Short-term stock price reversals after extreme downward price movements

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ABSTRACT

We studied the intraday effects of return overreactions around extreme negative one-minute interval returns of Nasdaq100 constituents based on nanosecond data. An extreme negative one-minute interval return is defined as the lowest return that occurs once in 1,000 one-minute intervals. We document that 31% of such an extreme one-minute interval's return is reversed in the subsequent trading minute. The relative magnitude of the reversal after extreme negative one-minute interval returns is particularly high for the 20% most liquid and the 20% largest firms of our sample.

1. Introduction

In market microstructure literature, a vivid discussion has emerged on the question of whether a new type of investors, so-called high frequency traders (HFTs), provide or detract liquidity on financial markets. HFTs are defined as "professional traders acting in proprietary capacity" who use "extraordinarily high-speed and sophisticated computer programs for generating, routing, and executing orders" by the U.S. Securities and Exchange Commission (SEC). The rise of electronic markets, increased computing power, algorithmic trading and reduced latency have been the primary enabling factors for the emergence of HFTs. Concerning van Kervel and Menkveld (2019) and Korajczyk and Murphy (2018), HFTs act as market makers in a normal market environment (i.e., provide liquidity), but trade in line with the market perception (i.e., detract liquidity) as soon as they detect a persistent trend. However, the general literature on the impact of HFTs on bid-ask spreads and price efficiency, as well as their contribution to extreme market movements such as the flash crash on May 3rd, 2010, is mixed. While Hasbrouck and Saar (2013), Chaboud et al. (2014), and Hasbrouck (2018) documented a negative correlation

between HFTs and crashes, Gao and Mizrach (2016), Boehmer et al. (2021), and Kirilenko et al. (2017) showed an increased frequency of crashes related to HFTs' activities.

This paper investigates short-term reversal returns after extreme downward price movements. At least two types of events can trigger large price movements: an update in information and imbalances of trades. While the information contained in news updates results in a rapid adjustment of prices on efficient markets, imbalances of trades push prices away from fundamental values. In recent times, the emergence of extreme transitory price movements has attracted significant attention from researchers and regulators alike. While the majority of studies have focused on systematic events to understand the role played by various automated traders (HFTs, algorithmic traders, etc.) from a market liquidity perspective, we aim at investigating differences in market conditions and trading behavior around an exogenous price shock.

Therefore, we analyzed investment returns around extreme negative short-term stock returns. Fig. 1 shows an example of such an idiosyncratic extreme negative stock price event for LBrands on February 23rd, 2017. The daily return calculated based on open and close price was −3.1% on this day. However, the development of intraday prices exhibited high volatility, i.e., prices took significant time to reach a new market equilibrium. Particularly during the fourth one-minute trading interval (09:33 AM to 09:34 AM) on this day, the stock price of LBrands declined by more than 1.04%

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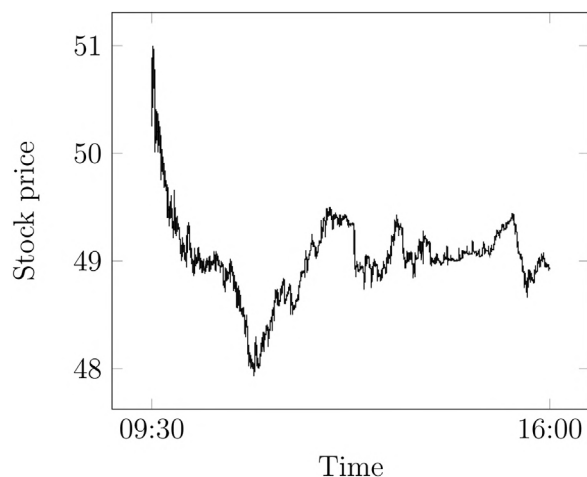
Fig. 1. Intraday price development of LBrands on February 23, 2017.

in one minute.[1] During the entire trading day, LBrands was trading −5% lower than its open price by 11:05 AM after exhibiting a steep declining pattern, followed by a period of recovery lasting up until 12:05, at which time LBrands was reporting −2% return for the day.

Hasbrouck and Saar (2013) and Chordia et al. (2008) found that HFTs increase liquidity in such extreme situations, being associated with greater market efficiency (Carrion, 2013; Brogaard et al., 2014; Chaboud et al., 2014). Moreover, Shkilko and Sokolov (2020) associate reduced HFTs activity with lower adverse selection and lower trading costs. Thus, we state the hypothesis that during an idiosyncratic price shock, market pricing is inefficient only for a very short period due to overreactions. This situation provides the opportunity to exploit the advantages of low-latency data transfer and increased computational power to trade against the wind (i.e., the observed negative price momentum), to provide short-term liquidity, and to gain returns from short-term stock price reversals.

On the topic of return reversals, a large body of literature addressed the risk-bearing capacity of intermediaries (Kirilenko et al., 2017; Nagel, 2012; Hameed and Mian, 2015). Nagel (2012) and So and Wang (2014) showed that providing liquidity during reversals is profitable. Furthermore, Handa and Schwartz (1996) show that placing a network of buy and sell limit orders as part of a trading strategy is profitable. HFTs can react marginally faster to market signals, and thus conduct so-called latency arbitrage and stale quote sniping (Foucault et al., 2003; Menkveld and Zoican, 2017; Budish et al., 2015). Brogaard et al. (2017) and Brogaard et al. (2018) studied HFTs during a short-sale ban and around extreme price movements. Empirical results (see Hasbrouck and Sofianos, 1993; Madhavan and Smidt, 1993) highlighted that intraday mean-reversion in inventories, and relatively high trading volume are noticeable characteristics of intermediation, which are categorized as HFTs or high-frequency market makers (Biais et al., 2015; Ait-Sahalia and Saglam, 2017; Jovanovic and Menkveld, 2016). Concerning the finding of Brogaard et al. (2018), HFTs speed up the reversal process after extreme price movements (Fig. 2).

To understand the short-term reversals around extreme downward price movements, we analyzed a sample of intraday quote and trade data of the Nasdaq100 constituents for the period from January 2014 to January 2019. We divided each trading day into 390 one-minute intervals and clustered intervals according to their returns in "crash" and "non-crash" intervals. In line with literature on stock price crash risk (e.g., Hutton et al., 2009), we defined a crash

interval as a one-minute interval with a return equal to or below the 0.1%-quantile return of the one-minute intervals' return distribution. Non-crash intervals are therefore all intervals with higher returns than this threshold. Fig. 3 portrays an example of how the algorithmic crash interval identification approach would flag and label the one-minute intervals based on an extreme event occurring around t, whereby $t − 1$, t, and $t + 1$ represent the cutoff points delimiting fixed one-minute intervals. The interval starting at $t − 1$ and ending at t would be flagged as a crash interval, while consecutively the interval beginning at t and ending at $t + 1$ constitutes the follow-up reversal interval. Consequently, it is important to note, that the algorithmic approach does not take the minimum price of each one-minute interval in calculating the returns, but rather relies on chronological delimiters (i.e., the bid and ask prices at the beginning and at the end of each a priori determined one-minute interval) which are ex-ante defined to be fixed. While this does potentially cause understatements of crash and reversal returns, this approach ensures the robustness and systematic nature of the identification algorithm.

Crash intervals exhibit characteristics (such as return and trading activity) significantly different from non-crash intervals. The one-minute return of a crash interval was 72 basis points lower than the return of a non-crash interval (see Fig. 2). Multivariate analyses show the existence of an after-crash reversal, which is about 31% of the crash interval return. The reversal has the highest proportion of the crash return for firms with highly-liquid stocks and high firm size. The economic implications of these findings are consistent with previous studies relating short-term reversals to the degree of market liquidity. The fact that the largest firms exhibited the smallest crash returns, as well as the strongest reversal, provides evidence that liquidity is playing a major role in the price path evolution throughout our observation period (Cox and Peterson, 1994; Chordia et al., 2002).

A closely related paper on the topic of short-term return reversals and HFTs activity is Brogaard et al. (2018), which investigated the role of HFTs around extreme stock price movements, in particular analyzing liquidity levels and quote imbalances around extreme price movement events occurring for single stocks or simultaneously for multiple stocks. In contrast, our study examines the return structure around extreme return intervals by relying on realized trade prices to capture real investment returns. Using recent advances and increasing affordability in cloud computing services the analysis included in this paper covers all the constituents in the Nasdaq100 over the period from January 2014 to January 2019, in contrast to the (post-)financial crisis period of 2008 and 2009 covered in Brogaard et al. (2018). Additionally, we focused on downward price movements and characterized the stock price development in an 11-minute time window around the crash minute.

The contribution of this paper to the related literature is twofold: First, it documents the existence of a reversal in realized returns in the one-minute interval following up after the crash interval, providing supporting evidence on the profitability of providing liquidity in periods of extreme downward price movements. In particular, HFTs with their low latency and computational power are in an ideal position to capitalize on these events. Second, the findings complement extant literature that ties low liquidity conditions to observed extreme negative period returns at the one-minute interval level.

The remainder of the paper proceeds as follows. In Section 2, we discuss the data employed in this paper. In Section 3, we present our empirical methodology and results. In Section 4, we conclude.

2. Data

We employed intraday trading data from the NYSE Daily Trade and Quote (DTAQ) database available over the WRDS Cloud plat-

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[1] A series of one-minute intervals with returns of −1.04% translates into a return of −47% in one trading hour or −98% for the entire trading day. Thus it is considered as an extreme negative stock price event.
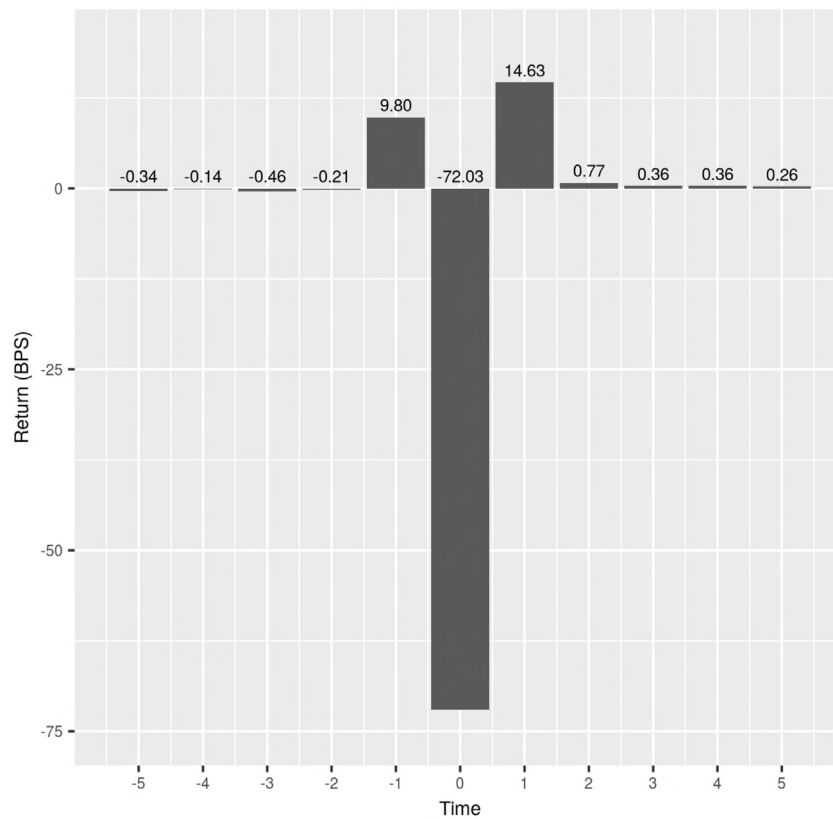
Fig. 2. This figure shows the average return profile across our set of 15,242 identified extreme return intervals. It displays the one-minute returns during the five individual one-minutes before and after extreme interval. All returns are expressed in basis points.
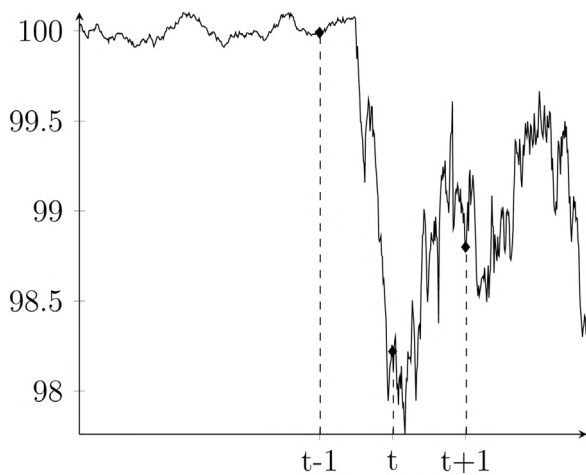

Fig. 3. Generic example of crash interval.

form. Specifically, we sourced data from the Daily TAQ files from where we retrieved millisecond-level data from January 1st, 2014, microsecond level data starting from July 27th, 2015, and nanosecond level data starting from October 24th, 2016. These data covered trade, quote, and national best bid and offer (NBBO) data for a basket of the 100 stocks comprising the Nasdaq100. Our observation period ranged from January 2014 to January 2019, yielding a sample of 1,564,388,227 analyzed trades in total.

We restricted our data to trades and quotes posted within the regular trading hours of the NYSE (9:30 AM to 4:00 PM). Concerning the handling of withdrawn quotes and quotes with abnormal conditions, we followed the methodology outlined in Holden and Jacobsen (2014). Namely, we considered crossed quotes (quotes where the bid price is higher than the ask price) if they arose because the ask price was zero while the bid price was non-zero. We excluded quotes with abnormal quote and trade conditions, such as situations where trading has been halted. Further, we focused on trades of common stocks in our sample. In this respect, we dropped any observation for which the quote and trade conditions are listed as A, B, H, K, L, O, R, V, W, and Z.[2] Implicitly, all situations where trading is halted, which could be the case in the event that a circuit breaker is triggered, are systematically excluded from our sample. We also excluded data points where the bid price is greater than the ask price, if listed by the same exchange, or for which either price or quantity was equal to zero. In line with Chordia et al. (2001), we also dropped any data points where the quoted spread was higher than 5 USD.

We corrected the original NBBO daily file considering data from all of the available exchanges following Holden and Jacobsen (2014). Subsequently, we matched trades with corresponding NBBO quotes at the microsecond level. Based on this matched data set, we classified trades as buyer- or seller-initiated trades with respect to the classification method proposed by Lee and Ready (1991).

3. Methodology and results

3.1. Identification of crash intervals

To investigate the reversal returns after stock price crashes, we split each trading day within the matched trade and NBBO quote data into fixed equal one-minute intervals. Hence, splitting a typ-

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[2] Table 6 in Appendix A defines all abnormal trade and quote conditions.

ical trading day resulted in 390 individual one-minute intervals. Similarly, Brogaard et al. (2018) considered 10-second-intervals, while van Kervel and Menkveld (2019) considered 30-minute time stamps. In particular, Brogaard et al. (2018) showed that prices continued to move in the direction of the largest return for several seconds after the first indication of an extreme price movement. Therefore, we decided to use one-minute intervals. In unreported tests, we varied the time horizon from 30 s to five minutes. The results stayed qualitatively similar.

For each one-minute interval, we then calculated the actual realized interval return based on the recorded trades, the standard deviation of the realized returns based on the within-interval realized trades, and the minimum and the maximum realized return within each interval. Additionally, we determined the average quoted spread, the total traded share volume, and the net volume of shares bought or sold within each one-minute interval.

Moreover, we relied on the literature on stock price crashes to identify extreme price changes across the one-minute intervals. Therefore, we assigned the strategy of Brogaard et al. (2018) and Hutton et al. (2009) and defined a one-minute interval as a crash interval if the actual return is an event occurring once in a thousand observations, i.e., the 0.1%-quantile. Eq. (1) shows the identification rule for crash interval variable $C_{i,t}^{m,k}$:

$$
C_{i,t}^{m,k} = \begin{cases} 1 & r_{i,t} \leq \mu_{i,t}^{m,k} + \Phi^{-1}(0.001) \cdot \sigma_{i,t}^{m,k}, \\ 0 & r_{i,t} > \mu_{i,t}^{m,k} + \Phi^{-1}(0.001) \cdot \sigma_{i,t}^{m,k}, \end{cases} \tag{1}
$$

where $r_{i,t}$ is the actual return of the respective one-minute interval t of firm i, k refers to the number of historical observations that are used in each procedure, $\mu_{i,t}^{m,k}$ is the expected return for firm i in one-minute interval t, $\sigma_{i,t}^{m,k}$ is the standard deviation of the expected return for firm i in one-minute interval t, and $\Phi^{-1}(0.001) = -3.09$ represents the critical value for the 0.1%-quantile of the standard normal distribution with mean zero and standard deviation one. We specified $\mu_{i,t}^{m,k}$ and $\sigma_{i,t}^{m,k}$ considering two different conceptual procedures ($m = \{1, 2\}$) to identify extreme downward price movements. We finally labeled a one-minute interval as a crash interval, when both procedures flag the return of that particular interval as a crash return.

The first procedure ($m = 1$) considered consecutive k previous one-minute intervals to estimate the expected interval return and its standard deviation. We used a varying number of observations k in Eq. (1) corresponding to 5, 15, and 60 previous one-minute intervals, as well as 390 one-minute intervals for one day, 1950 one-minute intervals for one week, 40,950 one-minute intervals for one month, and 122,850 one-minute intervals for one quarter.

Our second procedure ($m = 2$) used matched time intervals as opposed to consecutive time intervals. We defined a matched time interval as the interval corresponding to the identical time interval, albeit in a prior trading day. For instance, yesterday's first trading minute (9:30 AM to 9:31 AM) served as a matched interval for today's first trading minute. The second procedure addressed the significantly different intraday return pattern of large returns in the early morning, which leveled off during the day, as well as known seasonality in trading behavior (Brooks and Kim, 1997; Lien and Yang, 2005; Liu, 2009). Therefore, we assessed whether an interval classified as a stock price crash by determining the crash variable of Eq. (1) based on 5, 21, 63, and 252 matched intervals, corresponding to a week, month, quarter, and one year.

Finally, we defined a crash dummy variable $C_{i,t}$ for each one-minute interval t of a specific firm i. The crash dummy variable

equals one if all of the above-mentioned identification methods flag interval t of a firm i as a crash interval and zero otherwise:

$$
C_{i,t} = \begin{cases} 1 & C_{i,t}^{m,k} = 1 \quad \forall m, k, \\ 0 & \text{otherwise.} \end{cases} \tag{2}
$$

3.2. Summary statistics

In total, we identified 15,242 one-minute intervals, which we labeled as crash intervals, while 46,773,469 one-minute intervals show no extreme downward movements (see Table 1). Panel A of Table 1 provides pooled raw descriptive statistics of our data set, contrasting the characteristics of non-crash and crash intervals. The first set of columns reports values for the non-crash intervals. A complete list of variables and their detailed description could be found in Table 5 in the Appendix.

The mean bid-ask spread in a non-crash one-minute interval was 5.72 basis points (bp). This number almost tripled in crash intervals (14.67 bp). In particular, the standard deviation of the bid-ask spreads among the one-minute intervals is substantially higher for crash intervals than for non-crash intervals (43.52 vs 13.24 bp). While the return of non-crash one-minute intervals was 0.02 bp on average, crash intervals observed an average return of −72.03 bp. The standard deviation of the one-minute returns of crash intervals was ten times the size of non-crash intervals. In a 10th percentile one-minute crash interval, the return was −145.17 bp compared to −8.18 bp in a non-crash interval.

Moreover, we calculated the minimum and maximum returns between two subsequent trades in each one-minute interval. Non-crash intervals exhibited on average −4.9 bp for the minimum and 4.93 bp for the maximum. The range from the 10th percentile of the minimum return (−9.6 bp) and the 90th percentile of the maximum return (9.63 bp) was rather narrow. The respective quantities in crash intervals showed a substantially higher variation in trading returns. While the 10th percentile of the minimum return equaled a return lower than −100 bp, we also observed high positive returns of 50 bp (90th percentile of the maximum return).

We constructed a momentum indicator that counts the number of successive one-minute intervals with negative (positive) realized interval returns. I.e., if we obtained negative interval returns in intervals $t − 3$, $t − 2$, and $t − 1$, the value of the momentum variable for interval t is −3. Symmetrically, if the series of interval returns were positive, the momentum indicator takes the value of +3. Alternatively, if returns in intervals $t − 3$ and $t − 1$ were negative but positive in the interval $t − 2$, the momentum indicator for interval t is 0 as a change in sign has been recorded.

The average momentum of non-crash intervals is 0.28, the 10th percentile of the momentum is −1, and the 90th percentile of the momentum is 2. These values indicate a market structure with mostly alternating one-minute interval returns. Only 10% of the one-minute interval returns experience, at least, a series of two subsequent negative one-minute interval returns. Another 10% of the one-minute interval returns experience, at least, a series of three subsequent positive one-minute interval returns. Crash intervals occur on average after two prior one-minute intervals with negative returns. Only 10% of the crash intervals were preceded by a series of at least three one-minute intervals with a negative return.

A fundamental distinction between non-crash and crash intervals was the trading activity in the respective one-minute interval in terms of trading volume and number of trades. While the number of actual trades recorded within an interval increased more than threefold vs a non-crash interval, the average trading volume in the crash intervals was approximately 7.5 times higher. On average, 13,500 shares were traded in a non-crash one-minute interval, while 101,180 shares were traded in a one-minute crash interval.

Table 1

This table reports on pooled raw and standardized descriptive statistics for crash and non-crash one-minute intervals. Our sample consists of all trades and quotes for the constituents of the Nasdaq100 throughout an observation period ranging from January 2014 to January 2019 aggregated into one-minute intervals. The unit of the reported spread and return quantities is basis points.

	Non-crash intervals ($N = 46,773,469$)					Crash intervals ($N = 15,242$)				
	Mean	SD	10th%ile	Median	90th%ile	Mean	SD	10th%ile	Median	90th%ile
Panel A: Raw quantities										
BidAsk	5.72	13.24	1.55	3.30	10.59	14.67	43.52	1.94	5.55	26.96
Ret	0.02	8.94	−8.18	0.00	8.17	−72.03	80.16	−145.17	−46.39	−23.60
MinRet	−4.90	9.28	−9.60	−3.23	−1.27	−44.90	86.14	−106.77	−17.68	−4.65
MaxRet	4.93	9.37	1.28	3.24	9.63	22.65	67.69	2.04	9.04	52.80
SD	1.84	2.70	0.55	1.20	3.56	8.92	22.50	0.98	2.93	19.22
Mom	0.26	1.67	−1.00	0.00	2.00	−0.88	1.44	−3.00	0.00	0.00
Vol	13.50	54.63	0.51	3.99	29.35	101.18	292.14	2.30	23.80	235.63
NrTrd	215.46	381.79	20.00	95.00	504.00	717.98	1297.18	58.10	312.50	1660.00
LRQty	−0.61	39.94	−3.95	−19.00	3.68	−34.16	168.01	−71.08	−6.22	0.90
Panel B: Standardized quantities										
BidAsk	−5.84E−4	0.99	−0.64	−0.14	0.70	1.82	8.38	−0.40	0.22	3.71
Ret	2.66E−3	0.97	−0.93	−4.54E−4	0.93	−8.16	9.39	−15.98	−5.16	−3.04
MinRet	1.52E−3	0.98	−0.46	0.14	0.41	−4.66	10.24	−11.66	−1.39	−0.03
MaxRet	−6.56E−4	0.99	−0.41	−0.14	0.46	2.01	7.87	−0.28	0.44	5.55
SD	−9.96E−4	0.99	−0.50	−0.16	0.56	3.08	9.06	−0.25	0.51	7.80
Mom	2.26E−4	1.00	−0.81	−0.13	1.11	−0.70	0.88	−1.93	−0.24	−0.07
Vol	−8.13E−4	0.99	−0.40	−0.19	0.47	2.50	5.39	−0.22	0.87	6.38
NrTrd	−6.85E−4	1.00	−0.76	−0.27	1.03	2.10	3.40	−0.45	1.21	5.41
LRQty	4.27E−4	1.00	−0.26	4.27E−4	0.25	−1.31	4.50	−3.51	−0.50	0.08

The increased volume was due to a substantially higher number of trades in the respective intervals (215 vs 717). The negative average of the LRQty variable (the LRQty is the number of buyer-initiated trades minus the number of seller-initiated trades) indicated substantially more selling trades than buying trades occur during crash intervals compared with non-crash intervals.

Panel B of Table 1 provides the same statistics after a z-transformation for each firm of the interval statistics. We present these quantities to capture the effect of the difference in absolute values of single firms. For instance, trading volume significantly varies across firms. Even after controlling for firm-specific influences, the summary statistics display a similar relationship between non-crash and crash intervals. Since the average values of all variables in the non-crash sample were almost zero, the average z-scores of the crash sample indicated the significance level of the crash interval variables different from zero (alternative hypothesis). Except for the momentum and the LRQty variables, all other variables were significantly different from zero, and thus from the ones of the non-crash sample.

3.3. Return pattern around one-minute crash intervals

We continued focusing on crash intervals. We investigated the consecutive one-minute intervals five minutes before and after the crash interval to understand the development of the variables around such an extreme event. Therefore, we structured the bid-ask spread, the return standard deviation (between single trades), the average minimum return, the average maximum return, and the trade volume in event-time. Then, we aggregated each variable across the cross-section. Fig. 4 exhibits the development of these variables. We observed a gradual increase in the quoted bid-ask spread, peaking in the crash interval followed by a moderate, gradual recovery in the follow-up one-minute intervals (Fig. 4(a)). The recorded trading volume (Fig. 4(b)) exhibited a spike pattern with minimal increases in the five minutes running up to the crash, followed by a more than twofold increase in the actual crash interval. This pattern suggests that traders with a fast reaction could be behind such an increase in trading activity.

Turning to the metrics calculated based on the individual within-interval trades, we observed a similar pattern such as the one of the quoted spread for the standard deviation of realized returns (Fig. 4(e)). The average minimum return between two trades showed downward spikes, which were more than three times smaller during the crash minute than in the minutes before the event (Fig. 4(c)). Conversely, the average maximum return increased considerably, effectively doubling in $t − 1$ and staying at this level in t. It reached its peak only in $t + 1$, providing preliminary evidence supporting the idea of a trading strategy aimed at capitalizing on a potential overreaction taking place in t and a possible reversal in $t + 1$. Additional summary statistics for the one-minute interval returns of the period starting five minutes before the crash interval t and the five minutes following are presented in Table 7 in Appendix A. We split the entire sample into quintiles regarding firms' bid-ask spread, size, book to market, and momentum. The statistics exhibit similar patterns for all quintile groups.

3.4. Structure of one-minute interval returns

For the multivariate analysis of all one-minute interval returns, we ran OLS regression models with firm and year fixed effects, and clustered standard errors on firm-level (Eq. (3)):

$$Ret_{i,t} = \beta_0 + \Theta \cdot Controls_i + \alpha_i + u_t + \varepsilon_{it} \qquad (3)$$

where Θ is the vector of coefficients of the independent variables, α_i is the firm fixed effect, u_t is the time fixed effect, and ε_{it} is the error term. The dependent variable was the return (in basis points) of each of our 46 million one-minute interval observations. We organized the data in event time and used each one-minute interval as the interval under consideration once, i.e., its index is t.

We estimated five different model specifications. In the first model specification, we explained the variation of the one-minute interval returns of index t with the crash dummy variable (see Table 2). According to the estimation, the coefficient of the crash dummy in model specification (1) showed that intervals flagged as crash intervals exhibited on average a return which is about 72 bp lower than the average returns of non-crash intervals. The coefficient was significantly different from zero. We augmented this model specification by lagged and lead returns and their interactions with the crash dummy in model specifications (2)–(3). Although the coefficient of the crash dummy variable in these
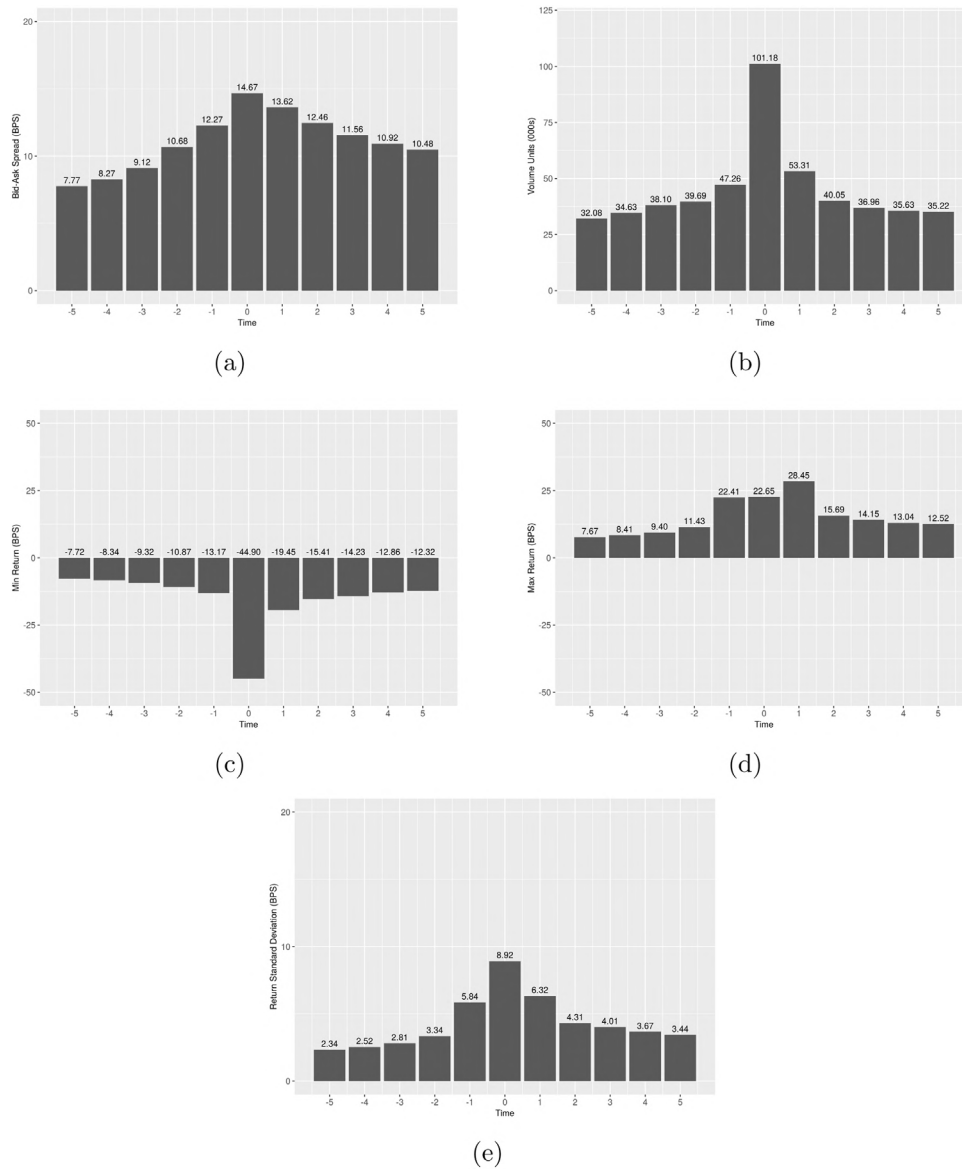
Fig. 4. This figure shows the average developments in (a) bid-ask spread, (b) standard deviation between trades, (c) maximum return, (d) minimum return and (e) trade volume across our set of 15,242 identified extreme return intervals. Spread and return figures are expressed in basis points, while volume figures are expressed in thousands of units.

model specification slightly reduced in magnitude, it remained significantly different from zero at a $p < 0.01$ level. The coefficients displayed for the four interval returns before the interval t are negative and statistically significant. The strongest effect was observed for the interval $t - 1$, where the negative coefficient for Ret_{t-1} suggests the occurrence of a reversal in t, quantifying to roughly 10% of the return recorded in interval $t - 1$.

The interactions between the crash dummy and the lagged and lead returns reveal the specific return structure before and after crash intervals. Overall, we documented that the occurrence of a crash in t has a statistically significant and amplifying effect on the observed return structure. For crash intervals, the reversal pattern was intensified since the coefficient of the interaction term of Ret_{t-1} and the crash dummy was about -0.5. Specifically, a one basis point increase in Ret_{t-1} is associated, on average, with a crash return which was 0.5 bp more negative than the return in a non-crash interval. I.e., if the one-minute interval t was a crash interval, the return in this interval was smaller by an additional $0.5 \cdot Ret_{t-1}$

than for a non-crash interval. Moreover, we observed the return reversal in the one-minute interval after the crash. This effect is symmetrical when looking at the observed coefficients reported for the interaction terms between the crash dummy and the lead five returns reported in model specification (3). The return of a firm experiencing a stock price crash in t showed a stock price reversal in the first minute after the crash which is $48\% \cdot Ret_t$ higher than the reversal after a non-crash interval.

In line with extant literature, we observed and confirmed a negative correlation structure between the returns experienced in the pre- and post-crash intervals. This negative correlation structure remains constant throughout model specifications (4) to (5). In these model specifications, we incrementally added the momentum observed in $t - 1$, the standard deviation of the returns during each one-minute interval, the bid-ask spread, and trading volume recorded across the previous individual five one-minute intervals to the set of control variables. Model specification (5) contains the entire list of control variables. For brevity, we do not report the

Table 2

This table reports on the structure of the one-minute interval returns. Our sample consisted of all trades and quotes for the constituents of the Nasdaq100 throughout an observation period ranging from January 2014 to January 2019 aggregated into one-minute intervals. We set up five model specifications and run corresponding OLS regressions with time and firm fixed effects, and firm clustered standard errors. The dependent variable is the one-minute interval return expressed in basis points in the one-minute interval t. The variable Crash represented a dummy variable which takes the value of 1 when the one-minute interval was classified as a crash observation using our previously described methodology. The return, standard deviation of within interval returns, and bid-ask spread are expressed in basis points. The trading volume is expressed in thousands of units. t-statistics are reported in parentheses.

| | Dependent variable: one-minute interval returns (Ret_T) | | | | | | | | | |
| | (1) | | (2) | | (3) | | (4) | | (5) | |
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Crash	−71.9571***	(−33.08)	−66.2842***	(−38.96)	−56.9403***	(−31.83)	−57.6979***	(−32.71)	−58.2999***	(−32.90)
Ret_{t-1}			−0.1006***	(−15.05)	−0.1007***	(−14.95)	−0.1037***	(−15.50)	−0.0964***	(−15.70)
Ret_{t-2}			−0.0111***	(−5.91)	−0.0118***	(−6.05)	−0.0148***	(−7.19)	−0.0123***	(−6.95)
Ret_{t-3}			−0.0074***	(−11.35)	−0.0080***	(−11.79)	−0.0095***	(−11.93)	−0.0085***	(−12.10)
Ret_{t-4}			−0.0074***	(−13.84)	−0.0074***	(−13.43)	−0.0081***	(−14.01)	−0.0075***	(−13.12)
Ret_{t-5}			−0.0004	(−0.61)	−0.0003	(−0.56)	−0.0007	(−1.14)	−0.0001	(−0.18)
$Ret_{t-1} \times$ Crash			−0.4681***	(−8.40)	−0.5050***	(−9.92)	−0.5280***	(−10.64)	−0.4883***	(−10.06)
$Ret_{t-2} \times$ Crash			−0.0265	(−0.36)	−0.0290	(−0.39)	−0.1163	(−1.46)	−0.0074	(−0.09)
$Ret_{t-3} \times$ Crash			0.0758	(1.09)	0.0876	(1.24)	0.0076	(0.11)	0.1133*	(1.97)
$Ret_{t-4} \times$ Crash			0.0052	(0.08)	0.0554	(1.14)	−0.0084	(−0.17)	0.0141	(0.28)
$Ret_{t-5} \times$ Crash			0.2059***	(3.18)	0.1656***	(2.89)	0.1223**	(2.17)	0.0998*	(1.84)
Ret_{t+1}					−0.0989***	(−13.16)	−0.0989***	(−13.15)	−0.0918***	(−13.38)
Ret_{t+2}					−0.0100***	(−5.06)	−0.0100***	(−5.06)	−0.0081***	(−4.48)
Ret_{t+3}					−0.0067***	(−10.26)	−0.0067***	(−10.26)	−0.0060***	(−10.42)
Ret_{t+4}					−0.0061***	(−14.08)	−0.0061***	(−14.07)	−0.0060***	(−13.60)
Ret_{t+5}					0.0005	(0.89)	0.0005	(0.87)	0.0007	(1.20)
$Ret_{t+1} \times$ Crash					−0.4794***	(−13.38)	−0.4806***	(−13.46)	−0.4882***	(−13.06)
$Ret_{t+2} \times$ Crash					−0.3593***	(−4.37)	−0.3576***	(−4.35)	−0.3442***	(−4.08)
$Ret_{t+3} \times$ Crash					−0.3188***	(−4.05)	−0.3194***	(−4.05)	−0.3438***	(−4.30)
$Ret_{t+4} \times$ Crash					−0.3339***	(−3.80)	−0.3372***	(−3.84)	−0.3054***	(−3.54)
$Ret_{t+5} \times$ Crash					−0.1896***	(−3.56)	−0.1845***	(−3.43)	−0.2094***	(−3.44)
Mom_{t-1}							0.0462***	(5.54)	0.0444***	(5.55)
$Mom_{t-1} \times$ Crash							3.4767***	(8.80)	2.8368***	(7.42)
$SD_{t-1} - SD_{t-5}$									Yes	
$BidAsk_{t-1} - BidAsk_{t-5}$									Yes	
$Vol_{t-1} - Vol_{t-5}$									Yes	
Cons	0.0271***	(11.26)	0.0270***	(10.75)	0.0263***	(9.45)	0.0095**	(2.44)	−0.0766***	(−5.82)
Year F.E.	Yes		Yes		Yes		Yes		Yes	
Firm F.E.	Yes		Yes		Yes		Yes		Yes	
N	46,301,174		46,300,674		46,300,175		46,300,175		43,291,019	
Adj. R^2	0.020		0.034		0.048		0.048		0.044	

*Denote significance at the $p < .1$ levels.
**Denote significance at the $p < .05$ levels.
***Denote significance at the $p < .01$ levels.

coefficients of the last three sets of lagged variables which cover the within interval standard deviation of returns, bid-ask spread, and trading volume. We observed a similar correlation pattern when looking at returns recorded in the four one-minute intervals after t in model specifications (4) to (5). The negative coefficient for Ret_{t+1} is symmetrical in magnitude and sign to the coefficient reported for Ret_{t-1} pointing to the existence of a return reversal, which is strongest in $t + 1$. This pattern supported an alternating return development in which the current return shows a 10% reversal of the return of the last one-minute interval.

Referring to model specification (4), we observed a positive, statistically significant impact of the momentum indicator on the return recorded in interval t. Given the average momentum of 0.2 as computed for non-crash intervals, momentum had a minor impact on the magnitude of the return recorded in t when no crash was recorded. This effect was substantially amplified when looking at crash intervals. Specifically, any unit decrease in momentum was associated with a crash return which was, on average, roughly 3.5bp lower.

3.5. Reversal return after crash intervals

We continued our analysis on the subset of crash one-minute intervals to study the return reversals after a crash. Therefore, we explained the variation of the returns of the one-minute crash interval one minute after the crash by the crash interval return and further control variables:

$$Ret_{i,t+1} = \beta_0 + \beta_1 \cdot Ret_t + \Gamma \cdot Controls_i + \alpha_i + u_t + \varepsilon_{it} \qquad (4)$$

where Γ is the vector of coefficients of the independent variables, α_i is the firm fixed effect, u_t is the time fixed effect, and ε_{it} is the error term.

The negative and statistically significant coefficients for Ret_t across all four model specifications showed that indeed, a reversal was present (see Table 3). The magnitude of this reversal one minute after the crash interval was about 31% of the size of the return during the crash interval (see model specification (4)). Furthermore, model specification (2) showed that the return of the interval before the crash interval was also associated with the return in the reversal interval $t + 1$. Namely, a positive return of one basis point recorded in the interval $t − 1$ is associated with a 0.2 bp reduction of the reversal in $t + 1$. Model specification (3) documented a positive and statistically significant association between the return in the reversal interval and the momentum variable before the crash. Specifically, a positive momentum up to the crash interval is linked to a stronger reversal. Each unit increase in the momentum variable was linked to

Table 3

This table reports the estimates of the OLS regression model with time and firm fixed effects, and firm clustered standard errors explaining the variation in the one-minute interval return in $t+1$ as a function of a set of independent variables. We estimated four model specifications. The return, standard deviation of within interval returns, and bid-ask spread are expressed in basis points. The trading volume is expressed in thousands of units. t-statistics are reported in parentheses.

	Dependent variable: post-crash one-minute interval returns (Ret_{T+1})							
	(1)		(2)		(3)		(4)	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Ret_t	−0.2682***	(−8.32)	−0.3115***	(−9.03)	−0.3144***	(−9.05)	−0.3060***	(−9.19)
Ret_{t-1}			−0.2040***	(−8.42)	−0.2168***	(−8.59)	−0.2312***	(−6.47)
Ret_{t-2}			0.0128	(0.31)	−0.0247	(−0.57)	0.0018	(0.04)
Ret_{t-3}			0.0796**	(2.10)	0.0464	(1.19)	0.0937**	(2.59)
Ret_{t-4}			0.1159**	(2.25)	0.0898*	(1.73)	0.0738	(1.47)
Ret_{t-5}			0.0554	(1.33)	0.0383	(0.92)	0.0403	(0.77)
Mom_{t-1}					1.4708***	(5.64)	1.3008***	(4.97)
SD_{t-1}							0.1028	(0.75)
SD_{t-2}							0.1756	(0.67)
SD_{t-3}							0.5654	(1.62)
SD_{t-4}							−0.0928	(−0.20)
SD_{t-5}							1.6303**	(2.11)
$BidAsk_{t-1}$							0.0395	(0.89)
$BidAsk_{t-2}$							−0.0995	(−0.89)
$BidAsk_{t-3}$							−0.0453*	(−1.73)
$BidAsk_{t-4}$							0.0173	(0.19)
$BidAsk_{t-5}$							−0.3130	(−1.31)
Vol_{t-1}							0.0050	(0.80)
Vol_{t-2}							−0.0212***	(−3.54)
Vol_{t-3}							−0.0063*	(−1.80)
Vol_{t-4}							−0.0069	(−1.30)
Vol_{t-5}							−0.0231***	(−4.21)
Cons	−6.0925***	(−2.72)	−7.3186***	(−3.21)	−8.0047***	(−3.42)	−9.6215***	(−4.14)
Year F.E.	Yes		Yes		Yes		Yes	
Firm F.E.	Yes		Yes		Yes		Yes	
N	15,104		15,102		15,102		14,135	
Adj. R^2	0.141		0.171		0.174		0.196	

*Denote significance at the $p < .1$ levels.
**Denote significance at the $p < .05$ levels.
***Denote significance at the $p < .01$ levels.

a 1.3 bp increase in the return observed in the recovery interval.

3.6. Firm characteristics and the magnitude of the crash reversal return

Given the strong statistical evidence documenting the occurrence of a reversal in interval $t+1$, we further analyzed the influence of firm characteristics on the size of the reversal. Accordingly, we split our sample of firms into quintiles, from smallest to largest, concerning the observed bid-ask spread, firm size, book to market ratio, and momentum. For each of these sub-samples, we repeated the estimation of the model specification (5) of Eq. (3) and model specification (4) of Eq. (4).

The results strengthened our previous findings. We observed statistically significant reversal coefficients across all sub-samples and are thus in line with our previous narrative (see Table 4).[3] We observed that the firms with the largest average bid-ask spread (Quintile 5 in *Panel A: Bid-Ask*) experienced the steepest crash, which was −76.93 bp (vs −44.2 bp for the most liquid firms in Quintile 1). The reversal after the crash was strongest in Quintile 1, where we observed a rebound quantified to 33.05% of the return

in the crash interval. This is as opposed to a recovery of only 19.73% of the crash drop observed for the least liquid firms.

Moreover, we observed a similar pattern when splitting our sample according to firm size measured by market capitalization. The largest firms exhibited the smallest crash returns of −41.59 bp, but the strongest reversal of 53.97% in terms of the proportion of the magnitude of the crash return. Moreover, under this specification, we also reported the best model fit with an adjusted R^2 of 0.371. Concerning the remaining two panels (book to market ratio and momentum indicator), the results across the quintile groups are not particularly distinctive.

These findings are consistent with existing literature considering the link between short-term reversals and the degree of market liquidity. As the largest firms exhibited the smallest crash returns and the strongest reversal, our findings, in line with Cox and Peterson (1994) and Chordia et al. (2002), suggest that liquidity is likely to play a major role in the price path evolution throughout our observation period.

4. Conclusion

In this paper, we investigated the structure of intraday returns around extreme downward price movements. We analyzed more than 46 million one-minute intervals of the Nasdaq100 constituents in the period ranging from January 2014 to January 2019. We identified 15,242 intervals with extreme downward price movements and furthermore found clear evidence supporting a return reversal after such an extreme negative return one-minute interval, which is about 31% of the crash return. These findings provided indications of short-term market inefficiency around idiosyncratic stock price crashes. High-frequency

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[3] For the brevity of the reported results, Table 4 contains only the coefficients of the crash dummy and the reversal coefficient for each panel-quintile combination, respectively. We quantified the magnitude of the average unexplained crash return at t and report the coefficient of the crash dummy variable of Eq. (3) in the first column of each panel-quintile combination. The second column in each panel-quintile combination contains the coefficient to quantify the reversal. Therefore, we reran the regression defined under model specification (4) in Eq. (4). Additionally, we report on model characteristics, i.e., the number of observations and the adjusted R^2 of the respective model.

Table 4

This table contains regression estimates of our two baseline regressions for different sub-samples concerning the bid-ask spread, firm size, (Ait-Sahalia and Saglam, 2017) book to market ratio and momentum quintiles. The dependent variable in the first column corresponding to each quintile is the return recorded for the interval at t expressed in basis points, while the dependent variable in the second column of each quintile is the return recorded for interval $t + 1$ expressed in basis points. The model specifications are similar to those listed under model specification (9) in Table 2 and under model specification (4) in Table 3, respectively. For brevity, we only report the values of the coefficients for the crash dummy and that of the observed return relevant for quantifying the magnitude of the reversal. All returns are expressed in basis points. t-statistics are reported in parentheses.

	(Q1)		(Q2)		(Q3)		(Q4)		(Q5)	
	Ret_t	Ret_{t+1}	Ret_t	Ret_{t+1}	Ret_t	Ret_{t+1}	Ret_t	Ret_{t+1}	Ret_t	Ret_{t+1}
Panel A: Bid-Ask										
Crash	−44.2005***		−56.2028***		−55.6882***		−61.5015***		−76.9334***	
	(−16.40)		(−18.47)		(−24.14)		(−16.81)		(−17.77)	
Ret_t		−0.3305***		−0.3621***		−0.3740***		−0.3044***		−0.1973***
		(−3.92)		(−4.96)		(−3.85)		(−5.59)		(−3.81)
N	9,341,941	3133	9,039,894	2798	8,800,280	2697	8,483,505	2858	7,625,399	2649
Adj. R^2	0.049	0.196	0.033	0.219	0.038	0.368	0.040	0.224	0.066	0.097
Panel B: Size										
Crash	−64.9713***		−65.3170***		−61.9671***		−60.2931***		−41.5934***	
	(−17.99)		(−20.43)		(−15.99)		(−16.97)		(−17.85)	
Ret_t		−0.1971***		−0.2401***		−0.3466***		−0.2764***		−0.5397***
		(−3.08)		(−5.38)		(−5.36)		(−3.98)		(−6.40)
N	8,010,362	2403	8,698,252	2670	9,023,101	3006	8,456,767	2971	9,102,537	3085
Adj. R^2	0.053	0.148	0.034	0.150	0.052	0.308	0.040	0.156	0.051	0.371
Panel C: Book/Mkt										
Crash	−62.3480***		−52.6448***		−56.5125***		−57.8163***		−60.5944***	
	(−14.13)		(−14.68)		(−15.72)		(−15.31)		(−15.55)	
Ret_t		−0.2989***		−0.3129***		−0.2438***		−0.3493***		−0.3184***
		(−3.68)		(−3.81)		(−4.34)		(−4.80)		(−4.83)
N	9,038,196	3025	8,247,436	2499	8,930,798	2984	8,878,798	2756	8,195,791	2871
Adj. R^2	0.046	0.186	0.054	0.282	0.038	0.138	0.040	0.173	0.046	0.279
Panel D: Momentum										
Crash	−66.8491***		−57.7690***		−54.5149***		−56.2890***		−55.0246***	
	(−15.75)		(−12.84)		(−16.17)		(−15.73)		(−17.09)	
Ret_t		−0.3479***		−0.3038***		−0.2798***		−0.3351***		−0.2460***
		(−4.45)		(−5.05)		(−3.43)		(−5.41)		(−3.49)
N	8,823,748	2899	8,596,338	2810	8,354,803	2558	8,866,479	2850	8,649,651	3018
Adj. R^2	0.049	0.209	0.043	0.178	0.045	0.326	0.035	0.209	0.054	0.147

* Denote significance at the $p < .1$ levels.
** Denote significance at the $p < .05$ levels.
*** Denote significance at the $p < .01$ levels.

traders may exploit such market overreactions by providing short-term liquidity in the minute after the stock price crash occurs. Future research might consider to apply alternative methodologies, such as the Mixed Data Sampling (MiDaS) methodology to investigate potential associations between patterns in lower frequency return intervals and higher frequency intervals.

Conflict of interest

The authors confirm that they have no conflicts of interest to disclose.

Appendix A. Appendix

Table 5

Complete list of variables and their corresponding description.

Variable name	Variable description
BidAsk	The average observed bid-ask spread within a one-minute interval measured in basis points.
Crash	Dummy variable which identifies one-minute intervals with an extreme negative return. The variable takes the value 1 if the condition listed under Eq. (1) is fulfilled.
MaxRet	The maximum return, in basis points, observed between individual trades taking place within the one-minute intervals.
MinRet	The minimum return, in basis points, observed between individual trades taking place within the one-minute intervals.
Mom	The momentum observed up until the start of the current one-minute interval. It is calculated as the count of successive intervals during which negative (positive) realized returns are observed. For example, if negative returns are observed in intervals $t − 3$, $t − 2$ and $t − 1$, the value of the momentum variable for interval t will be −3. Symmetrically, if the series of interval returns is positive, the momentum indicator will take the value of +3. Alternatively, if we observe negative returns in intervals $t − 3$ and $t − 1$ but a positive return in interval $t − 2$, the momentum indicator for interval t will be 0 as a sign change has been recorded.
LRQty	The net number, expressed in thousands of units, of buyer/seller initiated trades. The value is calculated as the number of buyer initiated trades minus the number of seller initiated trades. Trades are categorized using the algorithm presented in Lee and Ready (1991).
NrTrd	The number of trades recorded during a defined one-minute interval.
Ret	The return, in basis points, observed in a one-minute interval, calculated as the natural logarithm of the last trade price divided by the first trade price within a one-minute interval.
SD	The standard deviation, in basis points, of the returns observed between individual trades taking place within the one-minute intervals.
Vol	The number of units, in thousands, of common stock traded during a one-minute interval.

Table 6

Description of quote conditions which have been excluded in line with Holden and Jacobsen (2014), as well as the equity symbol suffixes for which observations from the daily trades dataset have not been included in our final sample.

	Description
Quote condition	
A	This condition indicates that the current offer is in 'Slow' quote mode. While in this mode, autoexecution is not eligible on the Offer side and can be traded through pursuant to anticipated Regulation NMS requirements
B	This condition indicates that the current bid is in 'Slow' quote mode. While in this mode, autoexecution is not eligible on the Bid side and can be traded through pursuant to anticipated Regulation NMS requirements.
H	This condition indicates that the quote is a 'Slow' quote on both the Bid and Offer sides. While in this mode, auto-execution is not eligible on the Bid and Offer sides, and either or both sides can be traded through pursuant to anticipated Regulation NMS requirements.
O	This condition can be disseminated to indicate that this quote was the opening quote for a security for that Participant.
R	This condition is used for the majority of quotes to indicate a normal trading environment. It is also used by the FINRA Market Makers in place of Quote Condition 'O' to indicate the first quote of the day for a particular security. The condition may also be used when a Market Maker re-opens a security during the day.
W	This quote condition is used to indicate that the quote is a Slow Quote on both the Bid and Offer sides due to a Set Slow List that includes High Price securities. While in this mode, auto-execution is not eligible, the quote is then considered Slow on the Bid and Offer sides and either or both sides can be traded through, as per Regulation NMS.
Equity suffix	
K	Non-voting shares.
L	Miscellaneous situations such as certificates of participation, preferred participation, and stubs.
V	Denotes a transaction in a security authorized for issuance, but not yet issued. All "when issued" transactions are on an "if" basis, to be settled if and when the actual security is issued.
Z	Miscellaneous situations such as certificates of preferred when issued.

Table 7

This table shows the development of the one-minute interval returns covering the period starting five minutes before the crash interval *t* and the 5 min following it, split into quintiles from smallest (Q1) to largest (Q5) according to our sample firms' bid-ask spread, size, book to market, and momentum. All figures are reported in basis points.

	$t-5$	$t-4$	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
Panel A: Bid-Ask											
Q1	−0.46	−0.21	−0.03	−0.10	7.49	−59.23	12.56	0.94	1.27	0.42	−0.01
Q2	−0.05	−0.08	−0.66	0.11	6.65	−65.37	12.82	1.15	−0.11	−0.40	0.17
Q3	−0.70	−0.63	−0.20	−0.52	8.37	−70.55	15.52	0.88	0.22	0.84	0.19
Q4	−0.15	0.02	−0.58	−0.25	7.66	−70.97	14.17	0.89	0.23	0.46	1.01
Q5	−0.41	0.13	−0.82	−0.33	18.95	−94.38	17.96	−0.04	−0.01	0.45	−0.15
Panel B: Size											
Q1	0.13	0.48	−0.47	0.17	17.94	−81.38	14.06	0.84	−1.00	0.66	0.11
Q2	−0.06	0.02	−0.17	−0.18	7.74	−74.30	14.14	0.73	0.42	0.20	−0.04
Q3	−0.67	−0.46	−0.35	−0.03	9.02	−75.41	16.32	0.33	0.50	0.05	−0.41
Q4	−0.48	−0.09	−0.86	−0.52	7.30	−70.97	13.63	0.59	0.79	0.87	1.01
Q5	−0.57	−0.57	−0.39	−0.45	7.96	−59.24	14.56	1.35	0.80	0.02	0.51
Panel C: Book/Mkt											
Q1	−0.28	−0.42	−1.14	−0.34	8.41	−74.08	15.19	0.37	0.45	0.34	0.32
Q2	−0.76	0.14	−0.18	−0.60	8.97	−69.65	16.40	1.18	0.72	0.62	−0.54
Q3	−0.19	−0.30	−0.64	0.32	8.16	−66.82	12.93	1.14	0.13	0.15	0.40
Q4	−0.16	−0.19	0.22	0.13	8.89	−69.39	13.20	0.51	0.66	−0.37	0.20
Q5	−0.40	0.08	−0.41	−0.61	14.50	−79.33	15.27	0.66	−0.20	1.02	0.74
Panel D: Momentum											
Q1	−0.84	−0.48	−1.40	−0.92	9.07	−80.30	18.28	0.07	0.24	−0.22	0.58
Q2	−0.26	0.00	0.13	−0.44	9.03	−72.13	14.70	1.02	1.20	0.27	1.13
Q3	−0.51	−0.36	−0.37	−0.45	7.65	−69.55	14.89	1.67	0.34	0.81	−0.16
Q4	−0.21	−0.41	−0.39	−0.36	8.04	−67.12	13.14	0.92	−0.12	0.30	−0.39
Q5	0.04	0.46	−0.20	1.02	14.69	−70.06	11.87	0.30	0.04	0.66	0.01

References

Ait-Sahalia, Y., & Saglam, M. (2017). *High frequency market making: Optimal quoting*. SSRN Working Paper.

Biais, B., Foucault, T., & Moinas, S. (2015). Equilibrium fast trading. *Journal of Financial Economics*, 116(2), 292–313. https://doi.org/10.1016/j.jfineco.2015.03.004

Boehmer, E., Fong, K. Y. L., & Wu, J. (2021). Algorithmic trading and market quality: International evidence. *Journal of Financial and Quantitative Analysis.*, https://doi.org/10.1017/S0022109020000782

Brogaard, J., Carrion, A., Moyaert, T., Riordan, R., Shkilko, A., & Sokolov, K. (2018). High frequency trading and extreme price movements. *Journal of Financial Economics*, 128(2), 253–265. https://doi.org/10.1016/j.jfineco.2018.02.002

Brogaard, J., Hendershott, T., & Riordan, R. (2014). High-frequency trading and price discovery. *Review of Financial Studies*, 27(8), 2267–2306. https://doi.org/10.1093/rfs/hhu032

Brogaard, J., Hendershott, T., & Riordan, R. (2017). High frequency trading and the 2008 short-sale ban. *Journal of Financial Economics*, 124(1), 22–42. https://doi.org/10.1016/j.jfineco.2017.01.008

Brooks, R., & Kim, H. (1997). The individual investor and the weekend effect: A reexamination with intraday data. *Quarterly Review of Economics and Finance*, 37(3), 725–737. https://doi.org/10.1016/S1062-9769(97)90020-X

Budish, E., Cramton, P., & Shim, J. (2015). The high-frequency trading arms race: Frequent batch auctions as a market design response. *Quarterly Journal of Economics*, 130(4), 1547–1621. https://doi.org/10.1093/qje/qjv027

Carrion, A. (2013). Very fast money: High-frequency trading on the NASDAQ. *Journal of Financial Markets*, 16, 680–711. https://doi.org/10.1016/j.finmar.2013.06.005

Chaboud, A. P., Chiquoine, B., Hjalmarsson, E., & Vega, C. (2014). Rise of the machines: Algorithmic trading in the foreign exchange market. *Journal of Finance*, 69, 2045–2084. https://doi.org/10.1111/jofi.12186

Chordia, T., Roll, R., & Subrahmanyam, A. (2001, apr). Market liquidity and trading activity. *Journal of Finance*, 56(2), 501–530. https://doi.org/10.1111/0022-1082.00335

Chordia, T., Roll, R., & Subrahmanyam, A. (2002). Order imbalance, liquidity, and market returns. *Journal of Financial Economics*, 65(1), 111–130. https://doi.org/10.1016/S0304-405X(02)00136-8

Chordia, T., Roll, R., & Subrahmanyam, A. (2008). Liquidity and market efficiency. *Journal of Financial Economics*, 87, 249–268. https://doi.org/10.1016/j.jfineco.2007.03.005

Cox, D. R., & Peterson, D. R. (1994). Stock returns following large one-day declines: Evidence on short-term reversals and longer-term performance. *The Journal of Finance*, 49(1), 255–267. https://doi.org/10.2307/2329143

Foucault, T., Roell, A., & Sandas, P. (2003). Market making with costly monitoring: An analysis of the SOES controversy. *Review of Financial Studies*, 16(2), 345–384. https://doi.org/10.1093/rfs/hhg005

Gao, C., & Mizrach, B. (2016). Market quality breakdowns in equities. *Journal of Financial Markets*, *28*, 1–23. https://doi.org/10.1016/j.finmar.2016.03.002

Hameed, A., & Mian, G. M. (2015). Industries and stock return reversals. *Journal of Financial and Quantitative Analysis*, *50*(1/2), 89–117. https://doi.org/10.1017/S0022109014000404

Handa, P., & Schwartz, R. A. (1996). Limit order trading. *Journal of Finance*, *51*(5), 1835–1861. https://doi.org/10.1111/j.1540-6261.1996.tb05228.x

Hasbrouck, J. (2018). High-frequency quoting: Short-term volatility in bids and offers. *Journal of Financial and Quantitative Analysis*, *53*(2), 613–641. https://doi.org/10.1017/S0022109017001053

Hasbrouck, J., & Saar, G. (2013). Low-latency trading. *Journal of Financial Markets*, *16*, 646–679. https://doi.org/10.1016/j.finmar.2013.05.003

Hasbrouck, J., & Sofianos, G. (1993). The trades of market makers: An empirical analysis of NYSE specialists. *Journal of Finance*, *48*(5) https://doi.org/10.1111/j.1540-6261.1993.tb05121.x, 1656-1593

Holden, C. W., & Jacobsen, S. (2014 jul). Liquidity measurement problems in fast, competitive markets: Expensive and cheap solutions. *Journal of Finance*, *69*(4), 1747–1785. https://doi.org/10.1111/jofi.12127

Hutton, A. P., Marcus, A. J., & Tehranian, H. (2009). Opaque financial reports, r2, and crash risk. *Journal of Financial Economics*, *94*, 67–86. https://doi.org/10.1016/j.jfineco.2008.10.003

Jovanovic, B., & Menkveld, A. J. (2016). *Middlemen in limit order markets*. https://doi.org/10.2139/ssrn.1624329 (SSRN Working Paper)

Kirilenko, A., Kyle, A. S., Samadi, M., & Tuzun, T. (2017). The flash crash: High-frequency trading in an electronic market. *Journal of Finance*, *72*(3), 967–998. https://doi.org/10.1111/jofi.12498

Korajczyk, R. A., & Murphy, D. (2018). High frequency market making to large institutional trades. *Review of Financial Studies*, *32*, 1034–1067. https://doi.org/10.1093/rfs/hhy079

Lee, C. M. C., & Ready, M. J. (1991). Inferring trade direction from intraday data. *Journal of Finance*, *66*(2), 733–746. https://doi.org/10.1111/j.1540-6261.1991.tb02683.x

Lien, D., & Yang, L. (2005). Availability and settlement of individual stock futures and options expiration-day effects: Evidence from high-frequency data. *Quarterly Review of Economics and Finance*, *45*(4), 730–747. https://doi.org/10.1016/j.qref.2004.06.002

Liu, S. (2009). The impacts of index options on the underlying stocks: The case of the S&P 100. *Quarterly Review of Economics and Finance*, *49*(3), 1034–1046. https://doi.org/10.1016/j.qref.2007.10.001

Madhavan, A., & Smidt, S. (1993). An anlaysis of changes in specialist inventories and quotations. *Journal of Finance*, *48*(5), 1595–1628. https://doi.org/10.1111/j.1540-6261.1993.tb05122.x

Menkveld, A. J., & Zoican, M. A. (2017). Need for speed? Exchange latency and liquidity. *Review of Financial Studies*, *30*(4), 1188–1228. https://doi.org/10.1093/rfs/hhx006

Nagel, S. (2012). Evaporating liquidity. *Review of Financial Studies*, *25*(7), 2005–2039. https://doi.org/10.1093/rfs/hhs066

Shkilko, A., & Sokolov, K. (2020). Every cloud has a silver lining: Fast trading, microwave connectivity, and trading cost. *Journal of Finance*, https://doi.org/10.1111/jofi.12969 (in press)

So, E., & Wang, S. (2014). News-driven return-reversals: Liquidity provision ahead of earnings announcements. *Journal of Financial Economics*, *114*, 20–35. https://doi.org/10.1016/j.jfineco.2014.06.009

van Kervel, V., & Menkveld, A. J. (2019). High-freqncy trading around large institutional orders. *Journal of Finance*, *74*(3), 1091–1137. https://doi.org/10.1111/jofi.12759