close gross stock return of day s.[2] Finally, I use the 5-year CDS spread on senior debt as an indicator for the company's default risk. The CDS spreads is denoted $C_{i,t}$, the data are provided by CMA.

2.4 Company News

Given a date (`mmddyyyy`) and a company, identified with its `RIC` (= Reuters instrument code), the domain `Reuters.com` returns a list of news articles for the uniform resource locator (url) `www.reuters.com/finance/stocks/companyNews?symbol=RIC&date=mmddyyyy`. I download all news stories for companies in the S&P500, FTSE100 or EuroStoxx50 for the time period June 01, 2007 to December 31, 2010 mechanically. Long news stories might span over more than one internet page. However, the download routine recognizes this and controls for it.

A news story consists of a headline, the full text or body, a time stamp (date and time), keywords and a list of companies, that indicates for which companies the news story might be important. In the following, this list is called 'related RICs'. The assignment of keywords and related RICs to a news story is done by Reuters. Keywords provide a rough, standardized categorization of the news story (e.g. Major Breaking News, Debt ratings news, Corporate Results, Mergers and Acquisitions). In a nutshell, company news inform about rating adjustments, analyst reports and changes for the stock price target, give summarizing statements on quarterly and annual reports, ad-hoc news and general news (e.g. macro-economic indicators, political events, articles in the Washington Post, New York Times, Wall Street Journal, etc.). Corrected or updated news are not excluded to capture the information flow correctly. For the observation period June 01, 2007 to December 31, 2010, there are more than 350,000 unique news stories with respect to the url. The average news article consists of 301.29 words (including numerical expressions and symbols) with a standard deviation of 239.64 words. The median of words per news article is 272 and indicates that the distribution of words per article is skewed to the right. The 99% quantile is 961 words. On average, a news article consists of 14.02 sentences with a standard deviation of 33.20. The median is 11, again,

[2] Even though the implied volatility is supplemented for the realized volatility, the time series V is found to be non-stationary for many companies and is, hence, differentiated. Since the realized volatility moves very slowly, it has only little impact on the first difference of V, such that the results do not depend on the realized volatility and its calculation.

indicating that the distribution of sentences per news story is skewed to the right, and the 99% quantile is 44.

Table 2.1 provides descriptive statistics for the number of news articles per day for all S&P500 companies jointly, for the components of the Dow Jones Industrial Average by January 01, 2011 and for some frequently used keywords. I have 210,495 news articles for all S&P500 companies on 1311 days. Hence, the daily, average number of news articles for all S&P500 companies is 160.56 with a standard deviation of 94.01. Ignoring Saturdays and Sundays, the average number of news releases per day increases to 212.63 with standard deviation 52.94. On October 22, 2009, 354 news stories were published, this is the maximum number of news stories per day in the observation period. There are 17,525 news stories labeled with the keywords ‘Corporate Result’, ‘Result Forecast’ or ‘Warnings’, this gives a daily average of 13.36 with a standard deviation of 20.13. The total number of news stories having the keywords ‘Broker research and recommendation’ is 1,867, the daily average is, hence, 1.42 and the standard deviation is 2.26. News stories on e.g. Bank of America (BAC.N), identified by searching for ‘BAC.N’ in ‘related RICs’, sum up to 11,974, with a mean of 9.13 news stories per day and standard deviation of 8.23.

Figure 2.1, upper plot, shows the time series of the daily number of news stories with the keywords ‘Bankruptcy’ or ‘Insolvency’ (blue curve) and its 3 day moving average (red curve). For some reason, there are no such news stories prior to November 23, 2007. Therefore, the plot starts at November 23, 2007. The large number of news stories in the middle of September 2008 marks the bankruptcy of Lehman Brothers and the peaks in 2009 and 2010 are mainly due to the sovereign debt crisis in Europe. The lower plot shows the time series of the daily number of news stories for Bank of America and the corresponding 3-day moving average. This time series starts at June 1, 2007. The time series displays a weekly cyclicality caused by the low number of news articles during the weekend. Again, the default of Lehman Brothers at September 15, 2008 can be identified clearly. The peak in January 2009 is caused by the arranged acquisition of Merrill Lynch by Bank of America.

Summary statistics for Reuters news	Sum	Mean	Std.	Max.
All	210495	160.56	94.01	354
All w/o Saturdays / Sundays	199238	220.64	52.91	354
Economic news / Macroeconomics	56531	43.12	38.61	196
General News	28085	21.42	21.00	118
Debt ratings / Credit Market News	2461	1.88	2.65	22
Society / Science / Nature	2426	1.85	4.17	30
Major Breaking News	5042	3.85	9.82	65
Bankruptcy / Insolvency	671	0.51	1.21	11
Broker Research and Recommendation	1867	1.42	2.26	17
Corporate Results / Results Forecasts / Warnings	17525	13.37	20.13	150
Mergers / Acquisitions / Takeovers	13598	10.37	11.47	60
AA.N	2770	2.11	4.16	49
AXP.N	2341	1.79	3.55	40
BA.N	4163	3.18	3.65	21
BAC.N	11974	9.13	8.23	77
CAT.N	2442	1.86	3.65	50
CSCO.O	3085	2.35	3.83	35
CVX.N	5687	4.34	3.67	29
DD.N	980	0.75	1.86	22
DIS.N	5326	4.06	3.86	26
GE.N	10236	7.81	5.98	42
HD.N	1546	1.18	2.99	34
HPQ.N	4593	3.50	4.31	31
IBM.N	4790	3.65	4.64	40
INTC.O	5219	3.98	5.26	40
JNJ.N	2860	2.18	3.01	29
JPM.N	11723	8.94	7.62	45
KFT.N	2171	1.66	3.43	35
KO.N	2080	1.59	2.54	18
MCD.N	2120	1.62	3.02	38
MMM.N	1043	0.80	2.32	28
MRK.N	3223	2.46	3.40	41
MSFT.O	10495	8.01	7.21	68
PG.N	2096	1.60	2.86	42
PFE.N	3803	2.90	3.61	52
T.N	4559	3.47	3.95	33
TRV.N	407	0.31	1.22	19
UTX.N	2026	1.55	2.59	20
VZ.N	3435	2.62	3.32	28
WMT.N	6676	5.09	5.19	45
XOM.N	8096	6.18	4.98	33

Table 2.1: This table gives summary statistics (sum, mean, standard deviation and maximum) for the number of news articles per day. The upper panel classifies news on the S&P500 companies by keywords and the lower panel show the statistics for all members of the Dow Jones Industrial Average separately. A news story is considered as relevant for a company if the company's RIC is mentioned in the field 'related RICs'.

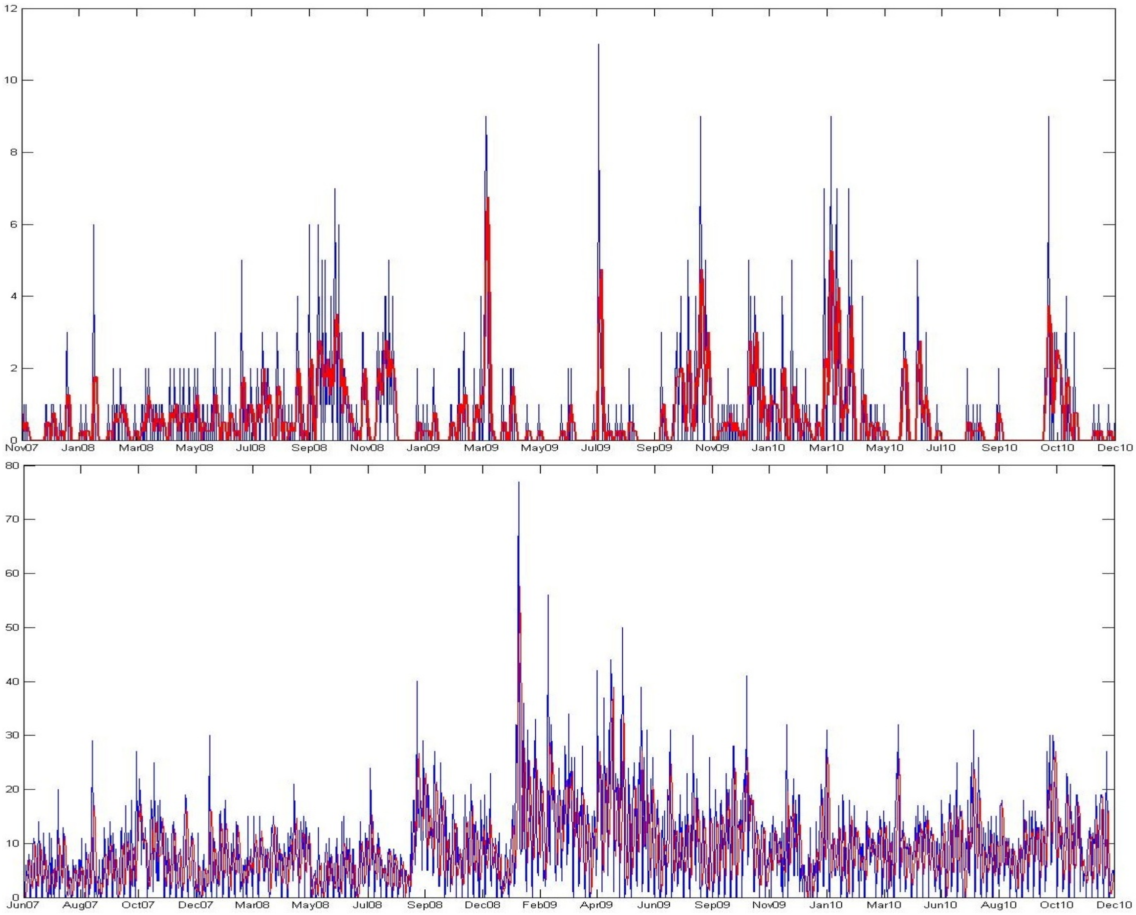

Figure 2.1: The upper figure shows the daily number of news stories with keywords 'Bankruptcy' or 'Insolvency' (blue curve) and the 3 day moving average (red curve), starting at November 23, 2007 to December 31, 2010. The lower figure shows the daily number of news stories for the Bank of America, starting at June 01, 2007.

2.5 Content Analysis

2.5.1 Variable Construction

According to Groß-Klußmann and Hautsch (2011), the relevance of a news article for a company determines the strength of the relationship between the sentiment of the news article and the market. Hence, I start with a narrow definition of relevant news:

> A news article is relevant for a company, if it mentions the company name or its nickname in the headline and has the company's RIC in the field 'related RICs'.

A broader definition is used for robustness checks. In the following, the term company name refers to the shortest fraction of the full company name that clearly identifies the company, e.g. 'Disney' instead of 'Walt Disney Co' or 'Conoco' instead of 'ConocoPhillips'. For most companies, I am also able to identify the company's nickname very accurately. For example, Bank of America is frequently called BofA, Johnson & Johnson is called J&J and American Express is AmEx. Texas Instruments, often called TI, and General Electrics, shortened GE, can only be identified with a small error rate. Synonyms for the company name are not recognized. The restriction on 'related RICs' in the above definition ensures that a news story with a headline such as '*BofA cuts Google price target*' is assigned to Google, but not to Bank of America.

Even though a news article is relevant for a company, it is unlikely that all words in the full text are important for the company as well. Hence, I define which passages in the full text of a relevant news story have to be analyzed. I define the relevant text by:

> All words in a sentence are relevant if the company name or nickname is mentioned within the same sentence.

I test an alternative definition of relevant test in the robustness section.

Given a company, I analyze the content of the relevant text of a relevant news story and assign a numerical value to it. The approach relies on the 'General Inquirer', see `http://www.webuse.umd.edu:9090/`. The 'General Inquirer' is a dictionary based content analysis algorithm. It assigns words to word categories and reports the number of hits in each cluster, relative to all analyzed words. There are about 80 word categories. However, I restrict myself to the categories 'positive', 'negative', 'strong' and 'weak'. Even though being very popular, the 'General Inquirer' is not perfect. Many words have more than one meaning and might be incorrectly assigned to a word category, see for example Loughran and McDonald (2011), who test the performance of the 'General Inquirer' by analyzing annual and 10-K reports, and find that a substantial fraction of negative words (about 60%) is misinterpreted. However, the content of the Reuters news articles is more general than 10-K reports, hence I expect a low error rate. Moreover, I use the word lists suggested by Loughran and McDonald for a robustness analysis.

Alternative content analysis algorithms are e.g. Bayesian classifier, vector-distance classifier and support vector machines, see Das and Chen (2007). However, these classifiers require a pre-classified training set, which determines the quality of the classification. Therefore, those classifiers might be subjective and are not consider here.

Consider, for example, the following news stories:

> Feb. 29, 2008, Northrop-EADS beats Boeing to built U.S. tanker
>
> WASHINGTON (Reuters) - The U.S. Air Force said on Friday it had picked a transatlantic team led by Northrop Grumman, instead of Boeing, to start building a new aerial refueling fleet in a surprise choice worth about $35 billion. Northrop Grumman Corp (NOC.N) and its European partner, Airbus parent EADS (EAD.PA), "clearly provided the best value to the government," Sue Payton, the Air Force's chief weapons buyer, told reporters at a briefing. The contract is to supply up to 179 tanker aircraft in a deal valued at about $35 billion over the next 15 years, the Air Force said in a statement. The aircraft will replace [...]

> Apr. 29, 2009, IBM Q1 rev disappoints, Texas Instruments solid
>
> NEW YORK/BOSTON (Reuters) - IBM disappointed investors on Monday with lackluster quarterly revenue, but Texas Instruments afforded the market some cheer with a solid sales performance. IBM reported a bigger-than-expected 11 percent fall in quarterly sales, showing that even one of the healthier U.S. technology companies is getting hurt by a slowdown in corporate spending. [...]

Clearly, the first news story is rather positive for Northrop and negative for Boeing, and the second is positive for Texas Instruments and negative for IBM. According to the 'General Inquirer' dictionary, the first sentence of the first news article is neutral. There are several positive words in the second sentence of the first news story ('clearly', 'provide', 'best'). There, Northrop (and EADS, respectively) is mentioned, but not Boeing. Hence, the overall sentiment of the (fraction of the) news article is consistent with our expectations. Now, let us consider the second news article. Texas Instruments and IBM are both mentioned in the first sentence of the second news story. Since positive words (e.g. 'cheer') are also associated with IBM and negative words (e.g. 'disappoint') with Texas Instruments, the sentiment of the (fraction of the) news article is the same for both companies, which is counterintuitive. In this case, the definition of relevant text might lead to wrong conclusions. However, the procedure performs very well for simple or well-structured news.

To homogenize market data and news stories, I assign news stories that were released after 4 p.m. New York time to the following trading day. News stories published between Friday, 4 p.m. and Monday, 4 p.m. are assigned to Monday. Assume there are $Q_{i,t} \in \mathbb{N}$ relevant news stories for company i on day t. Given the relevant text, let $Pos_{i,t,j}$ $[Neg_{i,t,j}]$ denote the number of positive [negative] words relative to the total number of words in the relevant text of news story $j = 1, \ldots, Q_{i,t}$. Then, the average, relative number of positive words and the average, relative number of negative words are used to measure positive sentiment, $P_{i,t}$, and negative sentiment, $N_{i,t}$, at t and for company i, i.e.

$$\begin{aligned} P_{i,t} &= \max\left\{ \frac{1}{Q_{i,t}} \sum_{j=1}^{Q_{i,t}} (Pos_{i,t,j} - Neg_{i,t,j}), 0 \right\}, \\ N_{i,t} &= \max\left\{ \frac{1}{Q_{i,t}} \sum_{j=1}^{Q_{i,t}} (Neg_{i,t,j} - Pos_{i,t,j}), 0 \right\}. \end{aligned} \tag{2.2}$$

$P_{i,t}$ and $N_{i,t}$ might be also interpreted as positive and negative public signals in the style of Harris and Raviv (1993). High values of $P_{i,t}$ or $N_{i,t}$ indicate strong signals.

It is likely that there is a monotone relationship between the average net sentiment of day t, i.e. $\frac{1}{Q_{i,t}} \sum_{j=1}^{Q_{i,t}} (Pos_{i,t,j} - Neg_{i,t,j})$, and the abnormal stock returns or the CDS spread, but trading volume and volatility are presumably not monotonically related to the net sentiment. Therefore, positive and negative sentiment are disentangled. I do not exclude days without news releases since these days are important as well and might indicate 'neutral' or 'calm' days. The sentiment for these days is set to zero.

Furthermore, I define two disagreement scores. If news stories disagree heavily, it is likely that investors disagree as well. Hence, the degree of difference of opinion among investors might be well approximated by the variation in the sentiment of news stories at the same day. I define

$$D^{\text{std}}_{i,t} = \sigma\left((Pos_{i,t,j} - Neg_{i,t,j})_{j\in Q_{i,t}}\right), \tag{2.3}$$

where $\sigma(\cdot)$ is the standard deviation. I set $D^{\text{std}}_{i,t} = 0$ if $Q_{i,t} \leq 1$.

Inspired by Das and Chen (2007), I construct a second measure for disagreement. Define the auxiliary variable $A_{i,t,j} := \mathbf{1}(Neg_{i,t,j} < Pos_{i,t,j}) - \mathbf{1}(Neg_{i,t,j} > Pos_{i,t,j})$. $\mathbf{1}(\cdot)$ is the indicator function. It is one if and only if the argument is true. Hence, $A_{i,t,j} = 1$ if the net sentiment of news j is positive, it is zero if $Pos_{i,t,j} = Neg_{i,t,j}$ and -1 otherwise. $A_{i,t,l}$ might be interpreted as buy- or sell-signal. Then, disagreement is alternatively measured by

$$D^{\text{pol}}_{i,t} = \frac{\max\left\{\sum_{j=1}^{Q_{i,t}} |A_{i,t,j}|, 1\right\}}{\max\left\{\left|\sum_{j=1}^{Q_{i,t}} A_{i,t,j}\right|, 1\right\}}. \tag{2.4}$$

D^{pol} measures the polarity of $(A_{i,t,j})_{j\in Q_{i,t}}$. If all news stories on day t and for company i have a positive sentiment or all have a negative sentiment, $D^{\text{pol}}_{i,t} = 1$. For days with less than two news stories, I set $D^{\text{pol}}_{i,t} = 1$, too, which indicates no disagreement. For all other days, $D^{\text{pol}}_{i,t} > 1$. $D^{\text{pol}}_{i,t}$ is high if there are many news stories with positive or negative sentiment (numerator is large) and the number of positive and negative news stories is balanced (denominator is small). These days might be associated with high disagreement across investors. Whereas $D^{\text{pol}}_{i,t}$ considers only the variation of the sign of net sentiment within a trading day and ignores variations the magnitude completely, D^{std} is sensitive to variations in the net sentiment even though the sign of the net sentiment might be the same for all news stories.

2.5.2 Descriptive Statistics

Table 2.2 shows company-individually the number of days with positive and negative sentiment and disagreement ($\#(\cdot > 0)$), the conditional means ($m(\cdot|\cdot > 0)$) and the conditional standard deviations ($\sigma(\cdot|\cdot > 0)$). The cross-sectional mean and standard deviation is given at the bottom of Table 2.2. Disagreement is measured by D^{std}. The companies listed in Table 2.2 are chosen because they have a liquid option and CDS market. Table 2.8 lists the company names and the RICs. Option data is available for most companies since June 2008 and determine the beginning of the joint observation period of market data and news, whereas the CDS spreads are available until October 2010 and determine the end. With the exception of Intel Technology (INTC.O) and Travelers Companies (TRV.N), I have 597 days without missing observations for each company. There are 479 observations for Intel and 660 observations for Travelers.

On average, news stories have a positive tenor. The cross-sectional average number of days with positive sentiment is 92 and the average number of days with negative sentiment is 41. The cross-sectional conditional mean of positive sentiment is 3.3174 and of negative sentiment is 2.4194. This gives an average net sentiment of 1.5489 per day with news. Compared to the cross-sectional average sentiment, American Express Co (AXP.N), American International Group Inc (AIG.N) and Travelers Companies Inc (TRV.N) have very low average net sentiment. One reason might be that these companies were hit hard by the financial crisis. For some reasons, The Boeing Company (BA.N), The Dow Chemical Co (DOW.N) and Fedex Corp (FDX.N) have low average net sentiment, too. On average, positive and negative sentiment are correlated by -0.0725, positive sentiment and D^{std} are correlated by 0.2613 and negative sentiment and D^{std} by 0.1727. The average correlation between D^{pol} and P respectively N are almost the same.

Regarding the market variables, the augmented Dicky-Fuller test cannot reject the unit-root hypothesis for the CDS spread and for the volatility spread for many companies. Hence, I replace these time series by the corresponding first differences for all companies to prevent spurious regressions, see Sarwar (2005). ΔV and ΔC denote the first difference of the volatility spread and the CDS spread, respectively. $\hat{\varepsilon}_{i,t}$, $T_{i,t}$ and $O_{i,t}$ are always stationary. The average correlation between the abnormal return and the change in the volatility spread across all companies is -0.2859. Stock and option trading volume are on average correlated by 0.3201 and the change in the volatility spread and the CDS spread are on average correlated by 0.2219. All other correlations between the market variables are close to zero.

RIC	$\#(P>0)$	$m(P\|P>0)$	$\sigma(P\|P>0)$	$\#(N>0)$	$m(N\|N>0)$	$\sigma(N\|N>0)$	$\#(D>0)$	$m(D\|D>0)$	$\sigma(D\|D>0)$
$AA.N$	79	3.2504	2.4254	48	2.7442	2.0826	54	2.4188	2.2592
$ABT.N$	64	2.9495	1.9430	20	2.3062	1.1289	31	1.6257	1.6121
$AIG.N$	173	3.6032	2.3316	136	3.9970	3.0133	209	3.2710	2.1547
$AMGN.O$	60	2.4562	1.4674	27	1.9520	1.8325	33	1.7816	1.6824
$APC.N$	56	4.2889	2.6812	25	3.7985	2.7814	32	1.8993	1.7249
$AXP.N$	64	3.8703	4.7347	65	3.1979	2.4588	54	2.7427	2.8239
$BA.N$	172	2.3197	1.7603	138	2.4733	2.0844	202	2.0917	1.7702
$BAC.N$	229	2.6885	2.0884	107	2.4113	2.1768	216	2.2327	1.9952
$BAX.N$	27	3.1350	2.3361	6	1.3261	1.0626	13	2.8396	2.5411
$BMY.N$	68	3.5177	2.1955	20	2.0438	1.6211	43	1.7008	1.7800
$BSX.N$	28	2.4508	1.9893	17	1.3504	0.9238	19	1.9882	2.4059
$C.N$	302	3.1279	2.0583	99	1.9581	1.6824	276	2.2967	1.6895
$CAT.N$	52	3.0266	1.8953	16	1.7822	1.3524	27	2.1223	2.3512
$COP.N$	130	2.9440	1.5714	84	2.8550	2.0177	103	2.3616	1.5052
$CSC.N$	7	5.2307	3.1978	2	2.8250	2.5809	2	1.8420	0.9650
$CSCO.O$	120	3.6380	2.6329	19	2.0095	1.6628	73	1.7396	2.1665
$CVX.N$	136	2.7571	2.0611	94	3.0215	1.9161	133	2.1836	1.8328
$DD.N$	42	3.4745	2.2462	23	2.8427	1.9362	21	1.1783	1.1597
$DELL.O$	99	2.7777	2.1504	42	1.8228	1.7795	78	1.3372	1.3688
$DIS.N$	123	3.1999	2.1781	31	1.9420	1.3118	86	1.3702	1.4605
$DOW.N$	28	4.2514	2.3947	31	3.9294	2.7804	29	3.1736	2.5388
$DVN.N$	32	3.4291	2.1876	8	1.8642	1.5859	20	2.4095	2.5574
$F.N$	198	3.0296	2.2643	88	2.4773	2.0080	177	1.6024	1.5340
$FDX.N$	40	2.7887	2.2183	30	3.2106	3.6588	31	2.4819	2.4811
$GE.N$	59	3.8617	2.7574	37	3.0648	1.9041	42	2.3322	1.9647
$GLW.N$	19	5.2515	3.9589	15	2.6617	3.9609	17	3.2953	3.3540
$GR.N$	20	4.7729	5.7485	2	1.4533	0.5704	8	1.8870	1.7545
$GS.N$	235	2.9275	2.1619	116	2.3064	1.9284	207	2.1838	1.7548
$HD.N$	172	2.1888	4.2864	21	0.1210	0.8923	94	0.6554	2.0871
$HON.N$	45	3.3022	2.1268	9	2.5706	1.5175	27	1.2727	1.2025
$HPQ.N$	119	3.0873	2.2698	52	2.1668	1.8391	88	2.1268	1.8925
$IBM.N$	138	3.6778	2.9647	37	2.7328	2.5395	111	1.6985	2.2262
$INTC.O$	112	2.9896	2.2001	48	2.2750	1.5690	94	1.8811	1.9041
$JNJ.N$	102	3.1333	2.6229	46	2.8465	2.7153	72	2.1668	1.9909
$JPM.N$	183	2.7744	2.2258	106	2.9178	2.6319	162	2.4532	2.5032
$KFT.N$	94	2.6039	1.6123	14	2.4609	1.9463	82	1.3556	1.1954
$KO.N$	50	3.3672	2.3124	20	5.2119	4.8020	23	3.1491	2.7196
$LLY.N$	56	2.9219	1.7841	25	3.2295	2.9857	33	2.3060	1.8998
$LMT.N$	105	3.5112	2.4568	44	2.1761	1.8434	55	1.6729	1.3771
$MCD.N$	70	3.4556	2.3593	31	2.0148	1.5340	53	1.8974	1.3850
$MDT.N$	38	3.5020	2.7540	21	1.6765	1.1224	32	1.7002	1.7557
$MO.N$	27	2.9978	2.6200	6	1.0153	1.2205	13	1.7484	0.9833
$MON.N$	65	3.9448	3.6470	30	2.3710	2.2904	35	2.3683	3.0473
$MMM.N$	27	3.5051	2.1892	5	2.2973	0.9381	12	1.4302	1.3572
$MRK.N$	99	3.4270	2.6114	48	2.3156	1.9083	69	2.2193	1.8914
$MS.N$	201	2.8148	2.1083	75	2.4378	1.9433	151	2.1024	1.8497
$MSFT.O$	226	2.6009	1.6957	72	1.8498	1.4563	212	1.8450	1.5528
$ORCL.O$	70	2.8478	2.2948	51	2.9248	2.5158	65	2.2632	2.4857
$OXY.N$	23	4.5061	3.3075	2	1.3525	0.6824	7	2.1770	1.7105
$PFE.N$	122	3.0920	2.3710	62	2.3397	1.5395	87	1.9404	1.7370
$PG.N$	52	2.5772	1.7435	48	2.2890	1.4934	49	1.8380	1.7458
$SLB.N$	34	3.2163	2.5419	12	2.5346	1.9957	22	1.7485	1.7624
$T.N$	102	3.0401	1.8108	36	2.0412	1.8221	77	1.2798	1.3578
$TRV.N$	9	1.8596	0.9999	8	3.3083	2.2270	8	2.2566	2.0838
$TWX.N$	75	3.0055	2.1811	21	1.8660	2.7775	59	1.1914	1.5567
$TXN.N$	21	5.6115	4.4692	5	2.4740	1.1307	15	2.6765	1.2774
$UTX.N$	8	5.0200	3.0939	7	3.9548	0.7271	3	1.4775	1.5095
$VZ.N$	121	2.8905	2.0383	26	1.5650	0.8817	76	1.4279	1.4429
$WFC.N$	84	3.4648	2.4066	54	2.3091	1.6347	62	1.6387	1.5371
$WMT.N$	180	2.7180	2.0239	62	2.6808	2.1770	137	1.7030	1.5085
$WLP.N$	36	3.7594	2.3134	9	1.3725	1.2788	18	1.7603	1.6106
$XOM.N$	160	3.2283	2.1963	89	2.6779	1.9955	149	2.0730	1.6049
Mean	92.0000	3.3174	2.4561	41.0000	2.4194	1.9093	72.0000	1.9982	1.8539
Std.	66.7503	0.7475	0.8025	34.5148	0.8016	0.7851	64.6547	0.5301	0.4964

Table 2.2: The table shows the number of days with positive sentiment (first column), negative sentiment (fourth column) and disagreement (seventh column) company individually. Moreover, it gives the conditional mean of positive and negative sentiment and disagreement and the standard deviations. Disagreement is measured by D^{std}. The last two rows show the cross-sectional mean and standard deviation.

2.6 Regression Results

2.6.1 Contemporaneous Analysis

I analyze the contemporaneous relationship between the financial market and sentiment, respectively disagreement. This analysis is motivated by the literature on difference of opinion and extends Das et al. (2005). It allows testing Hypotheses 2 to 5 on the co-movement of market variables and public signals and the degree of difference of opinion, respectively. The analysis does not allow to conclude on market efficiency and the predictability of market returns. Even though the news stories are unscheduled, a significant relationship between sentiment or disagreement and market returns on a daily frequency might be consistent with efficient markets if the market anticipates the news.

Company Individual Analysis

As shown in Blume, Easley and O'Hara (1994), volatility and historical stock prices might be valuable information for future stock returns. Pan and Poteshman (2006) document that option trading contains relevant information for stock returns, too, and according to Sarwar (2006) and Kyriacou and Sarno (1999), option trading volume and volatility interact. Cremers et al. (2008) report a significant relationship between equity markets and credit markets. Chordia, Sarkar and Subrahmanyam (2005) study the intertemporal association between liquidity, volatility and returns by applying a vector autoregressive model. Also, the difference of opinion literature implies positive autocorrelation in trading volume and negative autocorrelation in returns. To control for these associations and to determine the relationship between the financial market and sentiment and disagreement, respectively, accurately, I choose the most parsimonious regression model that allows for the aforementioned patterns, a vector autoregressive process with one lag. I estimate

$$\begin{aligned}&\left[\hat{\varepsilon}_{i,t}\ T_{i,t}\ \Delta V_{i,t}\ O_{i,t}\ \Delta C_{i,t}\right]' \\ &= \Lambda_i\left[\hat{\varepsilon}_{i,t-1}\ T_{i,t-1}\ \Delta V_{i,t-1}\ O_{i,t-1}\ \Delta C_{i,t-1}\right]' + \beta_i[P_{i,t}\ N_{i,t}\ D_{i,t}]' + K_i U_t + \eta_{i,t}.\end{aligned} \tag{2.5}$$

D stands for the disagreement score and refers to D^{std} or D^{pol}. Λ_i is a 5×5 matrix and captures possible inter-temporal associations between the abnormal returns, trading volume in the stock and stock options, and the change in the volatility spread and the CDS spread, respectively. β_i is a 5×3 matrix and measures the associations between the market and sentiment and disagreement, respectively. U_t is 5×1 vector with weekday dummies and K_i's dimension is 5×5. $\eta_{i,t}$ is a white noise vector.

Tables 2.3 show the - at the 10% confidence level - significant estimates for β_i. The first entry in a filed gives the impact of positive sentiment, the second entry corresponds to the impact of negative sentiment and the third to disagreement (D^{std}). Insignificant coefficients are replaced by the symbol '/'. Single underlined coefficients are significant at the 5% level and double underlined coefficients at the 1% confidence level. The lower panel of Table 2.3 gives the number of significant, positive and significant, negative regression coefficients and the number of companies for which positive and negative sentiment and disagreement are jointly insignificant. I do not show the regression estimates for Λ_i and K_i.

Positive sentiment and negative sentiment are frequently significant for the FF residuum. Often, the coefficient of positive sentiment is significant, positive (for 14 companies out of 62) and the coefficient of negative sentiment is significant, negative (for 14 companies), indicating that positive news are associated with positive abnormal returns and negative news with negative abnormal returns. This suggests that the General Inquirer and the relevant text identification procedure approximate the 'true' sentiment or the public company signal accurately. Disagreement is frequently significant, but the sign of the significant coefficients varies among companies. There are 9 significant, positive coefficients and 10 significant, negative coefficients. Hence, the dominant effect of disagreement in the cross section is ambiguous. The average R^2 of model (2.5) across all companies with respect to the abnormal return is 4.57%. Compared to an average R^2 of 2.99% in regression model (2.5) and omitting $\beta_i[P_{i,t}N_{i,t}D_{i,t}]$, positive and negative sentiment and disagreement account on average for 1.58 percentage points in R^2. This significant increase by more than 50% is exclusively due to the content analysis and highlights its accuracy.

The average R^2 of regression model (2.5) with respect to stock trading volume is 38.48% and the average R^2 of (2.5) and without the regressors $[P_{i,t}N_{i,t}D_{i,t}]$ is 34.92%, indicating that the content analysis adds about 4 percentage points. Regarding option trading volume, the average R^2 increases from 15.43% without the content analysis to 16.46%. To test Hypothesis 2, I use positive sentiment and negative sentiment to approximate the public signal's intensity and study its co-movement with the trading volume on the same day. The coefficient of positive sentiment

	$\hat{\varepsilon}$	T	ΔV	O	ΔC
AA.N	0.0017;−0.0035;/	/;−0.0356;0.1077	/;0.0088;/	0.0343;−0.0501;0.0469	/;2.9180;/
ABT.N	/;/;−0.0022	0.0249;/;0.0682	/;/;/	/;/;/	/;/;/
AIG.N	/;/;/	/;−0.0327;0.0653	/;/;/	/;/;0.0437	/;/;/
AMGN.O	/;/;0.0085	/;0.1162;0.2571	/;0.0048;−0.0051	0.0773;0.1479;0.1350	/;0.3611;−0.6805
APC.N	/;−0.0030;/	/;/;0.1083	/;0.0050;/	/;0.0395;/	/;3.0280;/
AXP.N	/;/;/	/;/;0.0749	/;/;/	0.0285;/;0.0277	/;2.1222;/
BA.N	/;/;−0.0018	/;/;0.0514	/;/;0.0013	/;/;/	/;/;/
BAC.N	/;/;/	/;/;0.0628	/;/;/	/;/;0.0367	/;/;/
BAX.N	/;−0.0240;−0.0024	/;1.2724;0.3327	/;0.0108;/	/;/;0.2572	/;/;/
BMY.N	0.0010;/;/	0.0273;/;/	/;−0.0025;/	/;/;/	−0.0914;/;/
BSX.N	/;/;−0.0124	/;0.7366;0.3925	/;/;0.0169	/;/;/	/;/;3.3971
C.N	/;/;/	/;/;0.0515	−0.0038;/;/	/;/;0.0234	/;/;/
CAT.N	0.0031;/;/	0.0587;/;0.1059	/;/;/	/;/;/	−0.6997;/;/
COP.N	/;/;/	/;/;0.0207	/;/;/	/;/;/	/;−0.1752;0.2143
CSC.N	/;0.0091;0.0128	/;0.1801;0.3420	/;−0.0080;0.0217	/;/;/	/;/;7.2457
CSCO.O	/;/;−0.0013	/;0.0783;0.0349	/;/;/	/;0.0588;/	−0.1287;/;/
CVX.N	−0.0006;/;0.0008	/;/;/	/;/;/	/;/;/	/;/;/
DD.N	/;/;/	/;0.0323;0.1190	/;/;/	/;/;/	/;1.8261;/
DELL.O	/;−0.0045;/	/;0.0706;0.0898	/;/;/	0.0468;/;0.1456	/;0.5376;/
DIS.N	/;−0.0024;0.0017	/;/;0.0797	/;/;/	/;/;/	/;/;−0.3150
DOW.N	/;/;/	/;/;0.2729	/;/;/	/;/;0.1078	/;/;/
DVN.N	/;−0.0088;0.0061	/;/;0.0848	/;0.0220;/	/;/;0.1263	/;/;/
F.N	/;/;/	0.0268;/;0.0440	/;/;/	/;/;0.0411	/;/;/
FDX.N	0.0040;/;−0.0029	0.0758;/;0.2532	/;/;/	0.1048;/;0.0986	−0.5887;/;0.9380
GE.N	/;/;0.0021	0.0266;0.0529;/	0.0033;/;−0.0058	/;/;/	/;/;/
GLW.N	0.0018;−0.0073;/	0.0226;0.2269;0.0610	/;/;/	0.0625;/;/	/;/;/
GR.N	−0.0015;0.0159;0.0096	0.1334;/;0.3587	/;/;/	0.0872;1.4221;0.4344	−0.2023;/;/
GS.N	/;−0.0019;/	/;0.0480;/	/;0.0034;/	/;0.0338;/	/;/;1.0095
HD.N	0.0004;/;/	0.0007;0.0291;0.0395	/;/;/	0.0130;/;0.0425	/;/;/
HON.N	/;/;/	0.0282;/;0.0832	/;/;−0.0046	/;/;/	/;/;/
HPQ.N	0.0010;−0.0022;/	/;0.0652;0.0813	0.0012;/;−0.0025	/;0.0419;0.0591	0.2170;0.3178;/
IBM.N	/;/;/	/;/;0.0592	/;0.0014;/	/;/;0.0982	/;/;/
INTC.O	/;/;/	/;/;0.0745	/;/;/	/;/;0.0864	/;−0.7197;0.2383
JNJ.N	/;/;/	0.0196;/;0.0272	0.0009;/;/	/;/;/	/;/;/
JPM.N	0.0010;/;−0.0010	/;/;/	/;0.0032;/	/;/;/	/;/;/
KFT.N	/;−0.0019;/	/;/;/	/;/;/	/;/;/	/;/;/
KO.N	0.0009;/;/	0.0328;/;0.0599	/;/;−0.0022	/;/;/	/;/;/
LLY.N	−0.0013;/;/	/;/;0.0413	/;/;/	/;/;/	/;/;0.2304
LMT.N	/;/;/	/;/;0.0861	−0.0008;/;/	0.0413;/;/	/;/;/
MCD.N	0.0010;/;/	0.0310;/;0.0846	/;/;/	/;/;/	/;/;/
MDT.N	/;/;−0.0045	/;0.1235;0.2090	/;0.0051;/	/;/;/	/;/;/
MO.N	/;/;−0.0033	/;/;0.1571	−0.0022;/;/	/;/;/	/;/;/
MON.N	0.0010;/;/	/;/;0.0819	/;/;/	/;/;0.0666	/;/;/
MMM.N	0.0022;/;/	0.0532;/;0.1856	/;/;/	/;/;0.3179	/;/;0.6947
MRK.N	/;−0.0023;/	0.0282;/;0.0479	/;/;0.0019	/;/;/	/;/;/
MS.N	/;−0.0028;/	/;/;/	−0.0036;/;/	0.0259;/;/	/;/;/
MSFT.O	/;/;/	/;/;0.0423	/;/;/	/;−0.0615;/	/;/;/
ORCL.O	/;/;/	0.0599;/;/	/;/;/	0.0971;/;/	/;/;/
OXY.N	/;/;/	/;/;/	/;/;/	0.0324;/;0.1249	0.2416;/;/
PFE.N	/;/;/	/;/;0.0358	/;/;/	/;/;/	/;/;0.3807
PG.N	/;/;/	0.0289;/;0.0588	/;−0.0023;/	/;−0.1008;0.1997	/;/;/
SLB.N	−0.0018;/;0.0064	/;/;0.0920	/;0.0084;−0.0071	/;/;0.0708	/;0.5508;−0.8166
T.N	/;/;/	/;/;0.0526	/;/;/	/;/;/	/;/;0.5071
TRV.N	0.0105;0.0075;−0.0081	0.1612;/;/	−0.0140;/;/	/;/;/	/;/;/
TWX.N	/;/;/	/;/;/	/;/;/	/;/;/	/;/;/
TXN.N	/;/;/	/;/;0.2319	/;/;/	/;/;0.2729	/;4.5247;/
UTX.N	0.0021;/;/	/;/;/	/;/;/	/;/;/	/;/;/
VZ.N	/;/;0.0019	/;/;0.0550	/;/;/	/;/;/	/;/;/
WFC.N	/;−0.0033;/	0.0387;0.0730;0.1155	−0.0066;/;/	/;/;0.0590	/;/;/
WMT.N	/;−0.0012;/	/;/;0.0763	/;0.0016;−0.0014	/;/;0.3018	/;/;/
WLP.N	/;/;/	0.0387;/;0.1351	/;/;/	/;/;/	0.4564;/;1.1201
XOM.N	/;/;/	/;/;/	/;/;/	/;/;/	/;/;/
+ & sig.	14;3;9	20;13;50	3;11;4	12;6;24	3;9;11
− & sig.	4;14;10	0;2;0	6;3;7	0;2;0	5;2;3
All insig.	23	8	34	29	36

Table 2.3: The table shows the - at the 10% confidence level significant - company-individual regression coefficients for positive sentiment (first entry), negative sentiment (second entry) and disagreement, measured by D^{std}, (third entry) on the market variables. Single [double] underlined coefficients are significant at the 5% [10%] confidence level. The last three rows show the number of significant, positive and significant, negative regression coefficients and the number of companies where positive and negative sentiment and disagreement are jointly insignificant.

is significant, positive for stock trading volume for 20 out of 62 companies. The coefficient of negative sentiment is significant, positive for 13 companies. Option trading volume shows similar patterns. Therefore, the signal's intensity seems to be positively related to trading volume, as stated in Hypothesis 2.

Hypothesis 3 relates stock and option trading volume to disagreement. High disagreement is associated with significantly higher stock trading volume for 50 companies out of 62. There is no company with a significant, negative regression coefficient. Regarding the relationship between option trading volume and disagreement, I find 23 positive and significant relationships out of 62 companies. Hence, I have very strong support for Hypotheses 3. Investors seem to trade on public signals and disagreement accelerates trading volume.

The relationship between the volatility spread and disagreement is ambiguous. The number of significant regression coefficients is small, and the number of significant, negative and significant, positive regression coefficients is almost balanced. Hence, it is infeasible to draw robust conclusions on the relationship between volatility and disagreement. However, Table 2.3 indicates that the volatility spread widens at days with negative sentiment (11 positive and significant coefficients). This finding is consistent with evidence on negative correlation between index returns and volatility, since days with negative sentiment are also associated with negative abnormal returns. The average R^2 of the full regression model with respect to the change in the volatility spread is 6.80% and the contribution of the content analysis in terms of average R^2 is 1.13 percentage points. Nevertheless, Hypothesis 4 is not supported.

The change in the CDS spread is often significantly negatively correlated with positive sentiment and positively correlated with negative sentiment. This is economically reasonable and consistent with the relationship between abnormal stock returns and sentiment, and with the relationship between the volatility spread and sentiment. The coefficient of disagreement is often significant and positive, which is consistent with Hypothesis 5, even though Hypothesis 4 is not supported. The content analysis increases the average R^2 of the change in the CDS spread from 5.91% to 7.11%.

Most results remain qualitatively unchanged if I consider D^{pol} as a measure of disagreement instead of D^{std}. Therefore, the results are not shown. A change worth mentioning is that the relationship between disagreement and abnormal stock returns is more often significant, negative. This is consistent with Yu (2011), who shows that stocks with high analyst forecast dispersion, which might be another measure of disagreement, underperform relative to stocks with low forecast dispersion. Perhaps as a consequence, the CDS spread increases with D^{pol} for many companies even though the volatility might not go up.

Pooled Analysis

Next, I analyze all companies jointly. The purpose of this analysis is to investigate the dominant relationship between the financial market and sentiment and disagreement, respectively, for all companies. It also simplifies the interpretation of the regression coefficients. I estimate

$$\begin{aligned}
&\left[s\hat{\varepsilon}_{i,t}\ sT_{i,t}\ s\Delta V_{i,t}\ sO_{i,t}\ s\Delta C_{i,t}\right]' \qquad (2.6)\\
&= \Lambda\left[s\hat{\varepsilon}_{i,t-1}\ sT_{i,t-1}\ s\Delta V_{i,t-1}\ sO_{i,t-1}\ s\Delta C_{i,t-1}\right]' + \beta[sP_{i,t}\ sN_{i,t}\ sD_{i,t}]' + KU_t + \eta_{i,t}.
\end{aligned}$$

The prefix s denotes standardized time series. The regression coefficients Λ, β and K are now independent of the company index i. Hence, I make the strong assumption that the relationships between the (standardized) market variables, measured by Λ, and between the market variables and the information extracted from company news, measured by β, are described by the same coefficients for all companies. Λ, β and K are estimated by

$$\begin{aligned}
\{\hat{\Lambda}, \hat{\beta}, \hat{K}\} &= \operatorname{argmin}_{\Lambda,\beta,K}\Big\{\mathbf{1}_{1\times G}\Big([s\hat{\varepsilon}\ sT\ s\Delta V\ sO\ s\Delta C] \qquad (2.7)\\
&- [s\hat{\varepsilon}_{-1}\ sT_{-1}\ s\Delta V_{-1}\ sO_{-1}\ s\Delta C_{-1}]\,\Lambda - [sP\ sN\ sD]\,\beta - UK\Big)^2 \mathbf{1}_{5\times 1}\Big\},
\end{aligned}$$

where, as an example, the vectors sT and sT_{-1} are given by

$$\begin{aligned}
sT_{-1} &= \left[\left[\frac{T_{1,t} - m(T_{1,\cdot})}{\sigma(T_{1,\cdot})}\right]_{t=1,\dots,G_1-1}, \dots, \left[\frac{T_{L,t} - m(T_{L,\cdot})}{\sigma(T_{L,\cdot})}\right]_{t=1,\dots,G_L-1}\right]' \quad \text{and}\\
sT &= \left[\left[\frac{T_{1,t} - m(T_{1,\cdot})}{\sigma(T_{1,\cdot})}\right]_{t=2,\dots,G_1}, \dots, \left[\frac{T_{L,t} - m(T_{L,\cdot})}{\sigma(T_{L,\cdot})}\right]_{t=2,\dots,G_L}\right]'.
\end{aligned}$$

$m(\cdot)$ denotes the mean, $\sigma(\cdot)$ is the standard deviation, L is the number of companies and G_i is the number of observations for company i. $G = \sum_{i=1}^{L}(G_i - 1)$, $\mathbf{1}_{a\times b}$ is a matrix of dimension $a \times b$ with 1s everywhere and U is the pooled matrix of weekday dummies. The square symbol in (2.7) refers to each component in the vector of residuals.

Pooling all observations gives in total 36,229 company-day observations. Table 2.4 shows $\hat{\Lambda}$, $\hat{\beta}$ and $\hat{K}$. In the upper panel, disagreement is measured by D^{std} and in the lower panel by D^{pol}. The regression estimates of Λ and K are similar for both approaches. Stock trading volume displays positive autocorrelation, which is consistent with the models of Harris and Raviv (1993) and Banerjee and Kremer (2010). Furthermore, there are several patterns, which are consistent with information asymmetry. Trading volume predicts abnormal stock returns, as discussed in Blume, Easley and O'Hara (1994). Also option trading volume predicts abnormal returns, which might be related to the result of Pan and Poteshman (2006), even though I do not study the ratio of traded put and call options, but the sum.

Large abnormal stock returns, strong increases in the volatility spread or the CDS spread and high option trading volume predict high stock trading volume. These findings are consistent with Barber and Odean (2008), who study attention-grabbing stocks, amongst others defined by stocks with large stock price movements, and find that these stocks have a higher turnover volume than stocks that do not attract attention. However, attention might also be gained by strong increases in the CDS spread or in the volatility spread. Consistent with structure models on credit derivatives, the CDS spread increases given an increase in volatility. Surprisingly, it also tends to increase given a positive abnormal return. The weekday dummies are frequently significant, indicating the presence of weekday effects.

Positive and negative sentiment are highly significant for abnormal returns. Consistent with the results in the previous section, positive sentiment is positively related to abnormal returns and negative sentiment negatively. The coefficient of D^{std} is insignificant, see upper panel. This does not necessarily mean that disagreement is not relevant for the abnormal return. The insignificance might be rather due to the heterogeneous relationship between stock returns and disagreement among news articles, e.g. Table 2.3 shows 9 significant, positive and 10 significant, negative relationships. Hence, both effects are likely to cancel out in the pooled regression. Furthermore, the alternative disagreement score D^{pol} detects a significant, negative relationship between abnormal returns and disagreement, see Table 2.4, lower panel. This is consistent with Yu (2011).

The R^2s in Table 2.4 with respect to the abnormal return are lower than the average R^2 of the firm individual regression analysis. So, the R^2 of $s\hat{\varepsilon}$ is 0.4% and 0.51%, respectively, whereas the average R^2 of $\hat{\varepsilon}_i$ in (2.5) is 4.57%. This decrease might be due to the restrictive assumption of identical regression coefficients for all compa-

Pooled Analysis - Contemporaneous	$s\hat{\varepsilon}$	sT	$s\Delta V$	sO	$s\Delta C$
$s\hat{\varepsilon}_{-1}$	-0.0010	0.0088^b	-0.0034	0.0063	0.0151^a
sT_{-1}	0.0221^a	0.5380^a	-0.0528^a	0.0854^a	-0.0049
$s\Delta V_{-1}$	0.0349^a	0.0734^a	-0.1591^a	0.0184^a	0.1232^a
sO_{-1}	-0.0190^a	0.0262^a	0.0037	0.2701^a	-0.0163^a
$s\Delta C_{-1}$	-0.0082	0.0274^a	0.0035	-0.0018	0.0876^a
sP	0.0273^a	0.0455^a	-0.0111^a	0.0237^a	-0.0069
sN	-0.0321^a	0.0374^a	0.0128^a	0.0088^c	0.0194^a
sD^{std}	0.0008	0.1187^a	-0.0058	0.0599^a	0.0142^a
Monday	0.0493^a	-0.2202^a	0.1149^a	-0.0089	-0.1259^a
Tuesday	0.0349^b	0.0616^a	-0.0621^a	0.0489^a	-0.1059^a
Wednesday	-0.0085	-0.0541^a	0.0538^a	-0.0091	-0.0880^a
Thursday	0.0203	0.0095	0.1196^a	0.0184	-0.0408^b
Constant	-0.0199	0.0387^a	-0.0445^a	-0.0097	0.0713^a
R^2	0.0041	0.3499	0.0340	0.1067	0.0297
$s\hat{\varepsilon}_{-1}$	-0.0017	0.0103^b	-0.0033	0.0063	0.0159^a
sT_{-1}	0.0237^a	0.5345^a	-0.0522^a	0.0849^a	-0.0043
$s\Delta V_{-1}$	0.0353^a	0.0731^a	-0.1605^a	0.0175^a	0.1220^a
sO_{-1}	-0.0169^a	0.0228^a	0.0044	0.2683^a	-0.0159^a
$s\Delta C_{-1}$	-0.0077	0.0250^a	0.0046	-0.0034	0.0870^a
sP	0.0429^a	0.0124^a	-0.0075	0.0016	-0.0125^b
sN	-0.0146^b	-0.0137^a	0.0176^a	-0.0230^a	0.0115^b
sD^{pol}	-0.0388^a	0.1650^a	-0.0131^b	0.0969^a	0.0237^a
Monday	0.0472^a	-0.2201^a	0.1138^a	-0.0120	-0.1259^a
Tuesday	0.0359^b	0.0568^a	-0.0616^a	0.0454^a	-0.1043^a
Wednesday	-0.0058	-0.0561^a	0.0528^a	-0.0119	-0.0893^a
Thursday	0.0206	0.0091	0.1199^a	0.0170	-0.0416^b
Constant	-0.0194	0.0402^a	-0.0443^a	-0.0076	0.0716^a
R^2	0.0051	0.3552	0.0341	0.1097	0.0299
#Obs.	36229	36229	36229	36229	36229

Table 2.4: The table shows the regression estimates for Λ, β and K in the pooled regression model, allowing for a contemporaneous relationships between the market variables and sentiment and disagreement, respectively, i.e. regression model (2.6). The upper panel measures disagreement with sD^{std} and the lower panel with sD^{pol}. a denotes significance at the 1% confidence level, b at the 5% confidence level and c at the 10% level.

nies. However, the contribution of the content analysis to the R^2 of $s\hat{\varepsilon}$ is about 0.2 percentage point and doubles the explained variation in abnormal returns.

The average R^2 of stock trading volume and allowing for company individual regression coefficients is 38.48% and reduces in the pooled analysis to 34.99% and 35.52%, respectively. The R^2 of standardized option trading volume is 10.67% and 10.97%, respectively, whereas the average R^2 of the company individual analysis about 16.46%. These rather moderate decreases in the R^2s indicate that the assumption of identical regression coefficients is not too restrictive for trading volume. The contribution of the text analysis to the R^2 is about 3 percentage points for stock trading volume and about 0.65 percentage points for option trading volume.

In the upper panel, standardized stock and option trading volume increase with positive and negative sentiment and disagreement. The relationships are highly significant and consistent with the company individual analysis and Hypotheses 2 and 3. Surprisingly, the coefficient of negative sentiment turns significant, negative for trading volume if disagreement is measured by D^{pol}, see the lower panel of Table 2.4. As argued by Barber and Odean (2008), investment restrictions, or liquidity dry-ups subsequent to negative news during the financial crisis, might explain the fragile relationship between negative sentiment and trading volume.

The volatility spread narrows with positive sentiment and it increases with negative sentiment. However, the estimated relationship between the volatility spread and disagreement is still inconclusive. Whereas the coefficient of D^{std} is insignificant in the upper panel of Table 2.4, the coefficient of D^{pol} is weakly significant and negative. Both results are inconsistent with Hypothesis 4. Nevertheless, and consistent with Hypothesis 5, the CDS spread increases with disagreement. As argued before, this increase is presumably due to the decrease in the market value, given high disagreement, and not due to an increase in the equity volatility and asset volatility, respectively. Moreover, the CDS spread increases with negative sentiment and, at least in the lower panel of Table 2.4, decreases with positive sentiment.

2.6.2 Predicting Market Activity

Now, I use the pooled regression model to study the predictive power of sentiment and disagreement. Hence, I do not analyze the contemporaneous relationship between market activity and sentiment and disagreement, respectively, but the relationship between the market and sentiment and disagreement from the previous trading day. Hence, the regression model changes to

$$\begin{aligned}\left[s\hat{\varepsilon}_{i,t}\ sT_{i,t}\ s\Delta V_{i,t}\ sO_{i,t}\ s\Delta C_{i,t}\right]' &= \Lambda\left[s\hat{\varepsilon}_{i,t-1}\ sT_{i,t-1}\ s\Delta V_{i,t-1}\ sO_{i,t-1}\ s\Delta C_{i,t-1}\right]' \\ &+ \beta[sP_{i,t-1}\ sN_{i,t-1}\ sD_{i,t-1}]' + KU_t + \eta_{i,t}. \qquad (2.8)\end{aligned}$$

Now, the residual in the objective function (2.7) is

$$\begin{aligned}&\left[s\hat{\varepsilon}\ sT\ s\Delta V\ sO\ s\Delta C\right] - \left[s\hat{\varepsilon}_{-1}\ sT_{-1}\ s\Delta V_{-1}\ sO_{-1}\ s\Delta C_{-1}\right]\hat{\Lambda} \\ &\qquad -\left[sP_{-1}\ sN_{-1}\ sD_{-1}\right]\hat{\beta} - U\hat{K}. \qquad (2.9)\end{aligned}$$

Table 2.5 shows the regression estimates for Λ, β and K. Again, the results in the upper panel are based on the disagreement measure D^{std} and the results in the lower panel are based on D^{pol}. The estimates for Λ and for K are very similar compared to the contemporaneous analysis. However, the R^2s decrease. Positive sentiment is still highly significant and predicts positive abnormal returns on the following day. Both disagreement measures predict negative abnormal returns on the following trading day. Negative sentiment is insignificant. However, the relationship between abnormal stock returns and positive sentiment and disagreement, respectively, are still unexpected and might be inconsistent with Hypothesis 1. Assuming efficient markets, prices should respond to new information immediately. However, the significance of lagged positive sentiment and lagged disagreement - even on a daily frequency - hints towards market inefficiencies. These results become even stronger if I consider excess stock returns instead of abnormal stock returns. Then, positive sentiment is significant, positive and negative sentiment is significant, negative. Disagreement is almost significant at the 10% confidence level.[3] The R^2 of the excess return in (2.8) increases to 1.16%. The others estimates do not change significantly.

The volatility spread increases significantly after negative sentiment and after disagreement, measured by D^{std}. D^{pol} is insignificant. Compared to the contemporaneous relationship between disagreement and the volatility spread, which is inconclusive, the result for the one-day lagged D^{std} is more consistent with Hypothesis 4. The delayed response of the volatility spread could be due to a rather slow information processing and might also hint towards market inefficiencies.

I find no significant relationship between the change in the CDS spread and the one-day lagged sentiment. In the lower panel, the p-value of disagreement with

[3] Consider that disagreement is measured by D^{std}. Then, the estimates of β in regression model (2.8) and using excess stock returns instead of abnormal stock returns is $(0.0135, -0.0133, -0.0085)$ with p-values $(0.0139, 0.0127, 0.1292)$. If disagreement is measured by D^{pol}, the estimate is $(0.0145, -0.0112, -0.0085)$ with p-values $(0.0132, 0.0613, 0.1972)$.

Pooled Analysis - Predictive	$s\hat{\varepsilon}$	sT	$s\Delta V$	sO	$s\Delta C$
$s\hat{\varepsilon}_{-1}$	-0.0005	0.0079^c	-0.0028	0.0054	0.0155^a
sT_{-1}	0.0239^a	0.5475^a	-0.0548^a	0.0910^a	-0.0044
$s\Delta V_{-1}$	0.0347^a	0.0751^a	-0.1605^a	0.0187^a	0.1224^a
sO_{-1}	-0.0182^a	0.0350^a	0.0033	0.2749^a	-0.0147^a
$s\Delta C_{-1}$	-0.0081	0.0272^a	0.0041	-0.0022	0.0871^a
sP_{-1}	0.0105^a	0.0093^b	-0.0058	0.0043	-0.0011
sN_{-1}	-0.0042	-0.0027	0.0149^a	0.0070	0.0074
sD^{std}_{-1}	-0.0163^a	-0.0248^a	0.0097^c	-0.0104^a	0.0071
Monday	0.0501^a	-0.2338^a	0.1152^a	-0.0190	-0.1275^a
Tuesday	0.0342^b	0.0687^a	-0.0615^a	0.0524^a	-0.1021^a
Wednesday	-0.0064	-0.0366^a	0.0513^a	-0.0013	-0.0874^a
Thursday	0.0200	0.0248^c	0.1189^a	0.0252	-0.0401^b
Constant	-0.0196	0.0331^a	-0.0440^a	-0.0116	0.0707^a
R^2	0.0025	0.3291	0.0340	0.1018	0.0291
$s\hat{\varepsilon}_{-1}$	-0.0010	0.0069	-0.0026	0.0052	0.0154^a
sT_{-1}	0.0242^a	0.5487^a	-0.0544^a	0.0906^a	-0.0033
$s\Delta V_{-1}$	0.0345^a	0.0746^a	-0.1605^a	0.0187^a	0.1222^a
sO_{-1}	-0.0179^a	0.0356^a	0.0033	0.2749^a	-0.0144^a
$s\Delta C_{-1}$	-0.0080	0.0275^a	0.0041	-0.0022	0.0872^a
sP_{-1}	0.0131^b	0.0151^a	-0.0055	0.0042	0.0015
sN_{-1}	0.0007	0.0067	0.0142^b	0.0082	0.0096
sD^{pol}_{-1}	-0.0179^a	-0.0319^a	0.0058	-0.0069	-0.0020
Monday	0.0500	-0.2342^a	0.1150^a	-0.0188	-0.1279^a
Tuesday	0.0337^b	0.0676^a	-0.0616^a	0.0524	-0.1026^a
Wednesday	-0.0064	-0.0367^a	0.0513^a	-0.0012	-0.0874^a
Thursday	0.0201	0.0251^b	0.1189^a	0.0252	-0.0399^a
Constant	-0.0193	0.0334^a	-0.0440^a	-0.0116	0.0708^a
R^2	0.0025	0.3292	0.0340	0.1017	0.0291
#Obs.	36229	36229	36229	36229	36229

Table 2.5: The table shows the regression estimates for Λ, β and K in the pooled regression model without contemporaneous relationships, i.e. (2.8). Hence, all explanatory variables are lagged by one day. The upper panel measures disagreement with sD^{std} and the lower panel with sD^{pol}. a denotes significance at the 1% confidence level, b at the 5% confidence level and c at the 10% level.

respect to ΔC is 0.1066, indicating - at best - a weak, positive relationship between disagreement and CDS spreads. Hence, the credit market seems to be efficient with respect to the information extracted from Reuters company news and in this framework. However, the company individual analysis (the results are not shown) indicates that negative sentiment and disagreement predict the change in the CDS spread for several companies.

Furthermore, positive sentiment predicts stock trading volume on the following day, indicating that positive signals have a long-lasting impact on trading volume. However, negative sentiment is insignificant. This heterogeneity might be due to investment restrictions, see Barber and Odean (2008). Surprisingly, the regression coefficients of both disagreement measures are significantly negative. One explanation might be that investors execute orders, which are scheduled to the following day, immediately, given disagreement. Then, the stock trading volume might be lower after days with disagreement.

2.6.3 Robustness

As a robustness check, I weight sentiment with uncertainty. Uncertainty is measured with two approaches. (1) Uncertainty in news articles might be measured with the 'General Inquirer' word categories 'strong' and 'weak'. However, there is a substantial overlap between the categories 'positive' and 'strong', and 'negative' and 'weak'. This might bias the results. Nevertheless, I measure the uncertainty of a news article by

$$H^{(1)}_{i,t,j} = \frac{Z_{i,t,j} + \vartheta}{W_{i,t,j} + Z_{i,t,j} + 2\vartheta},$$

where $Z_{i,t,j}$ denotes the number of strong words and $W_{i,t,j}$ is the number of weak words in the relevant text of news article j. ϑ is a small, positive constant that ensures the existence of $H_{i,t,j}$ even though there are neither strong nor weak words. Then, $H_{i,t,j} = 0.5$. If there are only strong words, $H_{i,t,j} \approx 1$ and if there are only weak words $H_{i,t,j}$ is close to zero. (2) Alternatively, if the author of a news article uses many positive and negative words in the relevant text of a company, she might discuss positive and negative scenarios, which indicates that she is unsure about the final consequences. Therefore, uncertainty is measured by

$$H^{(2)}_{i,t,j} = \frac{|Pos_{i,t,j} - Neg_{i,t,j}|}{\max\{Pos_{i,t,j} + Neg_{i,t,j}, \vartheta\}}.$$

If positive and negative words are almost balanced, $H^{(2)}_{i,t,j}$ is close to zero. If either positive words clearly dominate negative words or negative words clearly dominate positive words, $H^{(2)}_{i,t,j}$ is close to 1. ϑ is again a small, positive constant.

Now, by multiplying the net sentiment, i.e. $Pos_{i,t,j} - Neg_{i,t,j}$, in (2.2) with $H^{(1)}_{i,t,j}$ or $H^{(2)}_{i,t,j}$, the uncertainty that is related to a news article might be taken into account. All previously discussed results are robust against the uncertainty adjustment and remain qualitatively the same. For the sake of brevity, the results are not shown.

Moreover, I use a broader definition to identify relevant news stories for a company, i.e. I consider all news stories as relevant if the company's RIC appears in the field 'related RICs'. Hence, the company name or nickname is not required to be mentioned in the headline. As before, all sentences that mention the company name, the nickname or ticker symbol are analyzed. The results are consistent with the previously discussed findings and are not shown.

To investigate the robustness of the results with respect to the definition of relevant text, I consider all words with a distance of at most 5 words to the company name, nickname or ticker symbol as relevant. Words that contain numerical expressions (e.g. 'B330-200', '$35') are not counted for the word distance. This approach is sensitive to changes in the sentiment within a sentence. Most results stay quantitatively the same.

I use the financial word lists suggested by Loughran and McDonald (2011), see `http://www.nd.edu/~mcdonald/Word_Lists.html`, and the Porter word stemmer algorithm, see `http://tartarus.org/~martin/PorterStemmer/index.html`, to measure positive and negative sentiment and disagreement with an alternative classifier. These lists might account for specialties of financial text more accurately than the General Inquirer. $P_{i,t}$, $N_{i,t}$, D^{std} and D^{pol} are calculated according to equations (2.2), (2.3) and (2.4), but $Pos_{i,t,}$ and $Neg_{i,t,j}$ are now the number of hits in the positive and the negative word list of Loughran and McDonald. The results for regression model (2.6) are comparable to the estimates in Table 2.4 and indicate a strong contemporaneous relationship between company news and the financial market. However, the one-day lagged sentiment in regression model (2.8) is insignificant with respect to all market variables. This puzzling result might indicate that the financial word lists are too restrictive to analyze general company news.

2.7 Trading Strategies

According to the previous sections, positive sentiment and disagreement are statistically significant to predict abnormal stock returns and excess returns. However, this does not allow to conclude on the economic significance of sentiment and on market efficiency. Therefore, I study trading strategies based on positive and negative sentiment to gain insights on the economic relevance of news articles for the stock market.

Assume that an investor trades the previously considered 62 stocks simultaneously. The investor has no initial endowment. She observes the signals

$$X_{i,t} = \mathbf{1}(P_{i,t} > N_{i,t}) - \mathbf{1}(P_{i,t} < N_{i,t}).$$

$X_{i,t}$ can take on the value $+1, 0$ and -1. $X_{i,t} = 1$ might be interpreted as a long-signal and $X_{i,t} = -1$ as a short-signal. $X_{i,t} = 0$ might indicate a neutral position.[4] I assume that $X_{i,t}$ is observed at 4 p.m. New York time, even though news stories might be published much earlier, which might give insights on the value of $X_{i,t}$. This conservative assumption implies a delayed investment decision as a response to news stories, and rules out intraday trading, such as algorithmic trading.

Whenever $X_{i,t} = 1$, the investor borrows one USD at the risk-free rate and purchases (a fraction of) stock i at the closing price at day t. At the following day, the stock is sold at the closing price of day $t + 1$ and the loan is repaid, if the signal changes to neutral or to sell. Otherwise, the position is not closed until the long-signal disappears. If $X_{i,t}$ changes to -1, the investor short-sells one USD in stock i, invests this one USD at the risk-free rate R^f and holds the position until the signal disappears. Profits and losses, due to trading, are collected in her money account, which is grossed up with the risk-free rate. Furthermore, the investor has to pay transaction costs for each round-trip. For simplicity, I assume that the risk-free rate for lending and borrowing is the same and that the transaction costs are paid when the position is closed.[5]

More precisely, let M_t denote the value of the money account at day t, $S_{i,t}$ is the closing price of stock i at day t and R^f_t is the gross risk-free interest rate for one

[4]The variables X and A, as used in equation (2.4), differ since A is defined for each news story, but X refers to the average net sentiment of a trading day, and not to an individual news article.

[5]The transaction costs might also cover the bid-ask spread and different rates for borrowing and lending.

day. By assumption, $M_0 = 0$. The value of the money account at t is given by

$$M_t = M_{t-1} R_t^f + \sum_{i=1}^{62} \Big(Long_{i,t} + Short_{i,t} \Big), \qquad (2.10)$$

$$Long_{i,t} = \left(\prod_{s=\tau(t)+1}^{t} \frac{S_{i,s}}{S_{i,s-1}} - \prod_{s=\tau(t)+1}^{t} R_s^f - TC \right) \mathbf{1}(X_{i,t-1} = 1 \vee X_{i,t} \neq 1), \qquad (2.11)$$

$$Short_{i,t} = \left(\prod_{s=\rho(t)+1}^{t} R_s^f - \prod_{s=\rho(t)+1}^{t} \frac{S_{i,s}}{S_{i,s-1}} - TC \right) \mathbf{1}(X_{i,t-1} = -1 \vee X_{i,t} \neq -1), (2.12)$$

where $\tau(t) = \max\{s < t | X_{i,s-1} \neq 1 \vee X_{i,s} = 1\}$ denote the most recent change to a long-signal and $\rho(t) = \max\{s < t | X_{i,s-1} \neq -1 \vee X_{i,s} = -1\}$ the most recent change to a short-signal. TC denotes the transaction costs per round-trip. The indicator function in (2.11) and (2.12) is one if and only if a position is closed. Then, the profit or loss is assigned to the money account.

Alternatively, I study the above trading strategy, assuming that the investor finances long-trades at the market rate of return and invests at the market rate of return if she short-sells a stock. Both benchmarks, i.e. the risk-free rate and the market rate of return, are downloaded from the homepage of Kenneth French. Furthermore, I study trading strategies that consist only of long-signals, $X_{i,t}^+ = \max\{X_{i,t}, 0\}$, and only of short-signals, $X_{i,t}^- = \min\{X_{i,t}, 0\}$. I do not consider trading strategies that are based on disagreement to avoid conflicting signals between sentiment and disagreement. Furthermore, I do not incorporate the signal intensity, i.e. $P_{i,t} - N_{i,t}$, nor the trading volume in the corresponding stock, the stock volatility or the company's CDS spread. Those trading strategies might depend on parameter values and, hence, require an in-sample optimization and an out-of-sample performance evaluation. However, the short time span of my dataset is insufficient for such exercises.

The full observation period, i.e. June 01, 2007 to December 31, 2010, gives 56,110 company-day observations (62 companies × 905 trading days). There are 8,757 long-signals and 3,816 short-signals yielding 6,062 buy-transactions and 3,042 short-sell transactions. Hence, the portfolio consists on average of 9.68 long-positions and 4.22 short-positions. The former have an average duration of 1.44 days and the latter of 1.25 days, respectively. The lower number of short-signals and their shorter duration compared to long-signals is somewhat surprising since the observation period covers the financial crisis, but it is consistent with the positive tenor of news articles, see Table 2.2.

Excluding transaction costs and funding costs, the average gain of a buy-transaction is 29 bps with a standard deviation of 272 bps and the average gain of a short-sell transaction is 51 bps with standard deviation 365 bps. Hence, short-sell trades are more profitable. Furthermore, transaction and funding costs of 30 bps and more would render trading on long-signals, on average, non-profitable. Moreover, the returns of buy- and sell-trades are correlated by -0.45. Therefore, the trading strategy on $X^+_{i,t}$ might be an efficient hedge for the strategy on $X^-_{i,t}$.

Table 2.6 gives the terminal value of the money account, the minimum and maximum value for X, X^+ and X^-. It also shows the longest waiting time to establish a new high watermark in days ('Days below HWM') and the strongest absolute depreciation in the money account value ('Downturn'). The latter two statistics might help to grasp the 'degree of monotonicity' of the money account value.[6] In the left part of Table 2.6, the risk-free rate is used as a benchmark, and in the right part the market rate of return is applied. The upper panel ignores transaction costs, the transaction costs are 10 bps per round-trip in the second panel, and so on.

Without transaction costs and applying the risk-free rate as a benchmark, the money account of X increases from 0 USD by June 01, 2007, to 33.2485 USD by December 31, 2010 and ends very close to its maximum value of 33.3755 USD. The money account's minimum is -0.0406 USD. The strongest decrease in the value of the money account is 1.4523 UDS and the longest period without exceeding the high watermark is 64 days. Therefore, the investment strategy has an outstanding risk-return profile and might be seen as an approximate arbitrage opportunity. Applying the market rate of return as a benchmark, the figures change only marginally, e.g. the terminal portfolio value is 29.0575 USD.

Figure 2.2, left depicts the time series of the money account values of the three strategies, using the risk-free rate as benchmark and assuming 10 bps transaction costs per round-trip. The blue, solid curve shows the money account of $X_{i,t}$, the green, dashed curve is the money account of $X^+_{i,t}$ and the red, dotted curve of $X^-_{i,t}$. During the heydays of the financial crisis (June 2007 to April 2009), the trading strategy on long-signals appears to be stationary and centered at zero, indicating

[6] The strongest downturn and the longest waiting time to establish a new high watermark might also help to determine the equity capital buffer for the trading strategies, i.e. if the strongest downturn and the longest waiting period to exceed the high watermark appear jointly at the beginning of the investment period, the equity capital buffer should be large enough to withstand this stress scenario.

no arbitrage profits, but the performance of trades on short-signals is excellent and the value of the money account increases almost monotonically. However, in spring 2009, governments and central banks successfully calmed down the financial markets and the stock market recovered. In the aftermath, the trading strategy on short-signals fails to generate profits and the money account stays constant or decreases slightly. At the same time, trading on long-signals works very well. This example also nicely highlights the good hedging quality of trading on long-signals against trading on short-signals and vice versa. Combining both trading strategies give an almost globally, monotonically increasing money account value, that increases to 24.0594 USD and has a maximum of 24.2044 UDS and minimum of -0.1286 USD. Figure 2.2, left also shows the strongest decrease in the value of the money account of $X_{i,t}$ (black line, -1.81 USD in May and June 2009) and the longest waiting period to exceed the watermark (light blue line, 112 days during Spring and Summer 2010). Both figures appear to be moderate.

The assumption of 20 bps transaction costs per round-trip reduces the terminal values of the money accounts, the terminal value of trading on long- and short-signals jointly is now 14.8703 USD and 10.6793 USD, depending on the benchmark. The minimum portfolio value is -1.5261 USD and -1.6210 USD, respectively, and the maximum value is 15.3437 USD and 14.0891 USD, respectively. The trading strategies might still be attractive, profitable investment opportunities, but they now bears a higher shortfall risk. Transaction costs of 30 bps imply that the investor realizes, on average, losses on every buy-transaction and on many sell-transactions. Hence, the terminal value of the money account of $X^+_{i,t}$ is negative. However, $X^-_{i,t}$ might still be profitable. $X^-_{i,t}$ cannot compensate transaction costs of 50 bps or more.

Other approaches, which rely on the General Inquirer dictionary, such as using only the five words in the neighborhood of the company name to calculate the sentiment, give similar results. I also test the trading strategies on the sentiment calculated with the financial word lists of Loughran and McDonald. Figure 2.2, right shows the corresponding values of the money accounts of $X_{i,t}, X^+_{i,t}$ and $X^-_{i,t}$ assuming 10 bps transaction costs and using the risk-free interest rate as a benchmark. As already indicated by the regression analysis in the robustness section, the results weaken significantly. Trading on short-signals performs well during the financial crisis and attains a maximum of about 15 USD in February 2009, which is very similar to the trading strategy of short-signal based on the General Inquirer dictionary. However, it generates significant losses in the subsequent period. Also the performance of long-signals is reduced, even though the money account does not turn negative during

	Risk-free rate			Market rate		
Trading Strategy	$X_{i,t}$	$X_{i,t}^{+}$	$X_{i,t}^{-}$	$X_{i,t}$	$X_{i,t}^{+}$	$X_{i,t}^{-}$
No transaction costs						
M_T	33.2485	17.7226	15.5405	29.0575	15.4238	13.6477
$\max_{t\in[0,T]}\{M_t\}$	33.3755	17.7738	16.3134	29.1761	15.6800	13.7278
$\min_{t\in[0,T]}\{M_t\}$	-0.0406	-0.1168	-0.0917	-0.0549	0.0000	-0.2398
Downturn	1.4524	4.1878	3.0550	1.5805	1.8375	1.3536
Days below HWM	65	113	456	105	154	237
10 bps						
M_T	24.0594	11.6034	12.4646	19.8684	9.3046	10.5718
$\max_{t\in[0,T]}\{M_t\}$	24.2044	11.6657	14.7080	20.2108	10.5371	10.6630
$\min_{t\in[0,T]}\{M_t\}$	-0.1286	-2.2423	-0.1940	-0.1429	-0.0399	-0.3421
Downturn	1.8062	4.4204	3.4560	2.1110	2.1556	1.5123
Days below HWM	112	156	456	153	154	412
20 bps						
M_T	14.8703	5.4843	9.3888	10.6793	3.1855	7.4959
$\max_{t\in[0,T]}\{M_t\}$	15.3437	5.0716	13.1026	14.0891	6.6094	8.6155
$\min_{t\in[0,T]}\{M_t\}$	-1.5261	-4.8499	-0.3238	-1.6210	-0.9771	-0.6888
Downturn	2.2712	5.4333	4.1042	3.8634	3.7736	1.9210
Days below HWM	196	438	456	415	413	454
30 bps						
M_T	5.6812	-0.6349	6.3129	1.4902	-2.9337	4.4201
$\max_{t\in[0,T]}\{M_t\}$	8.9540	1.1072	11.4972	9.1693	3.2732	7.0032
$\min_{t\in[0,T]}\{M_t\}$	-3.4651	-7.6135	-0.6654	-3.5721	-3.1743	-1.2930
Downturn	3.5781	7.9613	5.1843	7.7805	6.4475	2.9819
Days below HWM	415	531	456	433	413	454
50 bps						
M_T	-12.6970	-12.8732	0.1612	-16.8880	-15.1720	-1.7317
$\max_{t\in[0,T]}\{M_t\}$	0.0809	0.1352	8.2864	0.1213	0.2978	3.7784
$\min_{t\in[0,T]}\{M_t\}$	-12.6970	-13.6701	-1.5818	-16.8880	-15.1946	-2.5643
Downturn	12.7780	13.8053	8.1253	17.0093	15.4924	5.5100
Days below HWM	900	900	456	900	898	454
Number of trades	9104	6062	3042	9104	6062	3042
Average duration	1.39 days	1.46 days	1.26 days	1.39 days	1.46 days	1.26 days

Table 2.6: The table shows the terminal value, the maximum and the minimum value of the money accounts for trading strategies on company signals and different levels of transaction costs. 'Downturn' gives the strongest downturn of the portfolio value and 'Days below HWM' gives the longest period of not exceeding the high watermark in days. $X_{i,t}$ incorporates of buy- and sell-signals, $X_{i,t}^{+}$ buy-signals only and $X_{i,t}^{-}$ sell-signals only. The risk-free interest rate (market rate of return) is used as a benchmark in the in the left panel (right panel).

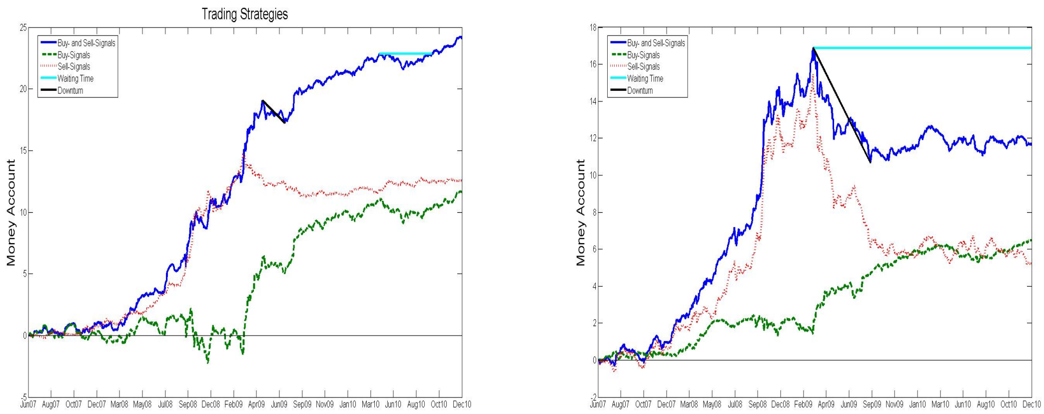

Figure 2.2: **Left:** The figure shows the value of the money accounts of trading on long- and short-signals (blue, solid curve), long-signals (green, dashed curve) and short-signals (red, dotted curve), assuming 10 bps transaction costs per round-trip and the risk-free interest rate as a benchmark. For the trading strategy on long- and short-signals, the black line marks the strongest downturn, realized in May and June 2009, and the cyan line marks the longest waiting period to establish a new high watermark, observed in Summer 2010. **Right:** The figure shows the value of the money accounts for the same trading strategies as in the left figure, but sentiment is calculated with the financial word lists suggested by Loughran and McDonald.

September 2009 to March 2010. The money account value of the trading strategy on long- and short-signals at December 31, 2010, is 11.6224 USD with a maximum downturn of 6.2212 USD (black line) and being far away from the high watermark of 16.8852 USD (cyan line). The lower performance of the trading strategies based the financial word lists indicates that non-financial expressions are important as well to measure the sentiment of rather general company news articles.

2.8 Conclusion

Das et al. (2005) analyzed chat-room postings and conclude that "people trade first and talk later" (Financial Management 34, p.135). I analyze company news of Reuters. These news are more reliable than chat room postings, which - at best - disseminate public information. Simple, dictionary based content analysis algorithms with rather general word lists might be applied to measure sentiment and disagreement of news articles. Both, sentiment and disagreement contain valuable information for financial markets.

My results are mostly consistent with the difference of opinion literature, i.e. investors are more likely to trade stocks and options when public signals occur. Disagreement across news articles, which might measure the degree of difference of opinion, is also positively correlated with stock and option trading volume and return volatility. Moreover, sentiment and disagreement are statistically significant to predict returns, volatility and trading volume. With moderate transaction costs, it might be possible to exploit market inefficiencies by trading on long- and short-signals based on mechanically evaluated company news. However, transaction costs of 30 bps and more render these trading strategies non-profitable. Therefore, only institutional investors might be able to take advantage of this inefficiency.

2.9 Appendix

2.9.1 News Coverage

I investigate the company characteristics that expose a company to news coverage. I consider the 61 large companies in the S&P500 with liquid option and CDS market, listed in Table 2.8.[7] The news coverage of a company is measured by its average number of news articles per day, identified by searching for the company's RIC in 'related RICs'. This measure is denoted Q_i. Alternatively, news coverage is measured by the number of days with at least one news story. This measure is denoted Y_i. Companies are characterized by the average market capitalization in the observation period, CAP_i, the average price-to-book ratio, $P2B_i$, the stock return during the observation period, Ret_i, and the corresponding return volatility, $\sigma(Ret_i)$.

The average company has an average market capitalization during June 01, 2007 to December 31, 2010 of 8,3223 millions USD and an average price-to-book ratio of 2.67. The average stock market performance in this period and across companies is -9.41% and the average stock return volatility is 42.63%. I estimate an ordinary linear regression model, i.e.

$$Q_i = \alpha + \beta_1 P2B_i + \beta_2 \ln(CAP_i) + \beta_3 Ret_i + \beta_4 \sigma(Ret_i) + \eta_i. \qquad (2.13)$$

Table 2.7 shows the regression estimates for (2.13) and for some straightforward modifications of the regression model. a indicates significance at the 1% confidence level, b at the 5% level and c at the 10% level. Even though this analysis excludes small and mid-sized companies, the company size is still a significant, positive determinant of the news coverage. The price-to-book ratio is significant and negative in all regressions. This indicates that companies with high ratios are less often in the news compared to companies with low ratios. One reason for this pattern might be that the latter companies have a higher potential for stock price increases. The stock return is weakly significant and negative. The stock return volatility is significant, too, and positive. Both indicate that troubled companies are frequently in the media. However, this result might also be due to the financial crisis.

All results are qualitatively the same if Y_i is considered instead of Q_i. Hence, large companies with low price-to-book ratios and volatile stock returns have a high media

[7] Time Warner (TWX.N) is excluded since I found no information on the price-to-book ratio.

	Q_i		Y_i	
constant	-20.8872^a	-23.0588^a	-2.0450^a	-2.0569^a
$P2B$	-0.3051^a	-0.2101^a	-0.0251^a	-0.0225^a
$\ln(CAP)$	2.2701^a	2.3374^a	0.2481^a	0.2501^a
Ret	-	-1.9734^b	-	-0.1547^b
$\sigma(Ret)$	-	6.9538^a	-	0.2916^b
R^2	38.73%	68.26%	54.58%	65.89%
# Obs.	61	61	61	61

Table 2.7: The table shows the regression estimates for model (2.13). The subscript a, b and c indicate significance at the 1%, 5% and 10% confidence level. Q_i denotes the average number of news per day of company i, and Y_i is the average number of days with at least one news story. A news story is relevant for a company if the company's RIC is mentioned in the field 'related RICs'.

coverage, or conversely, companies with a high media coverage are large, have a low price-to-book ratio and their stock price is rather volatile.

2.9.2 RICs - Company Names

RIC	Company Name
AA.N	Alcoa Incorporated
ABT.N	Abbott Laboratories
AIG.N	American International Group Inc
AMGN.O	Amgen Inc
APC.N	Anadarko Petroleum Corp
AXP.N	American Express Co
BA.N	The Boeing Company
BAC.N	Bank of America Corp
BAX.N	Baxter International Inc
BMY.N	Bristol Myers Squibb Co
BSX.N	Boston Scientific Corp
C.N	Citigroup Inc
CAT.N	Caterpillar Inc
COP.N	ConocoPhillips
CSC.N	Computer Sciences Corp
CSCO.O	Cisco Systems Inc
CVX.N	Chevron Corp
DD.N	E I Du Pont De Nemours And Company
DELL.O	Dell Inc
DIS.N	Walt Disney Co
DOW.N	The Dow Chemical Co
DVN.N	Devon Energy Corp
F.N	Ford Motor Co
FDX.N	Fedex Corp
GE.N	General Electric Co
GLW.N	Corning Inc
GR.N	Goodrich Corp
GS.N	The Goldman Sachs Group Inc
HD.N	The Home Depot Inc
HON.N	Honeywell International Inc
HPQ.N	Hewlett Packard Co
IBM.N	International Business Machines Corp
INTC.O	Intel Corp
JNJ.N	Johnson & Johnson
JPM.N	Jpmorgan Chase & Co
KFT.N	Kraft Foods Inc
KO.N	The Coca Cola Co
MCD.N	McDonald's Corp
MDT.N	Medtronic Inc
MO.N	Altria Group Inc
MON.N	Monsanto Co
MMM.N	3m Co
MRK.N	Merck and Co Inc
MS.N	Morgan Stanley
MSFT.O	Microsoft Corp
LLY.N	Eli Lilly And Co
LMT.N	Lockheed Martin Corp
ORCL.O	Oracle Corp
OXY.N	Occidental Petroleum Corp
PFE.N	Pfizer Inc
PG.N	Procter & Gamble Co
SLB.N	Schlumberger NV
T.N	AT&T Inc
TRV.N	Travelers Companies Inc
TWX.N	Time Warner Inc
TXN.N	Texas Instruments Inc
UTX.N	United Technologies Corp
VZ.N	Verizon Communications Inc
WFC.N	Wells Fargo and Co
WMT.N	Wal Mart Stores Inc
WLP.N	WellPoint Inc
XOM.N	Exxon Mobil Corp

Table 2.8: The table gives the list of companies that are included in the analyses and matches the company name with the company's RIC (= Reuters instrument code)

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Chapter 3

Leverage, Profitability and Risk of Banks - An Empirical Analysis

Abstract: This paper studies the relationship between the leverage ratio and profitability and risk-adjusted profitability, respectively, for European and U.S. banks. Risk-adjusted profitability is measured by accounting figures and, alternatively, by stock prices. Applying a dynamic panel regression and controlling for several bank characteristics (e.g. loan portfolio quality, liquidity endowment, size), I find that banks adjust their leverage ratio (defined as total assets over book equity) fast compared to industrial companies. Moreover, bank performance is non-monotonically, inversely 'u'-shaped related to the leverage ratio. When the leverage ratio of a European bank is high, CDS spreads tend to be high, too, indicating that expected default costs dominate benefits of the tax shield. For U.S. banks, I find no significant relation between the leverage ratio and the CDS spread. This puzzling result might be due to a restriction on the non-risk weighted capital structure of U.S. banks.

3.1 Introduction

Given various market imperfections, many papers investigate the optimal capital structure of corporations. Especially during the ongoing financial crisis, the capital structure of banks is discussed not only in academia, but also in public. The failure of Lehman Brothers caused financial distress for many poorly capitalized banks.

Strong support by governments and central banks helped to avoid the collapse of major financial institutions. There is an ongoing debate how to prevent such events in the future. Adjusting incentive systems for bank managers and raising risk-weighted equity capital requirements of banks are prominent suggestions. Also an upper limit for the non risk-weighted leverage ratio (defined as total book assets over book equity) of banks is imposed.[1] This raises the following questions: (1) How are bank profits related to the capital structure and how do they react if some maximum leverage ratio is implemented? (2) How is the default probability of a bank related to its capital structure? (3) What is an adequate limit for the leverage ratio? This paper tries to answer these questions by analyzing the relationship between the non risk-weighted leverage ratio and profitability, risk-adjusted profitability and expected default costs, respectively.

In a perfect market, the market value of a firm is independent of its capital structure, see Modigliani and Miller (1958). In reality, tax effects, bankruptcy costs and information asymmetry might affect profits and the firm value. According to the trade-off theory, the optimal capital structure balances the tax shield and bankruptcy costs. Alternatively, the pecking-order theory relates the costs of different funding sources to asymmetric information between the owners and external investors. This implies a preferred order of funding sources. Many empirical papers test these theories for industrial corporations. The results are mixed.

Compared to industrial corporations, financial institutions are different with respect to the capital structure and the flexibility of funding in liquid markets. Industrial firms have a fairly low leverage ratio and use long-term bonds and loans for funding, whereas financial institutions are more leveraged and use short-term loans to a large extent. Moreover, the capital structure of financial institutions must satisfy regulatory requirements. These issues might imply more active capital structure management and a different relationship between the capital structure and profitability for financial institutions than for industrial corporations. Hence, results for industrial corporations should not be transferred to banks.

Theoretical papers such as Diamond and Rajan (2000), Inderst and Mueller (2008) and Koziol and Lawrenz (2009) prove the existence of an optimal leverage ratio for profit maximizing banks under certain assumptions. The major determinants are

[1]See, for example, Report of the Financial Stability Board to G20 Leaders, "Improving Financial Regulation", September 2009 or Basel Committee on Banking Supervision "Strengthening the Resilience of the Banking Sector", December 2009

liquidity risk and credit risk, but also the degree of competition in the loan market or costs of adjusting the capital structure. However, the regulator is a powerful and important stakeholder in a bank and might have objectives different from those of the owners. As Allen Greenspan pointed out: " [...] it is useful to underline that regulators and banks have a common interest in using the evolving new technologies to meet their own separate objectives: maximizing shareholder value and maintaining a safe and sound banking system. One cannot be done without the other."[2] Therefore, the regulator might restrict the leverage ratio of banks to some reasonable limit, even though this could reduces profitability, if high leverage ratios are associated with high default probabilities, and hence with systemic risk.

This empirical paper separately analyzes the leverage ratio and profitability of European and U.S. banks over the time span 1994 to 2008 with a dynamic panel regression. Investment banks, special government banks, cooperative banks and bank holding companies are excluded to reduce the heterogeneity in the samples. The excluded banks might have non-common capital structures or objectives, which are not captured by fixed effects. Whereas the capital-asset ratios of U.S. banks are restricted by the FDIC to exceed 4% and in some exceptional cases 3%,[3] the non-risk weighted capital structure of European banks is not restricted. This major difference in bank regulation might cause different relationships between the leverage ratio and profitability, risk-adjusted profitability and default costs, respectively. Furthermore, these differences might provide insights on the usefulness of an upper limit on the leverage ratio.

First, I investigate whether banks adjust their leverage ratio actively towards some target leverage ratio. Then, I investigate the determinants of profitability and risk-adjusted profitability, respectively. Finally, I analyze the relationship between the leverage ratio and the CDS-spread to complete the analysis of bank performance and to relate the leverage ratio to systemic risk. Profitability and the overall bank risk can be measured by several statistics. Return on book equity and return on book assets are frequently used to measure profitability, but they do not account for the bank's risk. For listed institutions, risk may be measured by the volatility of the stock return and the Sharpe-ratio might be used as a risk-adjusted performance measure. However, many banks are not listed. Hence, I define two further risk-adjusted profitability measures using the total risk-charge according to the Basel

[2] Annual Convention of the American Banker Association 1996.

[3] see FDIC Law, Regulations, Related Acts, §325.3 Minimum leverage capital requirement

Accord as a risk measure.

The main findings are: (1) Bank managers adjust the leverage ratio faster than industrial corporations (i.e. the estimated time of closing half the gap between the target and the actual leverage ratio is 1.25 years for banks, whereas the literature documents on average 1.8 years for industrial corporations). This is consistent with the trade-off theory and renders a preferred order of funding sources less important for the capital structure decision. Furthermore, it indicates that a bank's tolerance with respect to an inefficient capital structure is rather limited. (2) Almost all performance measures for U.S. and European banks attain a maximum for some interior leverage ratio. Risk-adjusted profitability is highest for some lower leverage ratio compared to profitability. Whereas return on equity attains a maximum for a leverage ratio of 14.7 for U.S. banks and 25.5 for European banks, risk-adjusted profitability is maximized for a leverage ratio of about 13 for U.S. banks and 20 for European banks. For listed U.S. banks, this result is confirmed by the Sharpe-ratio. (3) The annual expected default costs of European banks, as measured by CDS spreads, are positively related to the leverage ratio. I find no such link between the leverage ratio and the default costs for U.S. banks. This puzzling result might be due to differences in bank regulation. Hence, an upper limit for the leverage ratio might decouple the leverage ratio and default costs. It could also reduce systemic risk in the economy. The leverage ratio that maximizes average risk-adjusted profitability might be a reasonable upper limit, which trades off the objectives of the regulator and the bank owners.

To the best of my knowledge, the relationship between the leverage ratio of financial institutions and risk-adjusted profitability and default probability, respectively, has been rarely analyzed empirically. Also implications gained from analyzing U.S. banks and European banks have been rarely compared within one study. The rest of the paper is organized as follows. Section 2 gives a literature review, section 3 derives testable hypotheses and describes the data. In section 4.1, I estimate the speed of adjustment in the leverage ratio of U.S. and European banks. Section 4.2 investigates the average, performance maximizing leverage ratio. In 4.3, I run some robustness tests and section 4.4 analyzes the relationship between the capital structure and expected default costs. Section 5 concludes.

3.2 Literature Review

There are three major explanations for the capital structure decision of corporations, the trade-off theory, the pecking-order theory and the market-timing theory. According to the trade-off theory, firms choose the capital structure so that marginal benefits of debt financing, such as tax benefits or the ability to finance additional projects, and costs of financial distress are balanced, see for example Frank and Goyal (2009) and Fischer, Heinkel and Zechner (1989). In general, tax benefits dominate bankruptcy costs if the leverage ratio is low, but bankruptcy costs dominate tax benefits if the leverage ratio is high. According to the pecking-order theory, funding costs are mainly driven by the costs of asymmetric information. Since retained earnings are not related to asymmetric information, a firm prefers this funding source to debt and issuing new equity. Furthermore, asymmetric information tends to make new equity more expensive than debt, see Frank and Goyal (2003). Finally, the market-timing theory says that managers base the capital structure decision on current and expected equity and debt market conditions, see Baker and Wurgler (2002).

Many papers investigate active capital structure management of industrial corporations and try to determine managers' objectives. A dynamic trade-off model for the capital structure in the presence of adjustment costs is presented by Fischer, Heinkel and Zechner (1989). They show that transaction costs may cause substantial deviations of the observed capital structure from the desired capital structure. For non-financial firms, Flannery and Rangan (2006) find partial adjustments to some target capital structure. This ratio is determined by firm characteristics such as profitability or size. On average, about 30% of the gap between the target capital structure and the actual capital structure is closed each year. Leary and Roberts (2005) also find evidence for active capital structure management. Harford, Klasa and Walcott (2009) study large acquisitions. Usually, the capital structure of the acquiring corporation changes substantially, but managers actively implement some target capital structure close to the capital structure that was held before the acquisition within the following 5 years.

Bharath, Pasquariello and Wu (2009) show that asymmetric information affects the capital structure of a firm. They suggest an index that measures information asymmetries between the owners and external investors. Their findings support the pecking-order theory. Fama and French (2005) find that firms issue equity more frequently than the pecking-order theory predicts and conclude that the pecking-order theory does not hold. Frank and Goyal (2003) also conclude that the pecking order theory is not supported by their comprehensive dataset. Leary and Roberts (2010) find support for a generalized pecking-order theory, where the firm's debt capacity depends on firm characteristics. However, Strebulaev (2007) shows by a simulation exercise that a simple model for the capital structure decision, which is consistent with the trade-off theory, and market imperfections may give wrong implications for the true relationship between profits and the capital structure.

The balance sheet of banks differs substantially from that of non-financial firms. Banks hold dynamic loan portfolios with frequently changing compositions and with frequently changing qualities. Furthermore, banks usually do not own the funded investment projects but participate only through interest payments if the projects succeed, which might cause underinvestment problems. In contrast, the portfolio of an industrial corporation has more stable characteristics and projects tend to be more homogeneous. This makes the valuation of industrial corporations easier. Because of the complexity of bank valuation, the bank manager should be incentivized carefully. The bank manager's and the shareholders' interests may be aligned by a fairly high leverage ratio, see Flannery (1994). A high leverage ratio motivates the bank manager to monitor and manage the loan portfolio very carefully. In addition, it enables the manager to own a large share of the bank, which further mitigates conflicts between the manager and the owners. However, the exposure to market risk, credit and liquidity risk and strong networks in the financial industry make banks vulnerable and may imply systemic risk. Bank regulation ought to constrain systemic risk.

Implications of bank regulation are complex and sometimes unintended. Blum (1999) presents a two-period model and studies the effect of regulation on banks' risk taking, finding the unintended consequence that regulation in later periods may increase today's risk taking. Adrian and Shin (2008) and Jokipii and Milne (2008) investigate implications of the Basel Accord. The authors find a pro-cyclical leverage ratio and cyclicality in the capital buffer, respectively. Both findings are unintended, too. Therefore, new regulation tools should be analyzed carefully before being implemented, such as a restriction on the leverage ratio. Blum (2008) discusses theoretically the implications of a restriction on the non risk-weighted leverage ratio in addition to the risk-based Basel Approach. Under certain conditions, this simple instrument ensures honest risk reporting and stabilizes the financial industry.

Theoretically, the optimal capital structure of financial intermediaries trades off high profits in fragile markets and low profits in safe markets. Diamond and Rajan (2000) present a model where banks benefit from lending and creating liquidity. Bank runs characterize fragile financial markets and destroy the bank's rent. The optimal capital structure is described by a reasonable mix of deposits and equity. Inderst and Mueller (2008) assume that banks are sophisticated lenders and run a credit risk analysis before granting a loan. Subject to the borrower's participation constraint, the bank determines the interest rate on the loan and maximizes profits. One implication of the model is that banks with too low leverage ratios act too conservatively with respect to granting loans. Koziol and Lawrenz (2009) assume that the bank's asset value follows a jump-diffusion process. Additionally, the bank has to satisfy regulatory restrictions similar to Basel II. Adjustments in the capital structure are costly and modeled by increasing or decreasing the deposit volume. The bank adjusts the capital structure if the diffusion process brings the equity value down to the minimum regulatory capital. Adjustments are also necessary if the equity value exceeds some upper boundary to take advantage of the tax shield. The optimal capital structure trades off the default probability, which is due to the jump process, and the frequency of adjusting the capital structure.

Ignoring industrial corporations and studying U.S. banks between 1983 and 1989, Berger (1995) finds that the capital-asset-ratio, or inverse leverage ratio, and return on equity positively Granger-cause each other. The causality from return on equity to the capital-asset-ratio is not surprising. Reinvesting profits in a multi-period model explains the interaction easily. The causality from the capital structure to profitability might be explained by controlling the costs of financial distress with the capital-asset-ratio. Berger and Bonaccorsi di Patti (2006) analyze U.S. banks between 1990 and 1995 and allow for a non-monotone relationship between the capital-asset ratio and profitability, measured by profit efficiency, and find that the capital-asset ratio negatively impacts profitability, without finding evidence for costs of very low capital-asset ratios. The latter might be attributed to bank regulation. Fiordelisi and Molyneux (2010) analyze the shareholder value creation of European banks. They find that cost and revenue efficiency are inversely related to shareholder value creation, and profit efficiency, credit risk and the leverage ratio are positively related to shareholder value creation. Since the aforementioned study applies a regression model that is linear in the leverage ratio, the estimated coefficient gives the dominating effect of the leverage ratio over the whole domain. Hence, an interior optimal leverage ratio is ruled out.

3.3 Hypotheses and Data Description

3.3.1 Hypotheses

According to the previous discussion, there are at least four major aspects that might imply fast adjustments in the leverage ratio of banks and a high sensitivity of bank performance with respect to the leverage ratio compared to industrial corporations: (1) Banks hold a rather dynamic loan portfolio. (2) Banks are subject to relatively low transaction costs. (3) Banks might be prone to underinvestment problems. (4) Banks are subject to regulatory restrictions. Hence

> ***Hypothesis 1:*** Banks manage their leverage ratio actively and adjust it fast compared to non-financial companies.

Low leverage ratios do not take full advantage of the tax shield and might not help to resolve conflicts between the owners and the manager. Hence, they might be inefficient. High leverage ratios might imply high expected default costs, which could increase funding costs such that they are inefficient as well. Hence, in line with the trade-off theory,

> ***Hypothesis 2:*** Bank profitability attains a maximum for some interior leverage ratio.[4]

If profitability increases with the leverage ratio up to a critical leverage ratio, risk-adjusted profitability might increase with the leverage ratio, too, up to some other, possibly lower, critical leverage ratio. Starting from a low leverage ratio, an increase in the leverage ratio might increase profits more than risk, so that risk-adjusted profitability goes up. Increasing the leverage ratio starting from a high leverage ratio, the bank's risk might be very sensitive to adjustments in the leverage ratio. Profitability might increase or even decrease if the leverage ratio is raised even more. In both cases, the increase in risk is presumably not offset by the change in profits. Risk-adjusted profitability is likely to decline. Therefore

> ***Hypothesis 3:*** Risk-adjusted profitability attains a maximum for some interior leverage ratio.

[4] The term 'interior' refers to the domain of observed leverage ratios in the corresponding sample.

3.3.2 Profitability and Risk-Adjusted Profitability

Profitability might be measured by return on equity and return on assets, i.e.

$$\begin{aligned} RoE_{i,t} &= PaT_{i,t}/BE_{i,t} \\ RoA_{i,t} &= PaT_{i,t}/BA_{i,t}, \end{aligned}$$

where $PaT_{i,t}$ is the after-tax profit of bank i in year t, $BE_{i,t}$ is the year's average book equity and $BA_{i,t}$ is the year's average book value of total assets. RoE (**R**eturn **o**n average book **E**quity) is a pure profitability measure. RoA (**R**eturn **o**n average book **A**ssets) is more robust and insensitive to replacing equity by debt. However, both measures ignore the substitution of rather safe assets by risky assets. Hence, this study also analyzes risk-adjusted performance measures. Define

$$\begin{aligned} RoRCH_{i,t} &= PaT_{i,t}/(8\% * TRC_{i,t}) \\ RARoE_{i,t} &= \frac{PaT_{i,t} - 8\% * 8\% * TRC_{i,t}}{BE_{i,t}}. \end{aligned}$$

$RoRCH$ (**R**eturn **o**n average **R**isk **CH**arge) and $RARoE$ (**R**isk **A**djusted **R**eturn **o**n average book **E**quity) rely on the bank's self reported average total risk charge according to the Basel Accord, TRC. $RoRCH$ standardizes the after-tax profits by the year's average minimum regulatory capital, $8\% * TRC$. $RARoE$ adjusts the after-tax profits for the opportunity costs of holding the minimum regulatory capital. I assume that the expected return of the investment opportunity is 8%.[5] Finally, the risk-adjusted profit is standardized by the average book equity.

If the bank is listed, performance might be measured by the Sharpe-ratio, too. Denote the excess stock return over the risk-free interest rate of bank i in year t by $r_{i,t}$. The corresponding annual stock return volatility, estimated with daily observations, is denoted $\sigma_{i,t}$. Then, the Sharpe-ratio is given by

$$SHR_{i,t} = \frac{r_{i,t}}{\sigma_{i,t}}.$$

The capital structure is measured by the leverage ratio, denoted $LR_{i,t}$, and defined by the year's average book value of total assets, $BA_{i,t}$, divided by the year's average book equity, $BE_{i,t}$.

[5] This assumption is not critical. Other opportunity costs give very similar results.

3.3.3 Controls

I use a two-way dynamic panel regression model to study the leverage ratio, profitability and their interactions. However, it is important to control for bank characteristics to measure the relationship between the leverage ratio and profitability accurately. Therefore, the following sections briefly discuss important control variables and how they are measured.

Fixed Effects

Inderst and Mueller (2008) argue that the optimal leverage ratio and the profitability of banks depend on the degree of competition in the loan market. In an empirical study, Bikker and Haaf (2002) analyze small, medium sized and large banks in 23 countries between 1988 and 1998 and estimate the degree of competition. They find that competition between banks in European countries differs, and that competition in Europe is on average higher than in non-European countries, especially the USA. The hypothesis of perfect competition between banks cannot be rejected for France, Germany, Greece, Netherlands and Switzerland. For the United States both the hypothesis of perfect competition and the hypothesis of a perfect cartel are rejected. Besides of the degree of competition within a region, other time invariant determinants of the capital structure and profitability of banks might be due to differences in the banking system, e.g. deposit insurance or the bankruptcy code, and taxation of profits across countries or states. According to Gropp and Heider (2010), the capital structure decision of banks is predominantly explained by unobservable, time-invariant, bank fixed effects. I allow for bank individual dummy variables, which, of course, cover country fixed effects, too. Global macroeconomic movements such as the stock market performance, the level of interest rates or real estate prices might be covered by year fixed effects.

Other bank characteristics might not be well captured by fixed effects since they are expected to vary strongly for a given bank over time.

Size ($SIZE$)

Walter (2003) argues that banks trade off the too-big-to-fail guaranty and economies of scale and scope against costs of complexity, and, hence, there might be a bank size that maximizes profitability. Rajan and Zingales (1995) analyze industrial corporations and find that size affects the capital structure decision. The same might be true for banks, too. The size of an industrial corporation is often measured by the logarithm of the book value of total assets. For financial institutions, this measure might be very noisy. Banks assets are hardly related to economic goods, hence, total assets might not measure the sustainable bank size. A more resilient bank size measure might be the logarithm of the (annual, average of) number of employees. However, the logarithm of total assets is used for robustness checks.

Regulatory Pressure ($REGP$)

Banks with a total risk-weighted capital ratio below 10% operate close to the minimum regulatory requirements, and might be subject to regulatory pressure. As a consequence, they might be restricted in their policy. Moreover, the bank's creditors and regulatory authorities might be alarmed, and, in efficient markets, funding costs are likely to be high. This might cause a decline in profitability. Also, the bank might be forced to adjust the balance sheet, which could affect the leverage ratio. Hence, regulatory pressure might be a determinant of profitability and the leverage ratio. I follow Flannery and Rangan (2008) and measure regulatory pressure by a dummy variable, denoted $REGP$, that is one if a banks (annual, average of) total risk-weighted capital ratio is below 10%.

Asset Structure (LPQ and LIQ)

The asset structure of a bank is measured by two variables, the loan portfolio quality (LPQ) and the liquidity endowment (LIQ). This is, among others, motivated by Diamond and Rajan (2000), who argue that credit risk and the liquidity endowment determine the capital structure of banks. Angbazo (1997) and Berger (1995) show that the loan portfolio quality, measured by the inverse of risk-weighted assets, of non-performing assets or the net charge-off, is positively related to profitability, i.e. the net interest margin and return on equity, respectively. Goddard et al. (2004) and Molyneux and Thornton (1992) analyze the relationship between profits and the liquidity endowment, but their results are ambiguous.

In this study, the loan portfolio quality is measured by the loan loss reserve relative to the average total value of the loan portfolio. Given that a bank has a constant charge-off policy, low values indicate high-quality loan portfolios and vice versa. Alternative measures of the loan portfolio quality are discussed in the robustness section. The liquidity endowment is approximated by liquid assets over the sum of customer deposits and short term funding.

Diversification (DIV)

Besides of interest income, commercial banks' major income sources are fees and commissions. Income from proprietary trading and off-balance sheet activity also contribute to the overall bank income. To account for the income structure of a bank, I measure the bank's income diversification by the ratio of other operational income - this is income others than interest, fee or commission income - divided by total operational income. A value close to zero indicates that a bank's business is focused on 'traditional' income sources such as the loan business. A high ratio indicates that the bank is heavily involved in e.g. proprietary trading or off-balance sheet activities.

Angbazo (1997) and Lepetit et al. (2008) study off-balance sheet activity and bank-income diversification, respectively, in detail, see also in Goddard et al. (2004). However, the effect of income diversification on bank profitability and bank risk are mixed. Diversification benefits might disappear fast since trading income and off-balance sheet activities are normally more volatile than interest income.

Education / R&D (EDU)

Flannery and Rangan (2006) find that R&D expenses of industrial companies are useful to explain the capital structures. R&D expenses are not available for banks. However, the logarithm of personnel expenses per employee of banks might approximate R&D expenses, since it also measures investments to develop and educate the existing staff and to hire new, talented employees.

3.3.4 Descriptive Statistics

I analyze the balance sheets and income statements between 1994 and 2008 of European and U.S. commercial banks, obtained from the Bankscope database. Due to their special business models, investment banks, cooperative banks, special government banks and bank holding companies are not considered. Acquired or closed banks are not excluded to mitigate the survivorship bias. The following European countries are included: Austria, Belgium, France, Germany, Great Britain, Italy, Ireland, Luxembourg, Netherlands, Portugal, Spain and Switzerland. Small banks are excluded. Therefore, I choose a minimum threshold for the book value of total assets of 5 billion USD for U.S. banks and of 1 billion USD for European banks. European savings banks are included, too. This measure and the lower threshold for total assets for European banks raise the number of observations for the European sample and allow to calculate robust estimates, even though they might increase heterogeneity. Removing obvious data mistakes, e.g. banks with negative equity, yields up to 1200 complete observations for about 175 U.S. banks and about 1000 observations for 205 European banks. The observations are almost equally spread across years, however, for some reasons there are slightly fewer observations for the years 2005 and 2006 than for the other years.

Table 3.10 in the appendix provides names of all listed banks in my sample. For these banks, I download daily stock prices, adjusted for dividend payments and stock splits, from Datastream. The LIBOR rate is used to approximate the risk-free rate. I calculate the annual Sharpe-ratio for the time span 1994 to 2007 and exclude the year 2008, since 2008 is characterized by extreme market turmoil for financial institutions. Those market prices presumably were not the fundamental values and are likely to bias the results. Even though the number of listed European banks is larger than the number of listed U.S. banks (36 vs. 22), there are 178 bank-year observations for the U.S. sample but only 132 observations for European banks. This is due to the relatively low number of missing accounting figure for U.S. banks.

Table 3.1 shows descriptive statistics for all variables for U.S. banks and for European banks. The upper panel gives the mean and the standard deviation across banks and over time, the lower panel shows the correlation matrix for both samples separately. Since the selection rule for European banks is less restrictive than for U.S. banks, the column 'EU Banks Cmp' in the upper panel provides the mean and standard deviation for European banks, applying the same selection rule as for U.S. banks, i.e. a minimum threshold for the book value of total assets of 5 billion USD and commercial banks only.

On average, U.S. banks are more profitable than European banks. The average RoE of U.S. banks is 14.7 whereas the average RoE of European banks with comparable size is 10.2. The differences in RoA are even more severe, 1.3 for U.S. banks and 0.56 for European banks. $RoRCH$ and $RARoE$ give similar results. The large differences between RoA of U.S. and European banks might be due to the - on average - lower

	U.S. Banks		EU Banks		EU Banks Cmp	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
LR	11.7999	3.3748	21.1021	9.0802	23.5038	10.4958
REGP	0.0042	0.0646	0.0568	0.2314	0.1101	0.3131
LPQ	1.7023	1.1348	2.9940	3.0658	2.8041	2.5520
LIQ	15.3627	20.3590	30.0273	21.6237	28.6799	21.4030
DIV	0.3475	0.3175	0.1027	0.6959	0.1754	1.2880
SIZE	8.2377	1.5900	6.5806	1.4078	7.6185	1.7174
EDU	4.0897	0.5750	4.2280	0.5300	4.4612	0.6103
RoE	14.7089	11.0919	8.1574	13.3700	10.2052	14.5427
RoA	1.3144	1.1532	0.5029	1.0259	0.5573	0.7781
RoRCH	1.8886	1.5233	1.1557	3.0795	1.1561	4.6706
RARoE	15.6323	11.5320	9.4067	11.9490	9.2052	14.7734
SHR	0.2837	1.1018	0.2717	1.0698	0.2717	1.0698

U.S. Banks

	RoE	*RoA*	*RoRCH*	*RARoE*	*LR*	*REGP*	*LPQ*	*LIQ*	*DIV*	*SIZE*	*EDU*
RoE	1.0000										
RoA	0.8820	1.0000									
RoRCH	0.7779	0.8327	1.0000								
RARoE	0.9585	0.8545	0.8312	1.0000							
LR	0.1549	−0.2150	−0.1003	0.1097	1.0000						
REGP	−0.1502	−0.1071	−0.1223	−0.1932	−0.0575	1.0000					
LPQ	0.1816	0.3627	0.1269	0.1461	−0.2931	−0.0258	1.0000				
LIQ	−0.0840	−0.0791	0.0178	−0.0789	0.0462	−0.0138	−0.0033	1.0000			
DIV	0.1232	0.1785	0.1272	0.1026	−0.0181	0.0592	0.1969	−0.0223	1.0000		
SIZE	−0.0167	−0.0182	−0.0775	−0.0081	−0.0147	−0.0412	−0.0030	0.1256	0.2350	1.0000	
EDU	−0.2163	−0.2729	−0.1060	−0.1634	0.1131	0.0177	−0.2580	0.2880	−0.0503	−0.0996	1.0000

European Banks

	RoE	*RoA*	*RoRCH*	*RARoE*	*LR*	*REGP*	*LPQ*	*LIQ*	*DIV*	*SIZE*	*EDU*
RoE	1.0000										
RoA	0.7221	1.0000									
RoRCH	0.3630	0.2419	1.0000								
RAROE	0.9380	0.6667	0.4253	1.0000							
LR	−0.1838	−0.5816	0.0040	−0.1782	1.0000						
REGP	0.0122	−0.0733	−0.0410	0.0481	0.0992	1.0000					
LPQ	−0.1021	−0.0767	−0.1186	−0.1276	−0.0758	0.0511	1.0000				
LIQ	0.0152	0.0047	0.2500	−0.0060	−0.0660	−0.1108	0.2139	1.0000			
DIV	0.3030	0.2374	0.0492	0.3040	−0.0697	0.0049	−0.1375	0.0066	1.0000		
SIZE	−0.0169	−0.2272	−0.0773	−0.0177	0.2934	0.0580	−0.1375	−0.2275	0.0948	1.0000	
EDU	−0.0556	−0.2144	0.2218	−0.0002	0.0490	−0.0319	−0.0375	−0.1583	0.0551	−0.1844	1.0000

Table 3.1: The upper panel shows the mean and standard deviation of bank characteristics, the lower panel gives the correlation matrices. $RoE\hat{=}$ return on equity, $RoA\hat{=}$ return on assets, $RoRCH, RARoE\hat{=}$ risk-adjusted profitability, $LR\hat{=}$ leverage ratio, $LPQ\hat{=}$ loan portfolio quality, $LIQ\hat{=}$ liquidity endowment, $DIV\hat{=}$ income diversification, $SIZE\hat{=}\ln$ # employees, $EDU\hat{=}\ln$ personnel expenses per employee.

profitability (see RoE) and the higher leverage ratio of European banks, 23.5 versus 11.8. This is consistent with Inderst and Mueller (2008), who argue that the optimal leverage ratio increases with the degree of competition in the loan market, and Bikker and Haaf (2002), who show that the competition in the loan market is stronger in Europe than in the USA. However, there is no significant difference between the Sharpe-ratios of European banks and U.S. banks. The average Sharpe-ratio of U.S. banks is 28.37% and 27.17% for European banks. The corresponding standard deviations are similar, too. The highest Sharpe-ratio of a U.S. bank [European banks] is 3.47 in 1997 [4.39 in 1997] and the lowest Sharpe-ratio is -2.46 in 2007 [-2.24 in 1999].

Consistent with Flannery and Rangan (2008), the total risk-weighted capital ratio of U.S. banks is mostly not binding. Only 0.5% of the bank-year observations (or 5 observations) undershoot the 10% total risk-weighted capital ratio. The total risk-weighted capital ratio of European banks is below 10% for about 50 bank-year observations. The liquidity endowment of U.S. banks is significantly lower compared to European banks. While U.S. banks hold on average about 15% of customer deposits and short term funding in liquid assets, European banks hold almost twice as much in liquid assets. Also, European banks have a higher loan loss reserve relative to the total loan portfolio. The income structure of U.S. banks seems to be more diversified than the income structure of European banks. Whereas U.S. banks generate on average about 35% of their total income through income sources other than interest income and commissions and fees, European banks seem to be more focused on these traditional income sources.

The lower panel of Table 3.1 gives the estimated correlation matrix of the bank characteristics. By construction, the profitability measures are highly correlated. The absolute values of the other correlation coefficients are almost always below 0.3, indicating that collinearity is not present.

3.4 Empirical Analysis

3.4.1 Active Capital Structure Management

I follow Flannery and Rangan (2006) to find out whether bank mangers actively implement some target leverage ratio and to estimate the speed of adjustment of the leverage ratio. The existence of a target leverage ratio and a high speed of adjustment towards the target leverage ratio would be consistent with the trade-off theory, see Flannery and Rangan (2006). I assume that the target leverage ratio is terminated by bank characteristics, and that it is terminated similarly among all banks within one sample and over time. $LR_{i,t}$ denotes the observed leverage ratio and $LR^*_{i,t}$ denotes the unobservable target leverage ratio. Then, I estimate the following regression model

$$LR_{i,t} - LR_{i,t-1} = \lambda(LR^*_{i,t} - LR_{i,t-1}) + \varepsilon_{i,t}, \tag{3.1}$$

where $\varepsilon_{i,t}$ is white noise. λ is the speed of adjustment. Whenever λ is positive and less than one, managers adjust the leverage ratio partially. $\lambda = 1$ implies that banks hold always the target leverage ratio, up to some noise. $\lambda = 0$ indicates no adjustment at all. Let $X_{i,t}$ denote a set of variables that determines the bank's target leverage ratio in the following year, i.e. $LR^*_{i,t} = \rho X_{i,t-1}$. I assume that RoE, LPQ, LIQ, DIV, $SIZE$ and EDU determine the target leverage ratio. Alternatively, RoA, $RoRCH$ or $RARoE$ are considered instead of RoE. Replacing $LR^*_{i,t}$ in (3.1), rewriting $X_{i,t}$ and allowing for bank-individual effects (α_i) and year-individual effects (γ_t) yields

$$\begin{aligned} LR_{i,t} &= (1-\lambda)LR_{i,t-1} + \lambda(\alpha_i + \gamma_t + \rho_1\pi_{i,t-1} + \rho_2 SIZE_{i,t-1} + \rho_3 LPQ_{i,t-1} \\ &\quad + \rho_4 LPQ_{i,t-1} + \rho_5 DIV_{i,t-1} + \rho_6 EDU_{i,t-1} + \xi Z_{i,t}) + \varepsilon_{i,t}. \end{aligned} \tag{3.2}$$

$\pi \in \{RoE, RoA, RoRCH, RAROE\}$ denotes the profitability measure. Z denotes control variables (dummy variables) to account for changes in accounting standards.[6] Regression model (3.2) is estimated for U.S. banks and for European banks separately by applying the two-step Arellano-Bond estimator, see Arellano and Bond (1991) and Holtz-Eakin, Newey and Rosen (1988). Fractional dependencies such as a large fraction of banks without debt, and hence a minimum leverage ratio of 1, might bias the Arellano-Bond estimator, see Elsas and Florysiak (2010). However, there are no banks without debt in the sample. Hence, fractional dependencies are not present.

Table 3.2 shows the regression results. Columns I to IV show the regression estimates for U.S. banks and columns V to VIII those for European banks. In columns I and V, I use return on equity to measure profitability and in columns II and VI I use return on assets, and so on. Significant parameters are marked with the index a, b and c.

[6] Very few banks changed the accounting standards within the observation period. This is not captured by bank-individual fixed effects.

	U.S. Banks				EU Banks			
Regression Number	I	II	III	IV	V	VI	VII	VIII
$LR_{i,t-1}$	0.4598^a	0.4308^a	0.3951^a	0.4084^a	0.6586^a	0.6603^a	0.6910^a	0.6913^a
$RoE_{i,t-1}$	-0.0155^a	-	-	-	-0.0051	-	-	-
$RoA_{i,t-1}$	-	-0.0926^a	-	-	-	-0.2081^b	-	-
$RoRCH_{i,t-1}$	-	-	-0.0067	-	-	-	0.6728^a	-
$RARoE_{i,t-1}$	-	-	-	-0.0128^a	-	-	-	0.0659^a
$SIZE_{i,t-1}$	-0.0840	-0.1097	-0.0669	-0.0488	1.8641^a	1.7533^a	4.8341^a	5.1169^a
$REGP_{i,t-1}$	0.2876	0.2726	0.1416	0.1419	-0.0451	-0.1146	-1.1219^a	-1.0031^a
$LPQ_{i,t-1}$	0.0394	0.0299	0.0271	0.0274	0.0630	-0.0716	0.0737	-0.2118^c
$LIQ_{i,t-1}$	0.0019	0.0028	0.0009	0.0015	-0.0149^a	-0.0186^a	-0.0073	0.0011
$DIV_{i,t-1}$	0.0696	0.0441	0.0088	0.0544	1.6748^b	1.7096^b	18.6304^a	21.5772^a
$EDU_{i,t-1}$	-0.0132	-0.04971	-0.0335	0.0346	1.6037	1.5307^a	4.3238^a	4.8093^a
# Obs	742	742	736	736	654	654	200	200
# Banks	151	151	151	151	185	185	65	65
Sargan test of over-identifying restrictions								
p value	0.2648	0.2438	0.2538	0.3194	0.6675	0.6851	0.9950	0.9987
Arellano-Bond test that average autocovariance in residuals is ...								
... of order 1 is 0: H0: no autocorrelation								
p value	0.7586	0.7442	0.3582	0.2230	0.3112	0.3303	0.2520	0.2360

Table 3.2: The table shows the regression estimates for partial adjustments in the leverage ratio towards a target leverage ratio for U.S. banks (left panel) and European banks (right panel), i.e. regression model (3.1). *a* denotes significance at the 1% confidence level, *b* at the 5% confidence level and *c* at the 10% level.

a denotes significance at the 1% confidence level, *b* at the 5% confidence level and *c* at the 10% level. The Sagran test fails to reject the hypothesis of correctly specified instrumental variables[7] and the Arellano-Bond test fails to reject the hypothesis of no autocorrelations in the residuals. The estimated speed of adjustments of U.S. banks is in the range 55% to 60% ($1 - 0.4598$ to $1 - 0.3951$). This means that the average bank closes half of the gap between the target leverage ratio and the actual leverage ratio within 14 to 15 months, or equivalently, about 40% to 44% of the gap each year.[8] The estimated speed of adjustment for U.S. banks is significantly higher than the estimated speed of adjustment of industrial corporations, which are analyzed by Flannery and Rangan (2006). They find that the average company closes half of the gap between the current and the target capital structure in about two years. For European banks, the estimated speed of adjustment is about 35% and of similar magnitude as in Flannery and Rangan (2006). The results are also consistent with Gropp and Heider (2010), who study European and U.S. banks jointly, and report a speed of adjustment of about 45%, which is within the interval given by the estimates for European and U.S. banks presented here.

The rather high estimate of λ for U.S. banks is consistent with the trade-off theory and with the hypothesis that financial institutions have a lower tolerance for holding an undesired capital structure than non-financial corporations. The estimated speed of adjustment of European banks is lower compared to U.S. banks, but might still be consistent with the trade-off theory, as argued by Flannery and Rangan (2006). This low adjustment speed might have two reasons: (1) European banks manage their capital structure less actively than U.S. banks. This might be due to the less restrictive bank regulation in Europe, i.e. no floor on the capital-asset ratio. (2) The higher degree of heterogeneity in the European sample, caused by the less restrictive minimum bank size, the joint analysis of commercial bank and savings banks, and the pooling across European countries, might bias the estimates towards a low adjustment speed.

Even though I apply other selection criteria and consider a different observation period, the estimates of the determinants of the target leverage ratio are generally consistent with Gropp and Heider (2010), i.e. profitability seems to be the most

[7]The instrumental variables are implicitly defined in the two step Arellano-Bond estimator.

[8]Consider the estimate for λ in regression I. The half-life time is calculated by $\ln 2/\lambda \approx 1.26$, which is about 15 months. Hence, the bank closes $\frac{1}{1.26} * 50\% \approx 40\%$ of the gap between the leverage ratios each year.

important determinant. Moreover, since profitability is interacted with risk in regressions III, IV, VII and VIII, new insights arise. For U.S. banks, all determinants of the target leverage ratio are insignificant with the exception for return on equity, return on assets and risk-adjusted return on equity, which have a significant, negative coefficient. The impact of return on assets is negative and significant for European banks, too. Hence, banks seem to use profits as a funding source and reduce the leverage ratio after realizing high profits. However, risk adjusted profitability is significant and positive for European banks. Therefore, at least in Europe, banks with a sound risk-return profile are - ceteris paribus - likely to leverage up in the following year. One reason might be to take advantage of the tax shield without suffering too much from high default costs. Since U.S. banks can leverage up only to some limit, this relationship might be mitigated and could explain the insignificant regression coefficient for $RoRCH$ and the significant, negative coefficient for $RARoE$.

For European banks, size turns out as a significant determinant of the leverage ratio, as hypothesized by Rajan and Zingales (1995). This result does not change if total book assets are used to measure size. The results are not shown. Furthermore, in regressions VII and VIII, banks that are confronted with regulatory pressure tend to reduce their leverage ratio. This finding is not robust and might depend on the sample, since regulatory pressure is insignificant in regressions V and VI, which are based on a larger number of observations.

3.4.2 Performance Maximizing Leverage Ratio

Given the evidence that banks manage their leverage ratio towards a target leverage ratio, I now investigate whether there is a performance maximizing leverage ratio. This leverage ratio might be important not only for the bank owners and the bank manager, but also for the regulator. Therefore, I assume that the bank manager maximizes profitability or risk-adjusted profitability. This assumption seems plausible since profitability and risk-adjusted profitability are the only consistently significant variables in the previous analysis.

Again, I use a two-way panel regression model to relate bank performance to the leverage ratio and the control variables. According to Berger et al. (2000), bank profits are highly persistent. To account for this, the regression model allows for autoregression of order 1 in profitability. Furthermore, and consistent with the trade-off theory and with Berger and Bonaccorsi di Patti (2006) and Korteweg (2010), I allow for a non-monotonic relationship between the leverage ratio and profitability, modeled by a quadratic polynomial. Hence

$$\begin{aligned}\pi_{i,t} &= \alpha_i + \gamma_t + \phi\pi_{i,t-1} + \beta_1 LR_{i,t} + \beta_2 LR_{i,t}^2 + \xi REGP_{i,t} + \delta_1 LPQ_{i,t} \\ &+ \delta_2 LIQ_{i,t} + \delta_3 DIV_{i,t} + \eta_1 SIZE_{i,t} + \eta_2 SIZE_{i,t}^2 + \zeta EDU_{i,t} + \rho Z_{i,t} + \varepsilon_{i,t}.\end{aligned} \quad (3.3)$$

$\pi \in \{RoE, RoA, RoRCH, RARoE, SHR\}$ denotes the performance measure. α_i allows for bank individual effects, γ_t allows for year specific effects and renders macroeconomic variables like interest rate levels or stock market performance redundant. $SIZE$ might affect profitability non-monotonically, as discussed before. Hence, $SIZE$ and $SIZE^2$ are incorporated in (3.3).

Regression model (3.3) is estimated with the two-step Arellano-Bond estimator, too. The results for U.S. banks are given in Table 3.3 and for European banks in Table 3.4. Again, the significance level is expressed by the indices a, b and c. The regression design and the estimation procedure are supported by the Arellano-Bond test and the Sargan test, i.e. the hypothesis of no autocorrelation in the residuals of order 2 or more and the hypothesis of correctly specified instrumental variables are not rejected.

Return on equity and return on assets are persistent in both samples, return on risk charge and risk-adjusted return on equity are only persistent in the European sample, and the Sharpe-ratio is never persistent. In all regressions with the exception of (B), (G) and (J), β_1 and β_2 are significant and imply a non-monotonic, inversely 'u'-shaped relationship between the leverage ratio and bank performance. This provides strong support for Hypothesis 2 and Hypothesis 3. The leverage ratio that is - on average - associated with the highest performance is denoted by LR^* in Tables 3.3 and 3.4. On average, U.S. banks generate the highest return on equity for a leverage ratio of 14.7, European banks for a leverage ratio of 25.6. Risk-adjusted performance is highest for some lower leverage ratio. For U.S. banks, $RoRCH$ attains a maximum for a leverage ratio of about 9.8 and $RARoE$ at 13.3. U.S. banks with a leverage ratio of 11.8 have on average the highest Sharpe-ratio. The risk-adjusted profitability of European banks is maximized for a leverage ratio of about 20. Therefore, even though return on equity still increases with the leverage ratio in the range 12 to 14.7 and 20 to 25.6, respectively, the increase in risk is not offset by the increase in profitability.

Figure 3.1 illustrates the relationship between the leverage ratio and bank performance. There, the unexplained variation in regression model (3.3) and ignoring the

	U.S. Banks				
Dependent Variable	*RoE*	*RoA*	*RoRCH*	*RARoE*	*SHR*
Regression Number	(A)	(B)	(C)	(D)	(E)
ϕ $(LAG\ \pi)$	0.2413^a	0.1684^a	-0.0064	0.0248	-0.2060
β_1 (LR)	2.5827^a	0.0417	0.1686^b	4.8405^a	13.0200^c
β_2 (LR^2)	-0.0881^a	-0.0040^c	-0.0086^a	-0.1822^a	-0.5508^c
ξ $(REGP)$	-14.9639	-1.3448	-2.3540	-32.4769	-
δ_1 (LPQ)	-1.3385^a	-0.1864^a	-0.5062^a	-2.3825^a	1.7776
δ_2 (LIQ)	-0.0777^a	-0.0075^a	-0.0018	-0.0915^a	0.2082
δ_3 (DIV)	-0.2294	0.1423^c	-0.0343	-2.2790	21.0180
η_1 $(SIZE)$	1.3738	0.1426	1.4555^a	2.1799	-10.1920
η_2 $(SIZE^2)$	-0.0398	-0.0117	-0.0853^a	-0.0684	0.5163
η_3 (EDU)	3.2564^a	0.3035^a	0.6308^a	3.9256^a	1.0961
LR^*	14.7	-	9.8	13.3	11.8
#of Obs / Banks	917 / 175	917 / 175	806 / 156	806 / 156	156 / 20
Sargan test of over-identifying restrictions					
pvalue	0.1333	0.2372	0.3776	0.1534	1.0000
Arellano-Bond test that average autocovariance in residuals is ...					
... of order 1 is 0: H0: no autocorrelation					
pvalue	0.0000	0.0009	0.0014	0.0010	0.2761
... of order 2 is 0: H0: no autocorrelation					
pvalue	0.3300	0.2077	0.1014	0.0924	0.8486

Table 3.3: The table shows the regression results of the determinants of bank performance for U.S. banks, i.e. regression model (3.3). Profitability is measured by return on equity, return on assets, return on risk-charge, risk-adjusted return on equity and the Sharpe-ratio. a denotes significance at the 1% confidence level, b at the 5% confidence level and c at the 10% level. LR^* denotes the on average, performance maximizing leverage ratio.

	European Banks				
Dependent Variable Regression Number	*RoE* (F)	*RoA* (G)	*RoRCH* (H)	*RARoE* (I)	*SHR* (J)
ϕ ($LAG\ \pi$)	0.3837^a	0.3793^a	0.7947^a	0.4907^a	-0.2802
β_1 (LR)	2.0777^a	0.0158	0.1157^a	1.2538^a	0.0413
β_2 (LR^2)	-0.0406^a	-0.0006^a	-0.0030^a	-0.0305^a	-0.0011
ξ ($REGP$)	1.3152^a	0.0944^a	0.0309	-1.2128^b	-0.5301
δ_1 (LPQ)	-1.1957^a	-0.1403^a	0.0021	-0.0026	1.2085
δ_2 (LIQ)	0.0052	-0.0006	0.0113^a	0.1731^a	0.0209
δ_3 (DIV)	-13.8234^a	-0.4679^a	-4.2824^a	-29.1219^a	2.3403
η_1 ($SIZE$)	-5.0860	-0.6635^a	0.6445	2.6687	24.8900^c
η_2 ($SIZE^2$)	0.1327	0.0294^b	0.0015	0.5762^b	-1.2944^c
η_3 (EDU)	-1.1755	-0.1470^a	0.7531^a	11.9212^a	3.1954
LR^*	25.6	-	19.3	20.6	-
#of Obs / Banks	828 / 208	828 / 208	199 / 61	199 / 61	95 / 24
Sargan test of over-identifying restrictions					
pvalue	0.8934	0.8792	0.9878	0.9989	1.0000
Arellano-Bond test that average autocovariance in residuals is ...					
... of order 1 is 0: H0: no autocorrelation					
pvalue	0.0051	0.0669	0.1695	0.1974	0.3006
... of order 2 is 0: H0: no autocorrelation					
pvalue	0.3012	0.3106	0.2237	0.1616	0.0230

Table 3.4: The table shows the regression results of the determinants of bank performance for European banks, i.e. regression model (3.3). Profitability is measured by return on equity, return on assets, return on risk-charge, risk-adjusted return on equity and the Sharpe-ratio. a denotes significance at the 1% confidence level, b at the 5% confidence level and c at the 10% level. LR^* denotes the on average, performance maximizing leverage ratio.

leverage ratio, i.e. $\pi_{i,t} - \hat{\alpha}_i - \hat{\gamma}_t - \hat{\phi}\pi_{i,t-1} - \hat{\xi}REGP_{i,t} \ldots - \hat{\zeta}EDU_{i,t} - \hat{\rho}Z_{i,t}$, where the symbol $\hat{\cdot}$ indicates parameter estimates in (3.3), is plotted against $LR_{i,t}$. The red solid graph is $\hat{\beta}_1 LR_{i,t} + \hat{\beta}_2 LR^2_{i,t}$. RoE is displayed in the first row, RoA in the second, $RoRCH$ in the third, $RARoE$ in the forth and the Sharpe-ratio in the fifth row. The left column shows the results for U.S. banks and the right column for European banks. Ceteris paribus, profitability of U.S. banks decreases moderately if the leverage ratio exceeds the corresponding profitability maximizing leverage ratio LR^*. Profitability of European banks seems to be more prone to leverage ratios above LR^* and declines fast if the leverage ratio exceeds LR^*.

Comparing the leverage ratios, which imply - on average - the highest performance, to the average leverage ratios, as shown in Table 3.1, suggests that the average U.S. bank (leverage ratio is 11.8) is slightly under-leveraged with respect to return on equity and over-leveraged or well leveraged with respect to risk-adjusted profitability. The same holds for European banks. Comparing the performance maximizing leverage ratios between both samples shows that the estimated optimal leverage ratio of European banks is higher compared to U.S. banks. This result is consistent with Inderst and Mueller (2008) and Bikker and Haaf (2002). However, it has to be mentioned that besides of differences in the degree of competition in the loan market, differences in bank regulation, such as a floor on the non-risk weighted capital-asset ratio in the United States, might affect this result, too.

The regression results give mixed evidence on the relationship between regulatory pressure, i.e. holding a total risk-weighted capital ratio of less than 10%, and profitability. For U.S. banks, the estimated impact of regulatory pressure has the expected negative sign, but is not significant. The corresponding p-values in regression (A) to (D) are between 0.11 and 0.31 and are on the edge of being significant.[9] Surprisingly, the estimated coefficient of regulatory pressure is positive and significant in regression (F) and (G). Hence, European banks seem to benefit in terms of return on equity and return on assets from holding a risk-weighted capital ratio of 10% or less. This might indicate that market discipline in Europe does not penalize poorly capitalized banks. However, regulatory pressure has a significant, negative impact on $RARoE$, indicating that low risk-weighted capital ratios imply high risks, which are not compensated by higher profits.

The coefficient of loan portfolio quality (LPQ) is significant and negative in regres-

[9] The variable *REGP* is dropped in regression (E) due to collinearity with the bank individual effects.

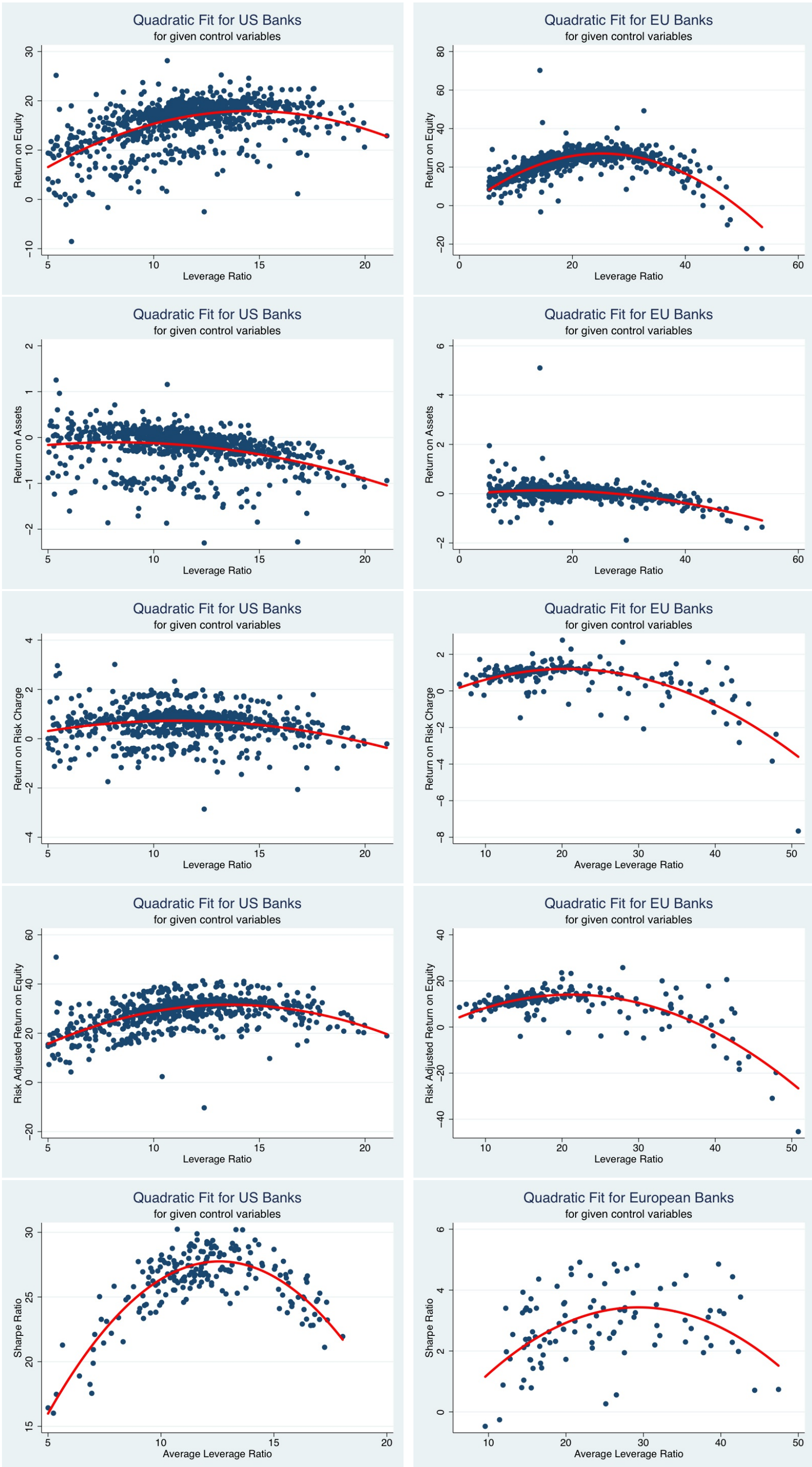

Figure 3.1: The scatter plots plot the residual in regression model (3.3), ignoring the leverage ratio, i.e. $\pi_{i,t} - \hat{\alpha}_i - \hat{\gamma}_t - \hat{\phi}\pi_{i,t-1} - \hat{\xi} REGP_{i,t} \ldots - \hat{\zeta} EDU_{i,t} - \hat{\rho} Z_{i,t}$ against the leverage ratio. The red curve gives the quadratic fit of the leverage ratio, i.e. $\hat{\beta}_1 LR_{i,t} + \hat{\beta}_2 LR_{i,t}^2$. RoE is in the first row, RoA in the second row, $RoRCH$ in the third row, $RARoE$ in the forth row and SHR in the fifth row. The left column considers U.S. banks and the right column for European banks.

sion (A) to (D) and (F) and (G). Since a high value of LPQ indicates a low loan portfolio quality, the regressions imply that profitability and risk-adjusted profitability are high for banks with high-quality loans. This finding is consistent with the literature, see e.g. Berger (1995). The estimated coefficient of liquidity endowment, $\hat{\delta}_2$, is negative and significant in (A), (B) and (D) and positive and significant for (H) and (I). $\hat{\delta}_2 < 0$ in (A) and (B) indicates that liquid assets tend to reduce return on equity and return on assets. Furthermore, the negative sign of $\hat{\delta}_2$ in (D) indicates that the decline in profits, caused by holding a high proportion of liquid assets, is not compensated by risk reduction. Hence, the dominant relationship between risk-adjusted profitability and liquidity is negative, too. RoE and RoA of European banks are not sensitive to the liquidity endowment, but $RoRCH$ and $RARoE$ are positively related to the liquidity endowment. Hence, a high liquidity endowment tends to reduce the bank's risk and does not affect profitability. So, risk-adjusted profitability increases.

Income diversification does not affect RoE, $RoRCH$ and $RARoE$ but is positive and significant for RoA in the U.S. sample. It is negative and significant for European banks in regressions (F) to (I). Lepetit et al. (2008) argue that non-interest income is more volatile than interest income. Hence, diversification benefits might be destroyed fast, such that banks with a high fraction of non-interest income spoil their risk-return profile. This could explain the negative relationship between risk-adjusted profitability and income diversification.

The regression estimates for the coefficients of bank size give no evidence for an optimal bank size. $\hat{\eta}_1$ and $\hat{\eta}_2$ are jointly significant in (C) and (G). In (G), the coefficients imply an 'u'-shaped relation between the logarithmic number of employees and bank performance, which contradicts the existence of an optimal bank size. Hence, it remains ambiguous whether an optimal bank size exists. The average personnel expenses per employees are positive and significant for all performance measures for U.S. banks, indicating that banks with well-trained employees generate - on average - higher profits and have a sound risk-return profile. $\hat{\eta}_3$ is insignificant in regression (F), negative and significant in (G) and positive and significant in (H) and (I). Even though profitability of European banks tends to increase if banks invest less in their employees, presumably due to cost advantages, risk-adjusted profitability is positively related to EDU.

There might be a lagged relationship between the leverage ratio and profitability, if benefits of holding the desired leverage ratio, loan-portfolio quality or liquidity endowment pay off in later periods. Therefore, I estimate regression model (3.3) with independent variables lagged by one year. Furthermore, this analysis might be used to predict bank profitability rather than to explain it. Table 3.5 shows the regression estimates. The Sharpe-ratio is not considered since the number of observations is insufficient. Due to collinearity between the dummy variable $REGP$ and the bank- and year-fixed effects, $REGP$ is excluded for U.S. banks. As can be seen in all regressions, the relationship between the leverage ratio and profitability and risk-adjusted profitability, respectively, is consistent with the previous estimates. The profitability maximizing leverage ratio of U.S. bank is about 14.6, see regression (A.1). However, return on assets is now inversely 'u'-shaped related to the leverage ratio, too, see (B.1). This gives further support to Hypothesis 2. The leverage ratio that maximizes average return on assets is about 13.1. Risk-adjusted profitability is maximized for a leverage ratio of about 12.8. European banks' return on equity is maximized for a leverage ratio of 25.4 and risk-adjusted profitability for 20.9 and 23.3, respectively. However, the sign of the loan portfolio quality is now significant, positive, indicating that the relationship between the loan portfolio quality and profitability is fragile or more complex.

3.4.3 Robustness

Capital Structure

The regression estimates in Tables 3.3, 3.4 and 3.5 support a non-monotone, inversely 'u'-shaped relationship between the leverage ratio and return on equity and risk-adjusted profitability, respectively. However, this result might be artificial. A globally increasing and concave relationship might be well approximated by a quadratic polynomial, which attains a maximum in the interior of the supported domain, if there are only few observations in the right tail and many observations in the left tail. Another shortcoming of a quadratic polynomial is that it implies a symmetric relationship. Furthermore, the control variables might affect profitability conditionally on high or low leverage ratios.

Therefore, I divide the sample into two subsamples, hereafter the left tail and the right tail. The tails depend on the performance measure. Since the previous section indicates that RoE, $RoRCH$ and $RARoE$ are consistently non-monotonically related to the leverage ratio, I consider only these three performance measures. Banks with a leverage ratio lower than $LR_1(\pi)$ are considered as moderately leveraged

	US Banks				European Banks			
Dep. Var.	*RoE*	*RoA*	*RoRCH*	*RARoE*	*RoE*	*RoA*	*RoRCH*	*RARoE*
Reg. #	(A.1)	(B.1)	(C.1)	(D.1)	(F.1)	(G.1)	(H.1)	(I.1)
ϕ ($LAG\ \pi$)	0.1856^a	-0.0093	-0.0302^c	-0.0303^c	0.1359^a	0.0007	0.1601^a	0.1432^a
β_1 ($LAG\ LR$)	1.7645^a	0.2490^a	0.2932^a	29.3936^a	0.9256^a	-0.0063	0.0963^a	11.5509^a
β_2 ($LAG\ LR^2$)	-0.0606^b	-0.0095^a	-0.0114^a	-1.1473^a	-0.0182^a	-0.0001	-0.0023^a	-0.2480^a
ξ ($LAG\ REGP$)	-	-	-	-	-0.8908^c	-0.0237	0.0290	4.3139
δ_1 ($LAG\ LPQ$)	2.4314^a	0.2181^a	0.1902^a	19.0280^a	1.5831^a	0.0304^b	-0.0186	3.1212
δ_2 ($LAG\ LIQ$)	-0.1390^a	-0.0108^a	-0.0029	-0.2916	-0.0528^b	-0.0015	0.0105^a	0.9747^a
δ_3 ($LAG\ DIV$)	-0.8027	-0.0633	-0.0607	-6.0425	-1.2434	-0.7887^a	-5.3712^a	-454.3791^a
η_1 ($LAG\ SIZE$)	-8.3440	1.2899	1.8383	184.2850	-3.1506	-0.4651^c	-2.7366^b	-279.8635^c
η_2 ($LAG\ SIZE^2$)	0.1239	-0.0510^c	-0.0671	-6.7227	-0.0094	0.0102	0.0570	6.7606
η_3 ($LAG\ EDU$)	-2.8796^a	-0.2835^a	-0.4937^a	-49.3927^a	-2.3956^b	-0.2992^a	-1.6473^a	-159.3791
LR^*	14.6	13.1	12.9	12.8	25.4	-	20.9	23.3
# of Obs / Banks	742 / 152	742 / 152	736 / 151	736 / 151	653 / 185	653 / 185	186 / 62	186 / 62
Sargan test of over-identifying restrictions								
p value	0.1178	0.3421	0.3088	0.3072	0.9843	0.9281	0.9972	0.9992
Arellano-Bond test that average autocovariance in residuals is ...								
... of order 1 is 0: H0: no autocorrelation								
p value	0.0001	0.0036	0.0302	0.0303	0.0007	0.0077	0.0483	0.0737
... of order 2 is 0: H0: no autocorrelation								
p value	0.2416	0.0656	0.0904	0.0904	0.0662	0.0759	0.2971	0.2976

Table 3.5: The table shows the estimated relationship between profitability and risk adjusted profitability, respectively, and the one-period lagged leverage ratio. All control variables are lagged by one period, too. The index a denotes significance at the 1% confidence level, b at the 5% level and c at the 10% level. Due to collinearity, $REGP$ is excluded in all regressions for U.S. banks.

	US Banks					
Dep. Var.	RoE	RoE	$RoRCH$	$RoRCH$	$RARoE$	$RARoE$
Reg. #	(A.2)	(A.3)	(C.2)	(C.3)	(D.2)	(D.3)
ϕ ($LAG\ \pi$)	0.3090^a	-0.0959^a	-0.0139	0.0374	0.2441^a	-0.3218
β_1 (LR)	0.9815^a	-0.4227^c	0.0718^a	-0.1663^a	1.1965^a	-1.7965^a
ξ ($REGP$)	-3.2605^a	-	0.0276	-	-68.2847^a	-
δ_1 (LPQ)	-0.8943^a	-7.0248^a	-0.4609^a	-0.6417^a	-0.1006	9.9390^b
δ_2 (LIQ)	-0.1882^a	-0.0530	0.0267^a	0.0066	-0.2450^a	-0.3559^a
δ_3 (DIV)	1.5552^a	-8.8276^a	1.4777^a	-1.1404^a	0.4837	-13.7470^a
η_1 ($SIZE$)	12.4471^a	-15.0888^a	1.9839^a	-1.3949^c	10.5650^a	27.8049
η_2 ($SIZE^2$)	-0.7825^a	0.8198^a	-0.1702^a	0.0944^b	-0.6681^a	-1.4752
η_3 (EDU)	2.0176^a	0.4128	0.3941^a	0.6330^a	3.7933^a	-0.1122
$LR_1(\pi)/LR_2(\pi)$	12	14	10	14	13	15.25
# of Obs	555	159	245	137	591	77
# of Banks	127	54	74	47	126	30
Sargan test of over-identifying restrictions						
pvalue	0.7353	0.9997	0.6134	1.0000	0.3479	1.0000
Arellano-Bond test that average autocovariance in residuals is...						
... of order 1 is 0: H0: no autocorrelation						
pvalue	0.0031	0.1155	0.0317	0.1060	0.0010	0.3122
... of order 2 is 0: H0: no autocorrelation						
pvalue	0.7039	0.0493	0.0859	0.1535	0.6928	0.4657

Table 3.6: The table shows the estimates for regression model (3.3) and omitting the squared leverage ratio term for U.S. banks. Regressions labeled with the suffix .2 correspond to the left tail, i.e. $LR_{i,t} \leq LR_1(\pi)$, and the suffix .3 indicates regressions for the right tail, i.e. $LR_{i,t} \geq LR_2(\pi)$. a denotes significance at the 1% confidence level, b at the 5% confidence level and c at the 10% level.

(with respect to π) and banks with a leverage ratio above $LR_2(\pi)$ are called highly leveraged. Both thresholds, i.e. $LR_1(\pi)$ and $LR_2(\pi)$, are in the close neighborhood of the profit maximizing leverage ratio and trade off the number of observations in the corresponding tail and the strength of the relationship between the leverage ratio and performance. A high threshold for the right tail, for example, gives only few observations of highly leveraged banks. The relationship between the leverage ratio and bank performance for these banks is presumably strongly negative. However, the small number of observations might weaken the regression estimates. I estimate regression model (3.3) omitting the squared leverage ratio term for each subsample.

	European Banks					
Dep. Var.	*RoE*	*RoE*	*RoRCH*	*RoRCH*	*RARoE*	*RARoE*
Reg. #	(F.2)	(F.3)	(H.2)	(H.3)	(I.2)	(I.3)
ϕ ($LAG\ \pi$)	0.3260^a	0.3464^a	-0.0630^c	1.7151^a	0.1220^b	2.1113^a
β_1 (LR)	0.4462^a	-0.6621^a	0.0378^b	-0.3984^b	1.0581^a	-4.2026^c
ξ ($REGP$)	1.1345^b	1.6674^a	-0.0630	-1.6390	0.6127^b	-131.2392^b
δ_1 (LPQ)	-1.3842^a	-3.2930^a	-0.0418	0.2838	-0.3848	23.5153^c
δ_2 (LIQ)	-0.0521^b	0.1397^a	-0.0074^a	0.0060	-0.1007^a	0.9388
δ_3 (DIV)	7.9432	-2.0131	1.2243^c	-14.9360^a	-0.6912	-56.6123
η_1 ($SIZE$)	-10.9317^a	13.2746^c	2.3130^a	-93.0234^b	1.7787	-6.6117
η_2 ($SIZE^2$)	0.5280^b	-0.9367^c	-0.1054^b	4.8953^b	-0.0004	5.6841
η_3 (EDU)	-2.0398^a	-3.2286^b	0.7403^a	-0.8637	1.5505	60.5416^c
$LR_1(\pi)/LR_2(\pi)$	25.5	25.5	19	19.5	20.5	21
# of Obs.	649	179	127	70	133	64
# of Banks	176	59	42	23	44	22
Sargan test of over-identifying restrictions						
p value	0.9974	0.9997	0.9915	1.0000	0.9946	1.0000
Arellano-Bond test that average autocovariance in residuals is ...						
... of order 1 is 0: H0: no autocorrelation						
p value	0.0295	0.1001	0.3607	0.6249	0.3128	-
... of order 2 is 0: H0: no autocorrelation						
p value	0.6296	0.8277	0.7934	0.4565	0.3961	-

Table 3.7: The table shows the estimates for regression model (3.3) and omitting the squared leverage ratio term for European banks. Regressions labeled with the suffix .2 correspond to the left tail, i.e. $LR_{i,t} \leq LR_1(\pi)$, and the suffix .3 indicates regressions for the right tail, i.e. $LR_{i,t} \geq LR_2(\pi)$. a denotes significance at the 1% confidence level, b at the 5% confidence level and c at the 10% level.

Table 3.6 gives the regression estimates for U.S. banks and Table 3.7 for European banks. The regression estimates for the subsamples with $LR_{i,t} \leq LR_1(\pi)$ are labeled with the suffix (.2) and estimates for subsamples with $LR_{i,t} \geq LR_2(\pi)$ are labeled with (.3). $LR_1(\pi)$ and $LR_2(\pi)$ are given in Tables 3.6 and 3.7, too. For all regressions the estimated coefficient for the leverage ratio, $\hat{\beta}_1$, is significant and positive for the left tail and significant and negative for the right tail. Hence, I conclude that the average RoE, $RoRCH$ and $RARoE$ are maximized for some leverage ratio close to the estimated optimal leverage ratio $LR(\pi)^*$ given in Table 3.3 and 3.4. Furthermore, $RoRCH$ and $RARoE$ are very prone to high leverage ratios and decrease fast if the leverage ratio exceeds $LR_2(\pi)$. This is consistent with Figure 1 and indicates an asymmetric relation between the leverage ratio and bank performance. Consider, for example, $RoRCH$ of European banks. $\hat{\beta}_1$ is about 0.04 in regression (H.2) and about -0.4 in (H.3). Ceteris paribus, the average risk-adjusted profitability tends to decreases 10 times faster if the leverage ratio exceeds the upper threshold than it increases up to the lower threshold.

Regulatory pressure is significant and negative in (A.2) and (D.2) and insignificant in (C.2). The dummy variable $REGP$ is excluded in regressions (A.3), (C.3) and (D.3) for highly leveraged U.S. banks due to collinearity. The significant, negative regression coefficients in (A.2) and (D.2) indicate that poorly capitalized banks generate below average profits. Consistent with regression (F), regulatory pressure is significant and positive in (F.2) and (F.3), indicating that market discipline is rather weak for European banks with respect to RoE. Regulatory pressure is also significant and positive in (I.2), but turns significant and negative in (I.3). Therefore, moderately leveraged banks may increase $RARoE$ by reducing total risk-weighted capital ratio even below 10%. This is not true for highly leveraged banks. This heterogeneous relationship between risk-weighted capital and performance for highly leveraged banks and moderately leveraged banks indicates that bank lenders monitor the non risk-weighted leverage ratio and the total risk-weighted capital ratio jointly.

The coefficient of the loan portfolio quality is significant and negative for to RoE and $RoRCH$ for U.S. banks, see (A.2), (A.3), (C.2) and (C.3) and indicates that a high loan portfolio quality is associated with high profitability. Comparing the magnitude of $\hat{\delta}_1$ in (A.2) and (A.3) and in (C.2) and (C.3), respectively, shows that profitability of highly leveraged banks is more sensitive to the loan portfolio quality than the profitability of moderately leveraged banks. Hence, market participants seem to interpret the risk of the loan portfolio conditional on the leverage ratio. Surprisingly, $\hat{\delta}_1$ is insignificant in (D.2) and turns even positive and significant in

(D.3). One explanation might be the low number of observations in regression (D.3). As Table 3.4 already reveals, the loan portfolio quality affects return on equity of European banks, but not *RoRCH* and *RARoE*. This result is confirmed in Table 3.7. (F.2) and (F.3) also show that return on equity of European banks is more prone to the loan portfolio quality if the bank's leverage ratio is high.

Consistent with regression (A), (A.2) and (A.3) show that high liquidity endowment is associated with low return on equity, irrespective of the leverage ratio. Regression (C.2) shows that moderately leveraged banks might improve *RoRCH* by reducing the liquidity endowment, whereas the liquidity endowment turns insignificant for highly leveraged banks, see (C.3). In contrast, I find a significant, negative relationship between *RARoE* and the liquidity endowment in (D.2) and (D.3), indicating that low liquidity buffers stimulate *RARoE*. Therefore, the overall impact of the liquidity endowment is ambiguous. Income diversification of U.S. banks positively impact profitability, given a moderate leverage ratio, but has the opposite effect for high leverage ratios. The estimated impact of the liquidity endowment and income diversification on profitability of European banks is ambiguous, too.

The relationship between bank size and profitability is still ambiguous. $\hat{\eta}_1$ and $\hat{\eta}_2$ change the sign frequently and give no clear implications. Whereas the average personnel expenses per employee are positively related to the return on equity of U.S. banks, *EDU* has a significant, negative coefficient in regression (F.2) and (F.3). Again, this might indicate that cost advantages are more important than benefits of well educated employees with respect to return on equity. However, this reverses if risk-adjusted profitability measures are considered.

Loan Portfolio Quality and Size

In this section, I test the robustness of the previous results by applying alternative measures of bank size and the loan portfolio quality. Even though the logarithm of the average book value of total assets is stronger correlated with the leverage ratio than the logarithmic number of employees, I use it in the following to measure bank size. The loan portfolio quality is measured by the net charge-offs divided by the annual, average book value of the loan portfolio. This measure does not rely on a constant charge-off policy. Table 3.8 gives the estimates of regression model (3.3), but with the alternative measure for the loan portfolio quality, $\widetilde{LPQ}$, and the alternative size measure, $\widetilde{SIZE}$. The alternative measures reduce the number of observations for European banks significantly since information about net charge-offs of European banks is sparse. The Sharpe-ratio is not considered due to an insufficient number of observations. The coefficients of the leverage ratio change only little compared to Tables 3.3 and 3.4. However, $\hat{\beta}_1$ and $\hat{\beta}_2$ are not significant in regression (H.4), indicating a fragile relationship between $RoRCH$ and the leverage ratio of European banks. Consistent with the previous results, $\hat{\delta}_1$ is negative and significant in all regressions. Again, this indicates that banks benefit from a high loan portfolio quality. For U.S. banks, there is no significant relationship between the logarithm of total assets and profitability or risk-adjusted profitability, respectively, confirming the previous results. Size is significant for European banks, but the coefficients give no implications for an optimal bank size.

3.4.4 Default Costs and Leverage Ratio

Section 4.1 shows that banks adjust their capital structure fast. Section 4.2 and 4.3 show that some interior leverage ratio is on average associated with the highest profitability and risk-adjusted profitability, respectively. Both decline fast for European banks if the leverage ratio exceeds this leverage ratio. According to the trade-off theory, the decline is due to a strong increase in default costs. In the following, I analyze the relationship between the expected default costs of banks and the leverage ratio. A positive relationship might support the implementation of a maximum leverage ratio in addition to a risk-based restriction on the capital structure to control systemic risks in the economy.

I use the annual average spread of 3 years credit default swaps on senior debt to measure the expected default costs of a bank. CDS spreads are taken from Datastream (CMA, respectively) and Credit Trade and are available from 2003 to 2008 for 27 European banks and only 9 U.S. banks. Banks with CDS spreads are marked with the symbol (*) in Table 3.10.[10]

Denote the average CDS spread of year t and bank i by $CDS_{i,t}$. Then, I estimate the following regression model

$$\begin{aligned} CDS_{i,t} &= \alpha_i + \gamma_t + \beta_1 LR_{i,t} + \xi REGP_{i,t} + \delta_1 LPQ_{i,t} + \delta_2 LIQ_{i,t} \\ &+ \delta_3 DIV_{i,t} + \eta_1 SIZE_{i,t} + \eta_2 SIZE_{i,t}^2 + \zeta EDU_{i,t} + \rho Z_{i,t} + \varepsilon_{i,t}, \end{aligned} \tag{3.4}$$

[10]European banks with CDS spreads and without traded stocks are Anglo Irish Bank, Northern Rock and Rabobank.

	US Banks				European Banks			
Dep. Var.	*RoE*	*RoA*	*RoRCH*	*RARoE*	*RoE*	*RoA*	*RoRCH*	*RARoE*
Reg. #	(A.3)	(B.3)	(C.3)	(D.3)	(F.3)	(G.3)	(H.3)	(I.3)
$\phi\ (LAG\ \pi)$	0.2059^a	0.1234^a	0.0029	0.0440^b	0.2503^a	0.4429^a	−0.1320^c	0.0023
$\beta_1\ (LR)$	2.2219^a	−0.0142	0.1516^b	4.8758^a	2.4124^a	−0.0040	0.0364	1.5584^a
$\beta_2\ (LR^2)$	−0.0678^a	−0.0011	−0.0079^a	−0.1778^a	−0.0452^a	0.0000	−0.0009	−0.0341^a
$\xi\ (REGP)$	−12.3083	−1.7343^b	−2.3261	−32.5543	0.4865	0.0360	−0.0161	0.1608
$\delta_1\ (\widetilde{LPQ})$	−2.3306^a	−0.2259^a	−0.2388^a	−2.1122^a	−0.4288^a	−0.0153^c	−0.0511^b	−1.1144^a
$\delta_2\ (LIQ)$	−0.0641^a	−0.0057^b	0.0019	−0.1010^a	−0.0961^a	−0.0074^a	−0.0025	−0.0621^b
$\delta_3\ (DIV)$	−0.3452	0.1685^c	0.0194	−1.1893	−0.1228	0.4706^c	−5.2125^a	−35.4799^a
$\eta_1\ (\widetilde{SIZE})$	1.8632	0.1172	−0.5328	6.4444	−21.2309^a	−2.0773^a	−2.1118^a	−27.8384^a
$\eta_2\ (\widetilde{SIZE^2})$	−0.0500	−0.0062	0.0102	−0.2127	0.5984^a	0.0598^a	0.0650^a	0.9429^a
$\eta_3\ (EDU)$	4.2826^a	0.4288^a	0.6842^a	4.2470^a	−0.1083	0.0596	−0.0201	−0.6607
# of Obs / Banks	916 / 174	916 / 174	806 / 156	806 / 156	378 / 102	378 / 102	146 / 46	146 / 46
Sargan test of over-identifying restrictions								
p value	0.1687	0.3653	0.3763	0.1066	0.9923	0.9928	0.9999	0.9985
Arellano-Bond test that average autocovariance in residuals is ...								
... of order 1 is 0: H0: no autocorrelation								
p value	0.0000	0.0006	0.0042	0.0008	0.0159	0.0263	0.1655	0.6533
... of order 2 is 0: H0: no autocorrelation								
p value	0.2224	0.1279	0.1758	0.0889	0.9765	0.4227	0.2734	0.0889

Table 3.8: The table shows the regression estimates for model (3.3) and the alternative measures for bank size and the loan portfolio quality. The left part of the table shows the estimates for U.S. banks, the right part shows the results for European banks. a denotes significance at the 1% confidence level, b at the 5% confidence level and c at the 10% level.

	US Banks		European Banks	
Dep. Var.	CDS - FE	CDS - RE	CDS - FE	CDS - RE
Reg. #	(K.1)	(K.2)	(L.1)	(L.2)
β_1 (LR)	19.1838	-9.4835	2.1192^b	1.4280^a
ξ $(REGP)$	-	-	-	-
δ_1 (LPQ)	-104.3315	23.3380	25.4782	2.8073
δ_2 (LIQ)	-8.2042^b	-0.9572	-1.3232^b	-0.9642^a
δ_3 (DIV)	540.0035	475.3193^b	-15.1900	-14.6168
η_1 $(SIZE)$	3260.2238	-1231.1076	-303.6667	55.3825^b
η_2 $(SIZE^2)$	-180.2572	55.9755	15.5824	-3.2681^b
η_3 (EDU)	-41.2182	88.1481	-769207.0000	-18.8590^c
# of Obs	30	30	74	74
# of Banks	9	9	27	27
overall R^2	0.0613	0.5759	0.2562	0.8076

Table 3.9: The table shows the estimated relationship between the leverage ratio and the CDS spread i.e. regression model (3.4). FE indicates fixed effects regression models and RE random effects regression models. a denotes significance at the 1% confidence level, b at the 5% confidence level and c at the 10% level.

This regression model tests for a linear relationship between the leverage ratio and the CDS spread. I do not consider a dynamic regression model for two reasons. (1) There is no evidence in the literature that supports autoregression in annual CDS spread. (2) CDS spreads are available from 2003 to 2008 only. The estimation of a dynamic panel regression model would reduce the number of observations significantly. Regression model (3.4) is a fixed effects regression model. Restricting $\alpha_i = \bar{\alpha}\ \forall i$ gives a random effects regression model. I estimate both types.

Table 3.9 shows the regression estimates. Column (K.1) and (K.2) show the estimates for U.S. banks and column (L.1) and (L.2) for European banks. I consider a fixed effects regression model in column (K.1) and (L.1) and a random effects regression model in (K.2) and (L.2). I find no significant relationship between the leverage ratio and the CDS spread for U.S. banks. One explanation for this finding might be that extreme leverage ratios are ruled out in the United States. This presumably weakens the relationship between the leverage ratio and the expected default costs. Therefore, the moderate decline in profitability of U.S. banks for leverage ratios above 14.7, as detected in sections 4.2 and 4.3, is presumably not due to an increase in expected default costs, but could be due to adjustment costs, if banks with high leverage ratios are forced to adjust their capital structure more often to satisfy the regulatory requirements than banks with low leverage ratios.

$\hat{\beta}_1$ is positive and significant for European banks, see (L.1) and (L.2). This indicates that high leverage ratios are associated with high default costs and might explain the sharp decline in profitability and risk-adjusted profitability if the leverage ratio exceeds 25 and 20, respectively. Furthermore, it seems that a restriction on the leverage ratio decouples expected default costs and the leverage ratio. It is likely that expected default costs of banks and systemic risk are positively correlated, hence, systemic risk might be reduced by an upper limit on the non-risk weighted leverage ratio.

The coefficients of size, measured by the logarithm of the average number of employees, are significant in (L.2), and imply that the CDS spreads of banks with at least 2,400 employees are negatively related to the (logarithmic) number of employees. This result is consistent with the implicit too-big-to-fail guarantee.

3.5 Conclusion

Banks adjust their capital structure fast, compared to industrial corporations. Besides of bank- and year-individual fixed effects, profitability and risk-adjusted profitability are consistently significant determinants of the leverage ratio. Moreover, profitability and risk-adjusted profitability of banks are non-monotonically, inversely 'u'-shape related to the leverage ratio. High and low leverage ratios reduce both, profitability and risk-adjusted profitability. Further determinants of profitability are the loan portfolio quality and the liquidity endowment. The results of diversification, size and personal expenses are ambiguous. I find evidence that default costs increase significantly with the leverage ratio for European banks. Hence, the decline in profitability of European banks is presumably due to high default costs. This result does not hold for U.S. banks. In addition to a restriction on the risk-weighted capital ratio, U.S. banks are restricted in their non-risk weighted capital structure. This additional restriction could weaken the relationship between the leverage ratio and expected default costs.

How should the regulator respond to the new challenges in the financial industry? As shown by Blum (2008), promoted by the Basel Committee on Banking Supervision, and applied in the USA, a restriction on the non risk-weighted capital structure in addition to the risk-based capital approach of Basel II might be appropriate to control systemic risk. Restricting the leverage ratio of European banks to the ratio, that is associated with the highest risk-adjusted profitability (≈ 20), might be a reasonable compromise between the regulators objectives and the bank owners objectives, as suggested by Allen Greenspan. This restriction reduces the average return on equity, ceteris paribus, by approximately 1.25 to 2.25 percentage points compared to the average profitability maximizing leverage ratio of about 25 and according to the estimates in regressions (F) and (F.2), respectively.

This study does not measure systemic risk explicitly. Further research might analyze the relationship between the capital structure of banks and other, explicit measures of systemic risk. Moreover, the regulator might impose further restrictions on banks (see Basel III), which are not discussed here, but will affect profitability and risk-adjusted profitability. Further empirical research might focus on those regulatory tools and evaluate the consequences.

3.6 Appendix

U.S. Banks	EU Banks
Bank of America, National Association (*)	ABN Amro Holding NV (*)
Bank of New York (*)	Banca Carige SpA
Branch Banking and Trust Company	Banca Popolare di Milano SCaRL (*)
Capital One National Association (*)	Banco Bilbao Vizcaya Argentaria SA (*)
Charter One Bank, NA	Banco de Sabadell SA (*)
Chase Bank USA, NA	Banco de Valencia SA
Citibank NA (*)	Banco Espanol de Credito SA
Comerica Bank	Banco Espirito Santo SA
Fifth Third Bank	Banco Pastor SA (*)
Huntington National Bank	Banco Popular Espanol SA (*)
JP Morgan Chase Bank, NA (*)	Banco Santander SA
Key Bank USA, National Association	Bank of Ireland (*)
Manufacturers and Traders Trust Company	Bankinter SA (*)
Northern Trust Company (The)	Barclays Bank Plc (*)
PNC Bank, National Association	BNP Paribas (*)
Regions Bank	Commerzbank AG (*)
Sallie Mae-SLM Corporation	Deutsche Bank AG (*)
State Street Corporation	Dexia Bank
SunTrust Bank	EFG Bank European Financial Group
Wachovia Bank, National Association (*)	Erste Group Bank AG
Washington Mutual Bank (*)	Gruppo Monte dei Paschi di Siena
Wells Fargo Bank, NA (*)	HSBC Bank plc (*)
	ING Bank NV (*)
	Intesa Sanpaolo (*)
	KBC Bank NV (*)
	Lloyds TSB Bank Plc (*)
	Mediobanca SpA
	Millennium Banco Comercial Portuguis (*)
	National Westminster Bank Plc
	Natixis (*)
	Raiffeisen International Bank-Holding
	Royal Bank of Scotland Plc (The)
	SNS Bank N.V. (*)
	Societe Generale (*)
	UBS AG (*)
	UniCredit SpA (*)
22 Banks	36 Banks
178 Observations	132 Observations

Table 3.10: The table shows the listed banks for which we calculate the Sharpe-ratio as risk adjusted profitability measure. The symbol (*) marks banks with CDS spreads. Those banks are used in section 4.3. Banks with CDS spreads and without listed stocks are Anglo Irish Bank, Northern Rock and Rabobank.

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Erklärung

Ich versichere hiermit, dass ich die vorliegende Arbeit

Essays on Portfolio- and Bank-Management

ohne unzulässige Hilfe Dritter und ohne Benutzung anderer als der angegebenen Hilfsmittel angefertigt habe. Die aus anderen Quellen direkt oder indirekt übernommenen Daten und Konzepte sind unter Angabe der Quelle gekennzeichnet. Weitere Personen, insbesondere Promotionsberater, waren an der inhaltlich materiellen Erstellung dieser Arbeit nicht beteiligt.[11] Die Arbeit wurde bisher weder im In- noch im Ausland in gleicher oder ähnlicher Form einer anderen Prüfungsbehörde vorgelegt.

Konstanz, 29.11.2011 (Ferdinand Graf)

[11]Siehe hierzu die Abgrenzung auf der folgenden Seite

Abgrenzung

Das erste Kapitel der Arbeit, *Does Portfolio Optimization Pay?*, habe ich zusammen mit Günter Franke von der Universität Konstanz verfasst. Die Idee für die Approximation stammt von Günter Franke, wir haben diese dann gemeinsam weiterentwickelt und das Papier gemeinsam geschrieben. Ich habe die Programme geschrieben und die Simulationen durchgeführt.

Kapitel 2, *Mechanically Evaluated Company News*, und 3, *Leverage, Profitability and Risk of Banks*, habe ich allein angefertigt.

Konstanz, 29.11.2011 (Ferdinand Graf)