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to my parents and grandma

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Introduction

> "The twin pillars of neoclassical finance are efficient markets and, closely related, the theory of asset pricing and, most notably, no arbitrage and risk neutral pricing." — *Stephen A. Ross*[1]

The above quote underscores the importance of the paradigm of (capital) market efficiency in financial economics. Since the 1960s and, in particular, since the publication of probably the most prominent article on the topic, Fama (1970), market efficiency has been the area of tremendous research efforts. In the three decades since the term was coined by Eugene F. Fama, the efficient market hypothesis has become the central proposition in financial economics, and, as such, widely accepted by academic scholars. Fama (1970)'s statement that "a securities market is efficient if security prices at any time fully reflect all available information" is probably the most classical definition of market efficiency and serves as the centerpiece of the *Efficient Market Hypothesis* (EMH).[2]

In recent years, in light of several instances where the EMH seemingly failed, such as the "Internet bubble" at the turn of the century and the recent financial crisis that originated in 2007 with the collapse of the subprime mortgage market, the concept of market efficiency has been increasingly challenged by academics. Moreover, a number of financial economists have started to believe that stock prices/returns are (to some extent) predictable based on historical prices as well as fundamental variables, such as the dividend yield or the book-to-market ratio. Another challenge for market efficiency with regard to the time-series characteristics of stock prices/returns is posed by several studies that suggest that stock returns do not follow a random walk but are mean-reverting (see, for instance, Poterba and Summers (1988), Lo and MacKinlay (1988), and Lo and MacKinlay (1999)). It remains an open question whether these time-series properties are compatible with an efficient market. At the same time, advocates of market efficiency have refuted these challenges and claimed that markets are far more efficient than asserted by the critics of the EMH.[3] Malkiel (2005), p. 2, explains that "if prices were often irrational and if market returns were as predictable as some critics of the efficient market

1 Ross (2002), p. 129.
2 Fama (1970), p. 383.
3 Malkiel (2003) provides a nice overview article on the EMH and its critics.

hypothesis believe, than surely actively managed investment funds should easily be able to outdistance a passive index fund that simply buys and holds the market portfolio." However, according to Malkiel (2005), the fact that empirical studies over the last three decades fail to support the ability of institutional investors to outperform the market portfolio can be seen as a strong indication that market efficiency holds.[4]

Fama (1970) and Fama (1991) argue that market efficiency can only be tested jointly with some equilibrium model for security prices, a statement that has become known as the *joint hypothesis problem*. That is, a formalization of the process of price discovery—or, in other words, of the statement that prices "fully reflect" all available information—is required. Following Fama (1970), the concept of market efficiency—i.e., the statement that in an efficient market securities prices at any time fully reflect all information available to market participants—can be formalized as follows:

$$E(S_{i,t+1}|\mathcal{I}_t) = [1 + E(R_{i,t+1}|\mathcal{I}_t)]S_{i,t}, \tag{1}$$

where E is the expected value operator, and $R_{i,t+1}$ denotes the expected one-period return of security i from time t to $t+1$, $S_{i,t}$ the price of security i at time t, and $S_{i,t+1}$ its price at time $t+1$; $R_{i,t+1}$ is defined as $R_{i,t+1} = \frac{S_{i,t+1}-S_{i,t}}{S_{i,t}}$, and $\mathcal{I}_t$ is the information set which is fully reflected in the security price at time t. $E(R_{i,t+1})$ is obtained from the expected return model under consideration.

Define the excess market value, $v_{i,t+1}$, as

$$v_{i,t+1} = S_{i,t+1} - E(S_{i,t+1}|\mathcal{I}_t). \tag{2}$$

Under the assumptions that the market equilibrium can be determined in terms of the expected return and that the expected return is based on the information set $\mathcal{I}_t$,

$$E(v_{i,t+1}|\mathcal{I}_t) = 0. \tag{3}$$

Consequently, trading rules which are based on information in $\mathcal{I}_t$ are not able to systematically generate returns larger than $E(R_{i,t+1})$—in other words, they are not able to earn excess returns.

Analogously, let excess return be defined as

$$\gamma_{i,t+1} = R_{i,t+1} - E(R_{i,t+1}|\mathcal{I}_t), \tag{4}$$

4 For details, see Malkiel (2005)'s article on the performance of professional investors over the period from 1970 through 2003.

then

$$E(\gamma_{i,t+1}|\mathcal{I}_t) = 0. \tag{5}$$

That is, the excess return, defined as the difference of the actual return observed at time $t+1$, $R_{i,t+1}$, and the expected return projected at time t based on information in $\mathcal{I}_t$, has an expected value of zero.

Denoting a trading strategy under which, at time t, an investor invests an amount $\zeta_i(\mathcal{I}_t)$ in each of the n available assets, as

$$\zeta(\mathcal{I}_t) = [\zeta_1(\mathcal{I}_t), \zeta_2(\mathcal{I}_t), ..., \zeta_n(\mathcal{I}_t)], \tag{6}$$

the excess market value of such a trading strategy at time $t+1$, V_{t+1}, is computed as

$$V_{t+1} = \sum_{i=1}^{n} \zeta_i(\mathcal{I}_t)[\underbrace{R_{i,t+1} - E(R_{i,t+1}|\mathcal{I}_t)}_{\gamma_{i,t+1}}]. \tag{7}$$

According to equation (5), the expected value of the excess market value, V_{t+1}, is equal to,

$$E(V_{t+1}) = \sum_{i=1}^{n} \zeta_i(\mathcal{I}_t)\, \underbrace{E([R_{i,t+1} - E(R_{i,t+1}|\mathcal{I}_t)])}_{=E(\gamma_{i,t+1}|\mathcal{I}_t)} = 0. \tag{8}$$

To sum up, in an efficient market, the expected excess return on any trading/investment strategy—and hence the excess market value of any strategy— is equal to zero.

Depending on the type of information in set, $\mathcal{I}_t$, Fama (1970) considers three categories of market efficiency:

- *weak form efficiency*—$\mathcal{I}_t$ contains all historical prices/returns
- *semi-strong form efficiency*—$\mathcal{I}_t$ contains any publicly available information
- *strong efficiency*—$\mathcal{I}_t$ contains all information, public and private

The different categories of market-efficiency and their corresponding definitions of the information set, $\mathcal{I}_t$, have different practical implications. Under the weak EMH, an investor cannot earn excess returns based on past prices/returns, i.e., systematic excess returns from technical trading are ruled out. In a more recent study, Fama (1991) slightly revises his categorization, and the first category now comprises all tests for return predictability; that is, the concept of weak EMH also includes tests for the predictive ability of variables, such as the dividend yield, the book-to-market ratio, and interest rates, for future stock returns, as well as tests for cross-sectional return predictability. Thus, if the weak EMH holds, an investor should not be able to earn excess returns based on such predictive models. The semi-strong EMH encompasses all tests/event-studies regarding the adjustment of prices to new information, and posits that new information is instantaneously reflected in stock prices (see Fama (1991)). This implies that active portfolio management is not able to beat the market, unless portfolio managers have private information. According to Fama (1991), the third category is now entitled tests for private information. Specifically, the concept of strong form market efficiency implies that an investor cannot earn excess returns even if she possesses private information not yet available to other market participants. In this case, market participants cannot expect to beat the market, and only passive portfolio management makes sense. In summary, "if the EMH holds, the market truly knows best" (Shleifer (2000), p. 1).

The ongoing debate about capital market efficiency contains a vast array of studies on both sides, i.e., work by EMH advocates and its critics. The latter, documenting that deviations from market efficiency are observable over long horizons, formed a new strand of literature, the field of behavioral finance. This thesis contributes to the literature on the efficiency of financial markets. The findings of the following three self-contained chapters underscore the challenge in definitively answering the question of whether markets are efficient or not, and the importance of differentiating between the various forms of the EMH as markets may be efficient according to the weaker form but not according to the stronger form. While Chapter 2 provides evidence that markets are efficient according to weak form efficiency in that market timing fails, Chapter 1 raises some doubts about the weak form EMH by documenting that information is not reflected simultaneously in parallel markets; Chapter 3 investigates market anomalies in relation to the semi-strong form EMH, and challenges its claim by showing that publicly available information is not immediately incorporated into stock prices. The main chapters of this thesis, each of which notationally self-contained, are based on three studies of different aspects of market efficiency.

Chapter 1 investigates the process of price discovery in spot and futures markets.[5] According to the efficient market hypothesis, new information should be reflected instantaneously in (all) prices, and, therefore, simultaneously in all securities traded in parallel markets.[6] In that sense, securities on parallel markets should contribute equally to the process of price discovery, and it should not be possible to predict future returns in one market by past returns in the other market. Yet, due to institutional differences, such as the magnitude of transaction costs, markets may differ in the speed of information

[5] This chapter is based on Schlusche (2009).
[6] See Fama (1965) and Fama (1970).

dissemination. We therefore investigate whether one of the parallel markets incorporates new information faster and, consequently, contributes more to the process of price discovery. Specifically, we examine the contribution of two derivative products of the German blue chip index DAX: Exchange traded funds and index futures. In order to eliminate noise caused by differences in the microstructure of the markets, we use transaction data only from electronic-trading markets. We apply a linear vector error correction model for our estimations and we use the common factor weights, first proposed by Schwarz and Szakmary (1994), to quantify the contribution of each market to the process of price discovery. Our results indicate that, while both markets do contribute to price formation, the futures market clearly leads in the process of price discovery. Hence, the weak form of market efficiency cannot be (fully) supported in this case. Furthermore, we show that volatility, and not liquidity, as would be conjectured by the transaction-costs hypothesis, is the driving factor for relative price leadership between the two markets.

Chapter 2 aims to quantify possible data-snooping biases in the market-timing literature and to test whether the considered market-timing rules are truly superior to a buy-and-hold strategy.[7] Market-timing rules build on empirical findings of the ability of certain fundamental and sentiment indicators to predict future stock returns. The literature has identified many useful indicators, such as the earnings-to-price ratio (Campbell and Shiller (1988b), Campbell and Shiller (1998)), the dividend yield (Shiller (1984), Fama and French (1988)), the dividend-payout ratio (Lamont (1998)), the maturity spread and the credit spread (Campbell (1987), Fama and French (1989)), and the gilt-equity yield ratio (Clare, Thomas, and Wickens (1994), Brooks and Persand (2001)). In an efficient market in the weak sense, however, return predictability based on past information should fail. Based on the predictive ability of certain indicators, a variety of market-timing rules have been investigated and found successful in the market-timing literature.[8] However, the studies on market-timing performance lack appropriate corrections for data-snooping biases, and the profitability of seemingly outperforming market-timing rules might therefore be due to biases in statistical inference rather than truly superior performance. We reassess the profitability of market-timing rules when controlling for data-snooping biases. On the one hand, a rejection of the null hypothesis that the best market-timing rules are not able to beat a buy-and-hold strategy would indicate that the stock market is not efficient in the weak form—unless risk premia are varying over time.[9] On the other hand, if the null hypothesis cannot be rejected, market efficiency cannot be denied. We find that, even though individual market-timing rules show significant outperformance when

[7] This chapter is based on joint work with Andreas Neuhierl (Neuhierl and Schlusche (2010)).

[8] The studies in the field of market timing are numerous and include, for instance, Breen, Glosten, and Jagannathan (1989), Prather and Bertin (1997), Prather and Bertin (1998), Copeland and Copeland (1999), Shen (2003), Fisher and Statman (2006a), and Fisher and Statman (2006b).

[9] For details on time-varying risk premia, see Section 2.7.5.

considered in isolation, these results do not remain significant after correcting for data snooping; this finding provides evidence in favor of market efficiency in that investment strategies based on historical information do not generate (risk-adjusted) excess returns.

Chapter 3 deals with the semi-strong form of market efficiency.[10] In a market that is efficient in the semi-strong sense, investors cannot earn excess returns based on any public information—or, as Shleifer (2000), p. 6, puts it, "[...] as soon as information becomes public, it is immediately incorporated into prices, and hence an investor cannot gain by using this information to predict returns." Event studies on the impact of news releases, e.g., earnings announcements or news on a company's investment decision, have shown well-know regularities, such as the post-earnings announcement drift ($PEAD$). If markets were efficient in the semi-strong form sense, any news should be incorporated into prices instantaneously. Previous literature in the field of event studies typically finds that news are reflected in stock prices within a day of the announcement.[11] A number of studies, however, documents anomalies, e.g., the $PEAD$, which cannot be reconciled with market efficiency. Having obtained a comprehensive dataset of corporate press releases issued between April 2006 and August 2009, we classify it into various news categories and then analyze the corresponding stock price reactions. In addition to confirming earlier findings regarding the market reaction to financial news, we document strong responses, along with prolonged drift patterns, to news about corporate strategy, customers and partners, products and services, management changes, as well as legal developments. We show that return volatility increases and liquidity typically decreases following most news announcements. Furthermore, we find that the market response to certain types of news changed during the period of the financial crisis. For example, news that are likely to result in higher and less volatile future cash flows (i.e., announcements of corporate reorganization, new customers and partners, new products, FDA and European drug approvals, as well as legal settlements) led to more positive price reactions; announced plans to raise funds through equity or debt offerings were perceived less negatively; and the market reaction to announcements of share repurchases became even more positive than during the pre-crisis period.

[10] This chapter is based on Neuhierl, Scherbina, and Schlusche (2010).

[11] Fama (1991) provides a summary of the implications of the findings from event studies on market efficiency.

Chapter 1

Price Formation in Spot and Futures Markets: Exchange Traded Funds vs. Index Futures

1.1 Introduction

In recent years, there has been a move in financial markets towards the trading of identical or closely related assets in parallel markets. For instance, futures contracts have been introduced for the indices, such as the US-based Dow Jones Industrial Average (DJIA), the S&P 500, as well as the German index DAX 30. More recently, a new market segment, the so-called exchange traded funds (ETFs), has drawn considerable attention. ETFs are closely related to mutual funds in that they hold portfolios of financial assets. However, unlike mutual funds, ETFs are traded or priced continuously during exchange trading sessions, similarly to stocks. The arrival of basket securities, such as financial futures and ETFs, facilitates market participation of uninformed traders and allows inexpensive index arbitrage (e.g., Subrahmanyam (1991) and Gorton and Pennacchi (1993)).

According to the efficient market hypothesis, new information should be impounded simultaneously in all markets. Yet, due to institutional differences, such as the magnitude of transaction costs, markets may differ in the speed of information dissemination. It is therefore an interesting research question to investigate which market incorporates new information faster and consequently contributes more to the process of price discovery. This question has drawn considerable attention in the financial literature. Due to the fact that indices and its derivative products are cointegrated, the model commonly used to investigate price formation in financial markets is some version of the vector error correction model (VECM) introduced by Hasbrouck (1995). Cointegration theory suggests that price differences between markets do not diverge infinitely. Rather, there exists a long-term relationship between prices in parallel markets. The VECM directly links changes in futures and spot prices to deviations from the long-run relation. The VECM specification stipulates that prices may deviate from their common long-run relation. However, arbitrage forces ensure that prices converge to their theoretically stipulated relation. One difficulty when estimating the VECM using spot and futures prices is the fact that the cointegration relation, which is induced by the cost-of-carry relation between the two markets, is time-varying. One possible solution is demeaning of the log price series for each trading day. This approach, which removes any average daily level difference between the spot and futures price series while leaving intraday returns unaffected, was introduced by Dwyer, Locke, and Yu (1996) and adopted by Theissen (2005), among others. In our analysis, we follow a different approach, applied by a variety of authors, such as Martens, Kofman, and Vorst (1998) and Tse (2001). Using a pre-specified cointegrating vector, we take the cost-of-carry relationship directly into account and base our analysis on discounted futures prices.

Despite all methodological differences, the majority of studies have shown that the futures market leads the index market in price discovery. Stoll and Whaley (1990) and Chan (1992) for the S&P 500 index, and Tse (1999), Tse (2001), and Tse, Bandyopadhyay, and Shen (2006) for the DJIA index report the dominance of the futures market in price discovery. For the German market, Booth, So, and Tse (1999), who consider the DAX index, index futures and index options in their investigation on price leadership in the German market, show that index futures dominate in the process of price formation. Similarly, Theissen (2005) finds that the futures market leads the spot market in terms of relative contribution to price discovery.

The empirical investigations have so far focused mainly on the index itself and the corresponding futures market. Despite the tremendous growth in ETF trading, few studies have been conducted on the relative price discovery of ETFs and index futures. Since the majority of previous studies have reported a leadership of the futures market relative to the index, the examination of whether the ETF market, in turn, leads the futures market in price discovery is the logical next step. Given their lower transaction costs and absence of short-sale restrictions, ETF markets may potentially incorporate new information faster than cash indices. Hence, the price leadership of the futures market, relative to the spot market, might be weakened in the new setting where the ETF market is considered in place of the index itself. Hasbrouck (2003) analyzes price leadership among the three S&P 500 index derivatives, the ETF, the electronically-traded small-denomination futures contract "E-mini," and the regular floor-traded futures contract. His main finding states that the "E-mini" leads the process of price discovery by contributing roughly 90% to price formation. However, his results are based on ETF data obtained from Amex, which uses floor-trading. Since electronic trading offers the advantages of lower trading costs and trader anonymity, the results of Hasbrouck (2003) may shift in favor of the ETF market. Tse, Bandyopadhyay, and Shen (2006) address this issue by including electronically-traded ETFs from ArcaEx, a computer-mediated trading system, in their examination of the price leadership of the DJIA index and its derivatives (ETFs, floor-traded futures contracts, and electronically-traded "E-mini futures"). In this setting, the authors find that the ETFs make a significant contribution to the process of price discovery.

Our goal is to examine the relative contribution to price discovery of the ETF market and the futures market in Germany, two derivative products of the German blue chip index DAX. We estimate the VECM using DaxEx (ETF) prices and DAX futures prices adjusted for the cost-of-carry. The contribution of this paper to the existing literature is twofold: First, even though previous papers have investigated price discovery in the German market, none of them has thus far included the increasingly important ETFs in their analysis. For instance, Grünbichler, Longstaff, and Schwartz (1994), Kempf and Korn (1998), and Theissen (2005) analyze the lead-lag relationship for the German spot and futures market, but do not consider the market for ETFs. Hence, our paper is the first empirical investigation of price discovery with respect to the ETF market and the futures market in Germany. Our results indicate that the futures market leads in the process of price discovery. Second, we extend the literature on price leadership in spot and futures markets by investigating which factors drive the price leadership of the futures market and potentially lead to a shift in price formation in favor of the ETF market. Precisely, we analyze whether liquidity and/or volatility affect relative price formation. Our results show that when volatility is high the contribution of the ETF market to the process of price discovery increases. Liquidity turns out to have no impact on price leadership.

In order to quantify the contribution of the two markets to the process of price discovery, we use the so-called common factor weights (CFW), first introduced by Schwarz and Szakmary (1994). This intuitive measure can be simply calculated from the coefficients of the VECM. In order to eliminate undesirable effects on the results due to differences in the microstructure of the markets, our analysis is based on data from electronic-trading markets. This procedure closely follows Tse, Bandyopadhyay, and Shen (2006).

The remainder of the paper is organized as follows. Section 1.2 presents the relevant economic and econometric models and discusses the measure we use in our study to assess the contributions to price discovery. Section 1.3 provides some details about the ETF market and the product itself. Section 1.4 describes the data used in our analysis and presents some descriptive statistics, as well as the results of the stationarity tests.

Section 1.5 documents the empirical results, and in Section 1.6 the determinants for price leadership are analyzed. Finally, Section 1.7 concludes.

1.2 Methodology

1.2.1 The Economic Model

The relation between spot and futures prices is described by the cost-of-carry model. Under the no-arbitrage condition, i.e., a situation where a futures contract is priced at its "fair value," which rules out arbitrage opportunities between the spot and the futures market, the model takes the following form:

$$F_{t,T} = S_t e^{(r_{t,T} - \kappa_{t,T})(T-t)}, \tag{1.1}$$

where $F_{t,T}$ is the price of a futures contract expiring at time T, S_t is the spot price, $r_{t,T}$ is the risk-free interest rate on an investment for the time period (t,T), and $\kappa_{t,T}$ is the expected dividend yield on the underlying asset.[1] Any deviation from the relation described by equation (1.1) creates arbitrage opportunities. If, for instance, $F_t > S_t e^{(r_{t,T} - \kappa_{t,T})(T-t)}$, arbitrageurs can earn a profit by taking a long position in the index, i.e., by buying the stocks in the index and shorting the futures contract. For $F_t < S_t e^{(r_{t,T} - \kappa_{t,T})(T-t)}$, the reverse arbitrage strategy should be executed.

Following the cost-of-carry relation, we define the pricing error as

$$z_t = p_t^S - (\underbrace{f_t - (r_{t,T} - \kappa_{t,T})(T-t)}_{\equiv p_t^F}), \tag{1.2}$$

where $f_t = \ln(F_t)$ and $p_t^S = \ln(S_t)$;[2] hence, z_t may be considered the percentage change of mispricing. Values of the pricing error different from zero indicate arbitrage opportunities, given that we assume zero transaction costs associated with index arbitrage. Since it takes time for arbitrageurs to take appropriate positions in the spot and the futures markets, this arbitrage opportunity has to be lagged by d periods of time, where d is the delay inherent in the arbitrage process. Hence, arbitrage activity takes place when the following inequality holds:

$$z_{t-d} \neq 0. \tag{1.3}$$

1 Henceforth, for convenience we drop subscript T, indicating the expiration day of the futures contract.

2 Note that p_t^F denotes the log futures prices adjusted for the cost-of-carry.

When arbitrageurs enter into the market, the next observations of the pricing error move fast towards zero.

1.2.2 The Econometric Model

In this section, we provide motivation and details of an econometric model for describing arbitrage activity and investigating whether the spot market or the futures market leads the process of price discovery.

Previous empirical literature (e.g., Martens, Kofman, and Vorst (1998) and Dwyer, Locke, and Yu (1996)) has concluded that spot indices and futures have unit roots, i.e., are non-stationary, whereas the respective pricing error, as defined above, is stationary. This, in turn, implies that spot and futures prices adjusted for the cost-of-carry are cointegrated with a coefficient of unity. As such, the relation between these time series can be characterized by an error correction representation (see Engle and Granger (1987)).[3] Such an error correction model directly links changes in futures and spot prices to deviations from the arbitrage relation, i.e., the pricing error. The error correction specification stipulates that prices undergo some short-term disruption, i.e., they deviate from the long-run relation (1.1). However, since prices possess the same long-run properties, this implies that they adjust due to arbitrage trading aimed at exploiting mispricing.

We follow other studies in this field, such as Dwyer, Locke, and Yu (1996) and Theissen (2005), and model current futures and spot returns by lagged futures and spot returns and by deviations from the cost-of-carry relation in the previous period, $z_{t-1} = p^S_{t-1} - p^F_{t-1}$.[4] Formally, the linear vector error correction model works as follows:

$$\begin{aligned}
\Delta p^S_t &= \alpha^S + \sum_{i=1}^{k} \gamma_{11i} \Delta p^S_{t-i} + \sum_{i=1}^{k} \gamma_{12i} \Delta p^F_{t-i} + \delta^S (p^S_{t-1} - p^F_{t-1}) + u^S_t, \qquad (1.4)\\
\Delta p^F_t &= \alpha^F + \sum_{i=1}^{k} \gamma_{21i} \Delta p^S_{t-i} + \sum_{i=1}^{k} \gamma_{22i} \Delta p^F_{t-i} + \delta^F (p^S_{t-1} - p^F_{t-1}) + u^F_t,
\end{aligned}$$

[3] See Brenner and Kroner (1995) for a summary of various applications of cointegration relations in financial research.

[4] Since in our study we use transaction prices rather than quotes, the time in our framework is transaction time rather than continuous clock time. Therefore, the time index t refers to observations in transaction time.

where Δp_t are logarithmic futures (F) and spot (S) returns and superscripts S and F identify coefficients relating to the respective markets.[5]

Following Martens, Kofman, and Vorst (1998) and Tse (2001), we use a pre-specified cointegrating vector which enters the model as the error correction term z_{t-1}, defined by equation (1.2).[6] This procedure takes the cost-of-carry relation explicitly into account and at the same time captures the time-variability of the cointegration relation.[7]

The coefficients on the error correction term, δ^S and δ^F, indicate which market dominates the process of price formation and how the system adjusts to deviations from the long-run equilibrium. If the futures market impounds information faster than the spot market, δ^F should be insignificant whereas δ^S will be significantly negative, indicating that the spot price exhibits adjustment tendencies. In other words, the futures market reflects information first and thus does not show adjustment movements. If instead information disseminates in the spot market first, δ^S will be insignificant and δ^F will be positive and significant.

1.2.3 Measure for the Contribution to Price Discovery: Common Factor Weights

In order to assess the contribution to price discovery of each market, we use the common factor weights (CFW) of Schwarz and Szakmary (1994) who propose a measure that is calculated by using the coefficients on the error correction term in model (1.4).[8] The

5 These two equations stem from the general vector error correction model developed to investigate the long-run and short-run relationships between price series that are cointegrated. This general model can be specified as

$$\Delta \mathbf{p}_t = \alpha + \mathbf{\Gamma}_1 \Delta \mathbf{p}_{t-1} + \mathbf{\Gamma}_2 \Delta \mathbf{p}_{t-2} + \ldots + \mathbf{\Gamma}_p \Delta \mathbf{p}_{t-p} + \delta(\beta' \mathbf{p}_{t-1} - \mu_e) + \mathbf{u}_t, \tag{1.5}$$

where $\mathbf{\Gamma}_i$ is the coefficient matrix of the ith lag in the returns of the price vector, α is the constant term, δ is the error correction coefficient, β is the cointegration vector, and $\mu_{\mathbf{e}}$ is the expected value of the cointegration relation. In our case, the term μ_e is expected to be zero ($\mu_e = 0$) and the cointegration vector is supposed to be $(1, -1)$.

6 Note that in the following analysis the expected dividend yield does not enter the cost-of-carry relation, since we consider DAX derivative products and the calculation of the DAX as a performance index is based on the presumption that dividends are reinvested.

7 Dwyer, Locke, and Yu (1996) and Theissen (2005), among others, follow a different approach to avoid the problem arising due to the non-constant cointegration relation. In their empirical analyses, they modify spot and futures time series by subtracting the daily mean from the logarithms of the spot and the futures price series.

8 Hasbrouck (1995) suggests an alternative measure, the so-called information shares (IS), to quantify the contribution of each market to the process of price discovery. In contrast to the common factor weights which are solely based on the coefficients on the error correction term, the IS approach of Hasbrouck (1995) relates the contribution of each market's innovation to the total innovation of the common efficient price. Since this approach may lead to ambiguous results, when the price innovations are correlated across the two markets—e.g., due to a small number of transactions per

relative magnitude of these coefficients quantifies the contribution of the two markets to price discovery. Formal justifications, which are based on Gonzalo and Granger (1995), are given, for instance, by Theissen (2002) and Booth, Lin, Martikainen, and Tse (2002). Specifically, the common factor weights are obtained as follows:[9]

$$CFW^S = \frac{\delta^F}{\delta^F - \delta^S} \text{ and } CFW^F = \frac{-\delta^S}{\delta^F - \delta^S}. \tag{1.7}$$

As mentioned in the previous section, the coefficients δ^S and δ^F indicate the way of adjustment of the system to deviations from the cost-of-carry relation. The higher the magnitude of δ^j $(j = \{S, F\})$, the slower the market impounds new information or, stated differently, the more the market has to adjust toward the new equilibrium price. That is, the market which leads the process of price formation does not follow but rather initiates the deviation from the cost-of-carry relation. For instance, if the futures market impounds information faster than the spot market, δ^S will be significant, indicating that the spot price exhibits adjustment tendencies, and δ^F will be insignificant. If price discovery occurs only in the futures market, $CFW^F = 1$; conversely, if price discovery occurs exclusively in the spot market, $CFW^F = 0$. If both markets contribute equally to the process of price discovery, $CFW^F = CFW^S = 0.5$.

The sum of the coefficients δ^j can be interpreted as the total adjustment of the system to a shock in at least one market. The common factor weights quantify the part of the total reaction attributed to a particular market. Simultaneous small/large values of the error correction coefficients for both markets indicate slow/fast adjustment dynamics. In the extreme case, where the coefficients δ^j are equal to zero, the supply of arbitrage services is zero. In this case, spot and futures prices are independent random walks and, as a result, not cointegrated. Standardizing the common factor weights, so that they sum up to one, yields a measure to quantify the relative price leadership.

1.3 Exchange Traded Funds

In the past few years, a substantial growth in trading volume and product coverage occurred in the ETF market showing the increasing popularity of those funds. Table 1.1 displays the increase in trading volume for the DaxEx, the most liquid ETF traded on

day—we decided to base our analysis on the common factor weights rather than the information shares.

9 This is equivalent to

$$CFW^S = \frac{|\delta^F|}{|\delta^F| + |\delta^S|} \text{ and } CFW^F = \frac{|\delta^S|}{|\delta^F| + |\delta^S|}, \tag{1.6}$$

as long as the coefficients δ^F and δ^S have the correct signs, i.e., $\delta^F > 0$ and $\delta^S < 0$.

XTF Xetra provided by Deutsche Boerse AG. ETFs cover a broad spectrum of investment options across domestic and global markets, diverse market capitalization, and investment styles. Thus, ETFs offer a great opportunity for diversification and therefore an interesting investment alternative. Trading ETFs allows to trade a whole basket of stocks in one transaction, a feature common with futures and certificates. For this reason, ETFs, similarly to other basket securities (such as index futures), facilitate market participation of uninformed traders, but simultaneously attract informed traders. We have been informally told that trades by institutional investors amount to 90-95% of the trading volume, indicating that the ETF market is a valid counterpart for the index itself in terms of information arrival. This fact, in conjunction with the previously mentioned advantages of the ETF market over the index, provides a reason to conjecture that relative price leadership between spot and futures markets may have shifted in favor of the spot market (ETF market).

Table 1.1: Volume DaxEx

Year	Volume in millions of EURO
2001	14,541
2002	13,654
2003	18,851
2004	14,897
2005	18,570
2006	27,965
2007	41,173

In Germany, ETFs are traded on the electronic market XTF, provided by Deutsche Boerse AG. In our study, we use data of the DaxEx (ISIN: DE0005933931) which represents one product on this market.[10] The DaxEx is (now) issued by Barclays Global Investors (Deutschland) AG and replicates the German blue chip index DAX.[11] Hence, as soon as the index composition or the relative weights of the DAX index are changed, the ETF fund management is forced to change the composition of the DaxEx. For replication purposes, it is allowed to solely use stocks of the index, certificates on the index, certificates on stocks of the index, forward contracts on the stocks of the index, and forward contracts on the index. Among these alternatives, the stocks in the index have absolute

[10] Due to a recent acquisition of INDEXCHANGE Investment AG through Barclays Bank PLC in 2007, the DaxEx was renamed and is now iShares DAX (DE). However, throughout this paper we refer to the ETF as the DaxEx.

[11] The DAX is a value-weighted index calculated from the prices of the 30 most liquid German stocks.

priority. ETF managers are supposed to meet a required degree of duplication of 95%.[12]

The DaxEx is an ETF which retains its profits, that is all dividends of the stocks in its portfolio are not distributed to the shareholders but are reinvested, as is the case for the DAX index. This feature allows the fund to hold a very close replication of the underlying index. Furthermore, administrative fees are deducted every day and a small fraction of the assets are held in cash. These features cause the fund to slightly underperform the index. The fund might also outperform the index, when markets are falling (this is referred to as cashdrag).

1.4 Data

We use high-frequency observations of transaction prices for both the DaxEx and the DAX futures (FDax). The starting point of our sample is the first trading day of July 2005 and the last data point is the final trading day of December 2005.

Futures contracts on the DAX are traded on EUREX exchange. These futures expire on the third Friday of the months of March, June, September, and December. Hence, our price series includes three expiration dates for futures contracts, the third Friday of September 2005, the third Friday of December 2005 and the third Friday of March 2006. All data are obtained from Deutsche Boerse AG.

Since the data include many more transaction prices for the FDax than for the DaxEx, we have to eliminate some futures prices in order to synchronize the two price series. We opt for an approach described in Harris, McInish, Shoesmith, and Wood (1995) where for every transaction price of the DaxEx we identify the most recent transaction price of the FDax and by this match the price series for our model.[13] Therefore, in each pair of transaction prices the observation of the FDax is usually slightly older (but never more recent) than the matched observation of the DaxEx. Consequently, this synchronization works clearly to the disadvantage of the futures market.

Another difficulty arises due to differences in the microstructure between the two markets, XTF (Deutsche Boerse's ETF segment) for the DaxEx and EUREX for the FDax.

[12] The degree of duplication (DG) is calculated by the following formula: $DG = 100\% - \frac{\sum_{i=1}^{n} |w_i^I - w_i^F|}{2}$, where w_i^I is the weight of stock i in the index in percent, w_i^F is the weight of stock i in the fund in percent, and n is the number of stocks in the index.

[13] There are, of course, alternative ways to synchronize the data. Harris, McInish, Shoesmith, and Wood (1995) provide a good comparison of alternative methods to synchronize transaction data. Their study finds that the results for alternative synchronizations are quite similar. We also checked for potential changes in the results due to variations of the synchronization method but the results are similar and the conclusions remain the same.

On XTF, there are three auctions for the DaxEx per trading day, but no such auction takes place on EUREX for the FDax. Both markets are electronic continuous trading markets, except for the three auction periods on XTF. Since differences in the market structure could influence our estimations, we only consider prices of the simultaneous continuous trading time of both markets and discard prices recorded during the auction periods on XTF.[14] Regular trading on XTF starts after the morning auction at 9.04 a.m. and extends until 5.30 p.m., when the final auction is held. We therefore eliminate all price data before 9.04 a.m. and from 5.30 p.m. onwards. We further discard all prices within a five minute interval from the time of the intraday auction which takes place from 1.10 p.m. to 1.12 p.m.

As outlined earlier, a time-varying cointegration relation between futures and spot prices is implied by the cost-of-carry relationship. In order to appropriately consider the time-variation of this cointegrating relation, we calculate adjusted futures prices by discounting the futures data series. As an approximation for the risk-free interest rate we use Eonia (Euro OverNight Index Average).[15] The daily risk-free interest rate is a good approximation for the interest rate in the cost-of-carry relation for futures traded on EUREX, since investors have to pay a collateral for their position.[16] The amount of the margin is calculated on a daily basis and the collaterals are invested at daily risk-free interest rates.

Table 1.2 gives some descriptive statistics for the return series of the two markets. The standard deviations (adjusted for autocorrelation) in both markets are nearly equal. Both markets show negative skewness and excess kurtosis, with both being more pronounced in the futures market. The return series show negative serial correlation, most likely due to the bid-ask bounce. The autocorrelation is considerably lower in the futures market, which may be due to the elimination of a significant number of DAX futures observations. There are about 30,000 daily transactions in the futures market, which exceeds the number of daily transactions in the ETF market by a factor of more than 100.

An important prerequisite for estimating an error correction model is that the price series are integrated of order one (I(1)), which means that the first differences have to be integrated of order zero (I(0)). Another necessary condition for our estimation is that the two series are cointegrated. Table 1.3 presents the results of the Augmented Dickey-Fuller test and of the Phillips-Perron test for the level and the first difference of the series,

[14] Previous papers, such as Grünbichler, Longstaff, and Schwartz (1994) and Kempf and Korn (1998), analyze various spot and futures markets. Their attention is focused on possible implications of different trading protocols for the process of price discovery.

[15] Eonia was extracted from Thomson Financial Datastream.

[16] For further information, visit `www.eurexchange.com`.

Table 1.2: Descriptive Statistics

	DaxEx	FDax
Return standard deviation	0.000550	0.000522
Skewness	−0.819285	−0.873453
Kurtosis	213.3106	249.9899
First order serial correlation	−0.078	−0.045
Avg. number of transactions per day	279.62	30,133.13

The table presents descriptive statistics for the DaxEx and the DAX futures returns series. The returns are calculated using transaction prices. The return standard deviations are corrected for autocorrelation. The numbers of transactions refer to daily averages.

respectively. The results of the two tests indicate clearly that both time series are I(1). That is, for the levels the null hypothesis of non-stationarity is not rejected, whereas for the first differences it is clearly rejected. Further tests indicate that the two price series are cointegrated according to the cost-of carry relation.[17]

Table 1.3: Stationarity Tests

	level		first difference	
	ADF	Phillips-Perron	ADF	Phillips-Perron
log(DaxEx)	0.5062	0.4565	0.0001	0.0001
log(FDax)	0.5304	0.5353	0.0001	0.0001

The table presents the p-values from the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron test applied to both the levels and the first differences of the time series.

1.5 Empirical Results

Model (1.4) is estimated by using ordinary least squares (OLS). Both the Schwarz information criterion (SIC) and the Akaike information criterion (AIC) suggest to include 16 lags. Table 1.4 thus shows the results of the estimation with $k = 16$ lags included. In order to conserve space, we only report the coefficients on the first four lags. The results show that the independent variables for the cash market have much more explanatory power than the independent variables for the futures market, as indicated by an adjusted R^2 of 0.058 in the spot market and 0.015 in the futures market.[18] The returns of both markets depend negatively on their own lagged returns, probably due to the bid-ask bounce, and

17 The results of the Augmented Dickey-Fuller test (p-value 0.0000) and of the Phillips-Perron test (p-value 0.0001) applied to the difference between the adjusted futures time series and the DaxEx time series suggest stationarity of the pricing error. The results of the Johansen tests (not shown in the paper) clearly indicate that the adjusted futures time series and the DaxEx time series are cointegrated.

18 Throughout the paper, we use the terms cash market and spot market interchangeably.

positively on the lagged returns of the respective other market. Bi-directional causality is indicated by the F-statistic. However, the t-statistics of the coefficients reveal that the cash market depends much more on the lagged returns of the futures market than the futures market on lagged returns of the spot market.

Table 1.4: Summary Results of the Vector Error Correction Model

	DaxEx	FDax
Constant	0.0018	-0.0006
	(-5.68)	(2.00)
DaxEx(-1)	-0.4456	0.2032
	(-33.80)	(15.87)
DaxEx(-2)	-0.3448	0.1554
	(-23.31)	(10.82)
DaxEx(-3)	-0.2722	0.1206
	(-17.41)	(7.94)
DaxEx(-4)	-0.2196	0.0902
	(-13.66)	(5.77)
FDax(-1)	0.423	-0.2275
	(31.94)	(-17.40)
FDax(-2)	0.341	-0.1634
	(22.60)	(-11.15)
FDax(-3)	0.2801	-0.1205
	(17.58)	(-7.79)
FDax(-4)	0.2168	-0.0957
	(13.23)	(-6.01)
Error correction term	-0.0487	0.0165
	(-5.69)	(1.99)
Common factor weights	0.253	0.747
R^2	0.058	0.015
F-statistic	67.76	17.04
Lags included	16	16

The table presents the results of the error correction model:

$$\begin{aligned}\Delta p_t^S &= \alpha^S + \sum_{i=1}^{k} \gamma_{11i} \Delta p_{t-i}^S + \sum_{i=1}^{k} \gamma_{12i} \Delta p_{t-i}^F + \delta^S (p_{t-1}^S - p_{t-1}^F) + u_t^S, \\ \Delta p_t^F &= \alpha^F + \sum_{i=1}^{k} \gamma_{21i} \Delta p_{t-i}^S + \sum_{i=1}^{k} \gamma_{22i} \Delta p_{t-i}^F + \delta^F (p_{t-1}^S - p_{t-1}^F) + u_t^F,\end{aligned}$$

where p_{t-1}^S denotes the lagged log price of the DaxEx, p_{t-1}^F denotes the lagged log of the adjusted futures price, and Δp_t^j denotes the log returns for the two markets $j = \{S, F\}$. We estimate the model using OLS, including 16 lags as suggested by both the SIC and the AIC criterion, but report the coefficients for the first four lags only. The cointegration vector is pre-specified as $(1, -1)$. The t-statistics of the coefficients are reported in parentheses. The last line reports the common factor weights for the DaxEx and the FDax, respectively.

The coefficient on the error correction term shows that the spot market responds to the futures market, as indicated by a negative sign on the error correction term

($\delta^S = -0.0487$). The impact of the error correction term in the futures market is much less significant than it is in the spot market ($\delta^F = 0.0165$), though it has the expected positive sign. While both markets contribute to the process of price discovery, the futures market appears to dominate the process. According to the CFW, which are reported in Table 1.4, the futures market clearly leads the process of price formation. It is assigned a 74.7% contribution to price formation, while the DaxEx contributes only the remainder of 25.3%. These results are consistent with the findings of Theissen (2005), who studies the process of price formation of the DAX index itself and DAX futures. When interpreting the results, one should keep in mind that the DaxEx prices are matched with the most recent corresponding futures prices, which is to the disadvantage of the futures market. Consequently, our results are even likely to understate the contribution of the futures market to the process of price discovery.

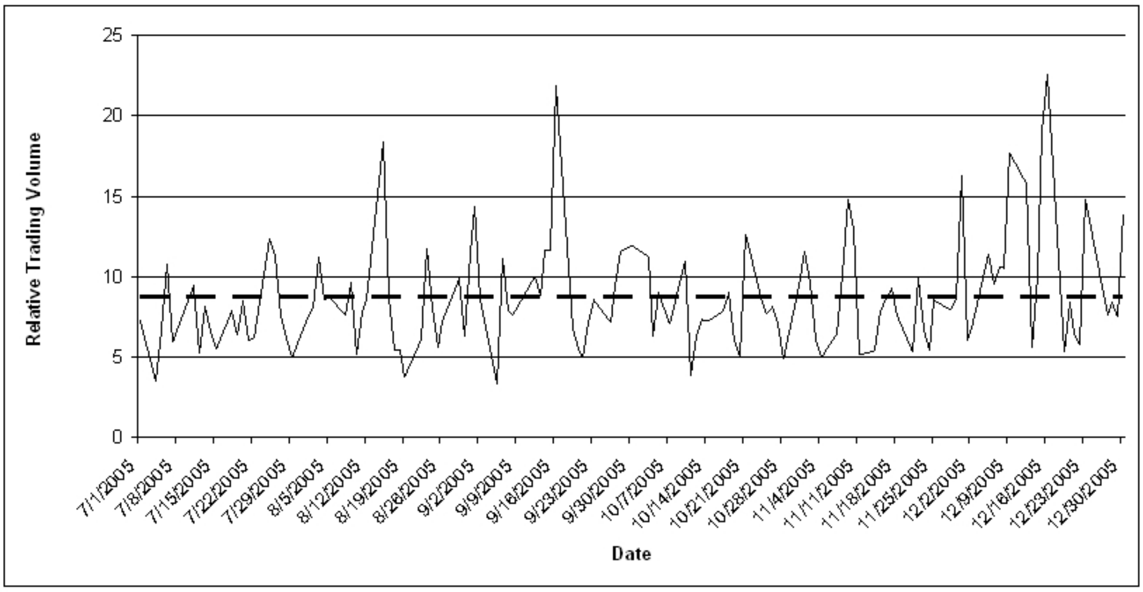
1.6 Determinants of Price Leadership

In this section, we investigate which factors drive the price leadership of the futures market. Specifically, we analyze to what extent liquidity and volatility affect relative price formation. One would expect market liquidity to be a determining factor, since (informed) traders prefer to trade in the market with the lowest transaction costs (or the highest liquidity). The trading-costs hypothesis is supported, for instance, by Fleming, Ostdiek, and Whaley (1996) in their analysis of relative price formation in stock, index futures, and option markets and by Kim, Szakmary, and Schwarz (1999) who test for lead-lag return relations across index futures markets and across cash markets. Both studies find that the highest trading activity is found in the low-cost market and that the magnitude of trading costs is the main determinant of price leadership. This, in turn, implies that measures for price leadership, such as the common factor weights, are correlated with trading activity (see, for instance, Theissen (2002)).

Bamberg and Dorfleitner (1998) find that the overall trading volume of DAX futures increases significantly just before contract expiration. This increase is particularly significant in the last two weeks of a quarter year, which, in this case, is the time interval between two contract expiration dates. This increase amounts to 70%, on average. Hence, one might expect that during periods with low trading volume in the futures market the price leadership of the FDax is weaker compared to periods just before expiration dates, i.e., in the last two weeks of each quarter. In addition, Bamberg and Dorfleitner (1998) and Bamberg and Dorfleitner (2000) find that the overall trading volume is heavily concentrated on the nearby contract, i.e., the contract with the shortest time-to-expiration, which is the only type of contract that we study in this paper. Hence, assuming the trading-costs hypothesis holds and using relative trading volume as a proxy for liquidity, one would expect time-varying trading intensity in the nearby futures contract to translate into time-varying price leadership of the futures market relative to the ETF market (unless similar trading patterns are found in the ETF market as well).

In order to illustrate the time variation of the relative trading volume and of the CFW, we plot the evolution of both measures on a daily basis.[19] Figure 1.1 plots the daily relative trading volume of the two markets, defined as the ratio of the trading volume in the futures market to the trading volume in the ETF market (thin line). We also show the average relative trading volume over the entire sample period, represented by the horizontal dashed line in Figure 1.1. The figure indicates that the relative trading volume fluctuates heavily over time with sharp peaks around the expiration days of the futures contracts. The CFW are calculated for each trading day separately and are plotted in Figure 1.2.[20] The figure indicates that also the CFW series is noticeably unstable over time.

Figure 1.1: Relative Trading Volume

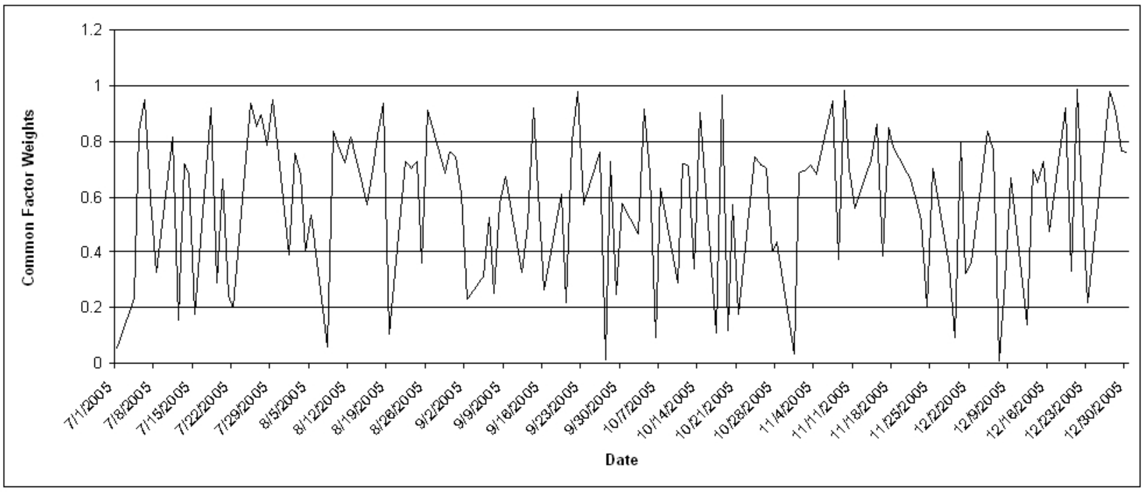


The figure shows the relative trading volume of the futures and the ETF market, defined as the ratio of the trading volume in the futures market to the trading volume in the ETF market (thin line). The horizontal dashed line represents the average relative trading volume over the entire sample period.

[19] Note that the CFW are solely calculated from the coefficients on the error correction term in model (1.4). Thus, we run stability tests for the coefficients, since instability of the coefficients implies instability of the CFW. Test results of the cumulative sum of recursive residuals (CUSUM) and CUSUM of squares test (see Brown, Durbin, and Evans (1975)), which are not shown in the paper, reject the parameter stability hypothesis.

[20] Since the coefficients on the error correction term do not have the expected sign for all trading days, we use formula (1.6) to calculate the common factor weights.

Figure 1.2: Common Factor Weights of the Futures Market



The figure shows the evolution of the common factor weights for the futures market. The common factor weights are calculated according to formula (1.6).

In contrast to the findings by Theissen (2002), among others, that price leadership is positively correlated with relative trading volume, Martens (1998) in his study of Bund futures contracts traded on LIFFE (floor market) and DTB (screen market) shows that not relative trading volume, but volatility is the driving force for relative price discovery. Precisely, he finds that in periods with low volatility relative trading volume on LIFFE increases, whereas the contribution to the process of price formation decreases. However, in their analysis of price leadership in floor-based and screen-based trading systems in several FX futures markets, Ates and Wang (2006) fail to find support for volatility as a determinant of price discovery.

In Section 1.5, we have shown that the futures market clearly dominates the process of price discovery for the entire sample period. We now examine to what extent liquidity and/or volatility drive the price leadership of the futures market relative to the ETF market. Specifically, we run the following regression with daily estimates for liquidity and volatility as explanatory variables:

$$\mathrm{CFW}_t^F = \beta_0 + \beta_1 \mathrm{RTV}_t^F + \beta_2 \mathrm{Vola}_t + \varepsilon_t, \tag{1.8}$$

where CFW_t^F denotes the common factor weight of the futures market on day t, RTV_t^F is the daily relative trading volume of the two markets, defined as the ratio of the trading volume in the futures market to the trading volume in the ETF market, and Vola_t denotes the sum of the realized volatilities of the two markets ($\mathrm{Vola}_t = \mathrm{Vola}_t^F + \mathrm{Vola}_t^S$), which are estimated for each trading day according to Hansen and Lunde (2005a) and Hansen and Lunde (2005b). The estimation procedure for the realized volatilities requires the choice of a sampling interval. Because of market microstructure noise, one should not use every tick for the estimation. In fact, the range between one and five minutes is often found to be the optimal sampling frequency (see, for instance, Hansen and Lunde (2006)). We choose a sampling interval of five minutes, which is rather on the upper end of the commonly used intervals, in order to minimize potential effects due to market microstructure noise.[21] In Appendix A.1, the estimation procedure of realized variances is described in more detail.

We estimate several specifications of model (1.8) using OLS and present the results in Table 1.5; the reported t-statistics are adjusted for time-series correlation using the Newey and West (1987) methodology. It can be seen from the table that the coefficients β_1 have the expected sign in all specifications. The coefficients on the relative trading volume are positive, but statistically insignificant in all specifications. However, the coefficients on the measures of volatility are significant in all specifications, with the volatility of the futures market being even more significant than the sum of the volatilities for the two markets. As can be seen from specifications (3)-(5), including each variable separately in the regression does not qualitatively change the findings. Our results show that, as indicated by the negative coefficient on volatility, higher volatility in the markets causes the price leadership of the futures market to decrease.

We now investigate to what extent the price leadership shifts to the ETF market during high volatility periods. In order to shed more light on the contribution of the two markets to price discovery conditional on volatility, we calculate their CFW during high and low volatility periods. Similar to Martens (1998), we first classify trading days based on the sum of the realized volatilities of the two markets, Vola_t, into "high volatility" and "low volatility" days according to the following rule:

$$\begin{aligned} &\text{if } \ \text{Vola}_t > \text{quantile}_{90^{th}} &:& \ \text{day } \ t \ \text{ is a high volatility day,} \\ &\text{if } \ \text{Vola}_t < \text{quantile}_{10^{th}} &:& \ \text{day } \ t \ \text{ is a low volatility day,} \end{aligned}$$

where $\text{quantile}_{x^{th}}$ is the x^{th} quantile of the sample distribution of Vola_t. Following Martens (1998), in addition to the quantiles, we also employ $\mu+\sigma$ and $\mu-\sigma$ as boundaries for high volatility and low volatility days, where μ and σ are the mean and the standard deviation of the sample distribution of Vola_t. Second, we estimate the error correction model (1.4) for each volatility subsample separately and from the obtained coefficients calculate the CFW for the two markets.[22] The results for the coefficients on the error correction term

21 As a robustness check, we have also tried sampling intervals of one minute and ten minutes; the results are similar and the conclusions remain the same.

22 Tsay (1998) shows that under certain assumptions the consistency of conditional least-squares parameter estimates and variance-covariance matrices holds.

Table 1.5: Regression Analysis of Factors Affecting Price Leadership

Specification	Intercept	RTV_t^F	Vola_t	Vola_t^F	Adj. R^2	F-statistic
(1)	0.7355^{***}	0.0010	-0.6614^{***}	-	0.0245	2.6211
	(8.62)	(0.16)	(-2.75)			
(2)	0.7051^{***}	0.0027	-	-1.2198^{***}	0.0456	4.0810
	(11.19)	(0.42)		(-4.03)		
(3)	0.5754^{***}	0.0004	-	-	-0.0078	0.0027
	(8.98)	(0.06)				
(4)	0.7436^{***}	-	-0.6597^{***}	-	0.0320	5.2622
	(11.63)		(-2.77)			
(5)	0.7258^{***}	-	-	-1.2000^{***}	0.0519	8.0620
	(16.81)			(-4.10)		

The table presents the results of the regression :

$$\text{CFW}_t^F = \beta_0 + \beta_1 \text{RTV}_t^F + \beta_2 \text{Vola}_t + \varepsilon_t,$$

where CFW_t^F denotes the common factor weight of the futures market (calculated according to formula (1.6)), RTV_t^F is the relative trading volume of the two markets, defined as the ratio of trading volume in the futures market to the trading volume in the ETF market, and Vola_t denotes the sum of the realized volatilities of the two markets (Vola_t^F and Vola_t^S), which are estimated according to Hansen and Lunde (2005a) and Hansen and Lunde (2005b). The t-statistics of the coefficients are adjusted for time-series correlation using the Newey and West (1987) methodology and reported in parenthesis. *,**,*** indicates significance at the 10%, 5%, and 1% level.

and the CFW for high and low volatility periods are summarized in Table 1.6. We also report the average trading volume (in millions of EURO), the average relative trading volume, and the average number of contracts traded in the two markets conditional on volatility. Panel A presents the results for the case when the $90^{th}/10^{th}$ quantiles serve as boundaries for high/low volatility periods (specification I), whereas in Panel B the definition of high/low volatility periods is based on the thresholds $\mu+\sigma$ and $\mu-\sigma$ (specification II).[23] As can be seen from Panel A, for both the futures market and the ETF market, trading volume and the number of contracts traded are higher in high-volatility than in low-volatility periods. However, for the ETF market, the rate of increase is much lower than for the futures market. For instance, trading volume in the ETF market during high-volatility periods is almost three times higher than in low-volatility periods, whereas in the futures market it is almost four times as high, leading to an increase in the relative trading volume of the futures market. According to the trading-costs hypothesis, higher (relative) trading volume should translate into a higher contribution to the process of price discovery. However, the results for the CFW fail to support the hypothesis, but show that the price leadership of the futures market decreases by 22.5% from low to high

[23] We have also tried the $5^{th}/95^{th}$ quantiles as boundaries for low and high volatility periods; the results are similar and the conclusions remain the same.

volatility periods. The contribution of the ETF market rises from roughly 5.5% to almost 27%. Hence, in high volatility periods the contribution of the ETF market is higher than its unconditional contribution (25.3%).

Table 1.6: Market Characteristics During High and Low Volatility Periods

Panel A: Quantiles

	FDax		DaxEx	
	high volatility	low volatility	high volatility	low volatility
Trading volume	1,126	309	150	50
Relative trading volume	8.2632	7.0731	-	-
Number of contracts	231,542	60,368	3,222,854	1,014,282
Error correction term	0.0262	-0.0006	-0.0717	-0.0105
Common factor weight	0.7326	0.9451	0.2674	0.0549

Panel B: Mean plus/minus standard deviation

	FDax		DaxEx	
	high volatility	low volatility	high volatility	low volatility
Trading volume	1,126	285	150	46
Relative trading volume	8.2632	7.1681	-	-
Number of contracts	231,542	55,026	3,222,854	940,830
Error correction term	0.0262	-0.0028	-0.0717	-0.0164
Common factor weight	0.7326	0.8545	0.2674	0.1455

The table presents the average trading volume (in millions of EURO), the average relative trading volume, the average number of contracts, the coefficient on the error correction term, and the common factor weights of the futures market (FDax) and the spot market (DaxEx) conditional on high/low volatility. The relative trading volume is defined as the ratio of the trading volume in the futures market to the trading volume in the ETF market. The coefficients on the error correction term are denoted by δ^F and δ^S in the error correction model (1.4). The common factor weights are calculated as specified in formula (1.6). In Panel A, the 90^{th} quantile and the 10^{th} quantile serve as boundaries for high/low volatility periods as described in the text. In Panel B, the mean plus/minus one standard deviation of the empirical distribution of the sum of the realized volatilities are used to define high/low volatility periods.

As can be seen from Panel B, using $\mu + \sigma$ and $\mu - \sigma$ as boundaries for high/low volatility periods does not qualitatively change the results.[24] The decrease in the CFW for the futures market from low to high volatility periods equals 14.3% and the drop is obviously less pronounced than in the specification of Panel A. Compared to low volatility periods, the relative trading volume increases by 15.3% and the increase is smaller than in specification I.

In order to provide formal statistical evidence for these findings, we evaluate, for both the DaxEx and the FDax, the null hypotheses that the average trading volume, the aver-

[24] Note that the boundaries and hence the market characteristics for the high volatility period are the same as in specification I.

age relative trading volume, and the average CFW do not differ in high and low volatility periods.[25] More specifically, we test whether the increase in trading volume for both markets, the increase in relative trading volume, and the decrease in the CFW of the FDax—and therefore its lower contribution to the process of price discovery—from low to high volatility periods are statistically significant. Table 1.7, Panel A reports the p-values of the corresponding t-tests for the case when the $90^{th}/10^{th}$ quantiles are used as boundaries for high/low volatility periods. The p-values presented in Panel B are from tests based on the thresholds $\mu + \sigma$ and $\mu - \sigma$ as boundaries for high/low volatility periods. The results in Panel A show that for both the DaxEx and the FDax the increase in trading volume from low to high volatility periods is significant (p-values are equal to 0.0000), whereas the increase in relative trading volume is insignificant. The p-value for the decrease in the CFW from low to high volatility periods, which is significant at the 5% level, provides statistical evidence for the previous finding that the price leadership of the futures market is lower when volatility is high, and vice versa. The results in Panel B, where the thresholds $\mu + \sigma$ and $\mu - \sigma$ define high/low volatility periods, are qualitatively the same as the ones in Panel A. The only quantitative difference is that the decrease in the CFW of the FDax is statistically significant at the 1% level.

Table 1.7: Statistical Test Results

Panel A: Quantiles

	FDax	DaxEx
Trading volume (p-value)	0.0000***	0.0000***
Relative trading volume (p-value)	0.2128	-
Common factor weight (p-value)	0.0154**	-

Panel B: Mean plus/minus standard deviation

	FDax	DaxEx
Trading volume (p-value)	0.0000***	0.0000***
Relative trading volume (p-value)	0.3403	-
Common factor weight (p-value)	0.0093***	-

This table presents the results of the t-test for the null hypothesis that the average trading volume, the average relative trading volume, and the average common factor weights are equal for the high and low volatility samples. The tests in Panel A are performed on samples which are constructed by using the 90^{th} quantile and the 10^{th} quantile to define high/low volatility periods as described in the text. In Panel B, the tests are performed on samples constructed by using boundaries specified by the mean plus/minus one standard deviation of the empirical distribution of the sum of the realized volatilities. *,** ,*** indicates significance at the 10%, 5%, and 1% level.

[25] The test for the change in the CFW is based on the statistical properties of the daily estimates of the CFW on low and high volatility days, respectively.

In summary, the results above show that volatility is the significant determinant of the degree of price leadership of the futures market. As volatility increases, trading volume and the number of contracts traded increase in both markets, and the relative trading volume of the futures market rises. This, however, does not imply an increase in the price leadership of the futures market. On the contrary, the contribution to price formation of the ETF market rises substantially, indicating a shift in informational efficiency in favor of the ETF market.

Since all our data are obtained from electronic-trading systems, but do not include transactions from floor-trading systems, our results might be explained by a potential shift of informational efficiency from floor-based to screen-based trading. In other words, from low to high volatility periods the screen-based ETF market apparently "gains" a substantial share of price discovery from the corresponding floor-based trading system. Due to the fact that the FDax is traded exclusively electronically, this shift in informational efficiency cannot occur in the futures market. If this conjecture held true, these results would be in contrast to Martens (1998) who finds that for the case of Bund futures contracts the share in the process of price discovery of the screen-based trading system decreases during high volatility periods.

1.7 Conclusion

This paper examines the process of price discovery in spot and futures markets which are linked by the cost-of-carry relationship. Our analysis assesses the contribution to price formation of the ETF market and the futures market in Germany. This question is important, since in recent years trading of basket securities, such as ETFs and futures contracts, has gained popularity among financial market participants. In order to investigate the process of price discovery in this new environment of electronically-traded basket securities, we estimate a vector error correction model using transaction data for the DaxEx and the FDax. In order to quantify the contributions of the two markets to the process of price discovery, we calculate the common factor weights for both markets. Our results indicate a clear price leadership of the futures market over the ETF market, although our chosen method for matching the two price series works to the disadvantage of the futures market. These results are in line with the findings of Theissen (2005) who argues that the futures market leads the cash index in terms of relative contribution to price discovery.

Furthermore, we extend similar studies on price leadership between spot and futures markets, as we investigate which factors influence the process of price discovery. More specifically, our paper is the first to analyze to what extent liquidity and volatility affect the process of price formation in spot (ETF) and futures markets. We find that volatility, but not liquidity is the driving force in the process of price discovery. From low to high volatility periods the share of price formation of the futures market decreases, whereas trading volume increases relative to the ETF market.

Chapter 2

Data Snooping and Market-Timing Rule Performance

2.1 Introduction

It has always been an investor's dream to time the market in order to earn excess returns. The methodology of market timing seems to be quite simple: Remain invested in the stock market when expected returns are high and switch to cash investments when the market is expected to underperform. The timing of the switch is indicated by signals based on fundamental or sentiment indicators. The potential of market-timing strategies to earn extraordinary profits is documented, for instance, by Shilling (1992), who found that, during the period from 1946 to 1991, investors could have increased their annual return from 11.2% to 19.0% by avoiding exposure to the stock market during the 50 weakest months and being long stocks the rest of the time. In contrast, missing the 50 strongest months in the stock market would have reduced annual returns to only 4% per annum. The problem, of course, is that successful market timing is a difficult, if not impossible, task.

Market-timing rules usually build on empirical findings of the ability of certain indicators to predict future stock market returns. The literature has identified many useful indicators, such as the earnings-to-price ratio (Campbell and Shiller (1988b), Campbell and Shiller (1998)), the dividend yield (Shiller (1984), Fama and French (1988)), the dividend-payout ratio (Lamont (1998)), the maturity spread and the credit spread (Campbell (1987), Fama and French (1989)), and the gilt-equity yield ratio (Clare, Thomas, and Wickens (1994), Brooks and Persand (2001)).[1] However, if capital markets are efficient, market-timing rules should not be able to beat a benchmark, such as a buy-and-hold

[1] The set of indicators to time the market can be found in Section 2.3, where we specify the market-timing rules for our experiment. An overview of relevant literature on each indicator is given in the corresponding subsections.

strategy.[2] In other words, publicly available information should not be useful for predicting future stock market movements.

When assessing the profitability of market-timing rules, it is critical to account for possible biases in statistical inference due to data snooping.[3] The danger of data-snooping biases is especially acute whenever economic theory is vague about the functional form of the relationship between economic variables. In such a situation, researchers can apply a variety of market-timing rules to the same data set and uncover a subset of rules that turn out to be profitable even though they would not generate superior performance out-of-sample. Lo and MacKinlay (1990) argue that data snooping might be the result of survivorship bias. That is, many rules that have been investigated in the past but have not generated profits superior to a benchmark are not published and are thus filtered out over time. Hence, the superior power of profitable rules is not due to any merit of the design of the rules. Because statistical inference that considers only the surviving rules will be biased, it is important to account for the full set of initial rules. The so-called "Reality Check" (RC), developed by White (2000), allows us to account for data-snooping biases when testing for possible superior performance of certain rules. The basic idea of this test is to draw statistical inference from an empirical distribution of a performance measure, considering the full universe of models (in our case, market-timing rules) from which the best rule is drawn. Hansen (2005) proposed the so-called test for superior predictive ability (SPA), which also allows for data-snooping correction and, under certain conditions, increases the test power of White's "Reality Check."

There is by now a vast literature reporting a variety of market-timing rules. For instance, Fisher and Statman (2006a) and Fisher and Statman (2006b) investigate the profitability of market timing based on financial ratios. Shen (2003) finds that the spread between the earnings-to-price ratio and a variety of prevailing interest rates can be used to successfully time the market. Studies of the ability of various interest rates to time the market include Breen, Glosten, and Jagannathan (1989), Prather and Bertin (1997), and Prather and Bertin (1998). The performance of market-timing rules based on index volatility changes is investigated, for instance, by Copeland and Copeland (1999). However, the studies on market-timing performance lack appropriate corrections for data-snooping biases. The purpose of our paper is therefore to assess the profitability of a large number of market-timing rules and to examine possible data-snooping biases. Our study is in the spirit of Sullivan, Timmermann, and White (1999)'s and Hsu and Kuan (2005)'s evaluations of the profitability of technical trading. They construct their rules based on

[2] Throughout the paper, we use a simple buy-and-hold strategy as the benchmark.
[3] The dangers of data snooping are highlighted, for instance, in Lo and MacKinlay (1990), Sullivan, Timmermann, and White (1999), Ferson, Sarkissian, and Simin (2003), and Ang and Bekaert (2007).

historical prices, but do not include information from indicators based on fundamentals and investor sentiment. Both studies show that, in certain markets and during certain periods, technical trading is useful to beat a benchmark. However, Sullivan, Timmermann, and White (1999) show that out-of-sample the superior performance of the best rules is no longer significant. Hsu and Kuan (2005) find that the best technical-trading rules are only capable of beating the benchmark in "young markets" such as the NASDAQ Composite and the Russell 2000. Sullivan, Timmermann, and White (2001), in a similar experiment, argue that calender rules do not show superior performance when adjustment for data-snooping biases is made. In yet another study on the profitability of technical-trading rules, Qi and Wu (2006) apply the RC methodology to examine the profitability of such trading rules in the foreign-exchange market and find that the significant outperformance of the best rules (when considered in isolation) is not robust to data-snooping effects.

Our paper is the first to quantify the possible data-snooping biases in the market-timing literature and to test whether the considered market-timing rules are truly superior to a buy-and-hold strategy. For this purpose, we use White (2000)'s RC methodology and Hansen (2005)'s SPA. As opposed to the previously mentioned studies on data-snooping biases in the context of technical trading, the rules in this paper are not constructed based on historical prices, but are based on a set of fundamental and sentiment indicators. We construct two sets of timing rules: a basic set of simple rules, each based on only one indicator, and an extended set which also includes complex rules based on information from various indicators.[4] Each universe of market-timing rules includes both rules described in the market-timing literature and rules that we construct ourselves based on indicators that were previously found to predict stock market returns.[5] For each rule, we employ various parameterizations, which gives us a comprehensive universe of 6,792 simple rules. The extended set comprises 8,768 rules.[6] As performance measures, we use the average return and the Sharpe ratio.

The results of our experiments suggest that, when considered in isolation, the performance of certain market-timing rules from both sets may indeed be highly statistically significant. However, once the effects of data snooping are appropriately accounted for, the best market-timing rules from the basic set are no longer significant for any period. For the full sample period and for the subperiod from 1995 to 2007, we find the same insignificant result for the extended set of rules. Only for the subperiod from 1981 to 1994

4 Henceforth, we refer to these sets of rules as the basic set and the extended set.

5 However, we do not consider market-timing strategies that rely on sophisticated models rather than on simple indicators. For instance, we do not include regression-based market-timing strategies as in Breen, Glosten, and Jagannathan (1989) and Fuller and Kling (1994).

6 For the subperiod from 1995 to 2007, the sets of market-timing rules are even larger, since for this time period we consider additional indicators based on data availability. Further details are found in Section 2.3.

does the outperformance of the best rule from the extended set remain significant. The results are quite similar for both performance measures, and our findings are robust to the impact of transaction costs and to allowing for short selling the index. Furthermore, changing the benchmark to holding the risk-free rate instead of the index leaves the results qualitatively unchanged.

The paper proceeds as follows: Section 2.2 explains the testing procedures (RC and SPA) used to correct for data-snooping biases. Section 2.3 discusses the intuition and specification of the market-timing rules to be tested. Section 2.4 describes the data. Section 2.5 shows the empirical results for the basic set of rules. Section 2.6 shows the empirical results for the extended set of rules. Section 2.7 presents some robustness checks on the results. Section 2.8 concludes.

2.2 Testing Procedures: The "Reality Check" and the SPA Test

The dangers of data snooping have long been recognized as a serious problem of empirical studies in finance (see, for instance, Lo and MacKinlay (1990), Brock, Lakonishok, and LeBaron (1992), and Ferson, Sarkissian, and Simin (2003)). As we are investigating a large universe of market-timing rules, a robust methodology to avoid spurious statistical inference due to data snooping is needed. We therefore employ the "Reality Check" (RC), introduced by White (2000), and the test for superior predictive ability (SPA), introduced by Hansen (2005). Both procedures allow for an intensive search for models while ensuring that the results are robust and do not result from mere chance. Both procedures build on the work of Diebold and Mariano (1995) and West (1996). In this section, we briefly outline both testing procedures and refer the reader to the original articles for rigorous derivations.

The RC tests the null hypothesis that the best model does not have superior predictive ability over a benchmark model, while taking into account the full set of models, against the alternative that the best model does have superior predictive ability. The test is based on the $l \times 1$ performance statistic,

$$\bar{\boldsymbol{f}} = \frac{1}{n} \sum_{t=R}^{T} \hat{\boldsymbol{f}}_{t+1}, \tag{2.1}$$

where l is the number of market-timing rules and n is the number of prediction periods indexed from R through T, so that $T = R + n - 1$. $\hat{\boldsymbol{f}}_{t+1} = f(\boldsymbol{Z}_t, \hat{\boldsymbol{\beta}}_t)$ is the performance measure, where $\boldsymbol{Z}_t$ is a matrix which contains a vector of dependent variables and a vector of predictor variables and $\hat{\boldsymbol{\beta}}_t$ is a vector of estimated parameters. It is assumed that these parameters satisfy the conditions of Diebold and Mariano (1995) and West (1996), so that parameter uncertainty vanishes asymptotically. In our experiment, we consider various parameterizations of each trading rule ($\beta_k,\ k = 1, ..., l$). The parameterizations directly produce returns, so there are no estimated parameters.

We use the returns generated from the l timing rules as a performance measure.[7] For a timing rule k, we follow Sullivan, Timmermann, and White (1999) and specify $f_{k,t+1}$ as

$$f_{k,t+1} = \ln\left[1 + \frac{S_{t+1} - S_t}{S_t} X_k(\boldsymbol{Z}_t, \boldsymbol{\beta}_k)\right] - \ln\left[1 + \frac{S_{t+1} - S_t}{S_t} X_0(\boldsymbol{Z}_t, \boldsymbol{\beta}_0)\right], \quad k = 1, ..., l, \tag{2.2}$$

where $\boldsymbol{Z}_t$ consists of the predictor variables (described in Section 2.3) and $\boldsymbol{\beta}_k$ denotes the different parameterizations of the timing rules; subscript 0 refers to the benchmark model. S_t is the price of the S&P index at time t. X_k and X_0 are "timing functions" which take on the value 1 for "invest in the stock market" and 0 for "hold cash." Based on this performance statistic, we test whether there is a timing rule that delivers superior performance over a simple buy-and-hold strategy, where $X_0 = 1$ at all times. Formally, the null hypothesis is:

$$H_0 : \max_{k=1,...,l} \{E(f_k)\} \leqslant 0. \tag{2.3}$$

If the null can be rejected, it has been established that a timing rule exists that outperforms the benchmark. It has been shown by White (2000) that, under weak assumptions about the stationarity, dependence structure, and moments of $\hat{\boldsymbol{f}}_t$, the distribution of the test statistic can be obtained by applying the stationary bootstrap of Politis and Romano (1994) as follows. In step 1, for each timing rule $k = 1, ..., l$, we generate a resample of $\{f_{k,t+1}\}_{t=R}^{t=T}$ by drawing (geometrically distributed) blocks from the observed return series, with mean block length $1/q$.[8] We shall denote the resampled series by $f^*_{k,t+1,j}$, where subscript j indicates the j-th repetition of the bootstrap. We repeat the process J times. In step 2, we calculate the mean of the bootstrapped return series, $\bar{f}^*_{k,j} = n^{-1} \sum_{t=R}^{T} f^*_{k,t+1,j}$, $\forall\, k = 1, ..., l$. In step 3, we compute the following statistics:

$$V_{RC} = \max_{k=1,...,l} \{\sqrt{n} \bar{f}_k\}, \tag{2.4}$$

$$V^*_{RC,j} = \max_{k=1,...,l} \{\sqrt{n}(\bar{f}^*_{k,j} - \bar{f}_k)\}, \quad j = 1, ..., J. \tag{2.5}$$

7 We first outline the procedure for using raw returns, but we will also use the Sharpe ratio (SR) as a performance measure.

8 The choice of the block length is discussed in more detail in Section 2.7.4.

We then compare V_{RC} with the quantiles of $V^*_{RC,j}$. A p-value of the RC is computed as

$$p_{RC} = \sum_{j=1}^{J} \frac{\mathbb{1}_{\{V^*_{RC,j} > V_{RC}\}}}{J}, \tag{2.6}$$

where $\mathbb{1}_{\{.\}}$ denotes the indicator function. In our empirical analysis, we set $J = 1000$ and choose a smoothing parameter of $q = 0.5$.[9]

Hansen (2005)'s SPA is very similar to the RC, yet it includes some refinements that can improve the test power in most cases. The SPA makes use of the following studentized test statistic:

$$V_{SPA} = \max\left[\max_{k=1,..,l} \frac{\sqrt{n}\bar{f}_k}{\hat{\sigma}_k}, 0\right], \tag{2.7}$$

where $\hat{\sigma}_k^2$ is a consistent estimate of $\sigma_k^2 = \text{var}(\sqrt{n}\bar{f}_k)$. We employ the estimator given in Hansen (2005), who also suggests invoking a different null distribution based on $N(\hat{\boldsymbol{\mu}}, \hat{\boldsymbol{\Omega}})$, where $\hat{\boldsymbol{\Omega}}$ denotes a consistent estimate of the asymptotic covariance matrix of $\bar{\boldsymbol{f}}$ and $\hat{\boldsymbol{\mu}}$ is an estimate for $E(\boldsymbol{f}_t)$. Hansen (2005) advocates the use of the following estimator:

$$\mu_k = \bar{f}_k \mathbb{1}_{\{\sqrt{n}(\bar{f}_k/\hat{\sigma}_k) \leqslant -\sqrt{2\ln\ln n}\}}. \tag{2.8}$$

By choosing this estimator, we make sure that irrelevant models do not asymptotically influence the distribution of the test statistic. This can be shown by applying the law of the iterated logarithm, which ensures that $\frac{\sqrt{n}\bar{f}_k - \mu_k}{\sigma_k}$ stays within certain bounds with probability 1 asymptotically.

The implementation of the SPA is also very similar to that of the RC. In step 1, for each timing rule $k = 1, ..., l$, we generate a resample of $\{f_{k,t+1}\}_{t=R}^{t=T}$ by drawing (geometrically distributed) blocks from the observed return series. We shall denote the resampled series $\{f^*_{k,t+1,j}\}$, where subscript j indicates the j-th repetition of the bootstrap. In step 2, we calculate $Z^*_{k,t+1,j} = f^*_{k,t+1,j} - \bar{f}_k \mathbb{1}_{\{\sqrt{n}(\bar{f}_k/\hat{\sigma}_k) \geqslant -\sqrt{2\ln\ln n}\}}$, $\forall\, k = 1, ..., l,\ t = R, ..., T$. In step 3, we compute the following statistics:

$$V_{SPA} = \max\left[\max_{k=1,..,l} \frac{\sqrt{n}\bar{f}_k}{\hat{\sigma}_k}, 0\right], \tag{2.9}$$

$$V^*_{SPA,j} = \max\left[\max_{k=1,..,l} \frac{\sqrt{n}\bar{Z}^*_{k,j}}{\hat{\sigma}_k}, 0\right], \quad j = 1, ..., J, \tag{2.10}$$

where $\bar{Z}^*_{k,j} = n^{-1}\sum_{t=R}^{T} Z^*_{k,t+1,j}$. We then compare V_{SPA} with the quantiles of $V^*_{SPA,j}$. A p-value of the SPA is given by

[9] Results of a sensitivity analysis for changes in the smoothing parameter are shown in Section 2.7.4.

$$p_{SPA} = \sum_{j=1}^{J} \frac{\mathbb{1}_{\{V^*_{SPA,j} > V_{SPA}\}}}{J}. \tag{2.11}$$

Throughout the paper, we refer to this p-value as the consistent SPA p-value (SPA-c). In addition, we calculate an inconsistent lower bound for the consistent SPA p-value, called SPA-l, which Hansen (2005) computes by replacing $\bar{Z}^*_{k,j}$ in equation (2.10) with $\bar{Z}^{l*}_{k,j}$, the average of the bootstrapped series $Z^{l*}_{k,t+1,j} = f^*_{k,t+1,j} - \max\left[\bar{f}_k, 0\right]$.

For both testing procedures, we use the Sharpe ratio, in addition to raw returns, as a performance measure. If the Sharpe ratio is used as a performance measure, the null hypothesis is:

$$H_0 : \max_{k=1,..,l} \{g(E(h_k))\} \leqslant g(E(h_0)), \tag{2.12}$$

where $\boldsymbol{h}$ is a 3×1 vector given by

$$h^1_{k,t+1} = \frac{S_{t+1} - S_t}{S_t} X_k(\boldsymbol{Z}_t, \boldsymbol{\beta}_k), \tag{2.13}$$

$$h^2_{k,t+1} = \left(\frac{S_{t+1} - S_t}{S_t} X_k(\boldsymbol{Z}_t, \boldsymbol{\beta}_k)\right)^2, \tag{2.14}$$

$$h^3_{k,t+1} = r^f_{t+1}; \tag{2.15}$$

r^f_{t+1} is the risk-free interest rate at time $t+1$ and $g(\cdot)$ is given by

$$g(E(h_{k,t+1})) = \frac{E(h^1_{k,t+1}) - E(r^f_{t+1})}{\sqrt{E(h^2_{k,t+1}) - (E(h^1_{k,t+1}))^2}}. \tag{2.16}$$

The expectations are estimated by the sample mean. We then construct the relevant statistic

$$\bar{f}_k = g(\bar{h}_k) - g(\bar{h}_0), \tag{2.17}$$

where $\bar{h}_k$ and $\bar{h}_0$ are arithmetic averages calculated over the sample period for trading rule k and the buy-and-hold strategy. The application of the bootstrap procedure to the difference of Sharpe ratios works similarly to the procedure described for the difference in raw returns (for details, see Sullivan, Timmermann, and White (1999), p. 1653).

2.3 Specification of Market-Timing Rules

In our investigation, we replicate the attempts of academics and the investment industry to find profitable market-timing rules. For a meaningful assessment of data-snooping biases, we have to construct a sufficiently large set of market-timing rules from which rules that have been applied or considered could possibly have been drawn. Sullivan, Timmermann, and White (1999) and Sullivan, Timmermann, and White (2001) point out that the selection of rules to be included in the analysis is especially important, since data-snooping biases are only corrected for relative to the universe of rules investigated. In particular, "the magnitude of data-snooping effects on the assessment of the performance of the best trading rule is determined by the dependence between all the trading rules' payoffs, so the design of the universe from which the trading rules are drawn is crucial to the experiment" (Sullivan, Timmermann, and White (1999), p. 1654). When conducting the data-snooping tests, two possible issues can arise. On the one hand, considering too many "irrelevant" rules dilutes the power of the test and could render genuinely significant rules insignificant (see Hansen (2005)).[10] This is why we discard trading rules based on new technology which has not been available for most of the sample period. On the other hand, if too few market-timing rules are included, the data-snooping correction would not account for the full set of rules from which effective rules conceivably could have been drawn; our estimated p-values would therefore be biased towards zero. Lo and MacKinlay (1990) refer to this as the "file-drawer" problem: Many rules that do not generate superior returns do not get published and are therefore no longer considered. It is therefore important not only to include the rules/parameterizations that have been publicly reported, but also other rules/parameterizations that may have been considered, since the successful rules are drawn from the entire set of successful and unsuccessful rules. For those reasons, we find a balance and choose a fairly large variety of market-timing rules and parameterizations that investors and academics may have considered. In a first experiment, we consider a set of 6,792 simple market-timing rules, each based on one indicator only (basic set). Our second universe of rules adds complex strategies to the basic set and spans a universe of 8,768 market-timing rules (extended set). Even though our sets of rules do not exhaust all the rules/parameterizations that have ever been applied, our experiment covers a reasonably large universe of the most common and most important trading rules and is by far the most comprehensive in the field of market timing. In our subsample from 1995 to 2007, the number of rules increases to 8,280 for the basic set and 10,256 for the extended set, since during this time period we include additional indicators based on the availability of data. (See Section 2.4 for details on the

[10] Yet, Sullivan, Timmermann, and White (2001), p. 259, also discuss the issue of including too many "irrelevant" rules, but argue that a loss of power is rather unlikely.

construction of indicators.)

In the following section, we describe the rules applied in our analysis. In order to trigger switching signals, several threshold values of the indicators are considered. Thresholds are either a historical value, such as the moving average or percentile (those are referred to as standard thresholds) or a fixed number (see Section 2.4 for details). The general assumption for all market-timing rules is that an investor is usually long the index but tries to temporarily exit the market and switch to holding cash in bad times, those being indicated by the timing indicators.

2.3.1 Rules Based on Financial Ratios

The indicators for market timing that have received the most attention in the literature are the financial ratios: the dividend yield, the earnings-to-price (E/P) ratio, and the book-to-market (B/M) ratio. Many investors assume that stock prices do not wander too far from their normal levels relative to such fundamental values as earnings, dividends, and book value, but revert back to their normal levels after periods of deviation. That is, financial ratios are assumed to fluctuate within historical ranges and to be positively related to expected returns. Return predictability by means of the book-to-market ratio is investigated, for instance, by Kothari and Shanken (1997) and Pontiff and Schall (1998). Shiller (1984), Campbell and Shiller (1988a), Campbell and Shiller (1988b), Fama and French (1988), Fama and French (1989), and Campbell and Shiller (2001), among others, argue that the dividend yield and the E/P ratio have predictive power. Based on these findings, Brennan, Schwartz, and Lagnado (1997) and Campbell and Viceira (1999) discuss the extent to which the predictive powers of the dividend yield and the E/P ratio are useful for timing the market. Fisher and Statman (2006a) and Fisher and Statman (2006b) also investigate the success of market timing based on financial ratios and find that the performance of buy-and-hold investors is usually higher than that of various timing rules based on E/P ratios and dividend yields.

2.3.1.1 Earnings-to-Price Ratio (E/P Ratio)

As outlined above, it is reasonable to assume that the E/P ratio generally follows a tendency of mean reversion; stock prices and the corresponding indicator of the fundamental value (earnings) are not expected to wander too far off. Considering the E/P ratio as the relative price of a stock, the economic rationale for using this ratio to time the market is quite simple. Stocks with a low E/P ratio provide low earnings relative to their price and are thus considered to be expensive. If the aggregate E/P ratio falls below a certain threshold, the market is considered to be overvalued and investors therefore switch from holding the index to cash. The rule applied in our investigation is specified as follows: When the E/P ratio falls below a certain threshold x, investors switch from being invested in the index to holding cash. When the ratio rises above x, investors revert to holding the index.

2.3.1.2 Dividend Yield

Market timing based on the dividend yield is quite similar to market timing by means of the E/P ratio. Stability of the dividend yield in the sense of mean reversion implies that, if stock prices are low relative to dividends, prices will increase in the future in order to ensure that the dividend yield returns to its normal historical range. The rule for testing the dividend yield is similar to the rule based on the E/P ratio: If the dividend yield is above a specified threshold x, market timers are invested in the index. When the ratio drops below the specified threshold, investors exit the index and hold cash.

2.3.1.3 Book-to-Market Ratio (B/M Ratio)

The third financial ratio used in our experiment is the B/M ratio. Like the two ratios above, the B/M ratio indicates whether the market is underpriced or overpriced. Given an overpriced market reflected by a low B/M ratio, future returns are assumed to be low since the overpricing will be corrected in the future. Thus, as for the E/P ratio and the dividend yield, market timers sell the index and switch to cash when the B/M ratio falls below a certain threshold value x. An increase in the B/M ratio above x triggers the reverse strategy.

2.3.2 Rules Based on Interest Rates

2.3.2.1 Short-Term Interest Rate and Discount Rate

The first macroeconomic indicators to be investigated as useful signals for market timing are the short-term interest rate (Treasury bills) and the discount rate announced by the U.S. Federal Reserve. Empirical studies find that falling short-term interest rates are associated with economic expansion and thus predict high stock market returns (e.g., Fama (1981)). Using a simple regression model, Breen, Glosten, and Jagannathan (1989) evaluate the ability of treasury bill rates to forecast stock market movements. More recent studies, such as Ang and Bekaert (2007), support the superior forecasting power of short-term interest rates compared to other variables. Prather and Bertin (1997) and Prather and Bertin (1998) test a trading rule based on discount-rate announcements by the U.S. Federal Reserve. Their strategy involves holding stocks when discount rates are decreasing and switching to T-bills when discount rates increase. The trading rule based on both short-term interest rates and discount rates entails exiting the market after the interest rates rise above a certain level x. A drop in the interest rates below the threshold is a signal to switch back to the index.

2.3.2.2 Long-Term Interest Rate

Since Treasury bonds qualify as a direct alternative to stock investments, the interest rate on such bonds should have even more predictive power for stock returns than the interest rates described in the previous section. If the interest rate increases, we would expect stock prices to go down, and vice versa. The trading rule based on the long-term interest rate is the same as that for the short-term interest rate. A speculator will exit the index and switch to holding cash if the interest rate rises above a certain threshold x; the reverse strategy is triggered if the interest rate drops below x.

2.3.2.3 Maturity Spread

Rather than focusing on interest rates themselves, many economists have tried to predict future real economic activity by using the maturity spread, defined as the spread between yields on long-term and short-term bonds. The term structure of interest rates contains useful information about expected real interest rates and expected inflation (e.g., Mishkin (1990b)) and is a useful tool to predict economic growth and thus stock-market returns.[11] Intuitively, economic growth and the return on stocks are linked, since stock market returns are expected to be higher during economic expansion. Campbell (1987) and Fama and French (1989), among others, show that the maturity spread is correlated with future stock returns and thus useful for predicting subsequent stock market movements. The theoretical underpinning for the indicator property of the maturity spread, as a proxy for the term structure of interest rates, is given by the expectation theory, according to which the relation between the short-term interest rate and the long-term interest rate depends on the expected short-term interest rate. Tight monetary policy causes economic agents to expect an increase in the short-term interest rate. The term structure of interest rates flattens. Consequently, a change in the maturity spread is associated with a change in the business cycle. In particular, a high maturity spread indicates economic growth and a low spread indicates an economic downturn.

The usefulness of the term structure of interest rates for predicting economic development was, for instance, examined by Estrella and Hardouvelis (1991), Harvey (1997), and Hamilton and Kim (2002). Estrella and Mishkin (1996) apply a probit model to assess the indicator property of the maturity spread and find that it has superior power for predicting recessions compared to other macroeconomic variables. Their model is extended by

[11] Since there is a separate line of research on the relationship between expected inflation and stock returns, we discuss the indicator property of the expected inflation component in the term structure of interest rates separately in Section 2.3.4.

Resnick and Shoesmith (2002), who find that the maturity spread can be used to forecast downturns in the stock market. Under a rule based on the maturity spread, when the current maturity spread falls below a threshold value x, an investor switches from the index to cash, since the market is expected to yield lower returns than cash during these periods. For values of the spread above the threshold, the investor invests in the index.

2.3.3 Rules Based on Investor Sentiment

2.3.3.1 Credit Spread

Sentiment indicators, such as the credit spread, measure the attitude of investors towards the stock market. Fama and French (1989), among others, find the credit spread to be the best predictor for future stock returns, besides the dividend yield and the maturity spread.[12] One widely used sentiment measure is the spread between the yields on BAA-rated and AAA-rated corporate bonds, as applied, for instance, by Fama and French (1989). A decrease in the credit spread indicates lower risk aversion on the part of investors and therefore a good climate for the stock market. An increase in the spread indicates higher risk aversion on the part of investors and therefore a poor climate for the stock market. The rule to be tested is specified as follows: If the credit spread rises above a certain threshold x, speculators switch from the index portfolio to cash holdings; if it falls below x, speculators invest in the index.

2.3.3.2 Put/Call Ratio

Another implicit measure of investor sentiment is the put/call ratio, defined as the trading volume of puts (or number of puts outstanding) relative to the trading volume of calls (or number of calls outstanding). Often, the ratio is used as a contrarian indicator.[13] That is, when the put/call ratio is high (a high number of puts being traded relative to the number of call options being traded), the market is highly pessimistic and a turnaround with an increase in stock prices is expected. On the contrary, a low put/call ratio indicates that the market is overly optimistic and is expected to adjust downwards. Thus, if the ratio falls below a certain threshold x, a sell signal is triggered, while an increase in the ratio above x is a trigger for buying the index.

12 Using sentiment indicators to predict future stock market movements falls into the literature which tries to link business conditions and expected stock market returns (e.g., Campbell and Diebold (2009)).

13 Even though Fisher and Statman (2000) do not explicitly consider the put/call ratio, they find that sentiment indicators should trigger contrarian investment strategies.

2.3.4 Rules Based on Expected Inflation

The negative relation between inflation and stock market returns has been extensively studied. For instance, Fama and Schwert (1977), Fama (1981), Geske and Roll (1983), Stulz (1986), and Kaul (1987) attempt to provide evidence for the stock-return/inflation puzzle.[14] In probably the most widely cited study on the abnormal relationship between expected inflation and stock returns, Fama (1981) claims that the negative relationship simply reflects the fact that anticipated real activity has opposite impacts on stock returns and on expected inflation, but that the relationship is not causal. Extending the work of Fama (1981), Geske and Roll (1983) and Kaul (1987) argue that the correlation between inflation and stock returns is due to monetary policy changes, real economic conditions, and monetization of budget deficits. As mentioned in Section 2.3.2.3, the maturity spread contains information about the expected inflation rate. In particular, Fama (1990) and Mishkin (1990a), among others, show that the term structures with maturities of more than nine months are useful for predicting expected inflation. We thus rely on the yield spread between the 1-year and the 2-year Treasury bonds as a measure for expected inflation. Under a rule based on expected inflation, investors will switch from being invested in the index to holding cash if the expected inflation rises above a certain threshold x. This may seem nonintuitive, as high inflation would hurt an investor holding cash even more; however, the downturn in the market is expected to be even larger, so that holding cash is the lesser of the two evils.

2.3.5 Rules Based on Implied Volatility Index

According to conventional wisdom, investors should decrease their stock holdings in periods of high volatility, a negative relation between expected stock returns and volatility having been widely documented. The theoretical underpinning for the risk-return relationship goes back to Merton (1980) and French, Schwert, and Stambaugh (1987). The former argues that, under certain conditions, the market risk premium is positively correlated with the variance of the market portfolio. French, Schwert, and Stambaugh (1987) find that, if there is an unexpected increase in market volatility, expected volatility is revised upward for future periods. Hence, given that the market risk premium is positively related to the expected volatility of the market portfolio, discount rates will increase and in turn reduce stock prices. Thus, a negative relation between (unexpected) volatility changes and returns is induced. The relation between market volatility and expected returns has been subject to considerable research, such as French, Schwert, and Stambaugh (1987), Breen, Glosten, and Jagannathan (1989), Campbell and Hentschel (1992),

[14] The observed negative relationship between stock market returns and different measures of expected and unexpected inflation appears to contradict the so-called Fisher Hypothesis (Fisher (1930)), according to which there should be a positive relationship between the expected inflation and nominal asset returns; claims on real assets, such as stocks, should provide hedging against inflation.

Glosten, Jagannathan, and Runkle (1993), and Whitelaw (1994). In the first theoretical study on the relationship between conditional mean independence and the predictability of asset-return signs as well as asset-return volatilities, Christoffersen and Diebold (2006) show analytically that sign predictability follows from volatility dependence. The performance of timing rules based on volatility changes has been investigated, for instance, by Copeland and Copeland (1999), who test the feasibility of market timing based on changes in the implied volatility index, VIX, and find profitable strategies which involve various style and size strategies.[15] Other studies, such as Fleming, Kirby, and Ostdiek (2001), Fleming, Kirby, and Ostdiek (2003), and Johannes, Polson, and Stroud (2002), applying more complex trading strategies than just switching between two asset classes, find that "volatility timing" leads to significant economic benefits. In our paper, under a volatility trading rule, an investor switches to cash if the VIX rises above a certain threshold x. A buy signal is triggered if the volatility index drops below that threshold. All volatility trading rules make use of implied volatility, which serves as a measure of the expected volatility.

2.3.6 Modified Rules and Combined Indicators

2.3.6.1 Rules Based on the Bond-Equity Yield Ratio

In addition to the traditional financial ratios, described in Section 2.3.1, the so-called bond-equity yield ratio (*beyr*) has become a popular indicator for future stock market movements.[16] Clare, Thomas, and Wickens (1994), Levin and Wright (1998), Harris and Sanchez-Valle (2000), and Brooks and Persand (2001), among others, find that this augmented financial ratio is a useful tool for predicting future stock returns and thus a useful instrument for market timing. The bond-equity yield ratio is defined as the ratio of the bond yield to the yield in the stock market, where the dividend yield and the earnings yield (E/P ratio) are commonly used as proxies for the stock market yield. It is assumed that *beyr* possesses a long-term level which reflects the long-run arbitrage relation between the government bond market and the stock market. If *beyr* becomes high relative to its long-term level, equity yields are considered to be low compared to yields on bonds. Stock prices are therefore expected to fall in order to reestablish the long-run equilibrium. In contrast, a low beyr indicates that equities are cheap compared to bonds and that equity yields are expected to decrease in order to restore the long-term relationship. Under a rule based on *beyr*, investors invest in the index if the ratio is below a certain threshold

[15] The VIX is constructed to represent the implied volatility of a synthetic at-the-money option contract on the S&P 500 index with a maturity of 30 days. It is constructed from eight S&P 500 index options and uses a dividend-adjusted Black-Scholes model.

[16] In the literature, the ratio is sometimes referred to as the gilt-equity yield ratio (*geyr*). See, for instance, Clare, Thomas, and Wickens (1994).

x. A rise in the ratio above x is a signal to sell the index and switch to cash.

Shen (2003) employs an indicator closely related to *beyr*. Instead of using the ratio explained above, Shen (2003) uses the spread between the E/P ratio and interest rates to construct market-timing strategies and finds that investors following such strategies can beat a buy-and-hold strategy.[17] Obviously, the spread contains the same information as the ratio explained above. Hence, we do not include the spreads used by Shen (2003) in our set of market-timing indicators, but rather the ratio of the 3-month Treasury bill rate to the earnings/dividend yield as well as the ratio of the 10-year Treasury bond rate to the earnings/dividend yield.

2.3.6.2 Rules Based on the Dividend Payout Ratio

Lamont (1998) suggests that, in addition to the dividend yield and the earnings yield, the dividend payout ratio, defined as the ratio of dividends per share to earnings per share, has predictive power for future stock market returns.[18] In particular, he argues that the dividend payout ratio should be positively correlated with future returns, since high dividends typically forecast high returns whereas high earnings typically forecast low returns. Lamont (1998) does not treat earnings and dividends as scaling variables for prices, but rather uses the dividend payout ratio as an explanatory variable for future stock returns. In our study, we identify buy (sell) signals when the dividend payout ratio crosses a threshold x from below (above).

2.4 Data and Indicator Construction

In our experiment, we apply the market-timing rules to the S&P 500 index and base our analysis on continuously compounded end-of-day returns. Our data for indicator construction are taken from different sources and cover all trading days from January 1, 1980 through December 31, 2007, for a total of 7,305 observations. The year 1980 is used as the observation window in order to compute percentiles and means for first signals. Hence, we compute performance measures of all market-timing rules from the year 1981 onwards.[19]

Since data for the put/call ratio and the VIX are not available before 1994, we decided to split the full sample into two subperiods of roughly equal length, 1981-1994 and

[17] Pesaran and Timmermann (1995) employ the spread between the E/P ratio and interest rates as an explanatory variable for future stock market returns, but do not explicitly assess its usefulness for market-timing strategies.

[18] However, Lettau and Ludvigson (2001), using a different data set, find the payout ratio to be statistically insignificant.

[19] Throughout the paper, a time period from year A to year B starts on the first trading day of year A and ends on the last trading day of year B.

1995-2007. Rules based on the put/call ratio and on the VIX are only considered in the latter subperiod. When considering subperiods, the years 1980 and 1994 are used as the observation windows.

The put/call ratio is obtained from Bloomberg. All other time series in our paper are extracted from Thomson Datastream. All time series are at a daily frequency. A detailed description of the applied time series and their codes in the source databases is given in Appendix B.1.

For indicator construction, the E/P ratio and the dividend yield can be directly extracted from Thomson Datastream, whereas the B/M ratio needs to be constructed. For the years 1980 through 2005, we calculate the B/M ratio for the S&P 500 by dividing the book value at the end of the previous month by the daily index price series. The book values are calculated from the end-of-month B/M ratios for the S&P 500, which are available on the MSCI Barra webpage.[20] For the years 2006 and 2007, we calculated the end-of-year book value for the index from the B/M ratios taken from the S&P webpage.[21] The daily B/M ratio is then calculated by dividing the book value at the end of the previous year by the daily index price. For indicators based on interest rates, we apply the yields of 3-month and 6-month Treasury bills as well as the discount rate announced by the U.S. Federal Reserve as short-term interest rates. The set of long-term interest rates, which are used as timing indicators, includes yields to maturity of 2-year, 3-year, 5-year, 10-year, and 30-year Treasury bonds. The maturity spread is calculated as the spread between the 3-month Treasury bill yield and the 10-year Treasury bond yield. The yield spread between the 1-year and the 2-year Treasury bonds serves as a proxy for expected inflation. The credit spread is measured as the difference between the yields on a BAA-rated corporate bond and a AAA-rated corporate bond. The bond-equity yield ratio can be calculated in two ways, dividing the yield of the 3-month Treasury bill by the E/P ratio or by the dividend yield. We use both. In addition, we replace the 3-month Treasury bill yield by the 10-year Treasury bond yield when constructing *beyr*. The dividend payout ratio is defined as the ratio of dividends per share to earnings per share whereas the dividends and the earnings time series can be simply obtained from the dividend yield and the E/P ratio, since the price series is given.

For each indicator in our analysis, we use several fixed numbers as well as the moving average over the preceding 5, 10, 40, and 60 days and the $80^{th}/20^{th}$, $90^{th}/10^{th}$, and $95^{th}/5^{th}$

[20] End-of-month B/M ratios for the S&P 500 for the years 1980 through 2005 are available at `http://www.barra.com/Research/Fundamentals.aspx`.

[21] End-of-year B/M ratios for the S&P 500 for the years 2006 and 2007 are available at `http://www2.standardandpoors.com/portal/site/sp/en/us/page.topic/indices_500/2,3,2,2,0,0,0,0,0,5,7,0,0,0,6,0.html`.

percentiles over the preceding 250 days as threshold values x to obtain switching signals as described in Sections 2.3.1 through 2.3.6.[22] For indicators that trigger selling the index when they reach high values, the 80^{th}, 90^{th}, and 95^{th} percentiles are used. The 5^{th}, 10^{th}, and 20^{th} percentiles are used for indicators that trigger switching to cash when they reach low values. When choosing fixed threshold levels for each indicator, we select a fairly large set of parameter values x that lie in the ranges investors and academics may have considered over time. We also consider, for all thresholds, holding a certain position for a period of c days, during which all other signals are ignored. We refer to this period as the waiting period. Alternatively, a time-delay filter is implemented, which requires that a buy/sell signal has to remain valid for d days before a transaction is made. For the waiting period and the time-delay filter, we consider parameter values $c = [1, 2, 5, 10, 20, 30]$ and $d = [1, 2, 5, 10, 20, 30]$. In Appendix B.2, we provide the parameterizations for the basic set of rules.

In our tests, we consider both the average return and the Sharpe ratio as performance measures. In order to compute the Sharpe ratio according to formula (2.16), we calculate the excess return of a specific rule as the difference between the return from the rule and the risk-free interest rate. As a proxy for the risk-free interest rate we use the Federal funds rate (reported per annum) and convert it into a daily rate according to the formula,

$$r_f^d = \frac{ln(1 + r_f^a)}{250}, \tag{2.18}$$

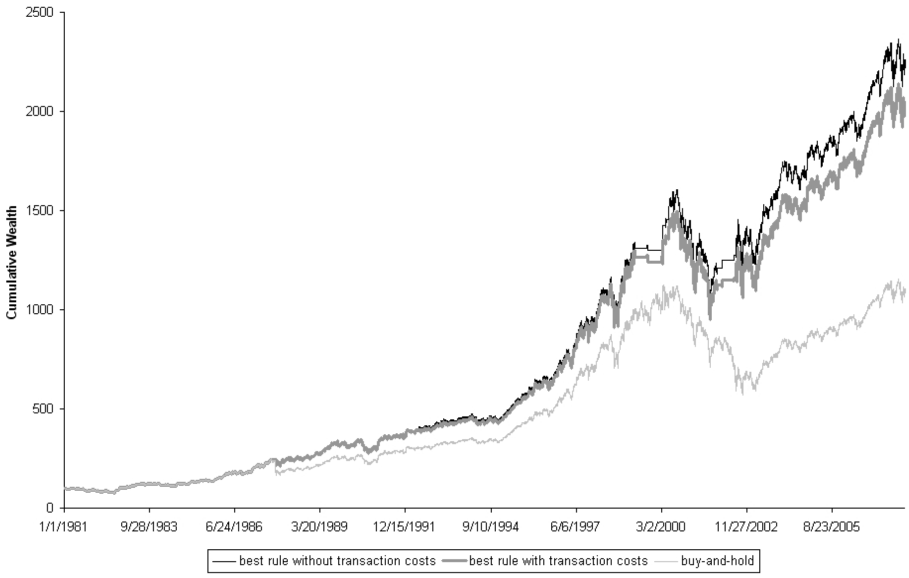
where r_f^d denotes the daily risk-free interest rate and r_f^a denotes the annual risk-free interest rate. The denominator represents the number of trading days per annum.

2.5 Results for Simple Market-Timing Rules

In a first step, we identify the best-performing (simple) market-timing rules for the various sample periods. Table 2.1 reports the performance of the best performers and the corresponding number of trades under both the mean return criterion (Panel A) and the Sharpe ratio criterion (Panel B). The table also contains the mean return and the Sharpe ratio of the benchmark. For the full sample, rules based on *beyr* turn out to be the best performers under both performance criteria, though with different thresholds and different waiting periods. For the first subperiod, exactly the same rule based on *beyr* is chosen under both performance criteria. For the second subperiod, yet another *beyr*-based rule is identified as the best rule under the mean return criterion, whereas the best performer under the Sharpe ratio criterion is a rule based on the dividend yield with a threshold $x = 1.75$ and a waiting period $c = 10$. Comparing the returns/Sharpe ratios of the best

22 Henceforth, moving averages and percentiles are referred to as standard thresholds.

Figure 2.1: Cumulative Wealth of the Best Market-Timing Rule and the Buy-and-Hold Strategy over the Full Sample



rules and the benchmark, it can be seen that the buy-and-hold strategy is outperformed under both criteria in all periods. Excess returns of the best rules over the benchmark lie between 2.93% (for the full sample) and 5.57% (for the first subperiod). The number of trades of the best performers varies substantially. The particularly high number of trades of the best rule in the first subperiod might indicate that, when transaction costs are included, other market-timing rules with less frequent trading might be optimal.[23]

In order to illustrate the performance of the best market-timing rule, Figure 2.1 plots its cumulative wealth for the full sample from 1981 to 2007, starting with an investment of 100 USD (thin black line). Figure 2.1 also includes the cumulative profits of the benchmark (buy-and-hold) strategy (light gray line) and indicates that the cumulative profit of the best-performing rule clearly dominates that of the benchmark strategy. Even though the return earned by the best rule does not necessarily exceed that of the benchmark at all times, an investor is uniformly better off in terms of cumulative wealth when following the best market-timing rule. Such an investor would have accumulated $2,217$ USD over the full sample period, whereas a buy-and-hold investor would have ended up with only $1,081$ USD. The cumulative profit of the best performer after one-way transaction costs of 50 basis points is indicated by the thick gray line. It can be seen that including transaction costs does not qualitatively change the dominance of the best timing rule relative to the benchmark strategy.[24]

[23] In Section 2.7.3, we check for the robustness of the results when transaction costs are included.
[24] A more detailed robustness check with respect to transaction costs is performed in Section 2.7.3.

Table 2.1: Best Market-Timing Rules in the Basic Set under the Mean Return Criterion and the Sharpe Ratio Criterion

Panel A	Mean Return Criterion			
Sample	Best Trading Rule	# Trades	Model Return	Benchmark Return
Full Sample (1981 - 2007)	Beyr-EP threshold 1.9, $c = 20$	20	12.15%	9.22%
Subperiod I (1981 - 1994)	Beyr-DY mean (20 lags), $d = 5$	244	14.59%	9.02%
Subperiod II (1995 - 2007)	Beyr-EP threshold 1.6, $c = 5$	22	12.70%	9.35%

Panel B	Sharpe Ratio Criterion			
Sample	Best Trading Rule	# Trades	Model SR	Benchmark SR
Full Sample (1981 - 2007)	Beyr-EP threshold 1.55, $c = 5$	58	0.457	0.237
Subperiod I (1981 - 1994)	Beyr-DY mean (20 lags), $d = 5$	244	0.582	0.122
Subperiod II (1995 - 2007)	DY threshold 1.75, $c = 10$	20	0.683	0.350

This table reports the performance of the best market-timing rule under the mean return criterion (Panel A) and the Sharpe ratio criterion (Panel B) for each sample period. The Sharpe ratio is denoted by SR. The table also contains the mean return and the Sharpe ratio of the buy-and-hold strategy (benchmark model). The mean returns and the Sharpe ratios are annualized. Lower case letters d and c denote the length of the time-delay filter and of the waiting period, respectively.

Table 2.2: Performance of the Best Market-Timing Rules in the Basic Set under the Mean Return Criterion

	Reality Check		SPA		
Sample	nom. p-value	RC p-value	nom. p-value	SPA-c	SPA-l
Full Sample (1981 - 2007)	0.030	0.598	0.030	0.569	0.361
Subperiod I (1981 - 1994)	0.035	0.275	0.035	0.257	0.169
Subperiod II (1995 - 2007)	0.073	0.885	0.073	0.884	0.742

This table presents the performance of the best market-timing rule under the mean return criterion. For each period, the table shows the "Reality Check" (RC) and the SPA p-values along with the corresponding nominal p-values. SPA-c refers to the consistent p-value of Hansen (2005)'s SPA; SPA-l is the lower bound of the consistent SPA p-value. The nominal p-values are obtained by applying the RC and the SPA testing procedures to the best market-timing rule only, without correcting for data-snooping biases.

2.5.1 Test Results under the Mean Return Criterion

Table 2.2 presents the test results for the performance of the best market-timing rule under the mean return criterion. For each time period, the RC p-values, the SPA p-values, and the corresponding nominal p-values are summarized; in the table, SPA-c refers to the consistent SPA p-value of Hansen (2005) and SPA-l refers to the inconsistent lower bound of the SPA-c p-value.[25] The nominal p-values for the full sample and the two subperiods are all well below 0.10, rejecting the null hypothesis of no outperformance of the best rules relative to a buy-and-hold strategy. This result might not be entirely unexpected due to the excess return of those rules relative to the benchmark. For the full sample and the first subperiod, we find the outperformance to be significant at the 5% level; for the second subperiod, the superior performance is signifiant at the 10% level. In sharp contrast, the RC and the SPA-c p-values are very high for all periods and the null hypothesis is not rejected at any conventional significance level. These findings show that, even though market-timing rules might generate statistically significant excess returns relative to the benchmark when evaluated in isolation, correcting for dependencies between rules leads to insignificant p-values.

Figure 2.2 demonstrates the effects of data snooping and the complexity of dependencies across the set of market-timing rules even more clearly than they can already be seen in Table 2.2. In Figure 2.2, we plot the number of the model against its average annualized return, measured on the left y-axis and identified by the scattered points. Also shown is the sequentially updated maximum average return (thin red line) from a certain number of models (indicated on the x-axis), the corresponding RC p-value (measured on

[25] In the following, we base our assessments on the RC p-value and the consistent SPA-c p-value. The inconsistent lower bound for the consistent SPA p-value, SPA-l, is reported for information purposes.

the right y-axis and represented by the solid blue line), and, for comparison, the benchmark return (horizontal green line).[26] For the final assessment, only the numbers on the far right of the graph (the terminal maximum mean return and the terminal RC p-value) matter, since the order of models is arbitrary. Nevertheless, the figure gives a fascinating picture of how the maximum mean return and the corresponding RC p-value evolve when additional models are sequentially included. The maximum mean return increases quickly to approximately 11%, well above the benchmark return, but rises no further after the first 3,900 trading rules have been evaluated. The p-value, however, does not remain constant, but increases gradually up to 0.74 after the same number of models have been considered. It can be seen that, while the marginal trading rules do not improve on the maximum mean return, the data-snooping adjusted p-value gradually increases, since the effective span of market-timing rules widens. After superior market-timing rules are included around model 3,900, the RC p-value drops to 0.52. From this point until all 6,792 rules are considered, the pattern is similar to that already described. Since no improvements occur in the maximum performance statistic as the number of rules increases, the RC p-value is subject to the same "dilution effect" as before and increases to a terminal value of 0.60.

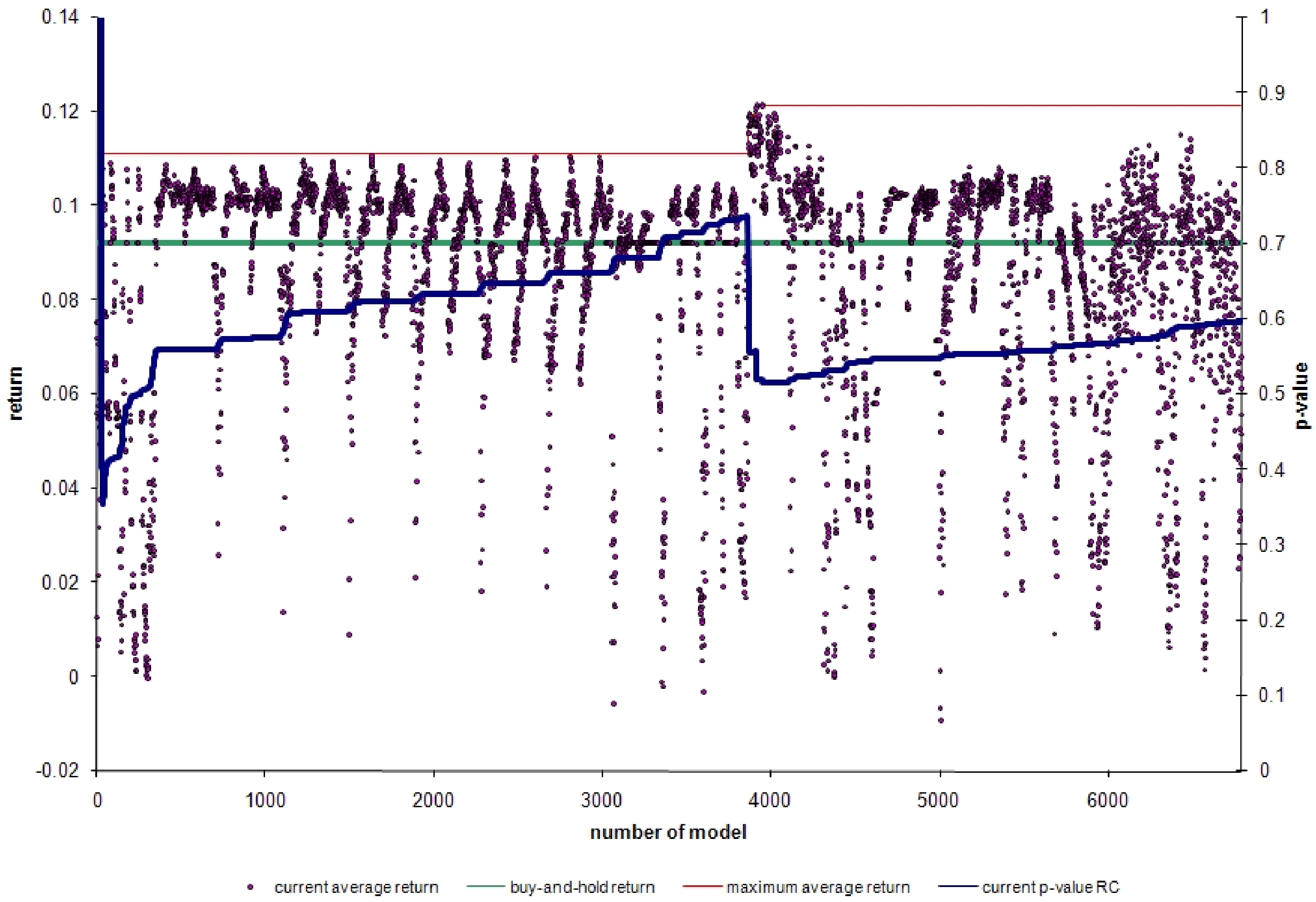
2.5.2 Test Results under the Sharpe Ratio Criterion

The test results for the best-performing rule under the Sharpe ratio criterion are summarized in Table 2.3, which reports the RC and the SPA p-values for all sample periods, as well as the corresponding nominal p-values. The results are qualitatively the same as those under the mean return criterion. Nominal p-values close to zero for the full sample period and the first subperiod suggest that, without taking data snooping into account, the best rules significantly beat a buy-and-hold strategy at the 5% significance level. The highest nominal p-value for the second subperiod, 0.09, is still significant at the 10% level. For all periods, data-snooping adjusted p-values are even higher than under the mean return criterion, indicating that the superior performance of the best rules is insignificant for the full sample and for both subperiods. Thus, accounting for dependencies between market-timing rules renders the significant performance of the best-performing rule (when considered in isolation) insignificant. Once more, our findings illustrate the effect of data snooping on statistical inference and emphasize the importance of using appropriate methods to correct for data-snooping biases.

As before, we graphically illustrate the evolution of the economic and statistical performance of the best-performing rule under the Sharpe ratio criterion for the full sample period. As can be seen from Figure 2.3, the maximum Sharpe ratio increases to a value

[26] Since the RC and the SPA provide similar results, we restrict all graphical illustrations to p-values obtained from the RC.

Figure 2.2: Economic and Statistical Performance of the Best Market-Timing Rule in the Basic Set under the Mean Return Criterion: Full Sample (1981-2007)



For each trading rule k, indexed on the x-axis, the annualized average return over the full sample (1981-2007) is identified by the scattered points. In addition, the current maximum mean return in the basic set of market-timing rules (thin red line), the associated current “Reality Check” p-value (solid blue line), and the benchmark return (horizontal green line) are plotted.

Table 2.3: Performance of the Best Market-Timing Rules in the Basic Set under the Sharpe Ratio Criterion

	Reality Check		SPA		
Sample	nom. p-value	RC p-value	nom. p-value	SPA-c	SPA-l
Full Sample (1981 - 2007)	0.027	0.981	0.027	0.917	0.628
Subperiod I (1981 - 1994)	0.014	0.867	0.014	0.685	0.316
Subperiod II (1995 - 2007)	0.088	0.933	0.088	0.914	0.750

This table presents the performance of the best market-timing rule under the Sharpe ratio criterion. For each period, the table shows the "Reality Check" (RC) and the SPA p-values along with the corresponding nominal p-values. SPA-c refers to the consistent p-value of Hansen (2005)'s SPA; SPA-l is the lower bound of the consistent SPA p-value. The nominal p-values are obtained by applying the RC and the SPA testing procedures to the best market-timing rule only, without correcting for data-snooping biases.

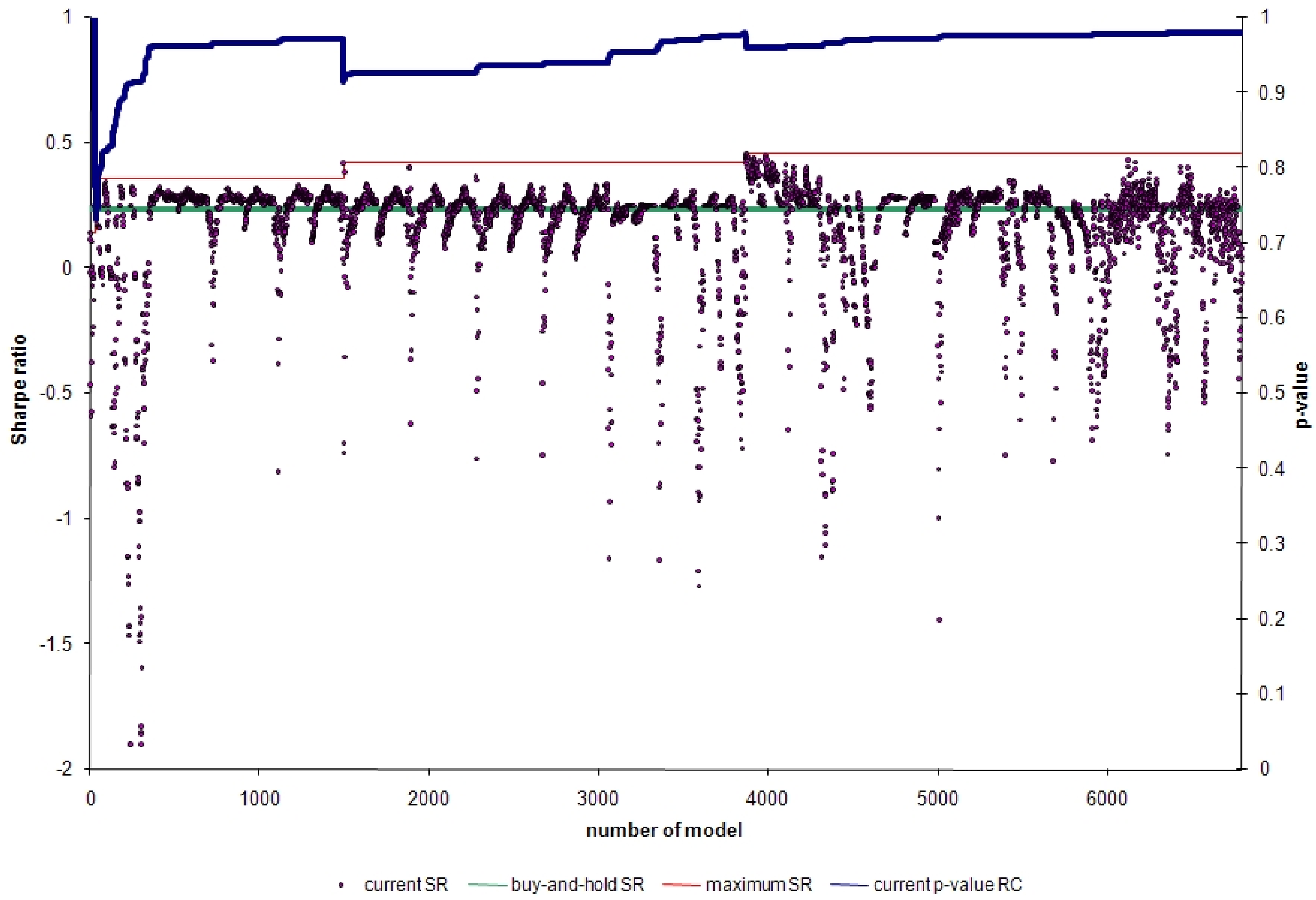
of 0.35 after including 35 models, which decreases the RC p-value to 0.73. Including an additional 300 rules—among them several models that remarkably underperform the benchmark—leads to a sharp increase in the RC p-value to 0.96. Over the next 1,200 models, the maximum performance statistic does not change and the RC p-value rises only slightly. At around model 1,500, we find an improvement in the maximum performance statistic, associated with a drop in the RC p-value. Over the remaining rules, the maximum Sharpe ratio improves only slightly to roughly 0.46. Since the improvement is small as the set of rules becomes larger, we observe that the RC p-value increases gradually to a highly insignificant terminal value of 0.98, displaying the effects of data snooping.

In summary, considering simple market-timing rules, each of which is based on one indicator only, we find that some of them, when considered in isolation, produce superior performance relative to a buy-and-hold strategy. This finding is consistent with the results of the market-timing literature. However, once we account for dependencies across rules—that is, once we cease to ignore the fact that the best rules are drawn from a large set of market-timing rules—we no longer observe that superiority.

2.6 Results for Complex Market-Timing Rules

So far, our set of market-timing rules has included only simple rules, each of which relies on the information from a single indicator only. In practice, investment decisions are likely to be based on a broader information set and thus on complex trading strategies that incorporate information from various indicators. We therefore add to our basic set of simple rules two groups of complex trading strategies: learning rules and voting rules. As before, all rules rely only on historically available information and may therefore be

Figure 2.3: Economic and Statistical Performance of the Best Market-Timing Rule in the Basic Set under the Sharpe Ratio Criterion: Full Sample (1981-2007)



For each trading rule k, indexed on the x-axis, the annualized Sharpe ratio over the full sample (1981-2007) is identified by the scattered points. In addition, the current maximum Sharpe ratio in the basic set of market-timing rules (thin red line), the associated current "Reality Check" p-value (solid blue line), and the benchmark Sharpe ratio (horizontal green line) are plotted.

implemented in practice. For all complex strategies, we consider, as in previous sections, holding cash as the exit position when the rule indicates selling the index.

Under a learning rule, an investor, at certain times, determines the best-performing rule among all simple trading rules over the last e days, the evaluation period, and then follows the signal of this particular rule. The performance of each simple rule is evaluated based on two measures: the sum of daily returns and the average (daily) log return, both over the preceding e days. In addition to the evaluation period e, we consider a review span r, which determines how often the evaluation process for the best-performing rule is conducted and a possible switching is initiated. This leaves us with a total of 1,482 learning rules.

Voting rules are defined as follows: Each simple rule in our universe has one vote, either to invest in the index (pro index) or to exit the market (contra index), according to that rule's switching signal. The signal for a voting rule is based on the ratio of pro index and contra index votes. Traders sell the index if b percent of all votes signal exiting the market, and vice versa. As with the learning rules, we implement a review span r, for a total of 494 voting rules. Parameterizations for all complex timing rules are given in Appendix B.3.

As with the basic set of simple rules, we first identify the best market-timing rules among all the rules in the extended set. In Table 2.4, Panel A, we report their mean returns and number of trades for all sample periods and, for comparison, the mean return of the benchmark. Panel B presents the Sharpe ratios of the best rules and of the benchmark, as well as the number of trades triggered by the best market-timing rules. We find that for each period the same rules are selected as best-performers under both performance criteria. Interestingly, for all periods, learning rules turn out to perform best in the extended set of rules. Hence, the maximum performance for all periods is higher than in the previous exercise, in which we considered only simple rules. We find the largest increase in the maximum performance for the first subperiod with a rise of the mean return from 14.59% (for the best rule in the set of simple rules) to 24.24%, which equals an outperfomance over the benchmark of more than 15% per annum. This remarkable excess return of the best-performing rule relative to the benchmark gives rise to the conjecture that this outperformance may be statistically significant, even after data-snooping adjustment. Since the number of trades of the best learning rules are even higher than for the best rules from the set of simple rules, the robustness check on the impact of transaction costs in Section 2.7.3 is even more valuable.

Table 2.4: Best Market-Timing Rules in the Extended Set under the Mean Return Criterion and the Sharpe Ratio Criterion

Panel A	Mean Return Criterion			
Sample	Best Trading Rule	# Trades	Model Return	Benchmark Return
Full Sample (1981 - 2007)	Learning Rule, $r = 10$, $e = 1$	328	12.40%	9.22%
Subperiod I (1981 - 1994)	Learning Rule, $r = 5$, $e = 1$	370	24.24%	9.02%
Subperiod II (1995 - 2007)	Learning Rule, $r = 5$, $e = 5$	306	16.23%	9.35%

Panel B	Sharpe Ratio Criterion			
Sample	Best Trading Rule	# Trades	Model SR	Benchmark SR
Full Sample (1981 - 2007)	Learning Rule, $r = 10$, $e = 1$	328	0.60	0.237
Subperiod I (1981 - 1994)	Learning Rule, $r = 5$, $e = 1$	370	1.72	0.122
Subperiod II (1995 - 2007)	Learning Rule, $r = 5$, $e = 5$	306	1.11	0.350

This table reports the performance of the best market-timing rule under the mean return criterion (Panel A) and the Sharpe ratio criterion (Panel B) for each sample period. The Sharpe ratio is denoted by SR. The table also contains the mean return and the Sharpe ratio of the buy-and-hold strategy (benchmark model). The mean returns and the Sharpe ratios are annualized. Lower case letters r and e denote the length of the review span and of the evaluation period, respectively.

Table 2.5: Performance of the Best Market-Timing Rules in the Extended Set under the Mean Return Criterion

	Reality Check		SPA		
Sample	nom. p-value	RC p-value	nom. p-value	SPA-c	SPA-l
Full Sample (1981 - 2007)	0.044	0.686	0.044	0.652	0.347
Subperiod I (1981 - 1994)	0.000	0.052	0.000	0.052	0.050
Subperiod II (1995 - 2007)	0.006	0.376	0.006	0.369	0.186

This table presents the performance of the best market-timing rule under the mean return criterion. For each period, the table shows the "Reality Check" (RC) and the SPA p-values along with the corresponding nominal p-values. SPA-c refers to the consistent p-value of Hansen (2005)'s SPA; SPA-l is the lower bound of the consistent SPA p-value. The nominal p-values are obtained by applying the RC and the SPA testing procedures to the best market-timing rule only, without correcting for data-snooping biases.

2.6.1 Test Results under the Mean Return Criterion

In order to assess the outperformance of the best-performing rule over a buy-and-hold strategy, we run the RC and the SPA for the extended set of market-timing rules, which includes complex strategies as well as simple rules. Table 2.5 presents nominal p-values and data-snooping adjusted RC and SPA p-values for each period based on the mean return criterion. As before, SPA-c denotes the consistent p-value of Hansen (2005)'s SPA and SPA-l is the lower bound of the consistent SPA p-value. Not surprisingly, due to the outperformance of the best rules over the benchmark, nominal p-values are significant at the 5% level (at least) for all periods. However, data-snooping corrected RC and SPA p-values are no longer significant at any conventional significance levels for the full sample and the second subperiod. That is, the best-performing rules, which showed significant outperformance over the benchmark when considered in isolation, no longer beat the buy-and-hold strategy once we correct for dependencies across all rules. Interestingly, according to the data-snooping adjusted RC and SPA p-values, the null hypothesis that market timing does not produce superior returns can still be rejected at the 10% level for the first subperiod. This result supports our previous conjecture that the best rule for the subperiod from 1981 to 1995 may still significantly beat the benchmark, even after data-snooping correction.

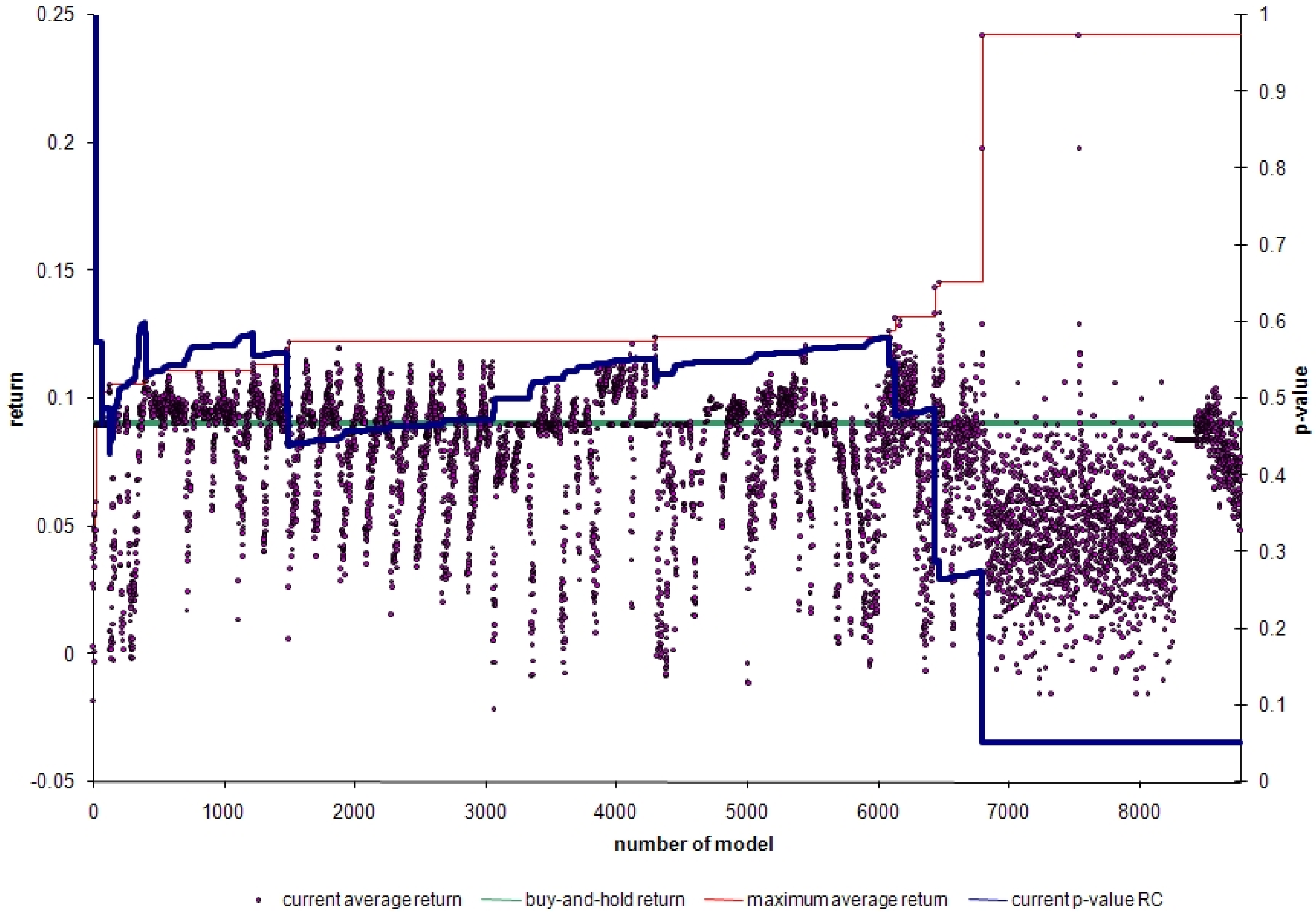
In Figure 2.4, we plot the evolution of the maximum mean return and the RC p-value across all rules from the extended set for the first subperiod (1981-1994), in which we found statistically significant outperformance of the best rule even after we corrected for data-snooping biases. The RC p-value terminates at 0.05, indicating that, even after adjustment for data snooping is made, the optimal rule does indeed contain valuable economic information. The graph of the maximum mean return for this subperiod shows that, after including only 67 models, the maximum performance statistic increases to 9.41% and thus above the return of the buy-and-hold strategy. Including roughly 1,400 additional rules increases the maximum performance statistic to 12.23% without rendering the RC p-value significant. Since from this point onwards the improvement of the maximum performance is small and the effective span of market-timing rules becomes larger, the p-value increases gradually to a value of 0.58 after around 6,100 models, displaying the effects of data snooping. Adding additional rules gradually increases the maximum mean return to approximately 25% after 6,793 models are inspected and causes a decline in the RC p-value to a significant terminal value of 0.05. This is even more interesting, given that only very few rules show remarkably high average returns, while the majority clearly underperform the benchmark. The performance of the best rule is apparently so strong that, even after data-snooping correction, it leads to a significant RC p-value.

2.6.2 Test Results under the Sharpe Ratio Criterion

Table 2.6 presents the test results for the best-performing rule, drawn from the extended set, under the Sharpe ratio (SR) criterion. We report the nominal p-values as well as the data-snooping adjusted RC and SPA p-values for all sample periods and denote the consistent p-value of Hansen (2005)'s SPA with SPA-c and the lower bound of the consistent SPA p-value with SPA-l. The results are very similar to those under the mean return criterion. Nominal p-values are zero or close to zero for all sample periods, suggesting that the best-performing rules significantly outperform a buy-and-hold strategy at the 1% level when data-snooping biases are ignored. As indicated by insignificant RC and SPA p-values for the full sample and the second subperiod, the best rules for these periods no longer significantly beat a buy-and-hold strategy when adjustment for data snooping is made. However, due to the remarkable outperformance of the best rule (SR = 1.72) over the benchmark (SR = 0.12) in the first subperiod, RC and SPA p-values remain significant at the 10% level, even after correcting for data snooping.

Figure 2.5 plots, for the first subperiod (1981-1994), the evolution of the maximum Sharpe ratio and the RC p-value across all rules from the extended set. As before, we present the graph for this subperiod since even data-snooping adjustments do not render the outperformance of the best-performing rule insignificant. Including about 130 models increases the maximum SR above the SR of the benchmark and leads to a decline in the RC p-value to slightly less than 0.80. From there onwards until model 6,792, the maximum performance statistic only improves a little and the RC p-value fluctuates but never becomes significant. Including the best performing market-timing rule (model 6,793) leads to a tremendous drop in the RC p-value from 0.87 to a significant value of 0.05. After model 6,793 the majority of rules underperform the buy-and-hold strategy, as

Figure 2.4: Economic and Statistical Performance of the Best Market-Timing Rule in the Extended Set under the Mean Return Criterion: Subperiod I (1981-1994)



For each trading rule k, indexed on the x-axis, the annualized average return over the first subperiod (1981-1994) is identified by the scattered points. In addition, the current maximum mean return in the extended set of market-timing rules (thin red line), the associated current "Reality Check" p-value (solid blue line), and the benchmark return (horizontal green line) are plotted.

Table 2.6: Performance of the Best Market-Timing Rules in the Extended Set under the Sharpe Ratio Criterion

	Reality Check		SPA		
Sample	nom. p-value	RC p-value	nom. p-value	SPA-c	SPA-l
Full Sample (1981 - 2007)	0.005	0.793	0.005	0.535	0.177
Subperiod I (1981 - 1994)	0.000	0.053	0.000	0.053	0.020
Subperiod II (1995 - 2007)	0.000	0.392	0.000	0.195	0.055

This table presents the performance of the best market-timing rule under the Sharpe ratio criterion. For each period, the table shows the "Reality Check" (RC) and the SPA p-values along with the corresponding nominal p-values. SPA-c refers to the consistent p-value of Hansen (2005)'s SPA; SPA-l is the lower bound of the consistent SPA p-value. The nominal p-values are obtained by applying the RC and the SPA testing procedures to the best market-timing rule only, without correcting for data-snooping biases.

under the mean return criterion, and very few rules show an SR significantly above that of the benchmark. However, the outperformance of the best-performing rule is strong enough to lead to a significant terminal RC p-value.

Overall, the results for the extended set of rules are very similar to those for the basic set. When no adjustment for data snooping is made, certain rules significantly outperform a buy-and-hold strategy. In general, however, data-snooping adjustments render the superior performance of the best rules insignificant. Only for the first subperiod (1981-1994) does the outperformance of the best-performing rule remains significant after we correct for data-snooping biases.

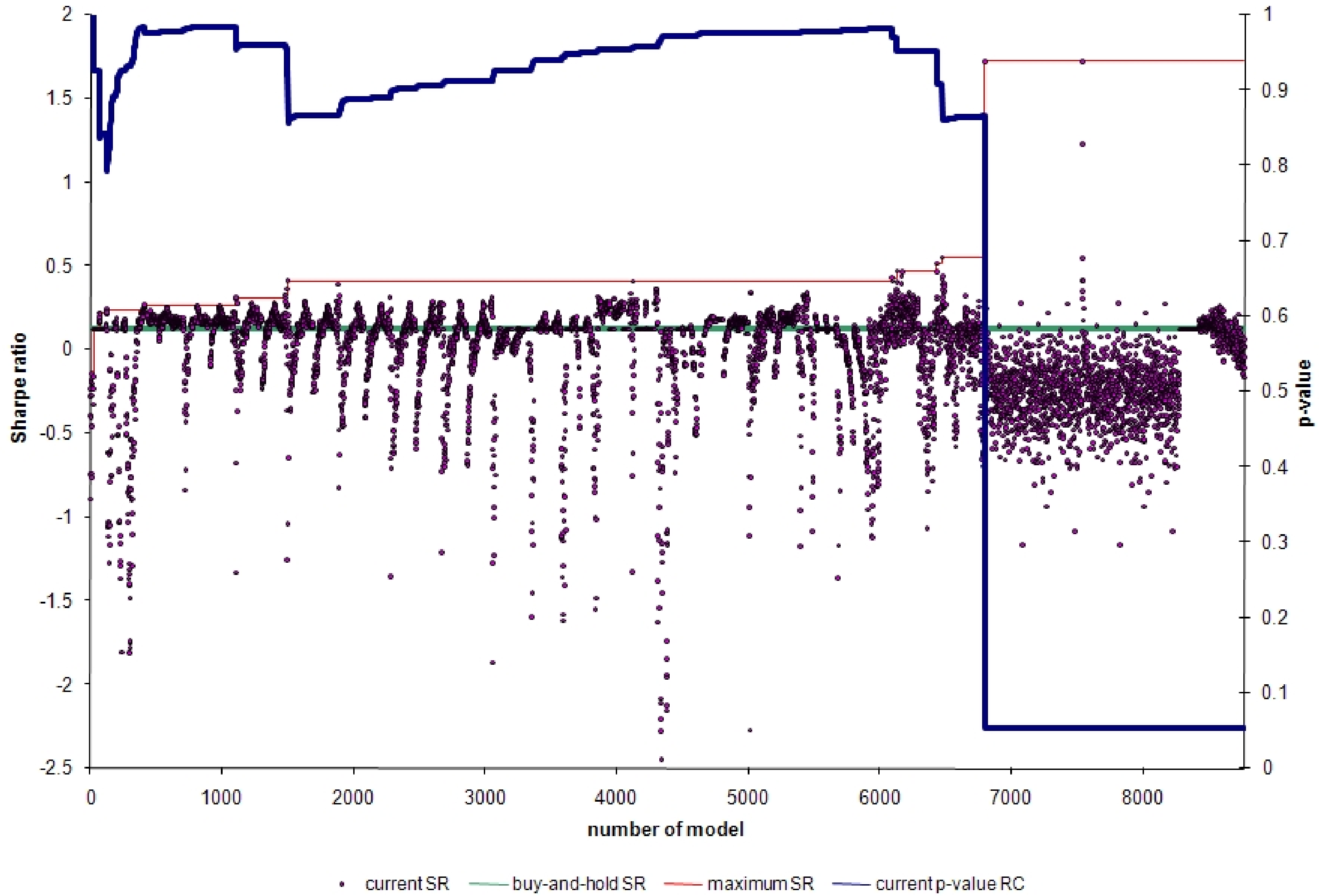
2.7 Robustness Checks and Modifications

We perform a series of robustness checks for both the basic and the extended sets of rules. Since the results under the two performance criteria are very similar in previous sections, we restrict all robustness checks to experiments based on the mean return criterion.

2.7.1 Out-of-Sample Analysis

Out-of-sample (OOS) testing is a way of eliminating the effects of data-snooping (see, e.g., Lo and MacKinlay (1990)) and, at the same time, it allows to investigate further the power of the testing procedures used in our experiments. As a first robustness check, we therefore conduct an OOS analysis to check whether the performance of the best in-sample market-timing rule holds OOS. In particular, we use the first subperiod (1981-1994) as the in-sample period and reserve the years from 1995 to 2007 as the OOS period. The best-performing rule in the extended set selected in the first subperiod (a learning rule

Figure 2.5: Economic and Statistical Performance of the Best Market-Timing Rule in the Extended Set under the Sharpe Ratio Criterion: Subperiod I (1981-1994)



For each trading rule k, indexed on the x-axis, the annualized Sharpe ratio over the first subperiod (1981-1994) is identified by the scattered points. In addition, the current maximum Sharpe ratio in the extended set of market-timing rules (thin red line), the associated current "Reality Check" p-value (solid blue line), and the benchmark Sharpe ratio (horizontal green line) are plotted.

with a one-day evaluation period and a five-day review span) performs poorly in the OOS period with a return of only 0.11%, making formal testing redundant. The best-performer, identified as of the end of 1994, apparently does not carry on the signifcant performance in the OOS period.

These results are in line with our earlier findings that, after data-snooping correction, there are no rules that significantly outperform a buy-and-hold strategy in the period from 1995 to 2007 (subperiod II), and therefore alleviate concerns regarding the power of the tests used in our study.

2.7.2 Impact of Relaxing the Short-Selling Constraint

In our second robustness check, we investigate the performance of market-timing rules when the short-selling constraint is relaxed. Thus far, we assumed that an investor receiving sell signals exits the market and switches to cash. However, instead of holding cash after selling the index, investors may want to short sell the index in order to gain from falling prices. Short selling the index has been facilitated by the emergence of basket securities, such as index futures and exchange-traded funds replicating indices, as they allow for inexpensive index tracking and for a potential short selling of the index. Consequently, short selling the index might realistically be considered by investors in practice and might change the results found in previous sections. On the one hand, if predictions from the indicators are correct—if market downturns are predicted successfully—short selling the index when exiting the market will yield superior returns relative to holding cash. The performance of market-timing rules would thus be higher than in previous sections and the test results of the superior performance of the best market-timing rules might become more significant. On the other hand, if market-timing strategies fail, investors who short sell the index instead of holding cash when indicators signal to exit the market will face higher losses. Test results of the superior performance of market-timing rules would consequently tend to be less significant.

In order to determine whether being short the index during predicted market downturns improves on the maximum return for the set of market-timing rules and thus on the significance of superior performance, we run the RC and the SPA while changing the values of the timing function in equation (2.2) to 1 for "invest in the stock market" and -1 for "short sell the index." Table 2.7 reports nominal p-values as well as RC and SPA p-values for the basic set of rules (Panel A) and the extended set of rules (Panel B). Nominal p-values in Panel A indicate that, considered in isolation, the best-performing simple rules outperform the benchmark at the 5% significance level in the full sample and in the first subperiod and at the 10% level in the second subperiod. After correcting for data

Table 2.7: Performance of the Best Market-Timing Rules When Relaxing the Short-Selling Constraint

Panel A	Basic Set of Rules				
	Reality Check		SPA		
Sample	nom. p-value	RC p-value	nom. p-value	SPA-c	SPA-l
Full Sample (1981 - 2007)	0.033	0.698	0.033	0.675	0.461
Subperiod I (1981 - 1994)	0.037	0.176	0.037	0.163	0.114
Subperiod II (1995 - 2007)	0.089	0.779	0.089	0.784	0.629

Panel B	Extended Set of Rules				
	Reality Check		SPA		
Sample	nom. p-value	RC p-value	nom. p-value	SPA-c	SPA-l
Full Sample (1981 - 2007)	0.038	0.677	0.038	0.645	0.338
Subperiod I (1981 - 1994)	0.000	0.078	0.000	0.078	0.063
Subperiod II (1995 - 2007)	0.060	0.896	0.060	0.895	0.775

This table presents, for each sample period, the performance of the best market-timing rule under the mean return criterion when relaxing the short-selling constraint. Panel A includes the results when only simple trading rules are considered, whereas the results in Panel B are based on the extended universe of rules, including complex market-timing strategies. For each period, the table shows the "Reality Check" (RC) and the SPA p-values along with the corresponding nominal p-values. SPA-c refers to the consistent p-value of Hansen (2005)'s SPA; SPA-l is the lower bound of the consistent SPA p-value. The nominal p-values are obtained by applying the RC and the SPA testing procedures to the best market-timing rule only, without correcting for data-snooping biases.

snooping, the outperformance of the best market-timing rule is not significant in any of the periods, as indicated by high RC and SPA p-values. Furthermore, we find that, while nominal p-values are very similar to those in Section 2.5.1, Table 2.2, where holding cash was used as the exit strategy, data-snooping corrected p-values show a relatively larger change. For both the first and second subperiods the RC and SPA-c p-values decrease, while for the full sample these p-values increase.

For the extended set of market-timing rules, we find that, in general, nominal p-values and data-snooping adjusted p-values change only slightly relative to the results in Section 2.6.1, Table 2.5. Only for the second subperiod do the RC and SPA-c p-values increase substantially. The significance of the results, however, remains the same; nominal p-values for the full sample and for both subperiods are low and significant. High data-snooping corrected p-values for the full sample and the second subperiod indicate that the outperformance of the best market-timing rule is not statistically significant after data-snooping adjustments are made. As in Section 2.6.1, RC and SPA p-values for the first subperiod are significant; correcting for data snooping does not render the outperformance of the best rule over the buy-and-hold strategy insignificant.

In summary, we find that, for both the basic set and the extended set of rules, allowing for short selling the index does not qualitatively change the test results obtained in previous sections.

2.7.3 Impact of Transaction Costs

Thus far, we have not considered the effects of transaction costs on the profitability of market-timing rules and thus on our test results. The impact might indeed be significant, particularly because various market-timing rules involve frequent switching between the index and cash. As a result of frequent trading, the outperformance of timing rules relative to the benchmark is lower. Furthermore, it may happen that rules with a lower trading frequency turn out to be the best performers once transaction costs are taken into account. Therefore, we perform the same exercises as before, but incorporate transaction costs in our analysis. Since a historical series for transaction costs is not available, and since the amount of those costs would vary among different types of investors, we follow Pesaran and Timmermann (1995) and use transaction costs equal to 50 basis point per one-way trade.[27]

Table 2.8 presents the test results for the performance of the best market-timing rule in both the basic set of rules (Panel A) and the extended set of rules (Panel B) when considering transaction costs of 50 basis points per one-way trade. Not surprisingly, for both sets of rules, all p-values are higher in the presence of transaction costs. For the set of simple rules, nominal p-values indicate that the outperformance of the best rule, when considered in isolation, is generally significant, even when transaction costs are included. However, as in the case without transaction costs, the null hypothesis of no superior performance of the best rule cannot be rejected at conventional significance levels for any period, once data-snooping adjustments are made.

For the extended set of rules, the test results are quite similar to those without transaction costs. Nominal p-values are significant for the full sample and for both subperiods. However, data-snooping corrected p-values for the full sample and the second subperiod are insignificant. For the first subperiod (1981-1994), the null hypothesis of no superior performance of the best rule is rejected at the 10% level.

Thus, including transaction costs does not lead to any qualitative change in the results for either the basic set of rules or the extended set of rules.

[27] We have also tried transaction costs of 20 basis points per one-way trade, taking into account that transaction costs might have been lower during our sample period. The results are very similar and the conclusions remain the same.

Table 2.8: Performance of the Best Market-Timing Rules When Including Transaction Costs

Panel A	Basic Set of Rules				
	Reality Check		SPA		
Sample	nom. p-value	RC p-value	nom. p-value	SPA-c	SPA-l
Full Sample (1981 - 2007)	0.038	0.937	0.038	0.749	0.472
Subperiod I (1981 - 1994)	0.087	0.939	0.087	0.843	0.608
Subperiod II (1995 - 2007)	0.128	0.968	0.128	0.918	0.696
Panel B	**Extended Set of Rules**				
	Reality Check		SPA		
Sample	nom. p-value	RC p-value	nom. p-value	SPA-c	SPA-l
Full Sample (1981 - 2007)	0.028	0.932	0.028	0.914	0.701
Subperiod I (1981 - 1994)	0.000	0.057	0.000	0.057	0.055
Subperiod II (1995 - 2007)	0.024	0.619	0.024	0.511	0.332

This table presents, for each sample period, the performance of the best market-timing rule under the mean return criterion when including one-way transaction costs equal to 50 basis points. Panel A includes the results when only simple trading rules are considered, whereas the results in Panel B are based on the extended universe of rules, including complex market-timing strategies. For each period, the table shows the "Reality Check" (RC) and the SPA p-values along with the corresponding nominal p-values. SPA-c refers to the consistent p-value of Hansen (2005)'s SPA; SPA-l is the lower bound of the consistent SPA p-value. The nominal p-values are obtained by applying the RC and the SPA testing procedures to the best market-timing rule only, without correcting for data-snooping biases.

2.7.4 Sensitivity to Changes in the Smoothing Parameter

In this section, we examine whether our test results are sensitive to the choice of the smoothing parameter q. The Politis and Romano (1994) bootstrap relies on the parameter q to determine the length of the blocks ($1/q$) resampled from the observed data. A smaller parameter value of q corresponds to a longer block length and is appropriate for data with more dependence, and vice versa.

Thus far, we have chosen a smoothing parameter of 0.5 in all experiments. We now consider parameter values of $0.5, 0.1$, and 0.01, corresponding to block lengths of $2, 10$, and 100. Table 2.9 provides RC and SPA p-values along with the corresponding nominal p-values for all sample periods and for the three different values of the smoothing parameter. In order to conserve space, we present the results of this robustness check only for the basic set of rules.[28] It can be seen that, for all subperiods, the nominal p-values deviate marginally for different choices of q, the maximum deviation amounting to 0.05 for the second subperiod and a change in the smoothing parameter from $q = 0.5$ to $q = 0.01$. The only qualitative change is found for precisely that subperiod, where the nominal p-value turns insignificant. Similarly, the data-snooping adjusted RC and SPA-c p-values for all

[28] We also performed this robustness check for the extended set of rules. The results are similar and the conclusions remain the same.

Table 2.9: Performance of the Best Market-Timing Rules for Various Smoothing Parameters q.

Panel A	Smoothing Parameter $q = 0.5$				
	Reality Check		SPA		
Sample	nom. p-value	RC p-value	nom. p-value	SPA-c	SPA-l
Full Sample (1981 - 2007)	0.030	0.598	0.030	0.569	0.361
Subperiod I (1981 - 1994)	0.035	0.275	0.035	0.257	0.169
Subperiod II (1995 - 2007)	0.073	0.885	0.073	0.884	0.742

Panel B	Smoothing Parameter $q = 0.1$				
	Reality Check		SPA		
Sample	nom. p-value	RC p-value	nom. p-value	SPA-c	SPA-l
Full Sample (1981 - 2007)	0.026	0.558	0.026	0.539	0.309
Subperiod I (1981 - 1994)	0.058	0.254	0.058	0.235	0.131
Subperiod II (1995 - 2007)	0.076	0.879	0.076	0.872	0.717

Panel C	Smoothing Parameter $q = 0.01$				
	Reality Check		SPA		
Sample	nom. p-value	RC p-value	nom. p-value	SPA-c	SPA-l
Full Sample (1981 - 2007)	0.047	0.518	0.047	0.494	0.319
Subperiod I (1981 - 1994)	0.044	0.168	0.044	0.154	0.072
Subperiod II (1995 - 2007)	0.122	0.857	0.122	0.828	0.609

This table presents, for each sample period, the performance of the best market-timing rule under the mean return criterion for alternative smoothing parameters q. The test results are based on the basic set of simple trading rules. For each parameter value, the table shows the "Reality Check" (RC) and the SPA p-values along with the corresponding nominal p-values. SPA-c refers to the consistent p-value of Hansen (2005)'s SPA; SPA-l is the lower bound of the consistent SPA p-value. The nominal p-values are obtained by applying the RC and the SPA testing procedures to the best market-timing rule only, without correcting for data-snooping biases.

periods fluctuate marginally. The highest deviation is found for the RC p-value in the first subperiod. With a change in the smoothing parameter from $q = 0.5$ to $q = 0.01$, the RC p-value decreases from 0.275 to 0.168. In none of the specifications do we find a qualitative change in the data-snooping adjusted p-values. Overall, we find that our results are robust, not sensitive, to the choice of the smoothing parameter q.

2.7.5 Risk Premia Tests

The benchmark used in all previous experiments is a buy-and-hold strategy. This approach allows us to investigate which market-timing rules/indicators are able to significantly outperform the market when correcting for data-snooping biases. Employing a proxy for the risk-free interest rate as the benchmark, instead of a buy-and-hold strategy, (and keeping everything else the same), we are able to answer the question whether any (and/or which) rules/indicators carry a significantly positive risk premium, and how these

Table 2.10: Risk Premia Tests

Panel A	Basic Set of Rules				
	Reality Check		SPA		
Sample	nom. p-value	RC p-value	nom. p-value	SPA-c	SPA-l
Full Sample (1981 - 2007)	0.025	0.310	0.025	0.307	0.260
Subperiod I (1981 - 1994)	0.034	0.465	0.034	0.455	0.335
Subperiod II (1995 - 2007)	0.014	0.290	0.014	0.290	0.264

Panel B	Extended Set of Rules				
	Reality Check		SPA		
Sample	nom. p-value	RC p-value	nom. p-value	SPA-c	SPA-l
Full Sample (1981 - 2007)	0.000	0.196	0.000	0.196	0.160
Subperiod I (1981 - 1994)	0.000	0.000	0.000	0.000	0.000
Subperiod II (1995 - 2007)	0.000	0.042	0.000	0.042	0.043

This table presents, for each sample period, the performance of the best market-timing rule under the mean return criterion when using the risk-free rate as the benchmark. Panel A includes the results when only simple trading rules are considered, whereas the results in Panel B are based on the extended universe of rules, including complex market-timing strategies. For each period, the table shows the "Reality Check" (RC) and the SPA p-values along with the corresponding nominal p-values. SPA-c refers to the consistent p-value of Hansen (2005)'s SPA; SPA-l is the lower bound of the consistent SPA p-value. The nominal p-values are obtained by applying the RC and the SPA testing procedures to the best market-timing rule only, without correcting for data-snooping biases.

risk premia evolve over time—a slightly different, but equally interesting question. In the case of significant time-varying risk premia, the profitability of market-timing rules is not necessarily an indication against market efficiency—that is, profits from timing strategies are simply the compensation for (time-varying) risk in an efficient market.

We therefore change the benchmark return in equation (2.2) from the market return to the Federal funds rate as a proxy for the risk-free interest rate and re-run the RC and SPA tests. The results are presented in Table 2.10, Panel A (basic set) and Panel B (extended set). We observe marginal changes in the nominal p-values and relatively larger drops in data-snooping adjusted p-values for both the basic and the extended sets. Qualitatively, though, the results remain mostly unchanged. The only qualitative change is found for the second subperiod, with significant RC and SPA p-value indicating a significant premium of the best rule over the risk-free rate.

2.8 Conclusion

This paper examines the profitability of market-timing rules drawn from a comprehensive universe of rules, while accounting for the potential effects of data snooping. Examining a very large set of rules on the same data set bears the risk of biased statistical inference due to data snooping. That is, potential superior performance of some rules over a benchmark may not be due to any genuine merit in the model (rule), but rather to pure chance. We address this concern by applying appropriate techniques to correct for data-snooping biases. Precisely, we use White (2000)'s "Reality Check" (RC) and Hansen (2005)'s test for superior predictive ability (SPA) in order to quantify such data-snooping biases and to investigate the superior performance of the best market-timing rule over a buy-and-hold strategy, while accounting for dependencies across all rules.

First, we perform the tests for a basic set of simple rules, each of which is based on a single indicator only, and find that, when considered in isolation, the best-performing rule beats a buy-and-hold strategy over the full sample period from 1981 to 2007 and over both subperiods. Applying the RC and SPA tests to adjust for the effects of data snooping, we do not find superior performance of the best market-timing rule over the benchmark in any period. These results emphasize the importance of using appropriate methods to correct for data-snooping biases. Second, we extend the set of market-timing rules to include complex strategies which are based on information from several indicators. As before, we find significant superior performance of the best rules when dependencies across rules are ignored. But when considered in the context of the full universe of rules, the best-performing rules do not significantly outperform the benchmark in either the full sample or the subperiod from 1995 to 2007. Interestingly, the outperformance of the best rule in the subperiod from 1981 to 1994 remains significant even after data-snooping adjustment is made. Finally, we perform a series of robustness checks and find that our results are not qualitatively changed by accounting for transaction costs, allowing for short selling the index, or changing the smoothing parameter which determines the block length of the bootstrap used in our tests.

Chapter 3

Market Reaction to Corporate News and the Influence of the Financial Crisis

3.1 Introduction

On January 9, 2007, Apple Inc. issued a press release, headlined "Apple Reinvents the Phone with iPhone," which stated:

> "iPhone ... ushers in an era of software power and sophistication never before seen in a mobile device, which completely redefines what users can do on their mobile phones."

It also contained a quote from Apple's CEO, Steve Jobs, stating that "...iPhone is a revolutionary and magical product that is literally five years ahead of any other mobile phone," and went on to describe its features. On the day of the announcement, the stock trading volume increased more than four-fold and remained almost as high on the following day before dropping by half the day after. The stock price also rose, and in the period from the day before to five days after the announcement Apple's stock earned a cumulative return of 9.31% in excess of the market. Moreover, the stock became much more volatile—in the 10 days following the press release, its idiosyncratic volatility increased by 28% relative to that in the 10 days before the announcement.

The strong market reaction to the press release and its glowing but carefully chosen wording illustrate just how important corporate news announcements are for stock prices. Corporate press releases became significantly more common following both the October 2000 adoption of the SEC's Regulation Fair Disclosure (Reg FD) and the July 2002 adoption of the Sarbanes-Oxley Act (SOX), which mandate that publicly traded companies disclose all private information that may have an impact on a firm's market value and report changes in their "financial conditions or operations" in a timely fashion and simultaneously to all market participants. In particular, Reg FD states: "With advances in information technology, most notably the internet, information can be communicated to shareholders directly and in real time, without the intervention of an intermediary."[1] Reg FD further suggests that communicating information via press releases should be the preferable way to achieve timeliness and non-exclusivity.

Corporate press releases reach investors almost instantaneously via services such as PR Newswire, BusinessWire, GlobeNewswire, Marketwire, and the like. Firms typically sign up for an account with one of the newswire services, and issue all of their press releases through that service. Typically, a basic account is free but a fee is charged for each press release. Newswire services then post press releases on their own websites and also distribute them, typically free of charge, to local and global media outlets, trade magazines, and financial internet sites. Often, firms must pay more for wider distribution. Newswire services compete on price, the breadth of their distribution network, and the quality of customer service.

We form our dataset of corporate press releases issued between April 2006 and August 2009 by combining observations of official corporate press releases from all major newswire services. We believe that our dataset contains nearly all press releases that were issued in this time period. We then manually classify these press releases into several major news categories and their subcategories based on their content. For example, Apple's press release mentioned earlier is classified under the major category *Products & Services* and subcategory *New Product*. After removing the press release categories for which we have no priors with respect to the expected market impact (such as announcements about establishing new awards, participation in new employee and industry initiatives, and the like) and eliminating infrequent news categories with fewer than 30 press releases, we are left with a total of nine major news categories, further subdivided into 52 subcategories. We analyze how various types of corporate announcements affect stock returns, liquidity, and volatility, with the magnitude of these impacts revealing the relative news-worthiness of the news.

The importance of firm-level news should not be assessed solely by its immediate impact on the stock price but also by its effect on the informational environment of the firm. It is not realistic to expect that the market will always be able to quickly quantify the impact of news on the firm value. In particular, when it comes to managerial decisions, the view that market participants should be able to evaluate them fully and instantaneously

[1] The entire document can be found at `http://www.sec.gov/rules/final/33-7881.htm`.

fails to recognize the value of managerial expertise and private information, as it implicitly presumes that investors could have made these decisions themselves.[2] Therefore, some time may pass before the market comes to an agreement on the resulting firm valuation. During the period in which the impact of the news on the firm value is being assessed, the informational asymmetries between the better- and worse-informed investors will be high. Consequently, immediately following the release of difficult-to-interpret news, stock liquidity (measured as the price impact of trade) should drop in order to compensate the market maker for the potential advantages of the better-informed investors. At the same time, the priors on the old valuation model will weaken, and each additional signal will have a relatively large impact on the stock price; as a result, idiosyncratic volatility will increase. To sum up, while routine and easy-to-interpret news will likely have a large immediate impact on the stock price and little impact on the subsequent informational environment of the firm (measured by liquidity and idiosyncratic volatility), non-routine and difficult-to-interpret news may have little immediate effect on the stock price but will greatly diminish subsequent liquidity and increase idiosyncratic volatility.

This paper contributes to the corporate event-study literature in five respects. First, we consistently apply the same event-study design to all types of corporate news (rather than focusing on one type of event at a time, as was done in prior literature) in order to evaluate in a systematic manner the various events' relative importance to the market. Second, owing to the breadth of our dataset, we are able to include types of corporate news events that have not been (extensively) studied before. Third, even for the news categories which have received considerable attention in the past, we investigate whether the documented regularities still hold in this more recent and significantly broader dataset. Fourth, we investigate the patterns of changes in stock volatility and liquidity following different types of news, which has not been consistently done in earlier papers. Fifth, we study how the market reaction to different types of news changed during the period of the financial crisis, which was characterized by a widespread difficulty in obtaining credit, low market prices, bankruptcy concerns, and a generally high perception of uncertainty.

The impact of financial news has been extensively studied in prior literature. We confirm that several documented regularities still exist in the most recent data. For example, announcements of better-than-expected financial results are accompanied by positive abnormal returns, whereas disappointing financial results and earnings restatements are accompanied by negative abnormal returns. Announcements of financial decisions, such as dividend payments, share repurchases, and forward stock splits lead to positive price reactions, while announcements of secondary debt and equity offerings lead to negative price reactions. Finally, news announcing mergers, acquisitions, and spinoffs all elicit a

[2] We appreciate this insight of Jack Treynor.

strong positive price response.

Moreover, we find that announcements of other corporate events and strategic plans are just as important as financial news. Such announcements were not mandatory in the past and became much more prevalent as a result of Reg FD, since it requires that firms disclose all news that could be deemed "material" for stock prices.[3] For example, we show that stock prices react strongly to news about customer losses and customer acquisitions. Such seemingly uninformative announcements as reaching a sales milestone or winning a company award are accompanied by significantly positive returns. The underlying reason might be a temporary or a permanent increase in investor attention (Merton (1987)).[4] The market reacts negatively to unfavorable legal news, management terminations, and announcements about FDA rejections and product defects. News releases about new products, patent awards, exiting unsuccessful ventures, new partnerships formed, legal settlements, management additions, FDA approvals, and successful research outcomes are all accompanied by significantly positive abnormal returns.

Ranking the news categories by the magnitude of the price response within seven trading days around the announcement date, the five categories that illicit the most positive market response are: (1) positive pre-announcements of financial results, (2) announcements of share buybacks, (3) announcements of FDA approvals, (4) spinoff announcements, and (5) announcements of pharmaceutical approvals in the European Union, although the last category is only statistically significant when using a one-sided test. The five news categories that illicit the most negative market reactions are: (1) negative pre-announcements of financial results, (2) FDA rejections, (3) announcements of customer losses, (4) announcements of poor financial performance, and (5) product defect announcements. It is worth noting that negative price responses tend to be larger in magnitude than positive ones.

Stocks' idiosyncratic volatility tends to increase following most types of news announcements, an indicator that investors become more sensitive to additional information coming to the market after the original news (potentially including interpretations by various market experts) and continue updating their valuation priors. Stocks' liquidity tends to decrease following most news announcements, indicating that in the post-announcement period the informational advantage of firm insiders is perceived as becoming more valu-

[3] We were told by staff at the SEC that the language of the regulation and the definition of the types of news that need to be disclosed are intentionally left vague in order to prevent firms from gaming the system. Hence, firms may disclose a wider range of news than what is considered "material" by investors.

[4] That newswire services compete on the breadth of their network is a testament to the importance of investor attention for firm valuations.

able. It is not surprising to observe a considerable overlap between the two measures—the informational advantage of firm insiders should be stronger when investors' priors about the correct valuation model are weak. Investigating all measures simultaneously allows us to identify important news that are easy for the market to process—they lead to large immediate prices reactions but small subsequent increase in liquidity and idiosyncratic volatility. Examples are press releases about customer losses, share buybacks, and the closing down of unprofitable subsidiaries. On the other hand, some news are very difficult to interpret, the immediate price reaction is low in absolute value, and liquidity greatly decreases and idiosyncratic volatility greatly increases in the subsequent 10 days. Examples are press releases about SEC investigations, the intent to acquire another firm, non-compliance with stock exchange requirements, and reverse stock splits. Yet other news, lead to both large immediate price reactions and high subsequent informational uncertainty. Examples of such press releases are financial pre-announcements (both positive and negative), financial restatements, FDA rejections, and announcements of good research outcomes.

We furthermore split our time series into two subsamples—before and during the period of the financial crisis. We assume that the financial crisis, which originated in the sub-prime mortgage crisis, ceased to be viewed as a problem affecting only sub-prime mortgage originators and started being perceived as a global predicament on March 17, 2008. This is the Monday that followed the weekend during which troubled Bear Stearns, having incurred considerable losses on its hedge funds with exposure to the sub-prime mortgage market, signed a merger agreement with JP Morgan Chase. This date splits our sample at about 23.5 months of data assigned to the pre-crisis period, and 16.5 months to the period following the start of the crisis. Investigating the price reactions to various news categories in the pre-crisis and in-crisis periods, we find that, on average, announcement-driven volatility increases became larger during the more uncertain crisis period. Similarly, the post-announcement decreases in liquidity also grew larger. This implies that investor valuation priors were generally weaker during the crisis, and, hence, corporate news announcements triggered larger revisions in the priors. However, the most intriguing result is that price reactions to certain types of news have changed. Given that the crisis was characterized by a difficulty in obtaining credit and generally low stock valuations, announcements of secondary equity offerings ceased to be perceived as a negative signal of the firm's equity being overpriced. Also, abnormal returns around announcements of share buybacks became significantly more positive. News potentially signaling larger and more stable future cash flows (such as announcements of US and European drug approvals, new product launches, acquisitions of new customers and partners, and good financial results) lead to higher contemporaneous returns than in the period before the crisis. Additionally, news of corporate reorganization and changes in the management team were viewed in a significantly more positive light.

This paper studies price reactions to news originating from the primary news source, i.e., corporations themselves. Another strand of literature that has recently gained momentum has focused on the importance of news media and the internet in disseminating new information to the market. These papers typically try to assess whether new information has a positive or a negative content based on the presence of positive or negative words in news stories or chat board messages and investigate whether thus quantified news stories can predict future returns (e.g., Chan (2003), Antweiler and Frank (2004), and Das and Chen (2007) for internet message boards; Tetlock (2007) and Tetlock, Saar-Tsechansky, and Macskassy (2008) for general news stories; and Engelberg (2008) for news stories that accompany earnings announcements). Moreover, Tetlock (2009) investigates the effect of being in the news on the stock's order flow and the informational environment, as well as the resulting return patterns. Unlike these papers, we work exclusively with information originating directly from firms. Moreover, besides simply classifying news into positive or negative categories, we also hand-classify the content of the news. (In the future, this classification can be automated via keyword searches.) We investigate which types of corporate announcements are deemed important and also unanticipated by the market such that they move prices at the time of the announcement and force revisions in the valuation priors. The purpose of this paper is to provide answers to these questions in a rather descriptive manner since the natural first step in studying corporate press releases—and the main focus of this paper—is to classify press releases into news categories and investigate their relative importance to the market. Questions about the factors that influence the speed of price discovery at the firm level for the various types of news are beyond the scope of this paper and are left to future research.

The remainder of the paper proceeds as follows. Section 3.2 describes the data. Section 3.3 explains the test methodology and shows the results of the basic hypotheses. It also presents additional empirical hypotheses and results for the crisis period. Section 3.4 concludes.

3.2 Disclosure Regulations and Data

3.2.1 New Requirement for More Complete and Timely Information Disclosure

Prior to the adoption of Reg FD, corporations were required to disclose important material information using the SEC's Form 8-K. Yet, these forms were allowed to be filed with the delay of four business days after occurrence of the event (page 2 of Form 8-K), and probably reached investors with a further delay. In that time, some of the market participants (notably, analysts and investment funds, could have benefited from selective information disclosure, and this knowledge would have already been partially reflected in stock prices at the time of the official disclosure).

The goal of the Regulation Fair Disclosure, implemented in October 2000, was to address the analyst scandal caused by firms' selective information disclosure to a subset of analysts in return for favorable stock recommendations. Reg FD states that firms must disclose all relevant information, favorable or unfavorable, to everyone at once and without delay. The Sarbanes-Oxley Act was adopted in July 2002 in response to a series of accounting scandals, and, among other objectives, aimed to improve the quality of financial information disclosure. The SEC responded by adding the new Section 13(1) to the Exchange Act that obligates public companies to disclose "on a rapid and current basis" nonpublic information "concerning material changes in the financial condition or operations."

Before the increased information disclosure requirements, press releases were a popular method of communicating information, but they likely predominately conveyed favorable news. Reg FD states explicitly that firms have to disclose *all* relevant information in order to eliminate the informational advantages of firm insiders. The SEC does not specifically list the types of news that have to be reported, for the fear that firms may try to game the system, but intentionally leaves the description vague, stating only that the information that must be disclosed should be "material" and "nonpublic" and such that "there is a substantial likelihood that a reasonable shareholder would consider it important" (page 9).

The advances in information technology and, specifically, the internet are singled out as the technological innovations that allow firms to disclose information to shareholders "directly and in real time, without the intervention of an intermediary" (page 3). The SEC further suggests that issuing a press release should be the first step in conveying new information to investors (page 15).

Our dataset of corporate press releases provides an improvement over a similar study that could have been conducted using Form 8-K reports. First, as discussed earlier, these forms reached the market with a significant delay and may have been already, at least partially, incorporated in stock prices. Second, the set of news that firms would disclose under Reg FD and SOX was wider than those that they have been required to report in Form 8-K. In the year 2000, the SEC estimated that the number of firm disclosures will increase by 70,000 relative to what it was before with the passage of Reg FD.[5] Finally,

[5] The document can be found on `http://www.sec.gov/rules/proposed/34-42259.htm`.

after the passage of the regulations, the SEC reduced the Form 8-K reporting requirement as part of the Paperwork Reduction Act. Our dataset contains more than 90% of all publicly traded firms. Hence, it appears that most firms comply with Reg FD and SOX by disclosing new information via press releases that appear on various newswire services.

3.2.2 Ad-Hoc Disclosures and Brief Literature Review: The Case of Germany

The German equivalent to Reg FD is section 15 of the German Securities Trading Law (§ 15 WpHG). Analogously to Reg FD, the German regulation requires that (publicly traded) companies report instantaneously any news that is deemed to affect their stock prices and that is not yet known to the public.[6] In most cases, companies mandate the dissemination of ad-hoc news to the "Deutschen Gesellschaft für Ad-hoc-Publizität" (DGAP). In particular, DGAP provides, on behalf of the companies, both regulators and stock exchanges with the corporate announcement and, as also required by code, distributes the news announcements to news agencies or other news service providers.[7] Even though the procedure of making ad-hoc announcements publicly available in Germany is very similar to that in the US, there are certain differences with regard to what type of news companies may release. While in the US firms may release all news that are deemed to be of interest to investors—i.e., also news that are not required to be published under prevailing regulations—companies in Germany are prohibited to publish any news other than these mandated by § 15 WpHG.

Beginning with the pioneering study of Fama, Fisher, Jensen, and Roll (1969) on the market reaction to stock splits, numerous event studies have investigated the impact of various corporate events on stock prices and the firm informational environment. Many of these event studies are based on information that is released by firms in their annual reports or other regularly disclosed information. Probably the most prominent event studies are on the announcement effects of dividends and earnings. Studies for the German market show significant stock price effects, for instance, following dividend announcements (e.g., Amihud and Murgia (1997) and Gerke, Oerke, and Sentner (1997)), earnings announcements (e.g., Coenenberg and Henes (1995)), stock splits (e.g., Wulff (2002)), as well as mergers and acquisitions (e.g., Gerke, Garz, and Oerke (1995)).

The adoption of the ad-hoc disclosure requirement has led to an increase in the number of news releases and facilitated research on the impact of corporate announcements. In particular, more comprehensive studies are now possible due to a larger breadth of the

[6] More details on § 15 "Wertpapierhandelsgesetzes" (WpHG) can be found on the web page of the German Department of Justice (`http://www.gesetze-im-internet.de/wphg/_15.html`).

[7] In more than 90% of the cases, the distribution is made through newswire services; see Röder (2000).

types of news that are released, as well as due to the availability of exact time stamps for the news releases, which, in turn, allows high-frequency examinations of the process of price discovery. The early literature on the announcement effects of ad-hoc disclosures in the German stock market comprises of empirical studies by Oerke (1999), Röder (1999), Röder (2000), and Nowak (2001), among others. Generally, the results suggest that ad-hoc announcements have a significant impact on firms' stock prices. Röder (2000) finds that the announcement effect of corporate news differs for large and small companies, with stronger stock price reactions of small-cap firms. The author, furthermore, shows that positive announcements lead to stronger market reactions than negative news.[8] However, most of the early literature, such as Oerke (1999), Röder (1999), and Röder (2000), suffers from methodological weaknesses, as discussed, for instance, by Kaserer and Nowak (2001) and Güttler (2005). Specifically, the methodology used in those studies may lead to significant results, even in instances where price movements are random and not caused by unexpected news (see Kaserer and Nowak (2001)).

While most of the above literature focuses on daily stock price reactions, more recent studies investigate intra-day effects of ad-hoc announcements. For instance, Muntermann and Güttler (2007), who study intra-day stock price reactions to corporate news releases, provide evidence that stock prices, generally, adjust to news within 30 minutes after the announcement is made. Several studies assess the intra-day effects of ad-hoc disclosures on stock trading volumes (e.g., Röder (2002) and Muntermann and Güttler (2007)). The latter show that abnormal trading volume caused by news announcements continues for an extended period of time.

3.2.3 Our Dataset

Our dataset comprises all corporate press releases issued by over 6,500 companies which are traded on NASDAQ, NYSE, and AMEX from April 2006 to August 2009. Corporate press releases are issued via newswire services which further disseminate the information via their web interfaces and their news distribution networks. The distribution networks include local and global media outlets (newspapers, magazines, radio and TV stations), trade magazines, internet sites (such as yahoo and google), financial news services (such as Bloomberg, Dow Jones/Factiva, Thomson Reuters), some of which, especially those with limited space capacities, then further decide whether or not to feature the press releases in their news stories. Newswire companies do not charge members of their news distribution networks but charge the firms that issues press releases.[9] Though there may be a tendency to release bad news to smaller networks, this practice is discouraged by

[8] For an overview of the results from the early studies see Nowak (2001).

[9] As an example, BusinessWire does not charge an annual fee for maintaining an account with them but charges for each press release based on its length and the width of the agreed upon distribution

regulators.

Our dataset is consolidated from all major newswire services, such as PR Newswire, BusinessWire, GlobeNewswire, MarketWire, and others. PR Newswire contains 50%-60% of all publicly traded firms, BusinessWire about 30%, and GlobeNewswire and Marketwire are the next in terms of coverage, and the rest contains significantly fewer firms. Our coverage improves over time; in 2006, 75.94% of all publicly traded firms appear in our dataset, in 2007 coverage increases to 91.00%, in 2008 to 97.23%, and in 2009 it changes to 96.67% of the publicly traded firms. The firms that are missing tend to be smaller than the firms that are present in the dataset. Over the entire sample period, the mean (median) market capitalization of the firms present in our dataset is equal to \$2,596 (\$321) million, while the mean (median) market capitalization of the firms absent from the dataset is equal to \$1,307 (\$228) million.[10]

Among all postings, official corporate press releases can be identified by the news "source" printed at the bottom of the report. We include only those news releases issued by corporations themselves rather than by news agencies. The press releases are then manually classified into various news categories based on their informational content. These manual classifications can be automated in the future based on word searches. Our objective in defining news categories was to achieve the best tradeoff between the precision of each category and its frequency of occurrence.

Perhaps as a result of the vagueness of the SEC's information release requirements, firms tend to err on the side of disclosing too much information. Additionally, firms may prefer to release immaterial news in order to attract the attention of potential investors. For the sake of brevity, we remove news categories for which we have no priors regarding their impact on the firm value; we, therefore, discard press releases announcing the firm's participation in charity events and environmental initiatives, establishing industry awards and competitions, making statements regarding labor strikes, describing new employee and industry initiatives, making known changes in internal policies, announcing participation in various corporate surveys (such surveys assessing the diversity of the labor force, security assessments, etc.), publicizing forthcoming speaking engagements of their executives, announcing participation in news campaigns, and so on. We also discard categories with fewer than 30 observations. This leaves us with 271,867 corporate press releases, which are split into nine major news categories each of which is further subdi-

network. Fees start at \$210 for the first 400 words and additional charges are added for photos and graphics.

[10] The firms that do not appear in our dataset probably file only 8-K reports with the SEC instead (these reports are meant to "announce major events that shareholders should know about"—see the description at `http://www.sec.gov/answers/form8k.htm`).

vided into 52 subcategories as described in Table 3.1. Besides providing the number of news announcements in each category, Table 3.1 also gives brief category descriptions.[11] Examples of press releases for each news category are provided in Appendix C.1.

The largest category, *Customers & Partners*, contains 54,552 observations and includes announcements about customer losses or wins, new partnerships formed, and various company milestones.[12] The second largest category, *Financial*, comprises of 54,054 announcements and contains announcements of earnings, dividends, accounting restatements, stock splits, secondary debt and equity offerings, as well as share buybacks. Next, with a total of 50,194 observations, comes the category *Products & Services*; it includes announcements about FDA and European drug approvals, new products, updates and upgrades to the existing products and services, patent awards, product approvals, as well as research project outcomes. After that, with a total of 48,625 observations, comes the self-explanatory category *Meetings & Events*, and then with 31,404 observations, the category *Management*; it describes various changes in the management team. The category *Awards*, which includes announcements of company and product awards, follows with 13,574 observations. *Corporate Strategy & Performance* comes next with 10,039 observations and includes announcements about decisions to expand or scale back firm operations, credit news, and trends in performance and profitability.[13,14] The category *M&A* includes news on mergers, acquisitions, spinoffs, and IPO filings and contains 6,213 observations. Finally, with only 3,212 observations, *Legal* is the smallest category, and contains announcements of (class action) lawsuits, SEC investigations initiated against the firm, and settlements of ongoing lawsuits.

Table 3.2 presents summary statistics on the monthly press release activity across firms (the table only includes the press releases that we kept for the analysis). Panel A

[11] Throughout the paper, we use the terms (corporate) press release, news event, and news announcement interchangeably.

[12] The subcategory *Reaching a Milestone* could have been also assigned to the major category *Corporate Strategy & Performance*, but it frequently describes milestones reached in sales to customers or anniversaries of customer and partner relationships, thus signifying enduring business ties.

[13] Subcategories *Profitability-Declining* and *Profitability-Improving* are related to the subcategories describing strong and weak financial results under the major category *Financial*, but instead of focusing on current earnings, these announcements rather provide the big-picture assessments of patterns and trends in firm sales, revenues, and profitability.

[14] The subcategory *Exchange Noncompliance* announces when a firm has received a notice of noncompliance from its stock exchange. These notices often follow periods of bad performance (for example, when the bid price stays below the exchange-set minimum for a pre-specified number of consecutive days, or when the total value of publicly held shares falls below an exchange-specified minimum). Alternatively, they can be triggered by delays in providing exchange-mandated information releases (such as annual and quarterly reports and disclosures about the firm's corporate governance). This category could have been potentially included under the major category *Legal*, however, since noncompliance is frequently set off by poor performance we have included it under the major category *Corporate Strategy & Performance*.

Table 3.1: Press Release Categories

	Category	Subcategory	Obs.	Description
1.	Awards	Company Award	10,903	Company is rewarded for achievements
	(13,574)	Product Award	2,671	Company receives award for one of its products
2.	Corporate	Credit News - Negative	152	Financing difficulties or debt downgrades
	Strategy &	Credit News - Positive	976	Success in securing new credit or debt upgrades
	Performance	Exchange Noncompliance	479	Receipt of notice of non-compliance/potential delisting
	(10,039)	Infrastructure - Downsizing	54	Company decides to close facilities or exit certain markets
		Infrastructure - Expansion	6,640	Company decides to expand its business or opens new facilities
		Profitability - Declining	283	Declining performance, e.g., decrease in sales
		Profitability - Improving	1,455	Improving performance, e.g., increase in sales or revenue growth
3.	Customers &	Customer Loss	67	Losing an existing customer
	Partners	Customer Win	27,954	Acquiring new business from a new or a pre-existing customer
	(54,552)	New Partnership	25,598	Signing a new strategic agreement with another firm
		Reaching a Milestone	933	Reaching a sales milestone or an anniversary
4.	Financial	Dividend	24,576	Declaration of dividend distribution
	(54,054)	Financial Results - Strong	15,352	Strong financial results, e.g. high earnings
		Financial Results - Weak	503	Weak financial results, e.g. low earnings
		Pre-Announcement - Negative	401	Negative expectations for financial results
		Pre-Announcement - Positive	689	Positive expectations for financial results
		Restatement	365	Revision of fiscal results or restatement of company's outlook
		Secondary Offering: Debt	3,754	Announcement of debt offering/issuance
		Secondary Offering: Equity	4,093	Announcement of stock offering/issuance
		Share Buyback	3,834	Repurchase of shares
		Stock Split - Forward	311	Announcement of forward stock split
		Stock Split - Reverse	176	Announcement of reverse stock split
5.	Legal	Class Action	649	Class action lawsuit filed against company
	(3,212)	Legal Problems	156	A new lawsuit filed against company; appeal dropped
		SEC Investigation	168	Announcement of initiation or outcome of SEC investigation
		Settlement	2,239	Settlement of litigation against company
6.	M&A	Acquisition	77	Plan to acquire another firm
	(6,213)	IPO	59	Filing for Initial Public Offering, e.g. of subsidiary, with SEC
		Merger	1,785	Plan to merge with another firm
		Spinoff	4,292	Sale of subsidiary or a line of business
7.	Management	Addition	20,560	Recruitment or election of new management members
	(31,404)	Compensation	66	Statements on compensation of management and employees
		Promotion	6,617	Promotion of management members
		Reorganization	1,068	Organizational change or change in the board/management
		Retirement	1,276	Retirement of members of management or the board
		Termination	1,817	Resignation/departure of management members
8.	Meetings &	Company-Sponsored Event	3,235	Company hosts or sponsors industry event
	Events	Industry Events	42,485	Presentation or participation in industry event
	(48,625)	Investor Meeting	2,905	Presentation or participation in investor conference or meeting
9.	Products &	FDA Approval	1,912	Approval of a product in the US by the FDA
	Services	FDA Investigation	767	Start of FDA investigation
	(50,194)	FDA Rejection	47	Rejection of product by the FDA
		New Product	36,482	Launch of new service or introduction of new product
		Patent Award	992	Company receives new patent for product
		Pharmaceutical Approval EU	325	Approval of a pharmaceutical product in Europe
		Product Approval	1,951	Authorization or certification of new business or product
		Product Defect	198	Issuance of a warning regarding a product or recall of a product
		Research Failure	149	Failure of a research effort
		Research Success	2,103	Successful completion of a research effort
		Updates & Upgrades	5,268	Improvement or update of product/service
		Total	271,867	

This table presents a description of the corporate press release data. Press releases are classified into 9 major news categories which in turn are divided into several subcategories. The number of press releases in each major category (in parenthesis) and in each subcategory are provided, as well as a brief description of each subcategory. The time period is April 2006 - August 2009.

Table 3.2: Descriptive Statistics on Monthly Press Release Activity
Panel A: Sample Statistics

Mean	Median	Std. Dev.	Obs.
1.24	1.00	0.28	271,867

Panel B: Sample Statistics by Size Quintile

	NYSE-Based quintiles				Sample-Based Quintiles			
Size	Mean	Median	Std. Dev.	Obs.	Mean	Median	Std. Dev.	Obs.
1 (small)	0.62	0.66	0.17	18,733	1.13	1.12	0.30	45,123
2	0.75	0.77	0.17	30,514	1.18	1.21	0.25	48,330
3	0.94	0.95	0.21	40,068	1.21	1.25	0.28	52,229
4	1.21	1.24	0.26	55,017	1.30	1.36	0.31	56,500
5 (large)	2.55	2.62	0.65	127,535	1.56	1.64	0.38	69,685

This table presents descriptive statistics for monthly press release activity across firms. Panel A shows the statistics for the entire sample and Panel B shows the statistics by size quintiles. The size quintiles in Panel B are formed every month based on NYSE size breakpoints (left-hand side) and based on sample-based size breakpoints, such each size quintile contains a roughly equal numbers of stocks (right-hand side). The time period is from April 2006 to August 2009.

reports the statistics for the entire sample and shows that the average (median) number of press releases per firm is 1.24 (1.00) per month. Panel B presents the same statistics arranged by firm size—the left-hand side of the panel for NYSE-based size quintiles, and the right-hand side for sample-based size quintiles, both formed every month, such that each sample-based quintile contains roughly the same number of stocks. Not surprisingly, the number of press releases tends to increase with firm size. In particular, the mean (median) number of monthly news announcements increases from 0.62 (0.66) for the smallest NYSE-based size quintile (it is 1.13 (1.12) for the smallest sample-based size quintile) to 2.55 (2.62) for the largest NYSE-based quintile (it is 1.56 (1.64) for the largest sample-based quintile).

Finally, return, volume and stock price data are obtained from the CRSP daily files. The dollar trading volume needed for the construction of the Amihud (2002) illiquidity measure in Section 3.3.2.2 is computed as the product of the daily trading volume (number of shares traded) and the end-of-day stock price.

3.3 Test Results

In this section, we investigate the impact of various types of news on stock prices, volatility and liquidity. News that the market deems most material for the firm value but that are also relatively easy to interpret and difficult to anticipate will be accompanied by large immediate price reactions. Yet, some of the news will have a greater tendency to be leaked out by customers, suppliers, and other entities involved with the firm, and, thus, price reactions in response to the announcement will be muted; however, there will be a price drift prior to the official announcement. Those news that are less common and have unclear ramifications for the firm value will probably not lead to an immediate price reaction, yet stock liquidity will drop to compensate for the potential informational advantage of firm insiders. Moreover, such news announcements will increase the demand for follow-up information and analysis and, therefore, result in higher idiosyncratic volatility. High volatility and low liquidity will persist until a sufficient amount of new information is released and market participants converge on the new equilibrium valuation.

3.3.1 News' Impact on Stock Returns

3.3.1.1 Event Study Methodology

To assess the immediate impact of news releases on stock prices, we follow the common event study methodology. For each firm i, the abnormal return on day t, AR_{it}, is specified as:

$$AR_{it} = R_{it} - E(R_{it}|X_t), \tag{3.1}$$

where R_{it} and $E(R_{it}|X_t)$ are the actual and expected returns, respectively, for day t, and X_t is the conditioning information for the predictive model. Assuming that returns can be described by the market model, the abnormal return is defined as:

$$AR_{it} = R_{it} - \hat{\alpha}_i - \hat{\beta}_i R_{mt}, \tag{3.2}$$

where R_{it} and R_{mt} are the day-t returns on security i and the market portfolio, which we proxy with the CRSP value-weighted index. The coefficients $\hat{\alpha}_i$ and $\hat{\beta}_i$ are the OLS estimates from the regression of firm i's daily returns on market returns over the 200 days prior to the event window.

The event window extends from one day before to five days after the day of the press release (as is common in event studies, we start the window one day before the actual announcement day in case the news has leaked to the market just before the actual press release). We keep the event window relatively short because (a) we are interested in the immediate impact of news on stock prices and (b) we want to minimize the chance that another press release is issued by the firm within this window. Thus, we compute the average daily abnormal return for each firm i issuing a press release on day t as:[15]

$$CAR_{it} = \frac{1}{7} \sum_{\tau=t-1}^{t+5} AR_{i\tau}. \tag{3.3}$$

Next, we calculate the average CAR ($\overline{CAR}$) for each news category across all press release observations and test whether it is different from zero ($H_0 : \overline{CAR} \neq 0$). In order to not understate the standard errors for statistical inference, we correct for possible correlation between individual CARs estimated over overlapping event windows by clustering errors by the week in which the press release was issued.

3.3.1.2 Event Study Results

Figure 3.1 plots individual CAR observations for each news category. The distributions appear to be right-skewed, but given the sufficient number of observations, according to the Central Limit Theorem, the sample means should come from the normal distribution. As mentioned earlier, to ensure normality of the distribution of the means, we discard samples with fewer than 30 observations. As an additional check, for the samples with fewer than 100 observations, we also conduct non-parametric Wilcoxon rank-sum tests to check whether sample median CARs are different from zero. In our tests of whether abnormal returns are different in the before- and in-crisis periods, we also employ the two-sample rank-sum tests of whether the two subsamples have the same median whenever either subsample contains fewer than 100 observations (in addition to the parametric tests). The outcomes of the nonparametric tests are mentioned in the text whenever they are sufficiently different from the t-test-based results reported in the tables.

Average CARs for all news categories are plotted in Figure 3.2. The figure shows that the news categories that lead to the most negative price reactions are *Pre-Anouncement-Negative*, *FDA Rejection*, *Customer Loss*, *Financial Results - Weak*, and *Product Defect.* The news categories that result in the most positive immediate returns are *Pre-Annuoncement - Positive*, *Share Buyback*, *FDA Approval*, *Spinoff*, and *Pharmaceutical Approval - EU.* Table 3.3 presents results of the formal test for whether the price reaction following different categories of news announcements is different from zero. The table reports the average CAR and the p-value of the two-sided t-test of the mean being different from zero. The results confirm previously reported regularities, especially when it comes to financial news, which have been extensively studied in prior literature.

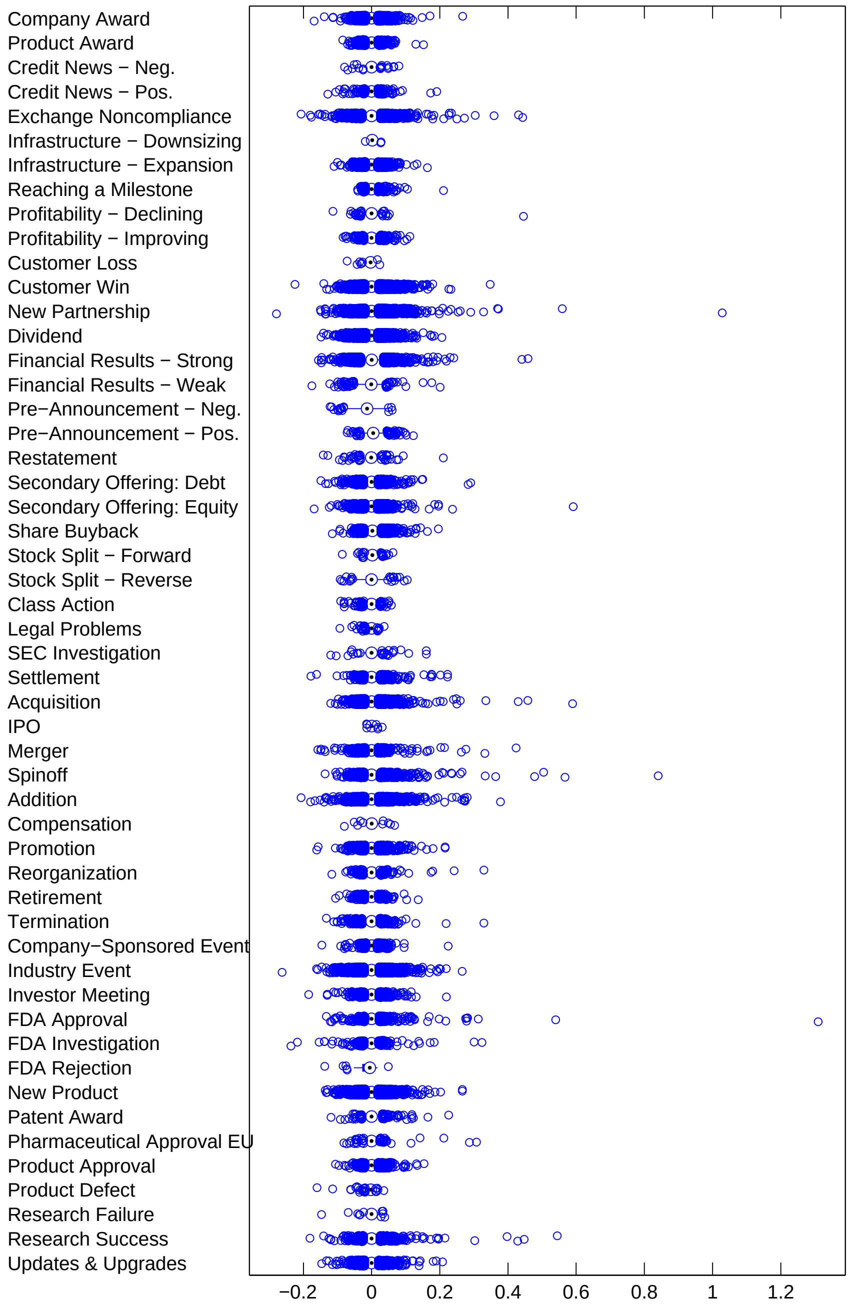
[15] Henceforth, for convenience we will refer to the average daily abnormal return as the cumulative abnormal return (CAR) despite the fact that it is in fact averaged over the seven days (from $t-1$ to $t+5$).

Table 3.3: Test Results for Cumulative Abnormal Returns

	Category	Subcategory	$\overline{CAR}$	p-value
1.	Awards	Company Award	0.045%	0.000
		Product Award	0.027%	0.282
2.	Corporate Strategy & Performance	Credit News - Negative	0.024%	0.901
		Credit News - Positive	0.060%	0.419
		Exchange Noncompliance	0.167%	0.382
		Infrastructure - Downsizing	0.309%	0.008
		Infrastructure - Expansion	0.016%	0.310
		Profitability - Declining	-0.051%	0.762
		Profitability - Improving	0.113%	0.006
3.	Customers & Partners	Customer Loss	-0.628%	0.002
		Customer Win	0.114%	0.000
		New Partnership	0.096%	0.000
		Reaching a Milestone	0.201%	0.000
4.	Financial	Dividend	0.073%	0.000
		Financial Results - Strong	0.193%	0.000
		Financial Results - Weak	-0.617%	0.000
		Pre-Announcement - Negative	-1.697%	0.000
		Pre-Announcement - Positive	0.776%	0.000
		Restatement	-0.275%	0.065
		Secondary Offering: Debt	-0.176%	0.000
		Secondary Offering: Equity	-0.083%	0.013
		Share Buyback	0.425%	0.000
		Stock Split - Forward	0.291%	0.001
		Stock Split - Reverse	-0.181%	0.407
5.	Legal	Class Action	-0.070%	0.260
		Legal Problems	-0.263%	0.042
		SEC Investigation	0.263%	0.233
		Settlement	0.238%	0.000
6.	M&A	Acquisition	0.121%	0.000
		IPO	0.160%	0.107
		Merger	0.124%	0.073
		Spinoff	0.385%	0.000
7.	Management	Addition	0.051%	0.000
		Compensation	0.188%	0.497
		Promotion	0.005%	0.789
		Reorganization	0.033%	0.615
		Retirement	-0.031%	0.460
		Termination	-0.209%	0.000
8.	Meetings & Events	Company-Sponsored Event	0.000%	1.000
		Industry Events	0.029%	0.000
		Investor Meeting	0.073%	0.041
9.	Products & Services	FDA Approval	0.419%	0.000
		FDA Investigation	-0.025%	0.828
		FDA Rejection	-1.482%	0.005
		New Product	0.031%	0.000
		Patent Award	0.225%	0.002
		Pharmaceutical Approval EU	0.322%	0.102
		Product Approval	0.075%	0.033
		Product Defect	-0.563%	0.000
		Research Failure	-0.068%	0.628
		Research Success	0.272%	0.000
		Updates & Upgrades	0.024%	0.250

This table presents the results of tests of the null hypothesis that the mean cumulative abnormal return is equal to zero. For each subcategory, the table shows the sample mean cumulative abnormal return ($\overline{CAR}$) and the p-value of the t-test.

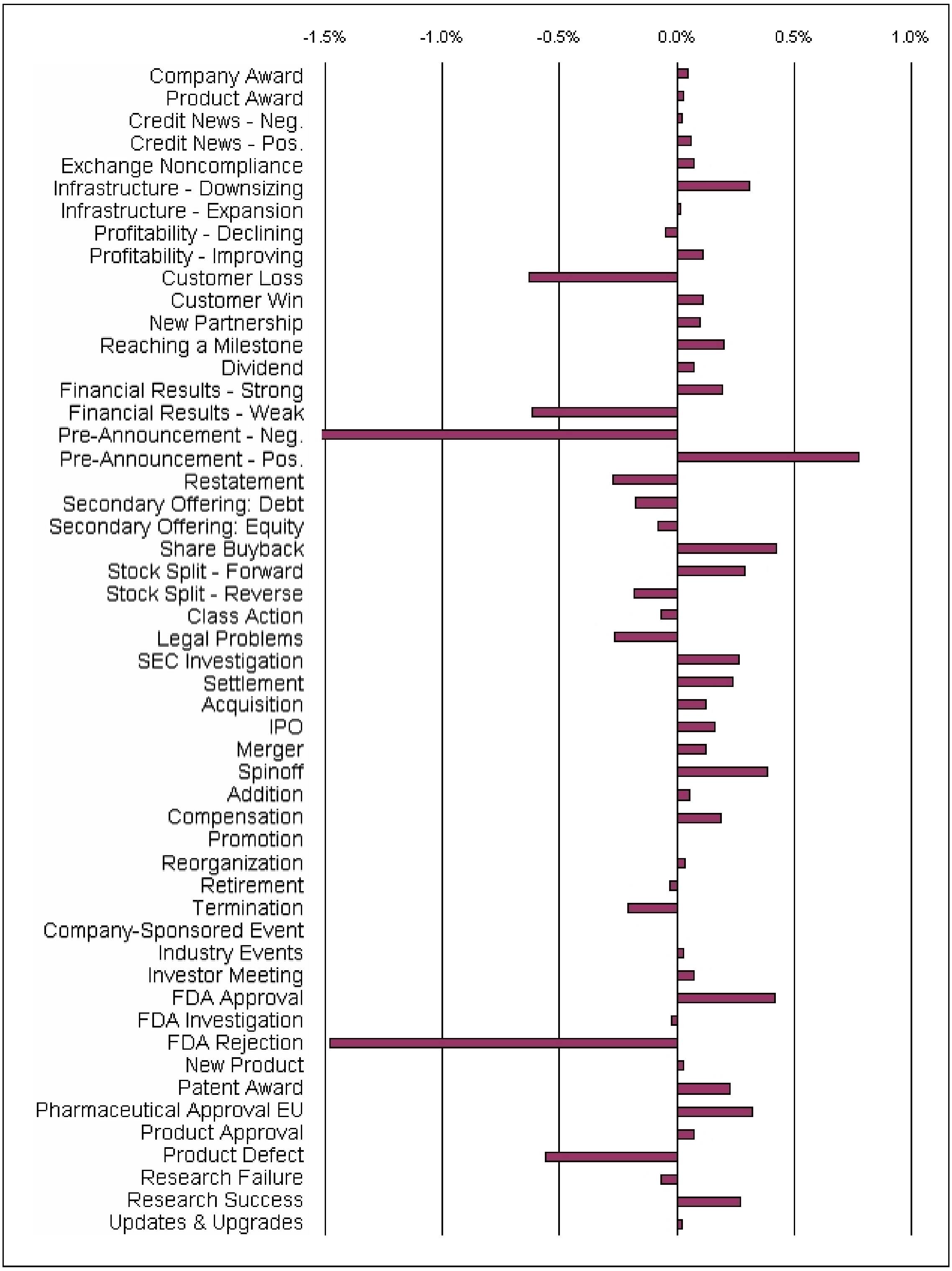
Figure 3.1: Boxplot of the Cumulative Abnormal Returns



For each news category, cumulative abnormal returns associated with each press release, computed relative to the market model, are plotted as circles. Circles with black dots in the middle represent the sample means.

3.3.1.2.1 Financial News Under the assumption of informational asymmetries between managers and investors, managerial financial decisions can be viewed as signals of managers' private information—i.e., whether the firm is under- or over-valued, or, relatedly, whether its future earnings will be high or low, and whether its projects are good

Figure 3.2: Means of the Cumulative Abnormal Returns



The figure plots the means of cumulative abnormal returns, computed relative to the market model, for each news category.

or bad.[16] In another strand of literature, Jensen (1993) argues that managers are likely

16 See, for example, the models of Myers and Majluf (1984), Myers (1984), and Miller and Rock (1985), as well as discussions in chapters 13-17 of Brealey, Myers, and Allen (2006).

to waste cash and therefore, decisions to pay out the excess cash should be treated as a good sign; he calls the managerial tendency to waste cash the "free-cash-flow problem."

Dividends signal both the availability of cash and the willingness to pay this cash out instead of wasting it; as a result, dividend announcements (and especially, dividend initiations or increases) are typically accompanied by positive returns (e.g., Asquith and Mullins (1983), Healy and Palepu (1988), and Yoon and Starks (1995)). In our sample, we do not distinguish whether the announced dividends constitute an increase or a mere upcoming payment, but confirm that the market reaction to dividend announcements is significantly positive, with an average CAR equal to 0.073% and significant at the 1% level.[17]

Share repurchases are another way to distribute excess cash back to investors, and announcements of share repurchases are typically accompanied by positive market reactions (e.g., Asquith and Mullins (1986) and Lakonishok and Vermaelen (1990)). In our sample, the average CAR associated with share repurchase announcements is 0.425% and significant at the 1% level.

Likewise, secondary equity offerings (SEO) signal that the stock might be overpriced or that the firm is running out of cash, and equity prices were shown to fall upon SEO announcements (e.g., Smith (1986) and Corwin (2003)). In our sample, the average CAR around SEO announcements is -0.083% and significant at the 5% level.

The issuance of debt might also be interpreted as a signal that the firm is overvalued and/or short of cash. However, the evidence on whether stock prices fall upon announcements of debt issuances is mixed. Smith (1986) documents a negative price reaction associated with announcements of convertible bond issuances but finds no price reaction associated with announcements of straight debt issuances (the latter result is also confirmed by Shyam-Sunder (1991)). However, Akhigbe, Easterwood, and Pettit (1997), show that prices react negatively to announcements of new straight debt issuances when they are motivated by the need to raise funds due to an unexpected cash shortfall.[18] We do not separate announced debt issuances into straight and convertible debt, but nonetheless find a significantly negative price reaction: The average CAR is equal to -0.176% and

[17] Since the reported CAR numbers represent the average excess return earned per day, this number should be multiplied by seven to obtain the cumulative excess return earned over the seven-day period around the announcement.

[18] Although the authors do not study separately price reactions to straight and convertible debt issuances, most observations in their sample, or 90% of the 399 total announcements studied in the paper, are for straight debt.

significant at the 1% level.

Press releases announcing forward stock splits were previously shown to be accompanied by positive price reactions, consistent with signaling models (e.g., Ikenberry, Rankine, and Stice (1996); see also Yildizhan (2009) for a literature survey). Our results are consistent with the previous findings: The average CAR is equal to 0.291% and significant at the 1% level.

Negative news about corporate performance (such as lower-than-expected earnings and profits) result in negative price reactions. Disappointing financial results, reported within the subcategory *Financial Results - Weak*, lead to significantly negative CARs, while strong financial results, reported within the subcategory *Financial Results - Strong*, lead to significantly positive CARs (these findings are consistent with the previously documented results that prices react strongly to positive and negative earnings surprises; e.g., Ball and Kothari (1991), Stice (1991), Kothari (2001), and Vega (2006)). Often, financial results (especially weak ones) are pre-announced, and, not surprisingly, the market reaction to positive and negative earnings pre-announcements is larger in magnitude than the reaction to scheduled earnings announcements. Indeed, the average CAR associated with a positive pre-announcement is 0.776% and thus higher than the abnormal return of 0.193% in reaction to a positive scheduled announcement; the average CAR associated with a negative pre-announcement is the lowest in our sample and equal to -1.697%, while the average CAR associated with a scheduled announcement of weak financial results is equal to -0.617% and thus less negative (all numbers are significant at the 1% level).

Finally, restatements, which are usually caused by either genuine accounting errors or deliberate earnings manipulation, are usually accompanied by negative price reactions, unless the accounting errors are to the firms' disadvantage (e.g., Callen, Livnat, and Segal (2006)). In our sample, the average CAR associated with restatements is equal to -0.275% and significant at the 10% level.

3.3.1.2.2 Other News Categories Among the less-frequently analyzed news categories, we show that news that potentially signal higher and more stable future cash flows, such as announcements about product and drug approvals, new products, new patents, successful research outcomes, the acquisition of new customers and partners, as well as press releases describing improvements in firm performance, are accompanied by positive price reactions.

Previous research (e.g., Bloom and Reenen (2002)) has documented that new patents lead to improved performance and higher market valuations. Furthermore, Austin (1993) showed that patent announcements are generally associated with positive abnormal returns, though a large variation in returns exists depending on the type of the patent (i.e., whether the patent is of a "broad" or a "narrow" scope, whether or not it is for a "key" product that is more likely to be produced or not, and so on). We do not separate patents into different patents categories, but show that, on average, the market reacts positively to patent award announcements; the average CAR is equal to 0.225% and significant at the 1% level. Likewise, the reaction to announcements about the successful completion of research projects leads to a market reaction of similar magnitude—the average CAR is equal to 0.272% and also significant at the 1% level.

The positive market reaction to announcements of a joint partnership that we observe has been also documented by McConnell and Nantell (1985) using a sample of 210 firms involved in 136 joint ventures and by Woolridge and Snow (1990) using 197 joint venture announcements. Our documented reactions to new product announcements are also consistent with Woolridge and Snow (1990), who show this effect using a sample of 241 such announcements.

Not surprisingly, news categories signaling lower future cash flows (e.g., *Customer Loss*, *FDA Rejection*, and *Product Defect*) are accompanied by significantly negative price reactions (consistent with earlier literature; e.g., Jarrell and Peltzman (1985), Barber and Darrough (1996), Alexander (1999), and Fornell, Mithas, Morgeson III, and Krishnan (2006)).[19] Since both of the subcategories *Customer Loss* and *FDA Rejection* have fewer than 100 observations, we have also applied the nonparametric rank-sum test to both samples to check whether the median CARs are different from zero. The respective p-values are 0.000 and 0.002 indicating that the market reaction for the median firm is also significantly negative for both news categories.

The reaction to spinoff announcements can be expected to be positive, as spinoffs signal that corporations refocus the attention on their core business (e.g., Cusatis, Miles, and Woolridge (1993), Desai and Jain (1999), and Chemmanur and Yan (2004), among others). Yet, examining 78 voluntary corporate spinoffs that were completed between 1972 and 1987, Seward and Walsh (1996) do not find that spinoff announcements are accompanied by positive abnormal returns. However, in our more comprehensive and more recent dataset, we document a significant positive reaction to spinoff announcements: The

[19] Interestingly, Jarrell and Peltzman (1985) find that for product recalls, the penalty in terms of negative stock returns even exceeds the direct costs associated with the recall.

average CAR is equal to 0.385% and significant at the 1% level.

When it comes to mergers and acquisitions, merged firms have been shown to be worth more together than apart due to synergies and economies of scale. The average CAR associated with merger announcements is indeed significantly positive in our sample (it is equal to 0.124% and significant at the 10% level). As for acquisitions, it has been shown that targets capture most of the value gains, and the price of acquirers, on average, declines; this decline is most pronounced for stock mergers and for large acquirers (Andrade, Mitchell, and Stafford (2001) and Moeller, Schlingemann, and Stulz (2004)). We have not subdivided the *Acquisition* category into cash- and stock-financed acquisitions. Targets are not prevalent in our dataset, perhaps because they are most often private firms. We have, therefore, kept only the acquisition announcements made by acquirers. The results show that the average CAR earned by acquirers in our sample is equal to 0.121%, significant at the 1% level. The nonparametric p-value is close to the one reported in the table and equal to 0.037.

Turning to corporate investment decisions, a study by Woolridge and Snow (1990) shows that the market tends to react positively to corporate investment announcements. We, however, document no significant reaction to such announcements (*Infrastructure - Expansion*). However, we do find that the market reacts positively to corporate decisions to shut down unprofitable operations (*Infrastructure - Downsizing*), consistent with the free-cash-flow concern of Jensen (1993). The average CAR associated with announcements in this category is equal to 0.309% and significant at the 1% level. When the non-parametric rank-sum test is used, the significance level drops to 5% (and the p-value is now equal to 0.015).

Announcements of negative legal issues, such as stockholder or patent infringement lawsuits lead to negative price reactions and announcements of legal settlements to positive price reactions, confirming the earlier findings of Bhagat, Brickley, and Coles (1994), Bizjak and Coles (1995), Romano and Bhagat (2001), Griffin, Grundfest, and Perino (2004), and Raghu, Woo, Mohan, and Rao (2008), among others. Interestingly, announcements of class action lawsuits lead to negative but insignificant price reactions.

As for announcements of changes in the management team, management additions are interpreted as good news, and management terminations (voluntary and involuntary combined), as bad news. These findings contribute to previous literature on stock price reactions following managerial turnover, such as Furtado and Rozeff (1987), Weisbach (1988), Bonnier and Bruner (1989), and Huson, Parrino, and Starks (2001).

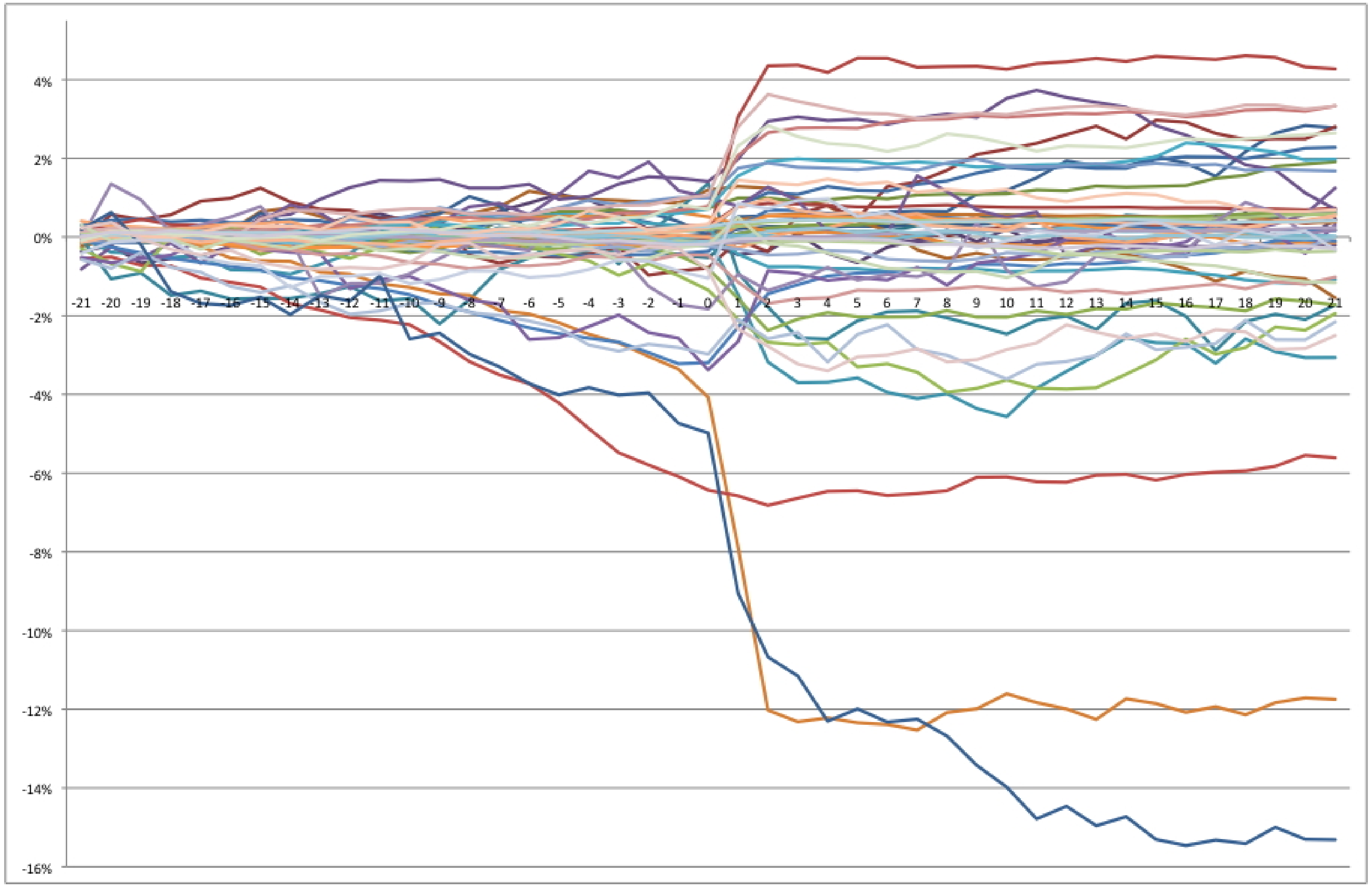
Finally, consistent with the Merton (1987) hypothesis that attention increases the investor base and decreases the cost of capital, the types of news that put firms in the limelight, even when they, arguably, provide no new information to the market, such as announcements in the categories *Company Awards*, *Reaching a Milestone*, *Industry Events*, and *Investor Meetings*, all lead to significantly positive CARs. This point is not lost on newswire services, which compete on the size of their press release distribution network.

3.3.1.2.3 Longer Event Windows Figure 3.3 plots cumulative abnormal returns, calculated over the period from 21 trading days before to 21 days after the news announcement ($t-21$, $t+21$), which is approximately equal to a calendar month before and after the announcement. The objective is to trace a possible pre-announcement reaction due to information leakage, as well as patterns of future return drifts or reversals. The plot shows that most press releases convey relevant information affecting firm valuations, as cumulative return plots start to fan out on the announcement day ($t = 0$). Moreover, most of the price reactions appear to be permanent as prices typically do not revert back for up to one month after the announcement. The reaction to bad news is typically larger in magnitude than the reaction to good news. Moreover, it appears that the reaction to bad news has a higher tendency to start before the actual announcement date, likely because of pre-announcement rumors. The lowest blue line in the plot corresponds to the announcement in the category *FDA Rejection*. The line indicates that stocks, on average, start to experience negative abnormal returns before the announcement day, and the negative reaction continues beyond day 5 after the announcement, the day on which our previous event window stops. The total abnormal return for *FDA Rejection* is estimated to be -10.4% during our event window, but when calculated over the longer window ($t-21$, $t+21$), it is equal to roughly -15%. The next-lowest line, which is yellow, corresponds to the category *Pre-Anouncements - Negative*, and the third-lowest, which is red, to the category *Legal - Class Action*.[20] The most positive line, which is also red, corresponds to the category *Pre-Announcement - Positive*, the light-pink line below it, to *FDA Approval*, the purple line, to *Stock Split - Forward*, and the dark-pink line below it, to *Spinoff*.

Individual cumulative abnormal return plots for the eight most negative CAR categories of Table 3.3 are presented in Figure 3.4, arranged in increasing order of the CARs. In these figures, the cumulative abnormal returns are also plotted over the longer window ($t-21$, $t+21$). (Note that some of the plots are more volatile because they are based on fewer event observations.) The reaction to *Pre-Anouncement - Positive* is very quick,

[20] Notice that the average CAR associated with this category calculated over the window (t-1, t+5) is not significantly negative—the majority of the market reaction occurs before the official announcement.

Figure 3.3: Plot of the Cumulative Abnormal Return for all News Categories



The figure plots cumulative abnormal returns for all subcategories over the period from 21 days before to 21 days after the press release date ($t = 0$). Abnormal returns are computed as the residuals of the market model.

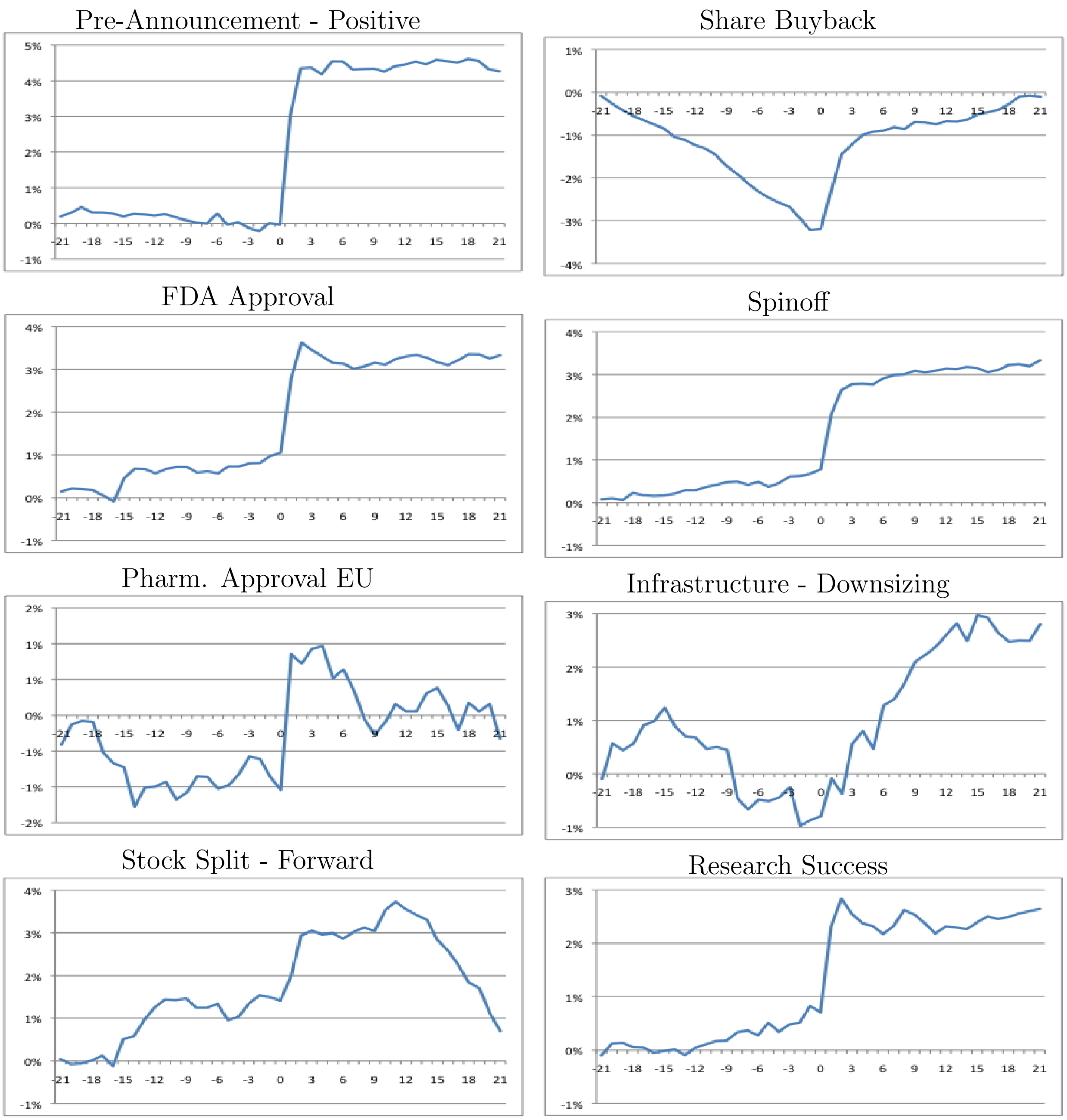
prices seem to incorporate all new information on the day of the announcement. As for the category *Share Buyback*, the news announcement is preceded by negative returns, lending support to the explanation that firms tend to buy their equity when it becomes undervalued, thus sending a positive signal to the market. This graph is consistent with previously documented evidence (e.g., Lakonishok and Vermaelen (1990) and Comment and Jarrell (1991)). The positive price reaction does not stop within our event window and continues until the end of the following month. For the *FDA Approval* category, prices start to go up even before the official announcement and adjust very quickly when the official announcement is made. In case of *Spinoff* announcements, there is small drift before and after the press release day. When it comes to *Pharmaceutical Approval EU* announcements, about half of the positive return in response to the announcement is later reversed. The reaction to *Infrastructure - Downsizing* is positive but slow: the total CAR calculated over the period $(t-21,\ t+21)$ is equal to almost 3%, while the CAR over our previously used shorter estimation window of $(t-1,\ t+5)$ is only 1.9%. *Stock Split - Forward*, not surprisingly, follows a period of positive returns and is accompanied by a significantly positive return upon the announcement. However, the return reversal over the following month more than erases the announcement return. Finally, *Research Success* announcements tend to be preceded by a positive return drift, and none of the announcement-day price gains are reversed in the following month.

Figure 3.5 plots cumulative abnormal returns calculated over the window $(t-21,\ t+21)$ for the eight news categories with the most negative price reactions in Table 3.3. The figure shows that *Pre-Anouncement - Negative* is typically preceded by a negative return drift. As mentioned earlier, *FDA Rejection* announcements are preceded and also followed by a negative drift. News in the category *Customer Loss* are preceded by positive returns, although this plot, based on only 67 observations, may not be very representative. The negative news of *Financial Results - Weak* and *Product Defect* take several days to be fully incorporated into prices, and the negative price reaction is partially reversed later in the month. The negative reaction to *Restatement* announcements is also somewhat reversed. As for announcements of *Legal Problems*, the negative drift lasts until day 6, and over half of the negative price reaction is later reversed. Finally, news of *Management → Termination* are preceded by negative abnormal returns, and also about half of the negative abnormal returns in response to the announcement is later reversed.

3.3.2 News' Impact on the Informational Environment

In addition to having an impact on stock prices, corporate press releases may affect the stocks' informational environment. The literature on firm disclosure has traditionally

Figure 3.4: Plots of the Cumulative Abnormal Return for Positive News Categories

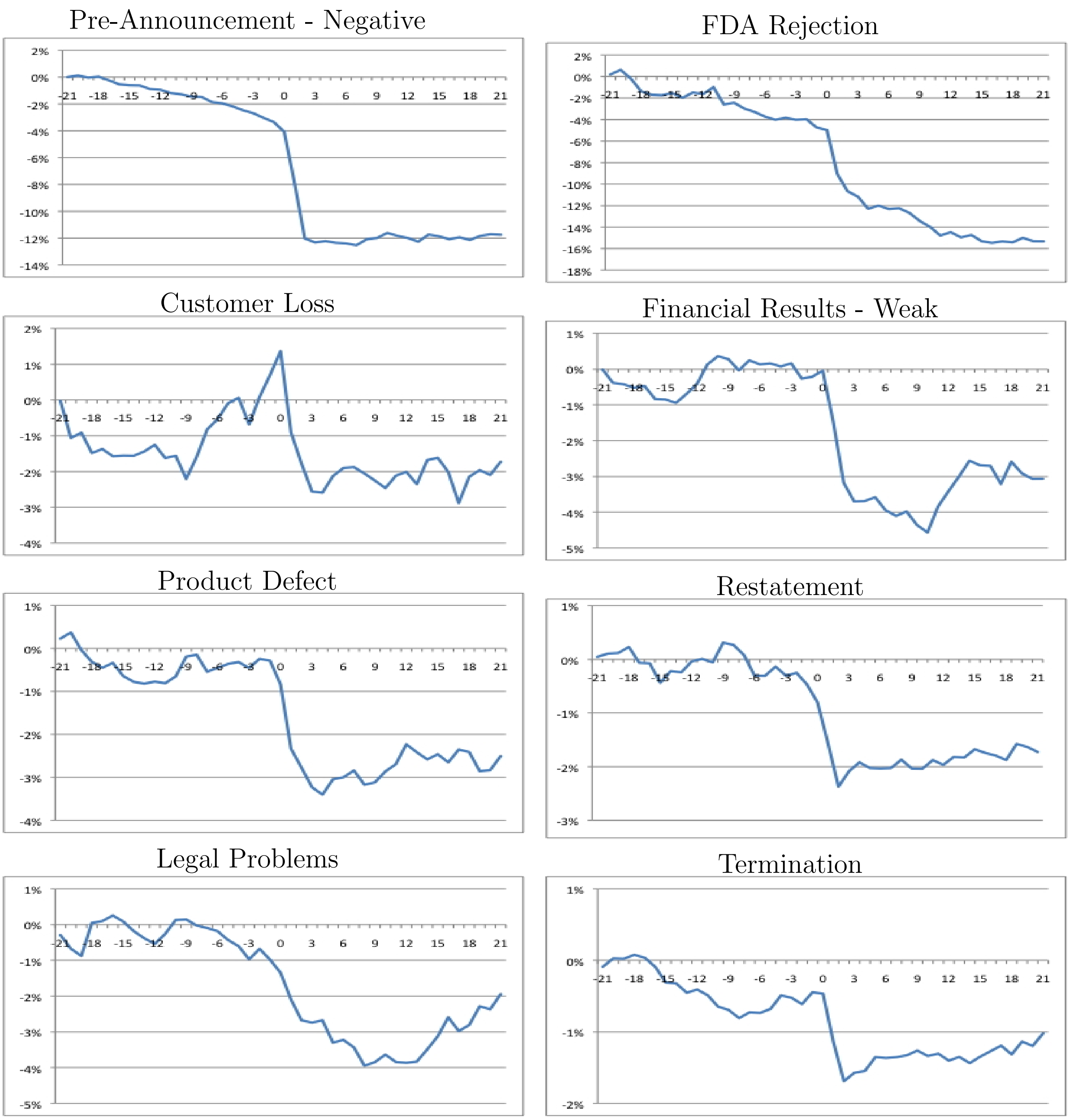


For the categories with the most positive CARs, the figure plots the cumulative abnormal return over the period from 21 days before to 21 after the press release date. Abnormal returns are computed as the residuals of the market model.

assumed that corporate news announcements should reduce the level of informational asymmetry.[21] However, when the new information is difficult to interpret, investors' val-

21 However, Harris and Raviv (1993) show that when agents use different valuation models and interpret new information differently, information arrivals will lead to an increased investor disagreement regarding the firm valuation.

Figure 3.5: Plots of the Cumulative Abnormal Return for Negative News Categories



For the categories with the most negative CARs, the figure plots the cumulative abnormal return over the period from 21 days before to 21 days after the press release date. Abnormal returns are computed as the residuals of the market model.

uation priors will be weakened, and the informational environment will become more uncertain. As a result, the stock price sensitivity to new information will rise, resulting in increased idiosyncratic volatility levels. At the same time, the potential informational advantage of firm insiders will become more valuable, and liquidity will decrease.

Idiosyncratic volatility measures how much prices respond to firm-specific news.[22] If the valuation priors are weakened as a result of a news announcement, the appetite for new information and for follow-up announcements will increase; prices will react strongly to this new information, as a greater degree of updating on the news is taking place. Therefore, news releases that increase valuation uncertainty will lead to volatility increases and news releases that decrease valuation uncertainty to volatility decreases.

Liquidity measures how much a unit of trade moves prices. Everything else equal, when traders are perceived to possess little private information about the firm value, prices will not respond strongly and permanently to trades, but trades would have rather a transitory impact on prices. When concerns about informational asymmetries are high, prices will move more in the direction of the trade and stock liquidity will be lower. We employ the Amihud (2002) measure of illiquidity, which can be calculated from daily return and volume data, and produces a good approximation for the level of stocks' illiquidity. If a news announcement is difficult to interpret, concerns might arise that some investors, perhaps the firm insiders, are better adept at processing this information, and, as a consequence, the stock's liquidity will decrease. If, on the other hand, the new information release removes the informational advantage of the better-informed traders, then liquidity should increase. We measure idiosyncratic volatility and illiquidity in the 10-day windows before and after news announcements (skipping the three days around the announcement ($t-1$, $t+1$) and then check whether these measures increase or decrease as a result of the news release.

3.3.2.1 Changes in Volatility

For each corporate press release, we calculate the ratio of the idiosyncratic volatility after the announcement to the idiosyncratic volatility before the announcement and test the null hypothesis that the average ratio (across firms) is equal to one using a t-test, with standard errors, as before, clustered by the week of the announcement to adjust for possible cross-sectional correlations in idiosyncratic volatility changes. We again check our results with nonparametric tests whenever the number of observations in a sample is lower than 100. Idiosyncratic volatility is defined as the standard deviation of the residuals of the market model (equation (3.2)), estimated over 200 days prior to the start of the estimation window for idiosyncratic volatility. The null hypothesis is stated as:

[22] Throughout the paper, we will use the terms "volatility" and "idiosyncratic volatility' interchangeably but will always mean the latter.

$$
\begin{aligned}
H_0: \quad \text{Vola}_{post} - \text{Vola}_{pre} &= 0, \qquad \text{or equivalently,} \\
\text{Vola}_{post}/\text{Vola}_{pre} &= 1,
\end{aligned}
$$

where Vola_{post} and Vola_{pre} are the post- and pre-anouncement idiosyncratic volatility measures, respectively.

Only few prior studies have investigated changes in idiosyncratic volatility following firm events, which is somewhat surprising since the consequences of event-induced volatility should be a matter of concern for several reasons. Clayton, Hartzell, and Rosenberg (2005), pages 1779-1780, write:

> "...increased volatility could alter the firm's investment policy going forward via an increased cost of capital or by a reduction in the attractiveness of the firm's equity as a medium for acquisitions or compensation. Increased volatility also could affect the various agency relationships in the firm, exacerbating conflicts between stockholders and bondholders and hindering resolution of stockholder-management problems..."

Among the few studies that have investigated this question, Kliger and Sarig (2000) find that when Moody's announces better- (worse-) than-expected ratings, the volatilities implied by prices of options on high-rated issuers' shares decline (rise). Clayton, Hartzell, and Rosenberg (2005) find that CEO departures, especially the forced ones, which in the authors' view create "higher uncertainty over the firm's strategic direction and management's ability to run the firm" (page 2), lead to significant increases in stock volatility. Besides, event-induced changes in volatility are found for announcements of stock splits by Ohlson and Penman (1985), Dubofsky (1991), and Koski (1998).

Table 3.4 presents the mean ratios of post- to pre-event volatilities for each news category. The p-values for the null hypothesis that the mean ratio is equal to one are listed in the rightmost column. It can be seen that idiosyncratic volatility increases following all types of news announcements, however, the percentage volatility increases are the largest for negative financial pre-announcements (76.6%), SEC investigation announcements (61.6%), press releases describing management compensation issues (53.2%), as well as announcements of reverse stock splits (51.7%) and FDA rejections (51.4%). These types of news appear to significantly weaken investors' valuation priors and, therefore, lead to higher price sensitivity to new information.[23]

[23] We have checked that the non-parametric rank-sum tests for changes in volatility produce qualitatively similar results for the news categories with fewer than 100 observations.

Table 3.4: Test Results for a Change in Volatility

	Category	Subcategory	Variance Ratio	p-value
1.	Awards	Company Award	1.220	0.000
		Product Award	1.246	0.000
2.	Corporate Strategy & Performance	Credit News - Negative	1.262	0.000
		Credit News - Positive	1.165	0.000
		Exchange Noncompliance	1.182	0.000
		Infrastructure - Downsizing	1.267	0.027
		Infrastructure - Expansion	1.201	0.000
		Profitability - Declining	1.298	0.000
		Profitability - Improving	1.208	0.000
3.	Customers & Partners	Customer Loss	1.188	0.079
		Customer Win	1.223	0.000
		New Partnership	1.229	0.000
		Reaching a Milestone	1.200	0.000
4.	Financial	Dividend	1.244	0.000
		Financial Results - Strong	1.413	0.000
		Financial Results - Weak	1.391	0.000
		Pre-Announcement - Negative	1.766	0.000
		Pre-Announcement - Positive	1.379	0.000
		Restatement	1.418	0.000
		Secondary Offering: Debt	1.114	0.000
		Secondary Offering: Equity	1.108	0.000
		Share Buyback	1.178	0.000
		Stock Split - Forward	1.294	0.000
		Stock Split - Reverse	1.517	0.000
5.	Legal	Class Action	1.090	0.006
		Legal Problems	1.204	0.000
		SEC Investigation	1.616	0.000
		Settlement	1.241	0.000
6.	M&A	Acquisition	1.236	0.000
		IPO	1.229	0.009
		Merger	1.275	0.000
		Spinoff	1.253	0.000
7.	Management	Addition	1.229	0.000
		Compensation	1.532	0.037
		Promotion	1.227	0.000
		Reorganization	1.218	0.000
		Retirement	1.208	0.000
		Termination	1.274	0.000
8.	Meetings & Events	Company-Sponsored Event	1.218	0.000
		Industry Events	1.196	0.000
		Investor Meeting	1.206	0.000
9.	Products & Services	FDA Approval	1.281	0.000
		FDA Investigation	1.313	0.000
		FDA Rejection	1.514	0.002
		New Product	1.218	0.000
		Patent Award	1.226	0.000
		Pharmaceutical Approval EU	1.185	0.000
		Product Approval	1.209	0.000
		Product Defect	1.264	0.000
		Research Failure	1.067	0.159
		Research Success	1.316	0.000
		Updates & Upgrades	1.226	0.000

This table presents the results of tests of the null hypothesis that the return volatilities before and after a press release are equal. Specifically, the ratio of post- to pre-announcement idiosyncratic volatility is tested for being different from one. For each subcategory, the table shows the sample mean of the ratio and the p-value of the t-test.

3.3.2.2 Change in Liquidity

We use the Amihud (2002) measure of a stock's illiquidity, defined as the ratio of the absolute daily stock return to its dollar trading volume.[24] The ratio reflects the absolute daily price response per dollar of trading volume and is computed as:

$$\text{Illiq}_{i,t} = \frac{|R_{i,t}|}{\text{Volume}_{i,t}}, \tag{3.4}$$

where $R_{i,t}$ is the return and $\text{Volume}_{i,t}$ is the dollar trading volume for stock i on day t.

In order to test for changes in (il-)liquidity across firms, we employ a similar procedure to the one we used to test for changes in idiosyncratic volatility. In particular, we calculate the ratio of a stock's average illiquidity measure, computed over 10 days after the announcement to the average illiquidity measure computed over 10 days before the announcement (as before, skipping the three days surrounding the announcement day). We then average this ratio across events and cluster the standard errors by the week of the announcement to adjust for possible cross-correlations in the ratios computed in overlapping event windows. We test the null hypothesis that the post- and pre-event liquidity levels are equal using a standard t-test. The null hypothesis is formalized as follows:

$$\begin{aligned} H_0: \quad \text{Illiq}_{post} - \text{Illiq}_{pre} &= 0, \qquad \text{or equivalently,} \\ \text{Illiq}_{post}/\text{Illiq}_{pre} &= 1, \end{aligned}$$

where Illiq_{pre} and Illiq_{post} denote Amihud (2002) illiquidity measures before and after a news announcement, respectively.

Most of the prior studies on liquidity changes around corporate events have focused on the impact of announcements of share repurchases (e.g., Singh, Zaman, and Krishnamurti (1994) and Ginglinger and Hamon (2007)), secondary equity offerings (e.g., Kothare (1997)), and index additions and deletions (e.g., Hegde and McDermott (2006)). Our results, reported in Table 3.5, are consistent with these studies. They show that stocks tend to become significantly more illiquid following most types of news announcements. The changes in liquidity are insignificant only for the announcements of strong financial results, positive earnings pre-announcements, press releases on managerial compensation and retirement, research failures, and various lawsuits. The announcements that lead to the largest decreases in liquidity are about investor meetings, reverse stock splits, negative earnings pre-announcements, FDA rejections, SEC investigations, and earnings restate-

[24] We chose this particular measure due to its simplicity, the minimal data requirements, and the previously-documented accuracy in measuring illiquidity when compared to the measures obtained from high-frequency trade-by-trade data.

ments. Not surprisingly, there is a considerable overlap with the news categories that result in the largest idiosyncratic volatility increases. The news that significantly raise the levels of informational uncertainty also considerably increase the benefits of private information.

3.3.3 The Impact of the Financial Crisis

The recent financial crisis has been called the worst crisis since the Great Depression. It originated in the collapse of the housing bubble. The after-effects of the bubble's collapse and scope of its impact on the rest of the economy emerged only gradually. In the period from 2006 to 2007, the effect of the collapsing bubble was felt by home construction and real estate lending companies, many of which reported significant losses and filed for bankruptcy. Over time, hedge funds and investment banks with exposure to mortgage-backed securities began reporting investment losses as well. We argue that the crisis turned global—affecting all sectors of the U.S. economy, as well as foreign markets—after the first investment bank, Bear Stearns, fell and had to be sold in a fire-sale to JP Morgan Chase on March 16, 2008, in order to avoid filing for bankruptcy. This major bank failure immediately raised the profile of the crisis, amid concerns about contagion, to an economy-wide phenomenon. Eventually, shortages of credit that used to be supplied by hedge funds and investment banks affected all sectors of the economy. It is possible to argue that the crisis really started with the collapse of Lehman Brothers, which did not happen until September 17, 2008. One could also make a convincing case that the crisis started earlier, when major mortgage lending companies had failed. While it is impossible to pinpoint the precise start date of the crisis, choosing any date between the third quarter of 2007 when the effects of the collapsing real estate market started to be widely felt and the fall of Lehman Brothers will likely not significantly change the outcome of our analysis. Here, we assume that the market became aware that the U.S. economy had entered the crisis period on Monday, March 17, 2008, the first trading day after the fire-sale of Bear Stearns to JP Morgan was finalized.

The financial crisis was characterized by a shortage of credit, falling consumer demand, and widespread legal scandals. In this environment, it is natural to expect that certain types of corporate news would be perceived differently by the market. For example, news about plans to raise additional capital would be viewed less negatively because it was believed that additional capital was truly needed due to (1) the freezing of the credit markets and (2) the perception that equity was likely underpriced rather than overpriced. Any good news about future cash flows would be perceived much more positively. Likewise, negative news about future cash flows might be perceived significantly more negatively

Table 3.5: Test Results for a Change in the Amihud Illiquidity Measure

	Category	Subcategory	Amihud Ratio	p-value
1.	Awards	Company Award	1.144	0.000
		Product Award	1.151	0.000
2.	Corporate Strategy & Performance	Credit News - Negative	1.206	0.001
		Credit News - Positive	1.114	0.000
		Exchange Noncompliance	1.120	0.000
		Infrastructure - Downsizing	1.197	0.018
		Infrastructure - Expansion	1.138	0.000
		Profitability - Declining	1.217	0.000
		Profitability - Improving	1.161	0.000
3.	Customers & Partners	Customer Loss	1.128	0.200
		Customer Win	1.162	0.000
		New Partnership	1.177	0.000
		Reaching a Milestone	1.145	0.000
4.	Financial	Dividend	1.164	0.000
		Financial Results - Strong	1.093	0.606
		Financial Results - Weak	1.202	0.000
		Pre-Announcement - Negative	1.459	0.000
		Pre-Announcement - Positive	1.043	0.892
		Restatement	1.309	0.000
		Secondary Offering: Debt	1.064	0.000
		Secondary Offering: Equity	1.083	0.000
		Share Buyback	1.165	0.000
		Stock Split - Forward	1.176	0.054
		Stock Split - Reverse	1.696	0.000
5.	Legal	Class Action	1.030	0.314
		Legal Problems	1.075	0.386
		SEC Investigation	1.387	0.000
		Settlement	1.193	0.000
6.	M&A	Acquisition	1.157	0.000
		IPO	1.261	0.007
		Merger	1.225	0.000
		Spinoff	1.187	0.000
7.	Management	Addition	1.160	0.000
		Compensation	1.095	0.368
		Promotion	1.179	0.000
		Reorganization	1.176	0.000
		Retirement	0.158	0.414
		Termination	1.171	0.000
8.	Meetings & Events	Company-Sponsored Event	1.148	0.000
		Industry Events	1.169	0.000
		Investor Meeting	2.106	0.080
9.	Products & Services	FDA Approval	1.180	0.000
		FDA Investigation	1.214	0.000
		FDA Rejection	1.393	0.007
		New Product	1.147	0.000
		Patent Award	1.160	0.000
		Pharmaceutical Approval EU	1.164	0.034
		Product Approval	1.151	0.000
		Product Defect	1.166	0.001
		Research Failure	1.035	0.357
		Research Success	1.232	0.000
		Updates & Upgrades	1.109	0.035

This table presents the results of tests of the null hypothesis that the Amihud illiquidity measures before and after a press release are equal. Specifically, the ratio of post- to pre-announcement Amihud illiquidity measure is tested for being different from one. For each subcategory, the table shows the sample mean of the ratio and the p-value of the t-test.

due to potential bankruptcy concerns. Moreover, the crisis period was associated with a highly uncertain informational environment. Therefore, investor priors on firm values were likely already very diffuse. Hence, it is not clear whether news announcements during the crisis period generally resulted in higher or lower changes in liquidity and idiosyncratic volatility than during the pre-crisis period. In the following, we formally check whether the market response to corporate news has significantly changed during the financial crisis period.

Before turning to the test results, it is informative to establish to what extent the content of corporate press releases changed during the period of the financial crisis compared to the pre-crisis period. Table 3.6 provides the numbers of observations for each news category and the frequencies of their occurrence in the dataset for the two subperiods.[25] We observe some interesting changes in the distribution of corporate announcements. Not surprisingly, the frequency of announcements in the categories *Financial Results - Weak* and *Profitability - Declining* doubled; the frequency of forward stock splits declined by almost three-quarters, and the frequency of reverse stock splits more than doubled.[26] IPO activity significantly declined. During the crisis period, firms were more likely to raise funds through debt rather than equity issuances. Finally, the frequency of news announcing the launch of new products decreased by more than three percentage points, which is the largest percentage decrease across news categories.

3.3.3.1 Test Results for Changes in CARs

Figure 3.6 provides a graphical illustration of the differences in the impact of news announcements on stock returns. For each subcategory, the figure plots the mean CAR for the periods before the crisis (indicated by the dark bars) and after the start of the crisis (indicated by the light bars). A quick look at the figure confirms that the market reaction to news became, generally, more extreme during the crisis period. Additionally, the plots of CAR variances in Figure 3.7 show that, with very few exceptions, the standard deviations of CARs in each subcategory increased during the crisis period relative to the pre-crisis period, indicating that the market became more discriminating in interpreting news and that market participants were paying more attention to the content and the circumstances of each specific announcement rather than relying on the rule-of-thumb.

[25] Since the time period before the crisis is longer than that after the start of the crisis, it contains more observations of press releases.

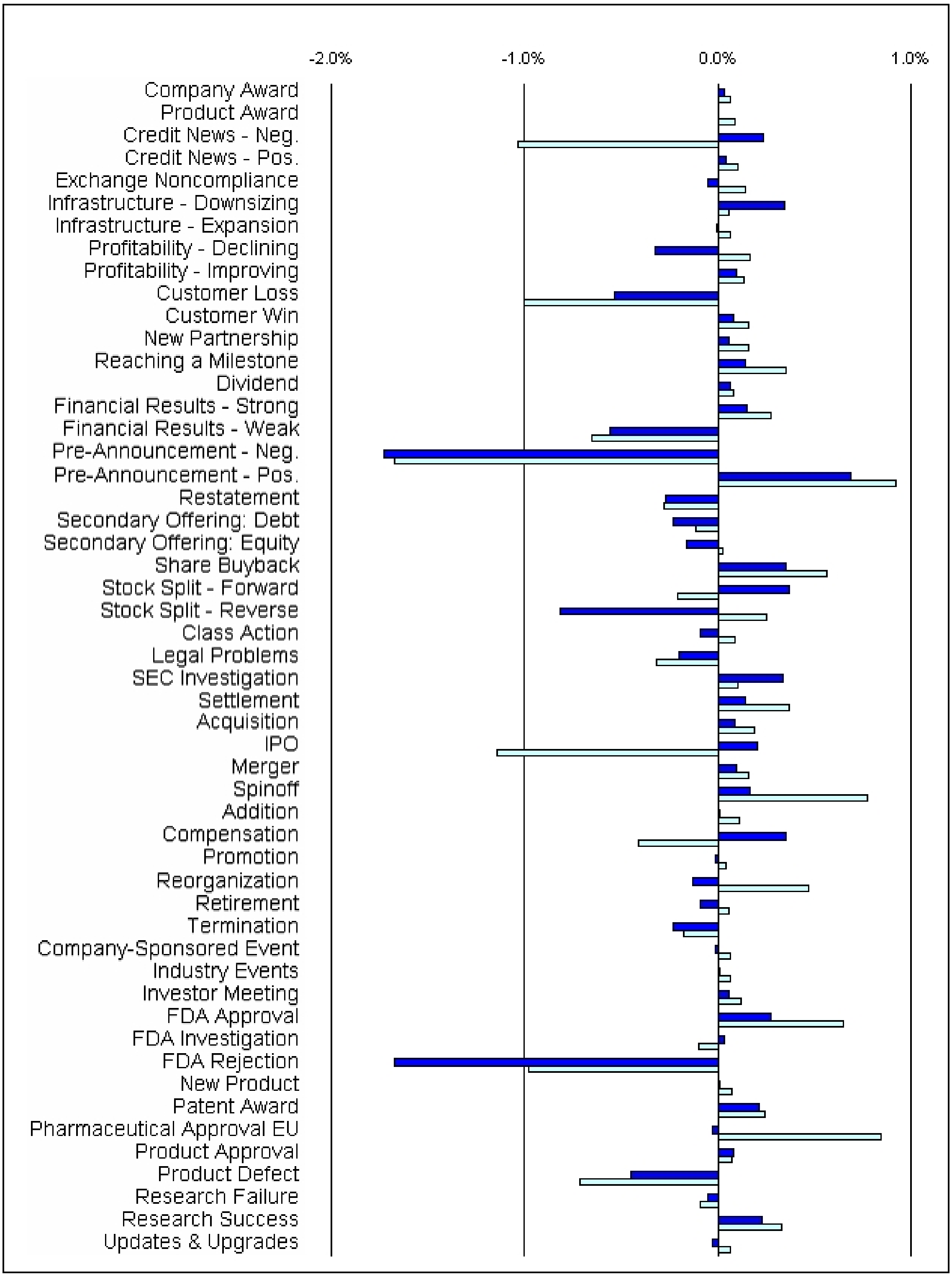
[26] Reverse stock splits likely became more prevalent due to the need to comply with the minimum-price requirements imposed by stock exchanges.

Table 3.6: Frequency of Corporate Press Releases: Before and During the Crisis

	Category	Subcategory	Before Crisis Obs.	Before Crisis Percent	During Crisis Obs.	During Crisis Percent
1.	Awards	Company Award	6,222	3.724%	4,681	4.467%
		Product Award	1,842	1.103%	829	0.791%
2.	Corporate Strategy & Performance	Credit News - Negative	126	0.075%	26	0.025%
		Credit News - Positive	695	0.416%	281	0.268%
		Exchange Noncompliance	156	0.093%	323	0.308%
		Infrastructure - Downsizing	47	0.028%	7	0.007%
		Infrastructure - Expansion	4,711	2.820%	1,929	1.841%
		Profitability - Declining	126	0.075%	157	0.150%
		Profitability - Improving	906	0.542%	549	0.524%
3.	Customers & Partners	Customer Loss	54	0.032%	13	0.012%
		Customer Win	16,805	10.059%	11,149	10.638%
		New Partnership	16,557	9.910%	9,041	8.627%
		Reaching a Milestone	685	0.410%	248	0.237%
4.	Financial	Dividend	12,283	7.352%	12,293	11.730%
		Financial Results - Strong	9,994	5.982%	5,358	5.113%
		Financial Results - Weak	191	0.114%	312	0.298%
		Pre-Announcement - Negative	196	0.117%	205	0.196%
		Pre-Announcement - Positive	438	0.262%	251	0.240%
		Restatement	289	0.173%	76	0.073%
		Secondary Offering: Debt	2,076	1.243%	1,678	1.601%
		Secondary Offering: Equity	2,403	1.438%	1,690	1.613%
		Share Buyback	2,446	1.464%	1,388	1.324%
		Stock Split - Forward	269	0.161%	42	0.040%
		Stock Split - Reverse	71	0.042%	105	0.100%
5.	Legal	Class Action	563	0.337%	86	0.082%
		Legal Problems	73	0.044%	83	0.079%
		SEC Investigation	115	0.069%	53	0.051%
		Settlement	1,307	0.782%	932	0.889%
6.	M&A	Acquisition	49	0.029%	28	0.027%
		IPO	57	0.034%	2	0.002%
		Merger	1,034	0.619%	751	0.717%
		Spinoff	2,733	1.636%	1,559	1.488%
7.	Management	Addition	12,461	7.459%	8,099	7.728%
		Compensation	52	0.031%	14	0.013%
		Promotion	4,266	2.553%	2,351	2.243%
		Reorganization	773	0.463%	295	0.281%
		Retirement	765	0.458%	511	0.488%
		Termination	1,149	0.688%	668	0.637%
8.	Meetings & Events	Company-Sponsored Event	2,560	1.532%	675	0.644%
		Industry Events	25,409	15.209%	17,076	16.294%
		Investor Meeting	2,118	1.268%	787	0.751%
9.	Products & Services	FDA Approval	1,169	0.700%	743	0.709%
		FDA Investigation	429	0.257%	338	0.323%
		FDA Rejection	34	0.020%	13	0.012%
		New Product	24,672	14.768%	11,810	11.269%
		Patent Award	674	0.403%	318	0.303%
		Pharmaceutical Approval EU	193	0.116%	132	0.126%
		Product Approval	1,051	0.629%	900	0.859%
		Product Defect	114	0.068%	84	0.080%
		Research Failure	79	0.047%	70	0.067%
		Research Success	1,253	0.750%	850	0.811%
		Updates & Upgrades	2,328	1.393%	2,940	2.805%
		Total	167,068	100%	104,799	100%

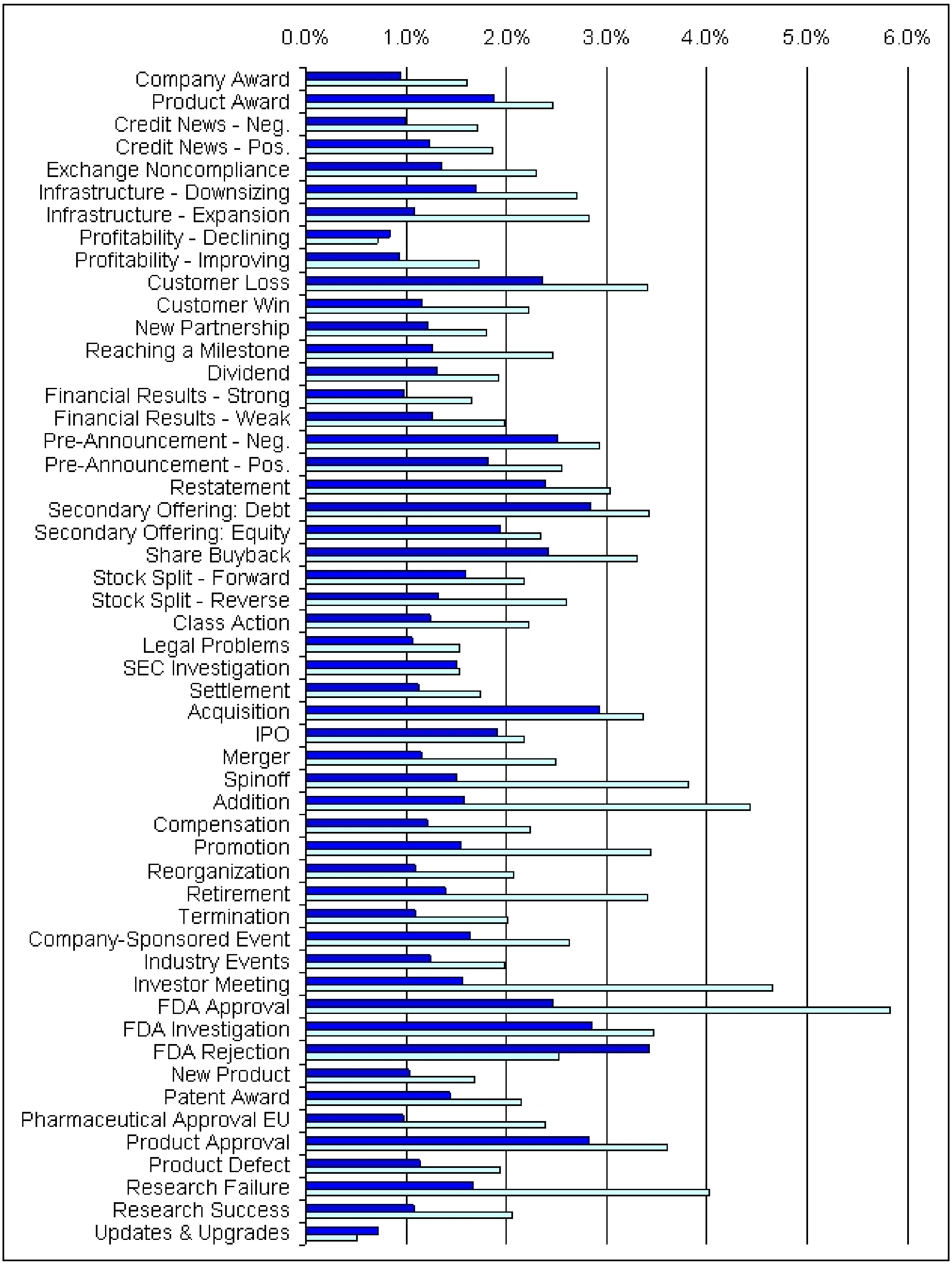
For the periods before and during the crisis, this table presents the number of corporate press releases in each category, as well as each category's percentage share in the total number of corporate press releases.

Figure 3.6: Means of the Cumulative Abnormal Returns Before and During the Financial Crisis



For each news category, the means of the cumulative abnormal returns are plotted for the period before (dark bars) and during the crisis (light bars).

Figure 3.7: Standard Deviations of the Cumulative Abnormal Returns Before and During the Financial Crisis



For each news category, the standard deviations of the cumulative abnormal returns are plotted for the period before (dark bars) and during the crisis (light bars).

Turning to the actual test results for differences in the market reaction to corporate press releases between the periods before and during the crisis, we first describe the differences in the stock price response to corporate announcements. For each subcategory, the mean of the CARs and the p-value of the corresponding t-test for the average CAR being equal to zero for the respective sample periods are provided in Table 3.7. Furthermore, the last column of the table presents, for each subcategory, the result of the t-test for the null hypothesis that the mean CARs for the periods before and during the crisis are equal. For the sake of brevity, we focus the description of the results on the most conspicuous and significant findings with respect to a change in the market reaction to news from the pre-crisis period to the period after the start of the crisis.[27]

It can be seen from the table that during the crisis, cash-flow stabilizing or, potentially, cash-flow increasing news, such as the launch of a new product, an FDA approval, a legal settlement, a new customer or partner, and a report of strong financial results are accompanied by more positive price reactions than before the crisis. Furthermore, the market places a significantly higher value on the positive signal of share buybacks during the crisis period, resulting in an increase in the mean CAR from 0.350% before the crisis to 0.560% during the crisis. (This increase is significant at the 1% level.) At the same time, the negative market reaction to issuances of new debt and new equity becomes significantly less negative (and in the case of SEOs, indistinguishable from zero). It appears that the market is less concerned about the possibility that firms are overvalued and more sympathetic to the view that firms do need capital in light of the prevailing credit crunch. Turning to news on management changes, we find that announcements of reorganization are no longer perceived negatively but rather positively (the average CAR before the crisis is -0.133% and during the crisis it is equal to 0.471%, with both means significantly different from zero at the 1% level, and the difference between the two is significant at the 1% level). Additionally, the reaction to other management changes, such as additions, promotions, and retirements, that are likely to bring change to how the firm operates, are met with significantly more positive price reactions. Finally, investigating the category *Products & Services*, the announcements of drug approvals in the U.S. and Europe, new product launches and updates to existing products and services are met with significantly more positive price reactions.

[27] We have compared the results of our t-tests for the difference in means with the two-sample rank-sum tests for categories for which the number of observations in at least one of the sub-periods is below 100. The results are generally very close. For example, for the category *Restatement*, the non-parametric p-value is equal to 0.500, for *Stock Split - Forward*, it is equal to 0.039, for *Stock Split - Reverse*, 0.005, for *Class Action*, 0.629, for *Legal Problems*, 0.438, for *SEC Investigation*, 0.000, for *Product Defect*, 0.384, and for *Research Failure*, 0.412.

Table 3.7: Test Results for Cumulative Abnormal Returns: Before and During the Crisis

	Category	Subcategory	Before Crisis		During Crisis		Diff.
			$\overline{CAR}$	p-value	$\overline{CAR}$	p-value	p-value
1.	Awards	Company Award	0.031%	0.010	0.063%	0.006	0.106
		Product Award	-0.001%	0.979	0.090%	0.122	0.074
2.	Corporate Strategy & Performance	Credit News - Negative	0.239%	0.231	-1.031%	-	-
		Credit News - Positive	0.043%	0.442	0.102%	0.588	0.381
		Exchange Noncompliance	0.118%	0.641	0.190%	0.499	0.093
		Infrastructure - Downsizing	0.347%	0.008	0.059%	-	-
		Infrastructure - Expansion	-0.005%	0.706	0.069%	0.077	0.037
		Profitability - Declining	-0.321%	0.042	0.166%	0.568	0.070
		Profitability - Improving	0.100%	0.005	0.134%	0.126	0.358
3.	Customers & Partners	Customer Loss	-0.538%	0.002	-1.001%	-	-
		Customer Win	0.084%	0.000	0.160%	0.000	0.000
		New Partnership	0.060%	0.000	0.162%	0.000	0.000
		Reaching a Milestone	0.146%	0.001	0.353%	0.003	0.050
4.	Financial	Dividend	0.066%	0.000	0.080%	0.000	0.205
		Financial Results - Strong	0.150%	0.000	0.274%	0.000	0.001
		Financial Results - Weak	-0.559%	0.002	-0.653%	0.001	0.358
		Pre-Announcement - Negative	-1.724%	0.000	-1.672%	0.000	0.435
		Pre-Announcement - Positive	0.692%	0.000	0.922%	0.000	0.109
		Restatement	-0.273%	0.084	-0.279%	0.433	0.494
		Secondary Offering: Debt	-0.228%	0.000	-0.112%	0.068	0.050
		Secondary Offering: Equity	-0.162%	0.000	0.029%	0.673	0.005
		Share Buyback	0.350%	0.000	0.560%	0.000	0.000
		Stock Split - Forward	0.368%	0.000	-0.206%	0.565	0.057
		Stock Split - Reverse	-0.814%	0.010	0.250%	0.418	0.007
5.	Legal	Class Action	-0.094%	0.177	0.085%	0.596	0.152
		Legal Problems	-0.198%	0.156	-0.320%	0.129	0.314
		SEC Investigation	0.338%	0.146	0.102%	0.831	0.327
		Settlement	0.145%	0.010	0.370%	0.000	0.007
6.	M&A	Acquisition	0.088%	0.000	0.190%	0.000	0.009
		IPO	0.205%	0.035	-1.139%	-	-
		Merger	0.098%	0.080	0.159%	0.270	0.346
		Spinoff	0.166%	0.000	0.770%	0.000	0.000
7.	Management	Addition	0.010%	0.352	0.115%	0.000	0.000
		Compensation	0.350%	0.126	-0.412%	-	-
		Promotion	-0.016%	0.325	0.044%	0.304	0.095
		Reorganization	-0.133%	0.007	0.471%	0.006	0.000
		Retirement	-0.092%	0.020	0.061%	0.480	0.053
		Termination	-0.228%	0.000	-0.176%	0.088	0.324
8.	Meetings & Events	Company-Sponsored Event	-0.016%	0.447	0.062%	0.309	0.112
		Industry Events	0.007%	0.376	0.063%	0.000	0.000
		Investor Meeting	0.056%	0.075	0.117%	0.174	0.255
9.	Products & Services	FDA Approval	0.274%	0.000	0.648%	0.002	0.045
		FDA Investigation	0.036%	0.801	-0.103%	0.584	0.278
		FDA Rejection	-1.675%	0.015	-0.976%	-	-
		New Product	0.012%	0.063	0.069%	0.000	0.000
		Patent Award	0.217%	0.005	0.243%	0.103	0.439
		Pharmaceutical Approval EU	-0.032%	0.779	0.843%	0.061	0.029
		Product Approval	0.077%	0.045	0.073%	0.249	0.480
		Product Defect	-0.450%	0.000	-0.714%	0.004	0.166
		Research Failure	-0.049%	0.668	-0.089%	0.745	0.446
		Research Success	0.231%	0.002	0.332%	0.019	0.264
		Updates & Upgrades	-0.030%	0.186	0.067%	0.069	0.012

For the periods before and during the financial crisis, the table presents the results of tests of the null hypothesis that the mean cumulative abnormal return is equal to zero in each of the subperiods. For each subcategory, the table shows the sample mean cumulative abnormal return for the two subperiods, as well as the p-value of the t-tests of the null hypotheses. The last column presents the results of the test of the null hypothesis that the mean cumulative abnormal returns for the periods before and during the crisis are equal. Dashes indicate that at least one of the two groups (before or during) has fewer than 30 observations.

3.3.3.2 Test Results for Changes in Volatility and Liquidity

This section describes the test results for differences in event-induced changes in stocks' volatility and liquidity. For the periods before and during the crisis, Table 3.8 presents, for each subcategory, the average ratio of post-to pre-event volatility. In addition, the table includes p-values of the t-tests for event-induced changes in volatility for both periods before and during the crisis, and the test results for the null hypothesis that these changes are the same for both periods. Similarly, Table 3.9 presents the results for event-induced changes in liquidity.[28] In Table 3.8, volatility ratios greater than one in conjunction with significant p-values for almost all news categories confirm that post-event volatility increases are significant for both sub-periods. Comparing the magnitudes of increases in idiosyncratic volatility, we find that during the crisis period, post-event volatility tends to experience significantly larger increases, relative to the before-crisis period, for news about changes in profitability and forward stock splits, FDA approvals and investigations, announcements of success in research endeavors, as well as announcements of all types of M&A activity. This implies that these types of news led to larger post-announcement valuation uncertainty during the crisis period. Yet, some types of press releases are found to create significantly smaller increases in volatility during the crisis period. Examples are announcements of both positive and negative financial results, as well as news on SEC investigations, and announcements of legal problems. Having become more prevalent at the time of the crisis, these types of news likely have grown easier for the market to interpret.

The results for event-induced changes in liquidity (Table 3.9) are similar to those for changes in volatility. For both the pre-crisis period and the period after the start of the crisis, corporate press releases, generally, lead to decreases in liquidity, and these decreases tend to be significantly larger during the crisis period, indicating higher post-event informational asymmetry in the second sub-period. Larger drops in post-announcement volatility decreases for the in-crisis period stand out for FDA approvals, new product announcements, updates and upgrades, successful research outcomes, merger announcements, managerial promotions, expansion of the infrastructure, and many financial news categories. As in the case of differential effects on post-event volatility, liquidity decreased significantly less during the crisis, relative to the pre-crisis period, for announcements of legal problems and weak financial results.

[28] As before, we also conduct non-parametric tests of the differences in volatility and liquidity ratios between the before- and the in-crisis periods for the news categories with fewer than 100 observations in either period. The results are qualitatively similar.

Table 3.8: Test Results for a Change in Volatility: Before and During the Crisis

	Category	Subcategory	Before Crisis Vola Ratio	Before Crisis p-value	During Crisis Vola Ratio	During Crisis p-value	Diff. p-value
1.	Awards	Company Award	1.211	0.000	1.234	0.000	0.101
		Product Award	1.247	0.000	1.244	0.000	0.465
2.	Corporate Strategy & Performance	Credit News - Negative	1.217	0.001	1.523	-	-
		Credit News - Positive	1.152	0.000	1.205	0.000	0.159
		Exchange Noncompliance	1.175	0.000	1.204	0.236	0.019
		Infrastructure - Downsizing	1.269	0.042	1.242	-	-
		Infrastructure - Expansion	1.190	0.000	1.232	0.000	0.027
		Profitability - Declining	1.207	0.001	1.385	0.000	0.050
		Profitability - Improving	1.171	0.000	1.278	0.000	0.011
3.	Customers & Partners	Customer Loss	1.219	0.099	1.036	-	-
		Customer Win	1.225	0.000	1.219	0.000	0.257
		New Partnership	1.228	0.000	1.233	0.000	0.313
		Reaching a Milestone	1.199	0.000	1.205	0.000	0.446
4.	Financial	Dividend	1.253	0.000	1.233	0.000	0.041
		Financial Results - Strong	1.481	0.000	1.267	0.000	0.000
		Financial Results - Weak	1.503	0.000	1.305	0.000	0.015
		Pre-Announcement - Negative	1.916	0.000	1.612	0.000	0.026
		Pre-Announcement - Positive	1.412	0.000	1.313	0.000	0.091
		Restatement	1.450	0.000	1.270	0.007	0.066
		Secondary Offering: Debt	1.094	0.000	1.155	0.000	0.006
		Secondary Offering: Equity	1.120	0.000	1.080	0.000	0.038
		Share Buyback	1.166	0.000	1.202	0.000	0.083
		Stock Split - Forward	1.248	0.000	1.605	0.006	0.047
		Stock Split - Reverse	1.483	0.000	1.547	0.000	0.343
5.	Legal	Class Action	1.082	0.033	1.160	0.025	0.167
		Legal Problems	1.283	0.003	1.087	0.137	0.036
		SEC Investigation	1.657	0.002	1.492	0.009	0.275
		Settlement	1.248	0.000	1.229	0.000	0.301
6.	M&A	Acquisition	1.229	0.000	1.252	0.000	0.083
		IPO	1.220	0.013	1.442	-	-
		Merger	1.188	0.000	1.452	0.000	0.000
		Spinoff	1.235	0.000	1.292	0.000	0.029
7.	Management	Addition	1.225	0.000	1.236	0.000	0.197
		Compensation	1.673	0.050	1.009	-	-
		Promotion	1.220	0.000	1.240	0.000	0.169
		Reorganization	1.210	0.000	1.243	0.000	0.278
		Retirement	1.232	0.000	1.166	0.000	0.062
		Termination	1.309	0.000	1.197	0.000	0.008
8.	Meetings & Events	Company-Sponsored Event	1.224	0.000	1.189	0.000	0.140
		Industry Events	1.178	0.000	1.228	0.000	0.000
		Investor Meeting	1.173	0.000	1.307	0.000	0.000
9.	Products & Services	FDA Approval	1.242	0.000	1.358	0.000	0.058
		FDA Investigation	1.270	0.000	1.393	0.000	0.073
		FDA Rejection	1.678	0.003	1.050	-	-
		New Product	1.215	0.000	1.227	0.000	0.106
		Patent Award	1.217	0.000	1.251	0.000	0.266
		Pharmaceutical Approval EU	1.193	0.001	1.170	0.017	0.402
		Product Approval	1.195	0.000	1.229	0.000	0.176
		Product Defect	1.269	0.001	1.256	0.013	0.461
		Research Failure	1.058	0.367	1.079	0.268	0.410
		Research Success	1.270	0.000	1.400	0.000	0.011
		Updates & Upgrades	1.223	0.000	1.229	0.000	0.385

For the periods before and during the financial crisis, the table presents the results of tests of the null hypothesis that the return volatilities before and after a press release are equal. Specifically, the ratio of post- to pre-announcement volatility is tested for being different from one. For each subcategory, the table shows the sample mean of the ratio, as well as the p-value of the t-test for the two subperiods. Furthermore, the table presents the test results of null hypothesis that the volatility ratios for the periods before and during the crisis are equal. Dashes indicate that at least one of the two groups (before and during) has fewer than 30 observations.

Table 3.9: Test Results for a Change in the Amihud Illiquidity Measure: Before and During the Crisis

	Category	Subcategory	Before Crisis Amihud Ratio	Before Crisis p-value	During Crisis Amihud Ratio	During Crisis p-value	Diff. p-value
1.	Awards	Company Award	1.144	0.000	1.143	0.000	0.480
		Product Award	1.159	0.000	1.132	0.000	0.200
2.	Corporate Strategy & Performance	Credit News - Negative	1.171	0.002	1.404	-	-
		Credit News - Positive	1.118	0.000	1.102	0.044	0.385
		Exchange Noncompliance	1.109	0.000	1.156	0.020	0.247
		Infrastructure - Downsizing	1.198	0.027	1.180	-	-
		Infrastructure - Expansion	1.120	0.000	1.190	0.000	0.003
		Profitability - Declining	1.195	0.009	1.239	0.010	0.353
		Profitability - Improving	1.141	0.000	1.199	0.000	0.104
3.	Customers & Partners	Customer Loss	1.133	0.261	1.103	-	-
		Customer Win	1.161	0.000	1.164	0.000	0.355
		New Partnership	1.164	0.000	1.208	0.000	0.157
		Reaching a Milestone	1.120	0.000	1.234	0.000	0.006
4.	Financial	Dividend	1.194	0.000	1.127	0.001	0.066
		Financial Results - Strong	1.045	0.872	1.195	0.000	0.295
		Financial Results - Weak	1.286	0.001	1.140	0.019	0.073
		Pre-Announcement - Negative	1.588	0.000	1.327	0.000	0.006
		Pre-Announcement - Positive	1.254	0.000	0.618	0.652	0.226
		Restatement	1.338	0.000	1.175	0.021	0.041
		Secondary Offering: Debt	1.054	0.000	1.085	0.001	0.147
		Secondary Offering: Equity	1.083	0.000	1.084	0.000	0.471
		Share Buyback	1.158	0.000	1.178	0.000	0.331
		Stock Split - Forward	1.131	0.221	1.481	0.007	0.040
		Stock Split - Reverse	1.423	0.001	1.935	0.001	0.043
5.	Legal	Class Action	1.038	0.130	0.955	0.668	0.220
		Legal Problems	1.263	0.004	0.798	0.197	0.005
		SEC Investigation	1.430	0.000	1.256	0.064	0.165
		Settlement	1.194	0.000	1.191	0.000	0.476
6.	M&A	Acquisition	1.124	0.001	1.237	0.019	0.145
		IPO	1.263	0.009	1.197	-	-
		Merger	1.163	0.000	1.351	0.000	0.000
		Spinoff	1.179	0.000	1.204	0.000	0.196
7.	Management	Addition	1.171	0.000	1.140	0.000	0.115
		Compensation	1.064	0.612	1.209	-	-
		Promotion	1.165	0.000	1.210	0.000	0.093
		Reorganization	1.171	0.000	1.194	0.000	0.328
		Retirement	1.060	0.437	-1.436	0.354	0.171
		Termination	1.183	0.000	1.145	0.002	0.277
8.	Meetings & Events	Company-Sponsored Event	1.130	0.000	1.231	0.000	0.048
		Industry Events	1.151	0.000	1.201	0.000	0.041
		Investor Meeting	2.363	0.140	1.323	0.000	0.131
9.	Products & Services	FDA Approval	1.156	0.000	1.228	0.000	0.066
		FDA Investigation	1.191	0.000	1.256	0.000	0.192
		FDA Rejection	1.547	0.005	0.957	-	-
		New Product	1.153	0.000	1.132	0.000	0.092
		Patent Award	1.162	0.000	1.154	0.000	0.438
		Pharmaceutical Approval EU	1.130	0.013	1.232	0.200	0.294
		Product Approval	1.157	0.000	1.142	0.000	0.299
		Product Defect	1.128	0.019	1.232	0.015	0.168
		Research Failure	1.015	0.742	1.061	0.352	0.283
		Research Success	1.196	0.000	1.299	0.000	0.044
		Updates & Upgrades	1.033	0.728	1.182	0.000	0.063

For the periods before and during the financial crisis, the table presents the test results of the null hypothesis that the Amihud illiquidity measures before and after a press release are equal. Specifically, the ratio of post- to pre-announcement Amihud illiquidity measures is tested for being different from one. For each subcategory, the table shows the sample mean of the ratio, as well as the p-value of the t-test for each subperiod. Furthermore, the table presents the test results of the null hypothesis that the Amihud ratios for the periods before and during the crisis are equal. Dashes indicate that at least one of the two groups (before and during) has fewer than 30 observations.

3.4 Conclusion

For this paper we have collected a comprehensive dataset of corporate press releases, which, since the increase in information release requirements, includes all corporate news that are deemed to be material for stock prices. Using this unique dataset, we further classified press releases into various categories and investigated the impact of the different types of news on stock prices and the informational environment. We then subdivided our time series into the sub-periods before and during the financial crisis. Not surprisingly, we found that announcements about secondary equity offerings were viewed less negatively and positive cash flow news were perceived significantly more positively by the market. In future work, we plan to further the scope of our analysis by conducting more in-depth investigations into the process of price discovery and uncovering factors that influence the speed of price discovery across firms and industries.

Appendices

A Appendix to Chapter 1

A.1 Calculation of Realized Variances

We use realized variance (RV) as an estimate of integrated variance (IV). Assume that the efficient log-price process can be described by the stochastic differential equation

$$dp^*(t) = \mu(t)dt + \sigma(t)dw(t), \tag{5}$$

where $\mu(t)$ and $\sigma(t)$ are smooth time-varying functions and w is a standard Brownian motion. We further assume that μ and σ are independent of w. Following the notation in Hansen and Lunde (2005b), we let integer values of t refer to trading day closing times and use trading days as the unit of time. Therefore, the close-to-close return on day t is defined as the difference between two log prices, i.e., $r_t \equiv p(t) - p(t-1)$. Unfortunately, the efficient price process cannot be observed and we, therefore, describe the observed price process as the efficient price process plus microstructure noise:

$$p^*(t) \equiv p(t) + \varepsilon(t). \tag{6}$$

Integrated variance over the time interval $[a, b]$, $\text{IV}_{[a,b]}$, is defined as

$$\text{IV}_{[a,b]} \equiv \int_a^b \sigma^2(t)dt. \tag{7}$$

Integrated variance is usually estimated with realized variance from intraday tick data. We follow Hansen and Lunde (2005b) and denote times at which prices are observed by $a = t_0 < t_1 < ... < t_m = b$. We define a partition of $[a, b]$, $\Xi \equiv \{t_0, .., t_m\}$. The RV sampled from this partition is thus given by

$$\text{RV}^{\Xi}_{[a,b]} \equiv \sum_{i=1}^{m} (p(t_i) - p(t_{i-1}))^2, \tag{8}$$

where $p(t_i) - p(t_{i-1})$ represents intra-day returns. Note that $\mathrm{RV}^{\Xi}_{[a,b]}$ is specific to the partition.

As $\mathrm{RV}^{\Xi}_{[a,b]}$ incorporates only prices that occurred during the trading day, it ignores information that arrives when the market is closed. Therefore, we employ the scaling estimator of Hansen and Lunde (2005a) and Hansen and Lunde (2005b). The scaling estimator incorporates the overnight return by scaling the RV by λ, which is given by

$$\lambda = \frac{\sum_{t=1}^{n} (r_t - \bar{r})^2}{\sum_{t=1}^{n} \mathrm{RV}^{\Xi}_{[a,b]}}. \tag{9}$$

Thus, our estimator of RV_t is defined as

$$RV_t = \lambda \mathrm{RV}^{\Xi}_{[a,b]}. \tag{10}$$

B Appendix to Chapter 2

B.1 Data Description

Table B1 summarizes the data used in our experiment covering the period from January 1, 1980 to December 31, 2007. The format of the table is *name* and *code*, as used in the source databases (Thomson Datastream and Bloomberg), as well as a brief *description* of each time series.

Table B1: Summary of Applied Time Series

Name	Code	Description
S&P 500 Composite	S&PCOMP	Index Price
S&P 500 E/P	S&PCOMP(PE)	Earnings-to-Price Ratio - S&P 500
S&P 500 DY	S&PCOMP(DY)	Dividend Yield - S&P 500
S&P 500 B/M	N/A	Book-to-Market Ratio - S&P 500
Fed Funds Rate	FRFEDFD	US Federal Funds Rate (Effective) (% Per Annum)
Discount Rate	USFDTRG	US Federal Funds Target Rate (% Per Annum)
AAA Bond	Y70461	Moody's US AAA Corporate Bond (% Per Annum)
BAA Bond	Y70462	Moody's US BAA Corporate Bond (% Per Annum)
3-Mo. T-Bill	FRTBW3M	U.S.Treasury Bills, 2nd Market, 3-Mo.(% Per Annum)
6-Mo. T-Bill	FRTBW6M	U.S.Treasury Bills, 2nd Market, 6-Mo.(% Per Annum)
1-Yr. T-Bond	S02556	U.S.Treasury Const. Maturities 1-Yr. (% Per Annum)
2-Yr. T-Bond	S02557	U.S.Treasury Const. Maturities 2-Yr. (% Per Annum)
5-Yr. T-Bond	S02559	U.S.Treasury Const. Maturities 5-Yr. (% Per Annum)
10-Yr. T-Bond	S02561	U.S.Treasury Const. Maturities 10-Yr. (% Per Annum)
30-Yr. T-Bond	S02562	U.S.Treasury Const. Maturities 30-Yr. (% Per Annum)
CBOE Put/Call Ratio	PCUSSPXR Index	CBOE Put/Call Ratio
CBOE VIX	T59165	Implied Volatility Index for S&P 500 Index Options

B.2 Parameterization for Simple Rules

Table B2 presents parameter values/thresholds x for each indicator used in our experiment. As described in the text, the moving averages over $5, 10, 20$, and 60 days and the $80^{\text{th}}/20^{\text{th}}$, $90^{\text{th}}/10^{\text{th}}$, and $95^{\text{th}}/5^{\text{th}}$ percentiles over the preceding 250 days are used as (standard) threshold values. For indicators that trigger selling the index when reaching high values, the 80^{th}, 90^{th}, and 95^{th} percentiles are used. The 5^{th}, 10^{th}, and 20^{th} percentiles are used for indicators that trigger switching to cash by reaching low values. In Table B2, we list only the additional threshold values x specific for each rule. We use the notation $x = [\textit{lowest value} : i : \textit{highest value}]$ to indicate that threshold values increase from *lowest value* to *highest value* in increments of i. For each indicator, we consider holding a certain position for a period of c days (waiting period), during which all other signals are ignored. Alternatively, a time-delay filter is implemented, which requires that a buy/sell signal has to remain valid for d days before a transaction is made. In our experiment, we consider parameter values $c = [1, 2, 5, 10, 20, 30]$ and $d = [1, 2, 5, 10, 20, 30]$.

Table B2: Parameter Values for Simple Rules

Indicator	Threshold Values
Financial Ratios	[0.02 : 0.01 : 0.12] for E/P
	[1 : 0.25 : 3] for DY
	[1 : 0.05 : 1.75] for B/M
Short-Term Interest Rates	[8 : 0.25 : 15]
Long-Term Interest Rates	[8 : 0.25 : 15]
Maturity Spread	[−3 : 0.25 : 1]
Expected Inflation	[0 : 0.25 : 1.5]
Credit Spread	[2 : 0.1 : 4]
Put/Call Ratio	[1 : 0.25 : 5]
Implied Volatility	[15 : 1 : 45]
Bond-Equity Yield Ratio	[1 : 0.05 : 1.8] for E/P and 3-Mo. T-Bill
	[1.5 : 0.05 : 2.4] for E/P and 10-Yr. T-Bond
	[2.5 : 0.25 : 5.5] for DY and 3-Mo. T-Bill
	[3 : 0.25 : 6] for DY and 10-Yr. T-Bond
Dividend Payout Ratio	[0.35 : 0.015 : 0.5]

B.3 Parameterization for Complex Rules

Learning Rules

The following parameter values for the evaluation period e and the review span r of the learning rules are used:

$e = [1 : 5 : 120, 130 : 10 : 250]$[29] and

$r = [1 : 5 : 120, 130 : 10 : 250]$.

Voting Rules

The following parameter values for the review span r and the proportion interval b of the voting rules are used:

$r = [1 : 5 : 120, 130 : 10 : 250]$ and

$b = [0.2 : 0.05 : 0.8]$.

[29] We use this notation to indicate that parameter values increase from 1 day to 120 days in increments of 5 days and from 130 days to 250 days in increments of 10 days. The same notation is used analogously for parameter values for the evaluation period and the proportion interval.

C Appendix to Chapter 3

C.1 Representative Press Release Headlines

Here we provide some examples of typical press release headlines within each news category. More than one example is given for some categories to achieve higher representativeness.

1. **Awards**

   (a) **Company Award**

   Dell Inc. (DELL) 26-04-2006 12:00:05 Dell Receives Top U.S. Government Award for Workplace Diversity Efforts

   Constellation Engy (CEG) 31-03-2006 9:44:40 Baltimore Gas and Electric Company Ranks Highest in the East Region With Business Customers According to the 2006 J.D. Power and Associates Electric Utility Business Customer Satisfaction Study

   (b) **Product Award**

   Oracle Corp. (ORCL) 07-06-2006 8:02:20 Oracle's Siebel Universal Customer Master Wins 'Gold Award' for Master Data Management in Bloor Research Study

   Xerox Corp. (XRX) 13-06-2006 6:00:01 Xerox Imaging and Repository Operations Earn ISO/IEC 27001 Accreditation for Security

2. **Corporate Strategy and Profitability**

   (a) **Credit News - Negative**

   Affiliated Computer Services, Inc. (ACS) 20-03-2007 15:49:27 Fitch Places Affiliated Computer Services on Rating Watch Negative on LBO Offer

   (b) **Credit News - Positive**

   Gasco Energy Inc. (GSX) 30-03-2006 16:15:27 Gasco Energy Secures Revolving Line of Credit

   Autonation Inc. (AN) 03-04-2006 8:47:50 AutoNation, Inc. Receives Lender Commitments for $600 Million Term Loan

   (c) **Exchange Noncompliance**

   Circuit City Stores, Inc. (CCTYQ) 30-10-2008 16:05:00 Circuit City Stores, Inc. Receives Notification from NYSE about Non-Compliance with a Continued Listing Standard

   (d) **Infrastructure - Downsizing**

   Furniture Brands International, Inc. (FBN) 05-02-2006 16:46:01 Thomasville Furniture Industries Announces Closing of Case Goods Manufacturing Facility

   PT Centris MultiPersada Pratama Tbk (CMPP) 05-03-2006 9:46:01 Champps Entertainment Announces Closure of Underperforming Restaurants

Arapaho Capital Corp. (AHO) 07-06-2006 17:13:53 Ahold intends to divest 46 Tops stores in Northeast Ohio

(e) **Infrastructure - Expansion**

Verizon Communications Inc. (VZ) 25-04-2006 8:57:07 Verizon Wireless Expands Its Network in Rensselaer County

Centerra Gold Inc. (CG) 29-03-2006 8:30:02 Centerra Gold Continues to Expand Kumtor SB Zone and Adds 1 Million Ounces of Reserves at the Gatsuurt Project

(f) **Profitability - Declining**

Williams-Sonoma, Inc. (WSM) 08-01-2009 06:00:03 Williams-Sonoma, Inc. Announces a 22.6% Decrease in 2008 Holiday Revenues

(g) **Profitability - Improving**

Abercrombie & Fitch Co. (ANF) 12-22-2008 9:30:25 Continues to Grow in Product Offerings, Customer Base and Profitability

3. **Customers and Partnerships**

(a) **Customer Loss**

America Service Group Inc. (ASGR) 21-08-2006 18:30:25 America Service Group to Terminate Contract with Florida Department of Corrections

(b) **Customer Win**

Electro Scientific Industries, Inc. (ESIO) 25-04-2006 21:22:01 ESI Receives Follow-on Multi-System Order from Hynix Semiconductor Inc. for Its Model 9830 Semiconductor Link Processing System; 9830 Order Furthers ESI's Momentum in the Asia Market

The Boeing Company (BA) 25-04-2006 5:00:33 Singapore Aircraft Leasing Enterprise Orders 10 More Boeing 737s

(c) **New Partnership**

Independence Holding Company (IHC) 25-07-2006 16:21:44 Independence Holding Company Announces New Relationship with Carolina Benefit Administrators to Market and Administer Group and Individual Major Medical

Dolby Laboratories, Inc. (DLB) 31-07-2006 8:00:51 Dolby Announces Deal With Infitec GmbH to Provide 3-D Technology for Dolby Digital Cinema; New technology to Provide High-Quality and Flexible Digital 3-D Solution

(d) **Reaching a Milestone**

Cyberonics, Inc. (CYBX) 05-01-2006 16:01:44 Cyberonics Announces 1,100th Patient Treated With VNS Therapy(tm) for Treatment-Resistant Depression (TRD) Since FDA Approval

4. **Financial**

   (a) **Dividend**

   NSC Groupe SA (NSC) 25-04-2006 9:41:49 Norfolk Southern Declares Quarterly Dividend

   Holly Energy Partners, L.P. (HEP) 25-04-2006 6:45:29 Holly Energy Partners Declares Distribution; Increases Quarterly Distribution From $0.625 to $0.64 Per Unit

   (b) **Financial Results - Strong**

   Kennametal Inc. (KMT) 26-04-2006 7:30:39 Kennametal Reports Strong Third Quarter

   (c) **Financial Results - Weak**

   Silicon Motion Technology Corp. (SIMO) 27-04-2006 17:00:43 Silicon Motion Technology Corporation Announces First Quarter Results for the Period Ended March 31, 2006: Market Conditions Contribute to Sequential Weakness but Growth Expected to Pick Up in Q2

   (d) **Pre-Announcement - Negative**

   Keynote Systems, Inc. (KEYN) 04-03-2006 7:30:02 Keynote's Preliminary Second Quarter 2006 Revenue Below Expectations

   (e) **Pre-Announcement - Positive**

   OM Group, Inc. (OMG) 25-04-2006 7:01:50 OM Group Increases Outlook for 2006 First Quarter Earnings Per Share

   (f) **Restatement**

   Richardson Electronics, Ltd. (RELL) 04-04-2006 19:00:27 Richardson Electronics, Ltd. to Restate its Financial Statements

   (g) **Secondary Offering: Debt**

   Dean Foods Company (DF) 05-10-2006 6:30:27 Dean Foods Announces Launch of $300 Million Senior Notes Public Offering

   (h) **Secondary Offering: Equity**

   Kimco Realty Corporation (KIM) 30-03-2006 8:01:40 Kimco Announces Offering of 10 Million Shares of Common Stock

   (i) **Share Buyback**

   AO Smith Corp. (AOS) 02-20-2007 11:00:00 A. O. Smith Announces Stock Repurchase Program

   (j) **Stock Split - Forward**

   Cascade Financial Corporation (CASB) 25-04-2006 20:00:10 Cascade Financial Corporation Declares 5-for-4 Stock Split

   (k) **Stock Split - Reverse**

   Idera Pharmaceuticals, Inc. (IDRA) 22-06-2006 9:00:12 Idera Pharmaceuticals to Effect a Reverse Stock Split

5. **Legal**

   (a) **Class Action**

   Pixelplus Co., Ltd. (PXPL) Shareholder Class Action Filed Against Pixelplus Co., Ltd. by the Law Firm of Schiffrin & Barroway, LLP

   (b) **Legal Problems**

   LifePoint Hospitals, Inc. (LPNT) 17-04-2006 14:07:01 Dissident Stockholder Files Suit against LifePoint Hospitals, Inc.

   (c) **SEC Investigation**

   One Liberty Properties, Inc. (OLP) 21-06-2006 16:30:01 One Liberty Properties Receives Notification of Formal Investigation from the SEC

   (d) **Settlement**

   Freddie Mac (FRE) 18-04-2006 15:53:42 Freddie Mac Settles With Federal Election Commission

6. **M&A**

   (a) **Acquisition**

   Plains Exploration & Production Company (PXP) 24-04-2006 7:58:41 PXP Announces Agreement to Acquire Stone Energy and Elimination of 2007 and 2008 Crude Oil Collars

   (b) **IPO**

   Stoneridge, Inc. (SRI) 23-10-2007 16:47:00 Stoneridge, Inc. Announces Brazilian Joint Venture IPO Filing

   (c) **Merger**

   Gerdau Ameristeel Corporation (GNA) 28-04-2006 16:14:05 Sheffield Steel Announces 53% Shareholder Agreement of Merger With Gerdau

   (d) **Spinoff**

   Level 3 Communications, Inc. (LVLT) 20-07-2006 16:19:01 Level 3 Signs Agreement to Sell Software Spectrum Subsidiary for $287 Million

7. **Management**

   (a) **Addition**

   Guest-Tek Interactive Entertainment Ltd. (GTK) 25-04-2006 9:03:26 Lottery Industry Veteran Connie Laverty Joins GTECH as Senior Vice President and Chief Marketing Officer

   (b) **Compensation**

   Duke Energy Corporation (DUK) 04-06-2006 16:05:31 Duke Energy Releases Details of CEO Compensation Package

(c) **Promotion**

EMCOR Group, Inc. (EME) 04-03-2006 10:32:01 Mark A. Pompa to Succeed Leicle E. Chesser as Chief Financial Officer of EMCOR Group; Mr. Chesser to become Vice Chairman of EMCOR Group, to retire at the end of 2006

(d) **Reorganization**

PepsiAmericas, Inc. (PAS) 15-05-2006 17:01:05 airforce(R) Nutrisoda(R) Announces New Management Team

(e) **Retirement**

Safeguard Scientifics, Inc. (SFE) 24-05-2006 11:37:01 Safeguard Scientifics Announces Retirement of Directors Anthony L. Craig and Robert Ripp

(f) **Termination**

Energy Partners, Ltd. (EPL) 19-04-2006 18:07:01 EPL Announces Departure of David Looney as Chief Financial Officer

8. **Meetings and Events**

(a) **Company Sponsored**

Arrow Electronics, Inc. (ARW) 26-04-2006 17:16:01 Arrow Electronics Works with Technology Suppliers to Facilitate 2006 Open Architecture Seminars

(b) **Industry Event**

Aspect Medical Systems, Inc. (ASPM) 25-04-2006 9:45:01 Aspect Medical to Webcast Presentation at Deutsche Bank 31st Annual Health Care Conference on May 2, 2006

(c) **Investor Meeting**

N S Group Inc. (NSS) 16-06-2006 9:26:01 NS Group to Present at the NIRI Regional Investor Conference in Cincinnati, Ohio; Presentation June 20th

9. **Products and Services**

(a) **FDA Approval**

General Electric Company (GE) 20-04-2006 9:00:07 U.S. FDA Approves GE Healthcare's Next-Generation Digital Mammography System for Improved Breast Care

(b) **FDA Investigation**

Pharmacyclics, Inc. (PCYC) 05-09-2006 7:30:56 Pharmacyclics to Submit New Drug Application for Xcytrin(R) for Treatment of Lung Cancer Patients With Brain Metastases

(c) **FDA Rejection**

Cephalon, Inc. (CEPH) 08-09-2006 17:02:18 Cephalon Receives Non-Approvable Letter on SPARLON(TM)

(d) **New Product**

Nokia Corporation (NOK) 25-04-2006 5:44:57 Digitally Divine Nokia N73 - the Ultimate Challenge to the Digital Camera

(e) **Patent Award**

Assurant, Inc. (AIZ) 28-06-2006 12:50:04 Assurant Awarded Patents for Call Processing System

(f) **Pharmaceutical Approval EU**

Biogen Idec Inc. (BIIB) 29-06-2006 2:30:21 TYSABRI(R) Receives Approval in European Union for the Treatment of Relapsing Remitting Forms of Multiple Sclerosis

(g) **Product Approval**

Broadridge Financial Solutions Inc. (BR) 11-10-2008 9:26:51 Broadridge Financial Solutions Receives ISO 27001 Certification for Information Security Management Systems

(h) **Product Defect**

Johnson & Johnson (JNJ) 31-03-2006 17:08:26 Ortho-Clinical Diagnostics Issues a Voluntary Product Recall for VITROS(R) Immunodiagnostic Products Signal Reagent

(i) **Research Failure**

Bristol Myers Squibb Co. (BMY) 18-05-2006 14:00:30 Bristol-Myers Squibb Announces Discontinuation of Development of Muraglitazar, an Investigational Oral Treatment for Type 2 Diabetes

(j) **Research Success**

Somaxon Pharmaceuticals, Inc. (SOMX) 04-10-2006 6:01:04 Somaxon Pharmaceuticals Announces Positive Phase 3 Results with SILENOR(TM) for the Treatment of Adults with Chronic Insomnia

(k) **Updates & Upgrades**

Sony Corporation (SNE) 06-01-2006 13:00:28 Sony Strengthens BRAVIA Flat-Panel LCD Line With Full HD Models and 1080p Inputs

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