Essays on Empirical Asset Pricing and Investor Behavior

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Introduction

This dissertation targets various questions related to asset pricing and investor behavior.

The first chapter examines the relation between risk and return and develops an appropriate test procedure to evaluate whether significant risk premia prevail. Early tests of the risk-return relation by Lintner[1] and Black et al. (1972) use a cross-sectional approach regressing mean returns for each asset on beta estimates. Fama and MacBeth (1973) introduce an alternative for estimating the risk-return relation. Instead of taking sample average returns, they regress asset returns on beta estimates for each month of the sample period. The sample mean of the slope coefficient represents the risk premium. Since its inception, the Fama-MacBeth test has been one of the standard econometric methodologies in the empirical asset pricing literature. We question the Fama-MacBeth test and evaluate the risk-return relation by applying a conditional approach to the Fama-French model. Subsequently, we develop a procedure to test if the risk is also priced according to the conditional approach. This procedure is compared to the Fama-MacBeth test.

Second, we investigate whether investors' expectations have predictive ability with respect to stock index returns and, more importantly, if such an effect is due to changes in expected cash flows or required risk premia. There has been vast evidence in the literature that measures of investor sentiment can, mostly cross-sectionally, predict stock returns. However, there has been no clear evidence of the reason for this predictability which could be due to mispricing or real economic reasons, i.e., changes in expected cash flows or required returns.

The third chapter has less to do with asset pricing as such, but with corporate insid-

[1] Douglas (1969) summarizes some of Lintner's unpublished results.

ers' use of private information to forecast their own firms' stock returns. Evidence from the literature has shown such an informational advantage to exist. The question of whether insiders use only their general long-term knowledge of their firms' prospects or also short-term information they have in advance has been tackled by a number of papers, each considering specific public information events and insiders' trading around the events' time. The evidence of these studies has been mixed. We argue that the existent studies lack in so far as they only consider short-term information that is subsequently published, rather than also that published only in aggregated form in later financial statements. The latter kind of information events can be considered to be related to less reputational or litigation risk so that it appears likely that insiders rather make use of their short-term information in cases of information events not previously considered in the literature. Due to their very nature, these events are not directly identifiable. We choose to use the variation in idiosyncratic volatility as our measure of information asymmetry to proxy for the existence of short-term information advantages.

Chapter I.[2] The first chapter challenges the widely used Fama-MacBeth test. According to asset pricing theory, in expectation there is a positive reward for taking risks. Investors are assumed to be risk averse and demand a compensation for holding risky assets. For this reason, riskier assets should yield higher expected returns. For instance, the expected market excess return, the difference between the market return and the risk-free rate, should be positive. To be in line with theory, empirical tests should find a positive relation between risk and expected returns. However, empirical tests are based on realized returns instead of expectations and realized returns are frequently negative. During periods of negative returns, the risk-return relation should be reversed, which is neglected by the standard Fama-MacBeth procedure. In order to take this into account, we make use of a conditional approach differentiating between periods with positive risk factor realizations and negative ones to test the risk-return relation. The conditional approach follows Pettengill et al. (1995). In contrast to the existent literature, we apply the conditional approach to the Fama-French three-factor model. We condition not only on the sign

[2]This chapter is based on joint work with Stefan Koch (2010).

of the market return, but on that of each of the three factors, and test if the book-to-market and size betas retain their explanatory power once the conditional nature of the relation between betas and return is taken into account. As predicted by theory, our results yield strong support for a positive risk-return relation when risk factor realizations are positive and for a negative one when risk factor realizations are negative. However, at this stage results are not comparable to the Fama-MacBeth test since the Fama-MacBeth approach tests if beta risk is priced. Thus, as a further contribution to the literature, we derive a test based on the conditional approach to evaluate if beta risks are priced, making the two tests comparable. This test extends the approach by Freeman and Guermat (2006) to multi-factor models. Our results provide evidence that the FG test produces very similar results as the standard Fama-MacBeth test. This finding not only holds for empirical data from the US stock market, but it is confirmed through simulations based on different return distributions. Therefore, the results of the first chapter justify the application of the Fama-MacBeth test.

In addition, our results stress the importance of the selection of test portfolios in empirical asset pricing. We detect that estimates for risk premia strongly rely on the choice of test portfolios, emphasizing the lack of robustness of asset pricing models to alternative portfolio formation.

Chapter II.[3] The second chapter investigates the response of stock index returns to investor expectations, as measured by survey data. Recent empirical research suggests that survey measures of investor sentiment have the ability to predict future stock returns over the intermediate and long term. There are at least two potential explanations for the predictive ability of sentiment indicators. First, sentiment indices may contain information about future expected returns that is not already captured by the control variables.[4] In this case, the predictive ability of sentiment indicators does not necessarily imply a violation of market efficiency. Second, senti-

[3] This chapter is based on joint work with Jördis Hengelbrock and Erik Theissen (2010).

[4] Alternatively, sentiment indicators could forecast higher expected future cash flows. In this case, the publication of the sentiment indicator should trigger an immediate price effect (i.e., a significant announcement day return), but should not predict future returns over longer horizons. The intermediate and long-term predictability reported in previous research is thus inconsistent with this interpretation.

ment indicators may be related to mispricing (as also proposed by Brown and Cliff (2005)). Positive sentiment, for example, may go hand-in-hand with share prices being driven above their fundamental values by the actions of overly optimistic investors. The resulting pricing errors are then corrected later on. Consequently, current sentiment indicators will be negatively related to future returns. In this case, the predictive power of sentiment measures provides evidence for a violation of market efficiency.

This chapter simultaneously considers intermediate and long-horizon predictability on the one hand, and the immediate market reaction to the publication of sentiment indicators on the other. This approach has a simple intuition. Current prices are inversely related to expected returns. If sentiment indicators contain information about future expected returns, the sign of the immediate market reaction should be opposite to that obtained from long-term predictive regressions. If, on the other hand, sentiment indicators are related to mispricing, we should find that the immediate market reaction has the same sign as that found from predictive regressions. This is due to the fact that smart investors exploit the information contained in the sentiment indicator. If bullish sentiment predicts positive [negative] future returns, smart investors will buy [sell] and thus cause an immediate positive [negative] market reaction.

Using data from Germany and the US, we find results consistent with a scenario of mispricing and of limited arbitrage. Smart investors are aware of the predictive power of the sentiment indicator and trade accordingly. However, they do not fully arbitrage the predictability away, possibly because of increased noise trader risk (as in the model of De Long et al. (1990)).

Chapter III.[5] Corporate insiders, i.e., executive directors, board members or large shareholders, are likely to possess superior information about the true value of their firm compared to outside investors. They are involved in decision making processes that affect the value of the firm such as investment or merger decisions, and they receive notice about major events in advance of official public announcements. Several empirical studies (e.g., Seyhun (1986), Chang and Suk (1998) or Jeng et al. (2003))

[5]This chapter is based on joint work with Jasmin Gider (2010).

document that corporate insiders are able to generate significant abnormal returns from trading. This indicates that they use their advantage for profitable trading strategies. Moreover, it is likely that the information asymmetry between informed and uninformed investors and consequently the information advantage of insiders varies over time. The question then arises whether corporate insiders time their transactions in such a way that they exploit high peaks of information asymmetry. The existing approach to use corporate announcement suffers from several shortcomings. First, the corporate announcement-approach necessitates an ex-ante selection of corporate news types. It is difficult to produce an exhaustive list of corporate news types. There may be types of temporary information advantages of insiders not covered by the events which have been considered so far. To be able to infer the absence of timing, one would have to collect information about every announcement the firm makes. Second, with the exception of earnings and dividend announcements of which analysts' estimates may exist, it is in general difficult to measure the surprise component of corporate announcements. It is hence difficult to distinguish informative announcements from uninformative ones, i.e., those which reduce the wedge between insider and outsider information and those that do not. Third, the risk of litigation and adverse publicity is likely to be higher before such disclosure types because the occurence of such events is easily verifiable. This is likely to prevent corporate insiders from blatantly exploiting this kind of information. Many firms even have self-imposed compliance guidelines which prevent insiders from trading before such events. Using relative idiosyncratic stock return volatility as a more direct measure of time-variant information asymmetry, we propose an alternative approach which does not suffer from these shortcomings. Idiosyncratic volatility as a measure of asymmetric information is motivated by the idea that informed traders only act when significant private information exists and that such trading causes stock price movements to deviate from those predicted by the assumed return generating process.

The chapter adds to the literature on corporate insider trading and presents the first study to analyze the likelihood of corporate insider trading. Its main innovation is to use a time-variant proxy for asymmetric information and link it to insider trading. This proxy allows for addressing the question of whether corporate insiders time their transactions according to variations in asymmetric information.

The findings indicate that corporate insiders appear to make use of short-term informational advantages. They tend to buy their firm's stocks more frequently when idiosyncratic volatility is high, i.e., at times during which it can be expected that private information is impounded into stock prices. However, the likelihood of selling is on average not significantly related to relative idiosyncratic volatility. This may be because of the lower informational content since sales are also motivated by other reasons than profit seeking, e.g., diversification or liquidation needs. Furthermore, there may be a trade-off with concerns about litigation and reputation risks, which are likely to be asymmetrically higher with respect to insider sales. Dividing the sample into small and large firms reveals an interesting insight. However, the empirical evidence does not establish a significant effect of timing on profitability.

Chapter 1

The Conditional Relation between Fama-French Betas and Return

1.1 Introduction

How does beta risk cross-sectionally affect asset returns? This question has inspired vast amounts of empirical research. However, this issue has not been sufficiently answered. Several recent articles put the standard Fama and MacBeth (1973) test procedure into question and argue that a conditional approach as developed in Pettengill et al. (1995) is more appropriate. While many papers applying the conditional approach find a systematic conditional relationship between risk and return, most of this literature neglects to investigate if beta risk is a priced factor. This study considers the conditional cross-sectional risk-return relationship in a three-factor model and tests subsequently if beta risks based on the three factors are priced. Finally, we compare the power of this test to the widely used Fama-MacBeth test.
The Capital Asset Pricing Model (CAPM), developed by Sharpe (1964), Lintner (1965) and Mossin (1966), is the first model which theoretically illustrates that market risk systematically affects returns. This model sets the foundation for modern asset pricing theory. Its central implication is that every asset's return is a linear function of its systematic risk, or market beta. Early research such as that of Black et al. (1972) and Fama and MacBeth (1973) empirically confirms the CAPM. In

the following, several studies yield contradicting results. For example, Reinganum (1981), Fama and French (1992), and Lettau and Ludvigson (2001) find that a systematic relationship between market beta and average returns across assets does not exist.

On top of this, the so-called anomaly literature provides a vast amount of evidence in the 80s and 90s that the CAPM does not hold empirically. Banz (1981) documents that small firms have on average higher risk-adjusted returns than large firms in the US. This anomaly is entitled as the size effect. Moreover, Fama and French (1992) show that the estimated market beta and the average returns are not systematically related once the size and book-to-market factor are included. Finally, Fama and French (1993, 1996) argue that many of the CAPM anomalies are captured by the Fama-French three-factor model. Besides the inclusion of the market excess return as in the CAPM, the three-factor model considers the size and book-to-market factor. Since its inception the Fama-French three-factor model has been the dominant model in empirical asset pricing.
However, Pettengill et al. (1995) propose a potential explanation of the observed weak relationship between market beta and stock returns. They point out that using realized returns implies that there exists a negative risk-return relationship in down-markets. Therefore, Pettengill et al. (1995) modify the Fama and MacBeth (1973) test procedure and develop a conditional approach incorporating the presumption that the risk-return relationship should be negative in down-markets. This is done by differentiating between periods with a positive realized risk premium (up-market) and a negative one (down-market). The conditional approach only tests the risk-retun relation and is not related to conditional asset pricing models producing time-varying risk premia as proposed by Jagannathan and Wang (1996). As predicted by the conditional approach, the authors find a positive risk-return relationship in up-markets but an inverse relationship in down-markets for US data. Many other authors have followed the conditional test procedure. For instance, Fletcher (2000) also reports a positive significant relationship between market beta and returns in up-markets as well as a negative significant relationship in down-markets for international stocks. The conditional approach has been applied for

several other countries and regions.[1]

However, the standard Fama-MacBeth procedure and the conditional approach test different hypotheses. Although both verify if there exists a systematic relationship between risk and return, the Fama-MacBeth procedure additionally tests if investors receive a positive reward for holding risk, i.e. it tests if the risk premium is positive. According to Pettengill et al. (1995) this is the case if the following two conditions are satisfied: 1) the average market excess return is positive, 2) there is a symmetric relationship between the market risk premium in down- and in up-markets. Though, Freeman and Guermat (2006) derive the inaccurateness of the second condition and clarify that, instead, market risk is not priced if a specific asymmetric relationship holds. Again, we want to emphasize that the detection of a conditional relationship between beta and return does not mean that the risk factor beta refers to is priced.

We make three contributions to the literature. Firstly, we apply the conditional approach to the predominant model in empirical asset pricing, the Fama-French three-factor model. We exceed the existant literature by not only conditioning on the sign of the market return, but on that of each of the three factors, and test if the book-to-market beta and size beta retain their explanatory power once the conditional nature of the relation between betas and return is taken into account. Our empirical results yield strong support for the conditional approach. All three factors exhibit a strong positive risk-return relationship in up-markets as well as an inverse relationship in down-markets. While other studies do not find a relationship between market beta and return in the presence of the size and book-to-market factor, e.g. Fama and French (1992), this study detects a strong one. Results are consistent for different subperiods and test portfolios.

Secondly, we do not only test if there is a systematic relationship between beta risk and return, but we extend a test proposed by Freeman and Guermat (2006) (FG test

[1]Faff (2001) applies the conditional approach for Australia, Crombez and Vennet (2000) for Belgium, Lilti and Montagner (1998) for France, Elsas et al. (2003) for Germany, Lam (2001), Ho et al. (2006), and Tang and Shum (2006) for Hong Kong, Hodoshima et al. (2000) for Japan, Sandoval and Saens (2004) for Latin America, Wihlborg and Zhang (2004) for Poland, Tang and Shum (2004) for Singapore, Isakov (1999) for Switzerland, Sheu et al. (1998) for Taiwan, Karacabey and Karatepe (2004) for Turkey, Hung et al. (2004) for the UK as well as Huang and Hueng (2007) for daily instead of monthly US data. Basher and Sadorsky (1991) use the conditional approach to examine the impact of oil prices on emerging market stock returns.

in the following) to multi-factor models and test if beta risk is a priced factor within the conditional approach. The FG test simultaneously tests both hypotheses. Thus, it enables us to compare the standard Fama-MacBeth test with the conditional test procedure and to shed some light on previous studies dealing with the conditional approach. Within the framework of the CAPM Freeman and Guermat (2006) show that the FG test has a power similar to that of the standard Fama-MacBeth test under the assumption of normally distributed returns. However, they conjecture that the FG test is more powerful when applied to empirical data because of the unconditional leptokurtosis in observed stock returns. In order to evaluate their conjecture, we use empirical stock market data and run simulations creating returns with fat tails. Using empirical data, our results show that the FG test and the Fama-MacBeth test produce qualitatively identical results. Our simulations confirm these results. We consider three different distributions: the normal distribution as well as the Pearson type IV distribution with and without skewness. Independent of the underlying distribution, we find that both tests exhibit a similar power and size. Thus, we cannot confirm the conjecture that the FG test has higher power even when modeling the unconditional leptokurtosis in stock returns.

Our study conflicts with other studies, like, e.g., Pettengill et al. (1995), who base their test on the above mentioned hypothesis that there is a symmetric relationship between the expected market excess return in down- and in up-markets. For most of our test portfolios we find an insignificant market risk premium within the conditional approach.

Thirdly, our results accentuate how crucial the choice of test portfolios in empirical asset pricing is. In contrast to most of the literature we make use of a variety of test portfolios. Applying both the Fama-MacBeth and the FG test, we find that the significance of market, size and book-to-market risk strongly depends on the selection of test portfolios. For the same risk factor we find positive, insignificant, and even negative risk premia.

The remainder of the paper is organized as follows. In the next section we introduce the conditional approach in the setting of the Fama-French three-factor model and the econometric methodology. Section 1.3 discusses the data and the construction of the size and book-to-market factor. Section 1.4 reports the empirical results of the standard Fama-MacBeth and the conditional test. Subsequently, we present the derivation of the FG test in a multi-factor setting as well as its empirical results. In section 1.6 we compare the size and the power of the two tests. Section 1.7 concludes.

1.2 Methodology

We consider the Fama-French three-factor model and, in contrast to most of the existing literature, allow for time-varying betas. The decision to allow the sensitivities to the risk factors to change over time is made in view of the several decades long data set used and the apparent change in asset and portfolio betas over time that is found in the data. The relevance of time-varying betas is emphasized in several papers, e.g. Harvey (1989), Ferson and Harvey (1991, 1993), and Jagannathan and Wang (1996). The three risk factors of the Fama-French model are denoted by m for market risk, smb for the size risk factor ('small minus big') relating to the market value of equity, and hml for the book-to-market factor ('high minus low'). Thus, the sensitivities of a portfolio i to the risk factors at time t are denoted $\beta^m_{i,t}, \beta^{smb}_{i,t}, \beta^{hml}_{i,t}$. Our estimation results are based on the Fama-MacBeth (1973) approach. Besides the advantage of an easy implementation it automatically corrects standard deviations for heteroscedasticity, which is a widespread problem among asset returns. We estimate the Fama-French betas for every portfolio from the following time-series regression,

$$r^e_{i,\tau} = \alpha_{i,t} + \beta^m_{i,t} r^e_{m,\tau} + \beta^{smb}_{i,t} r_{smb,\tau} + \beta^{hml}_{i,t} r_{hml,\tau} + \epsilon_{i,\tau} \quad \tau = t-60....t-1 \qquad (1.1)$$

where $r^e_{i,\tau}$ denotes the excess return of portfolio i, $r^e_{m,\tau}$ the market excess return, $r_{smb,\tau}$ and $r_{hml,\tau}$ the returns on the smb and hml portfolios, respectively. This procedure is repeated by rolling the window of 60 months of observations one month ahead. Rolling windows of five years make an appropriate compromise between adjusting to the latest changes and avoiding of noise in the monthly estimations. The rolling five year windows have also been suggested in earlier literature such as Groenewold and Fraser (1997), Brennan et al. (1998), and Fraser et al. (2004). The next step consists in estimating the risk premia $\lambda_{0,t}$, $\lambda_{m,t}$, $\lambda_{smb,t}$ and $\lambda_{hml,t}$ using the estimated betas $\hat{\beta}^{m}_{i,t}$, $\hat{\beta}^{smb}_{i,t}$ and $\hat{\beta}^{hml}_{i,t}$ from equation 1.1 , i.e. computing cross-sectional regressions for every month,

$$r^{e}_{i,t} = \lambda_{0,t} + \lambda_{m,t}\hat{\beta}^{m}_{i,t} + \lambda_{smb,t}\hat{\beta}^{smb}_{i,t} + \lambda_{hml,t}\hat{\beta}^{hml}_{i,t} + \eta_{i,t} \tag{1.2}$$

The factor risk premium, λ_j with $j = 0, m, smb, hml$, is estimated as the average of the cross-sectional regression estimate, $\hat{\lambda}_j = \frac{1}{T}\sum_{t=1}^{T}\hat{\lambda}_{j,t}$. λ_j is the factor risk premium which compensates the investors for the risk taken. The coefficient λ_0 is interpreted as the expected return of a zero beta portfolio, λ_m as the market price of risk, λ_{smb} and λ_{hml} as the price of size and book-to-market risk.[2] Since the betas are estimated from a first-step regression, standard errors for the second regression can be misleading. In order to circumvent the presence of this errors-in-variables problem we apply a correction to the standard errors as proposed by Shanken (1992). Yet, the Shanken correction has to be treated critically as shown by Shanken and Weinstein (2006) because in practical applications it often yields a modified cross-product matrix of the estimated beta vectors that is not positive definite as it should be.

Estimating equation 1.2 by the Fama-MacBeth procedure leads to conclusions on whether the risk factors are priced. For instance, if $\lambda_{m,t}$ is nonzero, market risk is a priced factor. If, on the other hand, $\lambda_{m,t}$ is not distinguishable from zero, then market risk is not priced. This can be the case either if there does not exist a relationship between beta and return or if it does exist but the market risk premium is not distinguishable from zero. Therefore, it is possible that beta is not priced despite the existence of a risk-return relationship. On this account we apply a procedure that has been suggested by Pettengill et al. (1995) in the context of the CAPM, which exclusively tests the relationship between market beta and realized returns conditional on whether the market excess return, i.e. the realized market risk premium, is positive or negative. This test takes into account that empirical tests are based on realized returns although the CAPM is stated in expectational terms.

[2]The interpretation of the size and book-to-market risk is discussed in the literature. For instance, according to Amihud and Mendelson (1986, 1991) size may proxy for liquidity risk and Vassalou and Xing (2004) argue that the book-to-market ratio captures default risk.

According to the CAPM the expected market excess return is always positive[3] and, thus, there should exist a positive risk-return relation. However, the realized market excess return can also be negative implying a negative relation between beta and return. In order to test the systematic relationship between risk and return the following equation is estimated:

$$r^e_{i,t} = \lambda_{0,t} + \lambda^+_{m,t}\delta_{m,t}\hat{\beta}^m_{i,t} + \lambda^-_{m,t}(1-\delta_{m,t})\hat{\beta}^m_{i,t} + \eta_{i,t} \tag{1.3}$$

While Pettengill et al. (1995) conduct this procedure for the CAPM and for beta constant over time, we apply the Fama-French three-factor model and allow for time-varying betas. That is, we estimate the following equation.

$$\begin{aligned} r^e_{i,t} &= \lambda_{0,t} + \lambda^+_{m,t}\delta_{m,t}\hat{\beta}^m_{i,t} + \lambda^-_{m,t}(1-\delta_{m,t})\hat{\beta}^m_{i,t} \\ &\quad + \lambda^+_{smb,t}\delta_{smb,t}\hat{\beta}^{smb}_{i,t} + \lambda^-_{smb,t}(1-\delta_{smb,t})\hat{\beta}^{smb}_{i,t} + \lambda^+_{hml,t}\delta_{hml,t}\hat{\beta}^{hml}_{i,t} + \lambda^-_{hml,t}(1-\delta_{hml,t})\hat{\beta}^{hml}_{i,t} + \eta_{i,t} \end{aligned} \tag{1.4}$$

The δs are dummy variables with the value 1 if the market, the *smb* and the *hml* factors, respectively, yield a positive excess return and 0 otherwise. We conduct cross-sectional regressions for each month as in the unconditional case. Our conditional estimates are $\hat{\lambda}^+_j = \frac{1}{\sum_{t=1}^T \delta_{j,t}} \sum_{t=1}^T \hat{\lambda}_{j,t}\delta_{j,t}$ and $\hat{\lambda}^-_j = \frac{1}{\sum_{t=1}^T (1-\delta_{j,t})} \sum_{t=1}^T \hat{\lambda}_{j,t}(1-\delta_{j,t})$, respectively. That means, the parameters are averaged conditional upon the sign of the risk factors. We would like to stress that the conditional approach sharply differs from the way of estimating conditional asset pricing models since we do not estimate conditional betas in the first-step regression. Furthermore, the conditional approach differs from studies differentiating between upside and downside betas such as Ang et al. (2006). Instead, we split our sample into different subsamples depending on positive or negative risk factors when conducting cross-sectional regressions in the second step.

While the Fama-MacBeth procedure tests whether betas are priced risk factors, the conditional approach as applied here only enables us to test whether there is a

[3] This follows from the assumption that agents are risk averse and that there is a positive net supply of market risk.

systematic relation between a risk factor and the realized returns. In other words, finding a significant relation between beta risk and return does not automatically imply that beta risk is priced and the model holds.

1.3 Data

This study uses monthly data from July 1926 through June 2008. The entire dataset is taken from Kenneth French's homepage. We deploy the 25 portfolios formed according to the same criteria as those used in Fama and French (1992, 1993), i.e., the portfolios are value-weighted for the intersections of five size and five book-to-market equity portfolios. The portfolios are constructed at the end of June, and size is measured by market capitalization of equity at the end of June. The book-to-market ratio is book equity at the last fiscal year end of the prior calendar year divided by the market capitalization at the end of December of the prior year. Additionally, we include 25 portfolios sorted by size and momentum, 10 portfolios sorted by momentum, 10 portfolios sorted by short-term reversal, 10 portfolios sorted by the earnings price ratio, 10 by the cash-flow price ratio and 10 by the dividend yield. 25 size and momentum portfolios are the intersections of five portfolios sorted on size and five portfolios formed on the previous eleven months return lagged by one month (past 2-12 return). In the same way, 10 momentum portfolios are constructed. 10 short-term reversal portfolios are constructed monthly formed on the return of the previous month. 10 portfolios sorted by the earnings price and cash flow price ratio are formed in June of year t based on the fiscal year $t-1$. Earnings are measured as earnings before extraordinary items. Cash flow are earnings before extraordinary items plus equity's share of depreciation plus deferred taxes. Finally, 10 portfolios are formed on dividend price ratio at the end of each June using NYSE breakpoints. The dividend yield used to form portfolios in June of year t is the total dividends paid from July of t-1 to June of t per dollar of equity in June of t.
Furthermore, this study employs the three Fama-French factors. Although the composition of the market portfolio is not observable, we approximate the market excess return by the return on the value-weighted CRSP index compromising all NYSE,

AMEX and NASDAQ stocks minus the one-month Treasury bill-rate (from Ibbotson Associates). The size and book-to-market factor base on six portfolios, which are the intersections of two portfolios formed on size and three portfolios formed on the book-to-market ratios. Portfolios consisting of small (big) firms are denominated as small (big) portfolios, whereas portfolios consisting of firms with a low (high) book-to-market value are denoted as growth (value) portfolios. The size factor (smb) is constructed as the difference between the average return on three small firm portfolios and the average return on three big firm portfolios. The book-to-market factor (hml) is the average return on the two value portfolios minus the average return on the two growth portfolios. The returns are based on all NYSE, AMEX and NASDAQ stocks for which book and market equity data are available.

1.4 Empirical Results

1.4.1 Fama-MacBeth regressions

Before presenting the results of the unconditional test resulting from conducting the Fama-MacBeth procedure, we want to stress the importance of using time-variant betas. Figures 1.1, 1.2, and 1.3 illustrate the variation in time of market, size and book-to-market betas. As our dependent variable we use the 25 size and book-to-market portfolios. Betas are calculated using equation 1.1. For the sake of clearness, we only illustrate portfolios 1, 25 and 10. Portfolio 1 contains the smallest growth stocks and is used as an example for large changes in betas over time. Portfolio 25 consists of the biggest value stocks and is an example for medium changes in betas over time. Portfolio 10 comprises stocks with the second smallest market capitalization and the highest book-to-market ratios. Its betas displays small changes over time.

The dashed lines represent the 95% confidence interval. In particular, portfolio 1 indicates a strong variation in the betas across time. Although the betas of portfolio 25, Figure 1.2, and particularly portfolio 10, Figure 1.3, appear to be much less variable, even in the latter case market beta varies between 0.62 and 1.25, size beta

Figure 1.1: Fama-French Betas for portfolio 1 (1931:07-2008:06)

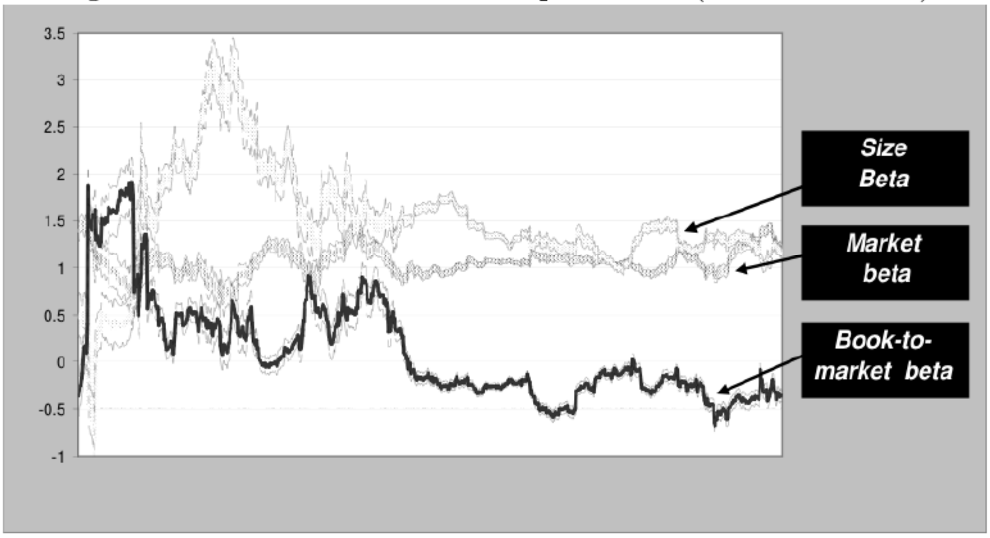


Figure 1.2: Fama-French Betas for portfolio 25 (1931:07-2008:06)

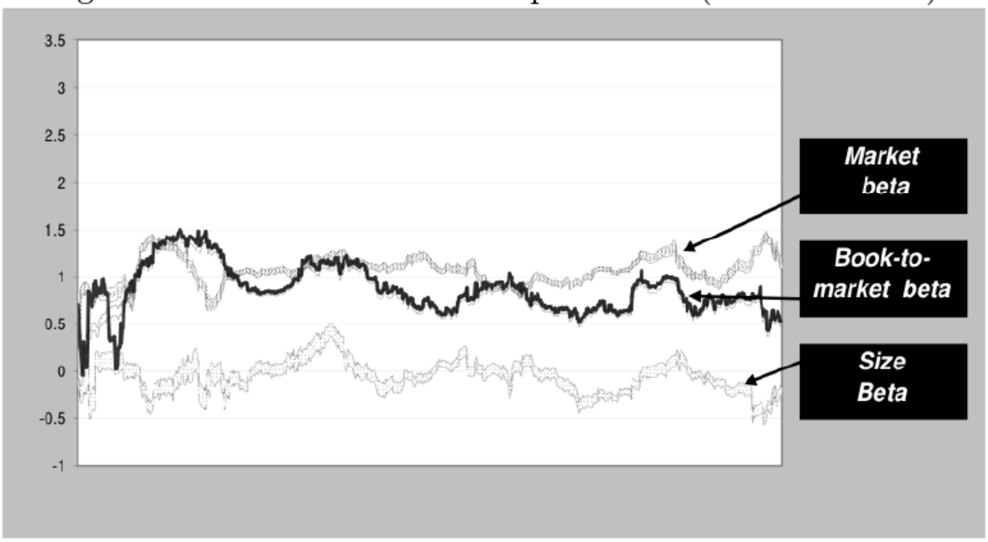
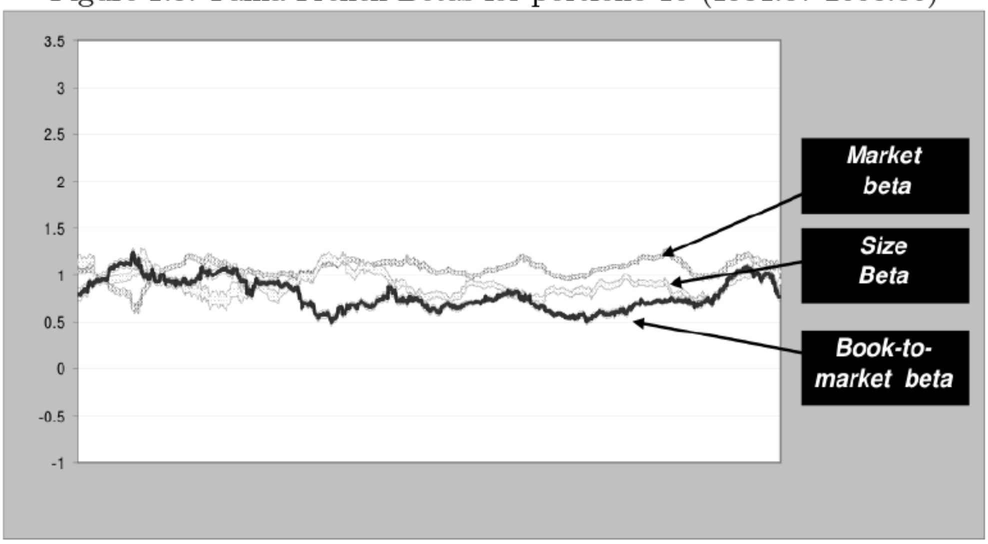


Figure 1.3: Fama-French Betas for portfolio 10 (1931:07-2008:06)



between 0.69 and 1.23 and book-to-market beta between 0.50 and 1.24.

Table 1.1 shows the results of the Fama-MacBeth estimation for the whole period using equation 1.2. The monthly estimates of the coefficients are averaged and a t-test is applied to determine the statistical significance of the mean of the estimated coefficients. The market risk premium is negative but insignificant and, thus, market risk is not found to be priced. Size risk is not found to be significant either while the coefficient of the book-to-market risk premium is highly significant. The constant representing the return of the zero-beta portfolio should be between the average riskless borrowing and lending rate. The estimated value is implausibly high. However, this is a feature occurring in most empirical studies that report the constant, for example Jagannathan and Wang (1996) and Lettau and Ludvigson (2001). In

Table 1.1: Fama-MacBeth test (1931:07-2008:06)

Variable	λ	t-stat	$\bar{R}^2$
cons	1.04	4.63***	0.47
market	-0.31	-1.35	
smb	0.18	1.64	
hml	0.41	3.49***	

*** significant (1-percent level)

This table depicts the results for the Fama-French three-factor model illustrated by equation 1.2. cons denotes the constant term, market the risk premium of the market risk, smb that of the size and hml that of the book-to-market risk. The coefficients are given as percentage points per month. $\bar{R}^2$ is the average cross-sectional R^2.

the following we conduct the same analysis for four subperiods, the results being detailed in Table 1.2. The subperiods are chosen such that they are of equal length. We observe that the size risk premium is not significant in any of the subperiods, the same holds for the market risk. The significance of the book-to-market premium varies, though, it is priced at the 1% level in the third period, while its coefficient, as that of the size premium, has the expected sign in all subperiods. Generally, though rarely done so in the literature, applying the Shanken (1992) correction to the standard errors would be advisable in order to overcome the errors-in-variables problem. We follow the heuristic in Shanken (1992) for the case of time-varying betas. The Shanken correction factors are negligible, increasing the standard errors by only 0.5% for the whole sample and by 1.7% on average for the subsamples, such

Table 1.2: Fama-MacBeth test (subperiods)

	1931:07-1950:09			1950:10:1969:12		
Variable	λ	t-stat	$\bar{R}^2$	λ	t-stat	$\bar{R}^2$
cons	0.80	1.17	0.42	1.14	3.98**	0.40
market	0.30	0.43		-0.32	-1.09	
smb	0.37	1.29		0.14	0.93	
hml	0.49	1.41		0.21	1.63	
	1970:01-1989:03			1989:04-2008:06		
Variable	λ	t-stat	$\bar{R}^2$	λ	t-stat	$\bar{R}^2$
cons	0.89	2.46**	0.55	1.31	3.74***	0.51
market	-0.49	-1.03		-0.75	-1.91*	
smb	0.16	0.86		0.05	0.22	
hml	0.64	3.49***		0.28	1.33	

* significant (10-percent level)

** significant (5-percent level)

This table depicts the results for the Fama-French three-factor model for four subperiods. cons denotes the constant term, market the risk premium of the market risk, smb that of the size and hml that of the book-to-market risk. The coefficients are given as percentage points per month. $\bar{R}^2$ is the average cross-sectional R^2.

that the significance of the coefficients is not changed. In the following, we disregard the correction factor.

1.4.2 Conditional Relationship

First of all we check how frequently the realized excess return is negative. If it were hardly ever negative, the conditional relationship would have an negligible impact on tests of the relationship between beta and return. The riskfree rate exceeds the market return in 40.2% of the observations for the entire period. Moreover, in 48.4% of the observations the size factor and in 44.0% the book-to-market factor is negative, which accentuates the relevance of the distinction between up-markets and down-markets. Table 1.3 depicts the results of the conditional test for the entire sample. All coefficients are highly significant. The fact that we observe a strong relationship between market risk and returns is, among others, consistent with Pettengill et al. (1995) and Fletcher (2000). Moreover, our results clarify that there also exists a strong conditional relationship between returns and size as well

Table 1.3: Conditional Relation between Fama-French Betas and Returns (1931:06-2008:06)

Variable	λ	t-stat
cons	1.04	4.63***
market-up	1.62	5.11***
market-down	-3.20	-8.54***
smb-up	2.17	14.82***
smb-down	-1.95	-9.13***
hml-up	2.26	16.19***
hml-down	-1.96	-8.17***

*** significant (1-percent level)

This table depicts the results of the conditional relation between Fama-French betas and return illustrated in equation 1.4 for the entire sample. cons denotes the constant term, market up (down) the risk premium of the market given that the excess market return is positive (negative), smb up (down) that of the size given that the smb factor is positive (negative) and hml up (down) that of the book-to-market risk given that the hml factor is positive (negative). The coefficients are given as percentage points per month.

as book-to-market beta.

Market beta is associated with increasing absolute returns, i.e. positively increasing returns in up- and negatively increasing returns in down-markets. The same applies to the size and book-to-market risk factors while the constant, as expected, does not change compared with the results of the Fama-MacBeth method. In contrast to Pettengill et al. (1995) the coefficients show asymmetry concerning the market risk. Returns increase less with beta when the market excess return is positive than they decrease when it is negative. This might intuitively explain why, while the market on average increases and beta relates asset returns to market returns, there is no significant risk premium for the market risk. In contrast, the coefficients for the size and book-to-market risk are not significantly asymmetric.[4] The results for the subperiods show similar results. In contrast to the findings of the standard Fama-MacBeth procedure the conditional approach leads to results that are consistent over time. All variables retain their significance in each of the four subperiods as illustrated in table 1.4.

We do not report the $\bar{R}^2$ since they comply with the values of the Fama-MacBeth

[4] Testing for asymmetric coefficients results in the following test values: -3.2*** (market), 0.87 (smb) and 1.09 (hml). The null hypothesis is $\lambda_j^+ + \lambda_j^- = 0$.

Table 1.4: Conditional Relation between Fama-French Betas and Returns (subperiods)

	1931:07-1950:09		1950:10:1969:12		1970:01-1989:03		1989:04-2008:06	
Variable	λ	t-stat	λ	t-stat	λ	t-stat	λ	t-stat
cons	0.80	2.38**	1.14	3.98***	0.89	2.46**	1.31	3.74***
market-up	2.38	2.37**	0.85	2.40**	2.06	4.13***	1.29	2.75***
market-down	-2.89	-2.98**	-2.37	-4.24***	-3.39	-5.01***	-4.07	-5.21***
smb-up	2.37	5.91***	1.64	9.37***	2.20	11.02***	2.46	8.46***
smb-down	-2.21	-4.37***	-1.36	-4.39***	-2.00	-4.61***	-2.25	-4.71***
hml-up	3.24	6.52***	1.32	10.01***	2.24	14.97***	2.35	10.24***
hml-down	-2.44	-3.95***	-1.29	-4.38***	-2.02	-3.97***	-2.04	-4.24***

* significant (10-percent level)
** significant (5-percent level)
*** significant (1-percent level)

This table depicts the results of the conditional relation between Fama-French betas and return illustrated in equation 1.4 for the four subperiods. cons denotes the constant term, market up (down) the risk premium of the market given that the excess market return is positive (negative), smb up (down) that of the size given that the smb factor is positive (negative) and hml up (down) that of the book-to-market risk given that the hml factor is positive (negative). The coefficients are given as percentage points per month.

procedure.[5]

1.5 Testing for Priced Betas

1.5.1 Derivation of the Test

Our findings in the last section exclusively provide strong evidence for a systematic relationship between Fama-French betas and return. In this section we go one step further and test not only if there exists a systematic relationship between beta and return but also if beta risk is priced within the conditional approach. Besides the existence of a systematic relationship a priced beta would require a reward to compensate investors for the risk taken. In the following we generalize the FG test

[5] The conditional approach is based on the same regressions as the Fama-MacBeth test but it splits up the variables in up-markets and down-markets. Therefore, the constant and the cross-sectional $\bar{R}^2$ are identical.

to a multi-factor framework and test if Fama-French betas are priced. Since the FG test and the standard Fama-MacBeth procedure are now based on the same hypothesis, it is possible to compare both procedures and to judge the relevance of the conditional approach. Freeman and Guermat (2006) base their test on the CAPM. We extend the test to multi-factor models. Moreover, we allow for time-variant betas. Consider the following return generating process:

$$r^e_{i,t} = E(r^e_{i,t}) + \beta^m_{i,t}[r^e_{m,t} - E(r^e_{m,t})] + \beta^{smb}_{i,t}[r_{smb,t} - E(r_{smb,t})] + \beta^{hml}_{i,t}[r_{hml,t} - E(r_{hml,t})] + \epsilon_{i,t} \tag{1.5}$$

The error term $\epsilon_{i,t}$, $E[\epsilon_{i,t}] = 0$, is assumed to be uncorrelated with both the betas and the excess returns.[6] Yet, the error terms can be cross-sectionally correlated. Additionally, consider the expected return process:

$$E(r^e_{i,t}) = \alpha_{i,t} + \beta^m_{i,t}\pi^m + \beta^{smb}_{i,t}\pi^{smb} + \beta^{hml}_{i,t}\pi^{hml} \tag{1.6}$$

$\alpha_{i,t}$ represents a compensation for other risk factors that are orthogonal to the three included factors. Hence, it is assumed that $\alpha_{i,t}$ and $\beta_{i,t}$ are uncorrelated. Choosing $\alpha_{i,t} = 0$, $\pi^m = E[r^e_{m,t}]$, $\pi^{smb} = E[r_{smb,t}]$ and $\pi^{hml} = E[r_{hml,t}]$ would imply that the return process equals the Fama-French three-factor model. To put it differently, if $\pi^j = 0$, the risk factor j is not priced. This approach enables us to verify if beta risk is priced. For instance, testing the sole hypothesis that market risk is not priced under the assumption of a three-factor model, corresponds to the null hypothesis $\pi^m = 0$. We begin with the linear regression equation of our model.

$$r^e_{i,t} = \lambda_{0,t} + \lambda_{m,t}\beta^m_{i,t} + \lambda_{smb,t}\beta^{smb}_{i,t} + \lambda_{hml,t}\beta^{hml}_{i,t} + \eta_{i,t} \tag{1.7}$$

According to the Fama-MacBeth procedure ordinary least squares regressions are conducted for all t.

Denote $\boldsymbol{\beta'_{i,t}} = [\beta^m_{i,t}\beta^{smb}_{i,t}\beta^{hml}_{i,t}], \boldsymbol{r'_t} = [r^e_{m,t}r_{smb,t}r_{hml,t}], \boldsymbol{\pi'} = [\pi^m\pi^{smb}\pi^{hml}]$ and $\boldsymbol{\lambda'_t} =$

[6] If we relax the assumption that beta is deterministic, our results will still be valid as long as we will take expectation conditional on beta instead of unconditional expectation.

$[\lambda_{m,t}\lambda_{smb,t}\lambda_{hml,t}]$. According to the properties of ordinary least squares we obtain

$$\begin{aligned}
\boldsymbol{\lambda_t} &= \text{var}(\boldsymbol{\beta_{i,t}})^{-1}\text{cov}(\boldsymbol{\beta_{i,t}}, r^e_{i,t}) \\
&= \text{var}(\boldsymbol{\beta_{i,t}})^{-1}\text{cov}(\boldsymbol{\beta_{i,t}}, E[r^e_t] + \boldsymbol{\beta'_{i,t}}(\boldsymbol{r_t} - E[\boldsymbol{r_t}])) \\
&= \text{var}(\boldsymbol{\beta_{i,t}})^{-1}\text{cov}(\boldsymbol{\beta_{i,t}}, \alpha_{i,t} + \boldsymbol{\beta'_{i,t}}\boldsymbol{\pi}) + \boldsymbol{r_t} - E[\boldsymbol{r_t}] \\
&= \boldsymbol{\pi} + \boldsymbol{r_t} - E[\boldsymbol{r_t}]
\end{aligned}$$

Testing, e.g., the null hypothesis that market risk is not priced we obtain the following equations:

$$\begin{aligned}
\lambda^+_m &= E[r^e_{m,t}|r^e_{m,t} > 0] - E[r^e_{m,t}] \\
\lambda^-_m &= E[r^e_{m,t}|r^e_{m,t} < 0] - E[r^e_{m,t}] \\
\lambda^+_m + \lambda^-_m &= E[r^e_{m,t}|r^e_{m,t} > 0] + E[r^e_{m,t}|r^e_{m,t} < 0] - 2E[r^e_{m,t}]
\end{aligned}$$

This formula shows that our generalization of the Freeman and Guermat (2006) test procedure to multi-factor models leads to the same test equation. As the formula illustrates the relation between λ^+_m and λ^-_m is generally asymmetric under the null hypothesis. By contrast, Pettengill et al. (1995) assume that priced beta risk corresponds to a symmetric relationship between λ^+_m and λ^-_m. However, there is no reasonable argument why the expected value of the risk premium conditional on it being positive or negative should have the same absolute expected size. Our test equation shows that this does not hold true. The Fama-MacBeth test is a special case of the FG test, disregarding the differentiation between λ^+_m and λ^-_m. In this case, we only consider unconditional expected values and, hence, under the null hypothesis, $\pi^m = 0$, we obtain $\lambda_m = 0$. This is the usual equation testing for the significance of market risk within the Fama-MacBeth framework.
In order to avoid messy notation the right hand side of the last equation is denoted as $\theta_m = E[r^e_{m,t}|r^e_{m,t} > 0] + E[r^e_{m,t}|r^e_{m,t} < 0] - 2E[r^e_{m,t}]$.

1.5.2 The Bootstrap

Since $\lambda_j^+ + \lambda_j^- - \theta_j = 0$ holds under the null hypothesis that risk factor j, $j \in \{m, smb, hml\}$, is not priced, this condition can be tested by a simple t-test:

$$t = \frac{\hat{\lambda}_j^+ + \hat{\lambda}_j^- - \hat{\theta}_j}{\hat{std}_j}. \tag{1.8}$$

θ_j can be consistently estimated by taking sample averages. Provided that the standard deviation of the numerator std_j can also be consistently estimated, the Central Limit Theorem can be applied and hence, the asymptotic normality of the statistic follows from White (1999). However, since the components of θ_j are based on different sample sizes, the covariances cannot be estimated directly. One way to overcome this obstacle is to apply a bootstrap. It helps us learn about the sample characteristics by taking resamples and using this information to infer about the population. As shown by Babu and Singh (1984) the bootstrap can be used to consistently estimate a wide range of statistics, including not only the sample mean but also the sample variance and smooth transforms of these statistics. In our setting the bootstrap is applied as follows. T observations are independently drawn with replacement. This gives us a new sample $(r_{j,t}^{e*}, \lambda_j^*)$. By calculating $\hat{\lambda}_j^{+*}$, $\hat{\lambda}_j^{-*}$ and $\hat{\theta}_j^*$ from the new sample, we obtain an estimate for the numerator. This result is saved and the whole procedure is repeated S times. Finally, the bootstrap variance is the sample variance of the S estimates of the numerator. In order to choose S sufficiently large, we take S equal to 10000.

However, this procedure relies on the assumption that returns are identically and independently distributed. In order to account for possible autocorrelation and clusterings we additionally conduct a block bootstrap. The Moving Block Bootstrap developed by Künsch (1989) draws blocks of length l instead of drawing T observations independently. Lahiri (1999) shows that the Moving Block Bootstrap performs better than other block bootstraps in terms of the mean squared error. With respect to this criterion, Künsch (1989) shows that $l = T^{\frac{1}{3}}$ is the optimal block length.

1.5.3 Empirical Results

This subsection presents the test results of the FG test developed in subsection 1.5.1 based on the simple bootstrap and the moving block bootstrap. Although θ_j is unknown and has to be estimated as well, we also consider the case of a known θ_j as a benchmark. By assuming a known θ_j the bootstrap becomes dispensable since the standard deviation can be solely calculated from the variances of $\hat{\lambda}_j^+$ and $\hat{\lambda}_j^-$. Under this simplifying assumption Freeman and Guermat reinterpreted the results in Pettengill et al., Fletcher (2000) and Hung et al. (2004) by testing if the market beta is a priced risk factor within the conditional approach. In the case of Pettengill et al., which is the only study dealing with monthly US data, they draw the conclusion that market risk is a priced risk factor. Therefore, comparing the benchmark with the case of an unknown θ_j enables us to shed some light on the results in Freeman and Guermat (2006).

Table 1.5 illustrates the results of the FG test for the entire period. Neither the market nor the size risk can be shown to be priced, independent of the method used for the computation of standard errors. The t-value generally decreases in absolute values when choosing the moving block bootstrap rather than the simple bootstrap. Under the assumption of known θ_j the t-values rather decrease in absolute values since the positive covariance between $\lambda_j^+ + \lambda_j^-$ and θ_j is neglected. The finding that the pricing of market beta cannot be confirmed stands in contrast to that of Freeman and Guermat (2006). Apart from the different sample period, the most plausible reason for this finding is that the inclusion of size and book-to-market distinctly decreases the explanatory power of the market factor and causes insignificance of the coefficient. Thus, with respect to the marker risk the results of the FG test are in line with previous tests, e.g., Fama and French (1992).

Although the results from the block bootstrap are qualitatively identical in comparison to the simple bootstrap, the t-values change, i.e. the book-to-market and size coefficient exhibit a slightly lower t-value. In the following results are exclusively based on the block bootstrap.

Table 1.6 illustrates the results from the FG test for the four subperiods. The coefficient for the market risk turns from positive to negative over time. Though,

Table 1.5: FG test (1931:07-2008:06)

Variable	$\lambda_j^+ + \lambda_j^- - \theta_j$	t-stat (known θ_j)	t-stat (simple B.)	t-stat (Block-B.)
market	-0.07	-0.14	-0.14	-0.14
smb	0.37	1.43	1.64	1.62
hml	0.86	3.09***	3.58***	3.27***

*** significant (1-percent level)

This table depicts the results of the FG test for the entire period assuming a constant θ_j as well as applying the simple bootstrap and the block bootstrap, respectively. market is the risk premium of the market, smb that of the size and hml that of the book-to-market risk. $\lambda_j^+ + \lambda_j^- - \theta_j$ are defined as presented in subsection 1.5.1.

each of the coefficients is insignificant. In contrast to the standard Fama-MacBeth test the FG test provides lower t-values for market risk except in the third period, where they almost coincide. Concerning the size risk all coefficients are positive but insignificant in each subperiod. The book-to-market risk factor is significant at the 1% level in the third period and insignificant in the others, which confirms the results from the standard Fama-MacBeth test. Moreover, both tests indicate large standard deviations and hence, smaller t-values for the subperiods, which leads to less significant and partly to inconsistent results.[7]

All in all, our results show that the book-to-market beta is a priced risk factor, size beta cannot be shown to be significant and market beta is not priced. Furthermore, we can subsume that the results from the FG test and the standard Fama-MacBeth test are qualitatively similar. Therefore, our findings place emphasis on the results of Freeman and Guermat (2006) but stand in sharp contrast to the results of Pettengill et al. (1995). Basing their test on the inaccurate hypothesis that beta risk is priced if there is a symmetric relationship between the expected market excess return in down- and in up-markets and if a positive market excess return exists, Pettengill et al. (1995) draw the conclusion that the market risk premium is positively priced.

[7] Additionally, we consider the same period as in Fama and French (1992) running from 1963 to 1990. Both, the Fama-MacBeth and the FG test, find insignificant premia for market and size risk but a priced book-to-market risk. These results differ from those in Fama and French (1992) who use firm characteristics rather than factor mimicking portfolios.

Table 1.6: FG Test (subperiods)

Variable	$\lambda_j^+ + \lambda_j^- - \theta_j$	t-stat	$\lambda_j^+ + \lambda_j^- - \theta_j$	t-stat
	1931:07-1950:09		1950:10:1969:12	
market	1.79	1.29	0.05	0.09
smb	0.82	1.64	0.26	0.69
hml	1.01	1.48	0.46	1.43
	1970:01-1989:03		1989:04-2008:06	
market	-0.85	-1.04	-1.19	-1.62
smb	0.33	0.74	0.10	0.22
hml	1.28	3.07***	0.58	1.03

*** significant (1-percent level)

This table depicts the results of the FG test for the four subperiods based on the block bootstrap. market is the risk premium of the market, smb that of the size and hml that of the book-to-market risk. $\lambda_j^+ + \lambda_j^- - \theta_j$ are defined as presented in subsection 1.5.1.

1.5.4 Robustness

In addition to the analysis based on portfolios sorted by size and book-to-market, we conduct the same procedure for other portfolios not or only partly sorted by the risk factors contained in the Fama-French three-factor model in order to verify the results we obtained previously. First, we choose 10 portfolios sorted by momentum since most asset pricing models come off badly in explaining momentum portfolios. For example, Fama and French (1996) and Grundy and Martin (2001) find that controlling for the market, the size effect and the book-to-market effect even increases the profitability of momentum strategies. Thus, this sorting appears to be an intuitive contrast to that with respect to size and book-to-market ratio and, it is a useful robustness check of our existing test results. As it is desirable to have a larger number of data points in the cross-sectional regressions in order to reduce the standard errors of the estimates, we also choose to try and explain the returns of 25 portfolios sorted by momentum and size. Additionally, we consider other characteristics based portfolios and include 10 cash flow-price portfolios, 10 earnings-price portfolios, 10 dividend-price portfolios and 10 short-term reversal portfolios.

Table 1.7 depicts the results of the Fama-MacBeth test and the FG test. In the case of the 25 momentum-size portfolios size risk is positively priced whereas market risk is negatively priced and book-to-market risk is insignificant. The results for the FG

Table 1.7: Fama-MacBeth Test and FG Test for diverse test portfolios

	λ	t-stat	$\lambda_j^+ + \lambda_j^- - \theta_j$	t-stat
Variable	25 momentum-size (1932:01-2008:06)			
market	-0.63	-2.18**	-0.90	-1.57
smb	0.35	2.82***	0.72	2.84***
hml	-0.13	-0.67	0.09	0.24
	10 momentum (1932:01-2008:06)			
market	-0.71	-1.68*	-0.88	-1.07
smb	-0.37	-1.90*	-0.69	-1.76*
hml	-0.37	-1.51	-0.36	-0.75
	10 cash flow-price (1956:07-2008:06)			
market	0.79	1.89*	2.20	2.60***
smb	0.07	0.36	0.20	0.46
hml	0.36	2.66***	0.75	2.80***
	10 earnings-price (1956:07-2008:06)			
market	0.66	1.91*	1.79	2.61***
smb	0.42	1.98**	0.88	2.09**
hml	0.41	2.93***	0.90	3.19***
	10 dividend-price (1932:06-2008:06)			
market	-0.26	-0.90	-0.04	-0.06
smb	0.02	0.10	0.11	0.23
hml	0.09	0.61	0.38	1.19
	10 short-term reversal (1931:02-2008:06)			
market	1.25	2.55**	3.18	3.43***
smb	-0.36	-1.21	-0.64	-1.13
hml	0.28	0.99	0.91	1.61

* significant (10-percent level)
** significant (5-percent level)
*** significant (1-percent level)

This table depicts the results for the Fama-French three-factor model illustrated by equation 1.2 when using the returns of 25 portfolios sorted by momentum and size, 10 portfolios sorted by momentum, 10 portfolios sorted by the cash flow-price ratio, 10 portfolios sorted by the earnings-price ratio, 10 portfolios sorted by the dividend-price ratio, and 10 portfolios sorted by short-term reversal as dependent variables. one month returns. market denotes the risk premium of the market risk, smb that of the size and hml that of the book-to-market risk. The coefficients are given as percentage points per month.

test are similar except that market risk is not significant at the 10% level. In contrast to the 25 size and book-to-market portfolio used in the the previous sections the book-to-market factor is not priced when considering the 25 size and momentum portfolios. This is confirmed for the ten portfolios exclusively sorted with respect to momentum. Size risk as well as market risk are negatively priced, whereas book-to-market risk is unpriced. Again, the FG test finds a priced size factor, though, an insgnificant coefficient for market and book-to-market risk. The relevance of size risk suggests that the risk of buying stocks of small firms has a negative influence on the momentum returns. An intuitive explanation is the following. This observation may be caused by the fact that winner stocks, in particular portfolios seven to nine, are negatively correlated with the size factor. After a period of exceptional performance small firms possibly have significant opportunities to continue their fast growth while bigger ones may be limited in their capacity to create further growth. Therefore, bigger companies may be considered riskier and, thus, require a higher return due to their size. The negative pricing of market risk may be explained by a negative correlation between momentum and market betas. For the other four test portfolios we find very similiar results in terms of the significance of the risk factors. As in the last subsections the results of the FG test affirm the results of the Fama-MacBeth test. Still, the similarity of the two tests can be accidental. In order to gain deeper insights we conduct a simulation to evaluate the power and the size of the two tests in the next section.

An interesting by-product is the finding that the significance of the risk factor highly depends on the way test portfolios are sorted. For instance, book-to-market is highly significant for the 10 cash flow-price portfolios and 10 earnings-price portfolios, though, it is not for the 10 dividend-price portfolios and 10 short term-reversal portfolios.

For the sake of completeness we also present the results for the conditional approach using different test portfolios as dependent variables. As depicted in Table 1.8, most coefficients are significant. Exceptions are the hml-up λ for the pure momentum portfolios, the market-down λ for the cash-flow portfolios and the smb-up λ for the 10 short term reversal portfolios. All coefficients are in line with our presumption

Table 1.8: Conditional Relation between Fama-French Betas and Returns for diverse test portfolios

Variable	25 momentum-size (1932:01-2008:06) λ	t-stat	10 momentum (1932:01-2008:06) λ	t-stat	10 cash flow-price (1956:07-2008:06) λ	t-stat
cons	1.47	4.92***	1.51	3.61***	-0.31	-0.74
market-up	1.64	4.18***	1.25	2.26**	2.14	4.17***
market-down	-4.04	-8.65***	-3.64	-5.40***	-1.15	-1.60
smb-up	2.28	12.95***	1.14	4.31***	1.18	4.37***
smb-down	-1.71	-7.70***	-1.98	-6.63***	-1.08	-3.29***
hml-up	0.69	2.68**	0.32	0.94	1.99	13.62***
hml-down	-1.18	-4.16***	-1.26	-3.53***	-1.87	-6.31***
	10 earnings-price (1956:07-2008:06)		10 dividend-price (1932:06-2008:06)		10 short term-reversal (1931:02-2008:06)	
cons	-0.12	-0.34	1.04	3.56***	-0.63	-1.32
market-up	2.34	5.31***	1.78	4.85***	2.97	4.35***
market-down	-1.75	3.01***	-3.34	-6.63***	-1.29	-1.85*
smb-up	1.69	5.53***	1.26	4.19***	0.65	1.45
smb-down	-0.91	-2.95***	-1.29	-3.41***	-1.43	-3.63***
hml-up	1.90	12.28***	1.41	7.31***	1.06	2.70***
hml-down	-1.63	-5.59***	-1.62	-6.35***	-0.71	-1.68*

* significant (10-percent level)
** significant (5-percent level)
*** significant (1-percent level)

This table depicts the results for the Fama-French three-factor model illustrated by equation 1.2 when using the returns of 25 portfolios sorted by momentum and size, 10 portfolios sorted by momentum, 10 portfolios sorted by the cash flow-price ratio, 10 portfolios sorted by the earnings-price ratio, 10 portfolios sorted by the dividend-price ratio, and 10 portfolios sorted by short-term reversal as dependent variables. cons denotes the constant term, market up (down) the risk premium of the market given that the excess market return is positive (negative), smb up (down) that of the size given that the smb factor is positive (negative)and hml up (down) that of the book-to-market risk given that the hml factor is positive (negative). The coefficients are given as percentage points per month.

finding a positive coefficient for positive realizations of the factors and negative coefficients for negative realizations of the factors such that we can draw the conclusion that that there exists a strong relationship between Fama-French betas and return, independently of the construction of test portfolios.[8]

1.6 Simulation

So far, our results suggest that the Fama-MacBeth and the FG test lead to qualitatively similar results. However, this might occur merely by coincidence. The number of ways test portfolios are sorted is limited and does not allow us to draw any firm conclusions. In order to compare the performance of the two tests in a more general way, a simulation approach seems appropriate. We calibrate a Monte Carlo simulation in order to determine the power and the size of the Fama-MacBeth and the FG test. Our simulation works as follows. Initially, we estimate betas from 25 portfolios sorted by size and book-to-market. We assume that our time varying betas are predetermined for the entire simulation.[9] As cross-sectional correlation among portfolio returns is to be suspected, we use the residuals of the 25 portfolios to estimate a cross-sectional correlation matrix. By multiplying the Cholesky decomposition of the correlation matrix with the generated residuals we incorporate cross-sectional correlation into our framework.

In the second step, we generate error terms. We consider three different ways to specify residuals. As a benchmark case we assume that residuals are normally distributed with mean zero. We obtain the variance by calculating the empirical variance of the residuals for each portfolio. Since normally distributed stock returns cannot model the observed unconditional leptokurtosis in stock returns, we examine two further approaches. In order to model residuals in a more realistic fashion, we generate residuals by the Pearson distribution. The Pearson system, developed by Pearson (1895), is a family of continuous probability distributions which is fully specified

[8] The results for the subperiods are consistent with those results and are available on request.

[9] Keeping the betas constant and modeling all factors alike enables us to evaluate if the power of the test depends on the way portfolios are sorted. For instance, using the 25 portfolios sorted by size and book-to-market we expect that both tests have lower power to detect a priced market factor than a book-to-market factor just because the variation in market betas is lower.

by its first four standardized moments. It enables us to construct probability distributions, which exhibit considerable skewness and kurtosis. The Pearson system can be subdivided into seven types. Our focus is on Pearson type IV, which is not related to any standard distribution.[10] In order to model the observed fat tails, we compute the empirical kurtosis in addition to the standard deviation and generate error terms.[11] Finally, we go one step further and model the skewness. The distributions so far are based on the assumption of symmetry, which is not fulfilled, e.g., for the size and book-to-market factor. The same holds true for some of the 25 portfolio residuals. Applying the test by Ekström and Jammalamadaka (2007) we find that the size and book-to-market risk factor and some portfolio residuals exhibit an asymmetric distribution. Therefore, we calculate the empirical skewness. In each iteration, we draw random variables from the Pearson distribution based on the estimated standardized moments of our residuals.

In the third step, we generate the market, size and book-to-market factors drawing random numbers in the same way as for the residuals. Again, we consider three distributions: Normal distribution, Pearson type IV distribution with and without skewness. The only difference is that we have to add the empirical mean of the factors to the generated values. For instance, Figure 1.4 depicts the histogram of the HML factor and compares it to the histogram of the simulated factor. The simulated factor realizations are chosen randomly.
Subsequently, we have all ingredients to specify the portfolio excess returns. In the case that market beta risk is priced, stock returns are generated from:

$$r^e_{i,t} = \beta^m_{i,t} r^e_{m,t} + \beta^{smb}_{i,t} r_{smb,t} + \beta^{hml}_{i,t} r_{hml,t} + \epsilon_{i,t}. \tag{1.9}$$

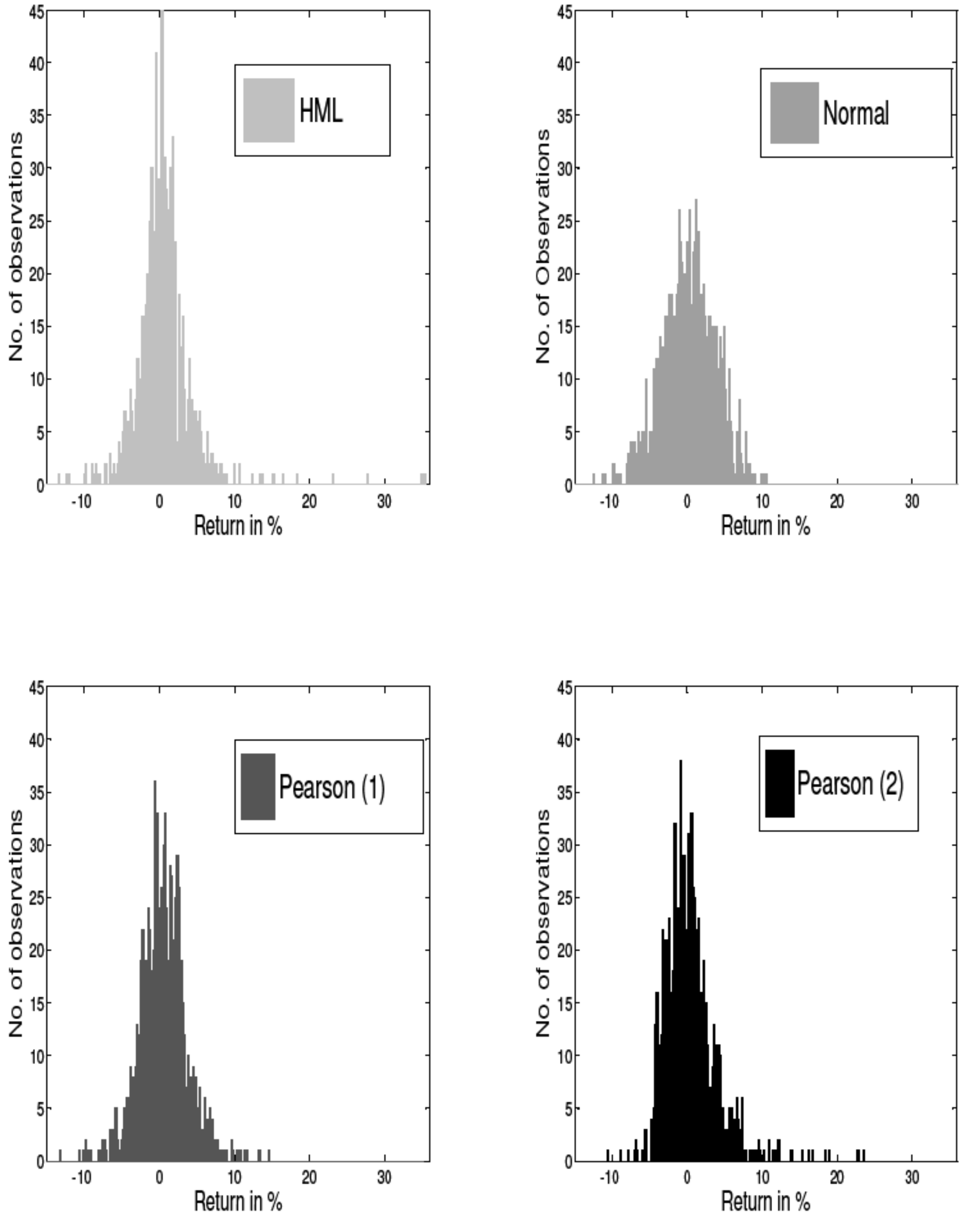
Alternatively, when market beta risk is not priced, we obtain the following equation:

$$r^e_{i,t} = \mu_m + \beta^m_{i,t}(r^e_{m,t} - \mu_m) + \beta^{smb}_{i,t} r_{smb,t} + \beta^{hml}_{i,t} r_{hml,t} + \epsilon_{i,t}, \tag{1.10}$$

[10]The density function is proportional to $(1 + ((x-a)/b)^2)^{-c} * \exp(-d * \arctan((x-a)/b))$.

[11]Numbers are generated by MATLAB using the "pearsnd" command. Given the first four moments, the parameters a,b,c and d can be identified.

Figure 1.4: Distribution of the HML factor



The first figure depicts the histogram of the HML factor (HML). The other figures illustrate the histogram of the generated HML factor based on random numbers drawn from three different distributions. Version 1 is based on the normal distribution (Normal), version 2 on the Pearson type IV distribution without skewness (Pearson (1)) and version 3 on the Pearson type IV distribution with skewness (Pearson (2)). The generated factors are taken arbitrarily.

Table 1.9: Power and Size of the Fama-MacBeth and the FG test (5% two-sided)

		Market		SMB		HML	
Distribution		FM	FG test	FM	FG test	FM	FG test
Normal	Size	0.042	0.041	0.057	0.056	0.051	0.052
	Power	0.672	0.670	0.678	0.678	0.941	0.945
Pearson (1)	Size	0.066	0.067	0.051	0.053	0.063	0.058
	Power	0.607	0.591	0.690	0.694	0.941	0.941
Pearson (2)	Size	0.031	0.033	0.053	0.053	0.050	0.047
	Power	0.612	0.610	0.708	0.710	0.956	0.957

Table 1.10: Power and Size of the Fama-MacBeth and the FG test (10% two-sided)

		Market		SMB		HML	
Distribution		FM	Adj. test	FM	Adj. test	FM	Adj. test
Normal	Size	0.097	0.090	0.110	0.107	0.095	0.101
	Power	0.779	0.780	0.794	0.797	0.974	0.974
Pearson (1)	Size	0.117	0.121	0.098	0.099	0.102	0.102
	Power	0.716	0.720	0.797	0.797	0.965	0.967
Pearson (2)	Size	0.077	0.075	0.010	0.094	0.099	0.097
	Power	0.726	0.726	0.811	0.814	0.979	0.980

This table depicts the power and the size of the Fama-MacBeth test (FM) and the FG test for each risk factor. Market denotes the market excess return, SMB the size factor and HML the book-to-market factor. Factors and residuals are generated drawing random numbers from three different distributions: Normal distribution (normal), Pearson type IV distribution without skewness (Pearson (1)) and Pearson type IV distribution with skewness (Pearson (2)). The value of the t-statistic in each case is then tested for significance at the 5 % (table 1.9) and at the 10% (table 1.10) two-sided level.

where $\mu_m = E[r^e_{m,t}]$. Analogously, returns for priced and not priced size and book-to-market risk are generated. The number of generated returns coincides with the number of observations (924) in section 1.4 and 1.5. The simulation exercise is based on 1000 replications. In each replication, factors and residuals are produced and equation 1.9 and 1.10 are used to generate portfolio excess returns.

The results of the simulation are depicted in Tables 1.9 and 1.10 and convey some very interesting insights. Results vary across factors. Testing for a priced market factor the Fama-MacBeth test offers a slightly higher power than the FG test at the 5% level but a smaller power at the 10% level independent of the choice of the distribution. In the case of the size and book-to-market factors, the FG test surpasses the power of the Fama-MacBeth test. However, the differences are small. The size of the two tests is almost identical. All in all, our findings indicate that the differences between the two tests are marginal, supporting the results in the last section. Moreover, we cannot support the conjecture of Freeman and Guermat (2006). They reckon that the power of the FG test exceeds the power of the Fama-MacBeth test in the presence of stock returns with fat tails.

Another insightful feature is that the power of the tests behaves very differently when we pass on to fat-tailed distributions. Both tests exhibit considerably lower power when using the market factor whereas the power tends to rise for the size and book-to-market factor. Including skewness slightly increases the power of the two tests no matter which factor we consider.

There is another noteworthy feature. Test results suggest that both tests have more difficulties to detect a priced market factor than a priced book-to-market factor. This finding could be due the fact that the first four moments are different. Though, even if all factors are identically constructed with the same first four moments, this phenomenon prevails because of the differences in betas. Variation in book-to-market beta across portfolios is much higher than the variation in market beta across portfolios, which suggests that a wide spread in betas substantially raises the power of the test independent of the distribution. This finding underlines how crucial the sorting criteria are.

1.7 Summary and Conclusion

Our results provide evidence that there exists a systematic relationship between the three Fama-French betas and return. Despite the inclusion of the size and book-to-market factors, we detect a systematic conditional relationship between market beta and return. Furthermore, the two additional factors of the three-factor model amplify their explanatory power once the conditional nature of the relation between beta and return is considered. This finding is consistent for different subperiods and test portfolios. Thus, the use of the conditional three-factor model betas estimated from historical price data by portfolio managers seems to be appropriate.

The main drawback of this procedure is that it does not test if risk factors entail a priced risk. On this account, we go one step further in this paper and generalize the FG test to multi-factor models in order to test for priced betas within the conditional approach. We compare the results of the FG test to the results of the classical Fama-MacBeth test. Based on different test portfolios we find qualitatively similar results for both test. The same holds true when we run simulations specifiying distributions with excess kurtosis and skewness. Hence, our study shows that the results of the FG test based on the conditional approach coincide with those from the standard Fama-MacBeth test procedure. Our findings suggest that the power of a test is not improved by the application of the conditional approach. To put it differently, our results confirm the standard Fama-MacBeth procedure. Because of the additional complexity of using the FG test the standard Fama-MacBeth test is favored.
Our findings stress the importance of the use of different test portfolios. Applying diverse test portfolios, we find starkly differing results. For some test portfolios risk factors seem positively priced, for some negatively priced and for others, they appear not to be priced at all. Thus, focusing on one selection of test portfolios, as often done so in the literature, can cause misleading results.

Many previous studies have applied the conditional approach as proposed by Pettengill et al. (1995). The conditional approach takes into account that the use of realized returns leads to a negative risk-return relationship in down-markets. Thus, the conditional approach appears more appropriate. However, either previous studies test if beta risk is priced within the framework of the conditional approach but based on a flawed hypothesis (symmetry of the λ coefficients) or they only test if there exists a conditional relationship between beta and return. In either case, the results of the test cannot be related to the results from the standard Fama-MacBeth procedure. In this paper, we make these tests comparable by using the conditional approach to derive the FG test for priced beta and discover that the FG test leads to qualitatively similar findings as the classical Fama-MacBeth test. We do not want to claim that the conditional approach is irrelevant but we want to point out that the choice of the test procedure depends on the research question. Testing for priced beta risk does not make the conditional approach necessary. Nevertheless, if we only focus on testing for a systematic relationship between beta risk and return, then the conditional approach is suitable.

Chapter 2

Market Response to Investor Sentiment

2.1 Introduction

Recent empirical research suggests that survey measures of investor sentiment have the ability to predict future stock returns over the intermediate and long term. The usual econometric approach is to regress future stock index returns on a sentiment indicator and appropriate control variables. The aim of using the controls is to account for variables (such as the term and yield spread) that are already known to predict future returns. A significant coefficient for the sentiment indicator is interpreted as evidence that sentiment predicts future returns.

There are at least two potential explanations for the predictive ability of sentiment indicators. First, sentiment indices may contain information about future expected returns that is not already captured by the control variables.[1] In this case, the predictive ability of sentiment indicators does not necessarily imply a violation of market efficiency. Second, sentiment indicators may be related to mispricing (as

[1]Alternatively, sentiment indicators could forecast higher expected future cash flows. In this case the publication of the sentiment indicator should trigger an immediate price effect (i.e., a significant announcement day return), but should not predict future returns over longer horizons. The intermediate and long-term predictability reported in previous research is thus inconsistent with this interpretation.

also proposed by Brown and Cliff (2005)). Positive sentiment, for example, may go hand-in-hand with share prices being driven above their fundamental values by the actions of overly optimistic investors. The resulting pricing errors are then corrected later on. Consequently, current sentiment indicators will be negatively related to future returns. In this case, the predictive power of sentiment measures provides evidence for a violation of market efficiency.

The implications of these two alternative explanations differ markedly. It is thus very important to discriminate between the 'expected return news' and 'mispricing' scenarios. The present paper makes a step in this direction. Our approach is to simultaneously consider intermediate and long-horizon predictability on the one hand, and the immediate market reaction to the publication of sentiment indicators on the other. This approach has a simple intuition. Current prices are inversely related to expected returns. If sentiment indicators contain information about future expected returns, the sign of the immediate market reaction should be opposite to that obtained from long-term predictive regressions. If, on the other hand, sentiment indicators are related to mispricing, we should find that the immediate market reaction has the same sign as that found from predictive regressions. This is due to the fact that smart investors exploit the information contained in the sentiment indicator. If bullish sentiment predicts positive [negative] future returns smart investors will buy [sell] and thus cause an immediate positive [negative] market reaction.

To the best of our knowledge, our paper is the first to empirically analyze the immediate response of stock returns to the publication of survey-based sentiment measures. We use data from Germany and the US. In the first part of our analysis we rely on the methodology proposed by Brown and Cliff (2005). We replicate their tests for medium and long-term predictability. Consistent with previous results in the literature, we find a significant negative relationship between the sentiment indicator and subsequent medium term (up to three months) index returns in the US for the earlier parts of our sample period (1987-1994 and, to a much lesser extent, 1994-2001). This relationship disappears towards the end of our sample period. In the final subperiod (2001-2008), the coefficients of the predictive regressions are predominantly positive but only weakly significant. The sentiment indicator for the

German market is correlated positively with future returns. This is consistent with the results from the US, because the German sample covers he years 2001-2008, which is precisely the period for which we also find positive coefficients in the US sample.

In the second step of our analysis, we use event study methodology to test whether daily index returns respond to the publication of the sentiment indicator. We do find a significant positive announcement day effect in Germany. However, not all of the predictive power of the indicator is captured on the announcement day. This pattern is consistent with a scenario of mispricing and of limited arbitrage. Smart investors are aware of the predictive power of the sentiment indicator and trade accordingly. However, they do not fully arbitrage the predictability away, possibly because of increased noise trader risk (as in the model of De Long et al. (1990)).

For the US market there is evidence of a negative publication day effect in the subperiod 1987-1994. As in the case of Germany this result is consistent with a scenario of mispricing and limited arbitrage. In later subperiods there is no such effect. This should come as no surprise, because the intermediate- to long-term predictability also largely disappears towards the end of the sample period.

Our paper is related to previous studies investigating the predictive power of sentiment indicators. Brown and Cliff (2004, 2005), Clarke and Statman (1998), Fisher and Statman (2000), Kaniel et al. (2008), Otoo (1999), Shiller (2000), Solt and Statman (1988) and Verma et al. (2008) all analyze survey-based sentiment measures for the US market.[2] Although the results are mixed (probably due to differences in sample periods, methodology, and the forecasting periods), on balance these previous studies find evidence of long-horizon predictability. Schmeling (2007) applies a similar methodology to data from the German stock market and also reports evidence of predictability. Although some papers have tested for short-term predictability (e.g.

[2]A large number of papers uses market-based sentiment measures. These sentiment proxies include, but are not limited to, mutual fund flows (Brown et al. (2003)), the closed-end fund discount (Elton et al. (1998), Lee et al. (1991), Neal and Wheatley (1998)), put-call ratios (Dennis and Mayhew (2002)) and various measures of trading activity (Barber and Odean (2008), Kumar and Lee (Kumar et al., 2006)). Baker and Wurgler (2006) construct a composite sentiment measure based on six underlying proxies. Brown and Cliff (2004) analyze market-based and survey-based sentiment measures and conclude that many of these measures are correlated.

at the weekly and monthly level as in Brown and Cliff (2004)), to our knowledge, the present paper is the first to test for announcement day effects.[3]

More generally, our paper also relates to previous research testing for return predictability (see Ang and Bekaert (2007) for a recent contribution). In particular, certain methodological concerns (the problem of using persistent regressors, first addressed by Stambaugh (1999), and the problem of using overlapping return data) are also present in our study. We account for these problems by adopting the bootstrap-based bias correction proposed by Brown and Cliff (2005).

The remainder of this paper is structured as follows. Section 2 describes our data set. In section 3, we present the methodology and results of our tests for predictability. Section 4 describes our tests for the existence of announcement day effects. Section 5 concludes.

2.2 Data

2.2.1 German Data

The analysis of intermediate and long-term predictability is based on weekly data. We use survey data from Sentix as our measure of investor sentiment. We prefer to use survey-based sentiment indicators over market-based ones because the publication of the survey results constitutes new information, while market-based indicators often only aggregate information that were already available.

Sentix conducts weekly surveys of institutional and private investors, and currently reaches over 2700 registered participants, about 800 of whom take part in the survey each week. Individual investors constitute on average about 76% of respondents, with this percentage generally varying between 70% and 80%. Voting is possible between Thursday afternoon and Saturday. Participants are asked whether they are bullish, bearish, neutral, or have no opinion with regard to the future trend of

[3]Schmitz et al. (2009) document short-term predictability (one and two days) of a sentiment measure constructed from data on warrant trades of retail investors. The data used to construct this measure is, however, not publicly available.

the DAX30 stock index over the following one and six months, respectively. In our analysis we only use data for the six month horizon because the AAII survey that we use in our US sample is also based on a six months forecasting horizon.

From the individual opinions obtained, Sentix computes the so-called value index, also known as the bull-bear spread. This is defined as

$$S_t = \frac{\#bullish - \#bearish}{\#total}$$

The Sentix index is published every Sunday evening or Monday morning prior to the opening of the market. It is available to all participants, and additionally, since January 2004, it has been available trough Thomson DataStream and Bloomberg. Furthermore, subindices that cover individual and institutional investors, respectively, are made available exclusively to participants.

The Sentix data starts on February 26, 2001 and ends on June 30, 2008. For our predictive regressions, we use forecasting horizons of 1, 4, 8, 13 and 26 weeks. To this end, we combine the Sentix data with data on the DAX index for the period February 26, 2001 to December 31, 2008. The aim of the predictive regressions is to test whether the sentiment indicator contains information about future returns beyond the information inferable from other publicly observable variables. We therefore control for variables that are known to predict future market returns. We include the return on the DAX30 for the pervious week, the exchange rate EUR/USD, the interest rate term spread between 10 year German government bonds and the Euribor 3 month rate, the credit spread (defined as the spread between yields on A rated corporate bonds of maturities between 3 and 5 years and the mean of 3 and 5 year German government bond yields[4]), the liquidity spread (defined as the spread between the Euribor 3-month and 1-month rates), and the Euribor 1-month rate.

For the analysis of announcement day effects of the Sentix index, i.e. the test whether the publication of the sentiment indicator has an immediate price effect,

[4]The number of corporate bonds issued by German firms and rated Aaa and Baa is to small to reliably estimate the credit spread as the difference between the yields on Baa-rated and Aaa-rated corporate bonds (as we do in our US sample). Therefore, we use the yield difference between A-rated corporate bonds and government bonds instead.

we use daily data. As the Sentix index is published on the weekend, we consider the return of the DAX30 between its closing value on Friday and that on Monday. To this end, we regress daily DAX returns on a variable which is equal to the sentiment indicator on Mondays and zero on all other days. The regression includes lagged DAX returns, lagged S&P 500 returns (to account for the fact that respondents may participate in the survey until Saturday and may therefore base their opinion on the US stock market return from the previous week) and a Monday dummy (to control for a weekend effect) as control variables.

Table 2.1 provides summary statistics of all the variables. The mean of the Sentix index is 0.12, indicating that the respondents are, on average, slightly bullish. The mean daily DAX return is very close to zero. The serial and cross correlations (shown in the last two columns of the table) indicate that the Sentix index is highly autocorrelated and depends on the previous values of the DAX index. Both these observations are consistent with the findings of previous research.

Table 2.1: Summary Statistics of German data

	Mean	Std. Dev.	ρ_i	$\rho_{s,i}$
Sentix$_t$	0.121	0.113	0.773	1.000
ΔSentix$_t$	-0.000	0.067	-0.301	0.335
InnoSentix$_t$	0.002	0.058	0.070	0.726
$r^{DAX}_{t-2,t-1}$	0.000	0.032	0.016	0.048
$r^{S\&P500}_{t-2,t-1}$	0.000	0.022	-0.054	0.007
EUR/USD$_{t-1}$	1.185	0.187	0.988	0.029
Term Spread$_{t-1}$	0.011	0.008	0.986	-0.107
Credit Spread$_{t-1}$	0.011	0.003	0.946	-0.243
Liquidity Spread$_{t-1}$	0.001	0.001	0.937	0.112
Euribor 1m$_{t-1}$	0.031	0.009	0.990	-0.025

The table presents summary statistics for the German data. All returns are from Friday close to the next Friday close. Other control variables (the EUR/USD exchange rate, the term, credit and liquidity spread and the Euribor 1-month rate) are from Friday. The Sentix index is published on Sunday evenings or Monday mornings. Sentix$_t$ denotes the index level, ΔSentix$_t$ denotes its weekly change, and InnoSentix$_t$ the unexpected component of the index (the residual of a linear regression of the index on its lagged value and the lagged DAX return). ρ_i denotes the first-order serial correlation of variable i, $\rho_{s,i}$ denotes the correlation between the Sentix index and variable i.

2.2.2 US Data

We use data obtained from the American Association of Individual Investors (AAII). The AAII conducts weekly surveys of its members, the results of which are published every Thursday[5] morning, before the stock market opens. Participants are asked whether they expect the direction of the stock market over the following six months to be 'up', 'no change', or 'down', and can participate once during every weekly period ranging from Thursday to Wednesday. We use a value index (bull-bear spread) that is calculated using these data for the period July 24, 1987 to June 26, 2008. As Table 2.2 shows, the mean, standard deviation and first order autocorrelation of the AAII indicator are comparable to those of the German Sentix index.[6]

The AAII survey does not specify which stock index it refers to. We therefore use the Dow Jones Industrial Average, the Standard & Poors 500, the NASDAQ 100, and the Russell 3000 indices. We estimate predictive regressions for forecasting horizons of 1, 4, 8, 13 and 26 weeks. As for the German case, we include other variables known to have predictive power for market returns as control variables. We include the same variables as for the German sample but replace the Euribor rates with Treasury bill rates. Thus, we control for the past week's return of the stock index in question, the exchange rate EUR/USD (DM/USD prior to the introduction of the Euro), the interest rate term spread between 10 year US Treasury bonds and the Treasury bill 3 month rate, the credit spread (defined as the yield spread between Baa and Aaa rated corporate bonds), the liquidity spread (defined as the spread between the US Treasury bill 3 month and 1 month rates) and the US Treasury bill 1 month rate.

In the analysis of announcement day returns, we again use daily data. We regress

[5]This applies to the period from November 1993 onwards. Before, the day of publication had been Friday. In case of public holidays, the index is published on the last trading day before that holiday. In our analysis, we take account of the exact publication days.

[6]Note that while the AAII index published on Thursday morning is more strongly related to the S&P return over the previous week (ending on the Wednesday prior to publication) in comparison to the German data, the relation is significant only for the later part of our sample. This is most likely due to the fact that, until 2000, the AAII survey was conducted by regular mail. This procedure obviously introduces a lag of several days. We find strong support for this conjecture when we estimate the correlation between the AAII index and the S&P return over the previous week separately for the period before and after the change in procedure. Prior to 2000 the correlation is 0.010 whereas after 2000 it is 0.287.

Table 2.2: Summary Statistics of US data

	Mean	Std. Dev.	ρ_i	$\rho_{s,i}$
AAII_t	0.099	0.188	0.670	1.000
ΔAAII_t	-0.001	0.152	-0.343	0.400
InnoAAII_t	0.008	0.135	-0.144	0.738
$r_{t-2,t-1}^{S\&P500}$	0.001	0.021	-0.053	0.134
USD/EUR_{t-1}	1.168	0.149	0.990	-0.198
Term Spread_{t-1}	0.017	0.012	0.992	0.026
Credit Spread_{t-1}	0.009	0.002	0.979	-0.202
Liquidity Spread_{t-1}	0.027	0.012	0.989	-0.132
Treasury bill 1m_{t-1}	0.017	0.008	0.988	-0.152

The table presents summary statistics for the US data. All returns are for the week prior to the publication of the AAII index. Other control variables (the USD/EUR exchange rate, the term, credit and liquidity spread and the 1-month T-bill rate) are from Wednesdays. The AAII index is published on Thursday morning. AAII_t denotes the index level, ΔAAII_t denotes its weekly change, and InnoAAII_t the unexpected component of the index (the residual of a regression of the index on its lagged value and the lagged S&P return). ρ_i denotes the first-order serial correlation of variable i, $\rho_{s,i}$ denotes the correlation between the AAII index and variable i.

daily index returns on a variable which is equal to the sentiment indicator on Thursdays and zero on all other days. The regression includes lagged index returns and a Monday dummy (to control for a weekend effect) as control variables.

2.3 Predictive Regressions

2.3.1 Results for Germany

In this section we analyze whether investor sentiment, measured using the Sentix survey, is able to predict asset returns for horizons from one to 26 weeks. As proposed by Brown and Cliff (2005), we use a bootstrap simulation to account for problems caused by overlapping observations and persistent regressors.[7] We estimate

$$(r_{t+1} + ... + r_{t+k}) = \alpha(k) + \Theta'(k)z_t + \beta(k)S_t + \epsilon_t^{(k)}, \tag{2.1}$$

[7] Compare also Brown and Cliff (2005), p. 418.

where r_{t+k} denotes the k week-ahead future DAX log return. $\alpha(k)$ is the constant for a forecasting horizon of k weeks, and z_t is a vector of the control variables listed in section 2.2.1. S_t is the value of the long-term Sentix survey. Using the bootstrap procedure, we obtain coefficient estimates and associated p-values based on the distribution of the estimated coefficients. Details of the procedure are explained in the Appendix.

Table 2.3 shows the results obtained using the procedure described above. It shows that the aggregate Sentix index, which, on average, consists of roughly three quarters individual and one quarter institutional respondents, has predictive power for future DAX 30 returns for periods from one to 8 weeks. The bootstrap coefficient estimates are always larger than the OLS estimates, although the differences are small. In spite of their larger numerical values, the bootstrap coefficients have higher p-values. Our interpretation of the results will be based on the more conservative bootstrap procedure.

Table 2.3: Sentiment Coefficient in k-Week Regressions for Aggregate 6 Month DAX Sentiment

Reg. Horizon	OLS		Bootstrap	
	$\hat{\beta}^{OLS}$	Sig. level	$\tilde{\beta}^{SIM}$	Sig. level
1 week	0.0395**	0.011	0.0403**	0.036
4 weeks	0.1101***	0.000	0.1156**	0.049
8 weeks	0.1783***	0.000	0.1887**	0.041
13 weeks	0.1337***	0.000	0.1519	0.194
26 weeks	-0.0455	0.712	-0.0179	0.958

The table presents the β coefficients of equation $(r_{t+1} + ... + r_{t+k}) = \alpha(k) + \Theta'(k)z_t + \beta(k)S_t + \epsilon_t^{(k)}$ obtained from OLS estimation (columns 1 and 2) and bootstrap simulations as explained in the appendix (columns 3 and 4). Results are presented for forecasting horizons of $k = 1, 4, 8, 13,\ 26$ weeks. The control variables are listed in section 2.2.1. $***$, $**$ and $*$ denote statistical significance at the 1%, 5% and 10% levels, respectively.

The sign of the relationship between the sentiment indicator and future DAX returns is positive. From the standard deviation of the Sentix index shown in Table 2.1 and the coefficient of the predictive regression shown in Table 2.3, it follows that a change of one standard deviation in the Sentix index is associated with a change in the DAX of almost 2%. over an 8-week horizon. This is not only statistically, but also economically significant.

These results could indicate that the sentiment index foreshadows future misvaluation. Interestingly, the coefficient in the 26-week predictive regression is the smallest of all the five predictive regressions. This pattern is consistent with the sentiment index indicating a future misvaluation which is subsequently corrected in the second half of the 26-week prediction period. Alternatively, the sentiment indicator may contain information on future expected returns. The analysis of the announcement day effects in section 4.1 will allow us to discriminate between these interpretations. As previously noted, if the sentiment indicator contains information about future expected returns, the announcement day effect should have a sign opposite to that in the predictive regressions.

2.3.2 Results for the US

We conduct the same analysis as for the Sentix data for the American Association of Individual Investors sentiment index. We use the Standard & Poors 500 index as the index whose return is to be predicted. However, the results are qualitatively identical for the Dow Jones Industrial Average, the NASDAQ 100, and the Russell 3000 indices. First, we apply our procedure to the whole period from 1987 to 2008. The results, shown in Table 2.4, indicate that US individual investor sentiment is inversely related to future S&P 500 returns. Using the bootstrap results, this relation is significant only for the 26-week ahead forecast. These findings are consistent with those of Fisher and Statman (2000) and Brown and Cliff (2005). These authors also find an inverse relationship between sentiment and future returns for samples covering the periods 1987-1998 and 1963-2000, respectively. Our negative coefficient is consistent with the sentiment index indicating a current misvaluation which is subsequently corrected over the forecasting period.

The record of the AAII sentiment index is much longer than that of the Sentix index. In order to check whether the results are stable over time we split the AAII data into three subperiods of approximately equal length and apply our bootstrap procedure to each of these subsamples. The third subsample coincides with the same period as our

German sample. Table 2.5 shows that the negative relationship between the AAII index and subsequent returns disappears over time. It is very pronounced and highly significant in the 1987-1994 sample. In the 1994-2001 sample the coefficients retain their sign but are smaller in magnitude and (at least when considering the bootstrap results) mostly insignificant. In the final subperiod, most coefficient estimates are positive, and the coefficients for the one- and four-week horizons are significant at the 10 percent level. In this subperiod, then, the results for the US are qualitatively similar to those obtained for the German case documented in Table 2.3. We also found coefficients that were unanimously positive and significant for short forecasting horizons in that case. We can only speculate about the reasons for the change in the predictive ability of the AAII index over time. One possible explanation is the change in the way the AAII survey is conducted. Originally, the votes were collected by post which resulted in a lag of some days. This lag ceased when AAII began to collect the votes via the internet in 2000. The change in the procedure may also have affected the composition of the subgroup of AAII members that respond to the survey. Finally, it is conceivable that the characteristics of the AAII members themselves have changed over time.

As noted above, for the period 2001 - 2008 we find positive coefficients in the predictive regressions both for Germany and the US. Although the signs of the coefficients are similar for the two countries, their magnitude is not. Consider the 8-week forecasting period as an example. As noted in the previous section a change of one standard deviation in the Sentix index is associated with a 2% change in the DAX over an 8-week horizon. The corresponding figure for the US is less than 0.5%. It thus appears that the predictive power of the Sentix index is stronger than that of the AAII index. This may be due to differences in the populations of the respective participants. The Sentix index is much younger than the AAII survey and is much less well known to the general public. Participants in the Sentix survey are likely to be active traders with a strong interest in financial markets. This may not be generally true for respondents to the AAII survey.[8]

[8]To shed more light on the differences between the Sentix and AAII indices we related them to the time series of flows into mutual funds (results are omitted from the paper). The results indicate that the AAII index is highly positively correlated to net flows into equity funds while

Table 2.4: Sentiment Coefficient in k-Week Regressions for AAII Sentiment and S&P 500

Reg. Horizon	OLS		Bootstrap	
	$\hat{\beta}^{OLS}$	Sig. level	$\tilde{\beta}^{SIM}$	Sig. level
1 week	0.0024	0.810	0.0029	0.371
4 weeks	-0.0159***	0.002	-0.0142	0.264
8 weeks	-0.0252***	0.000	-0.0223	0.273
13 weeks	-0.0433***	0.000	-0.0389	0.129
26 weeks	-0.0729***	0.000	-0.0651*	0.076

The table presents the β coefficients of equation $(r_{t+1} + ... + r_{t+k}) = \alpha(k) + \Theta'(k)z_t + \beta(k)S_t + \epsilon_t^{(k)}$ obtained from OLS estimation (columns 1 and 2) and bootstrap simulations as explained in the Appendix (columns 3 and 4). Results are presented for periods of $k = 1, 4, 8, 13, 26$ weeks. The control variables are listed in section 2.2. $***$, $**$ and $*$ denote statistical significance at the 1%, 5% and 10% levels, respectively.

2.4 Announcement Day Effects

2.4.1 Results for Germany

Having established that the German investor sentiment survey Sentix is indeed able to predict the future movements in the DAX index, we now test whether the market reacts to the publication of the sentiment indicator. To this end, we regress daily DAX log returns $r_{t-1,t}^{DAX}$ on their first lag[9] and on the variable $Sentiment_t$ which captures the information content of the sentiment indicator. Because the Sentix index is published on Sunday evenings or on Monday mornings prior to the start of trading, the variable $Sentiment_t$ is non-zero on Mondays and zero from Tuesdays to Fridays.

Respondents to the German survey can submit their statement after observing the

there is no significant relation for the Sentix index.

[9]The DAX index is calculated from the prices in Xetra, the by far most liquid market for German stocks. Until November 2003 trading in Xetra closed at 8 p.m. Since then, however, trading in Xetra closes at 5.30 p.m. while trading on the floor of the Frankfurt Stock Exchange (which coexists with Xetra) continues until 8 p.m. When survey respondents submit their opinion during the week end they know the prices from floor trading. Therefore, from November 2003 onwards, the lagged DAX return included on the right-hand side is the return of an index called Late DAX. It is based on the same formula and weighting scheme as the DAX but uses the prices from the floor of the Frankfurt Stock Exchange.

Table 2.5: Sentiment Coefficient in k-Week Regressions for AAII Sentiment and S&P 500 - Subperiods

	07/1987 to 06/1994			
Reg. Horizon	OLS		Bootstrap	
	$\hat{\beta}^{OLS}$	Sig. level	$\tilde{\beta}^{SIM}$	Sig. level
1 week	-0.0054*	0.090	-0.0042	0.662
4 weeks	-0.0526***	0.000	-0.0470**	0.045
8 weeks	-0.0699***	0.000	-0.0586	0.145
13 weeks	-0.1158***	0.000	-0.0974*	0.058
26 weeks	-0.1746***	0.000	-0.1439*	0.052
	07/1994 to 01/2001			
Reg. Horizon	OLS		Bootstrap	
	$\hat{\beta}^{OLS}$	Sig. level	$\tilde{\beta}^{SIM}$	Sig. level
1 week	-0.0015	0.827	-0.0004	0.926
4 weeks	-0.0520***	0.000	-0.0475**	0.047
8 weeks	-0.0550***	0.009	-0.0466	0.241
13 weeks	-0.0618**	0.022	-0.0481	0.408
26 weeks	-0.1118***	0.000	-0.0880	0.252
	02/2001 to 06/2008			
Reg. Horizon	OLS		Bootstrap	
	$\hat{\beta}^{OLS}$	(t-stat.)	$\tilde{\beta}^{SIM}$	Sig. level
1 week	0.0100	0.338	0.0111**	0.049
4 weeks	0.0219	0.458	0.0252*	0.078
8 weeks	0.0200	0.897	0.0257	0.189
13 weeks	0.0168	0.308	0.0250	0.267
26 weeks	-0.0182***	0.000	-0.0047	0.804

The table presents the β coefficients of equation $(r_{t+1} + ... + r_{t+k}) = \alpha(k) + \Theta'(k)z_t + \beta(k)S_t + \epsilon_t^{(k)}$ obtained from OLS estimation (columns 1 and 2) and bootstrap simulations as explained in the Appendix (columns 3 and 4). Results are presented for periods of $k = 1, 4, 8, 13, 26$ weeks. The control variables are listed in section 2.2. $***$, $**$ and $*$ denote statistical significance at the 1%, 5% and 10% levels, respectively.

closing prices on the US stock market. We therefore include the lagged log returns of the S&P 500 index, $r_{t-2,t-1}^{S\&P500}$in our regression.[10] Finally, we include a Monday dummy $\mathbf{1}_{Monday_t}$ in order to capture possible day-of-the-week effects. For daily returns, problems induced by serial correlation are not an issue. However, the pattern of OLS residuals indicates strong ARCH effects, for which we account by specifying a GARCH(1,1) model. We estimate the following equations[11]:

$$r_{t-1,t}^{DAX} = a_0 + a_1 Sentiment_t + a_2 r_{t-2,t-1}^{DAX} + a_3 r_{t-2,t-1}^{S\&P500} + a_4 \mathbf{1}_{Monday_t} + e_t \qquad (2.2)$$
$$\sigma_t^2 = b_0 + b_1 e_{t-1}^2 + b_2 \sigma_{t-1}^2.$$

We estimate three specifications. In the first, sentiment is measured as the level of the Sentix value index. The second specification includes the change in the value index rather than its level. The third specification only uses the unexpected change in the value index. We obtain the unexpected change by first regressing the sentiment index on its own lagged values and lagged DAX and S&P 500 returns and then using the residuals from this regression This procedure is implemented using expanding windows. Thus, the first-pass regression used to identify the unexpected component of the sentiment index only uses information available at time (t-1).[12] Results are presented in table 2.6.

We find a positive and significant announcement day effect irrespective of the specification used. Thus, all three sentiment variables are significantly positively correlated to daily closing log returns. Hence, the market appears to react to the publication of the investor sentiment index. The DAX increases after a rise and decreases after a fall in the sentiment indicator. Lagged index returns are also significant, while we

[10] If we omitted the lagged S&P500 returns, the sentiment indicator could be significant merely due to the possibility that it serves as a proxy for the US stock returns after the close of trading in Germany.

[11] As mentioned previously the Sentix index is published on Sunday evening or Monday morning prior to the opening of the market (time index t). We analyze whether the publication of the Sentix index affects the DAX return from Friday's close (time t-1) to Monday's close (t).

[12] We use the data for 2001 to initialize the procedure. The first observations included in the second-pass regression are those for January 2002. Therefore, the number of observations in model 3 is lower than in models 1 and 2.

Table 2.6: Estimation Results for Daily DAX Log Returns of Closing Prices

Specification	(1)	(2)	(3)
Variable	Coef. ($\lvert t-stat.\rvert$)	Coef. ($\lvert t-stat.\rvert$)	Coef. ($\lvert t-stat.\rvert$)
$Sentix_t$	0.012**		
	(2.12)		
$\Delta Sentix_t$		0.025**	
		(2.52)	
$InnoSentix_t$			0.025**
			(2.30)
$r_{t-2,t-1}^{DAX}$	-0.166***	-0.166***	-0.182***
	(5.98)	(5.83)	(5.99)
$r_{t-2,t-1}^{S\&P500}$	0.285***	0.287***	0.289***
	(8.91)	(8.51)	(8.05)
$\mathbf{1}_{Monday_t}$	-0.001	7e-04	3e-04
	(1.27)	(1.14)	(0.51)
$Const.$	6e-04**	6e-04**	7e-04**
	(2.33)	(2.32)	(2.52)
$Obs.$	1,916	1,911	1,695
$Adj.R^2$	0.033	0.034	0.035

The table shows the results of a GARCH(1,1) with mean equation $r_{t-1,t}^{DAX} = a_0 + a_1 Sentiment_t + a_2 r_{t-2,t-1}^{DAX} + a_3 r_{t-2,t-1}^{S\&P500} + a_4 1_{Monday_t} + e_t$. $r_{t-1,t}^{DAX}$ is the return on the DAX index, $r_{t-2,t-1}^{S\&P500}$ is the return on the S&P 500 index, $Sentiment_t$ is equal to our sentiment measure on Mondays and zero else, and 1_{Monday_t} is a dummy variable that is set to one on Mondays. We use three sentiment measures, the level of the Sentix index (column 1), the first difference (column 2) and the residual from a regression of the Sentix index on its lagged value and the lagged DAX and S&P 500 returns (column 3). ***, ** and * denote significance at the 1%, 5%, and 10% level, respectively.

find no clear evidence in favor of a Monday effect on the German stock market.

The announcement day effect is positive and thus has the same sign as the intermediate-term predictability documented in section 3.1. This finding is inconsistent with the idea that the sentiment indicator provides information about future expected returns. If it did, we would expect the announcement day effect to have the opposite sign to that found in the predictive regressions for the intermediate term. Our results thus support a misvaluation interpretation of the predictive power of sentiment indicators.

2.4.2 Results for the US

We conduct a similar analysis to that described above for the AAII sentiment survey.[13] Remember from section 3.2 that we found negative, but mostly insignificant coefficients in the predictive regressions over the full sample period. Consistent with this result, the first panel of table 2.7 shows that, for the whole period, there is no significant announcement effect on the day the AAII sentiment is published. By considering the three sub-samples, we find results that mirror those of the predictive regressions shown in table 2.5. The publication of the sentiment index triggers a negative announcement day effect in the first subsample. The respective coefficient is significant (at the 10% level or better) in two out of the three specifications. We do not find a significant announcement day effect for the later subsamples. This is not surprising because the predictive regressions presented earlier led to the conclusion that the AAII index is largely unrelated to future returns in these subperiods.

The announcement day effect in the first sub-period has the same sign as that of the coefficients in the predictive regressions. The results for the US, like those for Germany, are thus inconsistent with the expected return news scenario. Rather, they support the interpretation that investor sentiment is related to misvaluation.

[13]Model 3 again uses a expanding-window procedure. The first year of data (July 1987 - June 1988) is used to initialize the procedure, the analysis of the announcement day effects starts in July 1988.

Table 2.7: Estimation Results for Daily S&P 500 Log Returns of Closing Prices

	07/1987 to 06/2008			07/1987 to 06/1994		
Specification	(1)	(2)	(3)	(1)	(2)	(3)
Variable	Coef. ($\|t-stat.\|$)	Coef. ($\|t-stat.\|$)	Coef. ($\|t-stat.\|$)	Coef. ($\|t-stat.\|$)	Coef. ($\|t-stat.\|$)	Coef. ($\|t-stat.\|$)
$AAII_t$	0.000			-0.005**		
	(0.17)			(2.43)		
$\Delta AAII_t$		-0.001			-0.003	
		(0.77)			(1.23)	
$InnoAAII_t$			-0.000			-0.004*
			(0.06)			(1.71)
$r_{t-2,t-1}^{S\&P500}$	-0.007	-0.007	-0.007	0.006	0.003	0.011
	(0.43)	(0.48)	(0.47)	(0.20)	(0.10)	(0.46)
1_{Monday_t}	0.000	0.000	0.000	0.001	0.001	0.001**
	(1.15)	(1.17)	(1.40)	(1.22)	(1.33)	(2.18)
$Const.$	0.000***	0.000***	0.000***	0.000	0.000	0.000
	(3.50)	(3.63)	(3.06)	(1.58)	(1.28)	(0.42)
	07/1994 to 01/2001			02/2001 to 06/2008		
Specification	(1)	(2)	(3)	(1)	(2)	(3)
Variable	Coef. ($\|t-stat.\|$)	Coef. ($\|t-stat.\|$)	Coef. ($\|t-stat.\|$)	Coef. ($\|t-stat.\|$)	Coef. ($\|t-stat.\|$)	Coef. ($\|t-stat.\|$)
$AAII_t$	-0.001			0.002		
	(0.31)			(0.86)		
$\Delta AAII_t$		0.002			-0.001	
		(0.54)			(0.49)	
$InnoAAII_t$			0.001			0.001
			(0.24)			(0.30)
$r_{t-2,t-1}^{S\&P500}$	0.041	0.041	0.041	-0.061**	-0.061**	-0.061**
	(1.53)	(1.54)	(1.54)	(2.40)	(2.40)	(2.39)
1_{Monday_t}	-0.000	-0.000	-0.000	0.000	0.000	0.000
	(0.62)	(0.60)	(0.58)	(0.58)	(0.44)	(0.44)
$Const.$	0.001***	0.001***	0.001***	0.000	0.000	0.000
	(4.04)	(4.32)	(4.23)	(0.98)	(1.28)	(1.28)

The table shows the results of a GARCH(1,1) with mean equation $r_{t-1,t}^{S\&P500} = a_0 + a_1 Sentiment_t + a_2 r_{t-2,t-1}^{S\&P500} + a_3 1_{Monday_t} + e_t$. $r_{t-1,t}^{S\&P500}$ is the return on the S&P 500 index, $Sentiment_t$ is equal to our sentiment measure on Thursdays and zero else, and 1_{Monday_t} is a dummy variable that is set to one on Mondays. We use three sentiment measures, the level of the AAII index (column 1), the first difference (column 2) and the residual from a regression of the AAII index on its lagged value and the lagged S&P 500 return (column 3). ***, ** and * denote significance at the 1%, 5%, and 10% level, respectively.

2.5 Conclusion

If sentiment indicators predict future stock market returns over the intermediate and long term (as is suggested by previous empirical research), smart traders can be expected to exploit the information conveyed by the indicator and thus trigger an immediate market response to the publication of the sentiment indicator. The sign of the immediate price reaction will then be the same as that of the intermediate and long-term predictability. If, on the other hand, sentiment indicators provide new information about future expected returns, the sign of the immediate price reaction will be opposite to that of the intermediate and long-term predictability.

The present paper is the first to empirically analyze whether an immediate market reaction can be identified in the data, and whether the sign of such a reaction corresponds to the sign of the intermediate and long-term predictive ability. In order to investigate these matters, we use survey-based sentiment indicators from the US (the AAII sentiment index) and for Germany (the Sentix index). In a first step, we replicate earlier results showing that the sentiment indicators do indeed have predictive power for future stock market returns over the intermediate term. We further document that the predictive power of the AAII index has largely disappeared in recent years.

In the second step of our analysis, we use event study methodology to test whether the daily index returns respond to the publication of the sentiment indicator. We do find a significant positive announcement day effect in Germany. This pattern is consistent with mispricing and limited arbitrage. Smart investors are aware of the predictive power of the sentiment indicator and trade accordingly. However, they do not fully arbitrage the predictability away, possibly because of increased noise trader risk (as in the model of de Long et al. (1990)). For the US market, there is evidence of a negative publication day effect in the subperiod 1987-1994. As for the German case, this result is consistent with the mispricing scenario and limited arbitrage. In later subperiods, there is no significant publication day effect. This is unsurprising, because the intermediate to long-term predictability also disappears towards the end of the sample period.

Notwithstanding the differences between the results for Germany and the US , the results for the two countries share one characteristic. They are both consistent with a mispricing interpretation of the predictive power of sentiment and inconsistent with the hypothesis that the sentiment indicator contains information about future expected returns.

Chapter 3

Idiosyncratic Volatility and the Timing of Corporate Insider Trading

3.1 Introduction

Corporate insiders, i.e., executive directors, board members or large shareholders, are likely to possess superior information about the true value of their firm compared to outside investors. They are involved in decision making processes that affect the value of the firm such as investment or merger decisions, and they receive notice about major events in advance of official public announcements. Several empirical studies (e.g., Seyhun (1986), Chang and Suk (1998) or Jeng et al. (2003)) document that corporate insiders are able to generate significant abnormal returns from trading. This indicates that they use their advantage for profitable trading strategies. Moreover, it is likely that the information asymmetry between informed and uninformed investors and consequently the information advantage of insiders varies over time. The question then arises whether corporate insiders time their transactions in such a way that they exploit high peaks of information asymmetry. The welfare implications of corporate insider trading are ambiguous. On the one hand it is argued that insider trading leads to more informative prices as more private information is impounded into prices. Kyle's (1985) model, for instance, presents a situation in which market makers adjust prices dependent on the combined order flow of insiders and uninformed noise traders. On the other hand insider trading may prevent outsiders from trading in the stock because it imposes adverse selection costs (see, e.g., Bhattacharya and Spiegel (1991)). The question is whether corporate insiders trade on the foreknowledge of announcements or whether their transactions make prices more informative for their trading is based on information that would otherwise not be reflected in prices.

We use idiosyncratic volatility relative to firms' recent mean (henceforth *relivol*) as a proxy for asymmetric information. Under the assumption that variations in our measure of information asymmetry over time are due to changes in short-term information asymmetry, we analyze whether corporate insiders exploit their temporary informational advantage. To do so, we link up the likelihood of insider trading with *relivol*. Furthermore, we analyze whether timed trades, i.e., trades that are made when *relivol* is high, outperform non-timed trades.

The paper adds to the literature on corporate insider trading and presents the first paper to analyze the likelihood of corporate insider trading. Its main innovation is to use a time-variant proxy for asymmetric information and link it to insider trading. This proxy allows for addressing the question of whether corporate insiders time their transactions according to variations in asymmetric information.

The question of whether corporate insiders time their trades to exploit a short-term information advantage calls for a proxy for temporary information advantages. If we were to create an ideal experiment, we would exogenously shock the information set of the insider and leave the information set of the market participants constant. That shock would create an information advantage of insiders. As such an experiment is difficult to conduct in the real world, we need a proxy to know the points in time when there is a wedge between the knowledge of insiders and the knowledge of market participants. The main approach that has been taken so far is to use corporate announcements as a proxy. Studies following this approach investigate whether insiders use the foreknowledge of corporate announcements that are empirically found to have a significant price impact, such as dividend announcements, corporate bankruptcy, seasoned equity offerings, stock repurchases and takeover bids (e.g., Elliott et al. (1984), Noe (1999), Ke et al. (2003), Piotroski and Roulstone (2005)). These studies share the assumption that insiders have foreknowledge of these events or announcements, and upon announcement this private information vanishes as it is turned into public information. If insiders traded on early access to corporate news, one would observe insider buying activity before good news and insider selling activity before bad news. The extant empirical literature does not arrive at a conclusive result of whether corporate insiders exploit short-term information or not. The existing approach to use corporate announcement suffers from several shortcomings. First, the corporate announcement-approach necessitates an ex-ante selection of corporate news types. It is difficult to produce an exhaustive list of corporate news types. There may be types of temporary information advantages of insiders not covered by the events which have been considered so far. To be able to infer the absence of timing, one would have to collect information about every announcement the firm makes. Second, with the exception of earnings and dividend announcements of which analysts' estimates may exist, it is in general difficult to measure the surprise component of corporate announcements. It is hence difficult to distinguish informative announcements from uninformative ones, i.e., those which reduce the wedge between insider and outsider information and those that do not. Third, the risk of litigation and adverse publicity is likely to be higher before such disclosure types because the occurence of such events is easily verifiable. This is likely to prevent corporate insiders from blatantly exploiting this kind of information. Many firms even have self-imposed compliance guidelines which prevent insiders from trading before such events. Using *relivol* as a more direct measure of time-variant information asymmetry, we propose an alternative approach which does not suffer from these shortcomings. Idiosyncratic volatility as a measure of asymmetric information is motivated by the idea that informed traders only act when significant private information exists and that such trading causes stock price movements to deviate from those predicted by the assumed return generating process.

Our findings indicate that corporate insiders try to use short-term informational advantages. They tend to buy their firm's stocks more frequently when idiosyncratic volatility is high, i.e., at times during which it can be expected that private information is impounded into stock prices. However, the likelihood of selling is on average not significantly related to *relivol*. This may be because of the lower informational content since sales are also motivated by other reasons than profit seeking, e.g., diversification or liquidation needs. Furthermore, there may be a trade-off with concerns about litigation and reputation risks, which are likely to be asymmetrically higher with respect to insider sales. Dividing the sample into small and large firms reveals an interesting insight. For purchases, *relivol* appears to have a larger impact on trading in large firms' shares though the effect is significant for both large and small firms. The difference may be explained by the idea that insiders in small firms rather have the role of an entrepreneur who is less focused on trading profits than on maximizing firm value so that they try and impose less adverse selection costs on other shareholders than managers employed by large firms who may be more interested in realizing trading profits. There are also differences among types of insiders: CEOs' purchases are not significantly linked to *relivol*, whereas officers and directors buy shares if asymmetric information is high. This finding indicates that there may be a trade-off between the best access to superior information and on the other hand the increased exposure and scrutiny that come along with being at the top of the firm. Apparently, reputation and litigation risks are sufficiently high for CEOs to prevent them from timing their transactions according to variations in asymmetric information. However, the empirical evidence does not establish a significant effect of timing on profitability: trades during times of high *relivol* do not significantly outperform trades during times of low *relivol*.

The paper is structured as follows: Section 2 introduces *relivol* as a proxy of asymmetric information. Section 3 describes the data. Section 4 presents the results of the logit regression where we analyze the effects of *relivol* on the likelihood of insider trading. Section 5 deals with the analysis of the relationship of profitability and *relivol*. Section 6 concludes.

3.2 Idiosyncratic Volatility

We use idiosyncratic volatility as a proxy for information asymmetry between insiders and outsiders. The measure is based on the argument that informed trading induces volatility. This relationship is corroborated by theoretical models (Glosten and Milgrom (1985)) and empirical evidence (French and Roll (1986)). Trading on private information is likely to take place with respect to information about individual firms rather than general market information, which is typically publicly available. As a consequence, informed trading is expected to affect the idiosyncratic part of volatility which has to be distinguished from market volatility.

We argue that private information activities are positively associated with the level of information asymmetry between informed and uninformed traders. If information was public, there would not be any private information activities. Berrada and Hugonnier (2010) theoretically analyze the relationship between incomplete information and idiosyncratic volatility. They find that incomplete information is positively related to idiosyncratic volatility. Using analyst forecasts as a proxy, they find empirical support for their predictions. Dasgupta et al. (2006) give theoretical and empirical evidence that price informativeness decreases with idiosyncratic volatility, Arena et al. (2008) come to the same conclusion when considering the relation between idiosyncratic volatility and momentum profits.

There are several studies which use idiosyncratic volatility as a measure of asymmetric information. Dierkens (1991) analyzes the relevance of asymmetric information for the issuance of new equity. She finds that idiosyncratic volatility is high before new equity issues and drops after the equity issue is announced. Her results are consistent with the notion that managers time equity issues in order to exploit asymmetric information. Ferreira and Laux (2007) use idiosyncratic volatility as a measure of stock price informativeness which they relate to corporate governance. Krishnaswami and Subramaniam (1999) analyze the hypothesis of whether corporate spin-offs reduce asymmetric information, using idiosyncratic volatility as a measure among other proxies such as the precision or the diversion of analyst forecast errors. They find that idiosyncratic volatility is positively related to the likelihood of a spin-off and that idiosyncratic volatility drops after the spin-off.

Generally, there is no consensus in the literature as to whether a high or a low level of idiosyncratic volatility indicates large information asymmetries. However, these studies all look at firms' permanent level of idiosyncratic volatility. Our approach differs in so far as we look at deviations in idiosyncratic volatility from the firms' permanent levels. The literature agrees that informed trading increases idiosyncratic volatility and we argue that such trading can be expected to take place when information asymmetries are particularly large and that these asymmetries are not eliminated immediately.

Our measure is defined as the standard deviation of residual returns unexplained by market models. We compute idiosyncratic volatilities according to the Carhart 1997 four-factor model. The Carhart four-factor model is the Fama-French three-factor model augmented by the momentum factor. Accordingly, the four-factor model assumes that returns are determined by sensitivities with respect to the following risk factors: market factor, size factor, market-to-book factor and momentum factor. The firms' market model coefficients are estimated using 12 calendar month rolling windows of daily returns. To reduce biases caused by infrequent trading, we estimate the coefficients using the approach suggest by Dimson (1979) with one lead and one lag.

Our idiosyncratic volatility measure is based on the last 21 trading days, i.e., the idiosyncratic volatility used to estimate the probability and profitability of trades on day t is based on data from days $t-21 \ldots t-1$. While such a short sample renders the estimates inexact, these errors can be expected to even out over our whole sample of insider transactions. As we want to look at short-term variation in information asymmetry, we consider this choice an appropriate compromise.

We compute a measure of relative idiosyncratic volatility, i.e., the ratio of a firm's idiosyncratic volatility at a point in time to its mean idiosyncratic volatility during the prior calendar year. This serves the analysis of the effect of short-term asymmetric information as it corresponds to the abnormal idiosyncratic volatility in a firm's stock. It will be the main focus of our empirical analyses.

3.3 Data

Our analysis is based on a sample of U.S. corporate insider trades from the TFN database. The TFN database includes trades by corporate insiders which Section 16 of the Securities Exchange Act requires them to file via Form 4. Our sample starts in 1992, as from that year on details on insider transactions begin to be reported in the TFN database, and extends up to and including 2008. The database includes the trading date, the reporting date, the firm, the position of the insider within the firm, the number of shares traded, and the direction of the trade (purchase or sale).

Daily stock returns are from CRSP. For the market models we use the monthly Fama-French factors, momentum and the riskfree rate from Kenneth French's data library. Based on the stock returns and the factors, we compute idiosyncratic volatility for each firm and day in our sample.

We use annual accounting information from the firms' balance sheets and profit and loss statements as well as earnings announcement dates from COMPUSTAT. Information on the number of analysts following a firm is taken from I/B/E/S.

While the other firm characteristics are used as control variables in our empirical analyses, we compute book equity in order to remove stocks with a negative one, as it is frequently done in the literature. Also, we remove financial companies, because of their usually atypical firm characteristics compared to other firms, and regulated utilities, whose informational environment is likely to be different from that of other firms.

We merge the data and obtain a final sample that consists of 9883 firms and just over 15 million firm days. We define a dummy variable which is set to 1 if there was an insider trading day in the respective stock and to 0 otherwise. We avoid double counting due to several insiders trading on the same day.

There are 445,084 insider trades in our sample, 118,496 of which are purchases and 326,588 sales. Only 26.62% of all trades are purchases; corporate insiders are net sellers. However, this strong imbalance does not hold for the group of "other" insiders which include shareholders who hold more than 10% of the firm's shares. For this group, purchases represent 45.51% of their trades. The trade sizes defined as the number of shares multiplied by the transaction price display the same picture: while the volume of purchases represents only about a tenth of the volume of sales for CEOs and officers and a third of the volume of sales for directors, the volume bought by other insiders is roughly the same as the volume sold by other insiders.

3.4 Relative Idiosyncratic Volatility and the Likelihood of Insider Trading

3.4.1 Empirical design

The goal of the following analysis is to link up the likelihood of observing an insider trade with relative idiosyncratic volatility. We estimate logistic regressions with firm- and year-fixed effects where the dependent variable is a binary variable that is set to 1 if there was an insider trade (purchase or sale respectively) and to 0 if there was no such trade on the respective day.

We recognize the potential existence of an endogeneity problem. There is empirical evidence that insiders trade several times during short time horizons (see, e.g., Lebedeva et al. (2009)). If insider trading affects idiosyncratic volatility and insider trading occurs in clusters, a significant relationship between insider trading and idiosyncratic volatility may simply reflect the effects of insider trading on idiosyncratic volatility.

If there is a positive empirical relationship between *relivol* and insider trading, timing may not be the original cause. In order to control for changes in relative idiosyncratic volatility which stem from the effects of previous trades on idiosyncratic volatility, we include an interaction term between a dummy for previous trades and relative idiosyncratic volatility. We also include a dummy for the occurrence of previous trades in the ivol estimation window. This aims at controlling for the fact that insider trades are often split across several days such that days with insider trading cluster. Also, insider trades may increase idiosyncratic volatility and the interaction term serves to ensure that any effects of idiosyncratic volatility on the probability of insider trading do not merely reflect the clustering of trades.

We include several control variables in the analysis that account for firm- and time-specific characteristics, which are also likely to affect the likelihood of insider trading. We thereby control for the overall level of private information activities in a firm's stock, since our goal is to capture the effect of the deviation of idiosyncratic volatility from its permanent level.

We also include the relative systematic volatility $relsysvol$. Hereby, we control for the possible objection that idiosyncratic volatility simply reflects changes in the level of overall volatility. The measure is defined as the past 21 trading days' factor volatilities scaled by the stocks' factor betas.

We also control for the cumulative abnormal returns over the last 21 trading days and their absolute value to ensure that an apparent effect of idiosyncratic volatlity does not merely reflect trading as a response to past abnormal returns.

Quarterly earnings announcements represent a channel through which information about firm value is communicated to investors. On this account, many U.S. firms have self-imposed insider trading restrictions in place, according to which most of them allow insider trading only in the 30 days following the quarterly earnings announcement and prohibit trading in the 60 days preceding the next earnings announcement which represents the so called "blackout period" (see Bettis et al. (2000) or Roulstone (2003)). This restriction aims to prevent corporate insiders from exploiting asymmetric information that will be reduced by the following earnings announcement. When such trading restrictions are in place and enforced, insider trading is certainly more likely to occur outside blackout periods.

We therefore control for blackout periods. We assume that firms have a blackout period in place that restricts insider trading such that it is allowed to trade only during the 30 days following an earnings announcement. Our blackout dummy is 0 for the 30 days following the earnings announcement and 1 for the remaining days.

We include size in terms of the natural logarithm of market capitalization and the natural logarithm of the number of analysts following the firm as control variables that proxy for the firms' permanent information asymmetry between insiders and outsiders. Furthermore, we include book leverage defined as the book value of debt divided by the value of total assets, return on equity defined as net profit divided by the book value of equity and Tobin's Q defined as the sum of the market value of equity and the book value of debt divided by the sum of the book value of equity and the book value of debt.

We estimate the following model:

$$\ln\left(\frac{p_{i,t}}{1-p_{i,t}}\right) = constant + c_i + y_t + \beta_0 \cdot relivol_{i,t} + \beta_1 \cdot buys_{21i,t} + \beta_2 \cdot sells_{21i,t}$$

$$+ \beta_3 \cdot relivol_{i,t} \cdot buys_{21i,t} + \beta_4 \cdot relivol_{i,t} \cdot sells_{21i,t} + \beta_5 \cdot X_{i,t}, (3.1)$$

where $p_{i,t}$ is the probability of an insider trade in the stock of firm i on day t. c_i is a firm constant, y_t is a year constant, $buys_{21}$ ($sells_{21}$) is a dummy variable set to 1 if there was an insider purchase (sale) in the estimation window of *relivol*, and to 0 otherwise. X stands for the vector of firm- and time-specific control variables.

3.4.2 Empirical results

High vs low relivol

Table 3.1 shows the results of the regressions for purchases and sales. For the model in the right column, we have removed all observations for which there was an insider trade during the previous 21 trading days. This serves to demonstrate that the possible objection that, despite our controls for past trading, our results might be driven by the contamination with past trades executed during the estimation period is not valid. In the following we use the whole sample. Our results show that the likelihood of insider purchases is positively and significantly associated with *relivol*. This indicates that insiders time their transactions during times of high asymmetric information. The effect holds independent of the sample used. When there were insider purchases in the preceding 21 days, the effect of *relivol* on the likelihood of a purchase is significantly smaller. This finding indicates that, apparently, the suspicion does not hold that finding a positive relationship between *relivol* and insider trades is due to the facts that insider trades occur in clusters and insider trading leads to increases in *relivol*. The likelihood of insider purchases is also positively associated with *relsysvol*, i.e., insiders seem to conduct their purchases during times of high overall uncertainty. Also, insiders tend to be contrarian, i.e., the likelihood of insider trading rises with low returns. Large absolute returns also tend to increase insider trading, and trading takes place less often during the blackout period than outside it.

The negative coefficient of the blackout dummy indicates that insider trades tend to occur in the 30 days after the earnings announcement, which is in line with the findings by Roulstone (2003) and Bettis et al. (2001). We also find evidence for the fact that purchases occur in clusters. If there was a purchase transaction in the preceding 21 days, it is more likely to observe another insider purchase.

Table 3.1 also displays the results for the determinants of the likelihood of an insider sale. The coefficient on *relivol* is slightly negative, which suggests that insiders time their sales during times of rather low asymmetric information. However, the economic significance is much smaller compared to purchases. Insiders apparently do not time their sale transactions during times of high asymmetric information. If there were purchases in the preceding days, the likelihood of observing a sale is inversely linked to *relivol*. This is consistent with the assumption that if there are insider trades in opposite directions, they are unlikely to be highly informative. The finding that sales do not seem to be timed on average is consistent with the asymmetric litigation risk.

Small vs large firms

We conduct separate analyses for small and large firms, for firm size is considered a relevant characteristic of the information asymmetry between the firm and outsiders. The results are displayed in Table 3.2. For purchases, *relivol* appears to have a larger impact on trading in large firms' shares though the effect is significant for both large and small firms. If there were previous buys or sales, for large companies *relivol* has a smaller effect on the likelihood of insider trading. Insiders of large firms appear to be more contrarian than those of small firms for both purchases and sales. For sales, neither for small nor for large firms there is a significant effect of *relivol*. The

Table 3.1: Logistic regressions of probability of insider trading

	Purchases			
	Full sample		No previous trades	
	Coef.	St. Err.	Coef.	St. Err.
relivol	0.2329***	0.00952	0.2897***	0.0130
relivol*buys$_{21}$	-0.1519***	0.00982		
relivol*sells$_{21}$	-0.0180	0.0151		
car$_{21}$	-0.5425***	0.0155	-0.7471***	0.0240
abscar$_{21}$	0.2086***	0.0231	0.7381***	0.0332
relsysvol	0.0542***	0.00499	0.0716***	0.00923
blackout	-0.8238***	0.00634	-1.2504***	0.0115
buys$_{21}$	1.7171***	0.0138		
sells$_{21}$	-0.0302	0.0204		
lognumest	-0.0423***	0.0160	-0.0373	0.0291
bookleverage	0.0395	0.1001	-0.2478	0.1770
size	0.0304	0.0235	0.0430	0.0435
q	0.00443	0.0101	-0.0106	0.0190
roe	-0.00912	0.0131	-0.0170	0.0254
Obs	14878187		12638927	

	Sales			
	Full sample		No previous trades	
St. Err.	Coef.	St. Err.	Coef.	St. Err.
relivol	-0.0184**	0.00881	-0.1011***	0.0122
relivol*buys$_{21}$	-0.0319**	0.0139		
relivol*sells$_{21}$	-0.0236**	0.00928		
car$_{21}$	0.7627***	0.0117	1.1917***	0.0254
abscar$_{21}$	-0.0661***	0.0183	0.3579***	0.0391
relsysvol	-0.1025***	0.00411	-0.1708***	0.00853
blackout	-1.0016***	0.00403	-1.5335***	0.00892
buys$_{21}$	-0.00727	0.0179		
sells$_{21}$	1.7126***	0.0110		
lognumest	-0.0233**	0.00961	-0.2483***	0.0203
bookleverage	0.1189*	0.0693	0.1697	0.1449
size	-0.1021***	0.0152	-0.0867**	0.0350
q	0.00765	0.00472	0.0340***	0.0122
roe	0.00406	0.0107	0.0164	0.0270
Obs	15086279		11975831	

This table shows the results of the logistic regression of a binary variable that is set to one if there was an insider trade (purchase or sale respectively) and to zero if there was no insider trade on that day. The model is estimated with firm- and year-fixed effects. The observations consist of firm day data. *relivol* denotes the relative idiosyncratic volatility estimated using the 21 previous days based on the Carhart 4 factor model. $relivol{*}buys_{21}$ ($relivol{*}sells_{21}$) denotes an interaction term between the relative idiosyncratic volatility and a dummy variable that is set to 1 if there was an insider purchase (sale) transaction in the previous 21 days in the same stock. car_{21} and $abscar_{21}$ are the cumulative abnormal return with respect to the Carhart model over the past 21 trading days and its absolute value, respectively. *relsysvol* is the systematic volatlity, taking into account Carhart factor returns and the respective betas, in the preceding 21 days relative to that over the last calendar year. *blackout* is a dummy variable that is set to one during the two months prior to a quarterly earnings announcement and zero otherwise. $buys_{21}$ ($sells_{21}$) is a dummy variable that is set to 1 if there was another insider purchase (sale) in the same stock in the previous 21 days. *lognumest* is the natural logarithm of the number of analysts that follow the firm. *Bookleverage* is the book value of debt divided by the value of total assets. *Size* is the natural logarithm of the firm's market capitalization. Q is defined as the market value of equity plus the book value of equity divided by the value of total assets. Roe is defined as the net profit divided by the book value of equity. Obs denotes the number of observations. ***, ** and * denote statistical significance at the 1%, 5% or 10% level.

Table 3.2: Logistic regressions of probability of insider trading

Large vs Small	Purchases			
	Large Firms		Small Firms	
	Coef.	St. Err.	Coef.	St. Err.
relivol	0.3495***	0.0183	0.1279***	0.0161
relivol*buys$_{21}$	-0.1929***	0.0186	-0.0770***	0.0167
relivol*sells$_{21}$	-0.0605**	0.0252	-0.0659**	0.0292
car$_{21}$	-1.2888***	0.0429	-0.4598***	0.0228
abscar$_{21}$	0.1212*	0.0636	-0.3510***	0.0298
relsysvol	0.0848***	0.00970	0.0557***	0.00804
blackout	-0.8585***	0.0121	-0.7587***	0.0103
buys$_{21}$	1.4027***	0.0269	1.8398***	0.0230
sells$_{21}$	-0.00465	0.0340	0.0643	0.0391
lognumest	0.0283	0.0290	-0.0421	0.0298
bookleverage	-0.4911**	0.2150	0.2823*	0.1515
size	-0.1032*	0.0551	-0.1657***	0.0373
q	-0.00169	0.0195	0.0836***	0.0203
roe	-0.0603	0.0394	0.0339*	0.0184
Obs	4970358		5000453	
	Sales			
	Large Firms		Small Firms	
St. Err.	Coef.	St. Err.	Coef.	St. Err.
relivol	0.00235	0.0130	-0.00902	0.0193
relivol*buys$_{21}$	0.00526	0.0211	-0.0129	0.0287
relivol*sells$_{21}$	-0.0552*	0.0138	0.0408**	0.0201
car$_{21}$	0.9158***	0.0193	0.5473***	0.0216
abscar$_{21}$	-0.6017***	0.0291	0.3994***	0.0314
relsysvol	-0.1414***	0.00604	-0.0584***	0.00960
blackout	-1.1273***	0.00563	-0.7532***	0.0105
buys$_{21}$	-0.0302	0.0268	-0.0437	0.0388
sells$_{21}$	1.5245***	0.0162	1.9614***	0.0251
lognumest	-0.0242*	0.0134	-0.0230	0.0279
bookleverage	0.1206	0.1026	-0.1521	0.1460
size	-0.1175***	0.0252	-0.1257***	0.0316
q	0.0146**	0.00587	-0.00566	0.0127
roe	0.0122	0.0239	0.0105	0.0117
Obs	4938673		5002295	

This table shows the results of the logistic regression of a binary variable that is set to one if there was an insider trade (purchase or sale respectively) and to zero if there was no insider trade on that day. The model is estimated with firm- and year-fixed effects. The observations consist of firm day data. *relivol* denotes the relative idiosyncratic volatility estimated using the 21 previous days based on the Carhart 4 factor model. $relivol{*}buys_{21}$ ($relivol{*}sells_{21}$) denotes an interaction term between the relative idiosyncratic volatility and a dummy variable that is set to 1 if there was an insider purchase (sale) transaction in the previous 21 days in the same stock. car_{21} and $abscar_{21}$ are the cumulative abnormal return with respect to the Carhart model over the past 21 trading days and its absolute value, respectively. *relsysvol* is the systematic volatlity, taking into account Carhart factor returns and the respective betas, in the preceding 21 days relative to that over the last calendar year. *blackout* is a dummy variable that is set to one during the two months prior to a quarterly earnings announcement and zero otherwise. $buys_{21}$ ($sells_{21}$) is a dummy variable that is set to 1 if there was another insider purchase (sale) in the same stock in the previous 21 days. *lognumest* is the natural logarithm of the number of analysts that follow the firm. *Bookleverage* is the book value of debt divided by the value of total assets. *Size* is the natural logarithm of the firm's market capitalization. Q is defined as the market value of equity plus the book value of equity divided by the value of total assets. Roe is defined as the net profit divided by the book value of equity. Obs denotes the number of observations. ***, ** and * denote statistical significance at the 1%, 5% or 10% level.

differences for purchases may be explained by the idea that insiders in small firms rather have the role of an entrepreneur who is less focused on trading profits than on maximizing firm value so that they try and impose less adverse selection costs on other shareholders than managers employed by large firms who may be more interested in realizing trading profits.

Pre vs post Sarbanes-Oxley

The Sarbanes-Oxley Act (SOX) enacted more stringent insider trading regulation in August 2002. Since then, insiders have had to report their trade within two business days, whereas before, they were allowed to wait until the tenth calendar day of the following month to report their transactions[1]. It may be that SOX changed the way insiders exploit their inside information for their trades.

As Table 3.3 shows, the determinants of the likelihood of purchases are roughly similar when comparing the pre and post SOX era. However, there are differences when comparing sales pre and post SOX. Pre SOX, there is a negative relationship between *relivol* and the likelihood of insider sales. However, after the enactment of SOX, we observe a positive impact of *relivol* on the likelihood of an insider sale. These findings indicate, that, apparently, SOX has not substantially altered and in particular reduced the timing of insider trades.

One of the main differences between the post and the pre SOX sample is the reporting delay of the insider trades. Post SOX, the bulk of transactions is reported within two business days of the transaction. As a consequence, for post SOX trades, it is often the case that the report of the previous insider transaction lies within the estimation window for *relivol*. One may object that the coefficient of *relivol* being significant for insider sales in the post SOX era simply reflects the fact that the report of previous trades is the cause of higher *relivol*. According to this view, the positive and significant coefficient for *relivol* is a consequence of reverse causality: reports of insider trading affect *relivol*. However, with the $buys_{21}$ and $sells_{21}$ dummies and the interactions with *relivol*, we control for changes in *relivol* which

[1]Betzer et al. (2010) show that before SOX, insiders even took up to an average of 37 days to report their transactions.

Table 3.3: Logistic regressions of probability of insider trading

Pre vs Post SOX	Purchases			
	Pre SOX		Post SOX	
	Coef.	St. Err.	Coef.	St. Err.
relivol	0.2253***	0.0137	0.2438***	0.0136
relivol*$buys_{21}$	-0.1700***	0.0150	-0.1313***	0.0132
relivol*$sells_{21}$	-0.0288	0.0226	-0.0166	0.0206
car_{21}	-0.5085***	0.0177	-0.6886***	0.0293
$abscar_{21}$	0.4159***	0.0265	-0.2523***	0.0408
relsysvol	0.0433***	0.00714	0.0632***	0.00727
blackout	-0.7369***	0.00789	-0.9886***	0.0108
$buys_{21}$	1.6831***	0.0197	1.7027***	0.0207
$sells_{21}$	0.0201	0.0290	-0.0950***	0.0300
lognumest	-0.0412**	0.0203	-0.0350	0.0271
bookleverage	0.00460	0.1154	-0.00788	0.2145
size	0.0198	0.0277	-0.1900***	0.0505
q	-0.0179	0.0110	0.1439***	0.0294
roe	-0.0224	0.0150	0.0144*	0.0326
Obs	10029681		4772894	
	Sales			
	Pre SOX		Post SOX	
St. Err.	Coef.	St. Err.	Coef.	St. Err.
relivol	-0.0563***	0.0131	0.0255	0.0119
relivol*$buys_{21}$	-0.0413**	0.0205	-0.0310	0.0190
relivol*$sells_{21}$	0.0925***	0.0140	-0.1049**	0.0123
car_{21}	0.6130***	0.0143	1.1044***	0.0205
$abscar_{21}$	-0.0810***	0.0216	-0.0351***	0.0328
relsysvol	-0.0812***	0.00581	-0.1187***	0.00592
blackout	-1.0560***	0.00577	-0.9519***	0.00569
$buys_{21}$	0.00911	0.0259	-0.0101	0.0250
$sells_{21}$	1.6309***	0.0166	1.6904***	0.0148
lognumest	0.0302**	0.0139	-0.0568	0.0137
bookleverage	0.0312	0.0938	0.1516	0.1061
size	-0.0681***	0.0185	-0.1896***	0.0304
q	0.000579	0.00508	0.0177	0.0155
roe	-0.0174	0.0131	0.0533	0.0212
Obs	10184921		4901358	

This table shows the results of the logistic regression of a binary variable that is set to one if there was an insider trade (purchase or sale respectively) and to zero if there was no insider trade on that day. The model is estimated with firm- and year-fixed effects. The observations consist of firm day data. *relivol* denotes the relative idiosyncratic volatility estimated using the 21 previous days based on the Carhart 4 factor model. $relivol{*}buys_{21}$ ($relivol{*}sells_{21}$) denotes an interaction term between the relative idiosyncratic volatility and a dummy variable that is set to 1 if there was an insider purchase (sale) transaction in the previous 21 days in the same stock. car_{21} and $abscar_{21}$ are the cumulative abnormal return with respect to the Carhart model over the past 21 trading days and its absolute value, respectively. *relsysvol* is the systematic volatlity, taking into account Carhart factor returns and the respective betas, in the preceding 21 days relative to that over the last calendar year. *blackout* is a dummy variable that is set to one during the two months prior to a quarterly earnings announcement and zero otherwise. $buys_{21}$ ($sells_{21}$) is a dummy variable that is set to 1 if there was another insider purchase (sale) in the same stock in the previous 21 days. *lognumest* is the natural logarithm of the number of analysts that follow the firm. *Bookleverage* is the book value of debt divided by the value of total assets. *Size* is the natural logarithm of the firm's market capitalization. Q is defined as the market value of equity plus the book value of equity divided by the value of total assets. Roe is defined as the net profit divided by the book value of equity. Obs denotes the number of observations. ***, ** and * denote statistical significance at the 1%, 5% or 10% level.

may be caused by the *occurence* of insider trades. Controlling for the occurence is a good proxy for controlling for the *report*, when there are only two business days between trading and reporting.

Insider positions

Table 3.4 separates the data into trades by CEOs, other executives and directors on the one hand, and other insiders such as major shareholders on the other hand. Generally, it is debatable how much inside information the latter group possess since they are not directly involved in running the company. Our empirical results appear to confirm this suspicion. As the table shows, it is the former group of insiders that appear to be timing their purchases whilst the "outside" group act conversely, buying at times of rather low asymmetric information and selling when it is high. These results suggest that blockholders do not possess short-term private information that they could use to trade in the stock. In the following, however, we use the whole sample, so any results we obtain will rather understate the effects that might be found by looking only at the insiders actively involved in running the company.

Table 3.5 shows the results for purchases and sales concerning the insider positions referring to people working within the firm. The coefficient of *relivol* is positive for all three groups. However, officers and directors apparently time their purchases during times of high *relivol* more so than CEOs. On the one hand, according to the information hierarchy hypothesis, CEOs possess more information about the firm. On the other hand CEOs are highly exposed to the public and to investors and, accordingly, their transactions are expected to be followed very closely. While officers and directors may not have as much superior information as the CEO, their insider transactions are expected to be followed less closely, which is why they might be less reluctant to time their trades. Neither CEOs, nor officers or directors seem to time their sales. The coefficient is negative and insignificant.

Alternative motives like diversification and liquidity needs may dominate the objective of profit generation when it comes to insider sales. Furthermore, litigation risk is likely to be asymmetric and, accordingly, sales are more likely to be monitored by the public and by regulators compared to purchases.

Table 3.4: Logistic regressions of probability of insider trading

Others vs CEOs, executives, directors	Purchases			
	Others		Insider the Firm	
	Coef.	St. Err.	Coef.	St. Err.
relivol	-0.0919***	0.0284	0.2893***	0.0104
relivol*buys$_{21}$	-0.0778***	0.0283	-0.1038***	0.0108
relivol*sells$_{21}$	-0.0955***	0.0343	0.00358	0.0170
car$_{21}$	-0.2816***	0.0342	-0.6289***	0.0176
abscar$_{21}$	0.1202**	0.0505	0.2442***	0.0266
relsysvol	0.0961***	0.0107	0.0399***	0.00568
blackout	-0.1602***	0.0139	-1.0131***	0.00634
buys$_{21}$	2.7291***	0.0368	1.3995***	0.0155
sells$_{21}$	0.1045**	0.0427	-0.0583**	0.0235
lognumest	0.0507	0.0339	-0.0861***	0.0182
bookleverage	-0.3464	0.2374	0.1150	0.1119
size	-0.2272***	0.0560	0.0260	0.0261
q	0.00531*	0.0250	-0.00775	0.0113
roe	-0.0127	0.0351	-0.0233	0.0143
Obs	14878187		14878187	
	Sales			
	Others		Inside the Firm	
St. Err.	Coef.	St. Err.	Coef.	St. Err.
relivol	0.0644**	0.0258	-0.0266***	0.00936
relivol*buys$_{21}$	-0.0139	0.0320	-0.0321**	0.0152
relivol*sells$_{21}$	-0.0371	0.0260	-0.0367***	0.00994
car$_{21}$	0.3769***	0.0259	0.8364***	0.0129
abscar$_{21}$	0.1323***	0.0378	-0.1378***	0.0202
relsysvol	-0.0321***	0.0111	-0.1149***	0.00441
blackout	-0.3514***	0.0120	-1.0688***	0.00426
buys$_{21}$	-0.0412	0.0434	-0.00251	0.0195
sells$_{21}$	2.3159***	0.0330	1.6423***	0.0118
lognumest	-0.1140***	0.0279	-0.00743	0.0102
bookleverage	0.2481	0.1984	0.1144	0.0737
size	0.00434	0.0430	-0.1119***	0.0162
q	-0.0280**	0.0129	0.0127**	0.00501
roe	0.0122	0.0239	0.0105	0.0117
Obs	15086279		15086279	

This table shows the results of the logistic regression of a binary variable that is set to one if there was an insider trade (purchase or sale respectively) and to zero if there was no insider trade on that day. The model is estimated with firm- and year-fixed effects. The observations consist of firm day data. *relivol* denotes the relative idiosyncratic volatility estimated using the 21 previous days based on the Carhart 4 factor model. $relivol{*}buys_{21}$ ($relivol{*}sells_{21}$) denotes an interaction term between the relative idiosyncratic volatility and a dummy variable that is set to 1 if there was an insider purchase (sale) transaction in the previous 21 days in the same stock. car_{21} and $abscar_{21}$ are the cumulative abnormal return with respect to the Carhart model over the past 21 trading days and its absolute value, respectively. *relsysvol* is the systematic volatlity, taking into account Carhart factor returns and the respective betas, in the preceding 21 days relative to that over the last calendar year. *blackout* is a dummy variable that is set to one during the two months prior to a quarterly earnings announcement and zero otherwise. $buys_{21}$ ($sells_{21}$) is a dummy variable that is set to 1 if there was another insider purchase (sale) in the same stock in the previous 21 days. *lognumest* is the natural logarithm of the number of analysts that follow the firm. *Bookleverage* is the book value of debt divided by the value of total assets. *Size* is the natural logarithm of the firm's market capitalization. Q is defined as the market value of equity plus the book value of equity divided by the value of total assets. Roe is defined as the net profit divided by the book value of equity. Obs denotes the number of observations. ***, ** and * denote statistical significance at the 1%, 5% or 10% level.

Table 3.5: Logistic regressions of probability of insider trading

			Purchases			
	Officer		CEOs	Directors		
	Coef.	St. Err.	Coef.	St. Err.		
relivol	0.3132***	0.0187	0.2400***	0.0249	0.2978***	0.0142
relivol*buys$_{21}$	-0.1027***	0.0196	-0.1501***	0.0255	-0.1501***	0.0149
relivol*sells$_{21}$	-0.0105	0.0309	0.0902**	0.0382	0.0902	0.0234
car$_{21}$	-0.8873***	0.0338	-0.6077***	0.0384***	-0.4598***	0.0234***
abscar$_{21}$	0.1762***	0.0509	0.1859***	0.0591	0.2333***	0.0343***
relsysvol	0.0487***	0.0104	0.0132*	0.00568	0.0391***	0.00778
blackout	-0.9721***	0.0131	-1.0268***	0.0166	-0.9989***	0.0100
buys$_{21}$	1.2145***	0.0283	1.7683***	0.0365	1.3561***	0.0214
sells$_{21}$	-0.0457	0.0425	-0.1820***	0.0565	-0.0254	0.0320
lognumest	-0.0349	0.0331	-0.2212***	0.0428	-0.0601**	0.0251
bookleverage	0.0586	0.2145	0.6066**	0.2773	-0.0386	0.0369
size	-0.0580	0.0485	0.1664***	0.0567	0.0101	0.0567
q	0.0163	0.0223	-0.0375*	0.0221	0.0174	0.0161
roe	-0.0747**	0.0323	-0.0535**	0.0261	0.00865	0.0203
Obs	14878187		14878187	14878187		
			Sales			
	Officer		CEOs	Directors		
St. Err.	Coef.	St. Err.	Coef.	St. Err.		
relivol	0.00235	0.0126	-0.00091	0.0265	-0.0130	0.0158
relivol*buys$_{21}$	-0.0988***	0.0215	-0.0575	0.0404	0.0591**	0.0239
relivol*sells$_{21}$	-0.0654***	0.0135	-0.0409	0.0277	-0.0111	0.0167
car$_{21}$	0.9426***	0.0182	0.4355***	0.0263	0.5713***	0.0200
abscar$_{21}$	-0.3530***	0.0282	-0.2377***	0.0318	-0.1979***	0.0286
relsysvol	-0.1322***	0.00606	-0.0905***	0.0109	-0.0891***	0.00729
blackout	-1.1062***	0.00578	-0.7658***	0.0105	-0.9630***	0.00714
buys$_{21}$	0.0860***	0.0270	-0.0511	0.0518	-0.0849***	0.0312
sells$_{21}$	1.4915***	0.0159	1.8916***	0.0328	1.6773***	0.0199
lognumest	-0.00885	0.0139	0.0693***	0.0248	0.0600***	0.0171
bookleverage	0.1617	0.1008	-0.1939	0.1833	0.1033	0.1264
size	-0.1083***	0.0223	-0.1050**	0.0409	-0.0848***	0.0266
q	0.0296***	0.00652	-0.0105	0.0131	-0.0102	0.00859
roe	0.000868	0.0172	0.0579***	0.0214	-0.0454*	0.0250
Obs	15086279		15086279	15086279		

This table shows the results of the logistic regression of a binary variable that is set to one if there was an insider trade (purchase or sale respectively) and to zero if there was no insider trade on that day. The model is estimated with firm- and year-fixed effects. The observations consist of firm day data. *relivol* denotes the relative idiosyncratic volatility estimated using the 21 previous days based on the Carhart 4 factor model. $relivol*buys_{21}$ ($relivol*sells_{21}$) denotes an interaction term between the relative idiosyncratic volatility and a dummy variable that is set to 1 if there was an insider purchase (sale) transaction in the previous 21 days in the same stock. car_{21} and $abscar_{21}$ are the cumulative abnormal return with respect to the Carhart model over the past 21 trading days and its absolute value, respectively. *relsysvol* is the systematic volatlity, taking into account Carhart factor returns and the respective betas, in the preceding 21 days relative to that over the last calendar year. *blackout* is a dummy variable that is set to one during the two months prior to a quarterly earnings announcement and zero otherwise. $buys_{21}$ ($sells_{21}$) is a dummy variable that is set to 1 if there was another insider purchase (sale) in the same stock in the previous 21 days. *lognumest* is the natural logarithm of the number of analysts that follow the firm. *Bookleverage* is the book value of debt divided by the value of total assets. *Size* is the natural logarithm of the firm's market capitalization. Q is defined as the market value of equity plus the book value of equity divided by the value of total assets. Roe is defined as the net profit divided by the book value of equity. Obs denotes the number of observations. ***, ** and * denote statistical significance at the 1%, 5% or 10% level.

3.5 Relative Idiosyncratic Volatility and the Profitability of Insider Trading

3.5.1 Methodology

We hypothesize that by trading during times of high information asymmetry, insiders may increase their trading profits. This is why long-term profits of insiders are expected to be higher when they are conducted during periods of high relative idiosyncratic volatility. Higher profits may present a motivation for insiders to time their trades. We use a calendar-time-portfolio approach to study profits accruing to insiders following Mitchell and Stafford (2000).

This approach helps overcome possible problems stemming from event correlation and overlapping event periods such as difficulties in calculating abnormal returns on an event day level. We construct sale and purchase portfolios by adding a stock to the portfolio when an insider purchases (or sells) stock and assuming that he keeps this stock in the portfolio for a period of 6 months. The choice of a 6-month period is motivated by the short-swing rule according to Section 16(b) of the Securities Exchange Act of 1934. The rule intends to restrict corporate insiders from making short-term profits at the expense of outside shareholders. It mandates that profits made within less than six months have to be returned to the firm (see Jeng et al. (2003)).

We choose an equal-weighting of each portfolio constituent rather than one according to trading volume. While weighting according to trading volume makes sense when the goal is to estimate the total profitability of insider trading in dollar terms (see Jeng et al. (2003)), it adds additional noise when the aim is to identify whether timed trading is more profitable. There is empirical evidence that mid-size trades are the most informative ones (see Barclay and Warner (1993)). When using the value-weighted approach, the results also depend on the size of the trades. Extremely large trades carry less information, but would comprise large parts of the portfolio. Accordingly, this would produce a downward bias in the insider profits. This is why we opt to place equal weight on each insider trade.

We then run regressions of the excess monthly portfolio returns, i.e., the monthly returns minus the riskfree rate, on the four risk factors of the Carhart return model (market excess return, small-minus-big, high-minus-low and momentum). If timing increases profits from insider trading, we expect that a portfolio based on trades during times of high *relivol* outperforms a portfolio based on trades during times of low *relivol*. We compare the high and the low *relivol* portfolio by including both portfolio returns in one regression. As independent variables we use the four risk factors and a dummy for the returns of the high *relivol* portfolio. It may be the case that the high and the low *relivol* portfolio differ with respect to their factor loadings. This is why we also run a regression in which we include interaction terms of the high-dummy with the risk factors in order to capture potential differences in factor loadings.

3.5.2 Empirical results

Purchases vs sales

Table 3.6 shows the results of the regression of the purchase and the sale portfolio on risk factors according to the Carhart model. The intercept in the two first models can be interpreted as the abnormal return of the portfolio considered. The purchase portfolio generates an abnormal monthly return of about 1.84%. This suggests that insiders generate positive profits with insider purchases, most likely because they have superior information about the firm. However, the sale portfolio also generates a positive abnormal monthly return of about 0.42%. If insider sales were based on superior information, we would expect a negative and significant abnormal return for the sale portfolio. Although the abnormal return is small, it is nevertheless surprising that it is significant at the 1% level. Apparently, insiders incur losses, on average, when selling their shares. This suggests that on average other motives than profit generation drive the decision to sell shares. Alternatively, this may indicate that insiders sell shares too early when the share price is developing into a favourable direction.

The factor loading on the momentum factor is negative and significant for both the purchase and the sale portfolio. A potential explanation for this may be anti-cyclical timing of insider trades.

When including both the returns of the purchase and the sale portfolio in one regression, we find that the purchase portfolio outperforms the sale portfolio by 1.35% (coefficient for the purchase-dummy in Model 1) or 1.42% when controlling for differences in the sensitivities with respect to risk factors (coefficient for the purchase-dummy in Model 2). Model 2 also shows differences with respect to factor loadings. The purchase portfolio has a smaller sensitivity with respect to market risk and a higher sensitivity with respect to the market-to-book risk factor. Furthermore, the sensitivity of the purchase portfolio with respect to the momentum factor is also smaller.

Table 3.6: Profitability of insider trading (purchases vs sales)

	Purchases		Sales		Purchases vs sales			
					Model 1		Model 2	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
mkt	0.921	16.17***	1.091	20.85***	1.005	23.95***	1.091	19.98***
smb	0.706	10.69***	0.800	13.18***	0.752	15.45***	0.800	12.63***
hml	0.117	1.52	- 0.369	-5.25***	- 0.129	-2.28**	- 0.369	-5.03***
mom	- 0.364	-7.91***	- 0.136	-3.2***	- 0.250	-7.35***	- 0.136	-3.06***
purchase					1.353	4.34***	1.419	4.69***
purchase*mkt							- 0.171	-2.21**
purchase*smb							- 0.094	-1.05
purchase*hml							0.486	4.66***
purchase*mom							- 0.229	-3.65***
intercept	1.842	8.29***	0.424	2.07**	0.455	2.01**	0.424	1.98**
Obs	202		203		205		405	
Adjusted R-squared	0.7635		0.8585		0.7887		0.8206	
F-test	163.19***		307.35***		302.68***		206.39***	

This table shows the results of the regressions of the purchase and the sale portfolio according to the risk factors in the Carhart model, i.e., market risk (mkt), size (smb), book-to-market (hml) and momentum (mom). The monthly factors are obtained from Kenneth French's website. The last two regressions are based on both the purchase and the sale portfolio. The dummy "purchase" is set to 1 if the return belongs to the purchase portfolio and zero if the return belongs to the sale portfolio. purchase*mkt is an interaction term of the purchase dummy and the market excess return, purchase*smb is an interaction term of the purchase dummy and smb, purchase *hml is an interaction term of the purchase dummy and hml, purchase*mom is an interaction term of the purchase dummy and mom. Statistical significance at the 10%, 5% and 1% level is denoted by *, ** and ***.

High vs low relivol

Tabel 3.7 presents the results from comparing high and low *relivol* portfolios. We build high and low *relivol* portfolios by including trades with low and high *relivol*. A trade is considered as a trade occurring during times with high *relivol* when *relivol* is greater than 1. If *relivol* is smaller than 1, this trade is classified as a low *relivol* trade. The coefficient of the dummy variable *high* hence captures the difference in abnormal returns between the high and the low *relivol* portfolios. If trades executed at times of high *relivol* outperform those executed at times of low *relivol*, we expect a positive high-dummy for purchase portfolios and a negative dummy for sale portfolios. The coefficient of the high-dummy is positive for purchases but fails to be significant at the 10% level. This indicates that high *relivol* trades do not systematically outperform low *relivol* trades. For sales, the coefficient of the high-dummy is negative and significant at the 10% level, suggesting that insiders make higher profits when selling during times of high *relivol*. However, the significance of the high-dummy vanishes when we control for different factor loadings of the high and the low *relivol* portfolios.

Table 3.7: Profitability of insider trading (high vs low ivol

High vs low	Purchases				Sales			
	Model 1		Model 2		Model 1		Model 2	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
mkt	0.950	21***	0.922	14.53***	1.057	28.86***	0.999	19.78***
smb	0.754	14.38***	0.726	9.86***	0.765	18.01***	0.683	11.65***
hml	0.173	2.83***	0.231	2.68***	- 0.391	-7.92***	- 0.285	-4.16***
mom	- 0.360	-9.83***	- 0.269	-5.25***	- 0.128	-4.34***	- 0.110	-2.69***
high	0.329	0.98	0.512	1.46	- 0.462	-1.69*	- 0.413	-1.48
high*mkt			0.055	0.61			0.117	1.64
high*smb			0.057	0.55			0.163	1.97**
high*hml			- 0.115	-0.94			- 0.208	-2.17**
high*mom			- 0.181	-2.49**			- 0.038	-0.66
intercept	1.659	6.78***	1.568	6.3***	0.903	4.53***	0.884	4.45***
Obs	402		402		400		400	
Adjusted R-squared	0.7285		0.7328		0.857		0.8648	
F-test	216.15***		123.19***		479.16***		284.7***	

This table shows the results of the regressions of the high and the low *relivol* portfolios on the four risk factors suggested by the Carhart model, i.e., market risk, size (smb), book-to-market (hml) and momentum (mom). The monthly factors are obtained from Kenneth French's website. The high *relivol* portfolio consists of trades where the *relivol* of the underlying stock is higher than 1. The low *relivol* portfolio consists of trades where the *relivol* of the underlying stock is smaller than 1. The dummy "high" is set to 1 if the return belongs to the high *relivol* portfolio and zero if the return belongs to the low *relivol* portfolio. high*mkt is an interaction term of the high dummy and the market excess return, high*smb is an interaction term of the high dummy and smb, high*hml is an interaction term of the high dummy and hml, high*mom is an interaction term of the purchase dummy and mom. Statistical significance at the 10%, 5% and 1% level is denoted by *, ** and ***.

Small vs large firms

We divide the sample into a small firm and a large firm sample by looking at the top and the bottom terciles in terms of market capitalization. Table 3.8 shows the results with respect to small firms. We again observe that also among small firms, insiders who time their purchases and sales during times of high *relivol* do not generate higher profits compared to insiders who time their trades when *relivol* is low. The coefficients of the alphas are much higher than in the baseline regression: purchases generate an abnormal return of 2.53% to 2.68% while sales generate an abnormal negative return from the perspective of insiders of 1.41% to 1.36%. Analyzing abnormal returns of insider trades in large firms, see Table 3.9, also confirms the finding that high *relivol* trades do not generate higher profits compared to low *relivol* trades.

Although we find that insiders apparently do time their insider transactions, outside investors do not have to fear that insiders generate abnormal trading profits which occur at the expense of uninformed investors.

Table 3.8: Profitability of insider trading (small firms)

High vs low, small firms	Purchases				Sales			
	Model 1		Model 2		Model 1		Model 2	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
mkt	0.771	9.93***	0.828	7.58	0.943	18.21***	0.972	13.57***
smb	0.763	8.48***	0.697	5.5	1.147	19.09	1.074	12.9***
hml	0.092	0.87	0.277	1.87	- 0.291	-4.17***	- 0.054	-0.55
mom	- 0.266	-4.25***	- 0.198	-2.24**	- 0.093	-2.22**	- 0.125	-2.15***
high	0.424	0.73	0.713	1.17	- 0.315	-0.81	- 0.188	-0.47
high*mkt			- 0.117	-0.75			- 0.057	-0.56
high*smb			0.135	0.75			0.145	1.24
high*hml			- 0.372	-1.77*			- 0.465	-3.42***
high*mom			- 0.136	-1.09			0.062	0.76
intercept	2.678	6.39***	2.531	5.91***	1.409	5***	1.356	4.81
Obs	395		395		400		400	
Adjusted R-squared	0.4132		0.4164		0.7672		0.7784	
F-test	56.5***		32.24***		264.02***		156.7***	

This table shows the results of the regressions of the high and the low *relivol* portfolios on the four risk factors suggested by the Carhart model, i.e., market risk, size (smb), book-to-market (hml) and momentum (mom). The monthly factors are obtained from Kenneth French's website. The portfolios are restricted to small firms, that is firm that belong to the bottom tercile in terms of market capitalization. The high *relivol* portfolio consists of trades where the *relivol* of the underlying stock is higher than 1. The low *relivol* portfolio consists of trades where the *relivol* of the underlying stock is smaller than 1. The dummy "high" is set to 1 if the return belongs to the high *relivol* portfolio and zero if the return belongs to the low *relivol* portfolio. high*mkt is an interaction term of the high dummy and the market excess return, high*smb is an interaction term of the high dummy and smb, high*hml is an interaction term of the high dummy and hml, high*mom is an interaction term of the purchase dummy and mom. Statistical significance at the 10%, 5% and 1% level is denoted by *, ** and ***.

Table 3.9: Profitability of insider trading (large firms)

High vs low, large firms	Purchases				Sales			
	Model 1		Model 2		Model 1		Model 2	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
mkt	1.052	23.3***	0.993	15.64***	1.077	25.65***	1.042	19.81***
smb	0.423	8.07***	0.394	5.33***	0.356	7.32***	0.264	4.33***
hml	0.310	5.06***	0.300	3.49***	- 0.053	-0.94	- 0.431	-6.05 ***
mom	- 0.333	-9.1***	- 0.241	-4.69***	- 0.235	-6.92***	- 0.045	-1.06
high	0.197	0.58	0.308	0.88	0.185	0.59	0.172	0.59
high*mkt			0.119	1.33			0.070	0.94
high*smb			0.058	0.56			0.188	2.19**
high*hml			0.019	0.16			0.751	7.47***
high*mom			- 0.182	-2.51**			- 0.378	-6.32***
intercept	0.501	2.03**	0.443	1.76*	0.580	2.53**	0.578	2.79***
Obs	397		397		398		398	
Adjusted R-squared	0.7031		0.7085		0.7525		0.807	
F-test	188.57***		107.93***		242.45***		185.46***	

This table shows the results of the regressions of the high and the low *relivol* portfolios on the four risk factors suggested by the Carhart model, i.e., market risk, size (smb), book-to-market (hml) and momentum (mom). The monthly factors are obtained from Kenneth French's website. The portfolios are restricted to large firms, that is firm that belong to the top tercile in terms of market capitalization. The high *relivol* portfolio consists of trades where the *relivol* of the underlying stock is higher than 1. The low *relivol* portfolio consists of trades where the *relivol* of the underlying stock is smaller than 1. The dummy "high" is set to 1 if the return belongs to the high *relivol* portfolio and zero if the return belongs to the low *relivol* portfolio. high*mkt is an interaction term of the high dummy and the market excess return, high*smb is an interaction term of the high dummy and smb, high*hml is an interaction term of the high dummy and hml, high*mom is an interaction term of the purchase dummy and mom. Statistical significance at the 10%, 5% and 1% level is denoted by *, ** and ***.

Robustness checks

We also perform robustness checks by defining alternative cut-off values for the classification of low and high *relivol* trades. E.g., we experiment with looking at the top and bottom terciles and quintiles of values for *relivol*. The main result that the coefficient of the high-dummy is insignificant survives the robustness checks using alternative thresholds.

Medium-sized trades may be more informative compared to very small and very large trades. We follow the definition of a medium-sized trade as in Barclay and Warner (1993) and consider a trade involving 500 to 9,999 shares as a medium-sized trade. We build portfolios using only trades that satisfy this condition. Still, as Table 3.10 shows, we do not find that high *relivol* trades perform significantly better than low *relivol* trades.

As a further robustness check, we use a time horizon of three months rather than six months. The results, shown in Table 3.11, suggest that the findings remain robust also if we consider an alternative time horizon.

We perform additional robustness checks which are available upon request and shortly summarized in the following. Splitting the sample according to insider positions does not reveal significant differences in the profitability of timing between the different groups.

A possible objection is that portfolio returns are more erratic when the portfolio contains only few stocks. We approach this problem in two ways. First, we perform regressions excluding those 5% of observations with the smallest number of stocks contained in the portfolio. Second, we conduct a weighted least squares regression, using the natural logarithm of the number of stocks contained in the portfolio as the weighting factor. Our results remain robust to these additional tests.

Table 3.10: Profitability of insider trading (medium-sized trades)

High vs low medium-sized trades	Purchases				Sales			
	Model 1		Model 2		Model 1		Model 2	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
mkt	0.943	19.19***	0.920	13.32***	1.013	25.94***	0.958	17.75***
smb	0.725	12.73***	0.693	8.66***	0.759	16.77***	0.669	10.7***
hml	0.222	3.33***	0.265	2.83***	- 0.324	-6.16***	- 0.210	-2.88***
mom	- 0.311	-7.83***	- 0.208	-3.72***	- 0.076	-2.41**	- 0.075	-1.73 *
high	0.175	0.48	0.371	0.97	- 0.352	-1.21	- 0.330	-1.1
high*mkt			0.046	0.48			0.111	1.45
high*smb			0.065	0.57			0.178	2.02**
high*hml			- 0.086	-0.65			- 0.223	-2.17**
high*mom			- 0.207	-2.62***			- 0.003	-0.05
intercept	1.810	6.8***	1.712	6.33***	0.788	3.7***	0.783	3.68***
Obs	402		402		399		399	
Adjusted R-squared	0.6747		0.6793		0.8255		0.8346	
F-test	167.33***		95.4***		377.48***		224.13***	

This table shows the results of the regressions of the high and the low *relivol* portfolios on the four risk factors suggested by the Carhart model, i.e., market risk, size (smb), book-to-market (hml) and momentum (mom). The monthly factors are obtained from Kenneth French's website. The portfolios are restricted to medium-sized trades, that is trades that involve more than 500 and less than 9,999 shares. The high *relivol* portfolio consists of trades where the *relivol* of the underlying stock is higher than 1. The low *relivol* portfolio consists of trades where the *relivol* of the underlying stock is smaller than 1. The dummy "high" is set to 1 if the return belongs to the high *relivol* portfolio and zero if the return belongs to the low *relivol* portfolio. high*mkt is an interaction term of the high dummy and the market excess return, high*smb is an interaction term of the high dummy and smb, high*hml is an interaction term of the high dummy and hml, high*mom is an interaction term of the purchase dummy and mom. Statistical significance at the 10%, 5% and 1% level is denoted by *, ** and ***.

Table 3.11: Profitability of insider trading (3 months holding period)

High vs low, three month returns	Purchases				Sales			
	Model 1		Model 2		Model 1		Model 2	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
mkt	0.960	18.45***	0.904	12.35***	1.049	27.99***	1.011	19.51***
smb	0.741	12.28***	0.706	8.32***	0.772	17.75***	0.696	11.57***
hml	0.169	2.39**	0.192	1.94*	- 0.362	-7.15***	- 0.236	-3.37***
mom	- 0.363	-8.63***	- 0.278	-4.69*	- 0.120	-3.97***	- 0.091	-2.19**
high	0.384	0.99	0.508	1.26	- 0.291	-1.04	- 0.191	-0.67
high*mkt			0.112	1.08			0.077	1.06
high*smb			0.069	0.57			0.151	1.77*
high*hml			- 0.047	-0.33			- 0.246	-2.49**
high*mom			- 0.171	-2.05**			- 0.059	-1
intercept	2.029	7.21	1.967	6.86***	0.781	3.83***	0.737	3.62**
Obs	402		402		400		400	
Adjusted R-squared	0.6713		0.675		0.8478		0.8554	
F-test	164.82***		93.52***		445.37***		263.23***	

This table shows the results of the regressions of the high and the low *relivol* portfolios on the four risk factors suggested by the Carhart model, i.e., market risk, size (smb), book-to-market (hml) and momentum (mom). The monthly factors are obtained from Kenneth French's website. The portfolios assume a holding period of three months, i.e., the stocks are kept in the portfolio for three month. The high *relivol* portfolio consists of trades where the *relivol* of the underlying stock is higher than 1. The low *relivol* portfolio consists of trades where the *relivol* of the underlying stock is smaller than 1. The dummy "high" is set to 1 if the return belongs to the high *relivol* portfolio and zero if the return belongs to the low *relivol* portfolio. high*mkt is an interaction term of the high dummy and the market excess return, high*smb is an interaction term of the high dummy and smb, high*hml is an interaction term of the high dummy and hml, high*mom is an interaction term of the purchase dummy and mom. Statistical significance at the 10%, 5% and 1% level is denoted by *, ** and ***.

3.6 Conclusion

Using *relivol* as a measure of information asymmetry between firm insiders and outside investors rather than following the established approach in the literature of focusing on specific firm events, we find corporate insiders are likely to exploit their foreknowledge of short-term information. Using the insider trades on the US market that have been registered with the SEC, we find that insider purchases are significantly more likely on a given day when recent idiosyncratic volatility is relatively high. This effect does not appear to exist for sales, which suggests that these are less short-term information driven and that insiders may fear reputational or litigation risks when selling at times of high information asymmetry in anticipation of a negative development of their firm.

Further results indicate that chairpersons buy, with respect to information asymmetry, less aggressively than CEOs or other executives, suggesting that reputational costs for people in more prominent roles have importance though these may be counterbalanced by CEO's larger informational advantage concerning short-term information in comparison to chairpersons. Other insiders, who likely face less reputational costs than the top executives, buy when idiosyncratic volatility is high while their selling does not decrease with idiosyncratic volatility. Insiders do not appear able to significantly increase their profits when timing their trades during periods of high *relivol*.

The fact that timing, on average, does not appear to lead to higher insider trading profits lends support to the notion that timing does not significantly increase costs of insider trading to outsiders.

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Appendix

Similar to Brown and Cliff (2005), we regress future k-week returns on the current value of the sentiment index and control variables

$$(r_{t+1} + ... + r_{t+k}) = \alpha(k) + \Theta'(k)z_t + \beta(k)S_t + \epsilon_t^{(k)},$$

where the variables are defined as in section 2.3.1. The fact that we use overlapping observations for the regressand induces an $MA(k-1)$ structure in the error terms under the null hypothesis that $\epsilon^{(1)}$ is serially uncorrelated. Since robust standard errors, suggested by Hansen and Hodrick (1980), are known to perform poorly in small samples and the existence of persistent regressors leads to a bias in the coefficient estimates, we opt for a simulation approach to account for the bias and to obtain appropriate critical values for inference.

We replicate the bootstrap simulation of Brown and Cliff (2005), pp. 437, and start by estimating a VAR(1) model for $y_t = [r_t S_t z_t']$. After the estimation, we impose the null hypothesis that the Sentix sentiment survey does not predict 1-week returns, by setting the appropriate element in the coefficient vector of the return equation equal to zero. We then adjust the constant in the constrained model by adding the contribution of average sentiment to the returns obtained by multiplying the original slope value of the sentiment by the average sentiment level to the constant of the return equation. We bootstrap the residuals from the calibration estimates to account for heteroscedasticity, and generate and discard 100 additional observations to delete possible starting effects. In each of the replications, a number equal to our original sample of simulated observations is used to estimate our equation of interest for horizons from one to 26 weeks. Analogous to Brown and Cliff, we repeat the procedure 10,000 times in order to obtain a distribution of the values of $\hat{\beta}(k)$.

In order to gauge the statistical significance of the coefficient estimates we compare the sentiment coefficient of the original model with the simulated probability distribution in order to obtain p-values. Because these p-values are based on the actual distribution of the residuals, they are robust to deviations from the normal distribution.