Market Quality Breakdowns in Equities

Cheng Gao and Bruce Mizrach^{*} Rutgers University

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Abstract

A breakdown in market quality occurs when an order book thins to the point where extreme price movements are observed. These are frequently reversed as the market learns that nothing fundamental has occurred. The daily average breakdown frequency from 1993-2011 is 0.64%, with averages in 2010-11 below this amount. Controlling for microstructure effects, breakdowns have fallen significantly since Reg NMS. Spikes in market correlation and high frequency trading surges make breakdowns more likely. ETFs break down more often than non-ETFs. Both ETFs and high frequency trading Granger cause market correlation. Breakdowns are predictable for up to two days.

Keywords: market quality; breakdown; ETF; correlation; high frequency trading.

JEL Classification: G12, G14, G18;

^{*} Department of Economics, Rutgers University, e-mail: mizrach@econ.rutgers.edu, (908) 913-0253 (voice) and (732) 932-7416 (fax). http://snde.rutgers.edu. We thank seminar participants at Nasdaq OMX, the 2012 CFTC Research Conference, and the World Finance & Banking Symposium in Shanghai for helpful comments.

1. Introduction

The collapse and sudden rebound of market indices and nearly 2,000 equity prices during the May 6, 2010 "Flash Crash" was a singular event in the history of the equity markets. The Securities and Exchange Commission (SEC) and Commodity Futures Trading Commission (CFTC) both launched full-scale investigations into the causes of the collapse, and a growing body of academic literature has also examined causal mechanisms behind the crash. Although the regulators have implemented a set of rules after the Flash Crash, including single stock circuit breakers and a ban on stub quotes, trading glitches are still happening. These serious errors in 2012, such as BATS Global Markets' initial public offering (IPO) failure on March 23, Facebook's IPO miscue on May 18, and Knight Capital's erroneous order flood on August 1, are merely the latest in a series of breakdowns. These events were not confined to a single stock exchange and the effect of each of these incidents was not transitory: BATS withdrew their IPO, Nasdaq faces billions of dollar in lawsuits from market making firms, and Knight nearly went bankrupt. The run of technology snafus have raised the concern that they could rattle investor's confidence and result in reduced liquidity of the equity market.

The new circuit breakers now trip at a 10% movement intra-daily. Many of these movements will be due to information released about individual stocks. To filter these out, we isolate stocks where prices recover to at least 2.5% below the 09:35 price. Using this definition, we find that the "Flash Crash" is not an isolated event. For example, on April 4, 2000, more than 1,500 stocks fall more than 10% intra-day before recovering most of their losses. These breakdowns occur by more than 30,000 events in 2000.

We ask a simple and straightforward question: how frequently do these breakdowns in market quality occur. We analyze every change in the listing exchanges' best bid and offer for 1993-2011. In total, we examine more than 30 million files of intra-day bid and offer quotes. What we find is that market quality breakdowns have been endemic to the equity markets. The daily average breakdown frequency is 0.64% throughout our sample period, an average of 44 stocks per day.

There is an uptrend in breakdown frequency from 1993-2000. This trend reverses from 2000-2006 but then begins to rise again in late 2007, in the early stages of the financial crisis. Breakdowns continue to rise through 2008, a particularly volatile period for the market. In 2009 though and continuing through 2010, the breakdown frequency is declining. Despite the Flash Crash, 2010 has the fewest breakdowns of any year since 2007. The breakdown frequency is 0.39% in 2011, half

the rate of 1998 when humans provided the majority of quotes. Breakdowns in 2010-2011 occur less than once per year in a typical stock.

The academic literature has suggested a number of possible explanations for market quality breakdowns: (1) regulatory changes; (2) fragmentation; (3) excessive correlation; (4) exchange traded funds (ETFs); and (5) high frequency trading (HFT). We develop an explanatory model, with controls for volume and volatility, to assess the marginal effects of these potential causes of breakdowns. Also, by looking at a longer historical time frame, we hope to identify which explanations are robust.

Changes in the regulatory environment have dramatically effected quote and trade behavior. In 1996, the SEC adopted the display rule which placed electronic trading networks on an even playing field with dealers. Many others have suggested that the SEC's regulations governing the equity national market system has led to market quality deterioration. The biggest change was the adoption of Reg. NMS in April 2005. The new regulations were extended in stages and were fully in place by October 15, 2007. One of our most striking findings is that market quality breakdowns are 41.78% less frequent after Reg. NMS. This implies that approximately 4,000 fewer stocks are breaking down each year compared to the prior period.

Bennett and Wei (2006) claim that order flow consolidation improves market quality. Golub, Keane and Poon (2012) attribute mini-Flash crash episodes in the period 2006-11 to the use of inter-market sweep orders in fragmented markets. Madhavan (2012) suggests that fragmentation from equity market structure changes has made markets more fragile and may have contributed to the Flash Crash. Jiang, McInish and Upson (2011) take the contrary view, noting that order routing away from the primary exchange may result in better executions. O'Hara and Ye (2011) find that the volume share in off-exchange venues does not impact market quality. We use two measures of fragmentation in our analysis. The first is the Herfindahl index of each equity market's contribution to the national best bid and offer and the second is the market share of off-exchange volume. We do not find that either measure of fragmentation helps explain the frequency of breakdowns for the market as a whole.

Even though market structure differences have been reduced, exchanges still matter. Controlling for market capitalization, price, as well as volume and volatility, New York Stock Exchange (NYSE) stocks break down 20.03% less frequently than Nasdaq stocks, 43.91% less frequently than American Stock Exchange (AMEX) listings, and 69.04% less frequently than Archipelago (ARCA) listings.

Since we find that market structure changes appear not to be a primary factor in market breakdowns, we then consider the effects of rising security correlations. Acharya and Schaefer (2006) have noted that individual stocks become more highly correlated during financial crises. There has also been an uptrend in market correlation in recent years. The average correlation among the Fama-French industry portfolios rises from 37.16% in 1993 to 76.32% in 2011.

We construct a theoretical model with correlated liquidity shocks based on Sandås (2001). This model helps us to unify a number of factors in the literature which appear to operate through cross-equity correlation, including both ETFs and high frequency trading.

A market maker in stock A responds to a liquidity shock in stock B, and the limit order books thins to a larger degree when the shocks are more highly correlated. We confirm the model empirically, finding that correlation does spike during market quality breakdowns, raising the frequency of breakdowns by almost 25.62%.

Ben-David, Franzoni, and Moussawi (2012) note that ETFs exacerbate the volatility of the underlying stocks, and that ETFs may have served as an important propagation mechanism during the Flash Crash. We find that ETFs break down 90.33% more frequently than non-ETFs. ETF trading activity unidirectionally Granger causes the market correlation, revealing that ETFs are a source of stronger individual stock correlation and not vice versa.

The impact of HFT remains a widely debated issue. Brogaard (2011) analyzes a high-quality data set that identifies the trade and quote activity of high frequency trading firms. He shows that high frequency traders have become a dominant fraction of market activity, with approximately 70% of dollar volume in 2009. They also engage in highly correlated trading strategies. Several academic papers have suggested that HFT firms generally enhance market quality. Hasbrouck and Saar (2010) find that low-latency activity improves liquidity and dampens short-term volatility. Brogaard, Hendershott and Riordan (2012) argue that HFTs increase the efficiency of prices through their marketable orders.

Other papers suggest that HFT activity might be more harmful. Gao and Mizrach (2011) find that, when markets experience stressful events, HFT firms tend to scale back their liquidity provision. For example, during the Federal Reserve large scale auction purchases of Treasuries, HFT firms were 8% less likely to be providing the inside bid or offer. Zhang (2010) observes that HFT is positively correlated with stock price volatility and hinders the ability of the market prices

to reflect fundamental information. Somette and von der Becke (2011), in a report prepared for the U.K. Office of Science, argue that HFT has led to crashes and can be expected to do so more and more in the future. We find that HFT trading activity has a significantly positive impact, raising the breakdown frequency by 18.33%.

We also analyze breakdown frequency using a predictive model. Two lagged breakdown probabilities are statistically significant. Along with volatility at the market open, these factors improve upon a constant forecast by nearly 50%.

We examine the robustness of our results. Rapid increases in offer prices, which we call "breakups", are also positively related to correlation shocks. Restricting the sample to stocks with a market cap of over \$10 billion, we confirm the explanatory model for aggregate breakdown frequency. Large caps breakdown only 1/6 as often as other stocks, and only 118 large caps have broken down in the period 2009-11.

We also consider alternative microstructure definitions of breakdowns. We look at the national best-bid and offer (NBBO) rather than just the primary exchange. These results are very similar to our original specification. Secondary markets reduce breakdowns by 31.96% in 2008-11. We also show that our model fits breakdowns using trade prices rather than quotes. Finally, when we look at the worst bid or offer in the market place, all of our models fit poorly.

Section 2 introduces our definition of market quality breakdowns and compares it to the Flash Crash. Section 3 measures the unconditional daily average breakdown frequency. We develop a baseline model for the aggregate breakdown frequency in Section 4 and test the impact of changes in market structure including Reg. NMS, fragmentation and exchange effects. We then construct, in Section 5, a theoretical model to study the effects of cross-security correlation on the limit order book. The empirical results in Section 6 confirm our model of correlated liquidity shocks. We analyze the impact of ETFs in Section 7 and HFT activity in Section 8. Section 9 builds a predictive model. We conduct robustness checks in Section 10 before concluding.

2. Data and Definitions

Our empirical analysis relies on quotes rather than trades. This, of course, increases the computational burden, but we feel breakdowns in market quality impede trading, and that the consolidated quotes provide the best real time portrait of the market. Our focus is on the best bid and offer from the listing exchange, but we examine alternative definitions¹ in our robustness section.

We analyze stocks that are in both the Center for Research in Security Prices (CRSP) and the New York Stock Exchange Trade and Quote Database (TAQ). Stocks from all three major exchanges are available from April 6, 1993 forward. Our sample ends on December 30, 2011.

We look at movements in the time frame 09:35-15:55. We do this because opening and closing procedures vary across exchanges and may not be comparable.

A stock is identified as having a market quality breakdown if the best bid prices fall 10% below the 09:35 price. 10% is a natural metric because that is where circuit breakers are now placed. In addition, the tick must be repeated at least once in a subsequent calendar second. This avoids fleeting quotes or errors.

We want to try to filter out news driven price declines. We do this by looking at stocks that rebound to within 2.5% of the 09:35 price at 15:55.

We have a symmetric definition for break ups, using the best offer price.

2.1 Market quality metrics for the Flash Crash

On May 6, 2010, major U.S. stock indices, stock index products, and individual stocks experienced a sudden price drop of more than 5% followed by a rapid recovery within minutes. The unusual and severe event, commonly known as the Flash Crash, occurred in both futures and spot markets. The price of E-Mini S&P 500 futures fell in excess of 5% between 14:41 and 14:46. The Dow Jones Industrial Average (DJIA) plunged 998.5 points, the largest intraday point decline in history. Many individual stocks reached lows that exceeded 10%, and some were even traded down to a penny, e.g. Accenture.

The Flash Crash raises questions about the quality of U.S. financial markets. The CFTC and the SEC^2 jointly explored the market events of May 6, 2010 and identified the evaporation of liquidity in both the E-Mini and individual stocks. By analyzing the aggregate order books they found that reductions in liquidity may lead some stocks to trade at severe prices.

¹ The high frequency data provider Nanex has been analyzing mini-flash crashes for several years now. Nanex (2011) used the following criteria: "to qualify as a down-draft candidate, the stock had to tick down at least 10 times before ticking up – all within 1.5 seconds and the price change had to exceed 0.8%." They have a symmetric definition for up-drafts. We attempted to replicate their results, but we eventually used an alternative framework. Many Nanex breakdowns occur away from the primary exchange. It also does not work particularly well during the flash crash. In 2010, they identify 1,041 down-draft events, fewer than we find on the single day of May 6, 2010. Nanex does confirm our main message. Up and down drafts have been trending down since 2008.

² Commodity Futures Trading Commission and Securities and Exchange Commission (2010).

When we apply our filter to the Flash Crash day, we get very similar conclusions to the academic and policy literature. Our sample consists of 6,527 securities for May 6, 2010. Among them, 1,857 stocks experienced market quality breakdowns on the listing exchange.³ The breakdown frequency differs on each of the four primary exchanges, as shown in Table 1.

[INSERT Table 1 HERE]

ARCA is affected more than any other exchange with more than 60% of stocks crashed, while AMEX has the lowest frequency of 12.73%. The breakdowns on NYSE and Nasdaq are close to the average level of the market.

We then analyze in more detail the distribution of percentage decline in the best bid prices on the Flash Crash day. We want to compare our results to the CFTC-SEC finding, so we use the same stock filter here, i.e. a share price of more than \$3.00 and a market capitalization of at least \$10 million. The results are illustrated in Figure 1 Panel A.

[INSERT Figure 1 HERE]

The distribution displays a similar pattern to the finding in the CFTC-SEC report.⁴ In particular, 227 stocks have the lowest best bid that are almost 100% below the 09:35 price on the listing exchange. The number is a little greater than that given in the CFTC-SEC report since we analyze quotes rather than trades.

Figure 1 Panel B presents a scatter plot of the time and percentage decline of the best bid for all stocks during the period from 14:00-15:00 on May 6, 2010. Each point on the graph represents a stock. The result is consistent with the finding by the CFTC and the SEC.⁵ A few stocks began to crash shortly after 14:00 and the number of stocks increased steadily over the one hour interval. Many of the lows in the best bid occurred after 14:45, as represented by a dense area between -20% and 0% and a thick line around -100%.

Our results also suggest the same conclusions about ETFs as discussed in the CFTC-SEC report. ETFs were affected the most among all types of securities on May 6, 2010. Based on

³ It is shown in the CFTC-SEC report that approximately 14% of stocks traded at lows that are more than 10% away from the 14:40 prices. Given the fact that we analyze 10% price decline below the 09:35 price and our study relies on quotes instead of trades, it makes sense that our filter gives a higher frequency of 28.45%.

⁴ CFTC-SEC (2010), Figure 8, p.18.

⁵ CFTC-SEC (2010), Figure 10, p.24.

our filter, 559 out of 893 ETFs experienced market quality breakdowns. The number accounts for nearly one-third of the crashed stocks on the day. We present in Figure 2 the distribution of ETF lows measured by the best bid from the listing exchange. The spike of the left-most column in the figure indicates that a large portion of ETFs had almost 100% quality deterioration.

[INSERT Figure 2 HERE]

The timing of ETF lows by our filter, as shown in Figure 2 Panel B, is consistent with the finding in the CFTC-SEC report⁶ as well. The number of ETF crashes started to rise after 14:40. Beginning about 14:45 a great number of ETFs experienced 100% price drops, which is represented by a dense line around -100%.

Since our filter works for the Flash Crash, we then apply it to the full TAQ sample of 1993-2011. The natural question is how often do events like this occur.

3. Unconditional Breakdown Frequency

We analyze the unconditional probability of a random stock experiencing a market quality breakdown. The breakdown frequency is calculated by the number of broken stocks divided by the total number of traded stocks. We report results for all exchanges and all types of stocks in Figure 3 Panel A.

[INSERT Figure 3 HERE]

The daily average breakdown frequency is 0.64% throughout our sample period. There is an uptrend in breakdown frequency from 1993-2000 followed by a downtrend from 2000-2006. Breakdowns begin to rise again in late 2007 with the onset of the financial crisis and peak in 2008 during the near collapse of the financial system. As the market stabilizes in the second half of 2009, the breakdown frequency returns to the level in the late 1990s. By 2011, the breakdown frequency has fallen to 0.39%, half the rate in 1998. In 2010 and 2011, a typical stock will break down less than once per year.

On average, 44 stocks per day experience breakdowns. Figure 3 Panel B shows the number of breakdown events by year from 1993-2011. It presents a similar trend with the breakdown frequency in Panel A. The breakdowns reached their peak in 2000 with more than 30,000 events,

⁶ CFTC-SEC (2010), Figure 16, p.39.

and there is a significant rise in 2008 as well.

Even including the Flash Crash, there are fewer market quality breakdowns in 2010 than in 1998. Excluding the Flash Crash day, the breakdown frequency in 2010 is the fourth lowest in our sample.

When there are a large number of breakdown events in a year, it could be the case that some particular stocks break down more frequently or that stocks are essentially equally likely to break down. To distinguish between the two cases, we measure the distribution of breakdown incidence by the Gini coefficient in Figure 4.

[INSERT Figure 4 HERE]

The Gini coefficient of 0.52 implies that stocks are not equally likely to break down during our sample period. We show below that non-NYSE stocks are more likely to break down, and large capitalization stocks are less likely. Even though breakdown frequencies vary substantially year-by-year, the distribution across stocks is relatively stable during the period from 1993-2011.

4. Market Structure

We plan to explore the various theories in the literature by first developing a baseline model for the frequency of breakdowns. We will then extend this baseline model to see the time series impact of changes in market structure, both regulatory and competitive.

4.1 Baseline model

We now model the frequency of market quality events conditional on volatility and aggregate volume. We calculate the breakdown frequency on day t, π_t , by dividing the number of broken stocks by the total number of traded stocks. We measure market volatility using the opening value of the Chicago Board Options Exchange volatility index (VIX), $\sigma_t^{VIXopen}$. The daily aggregate volume, v_t , is the sum of trading activity on each exchange in its own listings. In the model, we use a dummy variable, \tilde{v}_t , to represent volume spikes.

$$\widetilde{v}_t = I_{\alpha=0.05} \left(\frac{v_t - \sum_{j=1}^{20} v_{t-j}/20}{\sigma_t^v} \right),$$
(1)

where $I(\cdot)$ is an indicator function and σ_t^v is the standard deviation of the volume over the proceeding 20 days. In other words, \tilde{v}_t is set as 1 if the volume becomes significantly higher than the

average of proceeding 20 days at the 5% level, and is 0 otherwise.

Given the fact that the breakdown frequency in most times is close to zero and not normally distributed, we use a generalized linear model with the assumption of $\pi_t \sim \Gamma(k, \theta)$, where k and θ are respectively the shape and scale parameter of the gamma distribution. The baseline model is written as

$$\log(\mathbf{E}[\pi_t]) = \alpha + \beta_1 \sigma_t^{VIXopen} + \beta_2 \widetilde{v}_t.$$
⁽²⁾

The model is estimated by quasi-maximum likelihood method using robust standard errors, and the results are shown in Table 2.

[INSERT Table 2 HERE]

All the estimated coefficients are statistically significant. The market volatility affects positively the aggregate breakdown frequency, which is consistent with intuition. The aggregate volume is positively associated with the breakdown frequency as well.

We measure goodness-of-fit using McFadden's measure, R_M^2 , which is defined as

$$R_M^2 = 1 - \frac{\log L(M_f)}{\log L(M_i)}$$
(3)

where $\log L(M_f)$ is the log-likelihood of the full model and $\log L(M_i)$ is the log-likelihood of the model with just an intercept. Since the log-likelihood is non-positive, R_M^2 ranges from 0 to 1 and has a higher value for the model with better fit. Our baseline model shows a 42.22% improvement over the intercept-only model to explain the breakdown frequency.

Next we examine whether breakdowns have increased since Reg. NMS.

4.2 Reg. NMS

On April 6, 2005, the Securities and Exchange Commission (SEC), in a 3-2 vote, adopted Regulation National Market System (Reg. NMS). The SEC rules were adapting the national market system concept to the modern electronic marketplace. There are four major provisions: (1) Rule 610, which provides equal access to markets; (2) Rule 611, which prohibits trade-throughs of displayed and accessible quotations; (3) Rule 612, which prohibits subpenny quotations except in limited circumstances; (4) Rule 600, 601 and 603, which set up rules for market data.

We model whether breakdowns increased after the rules were fully adopted on October 15,

2007⁷, by including a dummy variable d_t^{NMS} into the baseline model. The result in Table 2 shows that breakdowns become significantly less frequent after Reg. NMS, despite the Flash Crash. Quantitatively, breakdowns have fallen $-41.78\% = e^{-0.5410} - 1$ since the passage of Reg. NMS. With approximately 7,000 U.S. equity listings, this implies that 18 fewer stocks each day are experiencing breakdowns or approximately 4,500 fewer market quality breakdowns each year.

4.3 Market fragmentation

The academic literature is divided on the effects of fragmentation. We follow Madhavan (2012) and use the Herfindahl index as a measure of fragmentation.⁸

We first compile the national best bid and offer (NBBO) across all exchanges using the consolidated quotes from the TAQ database. The Herfindahl index is then computed as the sum of squared frequencies of the best national bid or offer that each exchange posts. Mathematically, the Herfindahl index for stock i on day t is expressed as

$$H_{i,t} = \sum_{j=1}^{M} (f_{i,t}^{j})^{2}, \tag{4}$$

where the frequency $f_{i,t}^{j}$ is calculated as the proportion of times exchange j is the national best bid or offer on day t, and M is the total number of exchanges where stock i has quotation activity. If multiple venues are the best bid or offer at the same time, we give an equal weight to each of these venues since they are competing to attract order flows. The market fragmentation on day tis measured by the average of Herfindahl index values across all stocks,

$$H_t = N_t^{-1} \sum_{i=1}^{N_t} H_{i,t}, \tag{5}$$

where N_t is the total number of stocks on day t. It is worth noting that the Herfindahl index is smaller when the market is more fragmented.

Consistent with the volume variable defined by (1) in our baseline model, we use a dummy variable, \tilde{H}_t , to represent spikes of market fragmentation. The dummy is set as 1 if the Herfindahl index H_t is significantly lower than the average of proceeding 20 days at the 5% level, and is 0 otherwise. Since the market quality breakdown is defined using the bid price, the Herfindahl index in the breakdown model is based on the best bid. When we add the Herfindahl measure to our

 $[\]overline{^{7}}$ Reg. NMS was implemented in steps from 2005 to 2007. Our result is robust to the choice of a break point. Even if we break at the beginning of Reg. NMS in 2005, breakdowns have fallen significantly.

 $^{^{\}hat{8}}$ The only difference from Madhavan (2012) is the way that we count the number of times for an exchange with the national best bid or offer. For example, if two exchanges have the best national quote at the same time, he counts one for each, while we assign one half to each to reflect the fact of their competition for orders.

baseline regression, its coefficient is not statistically significant, as shown in Table 2. Therefore, we conclude that fragmentation is not associated with the breakdown frequency for the market as a whole.⁹

Since March 5, 2007, the SEC has required that all off-exchange trades must report to a trade reporting facility (TRF). O'Hara and Ye (2011) have suggested using the share of off-exchange volume as an alternative measure of fragmentation. We use a similar metric in our analysis as well. The TAQ database provides aggregate information of trades reported to the Financial Industry Regulatory Authority (FINRA).¹⁰ We re-estimated the baseline model for the period from March 5, 2007 to December 30, 2011, and then explored the impact of this alternative measure of fragmentation. We find in Table 2, similar to O'Hara and Ye (2011), that the share of TRF volume is not a statistically significant contributor to market quality breakdowns.

4.4 Do exchanges still matter?

We now ask whether exchanges influence the frequency of breakdowns. We investigate it by modeling the number of breakdown occurrences of individual stocks, $n_{i,t}$. We analyze breakdowns at the monthly frequency, because the number of daily breakdowns is generally very small.

Since the time of the Nasdaq price fixing case (see e.g. Christie and Schultz (1994)), there has been an ongoing dialog of market quality across exchanges. The conclusion of the early literature was that the NYSE, despite having a monopoly market making specialist, typically had higher market quality. The debate continues to this day, especially involving the role and importance of market makers, e.g. Menkveld and Wang (2011). Recently some exchanges have proposed to offer market makers financial incentives to provide more liquidity in illiquid stocks. In December 2011 BATS filed and later was approved for the Competitive Liquidity Provider program that was designed to encourage market makers to post tight quoting spreads¹¹. The Nasdaq filed a revised

⁹ We also explored the impact of fragmentation for individual stocks on the Flash Crash day, as Madhavan (2012) did. We include as control variables of opening price, market capitalization, volatility, and volume. The estimated coefficient for the Herfindahl index is negative (-0.6542) and statistically significant at the 1% level. Our result is consistent with Madhavan's conclusion about fragmentation for the Flash Crash. However, we do not find this measure helps explain the breakdown frequency at the aggregate level for a longer historical period.

¹⁰ The FINRA trades include those from the Nasdaq TRF, the NYSE TRF and the Alternative Display Facility (ADF). The TRF data sample in O'Hara and Ye (2011) also includes trades reported to National Stock Exchange (NSX) TRF. However, based on their results, it accounts for only 2.46% of consolidated volume, compared to the total share of 24.75% in the sources captured by the FINRA.

¹¹ See e.g. "BATS Gets SEC Approval for Liquidity Provider Program," *Traders Magazine*, February 6, 2012.

plan with the SEC in December 2012 that would pay market makers in thinly traded ETFs¹².

Figure 5 presents the breakdown frequency on each of the four primary exchanges from 1993-2011.

[INSERT Figure 5 HERE]

We see that breakdowns occur less frequently on the NYSE than any other exchange. Even in 2008, the frequency is less than 0.9%, and the frequency in 2011 is very close to the levels in early 1990s. The breakdown frequency on the Nasdaq shows a similar trend to the result for all exchanges, but the magnitude is higher. Interestingly, the ARCA experiences a breakdown frequency as high as 2.6% in 2007 when the frequency is relatively low on other exchanges. After that, there is a substantial improvement of market quality for ARCA and it is the second best exchange in 2011.

The unconditional probabilities are not by themselves indications of exchange related effects. Stocks differ across exchanges, and we must control for these in our market quality inferences. To test for marginal effects from exchange structure, we include the covariates from the baseline model and add the log opening price of the stock, $p_{i,t}^{open}$, and its log market capitalization, $\kappa_{i,t}$. Since the dependent variable is the number of market quality events for stock *i* in month *t*, we use Poisson regression with the assumption of $n_{i,t} \sim \text{Pois}(\lambda)$,

$$\log(\mathbf{E}[n_{i,t}]) = \alpha + \beta_1 p_{i,t}^{open} + \beta_2 \kappa_{i,t} + \beta_3 \sigma_{i,t} + \beta_4 \widetilde{v}_{i,t}.$$
(6)

The model is estimated by the quasi-maximum likelihood method using robust standard errors. The results in Table 3 show that all the estimated coefficients are statistically significant. At the individual stock level, the opening price and market capitalization are negatively associated with the number of breakdowns, while volatility and volume¹³ are positively related to breakdowns.

[INSERT Table 3 HERE]

We then add three dummy variables, d^{NYSE} for the NYSE, d^{NASD} for the Nasdaq, and d^{ARCA} for the ARCA to (6), using ARCA as the omitted listing exchange. The results in Table 3 indicate that the exchange listing significantly affects the number of breakdowns for individual stocks. Even though the NYSE has lost market share in its own issues, NYSE listed stocks break down

¹² See e.g. "Nasdaq Seeks Approval for Revised 'Paid-for-Market-Making' Plan," *Traders Magazine Online News*, December 10, 2012

¹³ Volume here is the trading activity on the primary exchange, as calculated from the TAQ data.

approximately 20.03% less frequently than Nasdaq stocks, 43.91% less frequently than AMEX listings, and 69.04% less frequently than ARCA listings.

We now turn from issues of market and regulatory structure to examine whether cross-security correlation might be explaining market quality breakdowns.

5. The Theoretical Model

The model presented in this section follows Sandås (2001). We extend Sandås' model to include two risky equities and their corresponding limit order books. Our model contributes to the literature by introducing the correlation between securities and analyzing the cross-equity impact on limit order books. The theoretical results discussed here provide a framework for the subsequent empirical analysis.

5.1 Model setup

We consider two risky equities, A and B, in the model. Equity i, i = A or B, has a fundamental value X_t^i in period t, which incorporates all information available up to period t. The fundamental value for security i in the next period is

$$X_{t+1}^{i} = X_{t}^{i} + \mu^{i} + \varepsilon_{t+1}^{i}, \tag{7}$$

where μ^i represents the expected change in the fundamental value and ε^i_{t+1} is a random innovation in period t+1.

There are two types of agents, market makers and traders. Market makers provide liquidity by placing limit orders on one or both assets. They are risk neutral and profit maximizing. Traders are risk averse and their trades may be due to exogenous reasons, e.g. margin calls, rather than their best estimate of the fundamental value. Therefore, they want to trade quickly at the current price.

There are three stages in each period t. In the first stage, market makers submit new limit orders on one or both equities. They repeat the process until no market maker finds it optimal to place an additional order. Then a trader arrives and submits market orders on either security or both. The market order quantity on each equity may rely on the correlation between the two. Finally, market makers update their expectation about the fundamental values of the assets given the size of incoming trades and the process starts over.

For each limit order book we use a discrete pricing grid as follows. The bid prices in the book of

equity *i* are denoted by $\{p_1^i, p_2^i, \ldots, p_k^i\}$, where p_1^i is the best bid price. Let $\{Q_1^i, Q_2^i, \ldots, Q_k^i\}$ denote the order quantities associated with each price. The variables for the offer side may be denoted analogously, but we focus on the bid side only for market quality breakdowns. The market order quantity for equity *i* is denoted by m^i . It is positive for buy orders, and negative for sell orders.

5.2 Traders

Suppose that a trader buys or sells with equal probability. Following Sandås (2001) we assume that the market order quantities are exogenous and are exponentially distributed for simplicity. We focus on sell orders only when modeling market quality breakdowns. To incorporate the correlation between the two equities into the model, we use the bivariate exponential distribution¹⁴ with the following joint density function,

$$f\left(m^{A}, m^{B}\right) = \frac{1}{\lambda^{A} \lambda^{B}} e^{\frac{m^{A}}{\lambda^{A}} + \frac{m^{B}}{\lambda^{B}}} \left[1 + 4\rho \left(1 - 2e^{\frac{m^{A}}{\lambda^{A}}}\right) \left(1 - 2e^{\frac{m^{B}}{\lambda^{B}}}\right)\right], \ m^{A} \le 0 \text{ and } m^{B} \le 0.$$
(8)

It is not difficult to show that the marginal distributions of m^A and m^B are exponential with mean λ^A and λ^B respectively, and the correlation between m^A and m^B is ρ , where $-1 \le \rho \le 1$. We then mainly concentrate on the decision problem of the market makers.

5.3 Market Makers

Market makers observe trades on both equities and then update their best estimates of the fundamental values based on the market order quantities. Since equity A and B are symmetric in our model, only security A's fundamental value in the next period is given below,

$$E\left[X_{t+1}^{A}|X_{t}^{A}, m^{A}, m^{B}\right] = X_{t}^{A} + \mu^{A} + h\left(m^{A}, m^{B}\right),$$
(9)

where $h(m^A, m^B)$ is a non-decreasing price impact function. It captures the market order impact of both equities on the fundamental value of security A. We assume that the price impact function is linear with respect to the market order quantity of each of the equities, i.e.

$$h\left(m^{A}, m^{B}\right) = \alpha m^{A} + \beta m^{B}, \tag{10}$$

where α and β represent respectively the marginal price impact of market orders on security A and B. Since buy (sell) orders typically contain positive (negative) information about the fundamental value of the asset, both α and β are expected to be positive.

To simplify the analysis, we assume that market makers face a quantity-invariant order process-

¹⁴ We use one of the Gumbel (1960) versions of the bivariate exponential distribution because it clearly identifies the effect of the cross-asset correlation.

ing cost c. Then the profit of a limit order at the best bid price level p_1^A of equity A is given by

$$\pi_1^A = p_1^A - c - \mathbf{E} \left[X_{t+1}^A | X_t^A, m^A, m^B \right].$$
(11)

Under this setup, we can calculate the expected profit of a limit order placed on equity A's last unit q^A given a market order on equity B.

$$E\left[\pi_{1}^{A}|m^{B}\right] = E_{-m^{A} \ge q^{A}}\left[p_{1}^{A} - c - E\left[X_{t+1}^{A}|X_{t}^{A}, m^{A}, m^{B}\right]\right]$$

$$= \int_{-\infty}^{-q^{A}} \left(p_{1}^{A} - c - X_{t}^{A} - \alpha m^{A} - \beta m^{B}\right) \frac{1}{\lambda^{A} \lambda^{B}} e^{\frac{m^{A}}{\lambda^{A}} + \frac{m^{B}}{\lambda^{B}}} \left[1 + 4\rho \left(1 - 2e^{\frac{m^{A}}{\lambda^{A}}}\right) \left(1 - 2e^{\frac{m^{B}}{\lambda^{B}}}\right)\right] dm^{A}$$

$$= \frac{1}{\lambda^{B}} e^{-\frac{q^{A}}{\lambda^{A}} + \frac{m^{B}}{\lambda^{B}}} \left[\left(p_{1}^{A} - c - X_{t}^{A} + \alpha \left(q^{A} + \lambda^{A}/2\right) - \beta m^{B}\right) \left(1 + 4\rho \left(1 - 2e^{\frac{m^{B}}{\lambda^{B}}}\right) \left(1 - e^{-\frac{q^{A}}{\lambda^{A}}}\right)\right)$$

$$+ \frac{\alpha \lambda^{A}}{2} \left(1 + 4\rho \left(1 - 2e^{\frac{m^{B}}{\lambda^{B}}}\right)\right).$$

$$(12)$$

A zero-profit condition in (12) will characterize equilibrium.

5.4 Equilibrium

The model is in equilibrium if no market maker can profit by submitting an additional limit order at any price level. Therefore, the quantity placed at any price level must satisfy that the last unit breaks even, i.e. the expected profit of the marginal limit order at the end must be zero. From (12) we can obtain the quantity Q_1^A submitted at the best bid price level p_1^A by solving the equation.

$$\left(p_1^A - c - X_t^A + \alpha \left(Q_1^A + \lambda^A/2\right) - \beta m^B\right) \left(1 + 4\rho \left(1 - 2e^{\frac{m^B}{\lambda^B}}\right) \left(1 - e^{-\frac{Q_1^A}{\lambda^A}}\right)\right) + \frac{\alpha \lambda^A}{2} \left(1 + 4\rho \left(1 - 2e^{\frac{m^B}{\lambda^B}}\right)\right) = 0$$

$$\tag{13}$$

We are more interested in the cross-equity effect of market orders on the limit order book. To analyze it we take the derivative of Q_1^A with respect to m^B ,

$$\frac{\partial Q_1^A}{\partial m^B} = \frac{\beta + 4\rho C}{\alpha + 4\rho D},\tag{14}$$

where

$$C = \beta \left(1 - 2 e^{\frac{m^B}{\lambda^B}} \right) \left(1 - e^{-\frac{Q_1^A}{\lambda^A}} \right) + \alpha \frac{\lambda^A}{\lambda^B} e^{\frac{m^B}{\lambda^B}} + \frac{2}{\lambda^B} e^{\frac{m^B}{\lambda^B}} \left(1 - e^{-\frac{Q_1^A}{\lambda^A}} \right) \left(p_1^A - c - X_t^A + \alpha \left(Q_1^A + \lambda^A/2 \right) - \beta m^B \right) D = \alpha \left(1 - 2 e^{\frac{m^B}{\lambda^B}} \right) \left(1 - e^{-\frac{Q_1^A}{\lambda^A}} \right) + \frac{1}{\lambda^A} e^{-\frac{Q_1^A}{\lambda^A}} \left(1 - 2 e^{\frac{m^B}{\lambda^B}} \right) \left(p_1^A - c - X_t^A + \alpha \left(Q_1^A + \lambda^A/2 \right) - \beta m^B \right).$$

We see that both C > 0 and D > 0 if $1 - 2e^{\frac{m^B}{\lambda^B}} > 0$ and $p_1^A - c - X_t^A + \alpha \left(Q_1^A + \lambda^A/2\right) - \beta m^B > 0$. Therefore, when $m^B < \min\left\{-\lambda^B \log 2, \beta^{-1}\left(p_1^A - c - X_t^A + \alpha \left(Q_1^A + \lambda^A/2\right)\right)\right\}$, we have $\partial Q_1^A / \partial m^B > 0$. Since $m^B \le 0$, it suggests that an increase in the quantity of a market sell order on equity B will also reduce the depth at the best bid price level of equity A.

In addition, (14) indicates the impact of the correlation ρ on the order book depth. When ρ increases, $\partial Q_1^A / \partial m^B$ becomes greater, so the cross-equity effect of a market sell order is even stronger.

The condition of zero expected profit also satisfies for the price levels deeper in the limit order book. We obtain the same conclusions for the cross-equity effect of market orders and for the impact of the correlation as well. When the limit order book thins to the extreme price level, a market quality breakdown occurs. If the trades are based on exogenous reasons rather than the expected fundamental value, the market would learn later nothing fundamental has happened and therefore the price movements are reversed.

6. Market Correlation

The critical parameter in the model is the cross-equity correlation ρ . We first try to measure how the correlation across stocks has changed during our sample period.

Since 2008, there have been instruments¹⁵ that directly measure the market's implied correlation. These instruments are not available for our entire sample, so we construct our own measure using daily returns of 30 industry portfolios from Fama and French's website. We calculate the 20-day rolling correlation pairwise and use the median as measure of the market correlation.

We plot the market correlation over the sample period in Figure 6.

[INSERT Figure 6 HERE]

We include the median correlation in our explanatory model

$$\log(\mathbf{E}[\pi_t]) = \alpha + \beta_1 \sigma_t^{VIXopen} + \beta_2 \widetilde{v}_t + \beta_3 d_t^{NMS} + \beta_4 \widetilde{\rho}_t.$$
(15)

and present the results in Table 2. We construct our correlation variable, $\tilde{\rho}_t$, as a dummy variable that represents spikes in market correlation, just as we did with volume in (1).

The results suggest that it does explain a higher frequency of market quality events. Spikes in

¹⁵ The Chicago Board Options Exchange began to disseminate an implied correlation measure for the S&P 500 options basket and its components. There are also instruments which use this correlation as an underlying.

market correlation raise the breakdown frequency by 25.62%.

7. Exchange Traded Funds

The growing volume of trading in ETFs has changed the character of the market. ETFs broke down more frequently during the Flash Crash. We confirm, after controlling for individual equity and exchange effects, that ETFs suffer substantially more market quality breakdowns.

It is an open question whether ETFs make other stocks unstable. We find they do contribute to market-wide equity breakdowns through their effects on market correlation.

We investigate whether ETFs as an equity class break down more often by including a dummy variable for ETFs, d_i^{ETF} into the individual stock model, (6). We control for market capitalization, opening price, individual stock volume and volatility. We also want to ensure that our ETF results are not simply proxying for the effects of exchanges, so we include dummies variables for the NYSE, Nasdaq, and AMEX. As shown in Table 3, ETFs exhibit significantly higher likelihood of breakdowns, after controls, than non-ETFs. ETFs break down 90.33% more frequently. If the market consisted exclusively of ETFs, there would be greater than 9,000 more breakdowns per year.

We also explore the relationship between market correlation and the trading activity of ETFs. We use the Granger causality test to study whether an increase in trading volume of ETFs causes a change in market correlation, or the other way around. In order to do the test, we first fit the correlation and aggregate ETF volume into a vector autoregressive model,

$$\widetilde{\rho}_{t} = a_{\rho,0} + \sum_{i=1}^{M} a_{\rho,i} \widetilde{\rho}_{t-i} + \sum_{i=1}^{M} b_{\rho,i} \widetilde{v}_{t-i}^{ETF} + \varepsilon_{\rho,t},$$

$$\widetilde{v}_{t}^{ETF} = a_{v,0} + \sum_{i=1}^{M} a_{v,i} \widetilde{\rho}_{t-i} + \sum_{i=1}^{M} b_{v,i} \widetilde{v}_{t-i}^{ETF} + \varepsilon_{v,t},$$

$$(16)$$

where $\tilde{\rho}_t$ and \tilde{v}_t^{ETF} are dummy variables that represent spikes of market correlation and aggregate ETF volume respectively. The number of lags M = 4 is determined by the Akaike Information Criterion. Based on this specification, we obtain the Granger causality test results which are reported in Table 4 Panel A.

[INSERT Table 4 HERE]

There is a statistically significant causation of aggregate ETF volume for market correlation, but the reverse is not true. Because ETFs cause correlation spikes, they increase the probability that other stocks will break down the next day. A lagged ETF volume spike raises the probability of a correlation spike by as much as 73.60%.

8. High Frequency Trading

To examine whether HFT activity helps explain the market quality breakdowns, we use the data set analyzed by Brogaard (2011) and Gao and Mizrach (2011). The HFT data set includes all trades on the NASDAQ exchange for 120 stocks on each trading date in 2008 and 2009, as well as one week in February 2010. We focus only on 2008 and 2009 in our analysis. The data tells whether an HFT firm is a liquidity taker or a provider in each trade. We measure HFT activity as the share of volume executed by HFT firms in a trading day, either at the liquidity seeking side or at the passive side. We analyze the HFT effect using a dummy variable \widetilde{HFT}_t that measures spikes in the HFT share of trading volume, constructed in the same way as volume and correlation. We assume that HFT firms have similar trading activity in other stocks that we do not observe in this sample, and extrapolate the measure to the broader equity market.¹⁶

The impact of HFT activity on market quality breakdowns may operate through the correlation channel. Our theoretical model predicts that a high correlation between market orders will result in a larger cross-equity effect, thus contributing to a higher breakdown frequency. We investigate this possibility by the Granger causality test in the framework of the following vector autoregressive model,

$$\widetilde{\rho}_{t} = a_{\rho,0} + \sum_{i=1}^{M} a_{\rho,i} \widetilde{\rho}_{t-i} + \sum_{i=1}^{M} b_{\rho,i} \widetilde{HFT}_{t-i} + \varepsilon_{\rho,t}, \qquad (17)$$

$$\widetilde{HFT}_{t} = a_{h,0} + \sum_{i=1}^{M} a_{h,i} \widetilde{\rho}_{t-i} + \sum_{i=1}^{M} b_{h,i} \widetilde{HFT}_{t-i} + \varepsilon_{h,t},$$

where $\tilde{\rho}_t$ and \widetilde{HFT}_t are dummy variables representing spikes of market correlation and HFT activity respectively. The number of lags M = 4 is determined by the Akaike Information Criterion. The results in Table 4 Panel B suggest that HFT activity Granger causes market correlation significantly, but the reverse is only marginally significant. A lagged HFT volume spike raises the probability of a correlation spike by as much as 297.2%.

We re-estimate the explanatory model for the period from 2008 to 2009, controlling for correlation as our theoretical model suggests,

$$\log(\mathbf{E}[\pi_t]) = \alpha + \beta_1 \sigma_t^{VIXopen} + \beta_2 \widetilde{v}_t + \beta_3 \widetilde{HFT}_t + \beta_4 \widetilde{\rho}_t.$$
(18)

¹⁶ We test the assumption by estimating the model using only the 120 stocks in the data set for which we observe volume directly. The effects of HFT are similar to the extrapolated sample.

The results in Table 5 indicate that HFT activity has a significantly positive impact on market quality breakdowns, even when we include the effects of market correlation.

[INSERT Table 5 HERE]

The marginal effect of correlation spikes is 31.31% in 2008-2009, and spikes in HFT activity raise the breakdown frequency an additional 18.33%. If both variables trigger in a trading day, the breakdown frequency rises nearly 50%.

9. Prediction

We examine whether breakdowns are predictable. We take the only lagged variable from the explanatory model (15), the 09:30 opening value of the VIX, and then add the two prior days' breakdown probabilities π_{t-j} , j = 1, 2,

$$\log(\mathbf{E}[\pi_t]) = \alpha + \beta_1 \sigma_t^{VIXopen} + \sum_{j=1}^2 \eta_j \pi_{t-j}.$$
(19)

The results in Table 9 demonstrate that the breakdown frequency is positively autocorrelated.

[INSERT Table 9 HERE]

Both lags are statistically significant.¹⁷ The breakdown frequency rises by 25.26% if the frequency last day doubles the average. Following two days of breakdowns at twice the average rate, the breakdown frequency becomes 52.35% higher. The R_M^2 in the predictive model of breakdowns is 49.36%, slightly higher than 46.24% that we found in the explanatory model which included contemporaneous variables.

10. Robustness Checks

We recognize that researchers might use alternative definitions of a market quality breakdown. They might want to use 15% rather than 10% or have the day close flat rather than down 2.5%, etc. While not reported, our results are quite robust to perturbations in these values.

Order book breakdowns can also occur on the offer side of the book. This section studies these "breakups."

Menkveld and Wang (2011) note that liquidity risks are particularly acute for small cap stocks.

¹⁷ The AIC suggests including up to 8 lags, but the lags beyond the second are not statistically significant.

We want to make sure that our results are not being driven solely by a set of volatile, low-liquidity securities. We repeat our explanatory models for a purely large market capitalization sample.

We also consider here alternative microstructure definitions of our 10% decline by looking first at the national best bid or offer (NBBO). We also look at a less familiar but related concept, the worst bid or offer (WBO). Our results are quite strong and similar for the NBBO, but the WBO appears to be a challenge for any model.

In addition, we analyze market quality events using trade data rather than quotes. The results confirm our explanatory model.

10.1 Breakups

Market quality deterioration also results in rapid increases in offer prices. These are surprisingly as frequent as the breakdowns and tend to follow the same pattern over time in Figure 7.

[INSERT Figure 7 HERE]

The average breakup frequency is 0.63% in our sample from 1993-2011.

We effectively split the sample on October 15, 2007 using a dummy variable d^{NMS} for the full implementation of Reg. NMS. Breakups are more frequent than breakdowns after 2002, and we do not find a statistically significant decrease after Reg. NMS in Table 7.

[INSERT Table 7 HERE]

The effect of market correlation spikes is qualitatively similar to the results we found in Table 2. The results are not as strong as they are for breakdowns, with correlation spikes raising the breakup probability by 8.915%. The estimated effect is statistically significant at the 6% level.

10.2 Large caps

The literature often focuses on large cap stocks when studying equities. We want to explore whether our conclusions would change if we include only large caps in our sample. We construct a sub-sample that contains stocks with market capitalization of more than \$10 billion. On average, there are 246 stocks per day in this category.

We plot the aggregate breakdown frequency in Figure 7. On average during 1993-2011, the large cap daily breakdown frequency is 0.11% versus 0.64% for all stocks. Large caps break down

at a lower frequency in each year of the sample. Only 118 large caps have broken down in the period 2009-11. 77 of these occur during the Flash Crash.

Our explanatory model explains the breakdown frequency of large caps as well. The results are reported in Table 7. Adding the Reg. NMS dummy variable to the model reveals a significant reduction in breakdown frequency of 91.81% since October 15, 2007. A correlation spike raises large cap breakdowns by 121.9%.

10.3 NBBO

We plot the frequency of breakdowns based on the NBBO in Figure 7.¹⁸ After 2007, the NBBO breakdown frequency averages 31.96% lower than the frequency based on the listing exchange.

Market quality breakdowns in the NBBO are less frequent in 2011 than they were in 1993 when exchanges dominated liquidity in their own listings. From 2008-11, secondary exchanges were able to provide a liquidity buffer in cases where the primary exchange was experiencing a breakdown. This supports the conclusion of Jiang, McInish and Upton (2011) that competition could enhance market quality.

With our explanatory model, the change in definition confirms, in Table 7, our previous conclusions. NBBO breakdowns have decreased significantly since Reg. NMS by 60.61%. A correlation spike raises the NBBO breakdown frequency by 17.62%.

We feel that looking at the primary listing exchange for market quality effects is quite natural, but these results show that using the NBBO would result in nearly identical conclusions.

10.4 Trading events

We also apply our filter to trade prices as another robustness check. Specifically, we look at trade price movements from 09:35-15:55 in the listing exchange. A stock is identified to experience a breakdown if the trade prices fall 10% below the 09:35 price and rebound to within 2.5% of the 09:35 price by 15:55. In addition, the trade with the lowest price must be repeated at least once in a subsequent calendar second.

Figure 7 presents the frequency of trading breakdowns on the primary listing exchange. The trading events occur relatively more frequently in the 1990s. Consistent with the results based on the NBBO, breakdowns are less frequent in 2011 than they were in 1993.

¹⁸ Because the national best bid price may be higher than the listing exchange price at 09:35 or 15:55, the NBBO breakdown frequency can be larger than the same measure computed solely on the listing exchange.

The results using our explanatory model are shown in Table 7. Trading breakdowns have decreased significantly since Reg. NMS by 79.91%. A correlation spike raises the trading breakdown frequency by 31.19%.

10.5 WBO

There is a lot more exchange competition in the latter half of our sample, but that does not mean that every exchange plays an active role in liquidity provision for every stock. In particular, the presence of stub quotes of \$0.01 is important on the non-primary exchanges. These come into play on many days, not just on the Flash Crash.

Breakdown frequencies grow virtually monotonically in Figure 8 between 1997 and 2006.

[INSERT Figure 8 HERE]

The frequencies are also nearly 100 times higher. In 2010, stocks on the primary listing exchange break down 0.36% of the time, whereas the WBO breaks down nearly 35% of the time.

Not surprisingly, our model offers no explanatory power for these events. In Table 7, volume and correlation offer no improvement to the likelihood of the breakdown frequency.

We don't feel that the WBO is a proper measure of overall market quality, but we still think it provides some perspective on quote activity away from the listing exchange or NBBO.

11. Conclusions

Market quality, in our view, should be assessed using quotes as well as trade prices. We analyze the intra-daily consolidated bids and offers of every security in CRSP and TAQ during the period of 1993-2011. We examine stocks which fall more than 10% between 09:35 and 15:55 but recover within the day. These market quality breakdowns have a daily average frequency of 0.64%, approximately 44 stocks per day. Breakdowns in 2010-2011 average 0.38%, which is less than once per year in a typical stock.

Volume and volatility are still the prime causes of market quality breakdowns in our explanatory model, improving the likelihood by more than 40% over a model with just a constant term. Market quality has improved since the passage of Reg. NMS. A stock is 41.78% less likely to breakdown after mid-October 2007. We find no impact on breakdowns from a Herfindahl index of quote fragmentation or the market share of off-exchange volume. The NYSE, despite many changes and losses of market share, still has the highest market quality. ETFs break down 90.33% more frequently than non-ETFs.

We confirm our theoretical model of correlated liquidity shocks. Breakdowns are 25.62% more frequent when correlation between market sectors spikes. ETF and HFT trading volume Granger cause this correlation. Surges in HFT activity raises the breakdown frequency by 18.33%.

Breakdown effects are persistent up to two days. Lagged factors improve upon a constant forecast by up to 50%.

Stocks with market capitalization of more than \$10 billion have an average daily breakdown frequency of only 0.11%. During 2009-11, only 118 large cap stocks break down.

In 2008-11, NBBO quote activity away from the listing markets lowers the average breakdown frequency by 31.96%. This suggests that exchange competition may be beneficial to market quality.

References

Acharya, Viral and Stephen Schaefer (2006), "Liquidity Risk and Correlation Risk: Implications for Risk Management," New York University Working Paper.

Ben-David, Itzhak, Francesco Franzoni, and Rabih Moussawi (2012), "ETFs, Arbitrage, and Contagion," Dice Center WP 2011-20, ssrn.com/abstract_id=1967599.

Bennett, Paul and Li Wei (2006), "Market Structure, Fragmentation, and Market Quality," *Journal of Financial Markets* 9, 49-78.

Brogaard, Jonathan (2011), "The Activity of High Frequency Traders," U. of Washington Working Paper, ssrn.com/abstract=1938769.

Brogaard, Jonathan, Terrence Hendershott and Ryan Riordan (2012), "High Frequency Trading and Price Discovery," U. of Washington Working Paper, ssrn.com/abstract=1928510.

Christie, William G. and Paul H. Schultz (1994), "Why do NASDAQ Market Makers Avoid Odd-Eighth Quotes?" *Journal of Finance* 49, 1813–1840.

Commodity Futures Trading Commission and Securities and Exchange Commission (2010), Preliminary Findings Regarding the Market Events of May 6, 2010, Washington, D.C.

Cvitanic, Jaksa and Andrei Kirilenko (2010), "High Frequency Traders and Asset Prices," California Institute of Technology Working Paper, ssrn.com/abstract_id=1569067.

Gao, Cheng and Bruce Mizrach (2011), "High Frequency Trading in the Equity Markets During Large-Scale Asset Purchases," Working Paper.

Golub, Anton, John Keane and Ser-Huang Poon (2012), "High Frequency Trading and Mini Flash Crashes," U. of Manchester Working paper, ssrn.com/abstract=2182097.

Gumbel, Emil J. (1960), "Bivariate Exponential Distributions," Journal of the American Statistical Association 55, 698-707.

Hasbrouck, Joel and Gideon Saar (2011), "Low Latency Trading," NYU Working Paper, ssrn.com/abstract_id=1695460.

Jiang, Christine X., Thomas H. McInish and James Upson (2011), "Why Fragmented Markets Have Better Market Quality: The Flight of Liquidity Order Flows to Off Exchange Venues," U. of Memphis Working Paper, ssrn.com/abstract=1960115.

Krishnan, CNV, Ralitsa Petkova, and Peter Ritchken (2009), "Correlation Risk," *Journal of Empirical Finance* 16, 353–367.

Madhvan, Ananth (2012), "Exchange-Traded Funds, Market Structure and the Flash Crash," Working Paper, ssrn.com/abstract=1932925.

Menkveld, Albert J. and Ting Wang (2011), "How Do Designated Market Makers Create Value for Small-Caps?" Working Paper, ssrn.com/abstract=890526.

Nanex (2011), "Flash Equity Failures in 2006, 2007, 2008, 2009, 2010, and 2011," www.nanex.net/ FlashCrashEquities/FlashCrashAnalysis_Equities.html. O'Hara, Maureen and Mao Ye (2011), "Is Market Fragmentation Harming Market Quality?" Journal of Financial Economics 100, 459–474.

Sandås, Patrik (2001), "Adverse Selection and Competitive Market Making: Empirical Evidence from a Limit Order Market," *Review of Financial Studies* 14, 705–734.

Sornette, Didier and S. von der Becke (2011), "Crashes and High Frequency Trading: An Evaluation of Risks Posed by High-speed Algorithmic Trading," Swiss Finance Institute Working Paper 11-63, ssrn.com/abstract=1976249.

Zhang, Frank (2010), "The Effect of High Frequency Trading on Stock Volatility and Price Discovery," Yale University Working Paper, ssrn.com/abstract_id=1691679.

Table 1: Market Quality Breakdowns on May 6, 2010

This table gives the number of breakdowns in market quality on listing exchanges on May 6, 2010. Our sample is selected from all securities listed on the NYSE, Nasdaq, ARCA, and AMEX. We remove the securities that are not included in the Center for Research in Security Prices (CRSP) on May 6, 2010. Those include preferred, warrants, and units bundled with warrants. We apply our filter, as discussed in section 2, to identify market quality breakdowns for individual stocks.

	Listings	Breakdowns	Frequency
Total	6,527	1,857	28.45%
NYSE	2,382	691	29.01%
Nasdaq	2,821	582	20.63%
ARCA	829	521	62.85%
AMEX	495	63	12.73%

Table 2: Aggregate Breakdown Frequency Models 1993-2011

This table presents estimates from the aggregate breakdown frequency models and shows the impact of changes in market structure and correlation on breakdowns. The dependent variable π_t is the daily breakdown frequency from April 6, 1993 to December 30, 2011. Given the fact that it is close to zero and not normally distributed, we use the generalized linear model with the assumption that π_t follows the gamma distribution. The models are estimated by quasi-maximum likelihood method using robust standard errors. Column (1) shows estimates for the baseline model: $\log(E[\pi_t]) =$ $\alpha + \beta_1 \sigma_t^{VIXopen} + \beta_2 \widetilde{v}_t$. $\sigma_t^{VIXopen}$ is the opening value of the VIX. \widetilde{v}_t represents volume spikes, and equals 1 if the volume becomes significantly higher than the average of proceeding 20 days at the 5%significance level and 0 otherwise. The volume is measured as the sum of trading activity on each exchange in its own listings. R_M^2 denotes McFadden's R-squared. Column (2) displays the effect of Reg. NMS after the rules were fully adopted on October 15, 2007, by including a dummy variable d_t^{NMS} . We measure fragmentation in two ways, the Herfindahl index and the share of consolidated volume executed in trade reporting facilities (TRFs), as discussed in section 4.3. Consistent with the volume variable, H_t and TRF_t represent spikes of market fragmentation, respectively. They equal 1 if the market is significantly more fragmented compared to the proceeding 20 days and 0 otherwise. The Herfindahl index is in column (3) and the TRF volume in column (4). The TRF data are available from March 5, 2007 to December 30, 2011. The R_M^2 for the baseline model in this sub-sample is 0.5168. Column (5) shows the impact of market correlation on the breakdown frequency. We calculate the 20-day rolling correlation pairwise by using daily returns of 30 Fama-French industry portfolios and then use the median as a measure of the market correlation. Consistent with the volume variable and fragmentation measures, $\tilde{\rho}_t$ represent spikes of market correlation.

	(1)	(2)	(3)	(4)	(5)
	Baseline	Reg. NMS	Herfindahl	$\mathrm{TRF}\%^\dagger$	Correlation
$\sigma_t^{VIXopen}$	0.0749	0.0845	0.0845	0.0668	0.0841
	(47.66)	(49.97)	(50.19)	(27.35)	(50.02)
\widetilde{v}_t	0.5396	0.5932	0.5936	0.9207	0.5412
	(4.44)	(4.23)	(4.23)	(3.32)	(4.48)
d_t^{NMS}		-0.5410	-0.5416		-0.5463
		(-13.27)	(-13.37)		(-14.36)
\widetilde{H}_t			-0.0137		
,			(-0.27)		
\widetilde{TRF}_t				0.1706	
				(1.61)	
$\widetilde{ ho}_t$				· · · ·	0.2281
					(3.21)
$\operatorname{constant}$	-2.2814	-2.3848	-2.3843	-2.5000	-2.3947
	(-70.07)	(-71.74)	(-71.37)	(-36.58)	(-72.07)
R_M^2	0.4222	0.4587	0.4587	0.5185	0.4624

t-statistics in parentheses.

[†] denotes sample period from March 5, 2007 to December 30, 2011.

Table 3: Models for Individual Stocks 1993-2011

This table contains estimates from pooled panel regression models at the individual stock level. We analyze monthly data and the dependent variable $n_{i,t}$ is the number of breakdowns on stock i in month t. The sample period is from April 1993 to December 2011. We estimate the models by Poisson regression with robust standard errors using quasi-maximum likelihood method. Column (1) shows estimates for the baseline model: $\log(E[n_{i,t}]) = \alpha + \beta_1 p_{i,t}^{open} + \beta_2 \kappa_{i,t} + \beta_3 \sigma_{i,t} + \beta_4 \tilde{v}_{i,t}$, where i is the subscript representing each stock and t is the subscript for each month. $p_{i,t}^{open}$ is the log opening price of the stock, $\kappa_{i,t}$ is the log market capitalization, $\sigma_{i,t}$ is the monthly volatility, and $\tilde{v}_{i,t}$ is volume spikes on the listing exchange. Column (2) presents the exchange effects on breakdowns by including three dummy variables, $d_{i,t}^{NYSE}$ for the NYSE, $d_{i,t}^{NASD}$ for the Nasdaq, and $d_{i,t}^{ARCA}$ for the ARCA. The AMEX is used as the basis in the model. Column (3) shows market quality breakdowns in ETFs by including a dummy variable d_i^{ETF} . The estimates for the model with both exchange listing and ETFs are reported in column (4). R_M^2 denotes McFadden's R-squared.

	(1)	(2)	(3)	(4)
	Baseline	Exchange	\mathbf{ETF}	All
$p_{i,t}^{open}$	-0.3466	-0.3567	-0.4105	-0.3803
,	(-51.71)	(-53.91)	(-59.33)	(-54.30)
$\kappa_{i,t}$	-0.3193	-0.2942	-0.2782	-0.2792
	(-30.53)	(-26.79)	(-27.38)	(-25.25)
$\sigma_{i,t}$	0.2557	0.2546	0.2475	0.2514
	(9.97)	(9.76)	(9.49)	(9.60)
$\widetilde{v}_{i,t}$	0.2146	0.2264	0.2026	0.2195
	(38.35)	(28.28)	(27.11)	(27.37)
$d_{i,t}^{NYSE}$		-0.5783		-0.5305
,		(-44.47)		(-39.43)
$d_{i,t}^{NASD}$		-0.3548		-0.3072
.,.		(-34.71)		(-27.76)
d_{it}^{ARCA}		0.5942		0.0680
0,0		(18.02)		(1.55)
d_i^{ETF}		~ /	1.0071	0.6436
ı			(38.02)	(15.50)
$\operatorname{constant}$	-0.8051	-0.8949	-1.0329	-0.9826
	(-17.60)	(-19.06)	(-22.45)	(-20.33)
R_M^2	0.1974	0.2035	0.2016	0.2043

t-statistics in parentheses.

Table 4: Granger Causality Tests

This table demonstrates the relationship between market correlation, exchanged traded funds (ETFs) and high frequency trading (HFT) by Granger causality tests. Panel A shows the test results for ETFs during the sample period from 1993 to 2011. The tests are based on the vector autoregressive model in (16). Panel B presents the test results for HFT. The sample period is from 2008 to 2009 and the tests are based on the vector autoregressive model in (17).

Panel A: Exchange Traded Funds						
H_0 : ETF volume does not O	H_0 : ETF volume does not Granger cause market correlation.					
F-stat 7.20 p -value	0.0000					
H_0 : market correlation does not Granger cause ETF volume.						
F-stat 1.36 p -value	0.2446					
Panel B: High Frequency Trading						
H_0 : HFT% does not Granger cause market correlation.						
F-stat 3.65 p -value	0.0058					
H_0 : market correlation does not Granger cause HFT%.						
F-stat 2.07 p -value	0.0833					

Table 5: Aggregate Breakdown Frequency Models 2008-2009

This table presents estimates from the aggregate breakdown frequency models from 2008-2009, the period covered in the HFT data set. The dependent variable π_t is the daily breakdown frequency. We use the generalized linear model with gamma probability distribution and estimate models by quasimaximum likelihood method using robust standard errors. Column (1) re-estimates the baseline model over the period from 2008-2009. Column (2) shows the impact of market correlation spikes $\tilde{\rho}_t$ over the period from 2008-2009. Column (3) reports the estimates when both HFT activity and market correlation are included in the model, $\log(E[\pi_t]) = \alpha + \beta_1 \sigma_t^{VIXopen} + \beta_2 \tilde{v}_t + \beta_3 \tilde{HFT}_t + \beta_4 \tilde{\rho}_t$. The HFT activity is measured by the share of volume executed by HFT firms. Consistent with the volume and correlation variables, \tilde{HFT}_t is a dummy variable measuring spikes in HFT activity. R_M^2 denotes McFadden's R-squared.

	(1)	(2)	(3)	
	Baseline	Correlation	HFT	
$\sigma_t^{VIXopen}$	0.0526	0.0528	0.0532	
Ū.	(19.75)	(19.40)	(19.26)	
\widetilde{v}_t	0.5700	0.4766	0.4408	
	(3.87)	(4.22)	(3.80)	
\widetilde{HFT}_t			0.1683	
			(2.15)	
$\widetilde{ ho}_t$		0.2324	0.2427	
		(2.59)	(2.65)	
$\operatorname{constant}$	-1.7866	-1.8082	-1.8366	
	(-19.14)	(-18.68)	(-18.24)	
R_M^2	0.2316	0.2330	0.2340	
t statistics in parentheses				

t-statistics in parentheses.

Table 6: Predictive Models

This table contains estimates from a predictive models of breakdowns. We include the prior days' breakdown probabilities along with the opening value of the VIX, $\log(\mathbf{E}[\pi_t]) = \alpha + \beta_1 \sigma_t^{VIXopen} + \sum_{j=1}^2 \eta_j \pi_{t-j}$. R_M^2 denotes McFadden's R-squared.

	Breakdown
$\sigma_t^{VIXopen}$	0.0388
	(10.64)
π_{t-1}	0.3519
	(3.74)
π_{t-2}	0.3059
	(3.33)
$\operatorname{constant}$	-1.9544
	(-48.12)
R_M^2	0.4936
<i>t</i> -statistics in	n parentheses.

Table 7: Robustness Checks of Aggregate Frequency Models

This table presents estimates for a variety of robustness checks of our explanatory model. (15). Column (1) examines "breakups," rapid increases in offer prices from the listing exchange that are subsequently reversed. Columns (2)-(5) look at breakdown frequency. Column (2) is a sample of stocks with market capitalization of more than \$10 billion. In column (3), the breakdown frequency is based on the NBBO rather than the listing exchange. Column (4) uses trades rather than quotes as the breakdown measure. In column (5), the frequency is based on the worst bid or offer (WBO) on any exchange. We use the generalized linear model with gamma probability distribution, and the models are estimated by quasi-maximum likelihood method using robust standard errors. R_M^2 denotes McFadden's R-squared.

	(1)	(2)	(3)	(4)	(5)
	Breakups	Large Caps	NBBO	Trades	WBO
$\sigma_t^{VIXopen}$	0.0686	0.1325	0.0836	0.0804	0.0039
U U	(47.86)	(13.69)	(51.86)	(40.67)	(2.76)
\widetilde{v}_t	0.2094	1.9653	0.5138	0.6829	0.0623
	(4.70)	(4.32)	(5.30)	(4.30)	(1.19)
d_t^{NMS}	0.0100	-2.5028	-0.9316	-1.6050	0.6200
	(0.33)	(-10.05)	(-30.12)	(-36.46)	(28.36)
$\widetilde{ ho}_t$	0.0854	0.7971	0.1623	0.2715	0.0584
	(1.94)	(2.99)	(3.16)	(2.84)	(1.33)
$\operatorname{constant}$	-2.1231	-5.3716	-2.3821	-2.2085	2.5283
	(-73.12)	(-27.01)	(-78.69)	(-58.91)	(72.74)
R_M^2	0.3721	0.6466	0.5442	0.6095	0.0111

t-statistics in parentheses.

Figure 1: Market Quality Metrics on May 6, 2010

This figure presents the market quality metrics on May 6, 2010 by our filter. For comparison with the CFTC-SEC results, we apply the same stock filter here, i.e. a share price of more than \$3.00 and a market capitalization of at least \$10 million. Panel A shows the distribution of the percentage decline in the best bid prices on the Flash Crash day. Panel B displays the time and percentage decline of the best bid from 14:00 to 15:00. Each point on the graph represents a stock.



Panel A: Distribution of % Decline in the Best Bid





Figure 2: Market Quality of ETFs on May 6, 2010

This figure presents the market quality of ETFs on May 6, 2010 by our filter. Panel A shows the distribution of the percentage decline in the best bid prices for a sample of all ETFs. Panel B displays the time and percentage decline of the best bid from 14:00 to 15:00. Each point on the graph represents an ETF.



Panel A: Distribution of ETF % Decline in the Best Bid





Figure 3: Breakdown Frequency 1993-2011

This figure presents market quality breakdowns from 1993 to 2011. Panel A shows the breakdown frequency, which is calculated by the number of breakdowns divided by the total number of securities. Panel B plots the number of breakdowns in each year.



Panel A: Market Quality Breakdown Frequency



Panel B: Number of Market Quality Breakdowns

Figure 4: Breakdown Inequality by Gini Coefficient 1993-2011

This figure demonstrates the inequality of breakdown incidence among individual stocks by the Gini coefficient. For each year we include the securities that experience at least one breakdown in market quality.



Figure 5: Market Quality Breakdown Frequency by Exchange 1993-2011

This figure presents the breakdown frequencies from 1993 to 2011 on each of the four listing exchanges, NYSE, Nasdaq, AMEX, and ARCA. ARCA becomes a listing exchange in 2006 after its merger with NYSE. The breakdown frequency on each exchange is calculated by the number of breakdowns divided by the total number of securities on that exchange.



Figure 6: Rolling Correlation of Industry Portfolios 1993-2011

This figure illustrates the market correlation from 1993 to 2011. We calculate the 20-day rolling correlation pairwise using daily returns of 30 Fama-French industry portfolios, and then use the median as a measure of the market correlation.



Figure 7: Robustness Checks for Breakdown Frequency 1993-2011

This figure presents event frequencies from 1993 to 2011 for alternative measures of market quality. We plot "breakups," rapid increases in offer prices from the listing exchange that are subsequently reversed. We also plot three breakdown frequencies: (1) a sample of stocks with market capitalization of more than \$10 billion, "Large caps"; (2) the national best bid or offer (NBBO); and (3) trade prices ("Trading events").



Figure 8: WBO Breakdown Frequency 1993-2011

This figure presents market quality breakdown frequencies in the worst bid or offer (WBO) from 1993 to 2011.

