Intra-Day Characteristics of Stock Price Crashes

Manuel Ammann and Stephan Kessler*

Abstract

This article presents the first detailed analysis of the intra-day characteristics of idiosyncratic stock price crashes. The analysis focuses on the impact of large crashes in single stocks on their intra-day returns and liquidity in the US market. Furthermore, optimal intra-daily behavior during crashes is studied. Crashes are found to happen rather quickly, usually during a time interval of a few hours. In general, a strong increase in trading activity is observed during a crash, indicating that investors are able to sell their stocks even in distressed markets. The level of liquidity change is linked to the size of the crash. However, there is little evidence that the large sales volume during a crash drives down stock prices. After a stock price crash a significant momentum effect is found for several hours. Stock price crashes appear to reduce information asymmetries.

JEL: G11, G14, G32, G33

Keyword: Idiosyncratic crash, market microstructure, intra-day analysis, liquidity, risk

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1 Introduction

Stock price crashes are infrequent events with a large impact on shareholder wealth. For investors information on intra-day characteristics of crashes is of critical importance to reduce investment risks. During a crash investors have to react quickly in a highly volatile market. A priori it is not obvious if an investor should sell his position as fast as possible to prevent his wealth from declining further or if he should hold on to his position to benefit from a post crash intraday price reversal effect, as observed by Bremer and Sweeney (1991) for daily prices. In addition, liquidity might dry up around a stock price crash preventing an investor from selling his stock or making it at least costly to sell.[1] For hedge fund managers patterns during stock price crashes might provide possibilities for profitable trading strategies. While there is a large range of research studying crashes on a daily basis, such as Bremer and Sweeney (1991), Cox and Peterson (1994), and Atkins and Dyl (1990), little is known about the intraday characteristics of an idiosyncratic stock price crash.

Liquidity and stock price crashes might be linked in three different aspects. First, share price corrections are often caused by news arriving on the market (compare Graham, Koski, and Loewenstein (2005)). For such information-driven crashes liquidity is an indicator for information processing. *Possibly, news with a larger information content go along with larger (abnormal) volumes and a larger price correction (Hypothesis 1).* Furthermore, according to a model by Glosten and Milgrom (1985) spreads are expected to widen because of a temporary increase in the perception of information asymmetries.

Second, stocks with lower liquidity (as measured, e.g., by market capitalization or trade volume) are tracked by a smaller number of analysts, get less media coverage and price uncertainty is larger (compare Atiase (1985) and Chen, Lin, and Sauer (1997) for more information). Larger uncertainties might be associated with a larger crash.[2] *Thus, pre-crash liquidity figures might have an impact on crash depths and durations (Hypothesis 2).*

Third, the lack of buyers for a stock can lead to a large oversupply. According to microeconomic theory, a large oversupply leads to a subsequent price drop. This is the mechanism used in the crash models by Bouchaud and Cont (1998) and Gennotte and Leland (1990). *Thus,*

[1] A model by Morris and Shin (2003) illustrates how a stock market crash can trigger so-called liquidity black holes characterized by a small capacity to absorb selling pressure from active traders.

[2] This hypothesis is analog to the paper by Atiase (1985), stating that the response of the stock price to second-quarter earnings is inversely related to the market capitalization. This finding is attributed to the fact that the available information on a company increases with its capitalization.

excess sales during a crash might be a key element for explaining crash characteristics (Hypothesis 3). This article is first in studying whether these three links between crash characteristics and liquidity exist and how strong they are.

Our final hypothesis focuses on the information revealed during a crash. Models by Easley, Kiefer, O'Hara, and Paperman (1996) and Huang and Stoll (1997) are used to study information asymmetries around crashes. During a stock price crash often significant information on the fair price of a stock is processed. *Therefore, information asymmetries after a crash should be lower than before (Hypothesis 4).*

Although little research analyzes the intra-day characteristics of crashes, there exists a range of articles related to our research. In their seminal papers, De Bondt and Thaler (1985) and De Bondt and Thaler (1987) find that poorly performing equities experience positive excess returns in the future, reversing an overreaction (loser portfolios outperform the winner portfolios on average by 5.4%). Lasfer, Melnik, and Thomas (2003) find a negative momentum effect in the 10 days after a negative price shock. The post-shock price changes appear to be larger in markets with lower liquidity. In contrast, using data from 1962 to 1986, Bremer and Sweeney (1991) find an average rebound of 1.8% on the first and of 2.2% on the second day following a crash for the Fortune 500 companies and a triggering drop of -10%. The difference to Lasfer, Melnik, and Thomas (2003) could be caused by the different definition of a large price drop. Following a one-day price drop of at least 10%, short-term reversals of about three days are also observed by Cox and Peterson (1994). Another study finding evidence for overreaction is written by Atkins and Dyl (1990). On day one and two after a crash, they find significantly positive returns, resulting in a total abnormal return of 2.26%. After voluntary trading halts motivated by the release of bad news at the Singapure stock exchange Tan and Yeo (2003) find a negative price drift in the following 30 days. Muga and Santamaria (2007) establish a link between returns and liquidity by finding that portfolios consisting of loosing stocks have a higher turnover than stocks with average performance.

Only few articles have been written on the intra-day behavior of stocks around large price drops. An article by Goldstein and Kavajecz (2004) on trading halts analyzes trading strategies of NYSE market participants during the volatile market period in October 1997. They find that market participants withdraw liquidity from the electronic limit order book and choose the flexibility and discretion of floor trading instead. An article by Christie, Corwin, and Harris (2002) analyzes trading halts in NASDAQ stocks. They find that reopenings after longer quotation periods show significantly lower posthalt volatility, transaction costs, and generally higher liquidity. To our knowledge the only dedicated intra-day analysis of large price changes is Hamelink (2003). His sample consists predominantly of positive and negative price changes between 2.5 and 10%, whereas the sample is highly concentrated in the 2.5% to 5% bracket. Using French data he finds that the duration of a large price change is between 2.5 and 5.75 hours. Spreads increase strongly when a large price drop occurs but come back to mostly normal levels within 20 periods (whereas a period is defined as the time needed for the prices to change 0.25%). Trade volume decreases significantly when a large price drop occurs but increase before the drop, giving evidence that some market participants are better informed than others. Ranaldo (2006) analyzes intra-day dynamics around news arrivals and has a section on large price movements. He finds a strongly increased volatility, higher trade volumes, and a constant market depth around those price movements.

In this article the changes of liquidity and the return process are studied around stock price crashes. This article contributes to the existing literature by extending the research of Ranaldo (2006) and Hamelink (2003) in three important dimensions. First, the average price changes in Ranaldo (2006) and Hamelink (2003) are much lower than in this analysis. Hence, this article is the first analysis of extreme price changes (i.e., stock price crashes) on an intra-day level. Furthermore, we use the normal, physical time scale which differs from the less intuitive and difficult-to-interpret transaction time clock used by Hamelink (2003). Second, this article uses data from the US market, the largest equity market in the world. Thus, unlike Hamelink (2003) and Ranaldo (2006), who use French data, our results are of interest for a much larger community of investment managers and apply to an intermediated market as opposed to the pure limit-order book market in Paris. Third, the interaction of liquidity on the one hand and extent as well as duration of crashes on the other hand is analyzed. The analysis of order flow effects on crash characteristics is particularly important since it is an empirical test of the models by Bouchaud and Cont (1998) and Gennotte and Leland (1990). Finally, we study information asymmetries and their costs around crashes using market microstructure models.

The remainder of this article is structured as follows. The next section describes the dataset and the methodology. In Section 3 the dynamics of returns and liquidity around a crash are analyzed. In Section 4 the link between the extent of liquidity changes during a crash, the crash size and crash duration are analyzed. The following Section 5 links liquidity and returns by studying the impact of pre-crash liquidity on length and extent of crashes. The order flow, which is often assumed to have an impact on large price changes, is studied in Section 6. In Section 7 information asymmetries before and after crashes are analyzed. Section 8 concludes.

2 Data and Methodology

The dataset used in this study is the TaQ Database of the New York Stock Exchange (NYSE). The data ranges from August through October 2002.[3] This dataset contains all trades and quotes processed by the NYSE, the NASADAQ and the AMEX during the given time frame. The data is analyzed using a spacing of 5 minutes for the returns.[4] The analysis is performed with 138 companies (compare Table 8 in the appendix) experiencing a crash, which is characterized by a one-day price drop of more than 15%.[5] Thus, the analysis is performed on idiosycratic crashes of single companies and not on broad market crashes. The price drop is expressed in continuously compounded returns. Observing for some stocks more than one crash, the dataset contains a total of 162 crashes.[6] The stock prices have to be higher than 5 USD to prevent the tick size effect from introducing a bias.[7] The majority of the crashes are triggered by the publication of accounting figures or the correction of company outlooks on these accounting figures.

We *define* a crash as a substantial and rapid price decline preceeded and followed by a period of constant prices. Although other definitions for crashes are also possible, this approach allows the use of an objective and well-performing criteria for the detection of large intra-day price drops. The problem with the identification of a crash is to find the time during which it occurs. If we would know that a crash is in progress at a certain point in time, the identification of the beginning and the end of the crash could be achieved by going back and forth in time until periods of constant prices are found. We term such a reference point *crash identification period (CIP)*. The difficulty is to find a mechanism for the identification of the CIP. Having crashes with a minimum daily drop of 15% in the sample, one could set the CIP to the point in time when the price drops 15% below its opening price. However, the data shows that often the price drop exceeds the 15% threshold long after the crash itself (i.e., a strong price decrease before and after a period of constant prices) occured, leading to a missclassification.[8] This can be attributed to a momentum effect found in the data after the main price drop. Analyzing

[3]Unfortunately, we do not have access to a longer time frame of data.

[4]Longer spacings are also used, but do not return significantly different results in general.

[5]The analysis is repeated using a sample consisting of 30 S&P 500 companies to test if there are size associated effects. However, no size associated effect is found and the results are essentially the same. Hence, the results of the additional analysis are not discussed separately in this article.

[6]However, there has to be at least a time frame of one week between crashes of one company.

[7]For penny stocks the minimum tick size of 0.01 USD can be a considerable proportion of the total price, causing erratic returns which are not a consequency of information processing, but of the tick size.

[8]As an example, a frequent case in the dataset is a crash on a day with a total price decline of 15.5%. The main crash often causes a price drop of about 13%. The remaining 2.5% price decline occurs during an extended time period of many hours after the crash. Choosing the crash identification threshold to be 15% falsly identifies

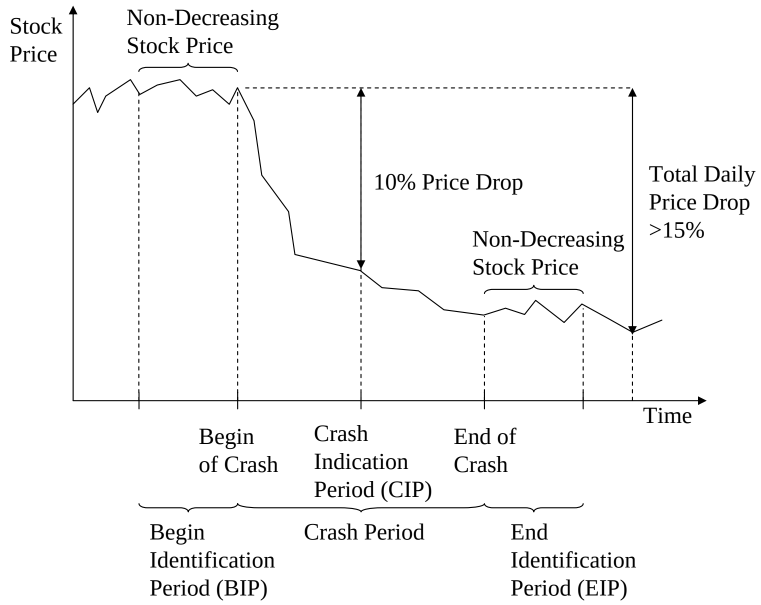

Figure 1: Timeline of the Crash Identification

the data we find out that a CIP at the 10% loss level compared to the opening price performs best in identifying crashes.[9] To check for robustness, other thresholds are also used, with little effect on the results.

Beginning and end of crashes are now identified by going back and forth in time from the CIP until a period of constant prices is found. More precisely, the beginning of a crash is indicated by the last x 5-minute intervals, termed *Begin Identification Period (BIP)*, before the *crash indication period* during which the average price is smaller or equal to the first price in the crash period (i.e., for $x = 5$, the last 25 minutes during which the price does not drop). The end of the crash is indicated by the first x 5-minute periods, termed *End Identification Period (EIP)*, during which the average price is larger or equal to the last price of the crash period. This approach is very similar to the one used by Hamelink (2003). In the course of the analysis, x is changed to analyze the effects of the crash period specification on the results. All crashes in our dataset have to occur during a single trading day. Crashes spanning multiple days are deleted. The crash identification procedure is illustrated in Figure 1.

the post-crash period as the crash period. Thus, facing the empirical evidence, it is useful to set the crash identification period to the point where two thirds of the minimum total crash size occured.

[9]This ensures that the CIP is during the time of the main price drop and not accidentially set to be during the post-crash momentum period.

To compare the behavior of the stocks around the crash, a period of eighty 5-minute intervals before and after the crash is analyzed. This accounts to a time period of little more than 6.5 hours, which is one trading day before and one after the crash. Longer periods have been analyzed by Bremer and Sweeney (1991) or Cox and Peterson (1994), who use daily data. To analyze a possible post-crash momentum effect, the mean returns after each crash, μ_i, are calculated as follows:

$$\mu_i = \frac{1}{T} \cdot \sum_{j=1}^{T} r_{i,j},$$

where $r_{i,j}$ is the continuously compounded return of asset i in period j after the crash. In this analysis, we set $T = 80$ for 5-minute returns. The μ_i are then averaged across all crashes and this average is tested for difference from zero, i.e.,

$$\mu_{Average} = \frac{1}{N} \cdot \sum_{i=1}^{N} \mu_i,$$

where N is the number of total crashes in the sample. The standard deviation of $\mu_{Average}$ is calculated as

$$\sigma_{Average} = \frac{1}{\sqrt{N}} \cdot \sqrt{\frac{1}{N} \cdot \sum_{i=1}^{N} (\mu_i - \mu_{Average})^2}.$$

The standard test statistic applied to test for a significantly positive or negative $\mu_{Average}$ is

$$t - statistic = \frac{\mu_{Average}}{\sigma_{Average}}.$$

For pre-crash returns, an analogous statistic is constructed to test for a pre-crash drift. The trading day starts at 9.30 a.m., ends at 4 p.m., and is covered by 5-minute intervals.[10]

The liquidity measures used in this article are chosen to reflect the trading activity and costs. These liquidity measures are applied to give information on the capital market frictions an investor faces when liquidating shares of a company in distress. Thus, the term liquidity is used in a broad sense. Trade volume is calculated in two ways: as the number of shares traded (Turnover by number) and as the sum of the dollar value (Volume in USD) of all transactions

[10]The 9.30 a.m. time point in the constructed grid only captures the first trade executed on the market. Since there are large trades reported right after the close of the market, we assume that those trades are entered in the NYSE trading system before the close but reported later. Although NYSE stops accepting orders at 4.00 p.m., specialists might still manage orders entered just prior to the close. Thus, the NYSE closing trade is sometimes recorded several seconds after the closing bell. For further information on opening and closing trades refer to Bacidore and Lipson (2001). Those trades are summarized in the last time interval finishing at 4.05 p.m.

in the stock during the respective 5-minute time interval. The bid-ask spread is calculated at each node of the time grid. For comparability reasons, the relative spread S is used:

$$S_t = \frac{a_t - b_t}{M_t}, \tag{1}$$

where t is the time index, a_t is the ask price, b_t is the bid price, and $M_t = \frac{a_t + b_t}{2}$ is the midquote. The effective spread, ES, gives a better description of the transaction costs faced by market participants and is defined as

$$ES_t = 2 \cdot |p_t - M_t|, \tag{2}$$

where p_t is the transaction price. The relative effective spread (RES) is calculated as

$$RES_t = \frac{2 \cdot |p_t - M_t|}{M_t}. \tag{3}$$

The realized half-spread measures the price reversal after a transaction which is the profit actually earned by the market maker. In accordance with Huang and Stoll (1996), we calculate the realized half-spread (RS) as

$$(RS_\tau | b_t) = [(p_{t+\tau} - p_t) \,|\, (p_t = b_t)] \tag{4}$$

if the transaction at time t takes place at the bid price, b_t, and

$$(RS_\tau | a_t) = -\left[(p_{t+\tau} - p_t) \,|\, (p_t = a_t)\right], \tag{5}$$

if the transaction at time t took place at the ask, where p_t is the price of the asset at time t. The parameter τ indicates the time at which the price reversal is measured. We set τ to 5 minutes. The bid distance (BD) and the ask distances (AD) indicate how large the spread is on the bid and the ask side, respectively. These measures are defined as:

$$BD_t = \frac{b_t}{p_t} \tag{6}$$

and

$$AD_t = \frac{a_t}{p_t}. \tag{7}$$

By studying the bid and the ask distance separately, it can be analyzed on which side of the market the market maker posts larger spreads and, thus, perceives information asymmetries

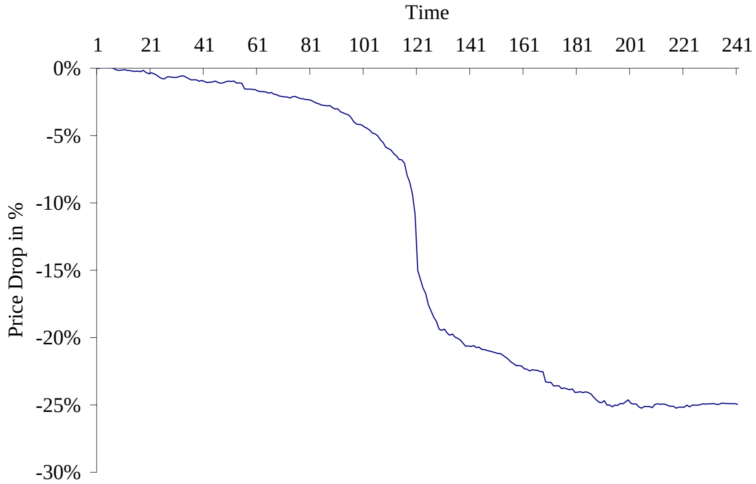

Figure 2: Cumulated Average Returns During a Crash

and risk to be larger. This is particularly interesting in times of distress studied in this analysis. The bid and ask sizes measure the USD value of the shares available at the bid and the ask prices.

3 Return and Liquidity Dynamics Around Crashes

In a first step, the characteristics of returns and liquidity around crashes are analyzed. Setting $x = 5$,[11] we find an average return of -2.053% per 5-minute interval during the crash. On average a crash causes a total price decrease of -14.71% during the crash period. The average returns show a negative sign before and after the crash, as can be seen in Table 1. The mean returns of -0.051% and -0.067% before and after the crash period are significant at the 1% level (t-statistics of -5.19 and -4.82, respectively). This negative mean return is evidence for a post-crash momentum effect, occuring after the 25 minutes of stable prices (i.e., after the EIP). Such a negative drift is a post-crash momentum effect. During the eighty 5-minute intervals used for the calculation, this accounts to a noticable cumulated return of -4.08% and -5.36% before and after the crash, respectively. Thus, even after the observed 25-minute period of stable prices following a crash – being caused by the method for identifying beginning and end

[11] $x = 5$ results in crash periods whose beginnings and ends are characterized by a period of 25 minutes during which the prices do not fall. To control for the effects of the chosen parameter x, the analysis is repeated using $x = 20$ (i.e., a BIP and an EIP of 100 minutes). In general, the results are comparable to the $x = 5$ case and not reported for brevity.

of crashes[12] – investors suffer more losses and there is no intra-day reversal. For an investor who wants to liquidate his position quickly after a crash it is on average best to sell the assets as soon as possible whereas waiting does not seem to be rational. Figure 2 shows the average cumulated crash returns for the 241 5-minute time periods around a crash. The 121st period is the CIP (i.e., the period during which the daily price drop exceeds 10% of the opening price).[13] Autocorrelations in the returns after the crash tend to be negative.[14]

The standard deviations of the returns increase significantly during the crash. Before the crash, an average standard deviation of 0.827% is found. During the crash the volatility of returns soars to 1.897% and decreases to 1.333% thereafter. Although the volatility levels are still higher than before the crash, the return volatilities seem to decrease fast. This is a sign for swift information processing in the respective stock. To test how fast the activity in stock returns reverts back to normal, the volatility of returns is analyzed for periods 1 to 40 (Post Crash 1) and periods 41 to 80 after the crash (Post Crash 2). Interestingly, an increase of the volatility from 1.11% (Post Crash 1) to 1.38% (Post Crash 2) is observed. Thus, volatility does not decrease continuously during the post-crash period.

The crash itself takes 61.55 minutes (i.e., 12.31 5-minute periods) on average. This extended crash duration gives a trader the possibility to react to the price decrease by selling his shares during the drop. The standard deviation of the crash duration is 7.11 5-minute periods and is comparably large. With such a standard deviation, crash durations from few minutes to over two hours are in the range of 1.96 standard deviations from the mean and hence not unlikely.

Figure 3 indicates an increased activity for stocks experiencing a crash. The turnover rises from an average of 16,777 to 49,876 during the crash and decreases to 39,706 after the crash,

[12] The end of the crash is determined by average prices being equal to or higher than the last price measured during the crash. Thus, average returns in the x 5-minute periods after a crash have to be non-negative by the research design.

[13] The cumulated return in period j is $r_{cum,j} = \sum_{t=1}^{j} \left(\frac{1}{N} \sum_{i=1}^{N} r_{i,j} \right)$, where i indicates the number of the crash and $r_{i,j}$ is a 5-minute return. In this graph the different crash durations are not taken into account.

[14] Results not reported in Table 1 for brevity. Before the crash, mean autocorrelations are -0.0537, -0.0177, and -0.0176 for lags 1, 2 and 3, respectively. The Ljung-Box test and the Breusch-Godfrey test (refer to Greene (2003) for details) show significant autocorrelations at the 10% level for 47 and 50 of the 162 crashes, respectively. After the crash mean autocorrelations of -0.0576, -0.0253, and -0.0131 are found for lags 1, 2, and 3, respectively. The significance of the Ljung-Box test and the Breusch-Godfrey test increases, returning a significant autocorrelation for 63 and 59 of the 162 crashes, respectively. Serial correlation of returns appears more pronounced after the crash than before. However, the level of this autocorrelation is limited.

Table 1: Price and Liquidity Statistics Before, During and After Crashes (5-Minute Intervals, $x = 5$, Minimum Crash Size 15%)

	Pre Crash		**During Crash**		**Post Crash**		**Increased After Compared to Before**	**Average Percentage Change**
	Mean	Stdv	Mean	Stdv	Mean	Stdv		Median
Returns	-0.051%	0.125%	-2.053%	2.937%	-0.067%	0.177%	51.2%	0.0%
Volatility	0.827%	0.715%	1.897%	1.520%	1.333%	1.211%	82.7%	68.2%
Turnover by Number	16777	58398	49876	134800	39706	91398	84.0%	136.9%
Volume in USD	233300	1034000	625530	1852300	447770	1101200	80.9%	102.6%
Number of Transactions	16.07	40.80	56.10	142.17	34.64	75.87	88.9%	95.3%
Spread	1.746%	1.736%	2.976%	5.103%	2.681%	6.681%	67.9%	18.9%
Effective Spread	0.065	0.052	0.118	0.120	0.088	0.065	69.7%	35.4%
Relative Effective Spread	0.007	0.007	0.013	0.012	0.010	0.007	80.0%	56.7%
Realized Half-Spread	0.003	0.040	-0.043	0.109	0.005	0.034	46.7%	-83.9%
Bid Distance	0.992	0.009	0.979	0.042	0.990	0.010	32.1%	-0.1%
Ask Distance	1.007	0.012	1.012	0.041	1.012	0.043	61.7%	0.1%
Bid Size (in USD)	8689	7322	7927	12755	9102	9757	51.2%	3.7%
Ask Size (in USD)	11675	12524	14741	19199	10896	12167	40.7%	-11.4%
Drop Size			-0.14713	0.10502				
Crash Duration			12.309	7.1099				

This table contains a summary of return and liquidity figures around a crash. The statistics are calculated for 5-minute intervals and a minimum price drop of 15%. Beginning and end of the crashes are determined by a 25-minute period of non-decreasing returns before and after the crash. The Pre Crash, During Crash, and Post Crash columns give the mean and standard deviation of the respective liquidity or return statistic before, during, and after the crashes. The Pre-Post Increase column indicates in how many percent of all crashes the respective statistic is higher after the crash than before. The percentage change column indicates the median percentage change of the respective statistic after the crash compared to before. Statistics for returns and volatility are calculated using the returns during the respective time interval. Turnover by number, volume in USD, and number of transactions are mean values across all crashes and calculated per 5-minute interval. Bid and ask distance, size, and spread are calculated at the end of each 5-minute interval and the mean value for each crash is taken. The effective spread, the relative effective spread, and the realized half-spread are determined on the transaction level. Bid and ask size are the USD value of shares available at the bid and ask price. The average and standard deviation of these means are given in the respective columns. Drop size is the price decrease measured from the start of the crash until the end. Crash duration is the time frame this price drop takes as measured in 5-minute intervals.

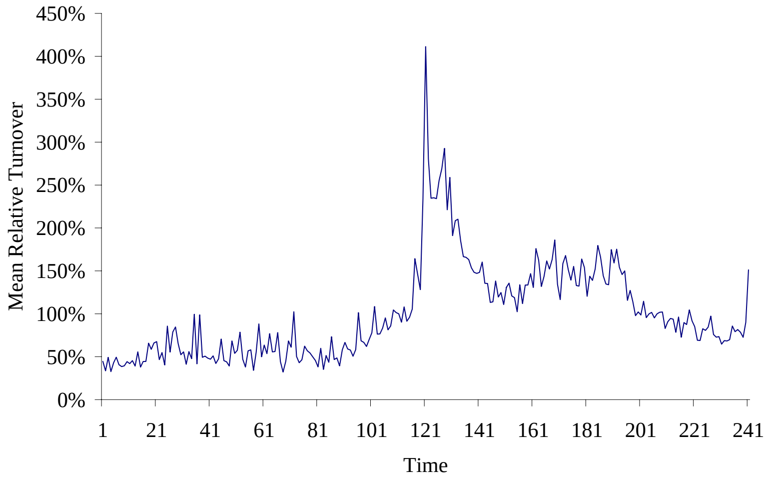

Figure 3: Mean Relative Turnover During 5-Minute Intervals Around A Crash

which is still high compared to pre-crash levels.[15] The mean increase is 561.3% and much larger than the median increase (136.9%), indicating that the distribution of turnover changes is right-skewed. Before the crash an average 5-minute trade volume of USD 233,300 is measured. During the crash shares worth USD 625,530 are traded per period, almost tripling the asset value traded before. Even after the crash volume stays high at USD 447,770, showing that investors continue to adjust their portfolios. This is an indication that a large number of investors sell their assets although the worst part of the crash is over. The number of transactions confirm the increase in liquidity by rising from 16.07 before to 56.10 transactions per 5-minute interval during the crash. After the crash the number of transactions decreases to 34.64. The average number of shares per transaction is 1,044 (=16,777/16.07) before, 889 (=49,876/56.10) during, and 1,146 (=39,706/34.64) after the crash. Therefore, the average trade size appears to be highest after the crash, indicating that large investors enter the market. Christie, Corwin, and Harris (2002) find that directly after a trading halt the average trade size is unusually low. These two findings are consistent if investors with smaller holdings are in general faster with their sell decision, but cannot implement their sell order during a trading halt.

The bid-ask spread increases from 1.75% before to 2.98% during and decreases to 2.68% after the crash (compare Figure 4, depicting the median spread during the observation period for all crashes). However, this increase in the spread could be caused by the simultaneous strong drop of the share price. Thus, absolute spreads (i.e., the difference between bid and ask

[15] The observed contemporaneous movement of return volatility and turnover can also be found when analyzing intra-day return seasonality (compare, e.g., Gwilym, McMillan, and Speight (1999) for an analysis of the LIFFE futures market).

price) are also analyzed. The mean absolute spread increases from 0.20 USD before the crash to 0.32 USD during the crash and decreases afterwards to 0.23 USD, which is consistent with Christie, Corwin, and Harris (2002)[16] and our results for the relative spread. This indicates that the market maker is responding to the increased uncertainty throughout the crash by a larger bid-ask spread. In contrast, Goldstein and Kavajecz (2004) find that quoted spreads stay on moderate levels during a market-wide crash. The effective spread supports the results for the quoted spread by increasing from 0.065 USD before to 0.118 USD during the crash and decreasing to 0.088 USD in the post-crash period. Thus, not only quoted spreads widen, but buyers and sellers actually end up paying larger transaction costs. The mean realized half-spread is at 0.003 USD before the crash and decreases significantly to -0.043 USD during the crash. Therefore, the market maker has to bear losses in times of a strong market decline.

The bid (from 0.992 to 0.979) and ask distances (from 1.007 to 1.012) are both increasing during the crash. Apparently, market makers react to the increased volatility and uncertainty by being careful on both sides. The ask distance reacts more weakly to the increased risk during a crash. This is evidence for an asymmetric reaction of the market makers to a crash. They possibly expect greater losses on the bid side.[17] The difference of the measured bid and ask distance during the crash is significantly different from zero at the 5% level (t-statistic of 1.964). This result is similar to the one by Christie, Corwin, and Harris (2002) who find market makers after a trading halt to adjust the quote on the side where they face the highest risk of losses to a better informed investor.

The market maker provides continued liquidity at the bid and ask prices. The average bid size is 8,689 USD before and 7,927 USD during the crash. After the crash the bid size increases to a fairly high 9,102 USD. During the crash the market maker holds the number of shares he is willing to buy at the bid fairly constant (from an average of 810 shares before to 812 during the crash and 1,013 thereafter), providing liquidity when it is needed the most.[18] On the ask side the liquidity is even increasing: The offered share volume (number of shares) increases from

[16]Christie, Corwin, and Harris (2002) find a median spreads of 0.625 USD after a mid-day trading halt and a median of 0.30 USD on a normal day.

[17]The asymmetry between bid and ask distances is particularly strong for the sample of the S&P 500 stocks, which is analyzed, but not discussed separately in this article. The sample is created by chosing the 30 stocks out of the S&P 500 with the largest daily price drop from August to October 2002. The bid price of the S&P 500 companies during the crash is at a mean discount of 4.86% (1 - 0.95136), whereas the ask price is only at a mean premium of 2.84% to the next transaction price. This asymmetry is supported by the fact that only the mean bid distance is significantly different from zero at the 1% level, in contrast to the ask distance, which is not even significant at the 10% level.

[18]Results on the bid and ask sizes as measured in number of shares are not reported in tables for brevity.

Table 2: Selected Statistics During the Subperiods of a Crash (5-Minute Intervals, $x = 5$, Minimum Crash Size 15%

	Subperiod		
	1	2	3
Returns	-1.14%	-1.23%	-2.21%***
Turnover by Number	27855	50181***	77888***
Volume in USD	379423	628005***	926483***
Number of Transactions	30.46	55.93***	81.48***

This table contains selected statistics characterizing trading activity and return during the subperiods of a crash. The three subperiods separate the total crash duration in three time frames of equal length. The mean of the returns, turnover by number, volume in USD, and number of transactions are calculated for 5-minute intervals. The table indicates if the change of the mean compared to the previous subperiod is significant. ***: Significant at the 1% level, **: Significant at the 5% level, *: Significant at the 10% level.

11,675 USD (1,057 shares) before to 14,741 USD (1,451 shares) during the crash and decreases afterwards to 10,896 USD (1,213 shares). This result confirms Goldstein and Kavajecz (2004) who do not find a significant change in the depth during market wide crashes. The findings this far show that liquidity during the crash is not decreasing, only the costs of trading with the market maker at the bid price (measured by the bid distance) are increasing.

It is frequently claimed that crashes accelerate (compare, e.g., Gennotte and Leland (1990)) because of hedging activity, stop-loss orders or sellers entering the market after the start of a crash. This acceleration causes a higher price drop and volume per given time interval as a crash holds up. Table 2 reports the means of selected statistics across crashes for three non-overlapping subperiods during a crash. A subperiod lasts for one third of the total duration of the respective crash.[19] The mean returns per 5-minute interval decrease continuously from -1.14% in the first to -2.21% in the third period. The average turnover by number increases from 27,855 in the first to 50,181 in the second and 77,888 in the third period. The mean volume in USD (from 379,423 in the first to 926,483 in the third period) and the mean number of transactions (from 30.46 in the first to 81.48 in the third period) also increase monotonically. The changes of the means of the statistics are mostly highly significant at the 1% level. For the other measures, although not reported in Table 2, an acceleration of the activity is observed as well. This result gives further evidence of the benefit of a fast reaction by investors when the beginning of a crash is recognized.

[19] Because of a crash duration below three periods or data errors, we eliminate 9 of the 162 crashes from the dataset for this analysis.

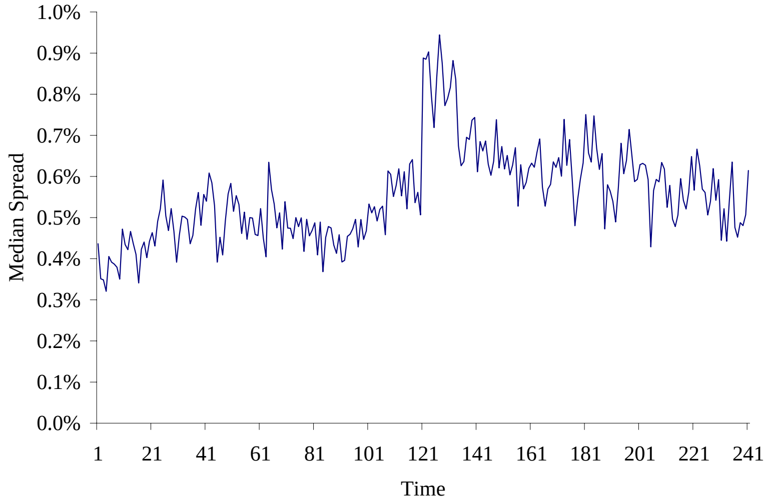

Figure 4: Median Spread During 5-Minute Intervals Around a Stock Price Crash

Our results can be compared with various findings of previous research. We find a strong increase in spreads during and after a crash just as Hamelink (2003) does in his study of large price changes. His results with respect to a momentum effect after large intra-day price changes are mixed, whereas we find a clear downward trend after the end of a crash. Furthermore, our results differ in finding a strong increase in trading volume during and after the crash, while he has evidence for a decrease in trading volume in response to a price drop. In Hamelink (2003) large price changes are found to take between 2:26 and 5:43 hours, which is much more than the average of 61.5 minutes found here for $x = 5$. Even for a very conservative setting of $x = 20$, crashes take less (2:13 hours) on average. Thus, crashes at the NYSE appear to take place more quickly than at the Paris stock exchange even though their extent in the studied sample is on average much larger than in the article of Hamelink (2003). We have no evidence for a mean reversal effect in prices after a crash. Therefore, an overreaction by investors, as found for daily data by Atkins and Dyl (1990), Bremer, Hiraki, and Sweeney (1997), and others, cannot be confirmed on an intra-day level. Ranaldo (2006) finds constant bid and ask sizes after large price changes. Our analysis confirms that the number of shares available at the bid stays constant, but the volume in USD and number of shares available at the ask is found to increase, providing higher liquidity as measured in shares of total equity.

4 Relationship between Liquidity Changes, Crash Duration and Extent

Having analyzed the behavior of returns and liquidity around crashes in Section 3, the focus is shifted to the analysis of the *link* between the observed liquidity changes and crash characteristics. In this section we test the hypothesis that larger price changes might be associated with larger changes in liquidity because of a more intensive information processing (Hypothesis 1). This hypothesis is analyzed by running regressions of crash size and duration on crash-induced changes of different liquidity measures.[20]

In the literature few research on the influence of liquidity on the extent and duration of idiosyncratic crashes can be found. Hence, there are no theoretical models giving a direct guidance on the specification of the regressions performed in this section. A theoretical model in an article by Amihud and Mendelson (1986) indicates that the expected return of a stock is an increasing and concave function of the bid-ask spread. The authors support the results of their model by empirical evidence. Furthermore, Brennan and Subrahmanyam (1996) find that the effect of variable transaction costs on the expected return of an equity is concave. These articles give an indication that the concept of liquidity is concave, meaning that doubling a proxy for liquidity leads to an underproportional change of the affected economic variables. This suggests to regress the crash extent and duration on the square root of the respective liquidity measure. In a preliminary univariate regression analysis we find that the changes in the turnover, the spread, the bid distance, and the ask size have a significant link with the crash size.

Having identified variables with a high explanatory power for the crash size, a multi-factor regression is performed to analyze the link between the changes in liquidity during a crash and the crash size. We implement this analysis by estimating the following parameters:

[20]The following analysis is also performed using levels of the liquidity variables during the crash and a strong link to the crash size is found. However, the explanatory content is lower than for the changes of the variables as discussed in this section. Although not in the focus of this article, our results can deliver insights to improve risk management systems which model the interaction of liquidity and stock price crashes. Compare, among others, work on liquidity adjusted Value-at-Risk by Bangia, Diebold, Schuermann, and Stroughair (1999), Jarrow and Subramanian (1997), or Angelidis and Benos (2006).

$$Crash\ Size = \alpha^{\Delta,S}_{Mult} + \beta^{\Delta,S}_{Mult,1} \cdot \sqrt{\Delta Turnover} + \beta^{\Delta,S}_{Mult,2} \cdot \sqrt{\Delta Spread}$$
$$+ \beta^{\Delta,S}_{Mult,3} \cdot \sqrt{\Delta BDistance} + \beta^{\Delta,S}_{Mult,4} \cdot \sqrt{\Delta ASize} + \epsilon^{\Delta,S}_{Mult},$$

where Δ indicates the ratio of the respective liquidity measure obtained when dividing its value during the crash by its pre crash value. The terms $BDistance$ and $ASize$ stand for bid distance and ask size, respectively. The superscripts Δ and S indicate that the regression is performed with the changes of the independent variables and the crash size as dependent variable, respectively. $Mult$ indicates that it is a multivariate regression. All mean values are calculated per 5-minute interval in the respective event period. The measures before the crash are calculated using the eighty 5-minute intervals before a crash.[21] This analysis is performed with $x = 20$. This increase of the length of the BIP and EIP from 25 minutes (compare Section 3) to 100 minutes is performed to be conservative in the analysis and insures that the pre-crash liquidity measures are not biased by a misclassification of the beginning of the crash.

The results in Table 3 indicate that the regression has a high explanatory power (R^2 of 0.3208). The estimated parameters show that the changes in liquidity are linked strongly with the severity of a crash. The parameter of -0.0259 for the square root of the change in turnover indicates that a larger increase in activity goes along with a more severe crash. For the change in the bid distance a significantly positive parameter of 1.0018 is observed. Having observed that the bid distance decreases during a crash from a pre-crash average level of 0.992 to 0.979, this result indicates that a more pronounced bid distance decay goes along with a deeper crash. We also perform regression analyses using the change in the ask distance. However, the estimated parameter is not significantly different from zero. This result supports our finding that during crashes market makers react differently on the bid and the ask side of the spread. The parameters for the changes in ask size and the spread are not significantly different from zero. Thus, although these liquidity measures change during the crash, they have no systematic impact on the crash size.

News with greater information content could lead to increased trade volume and a longer crash duration. Thus, the crash duration is regressed on different liquidity variables. However,

[21]The analysis is repeated with a longer time frame for the pre-crash means, using data from the beginning of the dataset until the last 5-minute period before the crash. The results are robust and are not reported here for brevity.

Table 3: Multivariate Regression of Crash *Size* on Changes in Liquidity Measures During the Crash ($x = 20$)

Explanatory Variable	Parameter		R^2
Intercept	-1.0566	***	0.3208
$\sqrt{\Delta Turnover}$	-0.0259	***	
$\sqrt{\Delta Spread}$	-0.0164		
$\sqrt{\Delta BDistance}$	1.0018	***	
$\sqrt{\Delta ASize}$	-0.0344	*	

This table summarizes the parameter estimates, significance levels and R^2 of the regression of the crash size on changes in various liquidity figures. ***: Significant at the 1% level, **: Significant at the 5% level, *: Significant at the 10% level. $\Delta BDistance$ is the change in the bid distance. $\Delta ASize$ is the change in the ask size.

the link between liquidity and the crash duration is limited.[22] The following specification returned the highest explanatory power:

$$Crash\ Duration = \alpha_N^{\Delta,T} + \beta_N^{\Delta,T} \cdot \sqrt{\Delta Number} + \epsilon_N^{\Delta,T}, \tag{8}$$

where the index T indicates that the dependent variable is the crash duration. The expression $Number$ stands for the number of transactions per given time interval. The regression of crash duration on $\sqrt{\Delta Number}$ returned an R^2 of 0.1475 with a parameter for $\sqrt{\Delta Number}$ of -5.432, indicating that a larger increase in the number of transactions is associated with a shorter crash. The parameter is statistically significant at the 1% level (t-statistic of -5.271). The intercept is 37.846 and also statistically significant at the 1% level. This is an interesting result, showing that the level of increase in trading activity is a fairly good indicator for the speed of information processing and subsequently for the duration of a crash. Similar results are obtained for the volume in USD and turnover by number of shares traded, which are highly correlated with the number of transactions. Thus, a larger increase in trading activity (as measured in number of transactions, volume in USD or turnover) is associated with deeper (see Table 3), but faster stock price crashes. All other liquidity variables deliver weaker results, indicating that the ties between different liquidity dimensions and crash duration are not as strong as for liquidity and crash extent.

Summarizing, as hypothesized in the introduction, larger crashes are found to be related to larger changes in the liquidity parameters and go along with more information processing.

[22]The following analysis is also performed using levels of the liquidity variables during the crash as explanatory variables for crash duration. However, a very weak link between the levels of liquidity variables and the crash duration is found.

For the crash duration, we find that a larger number of transactions leads to faster information processing and a shorter crash.

5 Relationship between Liquidity, Crash Duration and Extent

After the analysis of the link between liquidity *changes* and crash characteristics, the focus is shifted to the link between pre-crash liquidity *levels* and crash characteristics. The analysis builds on Hypothesis 2 which states that lower liquidity leads to less media coverage and a lower number of analysts tracking a company, increasing the uncertainty about the true value of a firm (compare Section 1). Subsequently, crash extent and duration might increase as liquidity decreases.

The duration and the crash size are regressed on the *pre-crash* liquidity variables in the analysis to test their forecasting ability. We average the value of the different explanatory variables in the eighty 5-minute periods before the crash to obtain an estimate of the pre-crash liquidity.[23] Consistent with the previous section we choose $x = 20$.[24] Having no direct theoretic guidance for the link between liquidity and crash characteristics, we borrow from the results obtained by Amihud and Mendelson (1986) and Brennan and Subrahmanyam (1996) in another context. In accordance with these articles, the duration and extent of crashes are modelled as a concave function of the respective liquidity measures.

First, we start with the regression of crash size on pre-crash liquidity measures. The regression of crash size on the square root of the bid size returns the highest R^2 of all regressions, but the magnitude of 0.0244 is still low. With the explanation power of the other regressions being even lower, the evidence for a link between pre-crash liquidity and the crash size is weak.

The crash duration is easier to forecast with the given liquidity variables. The following specifications are used to test for the impact of liquidity variables on crash duration:

$$Crash\ Duration = \alpha^{L,T}_{BDis} + \beta^{L,T}_{BDistance} \cdot \sqrt{BDis} + \epsilon^{L,T}_{BDis} \tag{9}$$

[23]The analysis is repeated with a pre-crash period lasting from the beginning of our dataset to the last 5-minute interval before the crash. The results stay essentially unchanged and are not reported here.

[24]Other settings for x give comparable results.

Table 4: Regression of Crash *Duration* on Liquidity Measures in the Pre Crash Window ($x = 20$)

Explanatory Variable	Parameter		R^2
Intercept	18.55	***	0.0375
Mean Spread	68.54	**	
Intercept	16.88	***	0.0473
Mean Bid Size	0.1106	***	
Intercept	1160	***	0.0518
Mean Bid Distance	-1138	***	

This table summarizes the parameter estimates, significance levels and R^2s of univariate regressions of the crash duration on different liquidity figures. ***: Significant at the 1% level, **: Significant at the 5% level, *: Significant at the 10% level.

$$Crash\ Duration = \alpha^{L,T}_{BSize} + \beta^{L,T}_{BSize} \cdot \sqrt{BSize} + \epsilon^{L,T}_{BSize}, \tag{10}$$

where $BSize$ stands for the bid size. Table 4 shows that the highest explanatory power for crash duration is found for the bid size (0.0473) and the bid distance (0.0518). The parameter of -1,138 for the bid distance is significant at the 1% level, indicating that a decrease in the pre-crash bid distance from 0.99 to 0.98 is prolonging the average crash time by about 29 minutes. Possibly, the uncertainty in a stock before substantial and long crashes is larger and increases the pre-crash bid distance. The parameter of 0.1106 of the bid size is also significant at the 1% level (t-statistic of 2.824) and shows that a larger pre-crash liquidity at the bid is associated with a longer crash. This opposes the hypothesis that larger liquidity leads to a higher information level and in the consequence to faster crashes. In contrast, the data supports the hypothesis that market makers offer higher liquidity (i.e., bid size) for stocks that are more likely to experience a longer crash. In a multi-factor regression using the square roots of the levels of all liquidity variables, an R^2 of 0.1785 is achieved. The parameter of the bid distance stays highly significant and negative (parameter value of -2,116 with a t-statistic of -2.548). The same applies to the bid size (parameter value of 0.2617 with a t-statistic of 4.502). Thus, the results for the bid size and distance are robust.

Summarizing, liquidity (as measured by spread) has an impact on crash size and duration, but it is only able to explain a limited amount of total variation. Thus, there is only a weak evidence for the hypothesized link between overall information level, pre-crash liquidity, and crash characteristics.

6 Order Flow and Crashes

In some theoretical papers, such as in Bouchaud and Cont (1998) or Gennotte and Leland (1990), the occurence of crashes is traced back to imbalances in the buy and sale order flow. The reasoning is that an excess sales volume causes prices to move downward. Thus, larger excess sales order flow should cause larger crashes and a smaller mean return during the crash period (Hypothesis 3). Possibly, a larger order flow imbalance could also cause a longer crash duration since the market needs more time to absorb the extra sales and find a new equilibrium. These hypotheses are tested in this section.

6.1 Methodology

The TaQ dataset does not give information on whether a transaction is buyer- or seller-initiated. Therefore, we apply the tick test by Lee and Ready (1991) to classify trades. Trades are classified as sales (purchases), if the transaction price is below (above) the last transaction price. If a trade is executed at the same price than the last one, then it is classified as a sale (purchase) if the price is below (above) the second last transaction price. If the second last transaction is also a zero tick, then the trade is not classified as a sale or purchase. Having identified buys and sells, the number of transactions and turnover induced by buyers or sellers are summed over the respective trade interval (e.g., 5-minute trade intervals) to calculate the buy and sell order flow. With this information we construct the order flow imbalance ratio for turnover (i.e., volume) of company i in period t ($OIT_{i,t}$) as

$$OIT_{i,t} = \frac{TS_{i,t}}{TP_{i,t}},$$

with $TS_{i,t}$ and $TP_{i,t}$ being seller and buyer-induced turnover for company i in period t, respectively. The order flow imbalance ratio in period t for numbers of transactions of company i ($OIN_{i,t}$) is

$$OIN_{i,t} = \frac{NS_{i,t}}{NP_{i,t}},$$

with $NS_{i,t}$ and $NP_{i,t}$ being the number of sales and purchases in period t for company i, respectively. The order flow imbalance for turnover and number of transactions is defined as a ratio instead of a simple difference to ensure the comparability of the measure across companies. The mean OIT for company i is calculated as

$$\overline{OIT}_i = \frac{1}{T}\sum_{t=1}^{T} OIT_{i,t},$$

where T denotes the total number of 30-minute returns in the sample. This gives the following expression for mean OIT across all companies:

$$\mu\left(\overline{OIT}\right) = \frac{1}{N}\sum_{i=1}^{N} \overline{OIT}_i,$$

where N denotes the total number of companies. The standard deviation of mean OIT across the different firms is given by

$$\sigma\left(OIT\right) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\overline{OIT_i} - \mu\left(\overline{OIT}\right)\right)^2}.$$

Similarly, mean and standard OIN can be calculated across the different companies, i.e.,

$$\overline{OIN}_i = \frac{1}{T}\sum_{t=1}^{T} OIN_{i,t},$$

$$\mu\left(\overline{OIN}\right) = \frac{1}{N}\sum_{i=1}^{N} \overline{OIN}_i,$$

$$\sigma\left(OIN\right) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\overline{OIN_i} - \mu\left(\overline{OIN}\right)\right)^2}.$$

6.2 Order Flow of Companies in Distress

We now analyze the order imbalance of equities before, during, and after a crash. The order flow imbalance ratios are calculated for 30-minute intervals. This extended return interval is used to ensure that there are enough transactions in each period for a meaningful calculation of order flow.[25] The results of this order flow analysis for the 138 companies in the sample are summarized in Table 5. Beginning and end of a crash are determined through 90 minutes of non-decreasing prices (i.e., $x = 3$).[26] The time frame before and after a crash streches over fourteen 30-minute periods.

[25] Unlike before, liquidity is split in buy side and sell side liquidity, making it necessary to use longer time intervals for stable liquidity statistics. Furthermore, a considerable number of transactions is not classified at all because of a lack of price changes. Robustness tests not reported here show that the results do not depend on the length of the interval.

[26] The parameter x is set to values ranging from 3 to 12 periods, which is very conservative, but results do not change substantially.

Table 5: Order Flow Imbalance Before During and After the Crash

x = 3	**Before** Estimation	**During** Estimation	Sig. Δ Pre-Crash	**After** Estimation	Sig. Δ Pre-Crash
$\mu\,(OIT)$	2.2842	2.9670	**	1.9632	
$\sigma\,(OIT)$	1.8631	3.4106		1.3866	
$\mu\,(OIN)$	1.3175	1.8308	***	1.1481	***
$\sigma\,(OIN)$	0.47737	1.3377		0.28581	

This table summarizes the order flow imbalance ratios before, during and after a crash. The crash threshold is 10% with a total daily crash size of at least 15%. The measures are calculated for 30-minute time intervals. The beginning and end of a crash is determined by 90 minutes of non-decreasing prices. Order flow imbalance ratios as measured by volume (i.e. number of shares traded) (OIT) and number of transactions (OIN) are calculated for each company in a sample before, during and after a crash. The averages (μ) and standard deviations (σ) of the order flow imbalance ratios for each sample and crash stage are reported. The column labeled *Sig. Δ Pre-Crash* indicates if the change in the respective measure compared to pre-crash levels is significant. ***/**/* means the change is significant at the 1%/5%/10% level, respectively.

A clear order imbalance is observed even before the crash. The pre-crash imbalance is stronger for turnover (average OIT of 2.284) than for the number of transactions (average OIN of 1.318). Both measures are significantly higher than the numbers for non-distressed companies.[27] During the crash, the imbalance rises significantly to 2.967 for average OIT and to 1.831 for OIN (standard difference t-statistics of 2.064 and 4.245 for mean OIT and OIN, respectively). This is evidence for a sales-driven market and selling pressure. These sales could drive or reinforce the crash extent and duration, which is analyzed in the next section. During the fourteen 30-minute periods after the crash the mean OIN comes back to 1.148, which is close to a balanced order flow. The mean OIT measure decreases to 1.963, but turnover remains sales driven. After a crash the average OIN ratio is significantly below the pre-crash level (t-statistic of -3.577) and the OIT measure is almost significantly below the pre-crash level (t-statistic of -1.624). Thus, it appears that after a crash markets move quickly to a balanced order flow.

[27] For comparability reasons we also analyze the order flow characteristics of 90 non-distressed companies. This sample of 90 companies contains the 30 Dow Jones companies, 30 mid-sized companies from the S&P 500, and the 30 smallest companies in the S&P 500. While the OIN measure indicates a balanced order flow for these stocks in our event period, the OIT measure indicates a sales surplus (average OIT between 1.541 for large and 1.764 for small companies). However, with the equity market indices being stable in this period, the sales surplus does not drive down the markets. When running tests for difference for the size-based company samples and our crash sample the following t-statistics are obtained for the pre crash period: T-statistics of -4.496, -3.906, and -2.986 for the OIT ratio as well as -8.546, -7.861, and -6.241 for the OIN ratio for *Large*, *Medium*, and *Small Companies*, respectively. Thus, order flow imbalance is higher for stocks about to experience a crash.

6.3 Impact of Order Flow on Crash Characteristics

Having seen that order flow imbalance increases noticably during a crash, the interaction of order flow with other market microstructure statistics during a crash is analyzed. We test theoretical work by Bouchaud and Cont (1998) or Gennotte and Leland (1990) which indicates that order flow imbalance is one of the key drivers for the extent of a crash (Hypothesis 3). Thus, crash size is regressed on the two order flow imbalance measures found for each company during the crash using 30-minute return intervals and $x = 3$. The highest, but in economic terms negligibly low, R^2 of 0.0296 is found for the logarithm of the OIN measure, having a parameter of 0.0474 which is significant at the 5% level and an intercept of -0.2244. For crash duration, the explanatory power of order flow imbalance is also negligible.[28] The highest explanatory power for the crash duration is found using the natural logarithm of the OIT measure as explaining variable, returning an R^2 of 0.0210 and a parameter estimate of 0.6363 (t-statistic of 1.8498). The regression intercept is 7.032 and significant at the 1% level. This evidence of a weak link between order flow and crash characteristics contrasts the microeconomic crash models by Bouchaud and Cont (1998) or Gennotte and Leland (1990). To study if order flow imbalance causes a constant price pressure we also regress the mean period return during a crash of length T, μ_i^{Crash}, on the two order flow imbalance ratios. We define μ_i^{Crash} as

$$\mu_i^{Crash} = \frac{1}{T} \cdot \sum_{t=1}^{T} r_{t,i}^{Crash},$$

where i is the indicator for the crash number. If a crash takes, e.g., 4 hours, the average is taken over the returns in the eight 30-minute periods of the 4 hour crash. Among a range of specifications, the highest explanatory power for the mean return is found using the natural logarithm of the OIN measure as independent variable (R^2 of 0.0265).[29] The increase of the order flow imbalance when a crash starts has no economically significant impact on crash characteristics as well. This is an interesting finding since it contradicts economic theory. However, Lin and Yang (2003) support our results by finding for Australian high-frequency data that a seller dominated regime is associated with positive returns, as opposed to the negative returns suggested by theory.

In summary, crashes are associated with strong order flow imbalances. The link between order flow imbalances and crash size, crash duration, as well as mean crash return is found to be

[28] For brevity, results are not reported here.

[29] The parameter of 0.0125 for OIN is significant at the 5% level (t-statistic of 2.0854). Constant selling pressure appears to have little impact on the intra-day price drift. The intercept is -0.0422 and is significant at the 1% level.

weak. The empirical evidence found in this study cannot support the models by Bouchaud and Cont (1998) and Gennotte and Leland (1990). [30] Therefore, crashes appear to be information-driven instead of order flow-driven.

7 Information Asymmetries Around Crashes

In this section we apply spread-based models by Easley, Kiefer, O'Hara, and Paperman (1996) and Huang and Stoll (1997) to obtain a deeper insight in the information processing and the perceived information asymmetries around crashes. In particular, we analyze if the information asymmetries after the crash are perceived to be lower than before (Hypothesis 4).

7.1 Spread Decomposition Using the Model by Easley et. al. (1996)

The model by Easley, Kiefer, O'Hara, and Paperman (1996) assumes the presence of informed and uninformed traders. Uninformed buyers and sellers arrive at rate ϵ at the market, where this rate is measured per minute of the trading day. Informed traders arrive only if there is an information event. The probability of an information event is ϕ for every trading day. The signal of the information event is negative with a probability of δ. Given there is a negative (positive) signal, informed traders arrive at rate μ on the sell (buy) side. While market makers are assumed to know the probabilities and rates of arrival for each possible state of reality, they do not know which state was selected for a given day by nature. The market maker determines the quotes conditional on the order sequence of the past and sets zero expected profit bid and ask prices. Given this model, Easley, Kiefer, O'Hara, and Paperman (1996) show that the probability of informed trading (PIN) can be determined as

$$PIN = \frac{\phi\mu}{\phi\mu + 2\epsilon}. \tag{11}$$

In their article the likelihood $L\left(B, S|\theta\right)$ for a number of buys B and sells S on a given day with the parameter vector $\theta = (\phi, \delta, \epsilon, \mu)$ is derived. The parameters can be estimated by maximizing the log likelihood of observing $M = (B_i, S_i)_{i=1}^{I}$ over I days:

$$\max_{\theta} \sum_{i=1}^{I} ln\left[L\left(\theta|B_i, S_i\right)\right]. \tag{12}$$

[30] However, the application of a cross-sectional regression analysis assumes that the relationship between the order flow imbalance measures and crash size are more or less equal across the companies in the sample. This might perhaps not be the case in reality.

In this section we estimate parameters for a time frame before (August 1st 2002 to the day before the crash) and for a time frame after the crash (day after the crash to October 31st 2002). The parameters are estimated using a 5-minute time spacing. We abandon our limited pre- and post-crash periods because of the need for enough observations for statistical stability.

The results are reported in Table 6. In the pre-crash period the parameters indicate a probability for an information event of 0.504, which is about the same level we find after the crash (0.490). The probability for a low signal (δ) decreases significantly (t-statistic of 1.760) after the crash (from a mean of 0.631 to 0.530). This decrease in the probability of bad news indicates that market makers forecast a more balanced news flow after a stock market crash. For the arrival rate of informed investors, we find a strong decline in the mean (from 1.194 before to 1.271 after the crash) and the median (from 0.110 before to 0.065 after the crash) of the parameter for the different crashes. Thus, although this change is not statistically significant, market makers appear to believe that after a crash fewer informed investors can take advantage of private signals. After a crash the probability of informed trading decreases slightly from a mean of 0.341 to 0.321, but this change is not statistically significant. In the model of Easley, Kiefer, O'Hara, and Paperman (1996) the decreasing PIN is consistent with the lower absolute spreads observed after the crash (mean spread decreases from 0.122 USD to 0.095 USD). The probability of informed trading is higher than the probabilities found by Easley, Kiefer, O'Hara, and Paperman (1996) (mean PIN between 0.164 and 0.220), showing that information asymmetries are perceived to be higher in stocks with a price crash. Summarizing, the changes in quotes after a crash are driven by the expectation of a more balanced news flow, a lower arrival rate of informed investors, and a lower probability of informed trading.

7.2 Spread Decomposition Using the Model by Huang and Stoll (1997)

The model by Huang and Stoll (1997) is similar in spirit to the Easley, Kiefer, O'Hara, and Paperman (1996) model by decomposing the spread in an adverse selection component (α), an inventory holding component (β), and an order processing cost component ($1-\alpha-\beta$). Weston (2000) states that the order processing component contains the market-maker rents. These parameters can be estimated using information on the intra-day spread (S_t), the initiation of trades (i.e., seller or buyer initiated), and changes of the midquote (ΔM_t) at every time t in the observed time period. Since the TaQ database does not contain information on the initiation of trades, the tick test by Lee and Ready (1991) is used for the classification. The direction of trades is summarized by Q_t, with $Q_t = +1$ for a buyer initiated transaction, $Q_t = -1$ for a

Table 6: Estimated Parameters for the probability of informed trading model by Easley et al. (1996)

	Before Crash			After Crash		
	Mean	Median	Stdv.	Mean	Median	Stdv.
ϕ	0.504	0.437	0.329	0.490	0.442	0.321
δ	0.631	0.631	0.330	0.530	0.448	0.337
ϵ	0.847	0.041	2.073	0.418	0.043	1.040
μ	1.194	0.110	2.323	1.271	0.065	2.902
PIN	0.341	0.216	0.403	0.321	0.169	0.372

This table summarizes the means, medians, and standard deviations of the parameter estimates for the model by Easley, Kiefer, O'Hara, and Paperman (1996) for the companies in the crash sample before and after the crash. ϕ is the probability of an information event, δ is the probability of a negative signal, ϵ is the arrival probability of informed and uninformed investors, μ is the arrival rate of informed investors, and PIN is the probability of informed trading.

seller initiated transaction, and $Q_t = 0$ if the transaction cannot be identified as buyer or seller initiated. For this analysis we use single trades and do not aggregate to a 5 minute grid. The parameters are estimated using the following equations derived by Huang and Stoll (1997):

$$E\left(Q_{t-1}|Q_{t-2}\right) = \left(1-2\pi\right)Q_{t-2} + e^a_{t-1}, \tag{13}$$

$$\Delta M_t = \left(\alpha+\beta\right)\frac{S_{t-1}}{2}Q_{t-1} - \alpha\left(1-2\pi\right)\frac{S_{t-2}}{2}Q_{t-2} + e^b_t, \tag{14}$$

where e^a_{t-1} and e^b_t are residuals and π is the probability of a trade reversal. The parameters of equations (13) and (14) can be estimated using the Generalized Method of Moments (GMM).[31] The results of this analysis are reported in Table 7. The analysis is performed once with our normal dataset (*unmodified sample*). In a second analysis subsequent trades with the same prices and quotes are summarized in one trade (*bunched trades*), assuming that these transactions belong to a larger order which is broken up in smaller parts (Huang and Stoll (1997) propose this approach). Since the *bunching* procedure summarizes also unrelated transactions and the *unmodified sample* does not take the splitting of orders into account, the "real" data set caused by the actual orders (as opposed to the recorded transactions) is inbetween these two extreme samples. Thus, the parameters estimated on both samples have to be interpreted

[31] We use a Newey-West procedure to obtain a robust covariance matrix, which is also used as weighting matrix in the estimation. A two step GMM procedure is applied, using the identity matrix as weighting matrix in a first step. The inverse of the resulting estimated covariance matrix is used as weighting matrix in the second GMM estimation. Our orthogonality condition is that all independent variables are orthogonal to the error term.

Table 7: Estimated Parameters for the Decomposition of the Bid-Ask Spread According to Huang/Stoll (1997)

		Before Mean	Median	Stdv.	After Mean	Median	Stdv.
Unmodified Sample	α	-0.004	-0.009	0.093	-0.002	-0.011	0.075
	β	0.231	0.222	0.101	0.238	0.237	0.089
	$1-\alpha-\beta$	0.773	0.802	0.099	0.764	0.767	0.092
	π	0.290	0.283	0.039	0.283	0.275	0.044
Bunched Trades	α	0.062	0.057	0.479	0.018	0.044	0.415
	β	0.237	0.208	0.451	0.303	0.249	0.414
	$1-\alpha-\beta$	0.730	0.729	0.136	0.698	0.683	0.127
	π	0.427	0.422	0.058	0.425	0.422	0.065

This table summarizes the means, medians, and standard deviations of the parameter estimates for the model by Huang and Stoll (1997) for the companies in the crash sample before and after the crash. The spread is decomposed in an adverse selection component (α), an inventory holding component (β), and an order processing cost component ($1-\alpha-\beta$). π is the trade reversal probability.

to obtain robust results.[32]

We start with the discussion of the *unmodified sample*. Before and after the crash we obtain an adverse selection component close to zero. The inventory holdings costs of the market maker cause 23.1% of the spread before and 23.8% after the crash. The order processing cost cause the largest part of the spread (77.3% before and 76.4% after the crash). This proportion is higher than the ones found by Huang and Stoll (1997) (their estimates are all well below 0.5). Thus, the order processing cost component in spreads of distressed companies appear higher than for non-distressed companies.[33] The changes of the spread components before and after the crash are minimal.

The sample of the *bunched trades* delivers comparable results.[34] However, the adverse selection component is now positive (mean of 0.062 before and 0.018 after the crash), which is in line with results by Huang and Stoll (1997). The drop of the adverse selection component after the crash could be caused by the information revelation and processing through the crash, but the difference is not significant (t-statistic of 0.766).

With the estimated parameters, the absolute USD spread can be decomposed.[35] According

[32]Compare De Winne and Platten (2003) for more details.

[33]Since the spreads of distressed companies are also higher than the ones of non-distressed companies, the order processing cost components in the spreads of distressed companies in USD are higher as well.

[34]As expected, the bunching procedure results in an increased trade reversal probability of 0.427 and 0.425 before and after the crash, respectively. These numbers are lower than the ones obtained by Huang and Stoll (1997) (their trade reversal probability is above 0.676). However, our numbers appear more realistic since they indicate a slight tendency towards trade continuation.

[35]The results in this paragraph are given using the parameters estimated for the *bunched trades* sample.

to this decomposition, the average adverse selection component decreases from 0.014 USD before to 0.007 USD after the crash (t-statistic for difference is -1.61). Thus, the provision for information asymmetries decreases after the crash, possibly because of the information processing during the price drop. The inventory holding costs stay fairly constant (0.016 USD before and 0.018 USD after the price drop). The average order processing costs drop from 0.095 USD to 0.072 USD. Since the pure processing costs are likely to be unchanged by a price drop, this decrease could be a sign of decreased market marker rents after the crash (compare Weston (2000)). However, the change in order processing costs is not significant (t-statistic of -1.367).

8 Conclusion

This article studies intra-day returns and liquidity around idiosyncratic stock price crashes on the US market. During the crash, liquidity is found to increase in general, resulting in higher turnover, more transactions per time interval, and at least as large a number of shares available at the bid and ask as before. The bid-ask spread increases, however, raising the costs of trading. Interestingly, there is some evidence that the spread increase during a crash is larger on the bid side than on the ask side. The magnitude of the changes in liquidity measures is strongly correlated with the crash size. The results give strong evidence for the hypothesis that larger crashes are triggered by news with a larger information content, resulting in a higher trading activity through portfolio rebalancing. During crashes, sales turnover and the number of sales are much higher than the respective figure for purchases. Unlike theory suggests, we find little evidence for an order flow effect on crash characteristics. Therefore, idiosyncratic crashes appear to be predominantly driven by new information and not by order flow. After a crash, returns are found to exhibit a negative price drift lasting for more than 6.5 hours. Thus, it is advisable to sell stocks as fast as possible once a crash started. The analysis of information asymmetries reveals a higher probability of informed trading in distressed stocks. The crash event itself appears to reduce information asymmetries because the probability of informed trading and the bid-ask spread component attributed to informed trading decrease after the price drop.

9 Appendix

Table 8: Companies in the Sample

Aaipharma	EMS Technologies	LSI Industries	Sierra Health Services
Abgenix	Emulex	Matria Healthcare	Silgan Holdings
American Capital Strategies	Endo Pharmaceuticals Holdings	Micros Systems	Salix Pharmaceuticals
AmeriCredit	El Paso	Midas	Stein Mart
A.C. Moore Arts & Crafts	Eresearchtechnology	Monolithic System Technology	Semitool
AEP Industries	Exelixis	MPS Group	Specialty Laboratories
Allmerica Financial	Falconstor Software	Medical Staffing Network Holdings	SS&C Technologies
AMR Corp.	FPIC Insurance Group	Marvell Technology Group	STATS ChipPAC
Andrew Corp.	Frontier Airlines	Midway Games	Stillwater Mining
On Assignment	Greater Bay Bancorp	Maxwell Technologies	Banc Corp.
Asyst Technologies	Griffon	Nash Finch	Teledyne Technologies
Aftermarket Technology	Gulf Island Fabrication	Neoforma	Fox & Hound Rest Group
AVNET	Gene Logic	Netflix	Tredegar
BE Aerospace	Green Mountain Coffee Roasters	NetRatings	Neslon Thomas
Ballard Power Systems	Genesis Microchip	Ohio Casualty	Tweeter Home Entertainment
Building Materials Holding	Georgia Pacific	O2Micro International	TXU
Brocade Comm. Sys.	GSI Commerce	OM Group	The TriZetto Group
Broadcom	Human Genome Sciences	OSI Pharmaceuticals	Unifi
Bio-Reference Laboratories	Harris	Overland Storage	Amerco
Bisys Group	HealthTronics	OmniVision Technologies	United Rentals
BUCA	Hughes Supply	Pacer International	USANA Health Sciences
Continental Airlines	Insight Communications	PC Connection	US Physical Therapy
Cross Country Healthcare	Integrated Device Technology	PDI	UTD Surgical Ptn
Central European Distribution	Interpublic Group of Companies	Palm Harbor Homes	Vector Group
Cerus	International Rectifier	Proxymed	Vical
Crompton	International Speedway	PerkinElmer	Virage Logic
Cleveland-Cliffs	Jabil Circuit	Penwest Pharmaceuticals	WCI Communities
Cantel Medical	Kendle International	Parkervision	WEBMETHODS
Carpenter Technology	Kyphon	Phoenix Technologies	MEMC Electronic Materials
CryoLife	Magma Design Automation	Pain Therapeutics	Willbros Group
Cholestech	Ladish Company	Pathmark Stores	World Acceptance
CTS	Ligand Pharmaceuticals	Sonic Automotive	ExpressJet Holdings
Cypress Semiconductor	LodgeNet Entertainment	Spanish Broadcasting System	Young Broadcasting
Dura Automotive Systems	LTX	Sepracor	
Electronic Data Systems	Level 3 Communications	Spherion	

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