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Exchange-Traded Funds, Market Structure, and the Flash Crash

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The author analyzes the relationship between market structure and the flash crash. The proliferation of trading venues has resulted in a market that is more fragmented than ever. The author constructs measures to capture fragmentation and shows that they are important in explaining extreme price movements. New market structure reforms should help mitigate such market disruptions in the future but have not eliminated the possibility of another flash crash, albeit with a different catalyst.

The "flash crash" of 6 May 2010 represents one of the most dramatic events in the history of the financial markets. Late that afternoon, major U.S. equity market indices began to decline sharply. The Dow Jones Industrial Average (DJIA) dropped 998.5 points, the sharpest intraday point drop in history, followed by an astounding 600-point recovery within 20 minutes. The flash crash is distinguished from other market breaks—such as the one in October 1987—by its speed and rapid intraday reversal. Unlike other sharp intraday market breaks, such as the one on 28 May 1962, multiple securities traded at clearly unreasonable prices, including some (e.g., Accenture, 3M) that traded for pennies. Also notable was the disproportionate representation of exchange-traded products (ETPs) among the securities most affected, with prices diverging widely from their underlying net asset values.

Despite its short duration, the flash crash affected many market participants. Exchanges ultimately canceled trades at prices below 60% of the 2:40 p.m. (EDT) price, but many retail investors with market stop loss orders still had orders executed at prices well below prevailing market levels earlier in the day. Professionals also suffered from the volatility: Liquidity providers who bought at distressed prices and hedged by short selling similar securities or futures contracts incurred steep losses as their long positions were canceled while the assets they had shorted rebounded in price.

It is difficult to overstate the potential negative consequences of another flash crash. Such an event could dramatically erode investor confidence and participation in the capital markets for years to come, leading to reduced liquidity and higher transaction costs.[1] A future flash crash toward the end of the day could severely disrupt the close and, hence, the pricing of index derivative products, with follow-on effects for foreign markets and the subsequent day's open. Finally, the flash crash has already prompted several public policy initiatives, and a repeat event could induce dramatic changes to market structure and the regulatory environment.

Given these concerns, a considerable effort has been made to understand and isolate the "cause" of the flash crash with a focus on the precise chronology of events. This article instead focuses on the relationship between market structure and the flash crash without taking a view on its catalyst. My hypothesis is that equity market structure is a key determinant of the risk of extreme price changes. Today's U.S. equity market structure is highly complex, with 12 for-profit exchanges (e.g., the NYSE) and some 30 odd dark pools competing for flow. Dark pools offer nondisplayed liquidity and include broker/dealer dark pools (e.g., Goldman Sachs' Sigma X), exchange-owned pools (e.g., Direct Edge), and independent pools (e.g., ITG's POSIT).

The result of this proliferation of venues is greater fragmentation of trading. Fragmentation usually refers to the actual pattern of volumes traded across different venues. In December 2011, based on trade-level data, the major market centers' share of total U.S. equity dollar volume traded showed considerable dispersion, with NASDAQ at 23.8%, NYSE Arca at 16.5%, NYSE at 12.6%, BATS at 11.9%, Direct Edge EDGX at 8.1%, and the remainder accounted for by other exchanges and dark pools/broker internalization, included under FINRA's Trade Reporting Facilities. Nor is this phenomenon limited to the United States or just equities. In Europe, such entrants as Chi-X Global and

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Turquoise have gained market share at the expense of traditional stock exchanges, and derivative trading (e.g., options) is increasingly fragmented.

Although volume is a natural metric for fragmentation, there is another dimension of interest—namely, a venue's quotation activity at the best bid or offer. Quote fragmentation captures the competition among traders for order flow and thus may be a better proxy for the dynamics of higher-frequency activity than a measure based on the pattern of volumes traded, which in turn could reflect a variety of other factors, such as rebates.

Table 1 shows the venue shares of the U.S. equity market for December 2011 based on all reported trades and quotes. The first column represents the share of dollar volume. The second and third columns capture the market shares in quotation frequency and total dollar quoted depth (i.e., liquidity available at the inside quote), respectively. In terms of the statistics reported above, markets are less fragmented from a quotation perspective. In particular, the shares of NASDAQ and NYSE Arca as a fraction of all quotes at the best bid or offer are larger—34.7% and 21.9%, respectively, versus 23.8% and 16.5% of total dollar volume. Note that in terms of venues' shares of total inside liquidity (i.e., total liquidity at the best bid or offer), the market is a little less concentrated compared with looking at just the frequency of quotes. At the single stock level, of course, these differences are not significant.[2]

■ *Discussion of findings.* I conjectured that prices are more sensitive to liquidity shocks in fragmented markets because imperfect intermarket linkages effectively "thin out" each venue's limit order book. I began with a time-series perspective using intraday trade data from January 1994 to March 2012 for all U.S. equities and found that fragmentation today is at the highest level ever. Fragmentation was also much greater than historical levels on the day of the flash crash. Cross-sectionally, I related fragmentation positively to company size and the use of intermarket sweep orders, typically used in aggressive liquidity-demanding strategies by nonretail traders. I showed that ETPs are more concentrated than other equities.

With respect to the relationship between market structure and the flash crash, I found strong evidence that securities that experienced greater prior fragmentation were disproportionately affected on 6 May 2010. This result is consistent with my hypothesis that market structure is important in understanding the propagation of a liquidity shock. Although quote fragmentation is related to volume fragmentation, the two measures are distinct, and they diverged on the day of the flash crash. Both volume and quote fragmentation measures are important risk factors in explaining the observed cross-sectional price movements in the crash.

My analysis provides insight into why ETPs were differentially affected (ETPs accounted for 70% of equity transactions from 6 May that were ultimately canceled) even though ETP trading is less fragmented than that of other equities.[3] For ETPs whose components are traded contemporaneously, widespread distortion of the prices of underlying basket securities can confound the arbitrage pricing mechanism for ETPs, thus delinking price from value.

Table 1. Market Share of Dollar Volume and Quotation Activity, December 2011

Venue	Share of Dollar Volume	Share of NBBO Quotes	Share of NBBO Dollar Depth
Amex	0.15%	0.34%	0.03%
BATS BYX Exchange	2.80	1.96	0.69
BATS BZX Exchange	11.92	11.27	10.94
BEX	2.27	1.25	0.53
CBOE	0.13	0.27	0.07
Chicago	0.69	0.39	2.99
EDGA	3.36	2.04	0.74
EDGX	8.05	8.04	3.62
FINRA	15.90	0.00	0.00
NASDAQ	23.76	34.71	43.18
NASDAQ OMX	1.43	1.46	6.00
National	0.45	1.91	0.96
New York	12.58	14.46	10.36
NYSE Arca	16.52	21.88	19.90

NBBO = National Best Bid and Offer.

From the public policy viewpoint, the fact that fragmentation is now at its highest level ever may help explain why the flash crash did not occur earlier in response to other liquidity shocks; the rapid growth of high-frequency trading and the use of aggressive sweep orders in a highly fragmented market are recent phenomena. Current policy proposals will help mitigate future sharp drawdowns, but another flash crash, albeit with a different catalyst or in a different asset class, remains a possibility.

A Review of the Flash Crash

Initial speculation regarding the proximate cause of the flash crash varied widely, but a common theme was that an event so unique in financial market history must itself have had an extraordinary cause. For example, early theories included incorrect order entry by a trader (the so-called fat finger theory), a software bug at a major exchange, and a malicious, deliberate "denial of service" type of attack intended to damage the financial system. Yet, no evidence for these explanations has since come to light. Similarly, the disproportionate impact of the flash crash on ETPs led some early commentators to draw a connection between the sharp market moves on 6 May 2010 and the pricing and trading of these instruments.[4] In a controversial report by Bradley and Litan (2010), the authors concluded that exchange-traded fund (ETF) pricing poses risks to the financial system, noting that "the proliferation of ETFs also poses unquantifiable but very real systemic risks of the kind that were manifested very briefly during the 'Flash Crash' of May 6, 2010" (p. 5). The authors proposed various ETF-related reforms and noted that in the absence of such rules, they "believe that other flash crashes or small capitalization company 'melt ups,' potentially much more severe than the one on May 6, are a virtual certainty" (p. 5). Ben-David, Franzoni, and Moussawi (2011) presented evidence from the flash crash that "ETFs served as a conduit for shock transmission from the futures market to the equity market" (p. 23).

The joint report of the U.S. Commodity Futures Trading Commission (CFTC) and the SEC provided a detailed chronology of events on 6 May 2010 and suggested a possible catalyst for the flash crash (CFTC and SEC 2010). Specifically, at 2:32 p.m., a fundamental trader used a broker algorithm to sell a total of 75,000 e-mini contracts with a notional amount of approximately \$4.1 billion on the Chicago Mercantile Exchange (CME). The trade was intended to hedge an existing equity position. The trader entered the order correctly and specified an upper limit on the amount sold as a percentage of volume but did not set a price limit for the trade. As a result, price movements were magnified by a feedback loop from the volume participation settings, precipitating the actual flash crash.[5] The CFTC/SEC report concluded that this *single* trade was the root cause of the flash crash.

The notion that the flash crash arose from an unlikely confluence of the factors discussed above is reassuring because it suggests that the chance of a recurrence is very low. It is also consistent with the absence of widespread and rapid price declines in any asset class or region in recent decades. However, serious questions remain. The CME e-mini futures order in question was large but not unusually so relative to the millions of contracts a day traded in e-mini futures and the actual volume traded during that period. Indeed, the fundamental trader's participation rate was about 9% of the approximately 140,000 e-mini contracts traded in from 2:41 to 2:44 p.m. The futures market did not exhibit the extreme price movements seen in equities, which suggests that the flash crash might be related to the specific nature of the equity market structure. There have also been recent instances where individual stocks experienced "micro" flash crashes.[6] For example, on 27 September 2010, Progress Energy—which had been trading at about \$44.50 per share—inexplicably fell almost 90% in price before recovering in the next five minutes. Other examples of very sharp price declines followed by rapid reversals without obvious cause include such well-known names as Citigroup and the Washington Post Company. Unlike the "macro" flash crash of 6 May, these "micro" flash crashes did not cluster in time and affected only individual stocks. Nonetheless, they are recent phenomena and suggest the presence of more systemic factors.

Recent analyses have provided more insight into other, more fundamental potential triggers. In particular, considerable debate has occurred regarding high-frequency trading activity and market quality. It is useful to distinguish between algorithmic trading, defined as rule-based electronic trading with specific goals for execution outcomes, and high-frequency trading, where orders are electronically routed to venues with a focus on minimal latency. The volume attributed to high-frequency trading (including statistical arbitrage, liquidity provision, and "order anticipation" strategies) has grown rapidly in recent years; Zhang (2010) reported that high-frequency trading accounts for up to 70% of dollar trading volume in U.S. equities.

The increase in high-frequency trading has raised concerns, especially given order cancellation rates of about 90% and the fact that these strategies are not well understood. For example, some high-frequency traders are alleged to use "quote stuffing" tactics—where they post and immediately cancel orders—in an effort to gain an advantage over rivals. Intentional quote stuffing allegedly works by jamming the signal bandwidth of other fast traders, who must process quotation changes that *only* the trader posting the rapid quote changes can safely ignore.[7] More generally, the term refers to sudden spikes in quotation activity that appear unrelated to fundamental news events or trading volumes. Egginton, Van Ness, and Van Ness (2011) provided an empirical definition of quote stuffing and found that during periods of intense quoting activity, affected stocks experience lower liquidity, higher transaction costs, and increased volatility.

But recent empirical evidence on the impact of high-frequency traders and faster trading is mixed. Hasbrouck and Saar (2010) examined low-latency strategies that respond to market events in milliseconds using one month of data from 2007 and one month of data from 2008.[8] They identified "strategic runs" that are a series of linked submissions, cancellations, and executions that are likely to have been parts of a dynamic strategy. Their results suggest that increased low-latency activity improves such market quality measures as short-term volatility, spreads, and displayed depth. Similarly, Hendershott, Jones, and Menkveld (2011) found that algorithmic trading narrows spreads, lessens adverse selection, and decreases trade-related price discovery. Zhang (2010) concluded that high-frequency trading has a positive correlation with stock price volatility after controlling for exogenous determinants of volatility. The correlation is also stronger during periods when high-frequency trading volumes are high, which impairs price discovery. Hendershott and Moulton (2011) provided empirical evidence that automation has mixed effects. Faster trading increases bid–ask spreads but also results in more efficient prices.

Kirilenko, Kyle, Samadi, and Tuzun (2010) examined the behavior of the e-mini S&P 500 Index futures market on 6 May 2010 using audit-trail transaction data. They classified more than 15,000 trading accounts that traded on the day of the flash crash into six subjective categories: high-frequency traders, intermediaries, fundamental buyers, fundamental sellers, opportunistic traders, and noise traders. The authors concluded that "High Frequency Traders did not trigger the Flash Crash, but their responses to the unusually large selling pressure on that day exacerbated market volatility" (p. 1).

Related concerns surround "venue toxicity" and aggressive order tactics that cause rapid shifts in liquidity, which, in turn, could have led to the flash crash. Easley, López de Prado, and O'Hara (2011) measured venue toxicity on the basis of the estimated probability of informed trading in a stock. They argued that there is "compelling evidence" that the flash crash could have been anticipated because increasing toxicity of order flow induces less liquidity provision by market makers. Similarly, Chakravarty, Wood, and Upson (2010) focused on the use of liquidity-demanding orders that sweep the entire book, known as intermarket sweep orders (ISOs). They found an increase in ISO activity in S&P 500 stocks during a short period around the time of the flash crash and concluded that these orders may have triggered the flash crash by aggressively taking bid-side liquidity.

These analyses contribute deeply to our understanding of the chronology of the flash crash and its possible catalysts. In contrast, this article focuses on analyzing the role of equity market microstructure in explaining the risk of an extreme price movement and remains agnostic about the specific trigger or spark. Specifically, I hypothesize that order book liquidity for securities that experience market fragmentation is more susceptible to the effects of transitory order imbalances. Fragmentation is normally measured in *ex post* terms—by actual volumes traded across venues—but quotation activity may present a better idea of the true competition for order flow. Measures of fragmentation based on quotations (rather than volumes) capture the competition among high-frequency traders and aggressive quote behavior that could cause the withdrawal of liquidity in times of market stress. The rapid growth of high-frequency trading, however, is a recent phenomenon—hence, my interest in both measures. My hypothesis is that securities with greater fragmentation prior to 6 May 2010 were disproportionately affected during the flash crash.

Data Sources and Procedures

I turn now to my empirical investigation, beginning with a review of my data sources and procedures to select the sample universe.

Sample Selection. The sample universe consists of all 6,224 exchange-traded equity instruments in the United States for which a complete trading history is available from the NYSE Trade and Quote (TAQ) database and Bloomberg for 6 May 2010 and the 20 prior trading days (7 April to 5 May). I excluded stocks that experienced corporate actions in the previous month, which reduced the sample modestly to 6,173 names.

The sample comprises 4,003 common stocks, 968 ETPs, 602 closed-end funds, and 319 American Depositary Receipts, with the remainder being REITs and miscellaneous equity types. Regarding the primary exchanges, there are 2,560 NASDAQ National Market (Capital Market/Global Market/Global Select Market) names, 2,314 NYSE-listed stocks, and 917 NYSE Arca securities, with the remainder on Amex.[9] It is also worth noting that the majority of ETPs (897 names) are listed on NYSE Arca.

Using the TAQ data, I computed a measure of how much a security was affected on the day of the flash crash. I defined the maximum drawdown as M, a continuous variable in the [0, 1] interval representing the largest price declines in the afternoon of 6 May 2010:

$$M = 1 - \left(\frac{p^{Lo}}{p^{Hi}} \right). \qquad (1)$$

That is, the drawdown is one less the ratio of the intraday low price to the intraday high price between 1:30 and 4:00 p.m. I collected data on a variety of stock-specific variables based on both daily and intraday data. These include equity type (e.g., ETP, REIT), market capitalization (in millions of U.S. dollars), primary exchange, Global Industry Classification Standard sub-industry, and average daily dollar volume for the 20 trading days prior to the crash. I also included volatility, which I defined as the standard deviation of five-minute returns over the 20 trading days prior to the crash in the interval 1:30–4:00 p.m.

Each trade in the TAQ data is flagged with one or more condition codes, including intermarket sweep orders. ISOs are limit orders that are exceptions to the order protection rule; they allow users to sweep all available liquidity at one market center, even if other centers are publishing better quotes. Traders using ISOs fulfill their Regulation National Market System (NMS) obligations to obtain the best price by simultaneously sending orders to all market centers with better prices. ISOs are most commonly used by market makers and institutional trading desks to sweep all available liquidity; they are rarely used by retail investors. I computed the percentage of dollar volume of trades flagged as ISOs (identified by Condition Code F) for 6 May and separately for the previous month.

Measures of Fragmentation. I used exchange codes at the trade- and quote-specific level to construct market structure metrics that capture the fragmentation of the market. Measuring fragmentation in terms of traded volumes is natural because it reflects the end result of traders' routing decisions across venues. The simplest (inverse) measure of fragmentation for a given stock is the k-venue concentration ratio, C_k, defined as the share of volume of the k highest share market centers. So, C_1 is the volume share of the venue with the highest market share, C_2 is the volume share of the two largest venues combined, and so on, with $C_1 < C_2 < C_3$. Although simple, the concentration ratio may miss nuances of market structure from competition beyond the largest market centers, so I focused on the Herfindahl index, a broader measure commonly used in the industrial organization literature. The volume Herfindahl index for a given stock on day t is defined as

$$H_t^v = \sum_{k=1}^{K} \left(s_t^k \right)^2, \qquad (2)$$

where s_t^k is the volume share of venue k on day t. The Herfindahl index ranges from 0 to 1, with *higher* figures indicating *less* fragmentation in that particular stock.

Fragmentation can also be measured in terms of competition to attract flow by determining the frequency with which a venue becomes the best intermarket bid or offer. Let n_t^k represent the proportion of times that venue k had the best offer price of all posted National Best Bid and Offer (NBBO) quote changes on day (interval) t. H_t^a is the ask-side Herfindahl index for a stock on day t, where

$$H_t^a = \sum_{k=1}^{K} \left(n_t^k \right)^2. \qquad (3)$$

H^a denotes the Herfindahl index averaged over the 20 trading days prior to the flash crash. Correspondingly, H^b can be defined as the average bid Herfindahl index. Intuition suggests a very high correlation between bid- and offer-side quote fragmentation, but they can differ because of short-selling constraints or other factors and over shorter intervals of time. For much of my analysis, I used the average quote Herfindahl index, $H^q = (H^a + H^b)/2$.

Note that there are other sensible definitions of quote fragmentation. For example, if the current best bid for a stock is \$34.48 (at venue A) and venue B improves that to \$34.47, you would tally one for venue B. If one second later another venue, venue C, joins the best bid at \$34.47, you would increment the count for venue C in computing Equation 3. As an alternative, you could exclude this latter quote change—because the best bid is unchanged—and restrict the count to only those observations offering real price improvement. In the former case, the total count K in Equation 3 would be lower and you would see higher reported fragmentation. I generally focused on straight quote competition at the NBBO (i.e., based on Equation 3).

I computed the average daily Herfindahl indices (volume and quote) and concentration ratios from 1:30 to 4:00 p.m. for the 20 trading days prior to the flash crash and for the day of the flash crash. Quote fragmentation and volume fragmentation are distinct, albeit closely related, economic measures. Volume fragmentation reflects the outcome of order-routing decisions based on price and such factors as make/take rebates and dark pool liquidity. In contrast, quote fragmentation captures the dynamic competition for order flow through quotation activity. Quote fragmentation is complementary to the volume-synchronized probability of informed trading (VPIN) measure used by Easley, López de Prado, and O'Hara (2011). Essentially, VPIN is a Level I metric (in that it uses time, traded volume, and price), whereas the measure proposed here is a Level II metric that uses the order book and its history. The correlation between the volume and quote Herfindahl indices is just 0.57, so it is evident that they capture different phenomena.

Empirical Analysis

In this section, I assess whether (controlling for other factors) fragmentation of trade and quote activity across exchanges played a role in the flash crash.

Descriptive Statistics. The role of equity market structure is highlighted in **Table 2**, which compares measures of concentration based on daily sample means (not weighted by market capitalization or dollar value to avoid distortion by mega-cap stocks) for the baseline period of the 20 trading days prior to the flash crash (7 April–5 May 2010) and for 6 May 2010. The table also shows the data for ETPs and for non-ETP equity instruments.

The results confirm that ETPs were differentially affected during the flash crash, as measured by the steepness of the price declines they experienced. As shown in Table 2, the average drawdown for ETPs is 0.24, versus 0.08 for other equity assets. The second moment of drawdown is also much larger for the ETP universe. Irrespective of the measure of fragmentation used, ETP trading volume is more concentrated than that of other equities. The average top venue concentration ratio, C_1, is 0.56 for ETPs, versus 0.48 for non-ETP equities. This result could reflect the fact that the NYSE trades only NYSE-listed securities; most ETPs are listed on NYSE Arca. Across all asset types, fragmentation was significantly *higher* on 6 May 2010 than in the previous 20 trading days. Note that all asset types showed a marked increase in volume on the day of the flash crash, but the relative increase in the dollar volume in ETPs was much greater than that of other equities. This finding is consistent with the fact that ETPs typically account for a higher percentage of volume on volatile days.[10]

Table 2. Market Structure Variables before and during the Flash Crash

		Baseline Period				6 May 2010			
	Maximum Drawdown	C_1	Volume Herfindahl	Quote Herfindahl	ISO Frequency	C_1	Volume Herfindahl	Quote Herfindahl	ISO Frequency
Universe									
Mean	0.106	0.49	0.36	0.31	0.27	0.46	0.33	0.33	0.37
Median	0.065	0.48	0.34	0.29	0.30	0.42	0.29	0.31	0.36
Std. Dev.	0.170	0.12	0.12	0.09	0.13	0.14	0.13	0.10	0.15
Non-ETPs									
Mean	0.080	0.48	0.35	0.31	0.28	0.45	0.32	0.33	0.36
Median	0.064	0.46	0.32	0.29	0.30	0.42	0.29	0.30	0.35
Std. Dev.	0.096	0.12	0.11	0.09	0.12	0.14	0.12	0.11	0.14
ETPs									
Mean	0.243	0.56	0.45	0.35	0.21	0.50	0.38	0.37	0.40
Median	0.078	0.55	0.42	0.33	0.23	0.47	0.34	0.35	0.42
Std. Dev.	0.338	0.14	0.15	0.10	0.16	0.16	0.15	0.12	0.20

Notes: The table provides summary statistics on market structure variables for the baseline period of the month prior to the flash crash (20 trading days) and for 6 May 2010 for the universe (6,173 stocks) and separately for 5,205 non-ETP equities and 968 ETPs. C_1 is the concentration ratio for the top venue. Herfindahl concentration indices are reported for actual volume and for counts of quote improvement on the bid and ask sides. ISO frequency is the average dollar-weighted frequency of intermarket sweep orders. The data are based on the NYSE TAQ database.

An increase in the use of aggressive tactics—based on the dollar volume with Condition Code F in the TAQ database—occurred on the day of the flash crash, and the increase was greater for ETPs than for other equities. For non-ETP equities, the mean frequency of Condition Code F (ISOs) was 0.36 on 6 May, versus an average of 0.28 for the baseline period. For ETPs, however, the mean ISO frequency was 0.40 on 6 May, versus an average of 0.21 in the month before. The difference in means is statistically significant for ETPs but not for common stocks. In both cases, the medians are close to the corresponding means, so results are not skewed by a few outliers.

I also examined whether other condition codes (e.g., stock option trades) showed marked differences between the day of the flash crash and the previous month. None of the differences are economically or statistically significant. The results show no clear relationship between drawdown and liquidity as proxied by market capitalization and trading volume, respectively. The concentration indices, however, generally decline with drawdown—consistent with my hypothesis—but the relationship is not monotonic.

Separating the data by liquidity is logical because fragmentation is likely to vary systematically in this dimension. **Table 3** provides means of key economic variables in the baseline period and the maximum drawdown on 6 May 2010 based on deciles of average daily dollar volume. Each decile contains about 622 stocks, so the standard error of the mean is relatively small. To avoid potential skew, the means are not weighted by size or volume. Note that two of the concentration measures—the top venue share (C_1) and the volume Herfindahl index—are strongly negatively related to volume, which is consistent with greater intermarket competition in more liquid stocks. The quote fragmentation measure does not vary much with volume, which suggests different drivers. As volume and company size increase, the ISO frequency (dollar weighted) monotonically increases, which is consistent with greater use of sweep orders in more liquid stocks and greater fragmentation. Finally, drawdown increases steadily to 13–14% in Deciles 5–7 before declining again to 10% in the top decile (i.e., the relationship with volume is not monotonic).

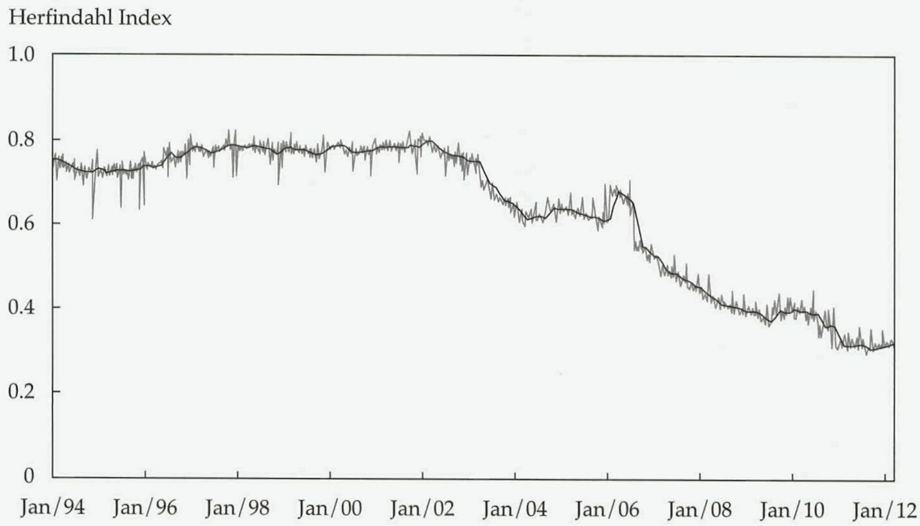
Time-Series Variation in Fragmentation. The time series of fragmentation can provide valuable historical context. I used 18 years of intraday TAQ data for all U.S. equities from 3 January 1994 to 30 March 2012, a period that includes many important market structure changes. There are 4,587 trading days in the sample and a total of 42.6 million stock-days. For each stock on each day, I computed the volume Herfindahl index using all trades in the TAQ database for that stock on that day—a computationally challenging task. I then computed the average stock's Herfindahl index (unweighted mean) to get an overall market concentration statistic for the day. **Figure 1** plots the time series of the daily marketwide Herfindahl index along with a 50-day moving average. There is variation from day to day, but the mean individual stock concentration was relatively constant from 1994 to the end of 2003,

Table 3. Market Structure Variables by Trading Activity

Volume Decile	Avg. Daily Dollar Vol. (millions)	Market Capitalization (millions)	ETP Proportion	ISO Frequency	C_1	Volume Herfindahl	Quote Herfindahl	6 May 2010 Maximum Drawdown
All	$ 42.7	$ 3,665.1	15.6%	26.9%	0.488	0.363	0.330	0.106
1	0.0	101.4	12.7	6.3	0.672	0.573	0.354	0.047
2	0.2	272.5	22.2	19.5	0.593	0.469	0.326	0.077
3	0.4	180.8	20.7	25.5	0.541	0.410	0.312	0.104
4	0.7	374.4	16.7	28.1	0.516	0.381	0.318	0.117
5	1.5	755.3	17.7	28.5	0.503	0.365	0.308	0.129
6	3.0	971.0	14.5	29.2	0.480	0.342	0.301	0.140
7	6.1	1,182.5	14.8	30.5	0.453	0.318	0.306	0.129
8	14.9	2,878.4	12.1	32.2	0.412	0.284	0.301	0.114
9	42.6	6,089.4	8.4	33.9	0.371	0.252	0.302	0.102
10	357.3	23,746.7	15.9	35.8	0.343	0.234	0.312	0.100

Notes: The table provides summary statistics for the 20 trading days prior to the flash crash (7 April–5 May 2010) for the universe of 6,173 equity instruments (stocks and ETPs) and for the 10 deciles of average daily dollar volume. ISO frequency is the average dollar-weighted frequency of intermarket sweep orders, C_1 is the concentration ratio or the share of the top venue, and the Herfindahl indices measure the concentration in traded volumes and quote competition (averaged on the bid and ask sides). The maximum drawdown on the day of the flash crash is also shown.

Figure 1. Daily Herfindahl Index for U.S. Equities and 50-Day Moving Average, 3 January 1994 to 30 March 2012



when the index was 0.752. A secular decline in concentration (an increase in fragmentation) is evident beginning in the second quarter of 2003. Several market structure changes are likely to have increased fragmentation in the past decade. Decimalization began in a phased manner starting in early 2001, when stocks began trading for the first time in minimum price increments of one cent. The ability of traders to undercut quotes by one cent versus an eighth or a sixteenth of a cent led to greater competition among venues. The introduction by the U.S. SEC of Regulation NMS in 2005 was also associated with a sharp increase in competition among primary exchanges from other venues, the entrance of many new venues (dark pools and electronic communications networks, or ECNs), internalization of flow by brokers, and the growth of higher-frequency trading. Many higher-frequency traders in particular prefer to trade on ECNs rather than on traditional exchanges.

By the end of the sample period in March 2012, the average stock's Herfindahl index was approximately 0.306. Although fragmentation has been increasing over much of the past decade, the new levels are unprecedented and may represent a tipping point in terms of the vulnerability of stock prices to an order flow shock or other impulse. Indeed, equity market fragmentation is now at its highest level ever and dramatically higher than it was 18 years ago.

The intraday evolution of the fragmentation measures on the day of the flash crash is also of interest. **Figure 2** shows the evolution of the volume and quote Herfindahl indices over the trading day on 6 May. For each one-minute interval, I calculated the volume and quote Herfindahl indices at the stock level and then estimated the sample mean across all stocks relative to the corresponding value for the same time interval on the day before (i.e., on 5 May). The figure shows five-minute moving averages for both indices. The relative quote index decreased sharply at the time of the flash crash, and at its lowest point, it was almost 10% below the corresponding level the day before. This result suggests greater venue fragmentation in the late afternoon as off-exchange competition increased. In contrast, the corresponding volume fragmentation figures instead show a marked increase in concentration at this time as intermarket linkages broke down and the NYSE entered its slow-trading mode. The divergent intertemporal behavior exhibited in Figure 2 is consistent with my previous assertion that trade fragmentation and quote fragmentation capture different phenomena and can exhibit divergent behavior.

Examining the market shares of major venues over the day provides additional insight. **Figure 3** shows the market shares of the major venues—NYSE Arca, BATS, NASDAQ (combined), NYSE—as well as the trade reporting facilities (TRFs) and all other exchanges.[11] For each five-minute window, I computed the market share of each venue as a percentage of dollar volume traded in the overall U.S. equity market. Market shares were relatively stable until the start of the flash crash, when intermarket linkages broke down and the NYSE's market share dropped sharply. Later in the day, the market share of off-exchange venues declined and a return to normalcy occurred. The dynamic nature of competition among the venues is quite apparent.

Figure 2. Herfindahl Indices on 6 May 2010 Relative to 5 May 2010: Five-Minute Moving Average

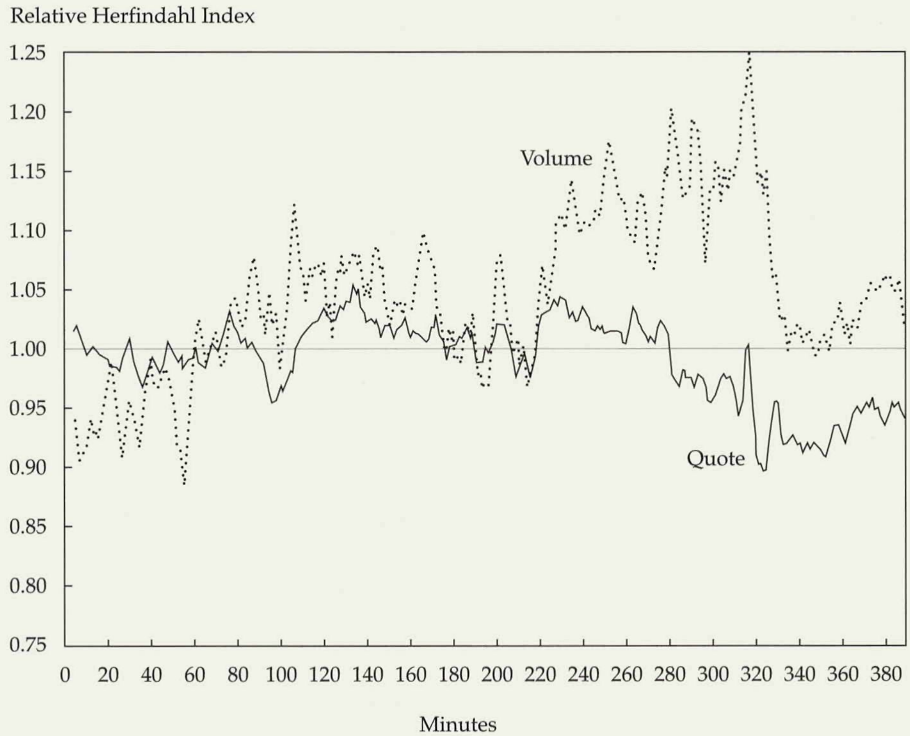
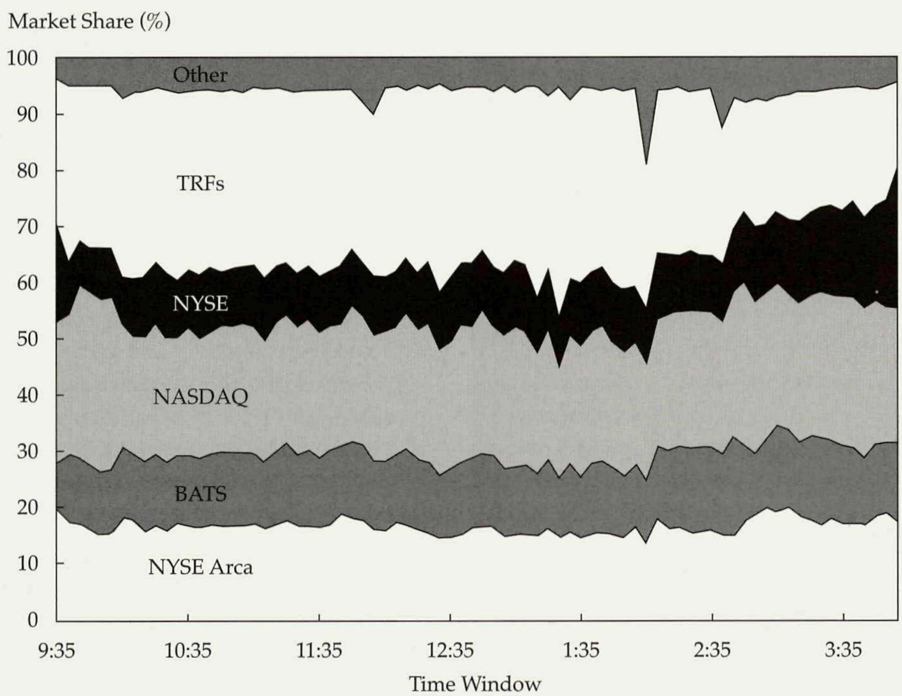


Figure 3. Venue Market Shares on 6 May 2010 in Five-Minute Time Windows



Determinants of Market Fragmentation. The complex interrelationships between the economic variables make it difficult to isolate the true determinants of fragmentation, necessitating a multivariate analysis. I modeled the Herfindahl volume and quote concentrations, H_i, in a given stock i as a function of various asset-specific characteristics. Given that the dependent variable is directly related to the ratio of outcomes to trials (e.g., a venue's share in total volume or quote changes), I used a logistic regression and model fragmentation:

$$\begin{aligned} H_i &= F(\mathbf{x}_i'\beta) + u_i, \text{ and} \\ \mathbf{x}_i'\beta &= \beta_0 + \beta_1 NYSE_i + \beta_2 \log(MktCap) \\ &\quad + \beta_3 Volatility_i + \beta_4 ISO_i + \beta_5 ETP_i + u_i. \end{aligned} \tag{4}$$

Here, $F(\mathbf{x}_i'\beta)$ is the logistic function and u_i is a stochastic error term. The independent variables are chosen to capture stock-specific factors and other controls. The most obvious of these are the primary listing exchange of the stock, proxies for trading activity (e.g., company size), and controls for asset type. I also included a measure of whether higher-frequency traders are active in the stock using intermarket sweep orders. Accordingly, I defined the independent variables as follows: *NYSE*, an indicator variable for whether the New York Stock Exchange is the primary exchange for the asset; log(*MktCap*), the log of market capitalization (in millions of dollars); *Volatility*, the standard deviation of five-minute returns (scaled by 10^{-6}) in the control period in the time window 1:30–4:00 p.m.; *ISO*, the average frequency of intermarket sweep orders over the 20 trading days prior to 6 May 2010; and *ETP*, an indicator variable for whether the asset type is an exchange-traded product.

Table 4 provides the logistic regression estimates for volume and quote concentration, estimated separately. Because the dependent variable is a concentration measure, negative coefficient signs imply more fragmentation. So, the negative sign on the *NYSE* indicator variable in both models implies more fragmentation for stocks whose primary exchange is the NYSE than for those listed on other venues. Consistent with the earlier results, I found clear evidence that there is more concentration in smaller-cap issues; across stocks, the volume Herfindahl index declines (i.e., fragmentation rises) as capitalization increases. Interestingly, this is not the case in the quote fragmentation model, which suggests that attributes other than size matter in price competition. This result may be due to the fact that the underlying driver of competition (i.e., the profitability of quote-improving strategies) is complex and may have other determinants beyond those captured in Equation 4. In both cases, there is no evident relationship between fragmentation and volatility. The ISO variable is highly significant and negative in both models, which indicates that ISO activity is positively associated with volume and quote fragmentation. This finding is consistent with the idea that high-frequency traders use these types of orders to sweep limit order books to access all available liquidity. The ETP dummy variable is not significant after controlling for other factors.

Table 4. Cross-Sectional Determinants of Fragmentation
(standard errors in parentheses)

	Volume Concentration	Quote Concentration
Intercept	0.646**	–0.701**
	(0.091)	(0.092)
NYSE	–0.189**	–0.429**
	(0.068)	(0.070)
log(*MktCap*)	–0.131**	0.035*
	(0.018)	(0.018)
Volatility	–0.142	–0.077
	(0.547)	(0.586)
ISO	–1.516**	–0.514**
	(0.253)	(0.260)
ETP	0.027	0.016
	(0.079)	(0.080)
Residual deviance	109.185	164.255
Null deviance	394.180	211.626
Degrees of freedom	6,155	6,155

Note: The table presents logistic models of Herfindahl concentration indices for volume and quote activity.

*$p < 0.05$.
**$p < 0.01$.

I also estimated linear models for fragmentation and obtained the same results. Residual deviance for a logistic model is analogous to the residual sum of squares in a linear regression (it has a chi-square distribution), and I used it to assess the overall fit of the model. The results suggest that the model for volume fragmentation is a better fit than the equivalent quote model. It may be easier to interpret this "goodness of fit" in terms of corresponding adjusted R^2s in the linear specifications: 0.72 and 0.21 for the volume and quote fragmentation models, respectively. The fact that some of the key variables are statistically significant means the logistic model (Equation 4) provides valuable information linking stock-specific factors to fragmentation.

Analysis of Drawdown. I turn now from the determinants of market fragmentation to an analysis of the role of market structure in explaining the pattern of *maximum drawdown* on 6 May 2010.[12] As noted previously, I wanted to examine both quote and volume fragmentation measures (H^q and H^v) in prior periods because my hypothesis is that stocks with greater fragmentation were more exposed to impulses that could trigger abrupt price declines.

The discussion in the previous section highlights the need for suitable controls at the stock-specific level, including liquidity, volatility, routing behavior, and asset type. I used dollar volume as the proxy for liquidity. Because this variable is highly skewed to the right and approximately lognormally distributed, I used a log transformation in my models to dampen the impact of large-volume outliers. For volatility, past research has shown a strong intraday seasonality that varies across stocks. Accordingly, I used an intraday measure (five-minute return volatility) estimated over the afternoons in the control period. Given that the drawdown is essentially a return, I included the inverse of the opening price on 6 May 2010 to capture any bid–ask spread or other microstructure effects related to price level. I also included past ISO activity as a control for the propensity for higher-frequency traders to trade that particular stock using aggressive order techniques. I expected greater ISO activity to be associated with more fragmentation. Finally, regarding asset type, the results from Tables 2 and 3 indicate that it is important to control for whether the stock in question is an ETP or another type of equity.

Table 5 contains estimates of multiple regression models where, for stock i, the dependent variable is the maximum drawdown, M_i, and the independent regressors include market structure variables and other control variables:

$$\begin{aligned} M_i = \beta_0 + \beta_{1,v} H_i^v + \beta_{1,q} H_i^q + \beta_2 \log(ADV_i) \\ + \beta_3 Volatility_i + \beta_4 InvPrice_i \\ + \beta_5 ISO_i + \beta_6 ETP_i + u_i. \end{aligned} \tag{5}$$

The control variables are computed over the 20 days prior to the flash crash and include

- $\log(ADV)$, the log of average daily volume in millions of dollars;

Table 5. Multivariate Analysis of Maximum Drawdown
(standard errors in parentheses)

	7 April–5 May 2010		5 May 2010	
	I	II	III	IV
Intercept	0.147**	0.166**	0.089**	0.130**
	(0.015)	(0.016)	(0.010)	(0.012)
Volume Herfindahl	–0.182**	–0.150**	–0.043*	–0.015
	(0.033)	(0.031)	(0.020)	(0.020)
Quote Herfindahl	—	–0.108**	—	–0.143**
	—	(0.024)	—	(0.020)
log(*ADV*)	–0.000	0.001	0.003**	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)
Volatility	–0.010	–0.010	–0.008	–0.010
	(0.043)	(0.043)	(0.043)	(0.043)
InvPrice	0.010	0.008	0.001	–0.002
	(0.006)	(0.006)	(0.006)	(0.006)
ISO	–0.019	–0.013	0.012	0.010
	(0.022)	(0.022)	(0.021)	(0.021)
ETP	0.181**	0.182**	0.171**	0.178**
	(0.006)	(0.006)	(0.006)	(0.006)
Adjusted R^2	0.131	0.134	0.141	0.136
F-statistic	155.6	136.5	135.4	135.4

Notes: The table presents cross-sectional regression models of maximum drawdown on 6 May 2010 regressed on control and market structure variables (6,151 observations):

$$M_i = \beta_0 + \beta_{1,v} H_i^v + \beta_{1,q} H_i^q + \beta_2 \log(ADV_i) + \beta_3 Volatility_i + \beta_4 InvPrice_i + \beta_5 ISO_i + \beta_6 ETP_i + u_i.$$

Here, $H_i^v\left(H_i^q\right)$ is the Herfindahl concentration index for volume (quote) activity in the control period, 7 April–5 May 2010, in Models I and II and on 5 May 2010 in Models III and IV.

*$p < 0.05$.
**$p < 0.01$.

- *Volatility*, the average volatility measured by the 20-day average of the daily standard deviation of five-minute return intervals scaled by 10^{-6} in the period 1:30–4:00 p.m.;
- *InvPrice*, the inverse of the opening price on 6 May 2010;
- *ISO*, intermarket sweep order activity measured by the dollar-weighted proportion of volume accounted for by Condition Code F orders;
- *ETP*, a dummy variable that takes a value of 1 if the asset is an ETP and 0 otherwise; and
- u_i, a stochastic error term.

Table 5 presents four models, two each for the control period (7 April–5 May 2010) and the day before the flash crash (5 May 2010). I estimated Model I using *only* volume fragmentation (i.e., I set $\beta_{1,q} = 0$), whereas for Model II, I allowed both volume and quote fragmentation effects, where fragmentation is measured over the previous month. Models III and IV are identical to Models I and II, respectively, except that they use the most recent measure of fragmentation (i.e., the Herfindahl indices based on the day before the flash crash).

Recall that larger values of the measures H^q and H^v mean more concentration, so a negative coefficient implies that more fragmented stocks are associated with larger values of the drawdown coefficient. For Models I and III, with volume fragmentation alone, the coefficient is negative in the control period, which is consistent with the hypothesis that more fragmented stocks experienced greater drops on 6 May after controlling for other factors. The coefficient is statistically significant at the 5% level for the control period (Model I), but it is not significantly different from zero using the fragmentation estimates from the day prior (Model III).

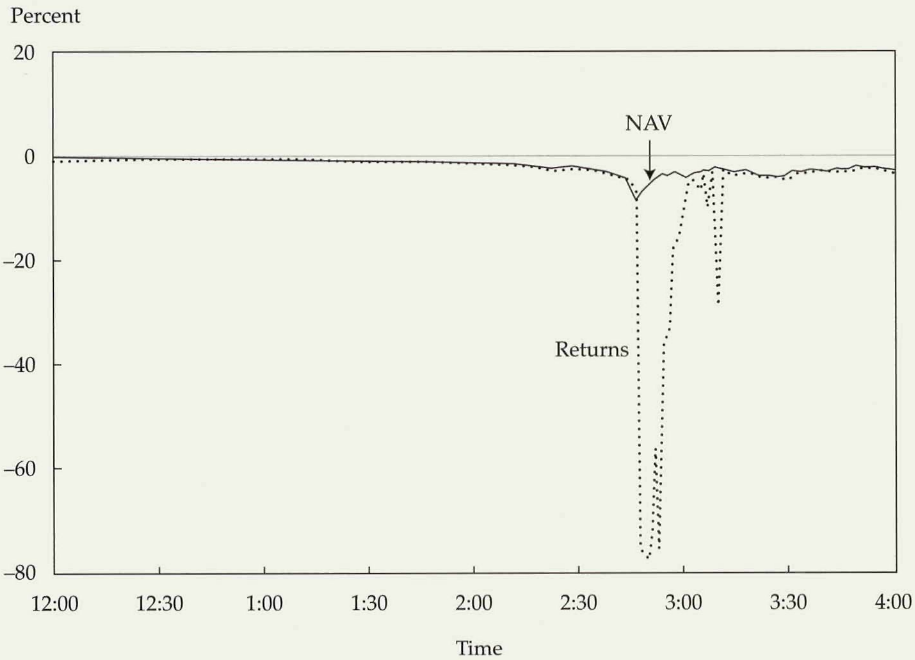
Of particular interest is that the inclusion of quote fragmentation (Models II and IV) adds explanatory power. Both volume and quote fragmentation measures are statistically significant at the 1% level in Model II, which uses the control period data. For Model IV, which uses the most recent day for the Herfindahl computations, the coefficient for volume fragmentation is statistically insignificant and the coefficient for quote fragmentation is negative and significant at the 1% level. This result confirms that volume fragmentation and quote fragmentation are different economic phenomena. Quote fragmentation is an important risk factor in explaining the propagation of the original liquidity impulse, consistent with the thinning out of order books in those stocks with the most aggressive quotation activity by higher-frequency traders. The importance of quote fragmentation in explaining the cross-sectional impact of the original liquidity shock highlights the importance of imperfect intermarket linkages, which are the root cause of fragmentation. In contrast, O'Hara and Ye (2011) did not find evidence that market fragmentation harms market quality, possibly because imperfect intermarket linkages matter most in times of stress.

Volatility does not appear to be a predictor of drawdown, which indicates that the events of 6 May 2010 were not related to the normal patterns of risk. The inverse price variable is positive in Models I–III, which suggests larger drawdowns in lower-priced stocks, but it is not statistically significant. Average daily volume effects are weak cross-sectionally; other control variables, including price, may capture the effect of liquidity. Prior ISO activity has a negative coefficient in Models I and II but is not significant. As documented in Table 5, this variable is positively associated with fragmentation, so the presence of the fragmentation variables already captures the impact of ISO activity. Note that omitting this variable has no real impact on the estimated coefficients or their significance levels.

The ETP indicator variable is positive and significant after controlling for other independent variables. Note that this result does not reflect a failure of ETF pricing. Rather, uncertainty in the quoted prices of component stocks makes it increasingly challenging for market makers as the normal arbitrage pricing mechanism breaks down. Of course, market makers routinely make tight markets in ETPs where quotes on the underlying component securities are not available or timely (e.g., international ETPs), but in such cases, they are not exposed to risk arising from those securities' being traded simultaneously. The iShares Russell 1000 Growth Index Fund (IWF) provides an illustrative case study. **Figure 4** plots the cumulative continuously compounded returns of the ETF and its intraday net asset value (NAV) in 60-second increments from 12:00 to 4:00 p.m.[13] Prior to the flash crash, the ETF price closely tracked the intraday net asset value of its constituent stocks, reflecting the smooth operation of the intraday creation/redemption arbitrage mechanism. The tight relationship of price and intraday net asset value held until about 2:45 p.m., at which point the constituents of the underlying basket themselves could not be correctly priced. The uncertainty caused a temporary delinking of price and value. The ETF then experienced a sharp price decline but recovered rapidly, with its price again closely tracking its intraday net asset value by 3:10 p.m.

The multivariate results are robust to a number of alternative specifications and controls. Specifically, I estimated logistic regressions to account for

Figure 4. Cumulative Intraday Returns and Net Asset Value for iShares Russell 1000 Growth Index Fund, 6 May 2010



the limited range of the dependent variable and reached the same conclusions.[14] I also estimated models that include primary exchange but found no evidence that primary exchange listing is a factor in explaining the cross-sectional patterns of price declines; the same is true for models that include asset type (other than ETP). Overall, the goodness of fit as measured by the adjusted R^2 is more than 13%, which is relatively high given the dispersion in the dependent variable.

Conclusion

Late in the afternoon on 6 May 2010, the sharpest intraday point drop in the history of the Dow Jones Industrial Average occurred. The so-called flash crash is distinguished from other market breaks by its speed, its rapid intraday reversal, and the fact that many stocks and ETPs traded at clearly unreasonable prices. This article highlights the role of equity market structure and the changing nature of liquidity provision in exacerbating the impact of an external liquidity shock, without taking a view as to its catalyst.

Specifically, I showed that the impact of the flash crash was greatest in stocks experiencing fragmentation *prior* to 6 May. Both volume fragmentation (which represents the actual pattern of trading activity across venues) and quote fragmentation (which captures the dynamic competition for flow) are important in explaining the propagation of the crash. Using tick data for all stocks traded in the United States in 1994–2012, I showed that fragmentation is now at its highest level ever. This fact may partly explain why a similar flash crash did not occur previously in response to some other catalyst.[15] In particular, market structure may matter less when the markets are functioning normally than in times of stress.

My research provides a framework to evaluate recent market structure debates in equities, derivatives, and other asset classes as new venues and technologies erode the notion of a single, primary market for a security. This is not to say that I support policies designed to increase market concentration at the possible expense of competition. Rather, my view is that recent policy proposals should be evaluated in the context of whether they address the root causes of fragmentation in the form of intermarket linkages that are inadequate or prone to failure in times of stress.[16]

- *Uniform mechanisms across exchanges to curb extreme price volatility.* Such mechanisms include individual security circuit breakers and price bands (which use a "limit up/limit down" for price movements similar to those used in futures markets worldwide) to pause trading during disruptions, allowing for contra-side liquidity to emerge. Although stock-specific circuit breakers would, by definition, prevent extreme price movements, they pose some challenges. For example, restrictions on price movements at the single-stock level intended to protect investors could complicate the pricing of basket instruments, such as ETPs, as shown in Figure 2. Further, the tiers of the limit up/limit down are consistent between stocks in a basket and the corresponding ETF. So, trading in an ETF could be temporarily halted even though the basket constituents continued to trade.[17] The converse is also possible. Circuit breakers also do not resolve the underlying issue of fragmentation, which remains a risk factor. Bethel, Leinweber, Rübel, and Wu (2011) suggested that market fragmentation signals gave warnings ahead of the flash crash on 6 May 2010. They noted that a more graduated approach relying on an early warning system for unusual market conditions based on such indicators could be more effective than a hard circuit breaker.

- *Clearer guidelines for intermarket order routing.* My results highlight the role of quote fragmentation and intermarket sweep orders. Policies designed to reduce the likelihood of orders being routed to venues with little liquidity are thus critically important. My results that show a relationship between ISO activity and fragmentation support the notion of a circuit breaker type of approach (see, e.g., Chakravarty, Wood, and Upson 2010) to limit the use of aggressive sweep orders in times of market stress. A widely discussed idea is a "trade-at" rule that would require off-exchange trades in dark pools or other internalization venues to be executed at prices better than the current national best bid or offer. The trade-at rule is controversial because it could reduce the profitability of brokers who internalize their flow. Critics of the trade-at rule cite unintended consequences in the form of higher execution costs from information leakage, greater latency, and fewer crossing opportunities. The trade-at rule could be difficult to implement and enforce because public quotes may not always be reliable indicators of prices actually obtainable in the market. Without a better understanding of how the trade-at rule would operate, it is difficult to predict whether the outcome would affect fragmentation; it might simply reduce intermarket competition.
- *Greater transparency regarding trade error cancellation rules.* Clear rules regarding when exchange trades will be canceled may prevent the withdrawal of liquidity provision in times of stress. If cancellation rules are arbitrary and nontransparent, liquidity providers, including market makers and some hedge funds, may fear that one side of their hedged trades may be canceled, exposing them to risk when they buy a security that has fallen in price while going short a related asset.
- *Clearly defining the obligations of lead market makers.* There was previously no guidance concerning minimum quoting standards for market makers to maintain two-sided markets. Consequently, market makers commonly relied on "stub quotes" (i.e., offers to buy or sell at a substantial premium above or discount below the best bid or offer). Stub quotes were not intended to be executed but, rather, provided a way for a dealer to participate only on one side of the market. The SEC eliminated stub quotes and implemented new rules that forced market makers to maintain continuous two-side quotations that are within a defined percentage around the best bid or offer. Given my results, this is a sensible approach to preventing the extreme trades (e.g., at pennies) that occurred during the flash crash.
- *Audit trail.* On 26 July 2011, the SEC, motivated by concerns that regulators lacked a complete view of the sequence of events during the flash crash, unanimously passed the "large trader reporting rule." The rule is intended to allow the SEC to reconstruct market events and aid investigations and enforcement actions. It is an important step toward a consolidated audit trail that will give regulators the tools necessary to monitor trading patterns across multiple exchanges and improve enforcement, although there are many technical questions that still need to be addressed, as noted in Bethel, Leinweber, Rübel, and Wu (2011).

In summary, my results show that the flash crash can be linked directly to current market structure—in particular, the pattern of volume and quote fragmentation—which supports the argument that a lack of liquidity is the critical issue that requires the greatest policy attention. Considerable progress on this issue has been made since the dramatic events of 6 May 2010. The safeguards and reforms that have been implemented in the U.S. equity markets should help slow down a potential future market disruption similar to the flash crash. But they have not eliminated the possibility of another flash crash, albeit one with a different catalyst or in a different asset class.

The views expressed here are those of the author alone and not necessarily those of BlackRock, its officers, or its directors. This article is intended to stimulate further research and is not a recommendation to trade particular securities or of any investment strategy. Information on iShares ETFs is provided strictly for illustrative purposes and should not be deemed an offer to sell or a solicitation of an offer to buy shares of any funds that are described in this article. I thank Hering Cheng, Jeff Dean, Jessica Edrosolan, Michael Gates, Joe Gawronski, Bhavna Kapoor, David Leinweber, Marcia Roitberg, Richard Rosenblatt, and Mike Sobel for their helpful suggestions.

This article qualifies for 1 CE credit.

Notes

1. See, for example, Barr (2010), who stated, "Whatever their cause, the frequent market outages only feed the sense that the entire market is either a casino rigged by the money never sleeps crowd or a house of cards on the verge of collapse. Neither view, it seems safe to say, is apt to restore investors' dwindling confidence."
2. A common (inverse) measure of fragmentation is the Herfindahl index, which is simply the sum of the squares of market shares. For a particular stock, if the shares in dollar volume of venues A, B, and C are 50%, 40%, and 10%, the Herfindahl index is 0.42 (= 0.25 + 0.16 + 0.01). If the relative frequencies with which venues A, B, and C become the best bid or offer (as a fraction of all quote changes) are 80%, 10%, and 10%, the index would be 0.66 (= 0.64 + 0.01 + 0.01), indicating less fragmentation. Ignoring the sub-breakdown within dark pools, the overall Herfindahl indices for volume, quotes, and depth in December 2011 for the U.S. market as a whole were 14.8%, 21.0%, and 25.5%, respectively. Clearly, the average of stock-level Herfindahl indices would produce a higher number because some stocks trade primarily in one venue.
3. Exchange-traded funds (ETFs) and exchange-traded notes (ETNs) are subsets of exchange-traded products. In an ETF, the underlying basket securities are physically represented, whereas an ETN is senior, unsecured, and uncollateralized debt that is exposed to credit risk. ETPs account for up to 40% of U.S. trading volume.
4. See, for example, Wurgler (2011). Ramaswamy (2010) examined the operational frameworks of exchange-traded funds and related them to potential systemic risks. The role of leveraged ETFs has also been discussed (see, e.g., Cheng and Madhavan 2009) in the context of end-of-day volatility effects.
5. Faced with increased volume, the NYSE entered "slow-trading mode" while stocks continued to trade in electronic venues, such as BATS, resulting in price distortions. Liquidity providers began to withdraw their liquidity, given concerns that some trades would be canceled under the "erroneous trade rule," resulting in some market sell orders—including stop loss orders—being executed at pennies.
6. See Bowley (2010b) and Barr (2010).
7. See Bowley (2010a).
8. A millisecond is one-thousandth (10^{-3}) of a second. Brogaard (2010) noted that some high-frequency traders execute trades with round-trip execution times measured in microseconds (i.e., in one-millionth [10^{-6}] of a second).
9. The NASDAQ Capital Market (1,285 names) consists of the smaller companies traded on the NASDAQ National Market. The NASDAQ Global Market (900 names) comprises the middle-tier companies on the NASDAQ National Market. The NASDAQ Global Select Market (375 names) represents the highest-cap companies on the NASDAQ National Market.
10. Borkovec, Domowitz, Serbin, and Yegerman (2010) argued that ETF market makers withdrew liquidity after suffering severe losses.
11. Alternative execution facilities, such as ECNs and broker/dealers, are required to report U.S. equity trades away from exchanges through TRFs. Other exchanges include Amex, the Boston Stock Exchange, the Chicago Stock Exchange, and the National Stock Exchange.
12. The results also hold for other measures of the magnitude of the flash crash, including intraday volatility after 2:40 p.m. on 6 May 2010 relative to benchmark afternoon (1:30–4:00 p.m.) volatility for the previous 20 days.
13. Intraday prices are from the TAQ database; net asset values are computed using market capitalization weights at the beginning of the day.
14. Note that there are differences in the empirical distributions of the market structure and return variables that informed my choice of model. That is, the fragmentation variables reflect the outcome of different trials (e.g., a venue's share in volume), whereas the drawdown measure is a return, albeit one constrained to a certain interval.
15. Of course, security prices can exhibit sharp price movements over short time intervals even in a centralized market structure. For example, on 28 May 1962, the DJIA fell sharply and IBM's stock price fell 5.3% in 19 minutes. The decline was broad (1,212 issues declined and only 74 rose), but unlike the flash crash, stocks did not trade at absurd prices. The cause of that event is unclear—perhaps a short-lived panic.
16. Some of the more fundamental market structure recommendations are from the Joint CFTC-SEC Advisory Committee on Emerging Regulatory Issues—a body created by legislation to investigate the flash crash (see CFTC and SEC 2010).
17. The current limit up/limit down proposal has an upper band and a lower band beyond which trading cannot take place. For Tier 1 stocks—which include those in the S&P 500 and the Russell 1000 Index as well as 344 ETFs—the upper and lower bands are 5% of the average price of the security over the preceding five minutes. For Tier 2 stocks (all other securities), the upper and lower bands are 10%. If one of these bands is reached and all orders above or below the band limit are neither canceled nor executed within 15 seconds, then a five-minute pause will occur.

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