# Studies on Stock Market Efficiency

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Für meinen Vater und alle die,

die meine Launen ertragen haben.

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## 1. Preface

This dissertation consists of three empirical studies on capital market efficiency in a broader sense. Two of the three papers are dedicated to the examination of short-term stock-returns in the wake of large one-day price changes – positive or negative. If significant abnormal returns can be found after large price changes this may indicate improper information efficiency. One if not the only way for listed companies do disseminate information is via investor relations. The release of ad-hoc statements levels the informational playing field for all investors and should thereby help to prevent overreaction or return drift. The third paper deals on the one hand with the causality chain of investor relations and liquidity and on the other hand with the question if insider trading and investor relations are positively correlated.

The literature on short-term returns after large one-day price changes has its roots in the literature on long-term overreaction: DeBondt and Thaler (1985) could show that the best performing stocks of a three-year-period underperform the stock market during the three following years. That phenomenon was termed overreaction. Inspired by this study for long-run stock returns, other authors like Atkins and Dyl (1990) and Bremer and Sweeney (1991) document short-term market overreaction after large one-day price changes of more than ten percent in either direction on the US stock market. International studies on overreaction were published for Japan (Bremer et al., 1997) and Hong Kong (Otchere and Chan, 2003). Although there exist numerous studies on the US market by Cox and Peterson (1994), Pritamani and Singal (2001), Larson and Madura (2003), and Sturm (2003), there was no study concerning short-term overreaction for the German stock market. The first paper of this dissertation closes that gap. Building on the earlier studies for the US market by Atkins and Dyl (1990) and Bremer and Sweeney (1991) it shows that there is a short-term overreaction after large one-day price changes of ten percent or more on the German stock market. That means that German stocks earn on average a significantly positive (negative) abnormal return on the trading day after a price decrease (increase) of more than ten percent. This phenomenon can be found among large caps (constituents of the DAX30 index) mid-caps (MDAX), small caps (SDAX), and technology stocks (NEMAX50/TecDAX) for the years since index inception. Like in the US the reaction to large one-day price changes is asymmetric on the German stock market. The abnormal returns after price decreases are economically and statistically more significant than after price increases. The results show, however, that it is not possible to implement a trading strategy of buying stocks with one-day price decreases of more than ten percent to exploit the overreaction.

During the literature review for the first paper it became clear that the literature provided no comprehensive study of the short-term stock returns after large one-day price changes for emerging markets. This study is represented by the second paper of this dissertation. It contains an analysis of short-term reactions to price shocks in 22 emerging country stock markets grouped in four geographic regions (Asia, Eastern Europe, Latin America, Middle East and Africa). Apart from the changed geographical focus the second paper is also different from the first with regard to the methodology. The methodology of the first paper is enhanced in three ways. First, the absolute event definition of the earlier literature that was also used in the first paper is replaced by a relative event definition. In the earlier papers a large price change is every price change with an absolute stock return of more than ten percent. By the relative definition that was first used by Pritamani and Singal (2001) a large price change is defined as a daily return that is more than three standard deviations away from the expected return. This definition is better suited to deal with the heterogeneous samples from different countries. That becomes evident if one compares for example the average large price decrease in Morocco, which is -5.7%, with the average large price decrease in Malaysia, which is -13.85%. Second, the expected return for the day of the large price change is calculated with a market model for an estimation period that ranges from 260 days to 10 days before the large price change. The expected return of the model is adjusted with the methodology of Dimson (1979), using a window of 5 days before and after the day with the large price change. Third, abnormal returns are not measured by plain t-statistics, but with the methodologies of Boehmer et al. (1991) and Corrado and Zivney (1992). The use of the more sophisticated test statistics renders it possible to account for higher volatility that is observed before and after large one-day price changes.

The main finding of the second paper is that, in contrast to developed markets, overreaction cannot be found persistently in emerging markets. Instead, stock return drift is the prevalent phenomenon. That means that stocks earn on average significantly positive abnormal returns after price jumps and significantly negative abnormal returns after price drops. Moreover, abnormal returns in emerging markets are more economically and statistically significant after price jumps, which stands in contrast to the results for developed markets, too. The analysis of size sub-samples shows that the extent of the return drift after large one-day price changes depends to a large extent on company size.

The third paper examines the interaction of investor relations, insider trading, and liquidity. Earlier literature by Amihud and Mendelson (1986 and 1988), Lev (1988), and Diamond and Verrecchia (1991) suggests that a firm's disclosure policy influences the liquidity of its stocks. In that context disclosure comprises all means by which information about that firm is made public. The three components of disclosure that are differentiated in the literature are annual reports, quarterly reports and investor relations (Lang and Lundholm, 1993). Investor relations comprise all activities that are undertaken by companies on an irregular basis. While most of the earlier studies focus on the relationship between either disclosure in general or investor relations and liquidity, Hong and Huang (2005) propose a model that links investor relations with liquidity and insider trading.

In the model by Hong and Huang insider trading and investor relations are intertwined, the common denominator being liquidity. The model suggests that investor relations activities are a means for company insiders to create liquidity for their own shares. The line of argumentation is as follows: stakeholders that have discretionary power over the investor relations policy have an incentive to overspend on investor relations if their advantages from higher liquidity outweigh the costs of increased investor relations efforts. Because the costs of investor relations are shared equally by all shareholders, those stockholders with large liquidity needs, for example company founders or board members have the most to gain from higher liquidity. This is due to liquidity discounts that buyers and sellers of blocks of shares face because of a lack of market depth.

The third paper is the first paper to provide empirical evidence for the model by Hong and Huang. It tests two hypotheses on the German stock market. The first hypothesis is that investor relations are a means to create liquidity and that good investor relations lead to higher liquidity. This hypothesis is based on earlier papers by Amihud and Mendelson (1986 and 1988), Lev (1988), Diamond and Verrecchia (1991), Lang and Lundholm (1996), Francis et al. (1997), Brennan and Tamarowski (2000), and Leuz and Verrecchia (2000). The second hypothesis is that firms with better investor relations are more prone to insider trading than those with worse investor relations. That hypothesis is based on the predictions of the model by Hong and Huang.

German data from 2003 through 2007 support both hypotheses. Regarding the first hypothesis it can be shown that companies with good investor relations enjoy higher liquidity as measured by Amihud (2002) ratios, spreads, share trading volume, and stock return volatility. Regarding the second hypothesis it can be shown that companies with heavy insider trading are more likely to have good investor relations than those with less insider trading. Even more surprising, the data suggest that good investor relations come along with subpar accounting quality. Therefore, it cannot be ruled out that large stakeholders put large efforts in investor relations and at the same time exert an influence on accounting policy to be diffuse. As a consequence investors should shy away from an investment in these companies' stocks. In contrast to earlier studies on the US market it is not possible to substantiate any relationship between a stock's return and the investor relations policy.

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## 2. Short-Term Market Overreaction on the Frankfurt Stock Exchange

(with Sebastian Lobe)

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**Abstract**

This paper offers out-of-sample evidence of subsequent short-term abnormal returns for stocks experiencing a price change of ten percent or more in either direction on the German stock market between 1988 and 2007. First, we find significant evidence of overreaction which is not exclusively concentrated in small-caps. Second, some well documented anomalies and stock characteristics seem to exhibit explanatory power. However, when controlling for size only a reversal effect can pervasively explain the abnormal 1-day stock market reaction to price shocks. Third, due to transaction costs and unpredictable market sentiment these anomalies can hardly be exploited. After all, our robust findings suggest no violation of the efficient market hypothesis.

JEL classification: G14, G01, G15

*Keywords:* Overreaction, price shocks, anomalies

## 2.1. INTRODUCTION

Since the beginning of the 1980s, there has been a lot of research on capital market anomalies like the size effect, the turn-of-the-year effect, the weekend effect and overreaction, which seem to contrast the Efficient Market Hypothesis (EMH). The aim of this paper is to provide out-of-sample tests of short-term reactions to price shocks on the German stock market. The paper is organized as follows. The next two subsections present a literature review on long-term and short-term overreaction. Section 2 describes the sample, provides our research questions and methodology. In section 3 we present and discuss the results. Section 4 concludes.

### 2.1.1. Related Literature: Long-Term Overreaction

DeBondt and Thaler (1985) inspired most other research on overreaction when they found that the 35 loser stocks of a five-year portfolio formation period on average outperformed the 35 winners over the following three years. Furthermore, they offered proof of asymmetric overreaction to new information, with losers exhibiting positive abnormal returns and winners earning negative abnormal returns compared to the market. Since then, international evidence of long-term overreaction was reported for example by Stock (1990) for the German market.

Trying to explain overreaction, some researchers, like Zarowin (1990), dismiss the overreaction phenomenon as a manifestation of the size effect, which is reported in the seminal work by Banz (1981). Zarowin (1990) could show that smaller winners, in terms of market capitalization, outperformed larger losers and vice versa. Conrad and Kaul (1993) contend that the perceived overreaction in long-term studies was due to arithmetical errors because DeBondt and Thaler (1985) and other researchers, following their methodology, report cumulated abnormal returns instead of buy-and-hold abnormal returns. However, research from several countries, such as that by Alonso and Rubio (1990) from Spain, daCosta (1994) from Brazil, Meyer (1994), Mun et al. (1999), and Schiereck et al. (1999) from Germany, or by Baytas and Cakici (1999), who examine seven developed countries, finding overreaction in all but the United States, shows that long-term overreaction is persistent even when the critic's arguments are accounted for.

### 2.1.2. Related Literature: Short-Term Overreaction

In the first study of daily overreaction, Arbel and Jaggi (1982) cannot find significant abnormal returns for stocks that are placed on the Wall Street Journal's Winner-Loser list. Using the same procedure, Atkins and Dyl (1990) show that losers earn average positive abnormal returns the next day, whereas the average abnormal return for winners is negative. Despite the significant abnormal returns, Atkins and Dyl (1990) argue that this overreaction was no violation of the EMH as it could not be exploited because of bid-ask spreads.

Bremer and Sweeney (1991) study price decreases only and implement a slightly different approach, defining event days for a stock by an absolute daily trigger return of -10%. They document return reversals as well, with an average abnormal return of 1.773% on the first day after an event and a cumulated abnormal return of 2.215% over the two days after the price shock. Cox and Peterson (1994) find significant reversals of 1-day price decreases, too, but only for the period before 1987. They therefore conclude that overreaction vanishes with rising market liquidity. However, Ma et al. (1998) document overreaction after 1987 for NASDAQ stocks, with a more pronounced overreaction of losers and smaller companies.

Contradicting evidence comes from Larson and Madura (2003), who find that instead of overreacting the market in general was too optimistic. Using the same methodology as Bremer and Sweeney (1991), they show that winners as well as losers earn significantly negative abnormal returns during the period from 1988 until 1995. Using monthly data, Ising et al. (2006) come to the same conclusion for the German stock market.

For the period between 1990 and 1992, Pritamani and Singal (2001) find underreaction to price shocks, with abnormal returns of 0.25% for winners and -0.29% for losers on day one after an event. Taking round-trip transaction costs of 0.5% into account, this underreaction is not exploitable. Neither Larson and Madura (2003) nor Pritamani and Singal (2001) document an influence of size on the reaction to price shocks.

Sturm (2003) offers more recent evidence of overreaction after negative price shocks. He is unable to find any significant reaction to positive events. Furthermore, he tests how company fundamentals like Earnings per Share (EPS) and Book Value per Share (BVPS) influence the market reaction to price shocks. He finds that EPS under some conditions have a positive influence on post-event returns, whereas BVPS cannot explain much of the price movements subsequent to events.

There are fewer studies of short-term overreaction outside the US than of long-term overreaction. Among them, Bremer et al. (1997) document short-term overreaction in Japan. Otchere and Chan (2003) find overreaction in Hong Kong during the period before the Asian crisis, too. But the reversals were not large enough to be exploited.

Although the German stock market is one of the largest stock markets of Continental Europe in terms of turnover and market capitalization there exists to the best of our knowledge no study on short-term overreaction on the cross-section of German stocks so far. We contribute to the literature in three ways. First, we provide evidence of short-term overreaction on the German stock market, and determine whether it is a size-related phenomenon. Second, we analyze whether other anomalies and characteristics correlate with the stock's reaction to price shocks. Third, we investigate the potential of implementing a profitable trading strategy based on the market reaction to price shocks.

## 2.2. SAMPLE AND METHODOLOGY

### 2.2.1. Sample

To avoid bid-ask-spreads and illiquidity biasing the sample towards overreaction, as reported by Cox and Peterson (1994), we take four measures. The first is to study only stocks belonging to one of the four major German stock indices traded on the Frankfurt Stock Exchange. These stocks are the most liquid in Germany, because index members are selected according to market capitalization and free float[1]. Secondly, following the methodology of Bremer and Sweeney (1991), stocks with a price of less than €10 are excluded from the sample to avoid biases caused by low stock prices and higher proportional bid-ask spreads. Stocks with a price of less than €10 are more likely to experience events because the tick size in percent of the price is higher than for more expensive stocks. The threshold value of ten monetary units, whether in US dollars or euros, which is chosen in most studies of short-term return reversals is somewhat arbitrary but can be interpreted as a psychological barrier for investors. Stocks with a price of less than ten monetary units are traded less frequently and are therefore less liquid than more expensive stocks. The third measure is to eliminate all stocks that do not show any non-zero return on at least four out of the five trading days after an event to avoid the inclusion of illiquid stocks. Finally, all events that occur on a company's dividend date or in the five preceding days are eliminated from the sample. Although Bremer et al. (1997) argue in a study of the Japanese market that the bias is negligible because only 8% of the positive events and 17% of the negative events occur near the ex-dividend date, in this study ex-dividend dates are removed to avoid the bias caused by the stock price loss due only to the dividend payment which could otherwise be mistakenly attributed to the event or the reversal.

The final sample consists of the returns of all constituents of the four major German stock indices since inception of the respective index. The examined period starts on January 1, 1988 for the DAX30, the index of the 30 largest German companies in terms of free-float and market capitalization. For the MDAX, the index of mid-caps, the screening starts on April 11, 1994. For

[1] See Deutsche Börse Group (2010) for further details.

constituents of the small-cap index SDAX and the technology index NEMAX50 the screening begins on July 1, 1999. On March 24, 2003 the NEMAX50 was replaced by the TecDAX[2]. The period examined ends on February 28, 2007 for all indices. Companies dropping out of an index are replaced by their successors at the date of the index change. From that date on, the return of the new index member is included in the analysis. Data on the index companies is hand-collected. A lot of research papers dealing with index constituents base their sample composition only on current index membership. Such a procedure induces many biases, e.g., such as the survivorship bias, which our study, however, is not prone to.

Returns come from DataStream International. In total, the study screens 565,462 daily return observations. How these return observations are distributed among the indices is shown in Table 1. Following Bremer and Sweeney (1991), days with a price change of more than 10% in either direction for a single stock are referred to as event days for that stock. The total number of event days over all indices and time periods considered is 3,765, of which 2,239 (about 60%) are price increases and 1,526 are price decreases. The distribution of the events among the respective indices can also be found in Table 1. If events happen to be within five trading days after another event, these events are referred to as reaction events.

To see whether the existence and the degree of return reversals is dependent on size or vanishes over time, as proposed by Cox and Peterson (1994), the total sample of events is split into four time periods. The comparison of the sub-periods can show whether the reversals become weaker when markets become more liquid. The time periods are chosen to coincide with the inception dates of the single indices.

[2] The NEMAX50 was suspended after the technology stock bubble burst and the index had lost more than 90% of its peak value in 2003. The TecDAX replaced the NEMAX50 as the German index for technology stocks.

To elaborate whether overreaction is a size phenomenon two approaches are chosen. The first is to divide the whole sample into five index sub-samples, that is, one for each index. The comparison of differences in the event probabilities and reversals in each of the index sub-samples can show whether there is a size effect, because the index membership is dependent on market capitalization and free-float, and therefore mainly, if not exclusively, on company size. The other approach is to include market value of equity in our regressions on post-event returns. For these regressions the sample is not divided into index sub-samples.

In order to investigate the possibility of asymmetric reactions to price increases and price decreases each of the eleven sub-samples is in turn split into three sub-samples – one for all events, one for price jumps, and one for price drops.

The simple net return for the first day after an event day t ($R_{i,t+1}$) and the buy-and-hold return for days 1 through 5 after each event ($R_{i,[t+1;t+5]}$) are calculated as

$$R_{i,t+1} = \frac{P_{i,t+1}}{P_{i,t}} - 1, \tag{1}$$

and $R_{i,[\mathrm{t+1;t+5}]} = \frac{P_{i,t+5}}{P_{i,t}} - 1,$ (2)

with $P_{i,t}$ denoting the closing price of stock i on event day t.

The average returns after the occurrence of price shocks are reported in Table 2 sorted into indices and sub-periods. More important, we calculate abnormal returns for every event stock compared to the respective index return (DAX30, MDAX, SDAX, Technology) for the first day after the event and over the five days following an event. These abnormal returns which are size- (respectively, industry-) and market-adjusted are calculated as

$$AR_{i,t+1} = R_{i,t+1} - R_{index,t+1}, \tag{3}$$

and $A_{i,[t+1;t+5]} = R_{i,[t+1;t+5]} - R_{index,[t+1;t+5]},$ (4)

respectively. For each sub-sample a t-test is conducted in order to establish whether the abnormal returns are significantly different from zero. If the size of a sub-sample is smaller than 30 observations, a Wilcoxon signed-rank test is used instead. To control for an individual stock's risk in our regression analysis, we also estimate the daily stock return volatility from a 60-trading day estimation window prior to the event i:

$$VO_{i,t} = \frac{1}{60-1}\sum_{t=-60}^{t=-1}\left(R_{i,t} - \bar{R}_i\right)^2 \qquad (5)$$

2.2 Factors influencing reversals

Having shown evidence of the existence of abnormal reversals, we run multivariate regressions to test whether anomalies and other stock characteristics influence the direction and the extent of the market's abnormal reaction to price shocks. Specifically, we test the influence of the abnormal event return itself (ER), the log of company size (MV), the log of the book-to-market ratio (BTM), the average (mean) daily return during the last 60 trading days (RET), the log of the price-earnings ratio (PE), and the estimated stock return volatility (VO) on post-event abnormal returns. Therefore, for each event stock, market value of equity (MV), number of shares (NOSH), book value per share (BVPS) and earnings per share (EPS) are obtained from WorldScope International. Prices (P), book-to-market ratios and price-earnings ratios are identified for each event stock on the event day. We control for size (MV) since the seminal work of Banz (1981) has shown its explanatory power for U.S. returns in the cross-section. To capture the value premium, we employ BTM as the premier value variable, and for robustness we also use PE in the spirit of Fama and French (1992). As a proxy for the momentum effect pioneered by Jegadeesh and Titman (1993) we refer to RET in line with Hong and Kacperczyk (2009). Finally, to account for stock-specific risk we include VO as outlined in equation (5). We regress these characteristics on $AR_{i,t+1}$ and $AR_{i,[t+1;t+5]}$, respectively. Hence, the regression equations are

$$AR_{i,t+1} = \beta_0 + \beta_1 ER_{i,t} + \beta_2 MV_{i,t} + \beta_3 BTM_{i,t} + \beta_4 RET_{i,t} + \beta_5 PE_{i,t} + \beta_6 VO_{i,t} + \varepsilon_{i,t} \qquad (6),$$

$$AR_{i,[t+1;t+5]} = \beta_0 + \beta_1 ER_{i,t} + \beta_2 MV_{i,t} + \beta_3 BTM_{i,t} + \beta_4 RET_{i,t} + \beta_5 PE_{i,t} + \beta_6 VO_{i,t} + \varepsilon_{i,t} \qquad (7)$$

for Model 1, where the subscripts i and t represent stock i and event day t, respectively. Regressions are run for each sub-sample (split into periods and events) with White (1980) heteroskedasticity-robust standard errors. The results of the multivariate regressions for Model 1 can be found in Table 3.

Furthermore, we run regressions on the different index sub-groups for each sub-period excluding the log of market value of equity (MV) as explanatory variable to capture the variation within a size group. The regressions take the form

$$AR_{i,t+1} = \beta_0 + \beta_1 ER_{i,t} + \beta_2 BTM_{i,t} + \beta_3 RET_{i,t} + \beta_4 PE_{i,t} + \beta_5 VO_{i,t} + \varepsilon_{i,t} \quad (8),$$

$$AR_{i,[t+1;t+5]} = \beta_0 + \beta_1 ER_{i,t} + \beta_2 BTM_{i,t} + \beta_3 RET_{i,t} + \beta_4 PE_{i,t} + \beta_5 VO_{i,t} + \varepsilon_{i,t} \quad (9)$$

labeled as Model 2. The results are reported in Tables 4 and 5.

As a robustness check to Model 1, we additionally incorporate in Model 3 R (=15) dummy variables for each relevant year (DRELYEAR) having more than 20 events[3]. We do this to account for possible seasonality effects of market reactions to price shocks. Model 3 is thus specified as

$$AR_{i,t+1} = \beta_0 + \beta_1 ER_{i,t} + \beta_2 MV_{i,t} + \beta_3 BTM_{i,t} + \beta_4 RET_{i,t} + \beta_5 PE_{i,t} + \beta_6 VO_{i,t} + B'\ DRELYEAR + \varepsilon_{i,t} \quad (10),$$

$$AR_{i,[t+1;t+5]} = \beta_0 + \beta_1 ER_{i,t} + \beta_2 MV_{i,t} + \beta_3 BTM_{i,t} + \beta_4 RET_{i,t} + \beta_5 PE_{i,t} + \beta_6 VO_{i,t} + B'\ DRELYEAR + \varepsilon_{i,t} \quad (11)$$

where B´ is the Rx1 vector of coefficients for the R relevant years. Results of the regressions including annual dummy variables are shown in Table 6.

### 2.2.2. Trading Strategy

The last step is to test whether trading strategies based on reactions to price shocks can beat the market. Due to short-selling restrictions for private investors in Germany we focus on strategies that could have been realized without short-selling only. Three trading strategies are

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[3] Only years with more than 20 events are included because otherwise the equation system cannot be solved properly.

implemented for each sub-sample: the first is to buy every stock that experiences an event at the end of the trading day and to sell it at the end of the next trading day. This strategy would have been successful if there had been overreaction to bad news and underreaction to positive news, as suggested from the uncertain information hypothesis by Brown et al. (1988). According to this, event stocks should earn positive returns after any kind of event. Hence, this strategy is referred to as uncertain information strategy. The second strategy is to buy losers at the end of the event day, which would have been successful if losers had overreacted, meaning if losers had earned positive returns after the price shock. We label this strategy as overreaction strategy. The momentum strategy, which would earn positive returns in the presence of momentum, that is, winners would earn positive returns on the post-event day, is to buy winners at the end of the event day and to hold them for one trading day.

Allowing for a realistic strategy, we restrict the holding period to one trading day only, because otherwise the problem of fixed capital could not have been avoided. If, for example, an investor were to buy a stock on the event day and to hold it for five days he would be unable to invest his money in another stock experiencing an event during the holding period, whereas with a one-day holding strategy it is possible to invest in event stocks on consecutive trading days. In the case of only one event the total capital is invested in the event stock. If more than one event occurs on the same trading day, the capital is split equally between the event stocks. The returns of the active strategies are compared to the passive buy-and-hold index returns during the corresponding period. The strategies are applied to each of the 33 sub-samples. We report the cumulated index return for the sub-samples of which the event stocks are index constituents of. The returns of our trading strategies are not compared to returns of a semi-active strategy where the index is bought at the end of an event day and sold at the end of the next day, because such investor behaviour is rather far-fetched: returns of such a strategy would have been negative in all but one sub-sample. Therefore, no rational investor would pursue such a semi-active trading strategy. The strategies of actively buying event stocks, be they winners or losers, are compared to the passive strategy of buying the respective index at the start of one sample period and holding it to the end of the sample period. The overall strategy return is the difference of the active versus the passive portfolio return during the analysed period. To account for the impact of trading costs all strategy returns are calculated also with trading costs deemed reasonable for private investors, that is, round-trip trading costs of 1%.

## 2.3. RESULTS

### 2.3.1. Descriptive Statistics

(Insert Table 1 here)

The overall event probability for the 30 largest German companies, the DAX 30 constituents, is fairly low with 0.19% over the whole examination period from January 1, 1988 to February 28, 2007. During that period a total of 276 events in the DAX30 were recorded. Despite the small number of events, in the five days following an event the probability of further events occurring rose to 4.53%. Events happening within these days are defined as reaction events. This reaction event probability remains stable for DAX30 companies over the whole period studied, although event probabilities are significantly different across the separate sub-periods. The event probabilities in the sub-periods range from 0.06% in the most recent period studied to 0.50% in the “Neuer Markt” period, the most volatile of all examined periods. Simple binomial tests show that probabilities for reaction events are significantly higher than event probabilities in all sub-periods.

For mid- and small-caps as well as for technology stocks the results are similar to those of the large-cap sub-samples. Across all indices event probabilities peak between 1999 and 2003. NEMAX50 constituents show the highest event probability of all sub-samples with 4.01%. The reaction event probability for those stocks even reaches 16.21% on each of the five post-event days. This means that four out of five NEMAX50 stocks which experience an event record another event within five days after the first price shock. In contrast to NEMAX50 stocks, TecDAX constituents are far less likely to experience events. Although they are still the most volatile stocks in the most recent examination period, their event probability of 0.35% is rather small compared to the 4.01% for technology stocks in the prior period. In this context it is important to note that 24 of the 30 original TecDAX constituents are former NEMAX50 members. Hence, from a more fundamental point of view, event probabilities should have been roughly equivalent for TecDAX and NEMAX50 over the two recent periods.

The event probabilities in all indices are significantly different from each other, whereas the differences in reaction event probabilities are not significant, indicating that if an event occurs, the probability for another event within five consecutive trading days is roughly the same across all indices. The probabilities for events and reaction events in each index can be found in Table 1.

### 2.3.2. Return Reversals

(Insert Table 2 here)

*Before 1999*

During the first period from 1988 to 1994, in which the sample consisted only of large-caps, average reaction returns to both kinds of price shocks are positive. The abnormal return after price decreases averages a significant 1.75% on the first trading day after an event. Over a five-day horizon this value increases to a significant 2.81% abnormal average return. The reaction to price increases is positive as well, although not significant.

In the following period, starting with the inception of the mid-cap index, the abnormal returns over the five trading days following price decreases (increases) are 3.03% (-0.48%) for large-caps and 2.89% (-1.77%) for mid-caps indicating overreaction.

*The "Neuer Markt" Era: 1999-2003*

Results for the bubbly "Neuer Markt" era suggest overreaction as well. MDAX, SDAX, and NEMAX50 show negative 5-day abnormal returns after price increases, and positive returns after price drops. The majority of these returns is economically and statistically significant.

*The recent period: 2003-2007*

Mid- and small-caps again overreact. MDAX stocks earn significantly negative abnormal returns of -1.38% (1 day) and -1.51% (5 days) after price increases and positive abnormal returns of 0.78% (1 day) and 1.53% (5 days) after price drops, albeit insignificant. SDAX constituents earn significant abnormal returns after any kind of event, with positive reactions to price decreases and negative reactions to price jumps. The reversals of small-caps in the most recent sample period are the most pronounced reversals of all sub-samples with returns of 3.56% on the post-event day and 4.51% during the five days following a price drop[4].

Overall, the significant results speak clearly for the overreaction hypothesis. Although there are differences in the behaviour of the constituents of the respective indices, we do not find persuasive evidence that abnormal returns are driven by a size effect when applying the proper size-adjusted market index. We do not find any signs of overoptimism in short-term reactions to price shocks, either. Therefore, our results are not in line with the findings of Larson and Madura (2003) for the US market and of Ising et al. (2006), who use monthly data of the German stock market. Throughout all periods the reactions to price shocks are asymmetric, meaning that the

[4] The DAX30 observations are removed from the last period in Panel B and C due to the very small number of observations.

abnormal returns are higher in absolute terms after price decreases. This is in line with earlier findings of Atkins and Dyl (1990) and Cox and Peterson (1994), as well as with the studies of long-term overreaction by DeBondt and Thaler (1985) and others.

### 2.3.3. Regression Results

#### *2.3.3.1. Model 1*

(Insert Table 3 here)

We investigate which factors are able to explain the abnormal 1-day return and the abnormal 5-day buy-and-hold return. In line with our prior findings, size is not able to explain the abnormal return behaviour.

For the abnormal 1-day return there seems to be no clear pattern for all events over the total sample period. However, when recognizing the nature of the event the past return (RET) is more than 2.32 standard errors from zero. RET is negatively correlated with abnormal returns after price increases (Panel B), but positively with abnormal returns after price drops (Panel C) thus canceling each other out in the total sample. This evidence can be interpreted as a reversal effect: a positive past return diminishes the abnormal event return after a price increase, but adds to the abnormal return after a price drop, and vice versa. This reversal effect also holds for the 5-day buy-and-hold return, however, to a lesser degree.

Other effects seem to have a much stronger impact on the abnormal 5-day buy-and-hold return. With regards to all events, Panel A reveals that the abnormal event return and past volatility are more than 2.49 standard errors from zero over the total sample period (last column). The volatility (VO) coefficient is negative implying that abnormal event returns are on average lower the higher the pre-event volatility is. A dissection of the total period shows that the results are mainly driven by the period 1994-2003. When further dividing the events, the volatility effect shows up over the total sample period for price increases (Panel B), and to a lesser extent for price drops (Panel C). The abnormal event return itself (ER) is negatively correlated with the abnormal 5-day buy-and-hold return. This pattern seems particularly strong since it holds irrespective of the time period or the nature of the event (price increase or price drop).

#### *2.3.3.2. Model 2*

(Insert Table 4 here)

The evidence so far seems to suggest that different reversal effects (RET, ER) and volatility (VO) are able to explain the abnormal event return behavior. However, it is paramount to test whether the results still hold when controlling for size groups. Are the anomalous patterns in abnormal returns marketwide or limited to relatively illiquid stocks representing only a small portion of the market portfolio?

Thus, we sort the events into size-related index groups ranging from big to small stocks, including technology stocks. The reversal effect (RET) within the abnormal 1-day return is particularly robust with respect to size as Panels B and C of Table 4 demonstrate confirming the prior results of Model 1.

(Insert Table 5 here)

Turning to the abnormal 5-day buy-and-hold return, the results clearly show that the reversal effect (ER) is driven by small-caps. The negative sign of the volatility effect (VO) is also mainly due to small-cap stocks and to a lesser extent to mid-cap stocks. The results for the 5-day buy-and-hold return across size groups are far from being pervasive.

#### *2.3.3.3. Further Robustness Checks*

Further robustness checks are carried out in this subsection to additionally control for seasonality and to test other variable definitions.

*Model 3:* In Model 3, we take seasonality into account. The main conclusions of Model 1 prevail although some degree of seasonality seems to be present entertaining the notion of market sentiment as a further possible driver.

(Insert Table 6 here)

*Other Models:* If we alternatively do not use log specifications our main findings stay unaltered. Likewise, removing the reversal effect (RET) leaves the remainder of the results intact.

We generally exclude BVPS and EPS as regressors from our models to avoid problems with multicollinearity, because BVPS and EPS are already used to calculate BTM and PE. Nevertheless, we run additional regressions, including EPS as a regressor, too, to ensure a better comparability with earlier findings by Sturm (2003). Whether Model 1 excluding EPS offers a better explanation for the data is decided according to the Akaike information criterion (AIC) and the Schwarz information criterion (SIC). When the two criteria lead to different results, where one prefers the model including EPS and the other does not, we base our decision on the SIC, because the AIC tends to prefer overparameterized models in contrast to the SIC and is therefore inconsistent in selecting the best model[5]. In the large majority of cases Model 1, that is, the model without EPS as explanatory variable, gave better estimates of stock returns on the days following an event. Hence, in contrast to the study by Sturm (2003), the inclusion of EPS does not improve the explanatory power of the model in our sample sufficiently to justify its inclusion.

#### *2.3.3.4. Summary*

Different reversal effects (RET, ER) and volatility (VO) seem to exhibit explanatory power. However, when controlling for size only a reversal effect (RET) can pervasively explain the

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[5] For a more detailed discussion of measures of fit, see Diebold (1998).

abnormal 1-day stock market reaction to price shocks. There is also some evidence that overall market sentiment could have an additional impact on abnormal returns. This will be an interesting topic for future research.

### 2.3.4. Trading Strategy Returns

(Insert Table 7 here)

Having documented the existence and an explanation of abnormal returns after price shocks on the German stock market, we examine the practically important question whether it is possible to implement a profitable trading strategy on these short-term anomalies.

#### *2.3.4.1. Uncertain Information Strategies*

Strategies of buying any event stock, regardless of the direction of the event would not have earned abnormal returns compared to the passive strategy of buying the index at the start of a period and holding it until the end of the period. Surprisingly, the strategy built on the uncertain information hypothesis would not have earned the highest returns in the sub-samples where the stocks behaved according to the hypothesis but in a sub-sample with significant overreaction, that is, in the mid-cap sub-sample of the "Neuer Markt" era. But even in that sub-sample, in which the strategy would have earned an absolute return of 128.0%, compared to an index return of -27.08%, the strategy would have returned 63.66% less than the index after accounting for trading costs of 0.5% per trade for a private investor. Due to the high trading frequency the absolute returns of the strategy and the returns after trading costs differ immensely.

#### *2.3.4.2. Momentum Strategies*

An investor following a momentum strategy would have bought the winners at the end of an event day and have sold them at the end of the following day. For the sub-samples, in which the stocks exhibit momentum, that is, those of large-caps and of NEMAX50 stocks during the "Neuer Markt"-period, this strategy would have earned positive absolute returns of 114.2% for

DAX30 constituents and an astonishing 616.6% for NEMAX50 stocks. The indices lost 49.52% (DAX30) and 91.83% (NEMAX50) during the same period. After trading costs, the momentum strategy for large-caps still would have earned an abnormal return of 69.88% compared to the index. For technology stocks the huge absolute return before trading costs would have shrunk to an abnormal return of 4.67% after trading costs. Considering the enormous losses of the NEMAX50 stock index during that time period, this equals a loss of more than 85% of the invested capital. Therefore, a momentum strategy could have been successfully implemented for large-caps only.

#### *2.3.4.3. Overreaction Strategies*

A strategy of buying losers at the end of the event day would not have earned any abnormal returns throughout all periods compared to the passive strategy of buying the index.

Even for sub-samples with significant return reversals the strategy for most of the time would not have even earned a higher absolute return than the index. Only the reversals of MDAX stocks from 1994 to 1999 and from 1999 to 2003 would have been large enough to generate higher absolute returns of the overreaction strategy with 22.98% and 65.11%, respectively, compared to the index returns of 57.15% and -27.08%. Nevertheless, accounting for trading costs a passive strategy would always have been the better choice compared to an overreaction strategy.

#### *2.3.4.4. Summary*

In only two cases out of the 33 sub-samples would an investor actively trading on events have earned higher returns after trading costs than a passive investor investing his money in the index. The two successful strategies would have been the momentum strategies for large-caps and for technology stocks in the bubbly period from 1999 to 2003. All other strategies would have been unsuccessful in generating excess returns compared to the index. Even the substantial overreaction to negative news, which can be found in all periods for mid- and small-caps, could not have been profitably exploited if the alternative had been an investment in the market portfolio.

Another problem of implementing the indicated trading strategies is that an investor could not have known in advance, which of the three strategies was best suited to the actual trading period, as different strategies would have been the most successful depending on the different sub-periods. Therefore, we can summarize that it is not possible to trade profitably on the reactions of German stocks to price shocks.[6]

## 2.4. CONCLUSIONS

First, this study establishes that German stocks which experience an event earn short-term abnormal returns afterwards. We find significant evidence of overreaction. The significant abnormal returns after price shocks do not become weaker over time. Hence, they cannot be explained by a lack of liquidity or the existence of bid-ask spreads. Another finding is that the reaction to price shocks on the German stock market is asymmetric; in other words the absolute values of the abnormal returns after price decreases are larger than those after price increases. This is in line with earlier findings for the US and other international stock markets. In contrast to longer-term studies we cannot offer evidence of overoptimism on the German market; that is, we do not find simultaneously negative abnormal returns after price increases and price decreases. Unlike others, we do not find that short-term overreaction is a small-firm phenomenon in our German sample, and establish this finding in various ways. Second, we analyse whether some well documented anomalies (e.g., value, momentum) and stock characteristics (e.g., volatility) exhibit explanatory power. Controlling for size, only a reversal effect can pervasively

[6] Results for a trading strategy, where event stocks are weighted according to their market capitalization, are not significantly different from those of the equally-weighted strategy.

explain the abnormal 1-day stock market reaction to price shocks. Third, abnormal returns of event stocks are not exploitable because the direction of the reaction cannot be foreseen and the existence of transaction costs prohibits the implementation of profitable trading strategies. After all, our robust findings suggest no violation of the efficient market hypothesis.

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## Table 1: Events and Event Probabilities: 1988-2007

This table shows in a summary statistic the event probabilities (EPs) of all index sub-samples. The whole sample is split into four sub-samples for each time period in order to ensure the comparability of the particular index samples. EP is calculated as the division of the trading days per index by the number of events. The reaction event probability (REP) is calculated as the number of reaction events divided by five times the number of events, because each event that occurs within five trading days after another event is defined as a reaction event. Z-value is the test statistic value of the binomial test of the hypothesis that REP is larger than EP in the respective sub-sample. One (two, three) asterisk(s) indicate(s) significance at the 90% (95%, 99%)-level.

| **Index** | **DAX 30** | | | | **MDAX** | | | **SDAX** | | **Technology Indices** | | **Total Sample** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | | **NEMAX50** | **TecDAX** | |
| **Period** | **1988-1994** | **1994-1999** | **1999-2003** | **2003-2007** | **1994-1999** | **1999-2003** | **2003-2007** | **1999-2003** | **2003-2007** | **1999-2003** | **2003-2007** | **1988-2007** |
| **Trading Days** | 47,070 | 39,240 | 28,410 | 30,210 | 91,560 | 66,290 | 50,350 | 84,422 | 50,350 | 47,350 | 30,210 | 565,462 |
| **Event Days** | 49 | 68 | 141 | 17 | 236 | 473 | 78 | 597 | 99 | 1,900 | 107 | 3,765 |
| **Event Probability (EP)** | 0.10% | 0.17% | 0.50% | 0.06% | 0.26% | 0.71% | 0.15% | 0.71% | 0.20% | 4.01% | 0.35% | 0.67% |
| **Positive Event Returns (Mean)** | 13.41 | 12.33 | 13.80 | 13.55 | 13.45 | 14.03 | 14.47 | 15.03 | 12.94 | 16.10 | 14.43 | 15.14 |
| **Negative Event Returns (Mean)** | -13.60 | -11.68 | -12.88 | -12.56 | -13.52 | -13.37 | -14.85 | -12.90 | -13.07 | -13.70 | -13.62 | -13.48 |
| **Reaction Events** | 7 | 17 | 35 | 4 | 41 | 180 | 7 | 325 | 14 | 1,540 | 21 | 2,191 |
| **Reaction Event Probability (REP)** | 2.86% | 5.00% | 4.96% | 4.71% | 3.47% | 7.61% | 1.79% | 10.89% | 2.83% | 16.21% | 3.93% | 11.64% |
| **Z-value** | 2.59*** | 4.08*** | 5.45*** | 2.02** | 6.03*** | 12.63*** | 2.44*** | 17.83*** | 3.53*** | 31.38*** | 4.25*** | 46.90*** |

## Table 2: Normal and Abnormal Post-Event Returns

This table shows the average (mean) post-event returns (%). The table splits the observations into different periods and indices ranging from big to small. Panel A presents all events, while Panels B and C divide the sample into price increases and price drops. $R_{i,t+1}$ and $AR_{i,t+1}$ are the normal and the abnormal return on the first day after an event, whereas $R_{i,[t+1;t+5]}$ and $AR_{i,[t+1;t+5]}$ are defined over the five trading days after an event. One (two, three) asterisk(s) indicate(s) significance at the 90% (95%, 99%)-level of the t-test. For sub-samples comprising less than 30 observations a Wilcoxon signed-rank test is conducted instead.

| **Period** | **1988-1994** | **1994-1999** | | **1999-2003** | | | | **2003-2007** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Index** | **DAX30** | **DAX30** | **MDAX** | **DAX30** | **MDAX** | **SDAX** | **NEMAX50** | **DAX30** | **MDAX** | **SDAX** | **TecDAX** |
| | | | | | **Panel A: All Events** | | | | | | |
| $R_{t+1}$ | 4.40 | 2.12 | 0.53 | 0.48 | 0.66 | 0.41 | 0.01 | -0.28 | 0.04 | 1.56 | 0.66 |
| $AR_{t+1}$ | 1.37*** | 0.70 | 0.42 | 0.21 | 0.65** | 0.33 | 0.04 | 0.07 | -0.19 | 1.57*** | 0.71 |
| $R_{[t+1;t+5]}$ | 8.56 | 2.48 | 0.48 | 1.12 | 0.87 | 0.13 | -0.12 | 4.97 | 0.78 | 1.20 | 1.94 |
| $AR_{[t+1;t+5]}$ | 2.20** | 0.81 | 0.15 | 0.09 | 0.63 | 0.02 | -0.53 | 2.54 | 0.16 | 0.95 | 1.32* |
| **Events (Total)** | 49 | 68 | 236 | 141 | 473 | 597 | 1,900 | 17 | 78 | 99 | 107 |
| | | | | | **Panel B: Price Increases** | | | | | | |
| $R_{t+1}$ | 0.83 | 1.45 | -0.31 | 1.36 | 0.54 | 0.28 | 0.80 | | -1.44 | 0.00 | 0.13 |
| $AR_{t+1}$ | 0.42 | 0.69 | -0.44 | 1.11* | 0.36 | 0.11 | 0.42* | | -1.38*** | 0.04 | 0.33 |
| $R_{[t+1;t+5]}$ | 0.50 | 0.69 | -1.15 | 2.12 | 0.21 | -0.97 | -0.34 | | -0.68 | -0.97 | 0.58 |
| $AR_{[t+1;t+5]}$ | 0.66 | -0.48 | -1.77** | 0.97 | -0.15 | -1.30** | -1.16*** | | -1.51* | -1.78* | 0.73 |
| **Price Increases (Total)** | 14 | 43 | 139 | 87 | 291 | 383 | 1,110 | | 35 | 56 | 69 |
| | | | | | **Panel C: Price Drops** | | | | | | |
| $R_{t+1}$ | 5.83 | 3.26 | 1.75 | -0.94 | 0.84 | 0.64 | -0.60 | | 1.26 | 3.58 | 1.62 |
| $AR_{t+1}$ | 1.75** | 0.72 | 1.65** | -1.24 | 1.12** | 0.72 | -0.48* | | 0.78 | 3.56*** | 1.40* |
| $R_{[t+1;t+5]}$ | 11.78 | 5.17 | 2.81 | -0.48 | 1.93 | 2.11 | 0.15 | | 1.97 | 4.03 | 1.10 |
| $AR_{[t+1;t+5]}$ | 2.81** | 3.03* | 2.89*** | -1.33 | 1.88** | 2.38** | 0.37 | | 1.53 | 4.51*** | 2.39 |
| **Price Drops (Total)** | 35 | 25 | 97 | 54 | 182 | 214 | 790 | | 43 | 43 | 38 |

## Table 3: Regressions on $AR_{i,t+1}$ and $AR_{i,[t+1;t+5]}$ for Model 1

The table reports results for the regressions of the abnormal 1-day return ($AR_{i,t+1}$) and the abnormal 5-day buy-and-hold return ($AR_{i,[t+1;t+5]}$) on the abnormal event return (ER), the company size, depicted by log market value of equity (MV), the log of the book-to-market ratio (BTM), the average daily return during the last 60 trading days (RET), the log of the price-earnings ratio (PE), and the daily stock return volatility (VO), which is estimated over a 60-day event window. Results are displayed for the whole sample period and the index-related sub-periods. Panel A presents all events, while Panels B and C split the sample into price increases and price drops. Differing sample sizes between this table and tables 1 and 2 are due to missing accounting data. Robust t-statistics are reported in parentheses.

**Panel A: All Events**

| **Holding Period** | | | **1-Day** | | | | | **5-Day** | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Period** | **1988-1994** | **1994-1999** | **1999-2003** | **2003-2007** | **1988-2007** | **1988-1994** | **1994-1999** | **1999-2003** | **2003-2007** | **1988-2007** |
| **ER** | -0.494 | -0.065 | -0.014 | -0.041 | -0.024 | -0.523 | -0.135 | -0.050 | -0.111 | -0.067 |
| | (-4.19) | (-1.83) | (-0.73) | (-1.62) | (-1.53) | (-2.35) | (-2.44) | (-1.88) | (-2.44) | (-3.03) |
| **MV** | -0.015 | 0.004 | -0.000 | -0.001 | 0.000 | -0.027 | 0.006 | -0.000 | 0.007 | 0.001 |
| | (-2.67) | (1.96) | (-0.03) | (-0.28) | (0.40) | (-2.32) | (1.61) | (-0.02) | (1.51) | (0.37) |
| **BTM** | 0.037 | 0.006 | -0.000 | 0.013 | 0.001 | 0.070 | 0.005 | 0.004 | 0.014 | 0.004 |
| | (2.84) | (1.21) | (-0.08) | (2.72) | (0.56) | (2.63) | (0.52) | (1.06) | (2.03) | (1.47) |
| **RET** | -0.197 | -0.004 | -0.001 | -0.001 | -0.001 | -0.367 | -0.020 | -0.011 | 0.017 | -0.010 |
| | (-2.57) | (-0.25) | (-0.35) | (-0.05) | (-0.37) | (-2.15) | (-0.85) | (-1.55) | (0.85) | (-1.48) |
| **PE** | -0.011 | -0.015 | 0.000 | -0.001 | -0.000 | -0.041 | -0.004 | 0.002 | -0.009 | 0.001 |
| | (-1.02) | (-2.36) | (0.28) | (-0.24) | (-0.19) | (-1.94) | (-0.44) | (0.66) | (-1.26) | (0.35) |
| **VO** | 3.026 | 0.114 | 0.022 | -0.054 | -0.020 | 4.728 | -0.764 | -0.328 | 0.264 | -0.355 |
| | (3.50) | (0.41) | (0.22) | (-0.22) | (-0.22) | (3.06) | (-0.72) | (-2.07) | (0.72) | (-2.49) |
| **c** | 0.195 | -0.016 | -0.001 | 0.009 | -0.001 | 0.403 | -0.047 | 0.002 | -0.075 | -0.001 |
| | (1.90) | (-0.53) | (-0.05) | (0.22) | (-0.07) | (2.09) | (-0.93) | (0.08) | (-1.15) | (-0.03) |
| | | | | | | | | | | |
| **n** | 41 | 227 | 1,810 | 232 | 2,310 | 41 | 227 | 1,810 | 232 | 2,310 |
| **$R^2$** | 0.59 | 0.07 | 0.00 | 0.06 | 0.00 | 0.39 | 0.07 | 0.01 | 0.07 | 0.01 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | **Panel B: Price Increases** | | | | | |
| **ER** | 0.254 | -0.045 | -0.024 | -0.109 | -0.033 | 0.499 | -0.041 | -0.143 | -0.038 | -0.126 |
| | (0.36) | (-0.84) | (-0.43) | (-1.35) | (-0.71) | (0.47) | (-0.47) | (-2.20) | (-0.31) | (-2.29) |
| **MV** | -0.009 | 0.003 | -0.000 | -0.005 | -0.000 | -0.033 | 0.006 | -0.001 | 0.002 | -0.001 |
| | (-0.42) | (1.10) | (-0.12) | (-1.53) | (-0.23) | (-0.97) | (1.33) | (-0.32) | (0.47) | (-0.46) |
| **BTM** | 0.027 | 0.001 | 0.001 | 0.010 | 0.002 | 0.069 | 0.002 | 0.001 | 0.013 | 0.002 |
| | (0.79) | (0.20) | (0.40) | (1.51) | (0.87) | (1.14) | (0.16) | (0.21) | (1.36) | (0.60) |
| **RET** | -0.103 | 0.003 | -0.011 | -0.006 | -0.010 | -0.210 | -0.027 | -0.016 | 0.001 | -0.015 |
| | (-0.55) | (0.17) | (-2.48) | (-0.35) | (-2.43) | (-0.71) | (-1.12) | (-1.94) | (0.03) | (-1.97) |
| **PE** | -0.011 | -0.004 | 0.001 | -0.001 | 0.001 | -0.043 | 0.006 | 0.003 | -0.012 | 0.003 |
| | (-0.58) | (-0.55) | (0.58) | (-0.28) | (0.37) | (-1.31) | (0.52) | (0.99) | (-1.19) | (0.99) |
| **VO** | -0.458 | 0.056 | -0.001 | -0.013 | -0.007 | 0.224 | -2.329 | -0.277 | 0.552 | -0.318 |
| | (-0.18) | (0.19) | (-0.01) | (-0.03) | (-0.07) | (0.06) | (-2.68) | (-1.44) | (0.98) | (-1.78) |
| **c** | 0.137 | -0.035 | -0.000 | 0.074 | 0.003 | 0.540 | -0.045 | 0.020 | -0.024 | 0.020 |
| | (0.45) | (-0.83) | (-0.02) | (1.25) | (0.17) | (1.08) | (-0.66) | (0.60) | (-0.28) | (0.68) |
| **n** | 11 | 133 | 1,079 | 125 | 1,348 | 11 | 133 | 1,079 | 125 | 1,348 |
| **$R^2$** | 0.34 | 0.02 | 0.01 | 0.05 | 0.01 | 0.61 | 0.16 | 0.01 | 0.03 | 0.01 |
| | | | | | **Panel C: Price Drops** | | | | | |
| **ER** | -0.719 | -0.131 | -0.014 | 0.268 | 0.010 | -0.495 | -0.156 | -0.086 | 0.039 | -0.064 |
| | (-3.28) | (-0.94) | (-0.14) | (2.41) | (0.15) | (-0.87) | (-0.91) | (-0.75) | (0.18) | (-0.73) |
| **MV** | -0.004 | 0.007 | 0.000 | 0.003 | 0.001 | -0.017 | 0.005 | 0.000 | 0.017 | 0.002 |
| | (-0.72) | (1.95) | (0.03) | (0.48) | (0.48) | (-1.37) | (0.78) | (0.05) | (2.27) | (0.74) |
| **BTM** | 0.034 | 0.015 | -0.002 | 0.015 | 0.000 | 0.059 | 0.009 | 0.007 | 0.022 | 0.008 |
| | (2.58) | (1.63) | (-0.52) | (2.01) | (0.00) | (1.98) | (0.64) | (1.17) | (2.00) | (1.44) |
| **RET** | -0.232 | -0.036 | 0.016 | 0.015 | 0.015 | -0.474 | -0.061 | -0.001 | 0.080 | 0.001 |
| | (-2.08) | (-1.18) | (2.25) | (0.84) | (2.32) | (-1.64) | (-1.15) | (-0.10) | (2.10) | (0.10) |
| **PE** | -0.010 | -0.029 | -0.000 | 0.000 | -0.002 | -0.029 | -0.018 | -0.001 | -0.009 | -0.003 |
| | (-0.82) | (-3.32) | (-0.05) | (0.01) | (-0.62) | (-1.27) | (-1.25) | (-0.13) | (-0.81) | (-0.71) |
| **VO** | 4.305 | 0.453 | 0.040 | -0.133 | -0.027 | 11.413 | 2.903 | -0.377 | 0.214 | -0.373 |
| | (2.06) | (0.73) | (0.24) | (-0.34) | (-0.18) | (1.70) | (2.29) | (-1.38) | (0.43) | (-1.60) |
| **c** | -0.000 | -0.041 | 0.005 | 0.003 | 0.008 | 0.126 | -0.110 | 0.002 | -0.188 | -0.008 |
| | (-0.00) | (-0.61) | (0.18) | (0.05) | (0.32) | (0.71) | (-1.05) | (0.05) | (-1.89) | (-0.18) |
| **n** | 30 | 94 | 731 | 107 | 962 | 30 | 94 | 731 | 107 | 962 |
| **$R^2$** | 0.74 | 0.14 | 0.01 | 0.19 | 0.01 | 0.48 | 0.14 | 0.01 | 0.16 | 0.01 |

## Table 4: Regressions on $AR_{i,t+1}$ for Model 2

The table reports results for the regressions of the abnormal 1-day return ($AR_{i,t+1}$) on the abnormal event return (ER), the company size, depicted by log market value of equity (MV), the log of the book-to-market ratio (BTM), the average daily return during the last 60 trading days (RET), the log of the price-earnings ratio (PE), and the daily stock return volatility (VO), which is estimated over a 60-day event window. The results are displayed for all index sub-samples occurring in the respective period. Panel A presents all events, while Panels B and C split the sample into price increases and price drops with DAX30 being removed from the last period due to a small number of observations. Differing sample sizes between tables are due to missing accounting data. Robust t-statistics are reported in parentheses.

| **Period** | **1988-1994** | **1994-1999** | | **1999-2003** | | | | **2003-2007** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Index** | **DAX30** | **DAX30** | **MDAX** | **DAX30** | **MDAX** | **SDAX** | **NEMAX50** | **DAX30** | **MDAX** | **SDAX** | **TECDAX** |
| | | | | | **Panel A: All Events** | | | | | | |
| **ER** | -0.563 | 0.020 | -0.073 | 0.136 | -0.045 | -0.040 | -0.010 | 0.074 | -0.033 | -0.085 | -0.036 |
| | (-3.82) | (0.35) | (-1.86) | (1.53) | (-1.77) | (-1.02) | (-0.34) | (0.68) | (-0.66) | (-1.75) | (-0.95) |
| **BTM** | 0.025 | 0.006 | 0.009 | 0.001 | 0.002 | -0.008 | 0.004 | -0.010 | 0.020 | 0.013 | 0.014 |
| | (2.19) | (0.75) | (1.60) | (0.17) | (0.63) | (-2.10) | (1.73) | (-0.81) | (1.22) | (1.27) | (1.96) |
| **RET** | -0.172 | -0.034 | -0.000 | -0.016 | 0.002 | -0.006 | -0.005 | 0.042 | 0.007 | -0.000 | -0.016 |
| | (-2.03) | (-1.30) | (-0.02) | (-0.68) | (0.24) | (-0.61) | (-0.92) | (0.86) | (0.26) | (-0.00) | (-0.74) |
| **PE** | -0.010 | 0.004 | -0.015 | -0.000 | -0.000 | 0.008 | -0.002 | -0.038 | -0.005 | -0.002 | 0.001 |
| | (-0.93) | (0.36) | (-2.27) | (-0.02) | (-0.02) | (2.59) | (-0.68) | (-2.56) | (-0.31) | (-0.36) | (0.12) |
| **VO** | 3.598 | -1.811 | 0.358 | 0.435 | 0.169 | -0.125 | 0.148 | 0.227 | 0.049 | -0.662 | 0.023 |
| | (3.21) | (-2.89) | (1.08) | (1.17) | (0.79) | (-0.55) | (0.94) | (0.24) | (0.07) | (-0.84) | (0.07) |
| **c** | -0.040 | 0.038 | 0.033 | -0.022 | 0.000 | -0.009 | -0.012 | 0.128 | -0.008 | 0.025 | -0.009 |
| | (-1.15) | (1.07) | (1.48) | (-1.14) | (0.01) | (-1.04) | (-1.00) | (2.53) | (-0.15) | (0.83) | (-0.42) |
| **n** | 41 | 52 | 175 | 129 | 393 | 413 | 875 | 12 | 62 | 78 | 80 |
| **$R^2$** | 0.50 | 0.12 | 0.08 | 0.08 | 0.01 | 0.03 | 0.01 | 0.33 | 0.05 | 0.05 | 0.10 |

| Period | 1988-1994 | 1994-1999 | | 1999-2003 | | | | 2003-2007 | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Index** | **DAX30** | **DAX30** | **MDAX** | **DAX30** | **MDAX** | **SDAX** | **NEMAX50** | **MDAX** | **SDAX** | **TECDAX** |
| **Panel B: Price Increases** | | | | | | | | | | |
| **ER** | 0.447 | -0.141 | -0.048 | -0.045 | -0.029 | 0.082 | -0.071 | -0.019 | -0.148 | -0.067 |
| | (1.12) | (-0.49) | (-0.88) | (-0.32) | (-0.75) | (0.48) | (-0.73) | (-0.13) | (-0.66) | (-0.50) |
| **BTM** | 0.021 | 0.006 | 0.001 | 0.009 | 0.004 | -0.006 | 0.002 | 0.016 | -0.021 | 0.017 |
| | (0.90) | (0.72) | (0.17) | (1.27) | (0.88) | (-1.30) | (0.70) | (1.53) | (-1.26) | (1.68) |
| **RET** | -0.062 | -0.043 | 0.008 | -0.032 | -0.008 | -0.014 | -0.013 | -0.008 | -0.019 | -0.006 |
| | (-0.49) | (-1.11) | (0.47) | (-1.08) | (-0.74) | (-1.57) | (-2.33) | (-0.44) | (-0.66) | (-0.26) |
| **PE** | -0.012 | 0.007 | -0.005 | -0.002 | 0.006 | 0.007 | -0.001 | 0.007 | 0.015 | -0.017 |
| | (-0.71) | (0.44) | (-0.65) | (-0.29) | (1.33) | (2.00) | (-0.38) | (0.56) | (1.16) | (-1.82) |
| **VO** | -0.940 | -2.316 | 0.204 | 0.885 | 0.562 | -0.172 | -0.092 | 0.175 | 1.394 | -0.000 |
| | (-0.56) | (-1.63) | (0.63) | (2.34) | (2.11) | (-0.73) | (-0.49) | (0.30) | (1.39) | (0.00) |
| **c** | 0.015 | 0.054 | 0.007 | -0.027 | -0.037 | -0.021 | 0.011 | -0.052 | -0.034 | 0.053 |
| | (0.43) | (0.69) | (0.29) | (-0.94) | (-2.20) | (-1.01) | (0.57) | (-1.25) | (-0.41) | (1.62) |
| **n** | 11 | 31 | 102 | 78 | 240 | 264 | 497 | 25 | 41 | 52 |
| **$R^2$** | 0.32 | 0.13 | 0.01 | 0.17 | 0.06 | 0.03 | 0.02 | 0.32 | 0.07 | 0.11 |
| **Panel C: Price Drops** | | | | | | | | | | |
| **ER** | -0.791 | -0.200 | -0.106 | 0.464 | -0.124 | 0.012 | -0.007 | 0.387 | 0.646 | -0.158 |
| | (-4.06) | (-0.79) | (-0.66) | (0.89) | (-0.64) | (0.03) | (-0.06) | (2.29) | (4.03) | (-0.98) |
| **BTM** | 0.032 | 0.001 | 0.024 | 0.000 | 0.001 | -0.012 | 0.006 | 0.017 | 0.017 | 0.007 |
| | (2.49) | (0.06) | (2.51) | (0.05) | (0.17) | (-1.95) | (1.32) | (0.74) | (1.53) | (1.23) |
| **RET** | -0.226 | -0.049 | -0.039 | 0.005 | 0.017 | 0.013 | 0.008 | 0.036 | 0.022 | -0.054 |
| | (-2.07) | (-1.07) | (-0.97) | (0.14) | (0.84) | (0.64) | (1.01) | (0.54) | (0.73) | (-2.27) |
| **PE** | -0.011 | 0.001 | -0.029 | 0.002 | -0.008 | 0.012 | -0.003 | -0.022 | 0.014 | 0.026 |
| | (-0.89) | (0.09) | (-3.11) | (0.17) | (-1.19) | (2.02) | (-0.62) | (-0.98) | (1.96) | (5.14) |
| **VO** | 3.848 | -1.908 | 0.934 | -0.067 | -0.400 | -0.114 | 0.464 | 0.282 | -2.268 | -0.159 |
| | (1.98) | (-1.97) | (1.22) | (-0.10) | (-1.04) | (-0.25) | (2.15) | (0.28) | (-2.98) | (-0.61) |
| **c** | -0.061 | 0.036 | 0.036 | 0.024 | 0.040 | -0.010 | -0.026 | 0.099 | 0.095 | -0.096 |
| | (-1.34) | (0.74) | (0.87) | (0.53) | (1.50) | (-0.25) | (-1.20) | (1.38) | (3.30) | (-3.74) |
| **n** | 30 | 21 | 73 | 51 | 153 | 149 | 378 | 37 | 37 | 28 |
| **$R^2$** | 0.73 | 0.19 | 0.14 | 0.05 | 0.04 | 0.04 | 0.02 | 0.23 | 0.47 | 0.42 |

## Table 5: Regressions on $AR_{i,[t+1;t+5]}$ for Model 2

The table reports results for the regressions of the abnormal 5-day buy-and-hold return ($AR_{i,[t+1;t+5]}$) on the abnormal event return (ER), the company size, depicted by log market value of equity (MV), the log of the book-to-market ratio (BTM), the average daily return during the last 60 trading days (RET), the log of the price-earnings ratio (PE), and the daily stock return volatility (VO), which is estimated over a 60-day event window. The results are displayed for all index sub-samples occurring in the respective period. Panel A presents all events, while Panels B and C split the sample into price increases and price drops with DAX30 being removed from the last period due to a small number of observations. Differing sample sizes between tables are due to missing accounting data. Robust t-statistics are reported in parentheses.

| **Period** | **1988-1994** | **1994-1999** | | **1999-2003** | | | | **2003-2007** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Index** | **DAX30** | **DAX30** | **MDAX** | **DAX30** | **MDAX** | **SDAX** | **NEMAX50** | **DAX30** | **MDAX** | **SDAX** | **TECDAX** |
| | | | | | **Panel A: All Events** | | | | | | |
| **ER** | -0.643 | -0.118 | -0.134 | 0.089 | -0.077 | -0.143 | -0.018 | -0.001 | -0.046 | -0.233 | -0.064 |
| | (-2.42) | (-1.54) | (-2.18) | (1.15) | (-1.63) | (-2.53) | (-0.46) | (-0.00) | (-0.68) | (-3.10) | (-0.87) |
| **BTM** | 0.050 | 0.012 | 0.005 | 0.018 | -0.003 | -0.008 | 0.009 | -0.029 | 0.013 | 0.012 | 0.039 |
| | (1.83) | (0.95) | (0.50) | (2.18) | (-0.47) | (-0.97) | (2.09) | (-1.33) | (0.66) | (0.77) | (3.95) |
| **RET** | -0.324 | -0.033 | -0.012 | -0.051 | -0.000 | 0.024 | -0.024 | 0.016 | 0.031 | 0.029 | -0.024 |
| | (-1.76) | (-1.10) | (-0.40) | (-2.71) | (-0.01) | (1.40) | (-2.66) | (0.17) | (0.64) | (0.86) | (-0.92) |
| **PE** | -0.040 | 0.004 | -0.004 | -0.001 | 0.002 | 0.009 | -0.001 | -0.023 | -0.027 | -0.011 | -0.021 |
| | (-1.86) | (0.19) | (-0.42) | (-0.06) | (0.40) | (1.69) | (-0.29) | (-0.74) | (-0.97) | (-1.14) | (-1.83) |
| **VO** | 5.714 | -0.168 | -0.849 | 0.493 | 0.416 | -0.739 | -0.341 | 0.057 | -0.554 | -0.399 | 0.442 |
| | (3.11) | (-0.18) | (-0.72) | (1.09) | (0.86) | (-1.81) | (-1.46) | (0.04) | (-0.56) | (-0.37) | (0.97) |
| **c** | -0.002 | -0.017 | 0.034 | -0.052 | -0.009 | 0.003 | 0.001 | 0.125 | 0.081 | 0.044 | 0.033 |
| | (-0.04) | (-0.26) | (0.76) | (-1.50) | (-0.34) | (0.17) | (0.05) | (1.42) | (0.91) | (1.15) | (0.99) |
| **n** | 41 | 52 | 175 | 129 | 393 | 413 | 875 | 12 | 62 | 78 | 80 |
| **$R^2$** | 0.29 | 0.16 | 0.06 | 0.09 | 0.01 | 0.04 | 0.02 | 0.21 | 0.05 | 0.12 | 0.19 |

| Period | 1988-1994 | 1994-1999 | | 1999-2003 | | | | 2003-2007 | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Index** | **DAX30** | **DAX30** | **MDAX** | **DAX30** | **MDAX** | **SDAX** | **NEMAX50** | **MDAX** | **SDAX** | **TECDAX** |
| | | | | | **Panel B: Price Increases** | | | | | |
| **ER** | 1.238 | -0.296 | -0.044 | -0.141 | 0.018 | -0.378 | -0.173 | 0.297 | 0.030 | 0.055 |
| | (1.30) | (-0.88) | (-0.54) | (-0.86) | (0.21) | (-2.06) | (-1.74) | (1.25) | (0.10) | (0.31) |
| **BTM** | 0.045 | 0.012 | 0.002 | 0.015 | -0.002 | -0.004 | -0.000 | 0.024 | -0.027 | 0.037 |
| | (0.99) | (0.92) | (0.16) | (1.43) | (-0.22) | (-0.53) | (-0.04) | (1.23) | (-1.11) | (3.22) |
| **RET** | -0.056 | -0.051 | -0.008 | -0.073 | -0.005 | 0.000 | -0.021 | 0.021 | -0.020 | -0.008 |
| | (-0.22) | (-1.16) | (-0.29) | (-2.63) | (-0.23) | (0.01) | (-1.94) | (0.48) | (-0.51) | (-0.30) |
| **PE** | -0.046 | -0.007 | 0.005 | -0.000 | 0.006 | 0.010 | 0.001 | -0.019 | 0.007 | -0.036 |
| | (-1.61) | (-0.30) | (0.46) | (-0.04) | (0.84) | (1.66) | (0.12) | (-0.55) | (0.37) | (-2.72) |
| **VO** | -1.619 | -1.172 | -2.453 | 0.821 | 0.467 | -0.756 | -0.410 | 1.257 | 1.707 | 0.445 |
| | (-0.55) | (-0.76) | (-2.75) | (1.55) | (0.89) | (-1.55) | (-1.47) | (0.84) | (1.03) | (0.80) |
| **c** | 0.074 | 0.072 | 0.038 | -0.033 | -0.036 | 0.031 | 0.035 | -0.054 | -0.047 | 0.065 |
| | (1.32) | (0.93) | (0.78) | (-0.77) | (-1.10) | (1.11) | (1.40) | (-0.51) | (-0.48) | (1.36) |
| **n** | 11 | 31 | 102 | 78 | 240 | 264 | 497 | 25 | 41 | 52 |
| **$R^2$** | 0.55 | 0.15 | 0.17 | 0.13 | 0.01 | 0.05 | 0.03 | 0.15 | 0.05 | 0.19 |
| | | | | | **Panel C: Price Drops** | | | | | |
| **ER** | -0.761 | -0.249 | -0.092 | -0.155 | -0.483 | 0.107 | -0.014 | 0.375 | 0.282 | -0.362 |
| | (-1.52) | (-0.89) | (-0.49) | (-0.45) | (-1.55) | (0.27) | (-0.11) | (1.94) | (0.83) | (-0.90) |
| **BTM** | 0.051 | 0.010 | 0.012 | 0.026 | -0.008 | -0.016 | 0.020 | 0.004 | 0.030 | 0.054 |
| | (1.76) | (0.40) | (0.70) | (1.90) | (-0.63) | (-0.95) | (2.45) | (0.13) | (1.68) | (3.42) |
| **RET** | -0.451 | -0.049 | -0.075 | -0.016 | 0.009 | 0.073 | -0.029 | 0.062 | 0.124 | -0.024 |
| | (-1.63) | (-1.00) | (-0.98) | (-0.60) | (0.23) | (2.26) | (-1.77) | (0.46) | (2.04) | (-0.37) |
| **PE** | -0.031 | 0.018 | -0.019 | 0.003 | 0.000 | 0.009 | -0.004 | -0.045 | 0.006 | -0.008 |
| | (-1.36) | (0.51) | (-1.23) | (0.18) | (0.02) | (0.86) | (-0.58) | (-1.07) | (0.78) | (-0.67) |
| **VO** | 9.732 | -0.108 | 3.220 | -0.365 | 0.269 | -0.511 | -0.149 | -0.607 | -1.835 | 0.318 |
| | (1.53) | (-0.08) | (2.12) | (-0.59) | (0.29) | (-0.63) | (-0.39) | (-0.37) | (-1.70) | (0.38) |
| **c** | -0.100 | -0.081 | -0.042 | -0.062 | -0.036 | 0.034 | -0.019 | 0.204 | 0.064 | -0.057 |
| | (-1.07) | (-0.74) | (-0.59) | (-1.05) | (-0.53) | (0.74) | (-0.48) | (1.57) | (1.54) | (-1.05) |
| **n** | 30 | 21 | 73 | 51 | 153 | 149 | 378 | 37 | 37 | 28 |
| **$R^2$** | 0.45 | 0.21 | 0.15 | 0.15 | 0.03 | 0.05 | 0.02 | 0.15 | 0.31 | 0.34 |

## Table 6: Regressions on $AR_{i,t+1}$ and $AR_{i,[t+1;t+5]}$ for Model 3: 1988-2007

The table reports results for the regressions of the abnormal 1-day return ($AR_{i,t+1}$) and the abnormal 5-day buy-and-hold return ($AR_{i,[t+1;t+5]}$) on the abnormal event return (ER), the company size, depicted by log market value of equity (MV), the log of the book-to-market ratio (BTM), the average daily return during the last 60 trading days (RET), the log of the price-earnings ratio (PE), and the daily stock return volatility (VO), which is estimated over a 60-day event window. Annual dummy variables for years with more than 20 events (DRELYEAR) are included to capture effects of seasonality. The first column shows the results for all events, while the second shows the results for price increases, and the last for price drops. Differing sample sizes between tables are due to missing accounting data. Robust t-statistics are reported in parentheses.

| **Events** | **All** | | **Price Increases** | | **Price Drops** | |
|---|---|---|---|---|---|---|
| **Holding Period** | **1-Day** | **5-Day** | **1-Day** | **5-Day** | **1-Day** | **5-Day** |
| **ER** | -0.02 | -0.06 | -0.03 | -0.11 | -0.04 | -0.09 |
| | (-1.48) | (-2.81) | (-0.65) | (-1.97) | (-0.47) | (-0.90) |
| **MV** | -0.00 | -0.00 | -0.00 | -0.00 | 0.00 | 0.00 |
| | (-0.12) | (-0.08) | (-0.45) | (-0.74) | (0.27) | (0.43) |
| **BTM** | -0.00 | 0.00 | 0.00 | 0.00 | -0.00 | 0.00 |
| | (-0.03) | (1.31) | (0.96) | (1.04) | (-0.90) | (0.87) |
| **RET** | -0.00 | -0.01 | -0.01 | -0.01 | 0.01 | -0.01 |
| | (-0.63) | (-1.75) | (-2.47) | (-1.87) | (1.64) | (-0.43) |
| **PE** | -0.00 | 0.00 | 0.00 | 0.00 | -0.00 | -0.00 |
| | (-0.17) | (0.59) | (0.42) | (1.23) | (-0.44) | (-0.51) |
| **VO** | 0.02 | -0.36 | -0.02 | -0.46 | 0.03 | -0.27 |
| | (0.17) | (-2.31) | (-0.16) | (-2.34) | (0.21) | (-1.03) |
| **D89** | 0.02 | 0.01 | 0.01 | -0.01 | 0.02 | 0.02 |
| | (1.72) | (0.49) | (0.45) | (-0.25) | (1.70) | (0.74) |
| **D94** | -0.03 | -0.07 | 0.00 | 0.00 | -0.02 | -0.07 |
| | (-1.70) | (-2.23) | (.) | (.) | (-1.48) | (-2.00) |
| **D95** | -0.02 | 0.00 | -0.02 | -0.05 | -0.02 | 0.02 |
| | (-1.48) | (0.04) | (-0.81) | (-0.97) | (-1.08) | (0.36) |
| **D96** | -0.00 | -0.02 | 0.00 | -0.04 | -0.00 | -0.00 |
| | (-0.09) | (-0.72) | (0.12) | (-0.78) | (-0.07) | (-0.06) |
| **D97** | 0.01 | -0.00 | 0.01 | -0.01 | 0.01 | 0.00 |
| | (1.20) | (-0.04) | (0.58) | (-0.29) | (1.33) | (0.09) |
| **D98** | 0.01 | 0.00 | 0.00 | -0.03 | 0.02 | 0.03 |
| | (0.86) | (0.06) | (0.00) | (-0.57) | (1.84) | (1.03) |
| **D99** | -0.01 | -0.03 | -0.01 | -0.04 | 0.01 | -0.03 |
| | (-0.82) | (-1.71) | (-0.37) | (-0.98) | (0.69) | (1.16) |
| **D00** | -0.00 | -0.00 | 0.00 | -0.02 | 0.00 | 0.01 |
| | (-0.09) | (-0.04) | (0.06) | (-0.39) | (0.35) | (0.45) |
| **D01** | -0.00 | -0.01 | -0.00 | -0.02 | -0.00 | -0.02 |
| | (-0.55) | (-0.63) | (-0.02) | (-0.35) | (-0.16) | (-0.73) |
| **D02** | -0.01 | 0.00 | 0.00 | 0.00 | -0.02 | -0.01 |
| | (-1.46) | (0.26) | (0.08) | (0.09) | (-1.71) | (-0.30) |
| **D03** | -0.01 | -0.02 | 0.00 | -0.02 | -0.04 | -0.04 |
| | (-1.69) | (-0.96) | (0.26) | (-0.44) | (-2.89) | (-1.28) |
| **D04** | -0.02 | -0.02 | -0.00 | -0.02 | -0.04 | -0.03 |
| | (-1.88) | (-1.09) | (-0.07) | (-0.52) | (-2.29) | (-1.14) |
| **D05** | -0.01 | -0.03 | -0.00 | -0.04 | -0.02 | -0.03 |
| | (-1.38) | (-1.55) | (-0.19) | (-0.92) | (-1.32) | (-1.22) |
| **D06** | 0.01 | 0.02 | 0.00 | -0.01 | 0.02 | 0.04 |
| | (1.27) | (0.87) | (0.20) | (-0.22) | (1.84) | (1.49) |
| **D07** | 0.03 | 0.03 | -0.00 | -0.02 | 0.06 | 0.05 |
| | (3.61) | (1.28) | (-0.04) | (-0.42) | (5.36) | (2.28) |
| **C** | 0.01 | 0.01 | 0.01 | 0.04 | 0.01 | -0.00 |
| | (0.49) | (0.43) | (0.20) | (0.82) | (0.21) | (-0.05) |
| **n** | 2,310 | 2,310 | 1,348 | 1,348 | 962 | 962 |
| **$R^2$** | 0.02 | 0.02 | 0.01 | 0.03 | 0.05 | 0.03 |

**Table 7: Trading Strategy Returns**

This table exhibits strategy returns where the trading strategy is to buy either every stock that experiences an event at the end of the event day (uncertain information strategy), to buy only stocks with positive price shocks (momentum strategy), or to buy only stocks with negative price shocks (overreaction strategy). For all active strategies, the holding period is one trading day. The respective passive index return (%) is the buy-and-hold return of the corresponding index in the same period for an investor buying the index on the first day and selling it on the last day of that period. The strategy return is the period return net of the respective index return before and after trading costs of 1% (round-trip).

| **Period** | **1988-1994** | **1994-1999** | | **1999-2003** | | | | **2003-2007** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Index** | **DAX30** | **DAX30** | **MDAX** | **DAX30** | **MDAX** | **SDAX** | **NEMAX50** | **DAX30** | **MDAX** | **SDAX** | **TecDAX** |
| **Index return** | 120.33 | 144.11 | 57.15 | -49.52 | -27.08 | -42.74 | -91.83 | 147.34 | 233.07 | 249.10 | 128.93 |
| **Panel A: Uncertain Information Strategy** | | | | | | | | | | | |
| **Before Trading Cost** | 25.47 | 58.79 | 69.57 | -28.63 | 128.00 | -42.85 | -84.98 | -6.65 | -49.71 | 25.18 | 85.28 |
| **After Trading Cost** | 8.15 | -3.57 | -71.57 | -72.76 | -90.74 | -98.31 | -99.97 | -19.78 | -73.50 | -37.98 | -26.88 |
| **Panel B: Momentum Strategy** | | | | | | | | | | | |
| **Before Trading Cost** | 4.87 | 46.89 | -29.49 | 114.21 | 96.48 | 35.54 | 616.56 | 11.55 | -36.42 | 10.33 | 19.37 |
| **After Trading Cost** | -4.16 | 2.64 | -77.00 | 20.36 | -77.97 | -88.70 | -87.16 | 0.99 | -54.58 | -27.63 | -33.96 |
| **Panel C: Overreaction Strategy** | | | | | | | | | | | |
| **Before Trading Cost** | 19.64 | 8.10 | 80.13 | -65.98 | 38.02 | -48.35 | -98.90 | -16.31 | -20.90 | 2.18 | 57.79 |
| **After Trading Cost** | 12.84 | -6.05 | -3.91 | -77.11 | -59.90 | -89.78 | -99.96 | -20.57 | -41.65 | -18.91 | 11.46 |

# 3. Short-Term Return Drift in Emerging Markets

(with Sebastian Lobe)


**Abstract**

In this comprehensive study of 21 emerging markets, we show that emerging-market stock returns display significant short-term return drift after extreme one-day price increases. This drift is stronger for small companies. To determine the significance of the abnormal returns, we use the tests developed by Corrado and Zivney (1992) and Boehmer et al. (1991). Running explanatory regressions on the abnormal short-term returns after stock price increases, we can show that the drift is persistent. It is influenced by the market value of equity. The extent of the event return itself does not have a significant influence on post-event returns. In contrast to developed markets, short-term investor overreaction after extreme one-day stock-price drops is uncommon in emerging markets.



*JEL classification: G12, G14, G15*

*Keywords:* stock return predictability; emerging markets; overreaction; stock return drift

## 3.1. INTRODUCTION

In the pursuit of alpha, many investment managers use the strategies of contrarian trading and momentum trading. The assumption behind both strategies, sparked by the research of Kahnemann and Tversky (1979), is that the market—or to be more precise, investors—is inefficient in gauging incoming news. Contrarians believe that the market overreacts, and momentum investors believe that the market underreacts. Either reaction would render stock returns predictable. If the market overreacts, return reversals can be observed. If the market underreacts, return drift is prevalent.

Of course, stock return predictability has also received a great deal attention in the behavioral-finance literature. We use stock return predictability as a generic term for overreaction, i.e., return reversals, and underreaction, i.e., return drift[1]. Shortly after DeBondt and Thaler's (1985) discovery of long-term overreaction, short-term stock return predictability became a focus of US researchers. Atkins and Dyl (1990) show that price drops of 10% or more are a manifestation of short-term overreaction in the US stock market because stocks that experience a 1-day price decline of more than 10% display abnormally positive returns the next trading day. Both Bremer and Sweeney (1991) and Cox and Peterson (1994) offer corroborating evidence for the US market. International evidence on short-term return reversals comes from Bremer et al. (1997) for Japan and from Otchere and Chan (2003) for Hong Kong. The assertion by Cox and Peterson (1994) that overreaction in the US stock market is a sign of underdeveloped liquidity that

[1] Another theory on return predictability, put forward by Brown et al. (1988), suggests that post-event returns are always positive due to an uncertainty discount caused by the large price amplitude on the event day. This phenomenon is therefore termed the uncertain information hypothesis (UIH).

vanishes over time with rising liquidity has been disproved by more recent evidence from Pritamani and Singal (2001), Larson and Madura (2003), and Sturm (2003).

Although the existence of over- and underreaction is well documented in the literature on industrialized nations, it is still unclear whether short-term return predictability is also detectable in emerging stock markets. The main reason that most existing studies on stock return predictability treat developed markets is a practical one: thin trading. The rise in trading volume in emerging markets that began during the mid-1990s makes these markets interesting enough for an analysis of stock return predictability. That emerging markets are different from industrialized countries' markets with respect to liquidity, market microstructure, listed companies' age and many other factors makes them even more interesting to analyze. For those reasons, emerging markets also differ from developed markets in terms of institutional investor attention. Therefore, one would suspect anomalies to be more pronounced than in developed markets, a notion that is also promoted by anecdotal evidence provided by mutual fund managers and the media. If this were true, emerging markets would be more prone to behavioral investor biases such as over- or underreaction. We want to test this hypothesis by scrutinizing all extreme short-term price increases and decreases that occurred during a 14-year time span on one of the 21 stock markets that constitute the MSCI Emerging Markets Index.

To prevent known biases such as the size effect, the book-to-market effect or return momentum from distorting our results, we correct for these biases. Furthermore, our methodology is more sophisticated than in earlier works on stock return predictability in that we use test statistics that are robust to increases in stock return variance that can be observed around events. In doing so, we avoid the pitfalls created by event-induced variance. Our test statistics include the non-parametric rank statistic by Corrado and Zivney (1992) and the parametric test by Boehmer et al. (1991).

This study closes a gap in the literature on emerging-market stock-return predictability. It offers a comprehensive view of the short-term reaction to price shocks across 21 emerging stock markets. To maximize practical relevance, we align our emerging-market definition with those of the constituent countries of the MSCI Emerging Markets Index, the most common reference on emerging stock markets. In addition to widening the market focus on emerging markets, we also implement the measures of Boehmer et al. (1991) and Corrado and Zivney (1992) in determining abnormal stock returns. To our knowledge, this is the first study to evaluate short-term stock-return predictability using this methodology on a global scale. Using a pooled global sample as our starting point, we investigate stock return patterns after extreme one-day stock price movements. The first drill-down divides the sample into four regions, which in turn are split into country samples. We test whether the respective stocks display signs of over- or underreaction, revealing that short-term underreaction after stock price increases is the prevalent phenomenon across the majority of emerging markets. In a second step, we run cross-sectional regressions on the event data to determine the driving forces behind these underreaction patterns and to determine whether those patterns remain persistent when those factors are controlled for. The paper is structured as follows. In the section 2, we describe the data and the construction of the regional, country, and size sub-samples. Section 3 outlines the research questions and methodology. Section 4 contains a univariate analysis of short-term returns after extreme stock price movements, and section 5 contains the results of the cross-sectional regressions and shows how company size, book-to-market-ratio, mid-term return momentum, and liquidity affect short-term stock return drift. Section 6 discusses robustness, and section 7 is the conclusion.

## 3.2. DATA

### 3.2.1. Plain Data

To improve the understanding of short-term return predictability on a global basis, we analyze short-term return predictability after extreme one-day price movements in all countries that comprised the MSCI Emerging Markets Index as of December 31, 2009. A country's index constituency ensures at least a certain amount of investor attention and therefore, a sample of sufficient size, provided we screened traded firms to sort out illiquid stocks. Our approach is to first analyze the worldwide stock sample regarding predictable short-term return patterns. Second, we group the sample countries by four geographic regions to determine whether geographical patterns influence the occurrence and extent of predictability. The regions are Asia (ASIA), Eastern Europe (EE), Latin America (LATAM) and the Middle East and Africa (MEA). Finally, we examine each of the 21 countries individually. Each sub-sample is itself divided into three size sub-samples. For each country, the size sub-samples are determined separately. To that end, all companies are ranked within their country according to the market value of their equity. The companies in the two top deciles are termed "large" companies. Companies from the bottom-three deciles are termed "small" companies. All firms ranked between these deciles are termed "medium".

Our basic population consists of all stocks listed on one of the 21 emerging-market stock exchanges. The sample includes all stocks for which it was possible to obtain the total return index (RI), adjusted for stock splits and dividend payments, closing price in local currency (P), trading volume in thousands of shares (VO), price-to-book value (PTBV), closing ask price in local currency (PA), closing bid price in local currency (PB), and market value of equity in millions of local currency units (MV) on a daily basis from the databases of Thomson Reuters DataStream and WorldScope. The sample period begins on January 1, 1994, and ends on January 30, 2009. To enable conversion of local currency into US dollars, we also obtained the respective daily exchange rate (FXR) for each country. The exchange rates are quoted as US dollars per local currency unit.

### 3.2.2. Derived Data

From the obtained data, we calculate derived data to perform our analysis. The daily stock return for stock i on day t ($R_{i,t}$) is calculated on the basis of a stock's return index as

$$R_{i,t} = \frac{RI_{i,t}}{RI_{i,t-1}} - 1. \tag{12}$$

Furthermore, we calculate turnover in US dollars ($TO_{i,t}$) as the product of $VO_{i,t}$ and $P_{i,t}$ multiplied by that day's exchange rate:

$$TO_{i,t} = VO_{i,t} \cdot P_{i,t} \cdot FXR_t. \tag{13}$$

Having calculated $R_{i,t}$ and $TO_{i,t}$, we use both variables to derive the Amihud (2002) illiquidity ratio (AIR). The AIR is calculated as the daily quotient of absolute daily return over daily turnover in US dollars. It can be interpreted as a daily version of Kyle's Lambda (Kyle 1985).

$$AIR_{i,t} = \frac{|R_{i,t}|}{TO_{i,t}}. \tag{14}$$

Estimation period AIR (AIREST) is the average AIR over all days of the estimation period. Days with zero turnover are removed from the average. Therefore, D represents the number of non-zero turnover days during the estimation period.

$$AIREST_{i,t} = \frac{1}{D}\sum_{t=-260}^{t=-10} AIR_{i,t}. \tag{15}$$

By using the Amihud (2002) illiquidity measure, we rely on Lesmond (2005) and Goyenko et al. (2009), who establish that the ratio is a useful measure when determining a stock's liquidity. Like Amihud (2002) and Lesmond (2005), we multiply $AIREST_{i,t}$ by $10^6$ to align our variables with respect to decimal places, thereby improving representation.

### 3.2.3. Screens

Some sources in the literature—e.g., Cox and Peterson (1994) and Park (1995)—argue that market microstructure effects make up for part of the return predictability reported in the wake of events. The most important of these issues is the bid-ask bounce of stock prices. In the case of a price jump (drop), the stock is more likely to close near the ask (bid) price. If the stock is equally likely to reopen at either the bid or the ask price, return reversals are measured erroneously. Whereas others such as Bremer and Sweeney (1991) exclude stocks with a price of less than USD10 to eliminate bias, we take a more differentiated approach.

To prevent market microstructure problems from distorting our results, we impose some screens on our data to filter all events from the sample that could bias our results to obtain valid estimates for estimation period parameters such as market values, average trading volumes, book-to-market ratios and illiquidity ratios.

The first screen involves dropping all event days with a return of more than 50% or less than -50% from the sample. Second, because most distortions are ascribed to a lack of liquidity, we combine several measures to exclude illiquid stocks. First, we sort out all stocks with 20 or more lacking Amihud illiquidity ratios ($AIR_{i,t}$) during the 260-day estimation period from the sample. We do not use the relatively straightforward approach to gauge liquidity by counting non-zero returns (such as, e.g., Lesmond et al. (1999)) because it is possible for stocks to be traded without a change in price. Because we do not want to drop stocks from the sample that have been traded, we enhance the information about zero returns by the information about whether the stock has been traded on the respective day. In doing so, we essentially drop all stocks with an insufficient amount of daily illiquidity ratios from the sample. AIREST combines the zero return measure with a measure of trading volume.

The third screen is to filter stocks with more than 1 lacking daily $AIR_{i,t}$ during the post-event period of 20 days. As a fourth screen, we drop all events with an $AIREST_{i,t}$ larger than 0.01

because ratios this high are very likely to be caused by poor data. To illustrate this point: an AIR of 0.01 would mean that 1 US dollar of trading volume would cause a stock return of 1 percent. Because we measure return as a change in each stock's total return index, we do not create a screen for changing numbers of shares outstanding because this information is already captured in the total return variable.

## 3.3. METHODOLOGY

### 3.3.1. Event Definition

In our definition, an event is recorded when the realized local-currency stock return for one day is more than 3 standard deviations in either direction from the mean return of the estimation period. Mean and standard deviation are calculated for the 250-day period ranging from Day -260 to Day -10 before the respective trading day (estimation period). The period of the event day until 20 days after the event is the event period. Because we need data until 260 trading days before an event to calculate estimation period variables and until 20 days after the event to obtain event period statistics, the studied events are restricted to those that occurred between January 5, 1995 and December 30, 2008. Events associated with a positive return are termed jumps, whereas events with a negative return are called drops.

Using a flexible rather than an absolute event definition, we follow the methodology of Pritamani and Singal (2001) because we think it is better suited for our heterogeneous sample of stocks from many different countries for three reasons. First, it is a more precise measure of market irregularities to define events as outliers in the return distribution than to set a fixed return threshold such as, e.g., 10%. Second, in contrast to earlier studies that use a fixed threshold—such as Atkins and Dyl (1990), Bremer and Sweeney (1991), and Bremer et al. (1997)—we study emerging market returns. Because emerging market stock returns are more volatile than those of industrial countries, thus stretching the return distribution, a relative event definition is more appropriate. Third, our study covers 21 markets simultaneously, each of which has its own market structure. These different market structures result in differing return characteristics that can only be captured through a flexible event definition. To illustrate this point, one can compare average event returns in Morocco, which are 5.72% for jumps and -5.70% for drops, with those of Malaysia, with 16.07% and -13.85%, respectively. Using the same trigger return for both countries to define an event day would be inappropriate and result in distorted event proportions across the different countries.

### 3.3.2. Significance of Post-Event Returns

In measuring the significance of an abnormal stock return the day after an event, we rely on the methodologies of Corrado (1989) and Boehmer et al. (1991). These methodologies are better suited to account for possible variance increases during the event period than are plain t-statistics; thus, they are less likely to reject the null hypothesis. Both test statistics have in common that they are especially suited for the needs of event studies in that they consider changes in return variance induced by the event. To account for irregular trading, we modify the Corrado statistic, following Corrado and Zivney (1992).

Corrado's (1989) approach is non-parametric and measures abnormal performance on a given day by the deviation of the actual rank of the day's abnormal return in the ranking of the observation-period abnormal returns from the expected rank in that ranking. Let the day succeeding the event be the observation day. The test statistic for that day is then determined by ranking the abnormal returns of the observation period beginning with the smallest return. The expected rank on the observation day is the middle of the sample period length measured in trading days. In our case, the observation period comprises the estimation period from day -260 to day -10, the event period from day -9 to day -1, the event day, and day 1 to day 20 after the event. Excluding the event day itself, we therefore rank 280 returns. To prevent irregular trading from distorting the results, we calculate abnormal ranks $U_{it}$ by subtracting the expected rank of 140.5 from the rank of the abnormal daily return:

$$K_{i,t} = Rank\left(AR_{i,t}\right) - 140.5 \tag{16}$$

Thus, the expected abnormal rank of the observation day return is 0. To standardize the abnormal ranks for lacking pre-event returns we apply the correction suggested by Corrado and Zivney (1992) and divide the abnormal rank by the number of non-zero returns during the sample period:

$$U_{i,t} = \frac{K_{i,t}}{1 + \sum_{-260}^{20} z_{i,t}}, \tag{17}$$

where z is a dummy variable that takes the value 1 if stock i was traded on day t. The modified Corrado test statistic, which is normally distributed, is given as

$$C = \sqrt{N} \cdot \frac{\frac{1}{N} \cdot \sum_{i=1}^{N} U_{i,d}}{S(U)}, \tag{18}$$

with $U_{i,d}$ denoting the standardized abnormal return on the very day for which the test statistic is calculated. The standard deviation of the standardized abnormal ranks, S(U), is calculated using the entire 280-day sample period, excluding day 0 for all stock N from the same country:

$$S(U) = \sqrt{\frac{1}{279} \cdot \sum_{t=-260}^{20} \left( \frac{1}{\sqrt{N_t}} \sum_i U_{i,t} \right)^2}. \tag{19}$$

To adjust our expected returns for infrequent trading, we use a Dimson (1979) market model to calculate expected return. The abnormal return is then obtained as the residual from the multivariate regression of the daily estimation period returns on the returns for 5 days before to 5 days after the observation day:

$$R_{i,t} = \alpha + \sum_{k=-n}^{n} \beta_k \cdot R_{m,t+k} + \varepsilon, \text{ with n = 5.} \tag{20}$$

Summing up the 10 $\beta_k$, we obtain the beta of our market model, from which we calculate the abnormal returns and residuals for each sample period day.

$$\tilde{\beta} = \sum_{k=-n}^{n} \beta_k \; . \tag{21}$$

The abnormal return is then given by

$$AR_{i,t} = R_{i,t} - \left(\alpha + \tilde{\beta} \cdot R_{m,t}\right). \tag{22}$$

Our second test statistic was developed by Boehmer et al. (1991). There, we standardize the abnormal return—again calculated using the Dimson model—of the day tested by the standard error of the abnormal returns of the estimation period:

$$SR_{i,t} = \frac{AR_{i,t}}{\sqrt{\frac{1}{N-1} \cdot \sum_{t=-260}^{t=-10} \left(AR_{i,t} - \overline{AR_{i,t}}\right)^2}} \; . \tag{23}$$

Next, we obtain the normally distributed test statistic,

$$B = \frac{\frac{1}{N} \sum_{i=1}^{N} SR_{i,e}}{\sqrt{\frac{1}{N(N-1)} \sum_{i=1}^{N} \left( SR_{i,e} - \sum_{i=1}^{N} \frac{SR_{ie}}{N} \right)^2}} \; , \tag{24}$$

which measures whether the observed standardized market model residuals are significantly different from zero.

### 3.3.3. Determinants of Post-Event Abnormal Returns

Because large one-day price changes in emerging stock markets entail abnormal returns on subsequent days, it is interesting to elaborate the determinants of the market's reaction to the event.

With respect to return drift, event return itself, which is represented by the event day's standardized residual (SR0), is the first candidate that comes to mind when explaining the extent of drift. Additionally, relying on Fama and French (1993) and Carhart (1997), we include market value—i.e., the natural log of market value of equity in USD millions 10 days before the event (LMVUS); book-to-market ratio; the quotient of book value per share and share price 10 days before the event (BTM); and return momentum, i.e., the return of the stock during the six months before the event (MOM)—as explanatory variables in our regression.

Furthermore, there is ample empirical evidence, e.g., Karpoff (1987) and Gallant et al. (1992), that large price changes go hand in hand with large trading volume (turnover, in our nomenclature). Similar insights are presented by Harris and Raviv (1993), who state that important news is accompanied by an increase in trading volume, and Blume et al. (1994), who note that trading volume measures information precision. In the context of large price changes, it is obvious to include variables measuring the precision of the signal causing the initial price change on the event day. We expect that high precision (i.e., low event-day turnover) leads to a lower post-event return, whereas low precision (i.e., high event-day turnover) leads to a higher post-event return. Based on this earlier research, we include average daily estimation period turnover in USD millions (TOEST) and event-day turnover in USD millions (TO) as explanatory variables in our regression to capture the price effect of turnover on post-event stock returns.

Because Cox and Peterson (1994) suggest that short-term return predictability might actually be a liquidity phenomenon, we account for a stock's liquidity by incorporating the dollarized Amihud illiquidity ratio of the estimation period (AIREST) in our model. We also include a December (DEC) and a January dummy (JAN) to account for calendar effects and a Monday (MON) and a Friday dummy (FRI) to capture day-of-the-week effects. To run pooled regressions over samples containing stocks from different countries, we convert all variables measured in local currency into US dollar variables. This conversion concerns the market value of equity, the Amihud illiquidity ratio and turnover variables.

We run regressions on the pooled global sample, the four pooled regional samples, the pooled country samples and the respective size sub-samples:

$$SR_{i,t} = \beta_0 + \beta_1 SR0_{i,t} + \beta_2 LMVUS_{i,t} + \beta_3 BTM_{i,t} + \beta_4 AIREST_{i,t} + \beta_5 MOM_{i,t} + \\ + \beta_6 TOEST_{i,t} + \beta_7 TO_{i,t} + MON + FRI + DEC + JAN \quad . \tag{25}$$

## 3.4. UNIVARIATE RESULTS

### 3.4.1. Descriptive Statistics

(Insert Table 8 here)

With the screens imposed, the final sample consists of 117,606 events. Table 8 contains the event distribution over the 21 sample countries and shows how many events are affected by each of our screens. To determine whether market participants react differently to good and bad news, we split the sample into price jumps and price drops. The proportion of screened events is indicative of the degree of market developments in the different countries. The least developed market in terms of the density of thinly traded stocks is that of Indonesia, where only 4% of the events occurred among stocks liquid enough to qualify for our final sample. Indonesia is closely followed by the Philippines, with 95% of events excluded. The most developed markets are—unsurprisingly—India and South Korea, with exclusion rates of 38% and 39%, respectively. India and South Korea are also the countries with the largest shares in our final sample, with totals of 23,645 and 31,343 events, respectively. The average event returns range from roughly +/- 6% in Morocco to 17% for jumps and -14% for drops in the Philippines. Both markets constitute only a small share in our final sample, with fewer than 200 events in each category.

(Insert Table 9 here)

Detailed descriptive statistics concerning the characteristics of the event firms are depicted in Table 9. Table 9 consists of two panels: panel A for price jumps and panel B for price drops. Both contain the number of event firms and country averages of LMVUS, BTM, AIREST, MOM, TOEST, and TO.

If we compare winner stocks to loser stocks, we observe that on average, loser stocks have a larger market capitalization and a lower average book-to-market-ratio than do winner stocks.

Initially, we would have expected that winners and losers would not have different pre-event market capitalization. However, we do not have an explanation for this phenomenon.

### 3.4.2. Stock Return Predictability across Emerging Markets

#### *3.4.2.1. Global Samples*

(Insert Table 10 here)

Analyzing the overall sample and the regional sub-samples, we test the hypothesis that emerging market stock returns after extreme one-day price changes are predictable in the short term. If that were the case, we should find either a significantly positive or a significantly negative abnormal return on the day after an extreme one-day price change. Therefore, we calculate Boehmer test statistics to learn whether standardized residuals on the day after an extreme price change are significantly different from zero. Our examination starts on the global and regional levels. Table 10 contains the results of the Boehmer tests for the global and regional sub-samples. Because the global and regional samples are themselves split into size sub-samples, Table 10 contains 4 panels. Panel A comprises the undivided sub-samples, Panel B holds big companies, Panel C holds medium companies, and Panel D holds small companies. We use these panels to determine whether our results are driven by a size effect. Each panel includes three sub-samples. The first sub-sample contains all returns on the first day after any event in the panel. The second and third sub-samples consist of price jumps and price drops, respectively.

In the pooled global sample of panel A that encompasses all jumps and drops in all countries, the average abnormal return is significantly positive. This would be empirical evidence for the uncertain information hypothesis (UIH) by Brown et al. (1988). However, the other two sub-samples of panel A of jumps and drops paint a different picture. A significantly positive average abnormal return after price jumps and a significantly negative average abnormal return after price drops are evidence of stock return drift following extreme price movements. The significance of the positive abnormal return in the pooled sample is therefore attributable to the impact of the price jumps on the panel. Similar results for panels B, C and D support this notion.

Gauging size effect, we see that the observed drift grows with as firm size shrinks. We observe the strongest drift among small companies after price jumps. On average, the standardized residual on the day after a price increase is 0.5465. In contrast, the average standardized residual after a small-company price drop is a mere -0.2356, which is—in absolute terms—still the strongest drift following price drops. Although economic significance is largest in the small-company panel, statistical significance is strongest in the medium-company panel, which can be ascribed to its large sample size. If we compare these results to the results of earlier developed-market studies by Pritamani and Singal (2001), Larson and Madura (2003), and Bremer et al. (1997), it is surprising to see that emerging-market investors seem to react more strongly to price increases than to price decreases. In developed markets, investor reactions are usually more pronounced after price drops. Moreover, the notion of drift contrasts with the results of earlier studies on developed markets, which document overreaction after price drops for most markets and mixed evidence for abnormal returns after price jumps. However, Otchere and Chan (2003) have documented the same phenomenon in Hong Kong.

#### *3.4.2.2. Regional Analysis*

On the regional level, the effect is the same as in the global sample. Whereas on first look, the pooled samples support the UIH, the separation in jumps and drops shows that this effect is caused by systematic return drift after price jumps. Return drift after price drops is significant in ASIA only. Asian stocks display significant drift throughout all sub-samples. The results for the other regions are mixed. Medium stocks in EE and MEA, and small stocks in MEA, earn abnormally positive returns after a price drop. Abnormal stock returns after price drops in Latin America are insignificant. Whereas big stocks earn significantly positive abnormal returns after price jumps in Latin American markets, we do not observe any effects after price drops. In EE and MEA, we observe a very distinct size effect. Whereas big stocks do not earn positive abnormal returns after price jumps, medium and small stocks display significantly positive abnormal returns. The standardized residual of small stocks is nearly double the residual of medium stocks in both regions. In MEA, the effect is so strong that it switches signs, and big stocks even earn abnormally negative returns.

The evidence for abnormal short-term stock returns after price drops is mixed. We find a significant post-event return drift in all of the Asian size sub-samples. The results in EE are inconclusive. Medium stocks display short-term return drift, whereas big and small stocks do not see any significant post-event returns. MEA is the only region where we find overreaction (albeit one that is slightly insignificant for big companies). Latin American stocks do not earn abnormal returns after price drops except for small stocks. In that very small sub-sample, overreaction can be observed.

On a regional basis, we conclude that the drift hypothesis is strongly backed by the findings for price jumps. With respect to price drops, the evidence is not clear and we do not find persistent drift or overreaction.

The fact that reactions are weaker for large companies is consistent with earlier literature that suggests that market anomalies are more likely to be found among small stocks.

#### *3.4.2.3. Country-Level Analysis*

(Insert Table 11 here)

In Asian countries, we observe significant drift after jumps in every country but Indonesia and the Philippines. Regarding the fact that both the Indonesian and Filipino sub-samples have a large screening percentage of illiquid stocks, it is not surprising that we do not observe any abnormal effects in those countries. With respect to price drops, the strong drift in four countries causes the effect that we see on the regional level. However, post-drop returns in the other countries also have a tendency to be negative. Overall, Asian countries support our findings on the regional level. Much like in the regional sample, the effects are weaker in the large-company sub-sample.

In Eastern Europe, we find drift after price jumps in the Czech Republic and Poland. Abnormal returns are insignificant in Hungary and Russia. In Hungary, we observe overreaction after price drops. In Russia, we find drift after price drops. If we divide the pooled samples into size sub-samples, we observe support for the drift hypothesis in Poland, where medium and small companies earn positive abnormal returns after price jumps. Large firms do not earn abnormal returns, which is in line with the notion that the effect is stronger for small and medium firms. The only sub-sample in the Czech Republic that is large enough for statistical inferences is that of big companies. Here, we find positive abnormal returns after price jumps. In Hungary, our results point towards overreaction with positive abnormal returns after price drops, whereas the evidence in Russia is in favor of drift after price drops as opposed to price jumps. Taken together, the picture of Eastern Europe is blurry. There is certainly no pervasive evidence in favor of either the overreaction hypothesis or the UIH. Based on our results, the hypothesis of drift after price jumps appears to be the most reasonable of the hypotheses.

In Latin America, we observe drift after price jumps in Brazil, Chile, and Mexico. Abnormal returns in the other two countries are positive but insignificant, which might be related to the small samples in these countries. In none of the markets are abnormal returns in either direction significant after price drops. It is rather difficult to break the results down to the size panels because the sub-samples for small companies are too small to draw valid inferences. We observe significantly positive abnormal returns in the medium sub-samples. Among the sub-samples of big companies, only the one for Chile exhibits positive abnormal returns. Abnormal returns in the other countries are insignificant. Taken together, the Latin American countries support the hypothesis of drift after price jumps. As in Asia, return drift shrinks with firm size.

In the Middle East and Africa, abnormal returns after jumps are significantly positive in all four countries, thus supporting the drift hypothesis. This finding remains stable for all sub-samples of medium and small companies. Large companies only display positive post-event returns in Morocco and Turkey. This is in line with the observation that drift is weaker among big companies. In Turkey, we also see drift after price drops with positive returns in all but the small company sub-samples. However, this effect cannot be spotted in the other countries. Therefore, we conclude that our results for MEA are in line with our results for Latin America and Asia in that we find persistent return drift after price jumps.

To summarize our findings on stock return predictability, we can state that emerging-market stocks earn positive abnormal returns on the day subsequent to a one-day price jump. In contrast to developed-market stocks, emerging-market stocks do not exhibit systematic abnormal returns after one-day price drops. They earn neither abnormally positive nor negative returns. In spite of the weak Eastern European evidence, we decided to examine price jumps only in our explanatory regressions because return drift after price jumps is the prevalent phenomenon in the vast majority of our samples.

## 3.5. CROSS-SECTIONAL REGRESSIONS

### 3.5.1. Global samples

(Insert Table 12 here)

The explanatory regressions corroborate our findings of return drift after price jumps. Nearly all explanatory regressions that we run on the standardized residuals of our (sub-)samples yield significantly positive constant terms. The economic significance of drift grows as firm size shrinks. This becomes obvious from the intercepts of the size sub-samples: the small-firm sub-sample exhibits a higher intercept than the medium sub-sample, which has a lower intercept than the large sub-samples. Negative coefficients of the market value variables are also evidence of a size effect within the sub-samples. Moreover, the influence of the market value variable shrinks if we move from small to large firms. In the global sample, the LMV coefficient for small firms is nearly three times as large as that for large firms. The extent of the abnormal event return has no influence on the extent of drift. That means that firms with higher jumps do not earn larger abnormal returns on the subsequent day. A negative coefficient of AIREST suggests that the more liquid the stock, the stronger the abnormal return. The liquidity effect that can be observed in the pooled sample is driven by the significantly negative coefficient in the sub-sample of small companies. There is no liquidity effect in the medium and large company sub-samples.

Medium-term return momentum also plays a role in explaining short-term return drift. With respect to small companies, there is a positive correlation between medium-term return and short-term abnormal return. For medium and big companies, the effect is negative. That means that investors tend to realize short-term gains after price jumps of big companies, with a higher probability if the stock's performance has been good during the 6 months before the event. If the stock price of a small company jumps, investors seem to interpret this as a buy sign, sparking short-term abnormal returns after the event. We hypothesize that this is related to media and analyst coverage, which is usually more extensive for big firms. Information about a good performance is well known among market participants if a firm is larger. Prompted by cautiousness, investors would rather realize their profits instead of speculating on even higher future gains.

Day-of-the-week effects have the potential to mitigate short-term drift effects, at least for events that take place on a Monday. Short-term abnormal returns of medium and small companies are nearly 15% and 19% smaller if the event occurs on a Monday. Conversely, Friday events lead to returns that are up to 44% higher than those on other days of the week.

### 3.5.2. Regional Analysis

#### *3.5.2.1. Pooled Samples*

The regional comparison of the explanatory regressions offers further evidence for the inferences of the univariate analysis and the explanatory regressions of the global sample. All of the regional regressions except for the one in Latin America yield a significantly positive intercept. The intercept of the Latin American regression is also close to being significant. These positive constant terms are supportive evidence of the drift that we observed earlier in the univariate analysis. Significantly negative coefficients of LMV—again with the exception of Latin America—offer corroborative evidence for the hypothesis that market value and the extent of drift are inversely related. This is consistent with our earlier finding that medium and small stocks tend to have higher returns after a large price increase. Whereas in EE, the extent of the preceding price increase and the extent of drift are inversely related, there is no such relationship in ASIA, EE or LATAM.

The influence of liquidity differs from region to region. In the pooled sub-samples, significantly negative coefficients of estimation period AIRs can be observed in all regions with the exception of MEA. This suggests a positive relationship between liquidity and post-event return because the illiquidity ratio is smaller for more liquid stocks. In Asia, the negative coefficients are significant across all size sub-samples. In Eastern Europe and MEA, the coefficient is significant only in the sub-sample of small companies.

The positive significance of the book-to-market ratio in the pooled Asian sample is subsistent in the sub-samples of large and medium firms but not in the sub-sample of small firms.

We find a negative influence of medium-term stock return momentum for large and medium Asian firms. The influence on small Asian firms is significantly positive. That suggests that investors in Asia tend to realize price gains after events of bigger companies rather than after price gains of small companies. In MEA, the influence is significant in the sub-sample of big companies only. As in Asia, it is negative.

In Asia, a significantly positive Friday effect can be observed in all size sub-samples. A significantly negative Monday effect can be observed in the sub-samples of medium and small companies.

3.5.2.2. *Size Sub-Samples*

The findings in the pooled regional samples are persistent if we further split the regional samples into sub-samples of large, medium and small companies.

We find significant return drift in ASIA for large companies. As in the pooled sample, return drift shrinks with increasing company size. AIREST, book-to-market-ratio, and midterm momentum also have a significant influence on post-event returns in Asia. A positive Friday effect can also be found.

Regressions in the medium company sub-samples support the drift hypothesis most strongly of all size sub-samples. Constant terms are significantly positive across all regions but Latin America. The economic significance of the drift returns is highest in EE, followed by MEA and ASIA. The highest statistical significance is displayed by Asian stocks, which is not surprising considering the huge sample size. Market value also has a negative influence on short-term post-event return in all regions. Like in the large company sub-sample, liquidity and mid-term momentum have a negative influence on drift returns in ASIA. The effect of AIREST is also significant in LATAM.

With respect to small companies, the explanatory regressions support the drift hypothesis in ASIA and EE. In both regions, the influence of AIREST is negative. Much like in the other size sub-samples, company size has a negative influence on post-event return drift. This influence is very significant in ASIA and close to significant in EE. The MEA sub-sample does not exhibit significant drift, and the LATAM sample is too small to derive any reliable inferences. In EE, the negative influence of abnormal event return on return drift is significant. An interesting side note is the positive mid-term momentum coefficient for small Asian stocks, which has the opposite sign from big and medium companies. This suggests that an event is more of a buy sign than a sell sign for small stocks that performed well during the preceding 6-month period.

It is interesting to note that in January, small Asian stocks exhibit stronger drift than in other months, whereas the coefficients for medium and large stocks are nowhere near significant for the January dummy.

In all, the regional analysis reinforces the finding in the global sample that emerging-market stocks earn significantly positive returns on the day subsequent to a large price increase. Furthermore, the notion that company size has a negative influence on return drift is strengthened.

### 3.5.3. Country-Level Analysis

#### *3.5.3.1. Pooled Samples*

(Insert Table 13 here)

Of the Asian countries, China, India, South Korea, and Taiwan display drift. In Indonesia, Malaysia, the Philippines and Thailand, significantly positive constant terms cannot be found. There exists a very strong positive relationship between event return and standardized post-event residual in China, South Korea, and Taiwan. That means that higher price increases spark a larger return drift in these countries if we look at the pooled samples.

Although we see a drift effect in the pooled sub-sample from the MEA region, we cannot detect post-event return drift in the pooled country sub-samples from the MEA region.

The country-wise regressions in Eastern Europe show that the positive constant term in the pooled regional sample is heavily influenced by the Polish stocks, which account for more than 50% of the regional sample and have a significantly positive constant. The residuals in the other

Eastern European countries are insignificant. Considering that we find significant return drift in 2 out of 5 Latin American countries (Brazil, Chile) and nearly significant constant terms in two others (Mexico, Peru), it is somewhat surprising that the positive constant term in the regional sample is insignificant.

*3.5.3.2. Size Sub-Samples*

In ASIA, post-event returns drift after price increases in 4 out of 8 large-company country samples. In India, Indonesia, and Malaysia, the coefficients are also close to being significantly positive. In EE, only Poland offers evidence for the drift hypothesis in the large-company sub-sample. The coefficient is also close to significant in the Czech Republic. Of the large Latin American stocks, only Mexican stocks show post-event return drift. Positive constant terms in Chile and Peru are insignificant. Large stocks in countries in the MEA region do not show any signs of post-event return drift, which is surprising due to the drift in the pooled sample of large regional firms. The exception is the Egyptian market, which shows significant drift. We believe that the lack of significance is related to the small sample sizes across MEA countries. In nearly all countries with post-event return drift, market value has a negative influence on the extent of that drift. In contrast to the pooled samples, liquidity has no influence on the reaction to price shocks.

In ASIA, 3 out of 8 countries (China, South Korea, Taiwan) display positive abnormal returns after sharp price increases. In two of these countries, LMV has a negative influence on the extent of the drift. This is not surprising because the medium company sub-sample comprises the 5 middle deciles of the market-value distribution. Therefore, the market-value difference within the sub-sample is much larger than in the large- and small-firm sub-samples. In India and Indonesia, intercepts are positive but slightly insignificant. The influence of market value is also negative in those two countries. The only Eastern European country with a significantly positive constant is Poland. The Hungarian constant is also positive, but insignificant. The Russian constant is negative and insignificant. On the regional level, the combined occurrences of post-event return drift in Poland and Hungary are apparently strong enough to mitigate the influence of the negative Russian coefficient. Among medium companies in LATAM, only Brazilian companies earn positive abnormal returns after strong price increases. The Chilean and Colombian samples are too small to perform regressions, and the Peruvian sample is very small. In MEA, we see positive abnormal returns in Egypt. Morocco and South Africa do not display abnormal returns. Turkey is the only country with a negative constant term, suggesting overreaction instead of return drift at the country level.

At the country level, many small company sub-samples are too small to perform the explanatory regressions. The biggest regional sub-sample of small firms is the one in ASIA. There, we have 6 countries that are large enough to make assertions regarding return drift. In Indonesia and the Philippines, we cannot observe enough events among small companies to run the explanatory regressions. Four out of the 6 countries with sufficiently large sub-samples display constant terms that are significantly positive. In all but one of those countries, the influence of market value is negative. From the Eastern European markets, only the Polish market is large enough to form a sub-sample of sufficient size. Post-event return drift in that country is significant. Where market value has no influence on post-event return drift, we find a negative influence of the abnormal event return. None of the Latin American sub-samples is large enough to run the explanatory regressions. Of the two MEA markets with sufficiently large sub-samples, only the Egyptian market shows signs of drift. Market value influences post-event returns negatively.

Taken together, the country-level analysis is in line with the findings on the regional and global levels. Following extreme price increases, there is short-term stock-return drift in most emerging markets. The drift becomes weaker when we move from small to large firms. The other variables only have selective influence on short-term post-event returns.

## 3.6. ROBUSTNESS

To ensure that we address the skepticism of Cox and Peterson (1994) regarding stock return predictability, we also performed every explanatory regression including average estimation period spread as an explanatory variable. The fact that the variable has no significant influence on the occurrence and extent of drift contradicts the hypothesis that bid-ask spread is a determinant for stock return predictability. Other robustness tests, such as running regressions with variables in local currencies and not using purged samples, also do not alter our results. Although not reported in our tables, our results based on the Corrado-Zivney-test are the same as the ones obtained with the Boehmer methodology.

## 3.7. CONCLUSIONS

Analyzing short-term stock return predictability after extreme one-day price movements in 21 emerging markets, we find strong evidence of post-event stock return drift after price jumps. In contrast to existing evidence for developed markets, we cannot detect any pervasive short-term overreaction. Instead, we find significant short-term post-event stock return drift after price drops in Asia. Considering that in developed markets the reaction to price decreases is usually more economically and statistically pronounced than the reaction to price increases, this result was unexpected.

Post-event return drift is widespread in all geographic regions and across all size sub-samples. We find that in the pooled samples and within the sub-samples, stock return drift shrinks with firm size. This is completely in line with the earlier literature. The post-event return drift that we find is not influenced by the extent of the preceding price increase. Other variables, such as liquidity, book-to-market-ratio, mid-term momentum, and trading volume exert no consistent influence on post-event return drift. Month-of-the-year and day-of-the-week effects are also not persistent in explaining short-term, post-event return drift.

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## Table 8: Country sample sizes

Table 8 contains screening statistics per country. We used the following screens to filter flawed data and illiquid stocks. $N_1$ represents the unscreened sample sizes, $N_2$ represents the sample size after exclusion of all events with an absolute event return (ER) of more than 50%, $N_3$ represents the sample size after excluding all stocks with more than 20 zero $AIR_{i,t}$s during the 250 days before the event window, $N_4$ represents the sample size after excluding all stocks with more than 1 zero $AIR_{i,t}$ during the 20 days after the event, and $N_5$ represents the sample size after excluding all stocks with an AIREST > 0.01. The screening percentage gives the percentage of events that are included in the final sample. The sample is split into jumps ($N_6$) and drops ($N_7$) and the average event return is given for each group.

| | | | | | | | | Jumps | | Drops | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Country | ISO-Code | $N_1$ | $N_2$ | $N_3$ | $N_4$ | $N_5$ | Screening Percentage | $N_6$ | Avg. ER | $N_7$ | Avg. ER |
| Brazil | BRA | 7,942 | 7,767 | 3,562 | 2,478 | 2,478 | 31% | 1,412 | 11.86% | 1,066 | -10.78% |
| Chile | CHL | 4,654 | 4,631 | 1,387 | 643 | 641 | 14% | 382 | 6.54% | 259 | -6.21% |
| China | CHN | 57,899 | 57,476 | 19,465 | 16,377 | 16,377 | 28% | 9,512 | 10.45% | 6,865 | -9.52% |
| Colombia | COL | 1,049 | 1,044 | 351 | 265 | 265 | 25% | 123 | 10.24% | 142 | -8.34% |
| Czech Republic | CZE | 1,540 | 1,536 | 342 | 323 | 323 | 21% | 153 | 9.19% | 170 | -9.09% |
| Egypt | EGY | 1,977 | 1,961 | 1,155 | 1,100 | 1,100 | 56% | 658 | 10.49% | 442 | -10.43% |
| Hungary | HUN | 1,955 | 1,932 | 897 | 624 | 624 | 32% | 345 | 10.75% | 279 | -10.40% |
| India | IND | 38,750 | 38,412 | 24,815 | 23,645 | 23,645 | 61% | 16,266 | 12.90% | 7,379 | -11.49% |
| Indonesia | IDN | 9,235 | 9,020 | 1,874 | 348 | 348 | 4% | 192 | 14.70% | 156 | -11.97% |
| Malaysia | MYS | 43,795 | 43,055 | 19,146 | 7,186 | 7,186 | 16% | 4,498 | 16.07% | 2,688 | -13.85% |
| Mexico | MEX | 5,112 | 5,085 | 2,295 | 2,021 | 2,021 | 40% | 1,109 | 9.48% | 912 | -8.96% |
| Morocco | MAR | 1,192 | 1,190 | 268 | 145 | 145 | 12% | 77 | 5.72% | 68 | -5.70% |
| Peru | PER | 2,720 | 2,682 | 408 | 325 | 325 | 12% | 158 | 9.90% | 167 | -9.13% |
| Philippines | PHL | 5,842 | 5,803 | 1,661 | 279 | 279 | 5% | 171 | 17.11% | 108 | -13.80% |
| Poland | POL | 8,308 | 8,191 | 5,390 | 2,751 | 2,745 | 33% | 1,729 | 13.76% | 1,016 | -11.48% |
| Russia | RUS | 3,070 | 2,991 | 1,753 | 1,612 | 1,607 | 52% | 716 | 12.33% | 891 | -11.73% |
| South Africa | ZAF | 15,586 | 14,910 | 7,064 | 2,950 | 2,950 | 19% | 1,548 | 10.44% | 1,402 | 9.68% |
| South Korea | KOR | 51,630 | 51,396 | 42,635 | 31,343 | 31,343 | 61% | 20,126 | 13.14% | 11,217 | -12.43% |
| Taiwan | TWN | 28,446 | 28,407 | 24,385 | 13,262 | 13,262 | 47% | 8,707 | 7.52% | 4,555 | -7.29% |
| Thailand | THA | 22,152 | 22,034 | 9,052 | 3,525 | 3,525 | 16% | 2,149 | 13.26% | 1,376 | -11.45% |
| Turkey | TUR | 11,378 | 11,336 | 10,332 | 3,658 | 3,403 | 30% | 2,070 | 13.49% | 1,333 | -12.22% |

## Table 9: Descriptive Statistics

Table 9 contains descriptive statistics of the sample stocks: the log market value of equity in USD millions ten days before the event (LMVUS), the log book-to-market ratio ten days before the event (BTM), the estimation period AIR in USD (AIREST), the stock return for the previous 6 months (MOM), the average estimation period turnover in USD (TOEST), and the average event day turnover in USD (TO). $\tilde{n}$ indicates the sample size of the sample from which average BTM has been calculated. The differences in sample sizes are the result of missing data related to book values.

**Panel A: Jumps**

| Country | n | LMVUS | BTM | $\tilde{n}$ | AIREST | MOM | TOEST | TO |
|---|---|---|---|---|---|---|---|---|
| Brazil | 1,412 | 6.742144 | 6.172148 | 1,324 | 42.85231 | -0.0228611 | 1,697,140 | 11,169,470 |
| Chile | 382 | 19.99571 | -0.4741891 | 371 | 81.42992 | 0.0318472 | 743,016,300 | 14,084,550 |
| China | 9,512 | 5.253612 | -0.662603 | 7,453 | 5.891481 | 0.1314284 | 4,876.061 | 2,615.5 |
| Colombia | 123 | 6.381629 | 0.209838 | 112 | 0.0046955 | 0.067721 | 1,735.76 | 17 |
| Czech Republic | 153 | 7.234898 | -0.156849 | 134 | 0.3585247 | 0.011109 | 11,417.63 | 56.4 |
| Egypt | 658 | 5.35229 | -0.4931973 | 587 | 17.10335 | 0.2165888 | 1,626.243 | 273 |
| Hungary | 345 | 5.501726 | -0.1815494 | 313 | 0.0086646 | 0.0051392 | 5,362.784 | 4.12 |
| India | 16,266 | 4.591677 | -0.4456648 | 13,577 | 4.320705 | 0.1321835 | 746.2043 | 26.7 |
| Indonesia | 192 | 6.445966 | -0.7060691 | 183 | 9.81E-06 | 0.0985869 | 2,586.734 | 7.66 |
| Malaysia | 4,498 | 4.336495 | -0.0349163 | 3,600 | 130.9636 | -0.1205169 | 693.0581 | 1,733.4 |
| Mexico | 1,109 | 7.252936 | -0.3899809 | 1,002 | 2.04033 | 0.0352026 | 5,708.102 | 838.3 |
| Morocco | 77 | 7.416358 | -0.9452405 | 64 | 1.375996 | 0.0804257 | 2,180.029 | 15.7 |
| Peru | 158 | 5.958266 | -0.6193053 | 150 | 49.70827 | 0.1112096 | 442.374 | 591.1 |
| Philippines | 171 | 5.081534 | 0.1500925 | 162 | 1.415763 | -0.1770044 | 1,127.559 | 570.9 |
| Poland | 1,729 | 4.11346 | -0.5125026 | 1,527 | 171.451 | 0.1929938 | 884.5257 | 401.3 |
| Russia | 716 | 7.667812 | -0.1573735 | 659 | 22.79611 | -0.0363855 | 25,380.94 | 2821 |
| South Africa | 1,548 | 6.814018 | -0.5945246 | 1,406 | 12.83865 | -0.0123064 | 6,383.968 | 799.3 |
| South Korea | 20,126 | 4.090086 | 0.2758867 | 18,381 | 0.0004473 | 0.0700936 | 3,089.097 | 1.47 |
| Taiwan | 8,707 | 4.905866 | -0.1804707 | 8,064 | 0.3159125 | 0.0765996 | 2,683.799 | 364.9 |
| Thailand | 2,149 | 4.7768 | -0.1396829 | 2,007 | 1.385198 | 0.0454881 | 1,188.679 | 1,732 |
| Turkey | 2,070 | 4.416599 | -0.2143512 | 1,691 | 547.5131 | 0.1139205 | 2,636.266 | 7,298.7 |

**Panel B: Drops**

| Country | n | LMVUS | BTM | $\tilde{n}$ | AIREST | MOM | TOEST | TO |
|---|---|---|---|---|---|---|---|---|
| Brazil | 1,066 | 6.995083 | 6.080361 | 1,014 | 28.01922 | -0.0085908 | 2,315,025 | 16,023,410 |
| Chile | 259 | 20.35783 | -0.6042188 | 257 | 52.35843 | 0.0820258 | 989,218,800 | 6,352,429 |
| China | 6,865 | 5.445644 | -0.8849058 | 5,537 | 4.348273 | 0.2230538 | 5,402.067 | 1,649.1 |
| Colombia | 142 | 6.873967 | 0.0626876 | 131 | 0.0029645 | 0.1855725 | 1,934.343 | 7.59 |
| Czech Republic | 170 | 7.463677 | -0.3487465 | 143 | 0.2816956 | 0.0812266 | 14,000.79 | 55 |
| Egypt | 442 | 5.983252 | -0.7090217 | 387 | 13.72474 | 0.1999123 | 3,183.049 | 148.9 |
| Hungary | 279 | 6.011905 | -0.468348 | 254 | 0.0059046 | -0.0172042 | 7,709.193 | 3.53 |
| India | 7,379 | 5.430948 | -0.7403436 | 6,677 | 1.654939 | 0.1825392 | 1,346.886 | 16.7 |
| Indonesia | 156 | 6.945304 | -0.8949132 | 152 | 5.05E-06 | 0.1143404 | 3,288.094 | 5.43 |
| Malaysia | 2,688 | 4.657564 | -0.2646977 | 2,118 | 87.12956 | -0.1497208 | 956.4049 | 1,124.6 |
| Mexico | 912 | 7.364693 | -0.4715279 | 827 | 0.9349465 | 0.0426409 | 6,193.918 | 816 |
| Morocco | 68 | 7.480977 | -1.107174 | 59 | 1.100184 | 0.0179907 | 2,414.309 | 14 |
| Peru | 167 | 6.22058 | -0.7673675 | 159 | 44.24217 | 0.0510501 | 498.6439 | 205.8 |
| Philippines | 108 | 5.962236 | -0.3799563 | 106 | 0.3025027 | -0.0277749 | 1,739.493 | 413.3 |
| Poland | 1,016 | 4.589438 | -0.6114163 | 891 | 156.6403 | 0.1163681 | 1,425.5 | 259.6 |
| Russia | 891 | 7.785127 | -0.242383 | 775 | 42.3423 | -0.1566024 | 28,012.95 | 2,644.2 |
| South Africa | 1,402 | 6.942847 | -0.757728 | 1,275 | 11.34169 | 0.070902 | 5,768.41 | 616 |
| South Korea | 11,217 | 4.426937 | 0.0672465 | 9,884 | 0.0002914 | 0.0708834 | 4,200.376 | 0.988 |
| Taiwan | 4,555 | 5.293107 | -0.3845378 | 4,170 | 0.2902939 | 0.1390895 | 4,561.147 | 236.8 |
| Thailand | 1,376 | 5.261933 | -0.3734117 | 1,257 | 1.041118 | 0.0013323 | 1,594.733 | 1,052.1 |
| Turkey | 1,333 | 4.789518 | -0.4341375 | 1,083 | 481.2531 | 0.1433853 | 3,131.756 | 4,439.9 |

**Table 10: Post-event day abnormal returns by region**

Standardized return residuals on the day after an extreme one-day stock price movement by region. The residuals are grouped by size panels. Panel A holds all companies, Panel B holds large companies, Panel C holds medium companies and Panel D holds small companies. Each panel consists of 15 sub-samples. Panel A is the pooled sample, which holds residuals for all companies. For each sub-sample, the average standardized return residual (POOLED, JUMPS, DROPS), the Boehmer test-statistic (TS) and the sample size (N) are given.

| | Panel A: All Companies | | | | | Panel B: Large Companies | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | GLOBAL | ASIA | EE | LATAM | MEA | GLOBAL | ASIA | EE | LATAM | MEA |
| POOLED | 0.1610 | 0.1638 | 0.0544 | 0.1056 | 0.2757 | 0.0650 | 0.0517 | 0.0433 | 0.0528 | 0.3858 |
| TS | (19.12)*** | (22.09)*** | (1.45) | (3.40)*** | (3.23)*** | (3.34)*** | (3.78)*** | (0.86) | (1.50) | (1.31) |
| N | 114,349 | 93,148 | 5,039 | 5,532 | 7,091 | 36,364 | 2,6231 | 1,979 | 3,823 | 1,964 |
| JUMPS | 0.3598 | 0.3892 | 0.1491 | 0.1794 | 0.1548 | 0.1721 | 0.2166 | -0.0123 | 0.0917 | -0.1634 |
| TS | (43.55)*** | (43.43)*** | (3.46)*** | (4.63)*** | (4.22)*** | (12.21)*** | (13.19)*** | (0.19) | (2.17)** | (2.66)*** |
| N | 71,656 | 59,733 | 2,834 | 3,047 | 4,187 | 20,953 | 15,595 | 1,008 | 2,098 | 1,022 |
| DROPS | -0.1725 | -0.2390 | -0.0672 | 0.0151 | 0.4501 | -0.0806 | -0.1899 | 0.1010 | 0.0054 | 0.9816 |
| TS | (9.76)*** | (18.70)*** | (1.03) | (0.30) | (2.23)** | (1.93)* | (8.09)*** | (1.29) | (0.09) | (1.61) |
| N | 42,693 | 33,415 | 2,205 | 2,485 | 2,904 | 15,411 | 10,636 | 971 | 1,725 | 942 |

| | Panel C: Medium Companies | | | | | Panel D: Small Companies | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | GLOBAL | ASIA | EE | LATAM | MEA | GLOBAL | ASIA | EE | LATAM | MEA |
| POOLED | 0.1713 | 0.1761 | 0.0008 | 0.2234 | 0.1889 | 0.2952 | 0.2862 | 0.2556 | 0.2306 | 0.3482 |
| TS | (17.62)*** | (17.13)*** | (0.01) | (3.48)*** | (4.67)*** | (18.05)*** | (16.78)*** | (2.59)*** | (0.91) | (4.56)*** |
| N | 56,257 | 4,7667 | 2,330 | 1,625 | 3,690 | 21,728 | 19,250 | 730 | 84 | 1,437 |
| JUMPS | 0.3925 | 0.4060 | 0.1980 | 0.4140 | 0.1962 | 0.5465 | 0.5546 | 0.3470 | -0.3571 | 0.3997 |
| TS | (33.51)*** | (32.68)*** | (3.13)*** | (4.91)*** | (4.06)*** | (27.73)*** | (27.19)*** | (2.86)*** | (1.13) | (4.24)*** |
| N | 35,956 | 31,028 | 1,334 | 899 | 2,212 | 14,747 | 13,110 | 492 | 50 | 953 |
| DROPS | -0.2206 | -0.2526 | -0.2632 | -0.0125 | 0.1780 | -0.2356 | -0.2871 | 0.0668 | 1.0949 | 0.2466 |
| TS | (13.11)*** | (14.27)*** | (2.27)** | (0.13) | (2.52)** | (8.33)*** | (9.67)*** | (0.40) | (2.87)*** | (1.90)* |
| N | 20,301 | 16,639 | 996 | 726 | 1,478 | 6,981 | 6,140 | 238 | 34 | 484 |

## Table 11: Post-event day abnormal returns by country

Standardized return residuals (SR) on the day after an extreme one-day stock price movement by country. The residuals are grouped by size panels. Panel A holds all companies, Panel B holds large companies, Panel C holds medium companies and Panel D holds small companies. Each panel consists of 12 sub-samples. Panel A is the pooled sample, which holds residuals for all companies. For each sub-sample, the average standardized return residual (SR1), the Boehmer test-statistic (TS) and the sample size (N) are given.

**Panel A: All companies**

| | CHN | IND | IDN | MYS | PHL | KOR | TWN | THA | CZE | HUN | POL | RUS |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| POOLED | 0.145 | 0.178 | -0.024 | 0.047 | 0.074 | 0.169 | 0.278 | -0.059 | 0.164 | 0.208 | 0.182 | -0.265 |
| TS | 9.02*** | 12.57*** | 0.16 | 1.33 | 0.46 | 13.03*** | 14.23*** | 1.33 | 1.18 | 1.94* | 3.81*** | 3.36*** |
| N | 16,021 | 22,817 | 333 | 6,840 | 265 | 30,504 | 12,957 | 3,411 | 312 | 607 | 2,676 | 1,453 |
| JUMPS | 0.328 | 0.246 | 0.042 | 0.115 | 0.226 | 0.463 | 0.746 | 0.197 | 0.486 | -0.051 | 0.240 | -0.061 |
| TS | 16.18*** | 14.95*** | 0.22 | 2.80*** | 1.10 | 28.96*** | 31.74*** | 3.70*** | 2.94*** | 0.43 | 4.42*** | 0.61 |
| N | 9,301 | 15,684 | 180 | 4,254 | 162 | 19,561 | 8,512 | 2,079 | 149 | 335 | 1,686 | 669 |
| DROPS | -0.107 | 0.027 | -0.102 | -0.064 | -0.164 | -0.357 | -0.617 | -0.459 | -0.130 | 0.527 | 0.084 | -0.440 |
| TS | 4.11*** | 0.99 | 0.42 | 0.98 | 0.62 | 16.88*** | 20.07*** | 5.91*** | 0.60 | 2.77*** | 0.94 | 3.69*** |
| N | 6,720 | 7,133 | 153 | 2,586 | 103 | 10,943 | 4,445 | 1,332 | | | | |

| | BRA | CHL | COL | MEX | PER | EGY | MAR | ZAF | TUR |
|---|---|---|---|---|---|---|---|---|---|
| POOLED | 0.090 | 0.181 | 0.158 | 0.091 | 0.101 | 0.975 | 0.327 | 0.025 | 0.239 |
| TS | 2.12** | 2.22** | 1.04 | 1.56 | 0.70 | 1.79* | 1.64 | 0.61 | 5.85*** |
| N | 2,407 | 635 | 237 | 1,939 | 316 | 1,062 | 133 | 2,866 | 3,593 |
| JUMPS | 0.105 | 0.277 | 0.317 | 0.208 | 0.259 | 0.490 | 0.759 | 0.108 | 0.557 |
| TS | 1.88* | 2.56** | 1.45 | 3.17*** | 1.17 | 3.41*** | 2.96*** | 2.15** | 10.32*** |
| N | 1,346 | 378 | 105 | 1,065 | 155 | 627 | 72 | 1,512 | 2,208 |
| DROPS | 0.072 | 0.039 | 0.031 | -0.051 | -0.052 | 1.675 | -0.181 | -0.067 | -0.268 |
| TS | 1.09 | 0.32 | 0.15 | 0.50 | 0.28 | 1.27 | 0.60 | 0.98 | 4.52*** |
| N | 1,061 | 257 | 132 | 874 | 161 | 435 | 61 | 1,354 | 1,385 |

**Panel B: Large companies**

| | CHN | IND | IDN | MYS | PHL | KOR | TWN | THA | CZE | HUN | POL | RUS |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| POOLED | 0.051 | 0.098 | -0.005 | 0.000 | -0.066 | 0.086 | 0.078 | -0.231 | 0.126 | 0.079 | 0.132 | -0.081 |
| TS | 1.69* | 3.84*** | 0.03 | 0.00 | 0.32 | 3.52*** | 2.12** | 4.06*** | 0.89 | 0.67 | 1.70* | 0.89 |
| N | 5,028 | 6,997 | 294 | 1,948 | 155 | 6,807 | 3,224 | 1,778 | 294 | 320 | 626 | 739 |
| JUMPS | 0.253 | 0.148 | 0.050 | 0.004 | -0.027 | 0.247 | 0.531 | -0.008 | 0.419 | -0.159 | -0.079 | -0.046 |
| TS | 7.05*** | 4.68*** | 0.25 | 0.05 | 0.10 | 8.33*** | 11.44*** | 0.12 | 2.52** | 1.12 | 0.83 | 0.36 |
| N | 2,895 | 4,328 | 154 | 1,145 | 83 | 4,130 | 1,848 | 1,012 | 137 | 164 | 343 | 364 |
| DROPS | -0.223 | 0.018 | -0.065 | -0.005 | -0.110 | -0.163 | -0.531 | -0.524 | -0.130 | 0.330 | 0.389 | -0.115 |
| TS | 4.36*** | 0.41 | 0.25 | 0.04 | 0.37 | 3.93*** | 9.77*** | 5.41*** | 0.59 | 1.74* | 3.08*** | 0.87 |
| N | 2,133 | 2,669 | 140 | 803 | 72 | 2,677 | 1,376 | 766 | 157 | 156 | 283 | 375 |

| | BRA | CHL | COL | MEX | PER | EGY | MAR | ZAF | TUR |
|---|---|---|---|---|---|---|---|---|---|
| POOLED | 0.002 | 0.190 | 0.156 | 0.032 | 0.072 | 2.596 | 0.174 | -0.0152 | 0.1113 |
| TS | 0.04 | 2.32** | 0.80 | 0.45 | 0.43 | 1.06 | 0.62 | -0.35 | 1.18 |
| N | 1,602 | 633 | 147 | 1,203 | 238 | 232 | 69 | 2,284 | 709 |
| JUMPS | -0.011 | 0.293 | 0.478 | 0.084 | 0.058 | -0.408 | 0.591 | 0.0260 | 0.3959 |
| TS | 0.20 | 2.70*** | 1.64 | 1.12 | 0.21 | 1.37 | 1.72* | 0.49 | 3.09** |
| N | 883 | 376 | 62 | 662 | 115 | 118 | 39 | 1,176 | 397 |
| DROPS | 0.018 | 0.039 | -0.080 | -0.031 | 0.085 | 5.704 | -0.369 | -0.0590 | -0.2508 |
| TS | 0.23 | 0.32 | 0.31 | 0.24 | 0.42 | 1.14 | 0.81 | 0.82 | 1.82* |
| N | 719 | 257 | 85 | 541 | 123 | 114 | 30 | 1,108 | 312 |

**Panel C: Medium companies**

| | CHN | IND | IDN | MYS | PHL | KOR | TWN | THA |
|---|---|---|---|---|---|---|---|---|
| POOLED | 0.169 | 0.168 | -0.173 | 0.161 | 0.339 | 0.142 | 0.288 | 0.122 |
| TS | 7.55*** | 8.56*** | 0.44 | 3.27*** | 1.18 | 8.00*** | 10.89*** | 1.63 |
| N | 7,783 | 11,804 | 39 | 3,231 | 102 | 16,033 | 7,255 | 1,420 |
| | | | | | | | | |
| JUMPS | 0.334 | 0.230 | -0.011 | 0.192 | 0.587 | 0.455 | 0.764 | 0.403 |
| TS | 11.50*** | 10.31*** | 0.02 | 3.30*** | 1.85* | 20.76*** | 24.33*** | 4.61*** |
| N | 4,482 | 8,268 | 26 | 2,156 | 74 | 10,258 | 4,852 | 912 |
| | | | | | | | | |
| DROPS | -0.054 | 0.024 | -0.497 | 0.097 | -0.317 | -0.414 | -0.673 | -0.381 |
| TS | 1.53 | 0.60 | 0.95 | 1.08 | 0.51 | 14.32*** | 15.93*** | 2.80*** |
| N | 3,301 | 3,536 | 13 | 1,075 | 28 | 5,775 | 2,403 | 508 |

| | CZE | HUN | POL | RUS |
|---|---|---|---|---|
| POOLED | 0.569 | 0.335 | 0.178 | -0.483 |
| TS | 0.78 | 1.77* | 2.50** | 3.67*** |
| N | 15 | 276 | 1,341 | 698 |
| | | | | |
| JUMPS | 0.645 | -0.039 | 0.327 | -0.061 |
| TS | 0.80 | 0.21 | 4.52*** | 0.38 |
| N | 10 | 163 | 863 | 298 |
| | | | | |
| DROPS | 0.419 | 0.874 | -0.092 | -0.798 |
| TS | 0.25 | 2.35** | 0.61 | 4.07*** |
| N | 5 | 113 | 478 | 400 |

| | BRA | CHL | COL | MEX | PER |
|---|---|---|---|---|---|
| POOLED | 0.271 | -2.639 | 0.041 | 0.193 | 0.191 |
| TS | 2.98*** | 38.94** | 0.14 | 1.91* | 0.70 |
| N | 761 | 2 | 60 | 727 | 77 |
| | | | | | |
| JUMPS | 0.372 | -2.639 | 0.360 | 0.420 | 0.837 |
| TS | 2.90*** | 38.94** | 0.95 | 3.44*** | 2.64** |
| N | 433 | 2 | 26 | 400 | 40 |
| | | | | | |
| DROPS | 0.136 | | -0.203 | -0.086 | -0.506 |
| TS | 1.09 | | 0.49 | 0.52 | 1.18 |
| N | 328 | | 34 | 327 | 37 |

| | EGY | MAR | ZAF | TUR |
|---|---|---|---|---|
| POOLED | 0.257 | 0.649 | 0.139 | 0.188 |
| TS | 1.85* | 2.08** | 1.27 | 3.31*** |
| N | 480 | 56 | 557 | 1,850 |
| | | | | |
| JUMPS | 0.371 | 1.033 | 0.349 | 0.560 |
| TS | 1.92* | 2.51** | 2.76*** | 7.39*** |
| N | 281 | 30 | 320 | 1,112 |
| | | | | |
| DROPS | 0.095 | 0.205 | -0.146 | -0.373 |
| TS | 0.49 | 0.44 | 0.76 | 4.64*** |
| N | 199 | 26 | 237 | 738 |

**Panel D: Small companies**

| | CHN | IND | IDN | MYS | PHL | KOR | TWN | THA | CZE | HUN | POL | RUS |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| POOLED | 0.235 | 0.343 | No obs. | -0.119 | -0.592 | 0.297 | 0.510 | 0.161 | 1.878 | 0.790 | 0.236 | 0.700 |
| TS | 6.56*** | 10.30*** | | 1.64 | 1.57 | 10.53*** | 11.01*** | 0.86 | 0.76 | 0.82 | 2.39** | 0.84 |
| N | 3,210 | 4,016 | | 1,661 | 8 | 7,664 | 2,478 | 213 | 3 | 11 | 709 | 16 |
| JUMPS | 0.426 | 0.427 | | 0.071 | -0.932 | 0.649 | 0.917 | 0.322 | 4.292 | 1.928 | 0.312 | -0.842 |
| TS | 9.30*** | 11.22*** | | 0.80 | 1.68 | 18.88*** | 17.22*** | 1.47 | 4.56 | 1.83 | 2.58** | 0.57 |
| N | 1,924 | 3,088 | | 953 | 5 | 5,173 | 1,812 | 155 | 2 | 8 | 480 | 7 |
| DROPS | -0.050 | 0.064 | | -0.376 | -0.026 | -0.433 | -0.595 | -0.270 | | -2.247 | 0.076 | 1.900 |
| TS | 0.89 | 0.94 | | 3.13*** | 0.13 | 9.38*** | 7.50*** | 0.77 | | 5.32** | 0.44 | 2.37** |
| N | 1,286 | 928 | | 708 | 3 | 2,491 | 666 | 58 | | 3 | 229 | 9 |

| | BRA | CHL | COL | MEX | PER | EGY | MAR | ZAF | TUR |
|---|---|---|---|---|---|---|---|---|---|
| POOLED | 0.202 | No obs. | 0.401 | -0.168 | No obs. | 0.887 | -0.597 | 1.197 | 0.424 |
| TS | 0.58 | | 0.88 | 0.25 | | 4.11*** | 1.04 | 1.62 | 5.58*** |
| N | 44 | | 30 | 9 | | 350 | 8 | 25 | 1011 |
| JUMPS | -0.335 | | -0.335 | -0.705 | | 1.102 | 0.184 | 1.270 | 0.661 |
| TS | 0.84 | | 0.55 | 1.08 | | 4.08*** | 0.15 | 1.44 | 6.73*** |
| N | 30 | | 17 | 3 | | 228 | 3 | 16 | 680 |
| DROPS | 1.354 | 1.364 | 1.364 | 0.101 | | 0.487 | -1.066 | 1.066 | -0.063 |
| TS | 2.24** | 2.22** | 2.22** | 0.10 | | 1.36 | 1.81 | 0.77 | 0.57 |
| N | 14 | 13 | 13 | 6 | | 122 | 5 | 9 | 331 |

## Table 12: Explanatory regressions by region

Explanatory regressions on standardized post-event return residuals of price jumps, using standardized event-day residuals (SR0), log market value of equity in USD millions (LMVUS), log book-to-market ratio 10 days before the event (BTM), average estimation period, Amihud (2002) illiquidity ratio in USD (AIREST), stock return of the previous six months (MOM), average daily estimation period turnover in USD millions (TOEST), event-day turnover in USD millions (TO) and dummy variables for Mondays (MON), Fridays (FRI), January (JAN) and December (DEC). Robust t-statistics are shown below the coefficient estimates. *, **, *** indicate significance on the 1%-, 5%-, and 10%-levels, respectively.

**Panel A: Global**

| | N | SR0 | LMVUS | BTM | AIREST | MOM | TOEST | TO | MON | FRI | JAN | DEC | Const. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| All | 62,363 | -0.00289 | -0.0849 | 0.0121 | -0.159 | -0.0487 | 0.000873 | 0.00310 | -0.113 | 0.289 | 0.0353 | 0.00234 | 0.767 |
| | | 0.31 | 17.99 *** | 1.89 | 3.46 *** | 3.18 ** | 7.44 *** | 0.67 | 5.51 *** | 11.61 *** | 1.11 | 0.07 | 16.66 *** |
| Big | 19,476 | -0.0263 | -0.0480 | -0.00249 | 0.123 | -0.0929 | 0.000539 | 0.00133 | 0.000370 | 0.131 | -0.0274 | -0.00710 | 0.586 |
| | | 1.62 | 5.68 *** | 0.32 | 0.99 | 3.82 *** | 4.40 *** | 0.30 | 0.01 | 3.22 ** | 0.54 | 0.13 | 6.59 *** |
| Medium | 31,273 | 0.00841 | -0.101 | 0.0191 | -0.0793 | -0.0654 | -0.795 | 0.459 | -0.149 | 0.330 | -0.00714 | 0.0327 | 0.798 |
| | | 0.66 | 7.39 *** | 1.57 | 1.24 | 2.85 ** | 0.53 | 0.19 | 5.16 *** | 9.23 *** | 0.16 | 0.68 | 9.68 *** |
| Small | 11,614 | 0.0165 | -0.141 | 0.00259 | -0.369 | 0.140 | -1.104 | -2.454 | -0.191 | 0.447 | 0.229 | -0.0396 | 0.880 |
| | | 0.65 | 5.78 *** | 0.12 | 5.54 *** | 2.98 ** | 1.33 | 2.81 ** | 3.69 *** | 7.11 *** | 2.67 ** | 0.50 | 7.03 *** |

**Panel B: Regional**

| | N | SR0 | LMVUS | BTM | AIREST | MOM | TOEST | TO | MON | FRI | JAN | DEC | Const. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Asia | 51,778 | -0.00172 | -0.0864 | 0.0371 | -0.572 | -0.0304 | 0.545 | -4.735 | -0.134 | 0.408 | 0.0273 | -0.0172 | 0.778 |
| | | 0.18 | 12.13 *** | 3.39 *** | 4.73 *** | 1.78 | 0.85 | 2.19 * | 6.09 *** | 14.86 *** | 0.79 | 0.47 | 15.52 *** |
| EE | 2,535 | -0.0740 | -0.113 | 0.0535 | -0.477 | 0.0110 | -0.596 | -12.54 | -0.127 | 0.294 | 0.233 | -0.192 | 1.085 |
| | | 2.87 ** | 4.91 *** | 1.00 | 2.43 * | 0.20 | 0.52 | 0.99 | 1.09 | 2.33 * | 1.50 | 1.13 | 5.98 *** |
| LATAM | 2,840 | -0.000492 | -0.0176 | -0.0228 | -0.660 | -0.158 | 0.000233 | -0.000216 | 0.125 | -0.0529 | -0.306 | 0.291 | 0.392 |
| | | 0.01 | 1.43 | 1.92 | 2.14 * | 1.86 | 1.74 | 0.05 | 1.16 | 0.46 | 2.40 * | 1.16 | 1.74 |
| MEA | 3,837 | 0.0600 | -0.0688 | 0.0254 | -0.0121 | -0.0604 | -6.900 | 0.548 | 0.0782 | -0.506 | 0.267 | 0.122 | 0.513 |
| | | 1.41 | 2.43 * | 0.51 | 0.24 | 1.07 | 2.06 * | 0.43 | 0.75 | 5.13 *** | 1.81 | 1.07 | 2.16 * |
| | N | SR0 | LMVUS | BTM | AIREST | MOM | TOEST | TO | MON | FRI | JAN | DEC | Const. |
| Asia | 14,443 | -0.0254 | -0.0586 | 0.0522 | -3.834 | -0.0703 | -0.523 | -3.522 | -0.0112 | 0.285 | 0.00116 | -0.0566 | 0.706 |
| | | 1.57 | 3.56 *** | 2.56 * | 3.92 *** | 2.52 * | 0.76 | 1.44 | 0.28 | 5.89 *** | 0.02 | 0.86 | 5.64 *** |
| EE | 958 | -0.0786 | -0.0334 | 0.0899 | 2.656 | 0.0666 | -1.460 | 0.627 | -0.142 | 0.290 | 0.0335 | 0.0229 | 0.517 |
| | | 2.09 * | 0.69 | 0.98 | 0.88 | 0.51 | 1.21 | 0.08 | 0.81 | 1.57 | 0.18 | 0.09 | 1.26 |
| LATAM | 1,998 | -0.0554 | 0.0133 | -0.0155 | -0.850 | -0.0400 | 0.0000483 | -0.000754 | 0.0806 | -0.138 | -0.311 | 0.155 | 0.229 |
| | | 0.77 | 0.89 | 1.16 | 1.74 | 0.32 | 0.34 | 0.18 | 0.76 | 1.11 | 2.04 * | 0.74 | 0.97 |
| MEA | 986 | 0.0633 | -0.0913 | 0.0925 | 0.158 | -0.107 | -3.608 | -0.680 | 0.150 | -0.705 | 0.0577 | 0.309 | 0.721 |
| | | 0.73 | 1.12 | 1.02 | 1.12 | 1.18 | 0.89 | 0.48 | 0.79 | 4.31 *** | 0.17 | 1.64 | 1.13 |
| | N | SR0 | LMVUS | BTM | AIREST | MOM | TOEST | TO | MON | FRI | JAN | DEC | Const. |
| Asia | 26,997 | 0.0101 | -0.0720 | 0.0451 | -0.563 | -0.0596 | -0.954 | -1.653 | -0.174 | 0.453 | -0.0388 | -0.0178 | 0.677 |
| | | 0.77 | 4.19 *** | 2.75 ** | 2.83 ** | 2.33 * | 0.16 | 0.35 | 5.78 *** | 11.84 *** | 0.82 | 0.35 | 7.51 *** |
| EE | 1,171 | -0.0439 | -0.154 | 0.00118 | -0.271 | -0.00666 | 56.72 | -45.77 | -0.205 | -0.0359 | 0.183 | 0.167 | 1.145 |
| | | 0.97 | 2.85 ** | 0.02 | 1.33 | 0.09 | 1.07 | 4.56 *** | 1.16 | 0.21 | 0.87 | 0.58 | 3.68 *** |
| LATAM | 809 | 0.113 | -0.271 | -0.0363 | -1.500 | -0.186 | -1.974 | 3.303 | 0.308 | -0.00898 | -0.264 | 0.593 | 1.602 |
| | | 0.95 | 2.28 * | 1.35 | 2.56 * | 1.46 | 0.87 | 0.87 | 1.14 | 0.04 | 1.08 | 0.92 | 1.76 |
| MEA | 2,030 | 0.00651 | -0.0784 | 0.0685 | 0.0990 | -0.0275 | -19.74 | 1.647 | 0.230 | -0.516 | 0.371 | 0.230 | 0.708 |
| | | 0.14 | 1.32 | 1.01 | 1.30 | 0.29 | 0.56 | 0.51 | 1.57 | 3.68 *** | 1.94 | 1.40 | 1.95 |
| | N | SR0 | LMVUS | BTM | AIREST | MOM | TOEST | TO | MON | FRI | JAN | DEC | Const. |
| Asia | 10,338 | 0.0101 | -0.159 | -0.00572 | -0.582 | 0.187 | -42.69 | -19.52 | -0.191 | 0.464 | 0.206 | 0.0445 | 0.983 |
| | | 0.40 | 6.09 *** | 0.25 | 3.89 *** | 3.47 *** | 2.34 * | 1.30 | 3.58 *** | 7.09 *** | 2.31 * | 0.52 | 7.76 *** |
| EE | 406 | -0.136 | -0.356 | 0.174 | -0.649 | -0.0119 | -115.6 | -22.34 | 0.0138 | 1.441 | 0.746 | -0.992 | 1.905 |
| | | 2.18 * | 1.59 | 1.24 | 3.27 ** | 0.09 | 0.20 | 1.39 | 0.04 | 3.36 *** | 1.29 | 3.11 ** | 2.79 ** |
| MEA | 821 | 0.174 | 0.181 | -0.180 | -0.146 | -0.295 | -250.9 | -27.88 | -0.273 | -0.180 | 0.213 | -0.400 | -0.370 |
| | | 1.42 | 1.50 | 1.47 | 1.98 * | 1.58 | 1.28 | 0.72 | 1.10 | 0.73 | 0.74 | 1.48 | 0.63 |

## Table 13: Explanatory Regressions by Country

Explanatory regressions on standardized post-event return residuals of price jumps, using standardized event-day residual (SR0), log market value of equity in USD millions (LMVUS), log book-to-market ratio 10 days before the event (BTM), average estimation period Amihud (2002) ratio (AIREST), the stock return of the previous six months (MOM), average daily estimation period turnover in USD millions (TOEST), event-day turnover in USD millions (TO) and dummy variables for Mondays (MON), Fridays (FRI), January (JAN) and December (DEC). Robust t-statistics are shown below the coefficient estimates. *, **, *** indicate significance on the 1%-, 5%-, and 10%-levels, respectively.

**Panel A – All Companies:**

| Country | N | SR0 | LMVUS | BTM | AIREST | MOM | TOEST | TO | MON | FRI | JAN | DEC | Intercept |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| CHN | 7,267 | 0.0355 | -0.110 | -0.0524 | -0.278 | 0.104 | -0.103 | -3.880 | -0.225 | 0.428 | 0.191 | -0.115 | 0.729 |
| | | 1.24 | 4.93 *** | 1.84 | 0.48 | 2.37 * | 0.12 | 1.18 | 4.05 *** | 6.81 *** | 1.97 * | 0.55 | 4.67 *** |
| IND | 13,091 | 0.0354 | -0.0580 | 0.0546 | 1.739 | -0.0620 | 7.621 | 364.7 | -0.0283 | 0.438 | -0.275 | 0.126 | 0.302 |
| | | 1.98 * | 4.23 *** | 2.49 * | 0.83 | 1.66 | 1.03 | 1.23 | 0.67 | 8.95 *** | 3.96 *** | 1.96 * | 3.01 ** |
| INA | 173 | -0.217 | -0.219 | -0.0818 | -9279927.7 | 0.369 | -86.41 | 13067.0 | -0.152 | 0.317 | 0.947 | -0.282 | 2.126 |
| | | 2.03 * | 1.33 | 0.33 | 2.29 * | 1.11 | 2.11 * | 0.92 | 0.28 | 0.69 | 1.55 | 0.53 | 1.84 |
| MAL | 3,403 | -0.0650 | -0.0596 | 0.0817 | -0.291 | -0.0434 | -3.246 | 0.936 | -0.663 | 0.599 | 0.000218 | -0.482 | 0.747 |
| | | 2.65 ** | 1.61 | 1.78 | 2.28 * | 0.55 | 0.36 | 0.38 | 6.29 *** | 4.77 *** | 0.00 | 2.80 ** | 3.66 *** |
| PHI | 153 | -0.0582 | -0.0707 | 0.383 | 18.17 | 0.337 | 65.11 | 48.18 | -0.407 | 0.598 | 1.071 | -0.152 | 0.719 |
| | | 0.41 | 0.53 | 1.42 | 0.75 | 1.64 | 0.45 | 0.49 | 0.77 | 0.87 | 1.30 | 0.18 | 0.84 |
| KOR | 17,870 | 0.0482 | -0.0854 | 0.00963 | 10503.0 | -0.0997 | 2.957 | -5021.7 | -0.0434 | 0.365 | 0.194 | -0.0236 | 0.557 |
| | | 2.65 ** | 6.54 *** | 0.53 | 0.99 | 3.59 *** | 2.07 * | 1.05 | 1.15 | 7.35 *** | 3.45 *** | 0.41 | 6.36 *** |
| TPE | 7,882 | 0.0858 | -0.132 | -0.0412 | 2.263 | 0.168 | -2.900 | -40.26 | -0.447 | 0.341 | 0.152 | 0.102 | 1.202 |
| | | 2.22 * | 6.00 *** | 0.99 | 0.21 | 2.54 * | 0.86 | 1.24 | 8.47 *** | 4.69 *** | 1.77 | 1.14 | 7.22 *** |
| THA | 1,939 | -0.0658 | -0.104 | 0.151 | -10.51 | -0.0608 | -6.112 | 3.199 | 0.142 | 0.259 | 0.00682 | -0.201 | 0.922 |
| | | 2.11 * | 2.38 * | 2.43 * | 1.17 | 0.94 | 0.44 | 0.60 | 1.02 | 1.79 | 0.04 | 1.17 | 3.37 *** |
| CZE | 131 | -0.112 | -0.0170 | 0.138 | 313.7 | -0.0731 | -16.05 | -240.6 | 1.216 | 0.433 | 0.450 | -1.245 | 0.907 |
| | | 1.58 | 0.08 | 0.58 | 2.48 * | 0.12 | 1.19 | 0.11 | 2.17 * | 0.86 | 0.70 | 3.53 *** | 0.65 |
| HUN | 305 | -0.242 | 0.0479 | 0.755 | 1601.7 | -0.118 | -9.613 | 4845.1 | 0.620 | 0.167 | -0.701 | -0.382 | 0.651 |
| | | 2.28 * | 0.45 | 2.81 ** | 0.33 | 0.59 | 0.78 | 0.30 | 1.66 | 0.58 | 2.28 * | 0.92 | 0.96 |
| POL | 1,482 | -0.0950 | -0.178 | 0.0723 | -0.258 | 0.00576 | 14.48 | -39.08 | -0.188 | 0.392 | 0.352 | -0.388 | 1.429 |
| | | 2.49 * | 4.42 *** | 0.99 | 1.30 | 0.09 | 1.06 | 2.59 ** | 1.30 | 2.36 * | 1.70 | 1.78 | 5.65 *** |
| RUS | 617 | -0.0205 | -0.0420 | -0.0718 | -0.853 | 0.172 | -1.043 | -12.15 | -0.619 | 0.117 | 0.342 | 0.383 | 0.450 |
| | | 0.50 | 0.65 | 0.73 | 8.37 *** | 0.88 | 0.84 | 0.90 | 2.42 * | 0.42 | 0.98 | 1.07 | 0.82 |
| BRZ | 1,266 | -0.00537 | -0.110 | -0.0699 | -0.917 | -0.115 | 0.0304 | -0.0291 | 0.216 | 0.0413 | -0.387 | 0.220 | 1.290 |
| | | 0.15 | 2.77 ** | 1.77 | 2.22 * | 0.82 | 0.98 | 0.48 | 1.58 | 0.24 | 2.53 * | 0.51 | 3.20 ** |
| CHL | 365 | 0.0727 | -0.242 | 0.543 | -1.918 | 1.131 | 0.000271 | -0.00168 | 0.290 | -0.493 | -0.195 | 0.780 | 5.084 |
| | | 0.87 | 2.18 * | 2.72 ** | 2.86 ** | 2.90 ** | 1.61 | 0.47 | 0.84 | 1.71 | 0.48 | 1.53 | 2.22 * |
| COL | 94 | -0.00599 | 0.399 | 0.345 | 3794.9 | -1.090 | 107.4 | 12630.3 | -0.779 | 0.208 | 1.309 | -1.453 | -2.706 |
| | | 0.08 | 2.08 * | 1.76 | 0.73 | 1.49 | 0.45 | 1.10 | 1.20 | 0.30 | 1.44 | 1.66 | 2.08 * |
| MEX | 968 | 0.120 | -0.0957 | 0.105 | -5.976 | -0.157 | -8.203 | 40.77 | 0.0615 | -0.185 | -0.352 | 0.142 | 0.633 |
| | | 1.01 | 1.38 | 1.31 | 5.07 *** | 1.10 | 1.45 | 0.89 | 0.31 | 0.98 | 1.68 | 0.52 | 0.98 |
| PER | 147 | -0.470 | -0.267 | 0.132 | -1.636 | -0.383 | -309.7 | 103.7 | -0.128 | -0.646 | -0.176 | -0.0668 | 4.092 |
| | | 2.43 * | 1.45 | 0.33 | 0.99 | 1.31 | 0.64 | 1.55 | 0.23 | 1.08 | 0.24 | 0.06 | 2.66 ** |
| EGY | 564 | -0.0742 | -0.497 | 0.243 | -7.278 | -0.0137 | -1.680 | -66.22 | -0.705 | -1.494 | 0.123 | -0.0545 | 4.417 |
| | | 0.59 | 3.59 *** | 1.02 | 2.63 ** | 0.06 | 0.05 | 0.32 | 1.57 | 4.90 *** | 0.25 | 0.11 | 5.14 *** |
| MOR | 61 | -0.0133 | 0.117 | 1.744 | -25.65 | 0.936 | 312.5 | 9296.6 | 0.390 | 0.981 | -0.951 | -1.240 | 0.232 |
| | | 0.11 | 0.35 | 2.02 * | 0.11 | 1.20 | 1.57 | 0.95 | 0.71 | 1.39 | 1.20 | 1.22 | 0.10 |
| RSA | 1,373 | -0.00692 | -0.105 | -0.0152 | 0.487 | -0.636 | 2.867 | -2.001 | -0.0900 | -0.0307 | -0.0194 | -0.0366 | 0.840 |
| | | 0.16 | 2.13 * | 0.25 | 0.37 | 4.07 *** | 0.72 | 0.49 | 0.65 | 0.23 | 0.13 | 0.18 | 2.26 * |
| TUR | 1,660 | 0.285 | 0.0595 | 0.00635 | -0.00488 | -0.408 | -7.496 | -0.252 | 0.119 | 0.420 | 0.332 | 0.236 | -0.953 |
| | | 5.73 *** | 1.28 | 0.07 | 0.10 | 3.23 ** | 1.78 | 0.20 | 0.74 | 2.57 * | 1.51 | 1.25 | 2.92 ** |

**Panel B – Large Companies**

| Country | N | SR0 | LMVUS | BTM | AIREST | MOM | TOEST | TO | MON | FRI | JAN | DEC | Intercept |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| CHN | 2,165 | 0.0195 | -0.128 | -0.152 | 77.97 | -0.0958 | -0.530 | -3.126 | -0.0728 | 0.362 | -0.0833 | 0.148 | 0.893 |
| | | 0.48 | 2.07 * | 1.90 | 0.35 | 1.32 | 0.54 | 0.87 | 0.73 | 2.92 ** | 0.47 | 0.36 | 1.98 * |
| IND | 4,180 | 0.000185 | -0.0343 | 0.0928 | 11.78 | -0.130 | 3.048 | 603.9 | 0.101 | 0.435 | 0.0600 | 0.0261 | 0.318 |
| | | 0.01 | 1.26 | 2.47 * | 0.69 | 2.16 * | 0.40 | 1.47 | 1.32 | 5.09 *** | 0.45 | 0.21 | 1.42 |
| IDN | 151 | -0.205 | -0.270 | -0.00425 | -6836068.1 | 0.199 | -76.02 | 5823.4 | -0.544 | 0.191 | 1.094 | -0.302 | 2.644 |
| | | 1.89 | 1.27 | 0.02 | 1.18 | 0.52 | 1.71 | 0.39 | 0.99 | 0.38 | 1.69 | 0.48 | 1.69 |
| MYS | 1,083 | -0.0184 | -0.140 | 0.137 | -3.493 | 0.0778 | 4.766 | 1.394 | -0.480 | 0.0496 | 0.00492 | 0.00954 | 1.117 |
| | | 0.41 | 1.44 | 1.74 | 3.03 ** | 0.72 | 0.45 | 0.68 | 2.16 * | 0.27 | 0.02 | 0.03 | 1.73 |
| PHL | 81 | -0.210 | -0.0295 | -0.139 | 568.1 | 0.0787 | -33.12 | 69.91 | -0.625 | 0.0200 | 0.902 | -0.339 | 0.889 |
| | | 1.24 | 0.09 | 0.41 | 0.71 | 0.44 | 0.20 | 0.76 | 0.69 | 0.03 | 0.85 | 0.21 | 0.38 |
| KOR | 4,010 | -0.0556 | -0.0780 | -0.00576 | -335172.7 | -0.0817 | 1.481 | 3260.4 | -0.0154 | 0.240 | 0.132 | 0.0540 | 0.881 |
| | | 2.18 * | 2.51 * | 0.15 | 1.49 | 1.66 | 0.89 | 0.58 | 0.23 | 2.65 ** | 1.46 | 0.56 | 4.05 *** |
| TWN | 1,800 | 0.0803 | -0.149 | 0.0530 | 127.7 | -0.133 | -3.457 | -39.43 | -0.0598 | 0.433 | 0.0642 | -0.103 | 1.369 |
| | | 1.82 | 2.48 * | 0.60 | 0.15 | 1.15 | 0.86 | 1.10 | 0.60 | 2.86 ** | 0.40 | 0.56 | 3.24 ** |
| THA | 973 | -0.124 | -0.144 | 0.140 | -46.64 | -0.0459 | 2.719 | -5.610 | 0.0488 | -0.0606 | -0.328 | -0.309 | 1.461 |
| | | 2.62 ** | 1.77 | 1.59 | 1.11 | 0.61 | 0.19 | 0.39 | 0.28 | 0.35 | 1.70 | 1.33 | 2.80 ** |
| CZE | 857 | 0.00292 | -0.0374 | -0.0790 | -0.873 | -0.0213 | 0.0365 | -0.0388 | 0.146 | -0.0872 | -0.381 | -0.288 | 0.805 |
| | | 0.09 | 0.79 | 1.86 | 0.83 | 0.12 | 1.17 | 0.65 | 1.02 | 0.63 | 2.15 * | 1.07 | 1.64 |
| HUN | 365 | 0.0727 | -0.242 | 0.543 | -1.918 | 1.131 | 0.000271 | -0.00168 | 0.290 | -0.493 | -0.195 | 0.780 | 5.084 |
| | | 0.87 | 2.18 * | 2.72 ** | 2.86 ** | 2.90 ** | 1.61 | 0.47 | 0.84 | 1.71 | 0.48 | 1.53 | 2.22 * |
| POL | 58 | -0.121 | 1.159 | 1.580 | 40913196.7 | -1.546 | -0.715 | -414065.7 | -1.059 | 0.273 | 1.682 | -2.606 | -7.595 |
| | | 1.12 | 1.40 | 1.82 | 0.67 | 1.52 | 0.00 | 1.22 | 0.90 | 0.28 | 1.46 | 2.03 * | 1.22 |
| RUS | 610 | 0.0180 | -0.0154 | 0.206 | -134.9 | -0.0978 | -12.10 | 2.041 | 0.0278 | -0.0542 | -0.592 | 0.346 | 0.487 |
| | | 0.15 | 0.12 | 1.98 * | 1.31 | 0.36 | 1.98 * | 0.06 | 0.15 | 0.23 | 2.12 * | 0.89 | 0.46 |
| BRA | 108 | -0.524 | -0.0984 | -0.767 | -4.053 | -0.545 | -584.4 | 89.21 | 0.235 | -0.765 | 0.0379 | 1.038 | 2.660 |
| | | 2.93 ** | 0.37 | 1.70 | 1.05 | 1.29 | 1.07 | 0.89 | 0.32 | 0.94 | 0.05 | 0.67 | 1.38 |
| CHL | 119 | -0.0908 | -0.354 | 0.194 | -1517.8 | 0.175 | -0.606 | -784.0 | 1.150 | 0.416 | 0.322 | -1.286 | 3.388 |
| | | 1.25 | 1.38 | 0.76 | 0.90 | 0.31 | 0.04 | 0.34 | 1.93 | 0.80 | 0.51 | 3.59 *** | 1.90 |
| COL | 145 | -0.216 | 0.289 | 0.768 | -61977.4 | 0.164 | -15.86 | -19004.5 | 0.489 | 0.226 | -0.478 | -0.542 | -0.832 |
| | | 1.26 | 1.63 | 1.72 | 1.18 | 0.24 | 1.25 | 0.89 | 1.26 | 0.70 | 1.55 | 1.31 | 0.60 |
| MEX | 337 | -0.0917 | -0.222 | 0.0357 | 2.727 | 0.142 | 27.03 | -80.81 | -0.0831 | 0.0743 | -0.0103 | 0.141 | 1.641 |
| | | 1.67 | 2.05 * | 0.21 | 0.83 | 0.81 | 1.64 | 2.35 * | 0.38 | 0.27 | 0.04 | 0.37 | 2.09 * |
| PER | 357 | -0.0676 | -0.163 | -0.200 | 2.719 | 0.0149 | -0.749 | 2.707 | -0.694 | 0.503 | 0.352 | 0.290 | 1.598 |
| | | 1.29 | 1.43 | 1.33 | 0.16 | 0.06 | 0.56 | 0.32 | 2.18 * | 1.37 | 0.84 | 0.69 | 1.58 |
| EGY | 111 | -0.221 | -1.035 | 0.399 | -109.0 | 0.173 | 0.422 | -344.1 | 0.395 | -2.201 | 0.406 | 0.409 | 9.928 |
| | | 0.81 | 2.85 ** | 1.20 | 2.01 * | 0.65 | 0.01 | 3.17 ** | 0.35 | 3.64 *** | 0.26 | 0.60 | 3.01 ** |
| MAR | 37 | -0.0608 | -0.0620 | 2.091 | 259.9 | 0.904 | 426.4 | 13245.3 | 0.455 | 1.047 | -0.633 | -1.217 | 1.584 |
| | | 0.23 | 0.10 | 1.54 | 0.57 | 0.47 | 1.26 | 1.08 | 0.46 | 0.99 | 0.51 | 0.52 | 0.33 |
| ZAF | 1,091 | -0.0300 | -0.0590 | 0.0240 | 12.48 | -0.325 | 1.497 | -3.873 | -0.0848 | -0.0889 | -0.000373 | -0.0720 | 0.595 |
| | | 0.68 | 0.77 | 0.33 | 1.47 | 1.87 | 0.34 | 0.97 | 0.57 | 0.59 | 0.00 | 0.33 | 1.02 |
| TUR | 348 | 0.345 | 0.0358 | 0.0407 | 0.130 | -0.967 | -5.134 | 0.400 | 0.154 | 0.504 | 0.677 | 0.585 | -1.168 |
| | | 3.77 *** | 0.27 | 0.21 | 1.03 | 2.52 * | 1.00 | 0.25 | 0.45 | 1.50 | 1.19 | 1.44 | 1.16 |

**Panel C – Medium Companies**

| Country | N | SR0 | LMVUS | BTM | AIREST | MOM | TOEST | TO | MON | FRI | JAN | DEC | Intercept |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| CHN | 3,328 | 0.0730 | -0.397 | -0.0234 | -37.13 | 0.151 | 31.68 | 6.834 | -0.272 | 0.562 | 0.308 | -0.169 | 2.038 |
| | | 1.39 | 5.11 *** | 0.46 | 4.86 *** | 1.97 * | 3.31 *** | 0.54 | 3.33 *** | 6.32 *** | 2.11 * | 0.58 | 4.63 *** |
| IND | 6,840 | 0.0567 | -0.0665 | 0.0548 | -2.605 | -0.0156 | -3.621 | -154.7 | -0.0999 | 0.471 | -0.476 | 0.0559 | 0.285 |
| | | 2.44 * | 2.24 * | 1.75 | 0.75 | 0.29 | 0.32 | 0.50 | 1.73 | 7.01 *** | 5.34 *** | 0.65 | 1.75 |
| IDN | 22 | 0.0604 | -2.239 | -3.407 | 17178972.9 | 1.981 | -1512.3 | 157150.1 | 3.618 | 4.749 | -0.743 | 3.678 | 5.391 |
| | | 0.18 | 2.58 ** | 3.13 ** | 1.17 | 2.13 * | 0.34 | 1.54 | 3.44 *** | 3.63 *** | 0.63 | 1.60 | 1.80 |
| MYS | 1,856 | -0.0575 | 0.0563 | 0.0303 | -0.144 | -0.242 | -60.06 | -11.36 | -0.565 | 0.920 | -0.135 | -0.381 | 0.235 |
| | | 1.69 | 0.69 | 0.42 | 0.77 | 1.90 | 1.22 | 0.54 | 4.15 *** | 5.23 *** | 0.79 | 1.74 | 0.63 |
| PHL | 69 | 0.328 | 0.477 | 1.007 | 47.04 | 1.022 | 1938.0 | 103.9 | -0.130 | 1.930 | 2.357 | -0.434 | -4.038 |
| | | 1.30 | 0.64 | 2.50 * | 1.43 | 4.43 *** | 1.80 | 0.25 | 0.21 | 2.10 * | 2.37 * | 0.53 | 1.36 |
| KOR | 9,461 | 0.0356 | -0.0853 | -0.0162 | 60418.1 | -0.135 | -3.860 | -19374.3 | -0.0232 | 0.335 | 0.0978 | -0.0353 | 0.620 |
| | | 1.37 | 2.46 * | 0.62 | 1.55 | 3.53 *** | 0.27 | 2.03 * | 0.45 | 4.86 *** | 1.32 | 0.42 | 3.61 *** |
| TWN | 4,587 | 0.205 | -0.0863 | 0.0261 | 173.1 | 0.189 | -23.57 | -122.2 | -0.608 | 0.276 | 0.161 | 0.0976 | 0.618 |
| | | 4.51 *** | 1.49 | 0.42 | 1.33 | 2.17 * | 1.51 | 1.45 | 8.55 *** | 2.94 ** | 1.49 | 0.82 | 2.01 * |
| THA | 834 | -0.0127 | 0.0294 | 0.136 | 12.11 | -0.0969 | -176.1 | 6.450 | 0.105 | 0.588 | 0.425 | -0.118 | 0.180 |
| | | 0.31 | 0.24 | 1.36 | 0.56 | 0.75 | 1.21 | 0.97 | 0.46 | 2.42 * | 1.11 | 0.45 | 0.35 |
| HUN | 156 | -0.229 | -0.313 | 0.714 | 1440.9 | -0.0194 | 100.3 | -3541.6 | 0.660 | 0.0858 | -0.988 | -0.0888 | 2.027 |
| | | 1.81 | 0.80 | 1.52 | 0.08 | 0.08 | 0.59 | 0.10 | 1.09 | 0.17 | 1.74 | 0.11 | 1.24 |
| POL | 748 | -0.0813 | -0.183 | 0.00722 | -0.501 | -0.0294 | -332.0 | -43.50 | -0.238 | 0.0351 | 0.316 | 0.157 | 1.597 |
| | | 1.19 | 1.93 | 0.07 | 2.55 * | 0.35 | 2.00 * | 1.44 | 1.17 | 0.18 | 1.41 | 0.45 | 3.18 ** |
| RUS | 257 | 0.0375 | 0.0660 | -0.00426 | 7.316 | 0.253 | 82.31 | -48.66 | -0.544 | -0.230 | 0.278 | 0.412 | -0.531 |
| | | 0.60 | 0.40 | 0.03 | 1.49 | 0.69 | 1.46 | 4.78 *** | 1.18 | 0.55 | 0.38 | 0.68 | 0.50 |
| BRA | 391 | -0.0353 | -0.359 | -0.0261 | -1.692 | -0.0935 | -2.561 | 3.802 | 0.385 | 0.241 | -0.408 | 1.121 | 2.479 |
| | | 0.39 | 1.95 | 0.32 | 2.28 * | 0.35 | 1.12 | 1.00 | 1.21 | 0.55 | 1.24 | 0.96 | 2.19 * |
| MEX | 356 | 0.220 | -0.280 | -0.0403 | -28.01 | -0.174 | -9.265 | 1152.3 | 0.214 | -0.216 | -0.0296 | 0.168 | 1.112 |
| | | 1.24 | 1.38 | 0.31 | 2.75 ** | 0.86 | 0.11 | 1.22 | 0.50 | 0.76 | 0.09 | 0.42 | 0.68 |
| PER | 39 | 0.523 | -1.059 | 1.522 | -3.254 | 0.760 | 6485.5 | 309.9 | 0.187 | -0.850 | -4.795 | -1.843 | 3.158 |
| | | 1.55 | 2.22 * | 5.23 *** | 1.84 | 1.84 | 3.26 ** | 3.07 ** | 0.21 | 1.12 | 2.50 * | 2.70 ** | 1.25 |
| EGY | 264 | -0.200 | -0.346 | 0.133 | -4.161 | 0.0351 | -89.66 | 1019.9 | -0.216 | -1.322 | 0.0666 | -0.126 | 3.658 |
| | | 1.47 | 1.36 | 0.36 | 0.77 | 0.08 | 1.11 | 2.58 ** | 0.31 | 3.09 ** | 0.09 | 0.17 | 2.61 ** |
| MAR | 21 | 0.360 | 0.530 | 5.294 | -918.1 | 1.558 | 2016.5 | -148231.7 | -0.439 | -0.0273 | -2.185 | -1.009 | -0.521 |
| | | 1.18 | 0.21 | 1.96 * | 1.05 | 1.31 | 0.54 | 1.24 | 0.37 | 0.03 | 1.42 | 0.54 | 0.03 |
| ZAF | 266 | -0.000892 | -0.267 | -0.211 | 0.933 | -1.379 | -120.6 | 68.07 | -0.266 | 0.123 | -0.115 | 0.0164 | 1.411 |
| | | 0.01 | 1.40 | 2.14 * | 0.50 | 4.22 *** | 0.35 | 1.27 | 0.85 | 0.39 | 0.29 | 0.04 | 1.28 |
| TUR | 868 | 0.260 | 0.131 | 0.0693 | 0.0634 | -0.352 | 27.99 | -1.138 | 0.144 | 0.433 | 0.731 | 0.410 | -1.231 |
| | | 3.93 *** | 1.11 | 0.55 | 0.86 | 2.15 * | 0.43 | 0.45 | 0.64 | 1.85 | 2.61 ** | 1.50 | 1.93 |

**Panel D – Small Companies**

| Country | N | SR0 | LMVUS | BTM | AIREST | MOM | TOEST | TO | MON | FRI | JAN | DEC | Intercept |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| CHN | 1,774 | 0.0114 | -0.208 | -0.0934 | -0.471 | 0.156 | -22.75 | -35.28 | -0.359 | 0.313 | 0.251 | -0.138 | 1.237 |
| | | 0.19 | 3.13 ** | 1.96 * | 0.77 | 1.62 | 1.22 | 1.79 | 3.03 ** | 2.46 * | 1.38 | 0.41 | 3.40 *** |
| IND | 2,071 | 0.0626 | -0.267 | -0.0404 | 1.236 | -0.132 | -10.49 | 1139.5 | -0.0786 | 0.282 | -0.145 | 0.410 | 0.759 |
| | | 1.66 | 5.25 *** | 0.70 | 0.46 | 0.98 | 0.04 | 1.30 | 0.74 | 2.19 * | 0.79 | 2.78 ** | 3.46 *** |
| MYS | 464 | -0.189 | -0.0644 | 0.164 | -0.425 | 1.057 | 132.7 | 86.51 | -1.301 | 0.707 | 0.824 | -1.116 | 1.610 |
| | | 3.18 ** | 0.36 | 1.29 | 2.35 * | 2.88 ** | 0.77 | 2.26 * | 5.09 *** | 1.84 | 2.11 * | 2.50 * | 2.93 ** |
| KOR | 4,399 | 0.215 | 0.00417 | 0.0296 | 3648.4 | -0.0199 | -132.9 | -15173.8 | -0.119 | 0.533 | 0.395 | -0.0842 | -0.235 |
| | | 4.38 *** | 0.06 | 0.82 | 0.31 | 0.22 | 1.88 | 0.78 | 1.34 | 4.98 *** | 2.90 ** | 0.63 | 0.96 |
| TWN | 1,495 | -0.218 | -0.514 | -0.368 | 0.00881 | 0.353 | -170.0 | -1495.0 | -0.136 | 0.505 | 0.206 | 0.276 | 3.508 |
| | | 2.08 * | 4.41 *** | 4.95 *** | 0.00 | 1.79 | 1.92 | 3.01 ** | 0.97 | 3.01 ** | 0.85 | 1.46 | 7.01 *** |
| THA | 132 | -0.0436 | -0.466 | 0.121 | -20.43 | -0.0582 | -236.4 | 45.33 | 0.986 | 0.432 | -0.109 | -0.801 | 1.244 |
| | | 0.37 | 0.82 | 0.42 | 1.70 | 0.08 | 0.34 | 1.38 | 1.40 | 0.44 | 0.13 | 0.96 | 0.76 |
| POL | 397 | -0.130 | -0.320 | 0.169 | -0.0660 | -0.0349 | 126.6 | -18.28 | -0.0978 | 1.336 | 0.774 | -1.020 | 1.631 |
| | | 2.08 * | 1.36 | 1.21 | 0.18 | 0.26 | 0.22 | 1.14 | 0.31 | 2.99 ** | 1.34 | 3.25 ** | 2.26 * |
| EGY | 189 | 0.0775 | -0.894 | 0.0546 | -9.554 | -0.209 | -329.6 | 329.4 | -1.864 | -1.351 | 0.00163 | -0.401 | 5.637 |
| | | 0.32 | 2.26 * | 0.10 | 2.09 * | 0.53 | 1.20 | 0.89 | 2.65 ** | 2.05 * | 0.00 | 0.66 | 2.97 ** |
| TUR | 444 | 0.304 | -0.239 | -0.0331 | -0.118 | -0.268 | 225.7 | -51.52 | 0.115 | 0.376 | -0.799 | -0.245 | -0.124 |
| | | 2.45 * | 1.07 | 0.19 | 1.50 | 1.08 | 0.59 | 1.26 | 0.35 | 1.19 | 2.01 * | 0.68 | 0.15 |

# 4. Investor Relations, Talking Insiders, and Liquidity

(with Sebastian Lobe)

**Abstract**

This is the first empirical study to provide corroborative evidence for the model by Hong and Huang (2005) that good investor relations are a means for corporate insiders to create liquidity for their own equity stakes. We validate the model in two steps for German stocks between 2002 and 2007. First, we place the quality of investor relations within the context of the amount of insider trading. Having shown that insider sales and investor relations are positively correlated, we move on to note that good investor relations indeed have the effect that insiders aim for, namely, increasing liquidity. We tackle the problem that investor relations scores are possibly endogenous by using the average investor relations quality of the respective industry as an instrumental variable. Considering our sample, the benefits of good investor relations are not affected by the quality of a company's annual reporting.

*JEL classification:* G14, G12, D83

*Keywords:* Investor Relations; Disclosure; Insider Trading

## 4.1. INTRODUCTION

What are investor relations activities good for? This question has been broadly addressed in the literature with a main focus on the interaction among investor relations, stock prices, and cost of capital. Until 2005, most theoretical studies, such as Merton (1987), Fishman and Hagerty (1989), Diamond and Verrecchia (1991), Trueman (1996), and Easley and O'Hara (2004), share the assumption that, if beneficial at all, good investor relations were beneficial to all investors due to various reasons that all more or less have to do with lower cost of capital. However, Hong and Huang (2005), hereafter denoted HH, proposed a theory that can explain why company insiders have a direct incentive to engage in investor relations, even absent any positive effects on share price. They argue that company insiders, who have discretionary power over the investor relations strategy, profit more from good investor relations than other shareholders because they usually own larger equity stakes than the dispersed outside shareholders. If the corporate insiders suffer from a sudden liquidity shock and have to sell part of their equity holdings, it is very important to them to ensure that they can place all of their shares on the market without a price discount, which is why they have to worry about market liquidity. Add to this the fact that previous research suggests investor relations might be a powerful means of creating liquidity, HH conjecture that insiders use investor relations to create liquidity for their personal stock holdings. We investigate empirically whether the inferences from their theoretical model provide a good intuition for reality. To do so, we elaborate first on whether heavier insider trading is associated with better investor relations. To explain why this could be the case, we then note that good investor relations do increase stock liquidity.

In section 2, we give an overview of the relevant investor relations literature before we present the data we use for our study in section 3. Section 4 describes the methodology, and section 5 contains the results. Section 6 concludes.

## 4.2. RELATED LITERATURE

### 4.2.1. Investor Relations and Insider Trading

In discussing investor relations, we refer to the aggregate of activities apart from regular reporting a company engages in to create or raise investor awareness. Following Lang and Lundholm (1993), investor relations are one of the three pillars of information disclosure: annual report disclosures, quarterly and other published information, and investor relations. Lang and Lundholm (1993) derive their definitions from the categories of the corporate disclosure ranking provided by the Financial Analysts Federation (FAF), today's CFA institute. Although, according to Brennan and Tamarowski (2000), the origins of corporate investor relations departments can be traced back to the middle of the last century, the exact effects of investor relations were widely unexplored until the 1990s. Since this time, an extensive body of scientific studies has been dedicated to the topic of why firms should engage in investor relations.

Most important for this study, HH establish a model to directly reproduce the incentive for company insiders to engage in investor relations activities. In their model, investor relations are a way for company insiders to create liquidity for their personal stock holdings. The essence of the model is that if better investor relations lead to higher liquidity, there is an incentive for insiders to engage in investor relations activities at the cost of the dispersed outside shareholders. This is because insiders usually own larger stakes of their company than the average outside shareholder. Therefore, insiders suffer from a negative price impact of their trades on an illiquid market and have an incentive to engage in investor relations to enhance liquidity. On the downside, the insiders lose the informational advantage from their private information when they decide to invest in investor relations activities. Because they also partially share with all other shareholders the cost of dedicating monetary resources to investor relations, the strength of their incentive depends on the size of their equity stakes and their liquidity needs. As a proxy to measure this incentive, HH suggest the volume of insider trading activities, especially insider sales.

### 4.2.2. Investor Relations and Liquidity

The argumentation of HH rests on one crucial assumption regarding the effect of investor relations on capital markets, namely, that better investor relations provide for higher liquidity. This assumption is based on earlier research by Amihud and Mendelson (1986 and 1988), Lev (1988), and Diamond and Verrecchia (1991). The relationship between liquidity and investor relations arises from the information asymmetry between corporate insiders and outside shareholders. The uneven informational playing field leads to higher bid-ask spreads (Amihud and Mendelson, 1986, Lev, 1988) and lower demand (Diamond and Verrecchia, 1991) for a company's stocks as market participants shy away from trading these stocks. However, how can good investor relations boost liquidity?

The first of the missing empirical links is presented by Lang and Lundholm (1996) and Francis et al. (1997). They find that higher liquidity for stocks with better investor relations can be attributed to a higher analyst following. They show that the number of security analysts grows with more forthcoming disclosures as a consequence of lower costs for security analysts to acquire information – a finding that is also reported by Germany by Gohlke et al. (2007). The second link comes from Brennan and Tamarowski (2000), who show that a higher number of analysts has a positive effect on share trading volume. Both the number of analysts and the share trading volume have, in turn, a positive effect on Kyle's (1985) lambda, which measures the price impact of one Dollar of trading volume on an intraday basis. Leuz and Verrecchia (2000) provide corroborative results for German firms that raise their disclosure levels by adopting international accounting standards (IAS) and suggest that higher levels of information disclosure can lower spreads and boost trading volume. Furthermore, they show that having good investor relations has a downside, as it increases stock return volatility, a finding that is endorsed by Botosan and Plumlee (2002) and Chang et al. (2008).

Because liquidity cannot be measured directly, proxies have to be used to model the effects of investor relations or disclosure quality on liquidity. The most common liquidity proxies used in the investor relations and disclosure literature are bid-ask spreads (Amihud and Mendelson, 1986, Leuz and Verrecchia, 2000, Heflin et al., 2005), trading volume (Diamond and Verrecchia, 1991, Brennan and Tamarowski, 2000, Leuz and Verrecchia, 2000), and stock return volatility (Bushee and Noe, 2000, Leuz and Verrecchia, 2000). Brennan and Tamarowski (2000) also introduce price impact as a liquidity measure into the investor relations literature.

### 4.2.3. Investor Relations vs. Annual Reporting

Most empirical studies thus far, with the exception of Heflin et al. (2005), Chang et al. (2007) and Chang et al. (2008), address the question whether better disclosure in general or better investor relations have positive effects on cost of capital and, mainly, stock prices. These studies include Lang and Lundholm (1993), Botosan (1997), Botosan and Plumlee (2002), Schachel and Vögtle (2006), and Agarwal et al. (2008). Whereas most of these studies report positive stock price effects of good investor relations and annual report quality, evidence regarding the effect of investor relations on measures of liquidity and variety in market participants' opinions is mixed. Bushee and Noe (2000) as well as Botosan and Plumlee (2002) show that the more timely disclosure categories of quarterly reporting and investor relations may increase stock return volatility by attracting trading-prone institutional short-term investors. Earlier hints for such a correlation can also be found in Lang and Lundholm (1993) and Healy et al. (1999). Corroborative evidence is presented by Leuz and Verrecchia (2000) and Chang et al. (2008).

Due to a lack of studies on the relationship between investor relations and liquidity for the German capital market, we take two steps to empirically validate the HH model. First, we place the quality of investor relations within the context of the amount of insider trading. Having shown that insider trading and investor relations quality are positively correlated, we move on to note that good investor relations have indeed the effect that insiders aim for, namely, increasing liquidity.

### 4.2.4. Hypothesis Development

To show that companies with large amounts of insider sales feature good investor relations, we regress insider trading volume on investor relations quality. If the assumptions of the HH model are correct, we should find a positive relationship between insider sales and investor relations. To ensure that this positive relation is caused by rising liquidity, we examine the liquidity effects of investor relations more closely. Therefore, we regress four liquidity proxies on investor relations quality: proportional quoted spreads and the Amihud (2002) illiquidity ratio serve as direct liquidity measures, and share trading volume and relative stock return volatility are indirect measures. Building on prior literature, we expect to find that good investor relations can provide for lower spreads and a lower Amihud (2002) illiquidity ratio. Furthermore, we conjecture that investor relations can boost trading volume. On the downside, earlier literature suggests that good investor relations incur costs for shareholders by increasing stock return volatility.

Because earlier studies suggest that investor relations might also have positive effects on stock returns apart from providing for enhanced liquidity, we take the opportunity to work out the relationship between investor relations and German stock returns to finalize our analysis of the interaction between investor relations and capital markets. Studies of the American market by Lang and Lundholm (1993) and Agarwal et al. (2008) as well as a small study of 33 German stocks by Schachel and Vögtle (2006) prompt us to conjecture that good investor relations have a positive influence on stock returns. To test this hypothesis, we calculate Jensen alphas for arbitrage portfolios built of good vs. bad investor relations stocks, and we incorporate investor relations quality into a regression model on monthly excess stock returns together with company size, book to market value, and market returns.

Our results deliver strong evidence in favor of the HH model, where investor relations are a means for corporate insiders to create liquidity for their stock holdings. We cannot find that good investor relations have a positive return impact.

Two features distinguish our study from the existing investor relations literature. First, our study is – to our knowledge – the first to provide empirical evidence in favor of the HH model. Second, we are the first to use disclosure quality proxies, i.e., one investor relations ranking and one annual report ranking, which are calculated by different data providers. This minimizes the risk of correlated measurement errors that is present when the rankings are conducted simultaneously by the same provider, such as the FAF ranking used in earlier studies. Additionally, we close two gaps in the German investor relations literature. On the one hand, we are the first to examine the influence of investor relations on stock returns over more than two years and using all firms ranked in the Capital investor relations ranking. On the other hand, our study is the first to provide evidence of the interaction of investor relations quality and the liquidity of German stocks.

## 4.3. DATA

### 4.3.1. Investor Relations and Annual Report Quality

#### *4.3.1.1. Investor Relations Quality*

The quality of a company's investor relations efforts is difficult to measure objectively. To assess the overall quality of investor relations, we therefore rely on Capital magazine, a German business magazine that publishes a ranking of investor relations activities of German companies annually. In the Capital ranking, companies are ranked according to the quality of their investor relations work on a scale from 0 points (very bad) to 500 points (very good). The Capital ranking, such as the FAF ranking used in earlier studies for the American market, is a qualitative ranking, which means it is based on analysts' subjective perception of the overall investor relations practices of the listed companies. To rank the companies, security analysts are asked to rate the information given by the companies listed in one of the major German stock indices. The rating categories are timeliness, credibility, and quality of information.[8] The ranking is conducted on an annual basis, published by Capital once a year, and comprises all constituents of the German large-cap index DAX30, the mid-cap index MDAX, the small-cap index SDAX, and the technology index TecDAX. To ensure that data for all control variables, especially annual report quality, are available, the sample period starts in 2002 and ends in 2007. During that period, 263 different companies were ranked in the Capital ranking, resulting in a sample of 989 firm-year observations.

*4.3.1.2. Annual Report Quality*

Botosan and Plumlee (2002) note that the effects of annual report quality might significantly overlap with and mitigate effects caused by investor relations quality. To solve this problem, we use annual report quality as a control variable throughout our study. Our data come from an annual report ranking conducted by Jörg Baetge from the University of Münster in cooperation with the manager magazin, another German business monthly. The criteria for the annual report ranking are the quality of the management report, detailed notes, and other information given in the report itself, plus the accessibility, understandability, and usability of the online annual report. Each of the four main categories consists of numerous sub-categories, and the overall ranking

[8] The qualitative statements of the analysts are transformed with neuronal webs following a procedure derived by a team of researchers from the University of Vienna led by Otto Loistl.

score has a range from 0% (worst) to 100% (best). The companies contained in this annual report ranking are exactly the same as those in the investor relations ranking. Our dataset comprises all companies for the period starting in 2002 and ending in 2007. With regard to the quality of the annual report data, we have a total of 978 firm-year observations, which are distributed among 258 firms for the years 2002 through 2007.

To have comparable variables regarding investor relations quality and annual report quality, the original score in the Capital ranking is divided by the maximum score of 500 to receive a percentage score similar to the other ranking. Because we use all observations from the Capital ranking, our sample is free from survivorship bias. Firms that are delisted during our sample period remain in the dataset until they are no longer traded.

### 4.3.2. Company and Return Data

All market and company data were obtained from the Thomson Reuters Datastream database. These data include the daily total return index (RI) for each stock, i.e., the stock price change adjusted for dividend payments, from which we calculate the daily stock return $r_{i,t}$ for stock i on day t as

$$r_{i,t} = \frac{RI_{i,t}}{RI_{i,t-1}} - 1. \tag{26}$$

To determine monthly stock returns, daily returns during the respective month are compounded. For market return, we use for each stock the return of the index the stock is a constituent of at the time of the ranking. The index affiliation of each stock is provided in the Capital ranking. The risk-free rate for each month is given by the quoted monthly EURIBOR at the beginning of that month. Stock return volatility ($\sigma_{i,m}$) is calculated as the volatility of daily stock returns during one month.

Apart from return data, we collected the market value of equity capital, price to book value, share price, closing ask price, closing bid price, and daily trading volume in thousands of shares for all stocks from Datastream.[9] Moreover, the company age and IPO date were hand-collected from the Internet. From the IPO date, we calculate the company age (LISTED) as the natural log of the number of years that have passed since the IPO. For companies that went public during the actual firm-year, we set the year counter to 0.5:

$$\text{LISTED}_{i,t} = \ln\left(1 + \max\left(\text{number of years since IPO}; 0.5\right)\right). \tag{27}$$

We decided to select the periods for our data survey according to the exact publication dates of the Capital ranking. One firm-year comprises all trading days between the publication dates of two subsequent rankings. Hence, we can ensure that details from the rankings were not publicly available and could not influence the stock market data we obtained for the respective time periods. Because the ranking was published earlier year after year, the length of the firm-years varies between 10 and 12 months. The first ranking was published in late September 2002 and the last in mid-June 2007. For all variables, firm-year observations of firms with less than 150 available daily observations are deleted from the sample. Moreover, we exclude foreign stocks with a dual listing in Germany, preferred stocks, and stocks from finance companies from our final sample.

Data on insider trading volume were gathered manually from the online database www.insiderdaten.de. To ensure the completeness of our dataset, we cross-checked the insider

[9] Data obtained from Datastream with their labels (in brackets): Total return index (RI), price to book value (PTBV), market value of equity capital in millions of Euros (MV), trading volume in thousands of shares (VO), share price (P), closing bid price (PB), closing ask price (PA).

trades with those from DGAP (Deutsche Gesellschaft für Ad-Hoc Publizität) and www.finanzen.net. Our original sample consists of 8,147 insider trades from which – after corrections for firm-years with no available investor relations ranking, trade records concerning option transactions, takeover bids, security lending and donation, and transactions among insiders[10] – 4,154 form the final sample. The sample period stretches from September 2002 until June 2008, and the insider trades are distributed over 613 firm-years.

## 4.4. METHODOLOGY

### 4.4.1. Insider Trading and Investor Relations

As HH suggest, we use data on insider trading volume to proxy for the liquidity needs of corporate insiders. We define insider trading volume as the absolute volume in Euros of all directors' dealings for one firm-year obtained from www.insiderdaten.de. Considering the trading volume variables, we distinguish buy order volume (BVO), sell order volume (SVO), and total insider trading volume (TAVO). All volume variables are given by the natural logs of the absolute trading volumes in Euros for each firm-year or are zero if no insider trades were recorded. To establish a connection between insider trading and investor relations, we annually regress the three trading volume variables on investor relations quality.

By regressing insider trading volume on investor relations quality, we face the problem that we cannot rule out that there is a reciprocal relationship between investor relations and insider trading. Corporate insiders could either adapt their trading behavior to their investor relations efforts or vice versa. Therefore, investor relations quality is potentially endogenous. To account for this potential endogeneity, we run two-stage least-squares regressions, using the mean

[10] The sample adjustments follow the methodology of Dymke and Walter (2008).

investor relations quality of the respective industry (IR_IND) as an instrumental variable for a firm's investor relations quality (IR). Like Sarin et al. (2000), who use a similar regression to explain insider holdings, we use stock return volatility, given by the average of monthly stock return volatilities for each firm-year (VOLA), and company age, measured as the number of years that have passed since the IPO of the respective company (LISTED), as control variables. By including company age, we can also account for the fact that, according to HH, their model should be especially relevant for younger companies. Apart from the young firm hypothesis, HH also conjecture that their model is better suited for small companies. Therefore, we also account for company size by including the natural log of the market value of equity (MV) at the end of June of the ranking year in the regression. For those years where the ranking was published before June 30, the market values of equity are taken from the day immediately before the publishing date (the date difference between June 30 and the earlier publishing dates never exceeds 12 days). We have to note, however, that we cannot offer substantive insights into the size hypothesis, as our sample is biased toward large stocks, as only the largest German companies are ranked by Capital. A similar bias is also observed by Heflin et al. (2005), who use the FAF ranking in their study.

To test the assumptions of the HH model, we estimate the following two-stage regression. We include cross-section fixed effects to account for constant firm-specific characteristics such as manager personality, and we use a heteroskedasticity robust White (1980) coefficient covariance matrix:

$$\text{Stage 1: } IR_{i,t} = \alpha + \beta_1 MV_{i,t} + \beta_2 VOLA_{i,t} + \beta_3 LISTED_{i,t} + \beta_4 REP_{i,t} + \beta_5 IR\_IND_{i,t}. \quad (28)$$

$$\text{Stage 2: } VO_{i,t} = \alpha + \beta_1 MV_{i,t} + \beta_2 VOLA_{i,t} + \beta_3 LISTED_{i,t} + \beta_4 REP_{i,t} + \beta_5 IR_{i,t}. \quad (29)$$

Equation (4) serves as a direct test for the hypothesis that higher insider trading volume is related to better investor relations. VO stands for the respective trading volume variable, i.e., BVO, SVO, or TAVO, and therefore measures annual insider trading volume. We control for annual report quality (REP) to rule out measuring any hidden influence from accounting quality.

### 4.4.2. Direct Liquidity Proxies

Having examined the relationship between insider trading and investor relations, we proceed by determining whether good investor relations actually have the desired liquidity effect. Although we have a clear intuition of what is meant by liquidity, there is no generally accepted measure for liquidity. Therefore, we use four proxies to examine the liquidity effects of investor relations. Proportional quoted spreads (SPR) and the Amihud (2002) illiquidity ratio (AIR) are meant to measure liquidity directly, whereas share trading volume (LVO) and relative stock return volatility (RVOL) are indirect liquidity measures.

#### *4.4.2.1. Proportional Quoted Spread*

Because spreads constitute the most widespread liquidity measure, we regress average proportional quoted bid-ask spreads on disclosure variables to determine whether investor relations can increase liquidity. We define those monthly proportional quoted spreads as the monthly average of the daily ratios of the difference between bid- and ask-price over the midpoint between the two prices:

$$SPR_{i,m} = \frac{1}{T}\sum_{t}\frac{PA_{i,t} - PB_{i,t}}{\left(PA_{i,t} + PB_{i,t}\right)/2}, \qquad (30)$$

where $PA_{i,t}$ is the closing ask price for stock i on day t, $PB_{i,t}$ represents the closing bid price on day t, and T stands for the number of trading days during the specific month. To control for other factors known to influence liquidity, we include company size, expressed as the natural log of the monthly average market value of equity (MV); share price, which is given by the natural log of the average monthly share price (LP); share trading volume (LVO), the natural log of each month's average daily share trading volume; and relative stock return volatility (RVOL), the ratio of each month's daily stock return volatility over daily market return volatility in our model. Our control variables are similar to those of Lesmond (2005) and Heflin and Shaw (2000). Together with the first stage, where IND_IR serves as an instrument for IR, we estimate the following model:

Stage 1:
$$\begin{aligned} IR_{i,m} &= \alpha + \beta_1 MV_{i,m} + \beta_2 AIR_{i,m} + \beta_3 RVOL_{i,m} + \\ &+ \beta_4 LP_{i,m} + \beta_5 LVO_{i,m} + \beta_6 REP_{i,m} + \beta_7 IND\_IR_{i,t} \end{aligned} \tag{31}$$

Stage 2:
$$\begin{aligned} SPR_{i,m} &= \alpha + \beta_1 MV_{i,m} + \beta_2 AIR_{i,m} + \beta_3 RVOL_{i,m} + \\ &+ \beta_4 LP_{i,m} + \beta_5 LVO_{i,m} + \beta_6 REP_{i,m} + \beta_7 IR_{i,t} \end{aligned} \tag{32}$$

All regressions on the direct and indirect liquidity proxies are estimated as two-stage least squares panel regressions on the respective monthly dependent variable. They are estimated with fixed cross-sections effects to capture company-specific constancy towards investor relations policy and a White (1980) heteroskedasticity robust coefficient covariance matrix.

*4.4.2.2. Amihud (2002) Illiquidity Ratio*

To account for the fact that spreads alone do not constitute a sufficient liquidity measure, as discussed by Heflin et al. (2005), we use a second proxy to verify our results. Because liquidity can, according to Pástor and Stambaugh (2003), be defined as "the ability to trade large quantities quickly, at low cost, and without moving the price", we also quantify illiquidity via the Amihud (2002) illiquidity ratio, which can be interpreted as a daily estimate of Kyle's (1985) lambda, which is also used by Brennan and Tamarowski (2000) to measure the liquidity impact of investor relations. AIR captures the daily price response of one euro of trading volume and is calculated as the daily ratio of absolute stock return over trading volume in Euros:

$$\mathrm{AIR}_{i,t} = \frac{|r_{i,t}|}{\mathrm{VO}_{i,t} \cdot P_{i,t}}. \tag{33}$$

To provide for a better smoothing of estimation errors, we calculate average daily AIRs for each company month in our sample, so that monthly AIR is given by:

$$\mathrm{AIR}_{i,m} = \frac{1}{T} \cdot \sum_t \frac{|r_{i,t}|}{\mathrm{VO}_{i,t} \cdot P_{i,t}}. \tag{34}$$

Apart from annual report quality (REP), we use company size (MV) and relative stock return volatility (RVOL) as control variables in the regressions on AIR. In contrast to Brennan and Tamarowski (2000), we did not add price and share trading volume to the regressors because both variables are already used to calculate the illiquidity ratio itself. To still be able to control for some type of trading volume, we decided to include turnover (TO), i.e., share trading volume in Euros relative to the market value of equity in Euros, as a second control variable in our regression. TO is calculated as the ratio of the monthly average of daily trading volume over the monthly average of daily market values of equity:

$$\mathrm{TO}_{i,m} = \frac{\frac{1}{T}\sum_t \mathrm{VO}_{i,t} \cdot P_{i,t}}{\frac{1}{T}\sum_t \mathrm{MV}_{i,t}} \tag{35}$$

The regression model is specified as follows:

Stage 1: $\mathrm{IR}_{i,m} = \alpha + \beta_1 \mathrm{MV}_{i,m} + \beta_2 \mathrm{RVOL}_{i,m} + \beta_3 \mathrm{TO}_{i,m} + \beta_4 \mathrm{REP}_{i,m} + \beta_5 \mathrm{IND\_IR}_{i,t}$ (36)

Stage 2: $\mathrm{AIR}_{i,m} = \alpha + \beta_1 \mathrm{MV}_{i,m} + \beta_2 \mathrm{RVOL}_{i,m} + \beta_3 \mathrm{TO}_{i,m} + \beta_4 \mathrm{REP}_{i,m} + \beta_5 \mathrm{IR}_{i,t}$ (37)

### 4.4.3. Indirect Liquidity Proxies

The first indirect liquidity proxy is trading volume. Intuition suggests that liquidity has to be positively correlated to trading volume because the more traders are available for a firm's stocks, the easier it is to find a trading counterparty. Therefore, liquidity must be higher for stocks that exhibit higher trading volumes. Assuming that investor relations have a positive influence on liquidity, they should be positively correlated to trading volume as well. Evidence for this hypothesis is offered in previous studies by Leuz and Verrecchia (2000) and Brennan and Tamarowski (2000). As with VO, we expect a positive influence of investor relations quality stock return volatility. This assumption is derived from earlier research by Healy et al. (1999) and Bushee and Noe (2000), in which good investor relations attract trading-prone institutional investors, leading to higher stock-return volatility. Although this might, following the argumentation of Harris and Raviv (1993), seem counterintuitive because good investor relations should lower the diversity of investor opinions and therefore lead to lower stock return volatility, a positive relationship is also documented by Lang and Lundholm (1993), Leuz and Verrecchia (2000), and Botosan and Plumlee (2002).

#### *4.4.3.1. Share Trading Volume*

As a variable for share trading volume, we use the natural log of the monthly average of daily share trading volume in thousands of shares (LVO). The control variables are stock return volatility (RVOL) and proportional quoted spread (SPR), as in Chalmers and Kadlec (1998), plus company size (MV) and annual report quality (REP):

$$\text{Stage 1: } IR_{i,m} = \alpha + \beta_1 MV_{i,m} + \beta_2 RVOL_{i,m} + \beta_3 SPR_{i,m} + \beta_4 REP_{i,m} + \beta_5 IND\_IR_{i,t}. \quad (38)$$

$$\text{Stage 2: } LVO_{i,m} = \alpha + \beta_1 MV_{i,m} + \beta_2 RVOL_{i,m} + \beta_3 SPR_{i,m} + \beta_4 REP_{i,m} + \beta_5 IR_{i,t}. \quad (39)$$

*4.4.3.2. Relative Stock Return Volatility*

Return volatility $\sigma_{i,m}$ for stock i in month m is defined as the volatility of that stock's daily returns during the specific month. To adjust the volatility of the single stocks for market-wide volatility shocks, we scale each monthly stock return volatility by the volatility of daily market returns during the corresponding month ($\sigma_{m,m}$) to obtain relative stock return volatility:

$$RVOL_{i,m} = \frac{\sigma_{i,m}}{\sigma_{m,m}}. \tag{40}$$

To isolate volatility effects caused by the investor relations quality, we, like Cheung and Ng (1992), control for company size, share price, trading volume and spreads. Our regression model takes the form:

$$\text{Stage 1: } IR_{i,m} = \alpha + \beta_1 MV_{i,m} + \beta_2 LP_{i,m} + \beta_3 VO_{i,m} + \beta_4 SPR_{i,m} + \beta_5 REP_{i,m} + \beta_6 IND\_IR_{i,t} \tag{41}$$

$$\text{Stage 2: } RVOL_{i,m} = \alpha + \beta_1 MV_{i,m} + \beta_2 LP_{i,m} + \beta_3 VO_{i,m} + \beta_4 SPR_{i,m} + \beta_5 REP_{i,m} + \beta_6 IR_{i,t} \tag{42}$$

### 4.4.4. Stock Performance

To estimate the influence of investor relations on stock performance, we follow Easley and O'Hara (2004) and suppose that estimation risk, the risk of misestimating future cash flows and therefore the fair stock price, is a risk factor, which until now has been omitted in asset pricing models. To determine the performance impact, i.e., the impact of IR on expected return, we perform two tasks. First, we form arbitrage portfolios for each ranking period by short-selling all stocks from the bottom decile of each investor relations ranking and buying all stocks from the top decile of the respective ranking. All portfolios are formed twice, once with equal-weighted and once with value-weighted portfolio positions. Monthly returns to these arbitrage portfolios ($r_{pf,m}$) are recorded and regressed on monthly returns to the market portfolio net the risk-free rate, which is given by the monthly EURIBOR interest rate. Returns to the market portfolio are represented by monthly returns of the DAX index. Therefore, we derive our Jensen alphas from the following calculation:

$$r_{pf,m} = alpha + market \cdot \left(r_{m,m} - r_{f,m}\right). \tag{43}$$

Second, we estimate two regression models on the monthly excess returns of all ranked companies. The first is a plain market model with the excess market return being the only influencing factor for a company's excess stock return over the risk-free rate. The other is a model that also includes company size and book to market ratio as explanatory variables. Model 1 is specified as follows:

Model 1a): $r_{i,m} - r_{f,m} = alpha + market \cdot (r_{m,m} - r_{f,m})$. (44)

Model 1b): $r_{i,m} - r_{f,m} = alpha + market(r_{m,m} - r_{f,m}) + \beta_1 IR_{i,t} + \beta_2 REP_{i,t}$. (45)

$r_{f,m}$, the risk-free return for one month, is given by the quoted EURIBOR interest rate for that month at the beginning of the month. The market return $r_{m,m}$ is represented by the return of the index that company i is a constituent of. To determine whether IR quality has additional explanatory power in the market model, we include the disclosure variables IR and REP as explanatory variables in Model 1b).

In Model 2, we regress monthly excess stock returns on the investor relations and annual report quality variables together with company size, book to market ratio, and excess market returns to obtain an impression of whether investor relations quality interacts with other variables influencing stock returns. The book to market ratio (BTM) is given by the book to market ratio of company i at the end of the preceding year, which in most cases (by far) is equal to the fiscal-year end. The ratio is calculated as the reciprocal value of the price-to-book-value variable (PTBV) obtained from Datastream. As in the regressions on insider trading volume, company size (MV) is represented by the natural log of the market value of equity in millions of Euros at the end of June before the ranking.

Model 2a): $r_{i,m} - r_{f,m} = alpha + \beta_1 BTM_{i,t} + \beta_2 MV_{i,t} + market(r_{m,m} - r_{f,m})$ (46)

Model 2b): $r_{i,m} - r_{f,m} = alpha + \beta_1 BTM_{i,t} + \beta_2 MV_{i,t} + market(r_{m,m} - r_{f,m}) + \beta_3 IR_{i,t} + \beta_4 REP_{i,t}$ (47)

All regressions on stock returns are pooled regressions with Newey-West (1987) standard errors.

## 4.5. RESULTS

### 4.5.1. Descriptive Statistics

Tables 14 and 15 present summary statistics of the number of insider transactions and the distribution of each year's ranking scores in the investor relations ranking we use in our study. Our sample of insider trades concerning firms ranked in an investor relations ranking consists of 4,154 transactions. Starting with these, we adjust for companies with unavailable annual report rankings, preferred stocks, financial industry stocks, and foreign stocks with a secondary listing in Germany. The final sample consists of 3,121 trades. Aggregating these transactions per firm-year, we receive 466 firm-years with at least one insider deal. The 466 firm-year observations are distributed among 209 firms.

(Insert Table 14 here)

Table 14 reveals that, although the number of insider buy orders is approximately 5% larger than the number of insider sell orders, the volume of sell orders exceeds the buy order volume by more than 100%. This occurs for two reasons. On the one hand, insiders usually sell more shares than they buy because stocks are a part of their compensation and are therefore not obtained via the stock market. On the other hand, insider buy orders are an important signal for other market participants that the stock is undervalued. Hence, insiders use the signaling effect of their buy orders to increase stock prices by buying small equity stakes from time to time. The proportions of sell and buy order volumes and the number of trades in both categories are broadly in line with existing studies for the German market by Betzer and Theissen (2007) and Dymke and Walter (2008).

(Insert Table 15 here)

The descriptive statistics of the investor relations ranking in Table 15 illustrate that the rating score distributions are all negatively skewed. This skewness is a hint of the selection bias that is due to only the largest German companies being ranked in the Capital ranking. Because most large companies dedicate significant monetary resources to investor relations, investor relations scores are reasonably high on average.

### 4.5.2. Correlation Analysis

Table 16 depicts the correlation analysis of all variables we use in our regressions. The triangle above the diagonal depicts the Bravais-Pearson correlation coefficients, whereas the bottom triangle shows the Spearman correlations.

(Insert Table 16 here)

An important inference that can be drawn from Table 16 is that both disclosure quality variables are positively correlated with company size. Whereas IR is only weakly correlated with company size, REP exhibits a correlation close to 50%. Concerning the correlation across the disclosure quality measures, we observe that the correlation of investor relations quality in general and the annual report quality is much weaker, at 25% compared with 40% in Lang and Lundholm (1993). This is because we use rankings from different providers to assess investor relations and annual report quality. The other correlations display no surprising results. As expected, the two direct liquidity proxies, proportional spreads and the Amihud (2002) illiquidity ratio are strongly correlated with each other and negatively related to company size, indicating that larger companies have more liquid stocks.

### 4.5.3. Insiders Talking and Trading

(Insert Table 17 here)

Our regressions of investor relations quality on insider trading volume show that there is a strong connection between the quality of investor relations and the amount of insider sales volume. As HH predict, investor relations have a significantly positive influence on the volume of insider sales. We cannot observe any influence on buy orders or total trading volume. Also, the economic significance of investor relations quality is highest for insider sales volume. If we are able to show that investor relations do indeed provide for enhanced liquidity, we can conclude that insiders use investor relations as a means to create liquidity for their own shares to avoid price discounts when they suffer from liquidity shocks.

Most interestingly, annual report quality has a negative influence on insider buy order volume. This means that insiders tend to buy less shares of their own company when their company's annual report quality is good, which could be for two reasons: either insiders do not need the signaling effect of their buy orders, or, more likely, they only buy stocks when their private information prompts them to do so. Because insiders have more private information when accounting quality is bad, they trade more in this case.

The conjecture of HH that their model is especially valid for young companies is not significantly supported by our data. Company age, proxied for by LISTED, instead has a positive influence on insider trading volume, which suggests that insider trading volume is larger for older companies.[11]

Whereas company size has a positive influence on insider buy volume, we cannot detect any influence on sell order volume. Hence, we can conclude that corporate insiders in large companies are more likely to buy stocks from their company than insiders in smaller companies. On the sell side, on the other hand, corporate insiders from both firm types are equally represented. This is weak evidence for the hypothesis by HH that their model should be more valid for smaller companies, which means that insiders of small companies sell disproportionally more stocks than insiders from large companies.

### 4.5.4. Investor Relations and Liquidity

#### *4.5.4.1. Direct Measures*

Having shown that good investor relations indeed come along with heavier insider trading, as HH predict, we move on to note the liquidity effects of good investor relations. As liquidity measures, we use proportional quoted spreads and the Amihud (2002) illiquidity ratio. Both measures are negatively correlated with liquidity and should accept higher values for less liquid stocks. Because we assume that good investor relations have a positive influence on liquidity, we expect negative betas for the disclosure quality variables as a result of our regressions. These expectations are confirmed: regarding proportional quoted spreads, we observe a significantly negative influence of investor relations quality. The coefficients of the other variables are in line with earlier literature: like Lesmond (2005), we also find that share price and trading volume

[11] Specifications including company age measured from the founding date of the company instead of the IPO date do not change our inferences.

have a negative influence on spreads, whereas AIR and volatility are positively correlated with spreads.

The regressions on AIR do not convey unanimous results. In our original specification for the years 2002 to 2007, we cannot find any influence of investor relations on AIR, due to the fact that TO has a positive influence on AIR in the year 2002. If we rerun the regressions starting from the year 2003 through 2007, we observe a very significant negative influence of investor relations quality on AIR, as seen from the results of Equations (5) and (6) of Table 18. Further evidence comes from estimating the same regression for different overlapping three-year sections from the sample. During the first section, from 2002 through 2004, the influence of investor relations is insignificant. For the periods 2003 to 2005, 2004 to 2006, and 2005 to 2007, the influence of IR on AIR is always significantly negative and growing with regard to its economic impact[12].

(Insert Table 18 here)

Summarizing the results for both direct liquidity measures, we observe a strong positive influence of good investor relations on liquidity. Hence, if insiders are able to exert a positive influence on investor relations quality, they really can create liquidity.

#### *4.5.4.2. Indirect Measures*

Based on earlier research, our expectations regarding indirect liquidity measures are indifferent. Concerning volatility, research by Bushee and Noe (2000), Botosan and Plumlee (2002), and Chang et al. (2008) suggests that we should find a positive correlation between volatility and investor relations quality. With respect to share trading volume, two offsetting effects determine

[12] Results are available from the authors by request.

the influence of investor relations. On the one hand, higher liquidity usually goes hand in hand with higher trading volume, a relationship that can also be derived from our regression results in Table 18, where trading volume is significantly associated with lower spreads. Our observation of this relationship is in line with earlier findings by, e.g., Brennan and Tamarowski (2000) and Lesmond (2005). On the other hand, better investor relations should level the informational playing field for all investors, resulting, according to, e.g., Harris and Raviv (1993), in less share trading and lower stock return volatility due to a higher convergence of market opinions.

Our regression results are in favor of the first hypothesis and in line with earlier investor relations and disclosure literature, as we observe a positive, nearly significant influence of investor relations on share trading volume and a significantly positive influence of investor relations on stock return volatility. This indicates that stocks with better investor relations become more attractive for short-term institutional investors, as is suggested by Healy et al. (1999) and Bushee and Noe (2000).

(Insert Table 19 here)

Both of our indirect liquidity proxies deliver corroborative evidence for the notion that investor relations provide an important tool for corporate insiders to create liquidity for their shares. The enhanced liquidity, however, incurs additional costs for the firm's shareholders via higher stock return volatility.

### 4.5.5. Investor Relations and Stock Performance

To gain a first impression of the relationship between investor relations and stock returns, Table 20 shows the abnormal performance of two rolling arbitrage portfolios formed on the basis of each year's Capital ranking. The portfolios are formed annually by short-selling all stocks from the bottom decile of the ranking and investing the proceeds in all stocks from the top decile. One of the portfolios is equal-weighted, and the other is value-weighted. The Jensen alphas of these portfolios are depicted in Table 20.

(Insert Table 20 here)

The equal-weighted arbitrage portfolio is able to generate significant excess returns compared with the market portfolio. This is, however, attributable to the equal-weighting of the portfolio constituents, as seen from the negative Jensen alpha of the value-weighted portfolio.

Table 21 holds the results of all regressions on monthly excess returns. Regressing monthly excess returns on investor relations quality should yield significantly positive betas for IR if good investor relations had a positive impact on stock returns, as is suggested, e.g., by Schachel and Vögtle (2006) and Agarwal et al. (2008).

(Insert Table 21 here)

Looking at the market model could lead to the conclusion that such is the case. However, the evidence is mitigated by the insignificance of the IR variables in the context of other explanatory variables, such as company size and especially book to market ratio. The book to market ratio, which has a highly significant coefficient, very strongly mitigates the influence of investor relations quality. Therefore, we conclude that the effects that can be spotted in the market model are a glamour effect in disguise. Moreover, adding IR and REP in Model 1b) and 2b) does not add noticeably to the explanatory power of Models 1a) and 2a), respectively.

Adding the lack of evidence from the Jensen alphas to the lacking influence in the regression models with company size, book to market ratio, and excess market returns, we conclude that good investor relations have no significant influence on excess stock returns of German companies.

#### 4.5.6. Robustness

We perform several tests to confirm the robustness of our results. Regressions on insider trading are estimated on the number of orders in each category instead of the trading volume, and none of the results changes significantly. Furthermore, measuring company age as the number of years from the founding date instead of the IPO date does not change our results. Lastly, all inferences regarding the relationship between investor relations and liquidity are robust to running our regressions on an annual basis.

That our sample is tilted toward large companies biases our results toward rejecting the hypotheses by HH, if the model is indeed more valid for small companies. Given this bias, our results seem even more robust.

### 4.6. CONCLUSIONS

Our study delivers strong empirical evidence for the model by Hong and Huang (2005) that investor relations are an instrument for corporate insiders to generate liquidity for their own batch of shares. We analyze all firms listed in one of the major German stock indices during the period from 2002 to 2007 using the Capital investor relations ranking as a measure of investor relations quality.

We find that good investor relations are very strongly associated with higher insider sales volumes, as predicted by Hong and Huang (2005). Why insiders prefer to have good investor relations becomes obvious from our regressions on four liquidity proxies. Because insiders have discretionary power over the investor relations strategy of their firm, they can create liquidity for their shares by dedicating resources to investor relations.

Apart from offering supportive evidence for the model as such, we find that the results are indeed influenced by company age, as Hong and Huang (2005) conjecture. Because our sample is biased toward large companies, we did not investigate this question in greater detail. This question offers a promising avenue for future research. In this context, measuring the investor relations quality of small companies could offer very interesting insights.

In contrast to earlier studies for the US market by, e.g., Agarwal et al. (2008) and for the German market by Schachel and Vögtle (2006), we cannot detect any systematic influence of investor relations on stock returns. Including investor relations quality in regressions on the monthly excess returns of German stocks neither yields a significant influence of investor relations on returns nor improves the explanatory power of our regression models. Grouping the companies of the investor relations rankings into deciles, we also cannot find that arbitrage portfolios built by buying the stocks from the top decile and short-selling the stocks from the bottom decile can earn any significant alphas compared with the market return adjusted for the risk-free rate.

To summarize our findings, we assess that the Hong and Huang (2005) model draws a good picture of the reality of the German stock market. It seems as though insiders have used investor relations as a means to create liquidity for their stock holdings.

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**Table 14: Insider Trading – Summary statistics**

Summary statistics for the insider trades used in this study. Data on insider trading were taken from the online database www.insiderdaten.de and cross-checked with data from DGAP and www.finanzen.net.

| | No. of trades |
|---|---|
| Total number of insider trades for the whole period, which involve a stock listed in at least one of the IR rankings | 8,147 |
| Trades concerning option transactions, security lending and donation, takeover bids, transactions among insiders, and transactions concerning a firm not ranked in an investor relations ranking during the corresponding period | 3,993 |

| Order Type | Buy Orders | | Sell Orders | | All Transactions | |
|---|---|---|---|---|---|---|
| | No. of trades | No. of firm-years | No. of trades | No. of firm-years | No. of trades | No. of firm-years |
| Adjusted number of insider trades | 2,172 | 426 | 1,982 | 400 | 4,154 | 613 |
| Annual report ranking unavailable | 36 | 3 | 9 | 4 | 45 | 6 |
| Preferred Stocks | 185 | 25 | 146 | 26 | 331 | 37 |
| Financial Industry Stocks | 311 | 67 | 259 | 61 | 570 | 100 |
| Foreign stocks with a German dual-listing | 35 | 4 | 52 | 3 | 87 | 4 |
| Final sample | 1,605 | 327 | 1,516 | 306 | 3,121 | 466 |
| Order volume in Euros | 3,540,005,753 | | 7,232,294,810 | | 10,772,300,563 | |

## Table 15: Summary statistics of the investor relations scores

Table 15 contains descriptive statistics of the Capital investor relations ranking, a ranking of overall investor relations quality. From 2002 to 2003, the number of rated companies (n) shrank because the provider of the German DAX family of stock indices, Deutsche Boerse, changed the number of index constituents.
Variables tabulated: mean ranking score, median ranking score, and standard deviation of the respective ranking scores, skewness of the score distribution, maximum score and minimum score.

| | **2002** | **2003** | **2004** | **2005** | **2006** | **2007** |
|---|---|---|---|---|---|---|
| n | 200 | 159 | 160 | 158 | 157 | 156 |
| Mean | 321.5 | 311.5 | 347.2 | 358.4 | 350.8 | 336.06 |
| Median | 333.4 | 330.1 | 338.1 | 377.45 | 359.1 | 344.4 |
| St.-Dev. | 74.94 | 63.66 | 76.17 | 79.43 | 70.97 | 66.10 |
| Skewness | -0.274 | -0.242 | -0.841 | -1.744 | -0.642 | -0.598 |
| Max Score | 479.7 | 455.2 | 492.7 | 476.7 | 493.5 | 451.1 |
| Min Score | 75.5 | 74 | 50.9 | 25.8 | 127.9 | 140.6 |

## Table 16: Variable correlations

Table 16 contains a monthly correlation analysis of all factors used in our regression estimates. IR is the percentage scores of the Capital ranking, and REP stands for the percentage score of the annual report ranking. MV represents the natural log of average daily market value of equity in millions of Euros during each month, LP the natural log of the monthly average of daily closing prices, and LVO the natural log of average daily share trading volume each month. RVOL is given by each month's volatility of daily stock returns divided by the daily volatility of that month's market returns, SPR is calculated as the monthly average of the daily ratio of the difference of ask- and bid-price over the midpoint between the two prices, and AIR is calculated as the average of daily Amihud (2002) illiquidity ratios for each company month. TO is given by the ratio of the monthly average of daily trading volume in Euros over the monthly average of daily market values of equity in millions of Euros. BVO, SVO, and TAVO denote the natural logarithm of absolute trading volume from insider buy, sell, and total transactions, respectively. IND_IR is the mean investor relations quality of the industry a company belongs to.
The sample period for which correlation coefficients were calculated ranges from September 30, 2002, to June 18, 2008, and contains 8,524 observations. The Pearson correlation coefficients are tabulated in the upper triangle, and the Spearman correlation coefficients are tabulated in the lower triangle. One (two, three) asterisk(s) means significance at the 10% (5%, 1%) level.

| | IR | REP | MV | LP | LVO | RVOL | SPR | AIR | TO | BVO | SVO | TAVO | IND_IR |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| IR | 1 | 0.25*** | 0.44*** | 0.40*** | 0.05*** | -0.28*** | -0.31*** | -0.06*** | -0.12*** | 0.08*** | 0.14*** | 0.18*** | 0.61*** |
| REP | 0.26*** | 1 | 0.41*** | 0.20*** | 0.09*** | -0.16*** | -0.23*** | -0.05*** | -0.14*** | 0.04*** | -0.03*** | -0.02** | 0.15*** |
| MV | 0.45*** | 0.45*** | 1 | 0.57*** | 0.27*** | -0.41*** | -0.55*** | -0.14*** | -0.18*** | 0.15*** | 0.01 | 0.09** | 0.37*** |
| LP | 0.39*** | 0.22*** | 0.58*** | 1 | -0.27*** | -0.36*** | -0.47*** | -0.15*** | -0.14*** | 0.08*** | 0.13*** | 0.17*** | 0.31*** |
| LVO | 0.07*** | 0.11*** | 0.24*** | -0.27*** | 1 | -0.01 | -0.38*** | -0.09*** | 0.48*** | 0.08*** | 0.03*** | 0.06*** | 0.04*** |
| RVOL | -0.24*** | -0.21*** | -0.46*** | -0.31*** | -0.07*** | 1 | 0.38*** | 0.13*** | 0.16*** | -0.05* | 0.04*** | -0.01 | -0.19*** |
| SPR | -0.37*** | -0.33*** | -0.71*** | -0.47*** | -0.51*** | 0.40*** | 1 | 0.43*** | -0.02* | -0.11*** | -0.13*** | -0.17*** | -0.29*** |
| AIR | -0.34*** | -0.27*** | -0.63*** | -0.32*** | -0.75*** | 0.34*** | 0.86*** | 1 | 0.09*** | -0.01 | -0.05*** | -0.04*** | -0.08*** |
| TO | -0.21*** | -0.33*** | -0.53*** | -0.43*** | 0.56*** | 0.29*** | 0.06*** | -0.20*** | 1 | -0.01 | 0.02** | 0.02* | -0.17*** |
| BVO | 0.10*** | 0.07*** | 0.15*** | 0.10*** | 0.08*** | -0.04*** | -0.14*** | -0.10*** | -0.02* | 1 | 0.20*** | 0.66*** | 0.09*** |
| SVO | 0.15*** | -0.03*** | 0.01 | 0.16*** | 0.02* | 0.04*** | -0.13*** | -0.10*** | 0.06*** | 0.21*** | 1 | 0.74*** | 0.09*** |
| TAVO | 0.19*** | -0.01 | 0.09*** | 0.20*** | 0.05*** | 0.00 | -0.20*** | -0.15*** | 0.04*** | 0.61*** | 0.81*** | 1 | 0.12*** |
| IND_IR | 0.59*** | 0.16*** | 0.35*** | 0.31*** | 0.02** | -0.16*** | -0.30*** | -0.25*** | -0.21*** | 0.10*** | 0.10*** | 0.13*** | 1 |

## Table 17: Regressions on Insider Trading Volume

This table presents regression results for regressions of insider trading volume on investor relations quality. The dependent variables are the natural log of the Euro volume of insider buy orders (BVO), insider sell orders (SVO), and overall insider trading volume (TAVO). The instrumental variable IND_IR represents the mean percentage investor relations score for the respective industry in the respective ranking year. MV stands for the natural log of market value of equity at the end of June of the respective ranking year. LISTED stands for the natural log of the number of years that have passed since the IPO, VOLA is calculated as the average of monthly volatilities of daily stock returns per firm-year, IR is given by the percentage rating in the IR ranking and REP represents the percentage score in the annual report ranking. Regressions (1), (3), and (5) are panel regressions with cross-section fixed effects and a heteroskedasticity robust White (1980) coefficient covariance matrix. Regressions (2), (4), and (6) were estimated as two-stage least-squares panel regressions with cross-section fixed effects and a heteroskedasticity robust White (1980) coefficient covariance matrix. One (two, three) asterisk(s) means significance at the 10% (5%, 1%) level.

| Dependent Variable | | BVO | | SVO | | TAVO | |
|---|---|---|---|---|---|---|---|
| | First Stage | (1) | (2) | (3) | (4) | (5) | (6) |
| IND_IR | 0.878 | | | | | | |
| | (14.09)*** | | | | | | |
| IR | | | 1.893 | | 10.545 | | 8.039 |
| | | | (0.42) | | (2.00)** | | (1.60) |
| REP | 0.134 | | -6.076 | | -1.777 | | -5.493 |
| | (2.80)*** | | (2.25)** | | (0.51) | | (1.73)* |
| MV | 0.056 | 2.333 | 2.012 | 0.515 | -0.279 | 1.922 | 1.188 |
| | (6.51)*** | (4.21)*** | (3.06)*** | (0.84) | (0.37) | (3.21)*** | (1.62) |
| VOLA | -0.058 | 59.169 | 56.706 | -108.926 | -95.672 | -39.526 | -32.903 |
| | (0.13) | (2.14)** | (2.01)** | (3.24)*** | (2.67)*** | (1.57) | (1.13) |
| LISTED | -0.067 | 2.128 | 2.590 | 1.476 | 2.181 | 1.304 | 2.083 |
| | (3.16)*** | (1.59) | (1.90)* | (0.97) | (1.40) | (0.98) | (1.50) |
| Constant | -0.210 | -17.268 | -13.873 | 1.212 | -1.539 | -6.902 | -6.203 |
| | (2.68)*** | (4.56)*** | (3.11)** | (0.28) | (0.28) | (1.80) | (1.30) |
| Adj. $R^2$ | 0.63 | 0.27 | 0.27 | 0.27 | 0.27 | 0.30 | 0.29 |
| N | 736 | 736 | 736 | 736 | 736 | 736 | 736 |

## Table 18: Effects of investor relations on direct liquidity measures

Results of regressions with two liquidity proxies as dependent variables: proportional quoted spread (SPR), the monthly average of daily proportional quoted bid-ask spreads, and the Amihud (2002) illiquidity ratio (AIR), calculated as the monthly average of the ratio of daily stock return over trading volume in Euros. The instrumental variable IND_IR represents the mean percentage investor relations score for the respective industry in the respective ranking year. MV stands for the natural log of the average monthly market value of equity. RVOL is given by the monthly ratio of daily stock return volatility over daily market return volatility. LP is the natural log of the monthly average of daily closing prices. LVO represents the natural log of average daily share trading volume per month. TO is calculated as the ratio of the monthly average of daily trading volume in Euros over the monthly average of daily market value of equity in millions of Euros. IR stands for the percentage rating score in the Capital ranking, and REP is the percentage score in the annual report ranking. All regressions are estimated with fixed cross-section effects and a heteroskedasticity robust White (1980) coefficient covariance matrix. Regressions (1), (3), and (5) are panel regressions, and (2), (4), and (6) are two-stage least-squares specifications. T-statistics are tabulated in parentheses. One (two, three) asterisk(s) means significance at the 10% (5%, 1%) level.

| Dependent Variable | SPR | | | AIR | | | AIR | | |
|---|---|---|---|---|---|---|---|---|---|
| | First Stage | (1) | (2) | First Stage | (3) | (4) | First Stage | (5) | (6) |
| Time period | | 09/02-06/08 | 09/02-06/08 | | 09/02-06/08 | 09/02-06/08 | | 07/03-06/08 | 07/03-06/08 |
| IND_IR | 0.887 | | | 0.887 | | | 0.922 | | |
| | (56.68)*** | | | (55.93)*** | | | (8.05)*** | | |
| IR | | | -0.010 | | | 0.001 | | | -0.001 |
| | | | (6.51)*** | | | (0.89) | | | (8.27)*** |
| REP | 0.052 | | -0.010 | 0.000 | | 0.000 | 0.086 | | -0.000 |
| | (4.31)*** | | (11.18)*** | (5.96)*** | | (0.61) | (6.42)*** | | (2.25)** |
| MV | -0.069 | -0.003 | -0.004 | 0.021 | -0.002 | -0.002 | 0.026 | -0.000 | -0.000 |
| | (10.50)*** | (5.09)*** | (6.51)*** | (11.33)*** | (2.52)** | (2.44)** | (11.29)*** | (7.48)*** | (2.25)** |
| AIR | 0.455 | 0.234 | 0.240 | | | | | | |
| | (4.53)*** | (5.12)*** | (5.09)*** | | | | | | |
| RVOL | -0.002 | 0.000 | 0.0002 | -0.001 | 0.000 | 0.000 | -0.001 | -0.000 | -0.000 |
| | (3.53)*** | (3.29)*** | (2.94)*** | (2.06)** | (0.35) | (0.35) | (1.19) | (0.73) | (0.72) |
| P | 0.106 | -0.004 | -0.002 | | | | | | |
| | (14.40)*** | (5.45)*** | (3.08)*** | | | | | | |
| VO | 0.010 | -0.002 | -0.002 | | | | | | |
| | (7.38)*** | (15.42)*** | (14.64)*** | | | | | | |
| TO | | | | 0.002 | 0.001 | 0.001 | -0.001 | -0.000 | -0.000 |
| | | | | (2.76)*** | (1.75)* | (1.76)* | (0.98)*** | (2.62)*** | (2.86)*** |
| C | 0.201 | 0.049 | 0.063 | -0.109 | 0.015 | 0.015 | -0.181 | 0.002 | 0.002 |
| | (7.01)*** | (20.59)*** | (20.60)*** | (6.26)*** | (2.65)*** | (2.86)*** | (8.05)*** | (8.90)*** | (10.45)*** |
| Adj. $R^2$ | 0.72 | 0.78 | 0.77 | 0.71 | 0.19 | 0.19 | 0.73 | 0.64 | 0.64 |
| N | 8,534 | 8,534 | 8,534 | 8,536 | 8,534 | 8,534 | 7,087 | 7,085 | 7,085 |

**Table 19: Indirect liquidity measures**

We estimate two-stage least-squared panel regressions on share trading volume (LVO) and relative stock return volatility (RVOL). LVO is the natural log of average daily share trading volume per month, and RVOL is the monthly volatility of daily stock returns scaled by the corresponding monthly volatility of daily market returns. IR represents the percentage rating score in the Capital investor relations ranking, and REP is the percentage score of the annual report ranking. The instrumental variable IND_IR represents the mean percentage investor relations score for the respective industry in the respective ranking year. MV stands for the natural log of the average monthly market value of equity. LP is the natural log of the monthly average of daily closing prices, and SPR is the monthly average of daily proportional quoted bid-ask spreads. All regressions were estimated with cross-section fixed effects and a heteroskedasticity robust White (1980) coefficient covariance matrix. Models (1) and (3) are panel regressions and (2) and (4) are two-stage least-squares specifications. T-statistics are tabulated in parentheses. One (two, three) asterisk(s) means significance at the 10% (5%, 1%) level.

| Dependent Variable | LVO | | | RVOL | | |
|---|---|---|---|---|---|---|
| | First Stage | (1) | (2) | First Stage | (3) | (4) |
| IND_IR | 0.888 | | | 0.891 | | |
| | (55.79)*** | | | (56.67)*** | | |
| IR | | | 0.183 | | | 0.906 |
| | | | (1.26) | | | (2.64)*** |
| REP | 0.075 | | -0.015 | 0.059 | | -0.393 |
| | (6.14)*** | | (0.14) | (4.83)*** | | (1.90)* |
| MV | 0.022 | -0.227 | -0.234 | -0.065 | -0.969 | -0.961 |
| | (10.64)*** | (9.74)*** | (9.50)*** | (9.79)*** | (6.63)*** | (6.32)*** |
| SPR | 0.194 | -22.119 | -22.068 | 0.483 | 17.774 | 17.363 |
| | (1.41) | (12.40)*** | (12.34)*** | (3.46)*** | (3.95)*** | (3.83)*** |
| RVOL | -0.001 | 0.129 | 0.129 | | | |
| | (1.47) | (18.61)*** | (18.66)*** | | | |
| LP | | | | 0.104 | 0.649 | 0.591 |
| | | | | (14.17)*** | (3.62)*** | (3.12)*** |
| LVO | | | | 0.009 | 0.747 | 0.739 |
| | | | | (6.94)*** | (17.48)*** | (17.07)*** |
| c | -0.120 | 4.146 | 4.080 | 0.159 | 5.146 | 4.891 |
| | (6.01)*** | (23.85)*** | (21.43)*** | (5.33)*** | (9.30)*** | (7.12)*** |
| Adj. $R^2$ | 0.71 | 0.88 | 0.88 | 0.72 | 0.43 | 0.43 |
| n | 8,536 | 8,534 | 8,534 | 8,534 | 8,534 | 8,534 |

## Table 20: Arbitrage portfolio returns: good vs. bad investor relations

Table 20 shows the alphas generated by arbitrage portfolios of top-decile and bottom-decile stocks of the Capital investor relations ranking. All stocks from the top decile are bought, and all stocks from the bottom decile are sold short. The arbitrage portfolios are rebalanced at each ranking date. Returns to the one arbitrage portfolios are equal-weighted, returns to the other are value-weighted. Monthly arbitrage portfolio returns are regressed on monthly returns of the DAX index net of the risk-free rate, which is represented by the monthly EURIBOR. All regressions were estimated with Newey-West (1987) standard errors. One (two, three) asterisk(s) means significance at the 10% (5%, 1%) level.

| | **Equal-weighted** | **Value-weighted** |
|---|---|---|
| **Period** | **09/02-06/08** | **09/02-06/08** |
| **Dependent Variable** | **Portfolio Return** | **Portfolio Return** |
| alpha | 0.012 | -0.003 |
| | (1.89)* | (-0.46) |
| market | -0.002 | 0.429 |
| | (-0.01) | (3.29)*** |
| Adj. $R^2$ | -0.01 | 0.18 |
| n | 70 | 70 |

## Table 21: Regressions on monthly excess returns

Table 21 presents the results of two regression models. In Model 1, monthly excess stock returns are regressed on monthly excess returns of the corresponding market index of each stock. In Model 2, company size (MV) and book-to-market ratio (BTM) are also included as regressors. MV is the natural log of the market value of equity in millions of Euros at the end of June of the respective ranking year. BTM is given by the book-to-market-ratio at the end of the year before the ranking. IR represents the percentage rating score in the Capital ranking. REP stands for the percentage score in the annual report ranking. Market is given by the monthly excess return of the DAX index over the risk free rate, which is determined by the monthly EURIBOR interest rate. T-statistics are shown in parentheses. All regressions were estimated with Newey-West (1987) standard errors. One (two, three) asterisk(s) means significance at the 10% (5%, 1%) level.

| | (1a) | (1b) | (2a) | (2b) |
|---|---|---|---|---|
| IR | | 0.017 | | 0.012 |
| | | (1.70)* | | (1.29) |
| REP | | 0.008 | | 0.005 |
| | | (0.85) | | (0.48) |
| MV | | | 0.000 | -0.000 |
| | | | (0.66) | (-0.14) |
| BTM | | | 0.007 | 0.007 |
| | | | (2.19)** | (2.13)** |
| market | 1.040 | 1.040 | 1.024 | 1.023 |
| | (24.15)*** | (24.12)** | (26.92)** | (26.86)** |
| alpha | 0.001 | -0.015 | -0.006 | -0.013 |
| | (0.75) | (-1.89)* | (-0.99) | (-1.68) |
| Adj. $R^2$ | 0.27 | 0.27 | 0.28 | 0.28 |
| n | 8,555 | 8,555 | 8,326 | 8,326 |

## 5. Summary

The first paper shows three things. First, it offers empirical evidence for the fact that German stocks overreact. Overreaction means that stocks earn significantly positive abnormal returns after a large one-day price decline, being defined by a return of minus ten percent, and significantly negative returns after a price increase, being defined by a return of plus ten percent. The magnitude of the abnormal returns after large price changes does not become smaller over time. Therefore, earlier evidence from the US that overreaction vanishes with rising liquidity and shrinking spreads, cannot be corroborated.

Second, the reaction to price shocks on the German stock market is asymmetric; in other words the absolute values of the abnormal returns after price decreases are larger than those after price increases. This is in line with earlier findings for the US and other international stock markets.

Dividing the total sample into size sub-samples according to index constituency it can be shown that overreaction is not a small-firm phenomenon on the German market. Instead, overreaction can be found across all size sub-samples and time periods. That finding is different from parts of the existing literature on the US market.

Third, although German stocks earn short-term abnormal returns after large one-day price changes, it is not possible to implement a profitable trading strategy to exploit this phenomenon, which is due to transaction costs and single events with very large negative returns on subsequent trading days.

The second paper is an evolution of the first paper and provides empirical evidence of short-term stock return drift after large one-day price increases in emerging stock markets. The fact that no pervasive overreaction can be detected, posts a contrast to the findings for the German market of the first paper. Short-term stock return drift can be found in all geographic regions and in all size sub-samples. The extent of the drift shrinks with firm size. Like in Germany none of the factors of the explanatory regressions has a significant influence on short-term return drift. The methodology of the second paper differs widely from the methodology of the first. Instead of using plain t-statistics to test for abnormal returns the methodologies of Boehmer et al. (1991) and Corrado and Zivney (1992) are implemented. The existence of short-term stock return drift does not depend on the choice of methodology, as both methodologies lead to the same results.

The third paper has two main findings. First, it establishes that good investor relations are a means for a company to increase stock market liquidity, as measured by Amihud illiquidity ratio, proportional quoted bid-ask spreads, share trading volume, and stock return volatility relative to market volatility. Second, it shows that good investor relations and large insider sales are positively correlated. Taken together these two findings offer corroborative empirical evidence for the model by Hong and Huang (2002) that investor relations are a means for corporate insiders to generate liquidity for their own shares. The rationale behind the model being that corporate insiders with discretionary power over investor relations policy, such as CEOs and/or CFOs usually own more shares than the average outside shareholder. Therefore, the profit disproportionally from higher market liquidity in case they want to sell their shares. This results in an incentive to spend more on investor relations than optimal.

A question that is not investigated in greater detail is whether the hypothesis of Hong and Huang explains reality better for small companies. That is due to the fact that there is no available investor relations ranking for small companies. Measuring investor relations quality of small firms could offer very interesting insights in its own right and could improve the understanding of the relationship between investor relations and insider trading.