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Price clustering and the stability of stock prices

Benjamin M. Blau [a,*], Todd G. Griffith [b]

[a] Department of Economics and Finance, Utah State University. 3565 Old Main Hill, Logan, UT 84322, United States
[b] Department of Finance, University of Mississippi. 253 Holman Hall, University, MS 38677, United States

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ABSTRACT

Understanding factors that influence volatility is vital to analysts, investment professionals, and firm managers. In this study, we take a non-traditional approach to identify the determinants of volatility by examining how frictions in the formation of prices affect the stability of stock prices. In particular, we test the hypothesis that clustering on round pricing increments will result in more volatile financial markets. A possible explanation for clustering-induced volatility may be that stocks with a greater degree of clustering will have less informative prices and thus exhibit greater volatility. Our multivariate tests seem to confirm our hypothesis as we observe a strong, positive relation between price clustering and stock price volatility. A variety of additional tests suggest that causation flows from clustering to volatility instead of the other way around.

1. Introduction

Much of economic theory revolves around the formation of equilibrium prices. However, in practice, frictions might adversely affect the ability of prices to find their equilibrium. For instance, empirical research shows that prices tend to cluster on round increments in both equity and commodity markets (Wyckoff, 1963; Niederhoffer and Osborne, 1966; Ball, Torous, and Tschoegl, 1985; Harris, 1991; Alexander and Peterson, 2007; Ikenberry and Weston, 2008). Explanations for this type of anomalous price behavior generally fall into two camps. The first explanation suggests that investors' prefer round numbers in attempt to mitigate cognitive processing costs (Wyckoff, 1963; Niederhoffer and Osborne, 1966; Ikenberry and Weston, 2008). The second explanation, which is not mutually exclusive from the first explanation, is predicated on the idea that investors prefer to deal in round prices in attempt to minimize negotiation costs (Ball et al., 1985; Harris, 1991).[1]

While prior research has documented the presence of clustering in financial markets, few, if any studies, have examined the effect of clustering on the quality of financial markets. The main objective of this paper is to take a step in this direction. In particular, we test the hypothesis that the degree of clustering on round pricing increments leads to less stable stock prices. The theory underlying this hypothesis is based on the notion that the price system transmits information to market participants (Hayek, 1945; Friedman, 1977). When clustering on round increments exists, the lack of granularity in stock prices may reduce the informativeness of prices. Therefore, stocks with more clustering may exhibit higher levels of volatility. The implications of our tests are broad, as they suggest that investors' preferences for round prices – whether because of cognitive biases or an aversion to negotiation costs – can adversely affect the informativeness of prices and subsequently increase the volatility of stock prices.

Besides extending the literature that discusses both clustering and volatility, our tests have important practical implications. Analysts and other investment professionals use models that rely on volatility forecasts (Hamid and Iqbal, 2004). Furthermore, managers attempting to maximize the value of shareholders must also be concerned with the level of volatility in the firms' stock price, given that volatility can affect the firms' cost of capital projections. While prior research has found that financial markets exhibit excess volatility (Shiller, 1981), we argue that frictions in how prices are formed can, in part, explain this excess volatility.

In our empirical analysis, we calculate the level of clustering as the percent of daily prices that close on round increments (Harris, 1991). Because our sample time period runs from 1995 to 2012, we control for the structural change in tick sizes (decimalization) that occurred during the beginning of 2001. Consistent with the presence of clustering, we do not find closing prices to be uniformly distributed across all pricing increments. Instead, we find an abnormally high level of clustering in both the pre-decimalization period and the post-decimalization period, respectively.

* Corresponding author.
E-mail addresses: ben.blau@usu.edu (B.M. Blau), tgriffith@bus.olemiss.edu (T.G. Griffith).

[1] An additional explanation also exists for the presence of clustering, which Alexander and Peterson (2007) define as the *collusion explanation*.Christie and Schultz (1994) and Christie, Harris, and Schultz (1994) show that quotes by NASDAQ dealers tend to cluster on even-eighths of dollars and argue that collusion among dealers is the only viable explanation for this type of phenomenon. Similar conclusions are drawn in Dutta and Madhavan (1997) and Simaan, Weaver, and Whitcomb (2003).

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Additional results in this study show a strong contemporaneous correlation between the degree of price clustering and volatility. These results hold in both univariate and multivariate tests. Our results are also robust to measures of return volatility as well as price volatility.[2] These latter tests are important. Our measure of return volatility captures the width of distribution of daily returns whereas our measure of price volatility captures the size of daily price movements.

We recognize that observing correlation between clustering and volatility in stock prices is not tantamount to identifying a causal link. In fact, it is possible that greater levels of volatility might magnify the biases associated with preferences for round prices and lead to higher levels of clustering. We therefore conduct a number of tests that begin to allow us to infer the direction of the relation between clustering and volatility. Additional multivariate tests find that last month's clustering levels are directly related to the current month's volatility. These results hold when we include last month's volatility as an additional control variable.

In unreported tests, we estimate the relation between last month's return volatility and the current month's clustering levels, we do not find a direct association. While we do find a positive relation between last month's price volatility and the current month's clustering level, the relation is markedly weaker when we control for last month's clustering as an additional independent variable. In other unreported tests, we replicate these types of Granger-like tests but apply the intuition to intraday data.[3] In particular, we find that the level of price clustering during the previous 15-minute interval is directly associated with both return and price volatility during the current 15-minute interval – even after controlling for volatility during the previous 15 min. We do not, however, find that price volatility during the previous 15 minute interval predicts the level of contemporaneous clustering, particularly when we control for previous clustering levels. Admittedly, we do find that prior return volatility is directly associated contemporaneous clustering, although the relationship weakens by nearly 30% when we control for prior clustering levels. Again, these Granger-like causality tests suggest that causation flows from clustering to volatility instead of the other way around.

Thus far, our attempts to identify causality only allow us to weakly infer support for our hypothesis that clustering leads to greater volatility. To better determine the direction of this relation, we examine both clustering and volatility surrounding exogenous events that affect the quality of markets. In an ideal world, we would like to examine the level of volatility surrounding an exogenous shock to clustering. However, identifying such shocks is difficult. Therefore, we take a non-traditional approach and attempt to rule out the possibility of reverse causation by examining the level of clustering surrounding exogenous shocks to volatility. Admittedly, these tests do not directly examine the casual inferences that we make in our analysis. However, these tests do speak about the presence of reverse causality. First, we examine both clustering and volatility surrounding the implementation of the Securities and Exchange Commission's Regulation SHO in May 2005. Regulation SHO (Reg SHO hereafter) eliminated the uptick rule for a group of 1000 randomly selected pilot stocks.[4] Prior research (see Alexander and Peterson, 2008; Diether, Lee, and Werner, 2009) shows a significant decrease in volatility surrounding the implementation of Reg SHO. Therefore, using Reg SHO as a natural, randomized experiment, seems to be an appropriate identification strategy.

Both univariate and multivariate tests show that while volatility markedly decreases for pilot stocks surrounding Reg SHO, clustering levels do not. Furthermore, we test whether the results hold when we compare Reg SHO-changes in volatility and clustering levels for pilot stocks to similar changes in non-pilot stocks. Again, results from this difference-in-difference type approach show that while volatility decreases for pilot vis-à-vis non-pilot stocks during Reg SHO, clustering levels are unaffected. We are able to deduce from these tests that exogenous changes in volatility do not cause changes in price clustering. Combined with the findings from our Granger-like causality tests, the results from the Reg SHO tests seems to support our hypothesis that causality flows from clustering to volatility instead of the other way around.

In our final set of tests, we examine both clustering and volatility surrounding the September 11th, 2001 terrorist attacks. Again, this exogenous and unanticipated event, which we argue is an appropriate identification strategy, resulted in the closure of U.S. financial markets from the morning of September 11th until September 17th, and created an unusual level of volatility in stock prices. As expected, results from both our univariate and multivariate tests show that stocks became much more volatile during the month after the attacks than compared to the month before the attacks. In fact, in economic terms, we find that return volatility increased nearly 40% during this period while price volatility increased approximately 23%. Despite these large changes to volatility, we again do not find that price clustering changed in a meaningful way. We recognize that this event study is not a perfect, natural experiment in our attempt to test our hypothesis as we are only able to infer that exogenous changes to volatility do not affect the level of price clustering. However, given the findings from the entire set of tests, we argue that the results from our empirical analysis seem to support the idea that increases in clustering tends to increase the volatility of stock prices.

This study provides an important contribution to the literature and our understanding of the formation of equilibrium stock prices. We contribute to the growing body of evidence that the volatility observed in financial markets can, in part, be attributed to cognitive biases (LeRoy and Porter, 1981; Shiller, 1981; Barberis and Thaler, 2003; Huang, Lin, and Yang, 2015). In the presence of cognitive biases and/or high negotiation costs, our findings suggest that investor preferences for round pricing increments can create instability in stock prices. The externalities of such preferences include less informative prices, potentially higher risk, and the possibility of less efficient financial markets.

2. Data description

To empirically test our research question, we collect data from the Center for Research in Security Prices (CRSP) for the period 1995 to 2012. From these data we observe firm-specific information on daily prices, volume, shares outstanding, exchange listing, and closing bid/ask prices. We retain all stocks defined as CRSP common shares (i.e. share codes 10 & 11). We follow Harris (1991) and exclude firm-observations with a daily stock price of less than \$2. In addition, we require stocks to trade in at least 200 days during any particular year. These restrictions reduce the possibility of the bid/ask bounce and/or infrequently traded stocks biasing our results. The final sample consists of 10,195 unique firm observations and 801,030 firm-month observations.

We recognize that this time period includes two distinct tick-size regimes. In January of 2001, the NYSE reduced its minimum tick-size from sixteenths (\$0.0625) to decimals (i.e. \$0.01).[5] Shortly thereafter, NASDAQ followed suit and decreased its minimum tick size to decimals. The period preceding the tick-size reduction is generally referred to as the pre-decimalization period, to distinguish it from the post-

[2] While these results are obtained using monthly data, we also find a robust association between price clustering and volatility using quarterly data as well as annual data. Furthermore, we conduct a series of tests using non-calendar monthly data, which is obtained from randomly selecting four-week periods as the starting point of our analysis. In each of these tests, we find a strong positive relationship between price clustering and volatility.

[3] We extract trades from the NYSE Euronext Daily Trades and Quotes (DTAQ) database for the first three months of 2015. The results using intraday stock prices are seemingly identical to those of the daily analysis.

[4] The uptick rule restricts investors from shorting stocks on down- or even-ticks and had been enforced since the 1934 Securities Exchange Act.

[5] On June 24th, 1997 the NYSE reduced the minimum price increment from eighths to sixteenths.

decimalization period. Given this structural change in tick sizes, we control for year fixed effects in all of our panel regression analyses.

Throughout our study, the variables of interest are clustering frequency, return volatility, and price volatility. We estimate clustering frequency (*Cluster%*) as the proportion of closing prices that are divisible by round increments.[6] The different tick-size regimes across the sample period lead to two different definitions of round increments. Following prior work that examines quote clustering in the pre-decimalization period (Christie and Schultz, 1994; Christie et al., 1994; Bessembinder, 1999), we define round increments as even eighths ($0.25). In contrast, during the post-decimalization period we define round increments as multiples of $0.05 (Chung, Van Ness, and Van Ness, 2004; Alexander and Peterson, 2007).

We construct two measures to proxy for the stability of stock prices. The first is return volatility (*Rvolt*), which we estimate for each stock by month, as the standard deviation of daily returns. Harris (1991) reports the existence of a positive relation between clustering frequency and return volatility, although the results are not robust to each year in the observed sample period. More recent studies also document a positive relation between volatility and stock price clustering (see Chung et al., 2004; Alexander and Peterson, 2007; Ikenberry and Weston, 2008), and generally attribute the finding to the *price resolution hypothesis* of Ball et al. (1985), which assumes price clustering depends on how well known is the value of the security.

Our second proxy for stock price stability is a low-frequency measure of price volatility (*Pvolt*), calculated as the difference between CRSP monthly high and monthly low prices, scaled by the monthly high price (Diether et al., 2009). We include several other measures as control variables in the multivariate analysis. *Mktcap* is the market capitalization calculated as the closing price multiplied by the number of shares outstanding. The size of the firm should be negatively related to the frequency of price clustering because, in general, larger firms have more analyst coverage and, consequently, the information pertaining to their stocks is more widely distributed. In addition, large firms are typically better diversified than small firms making valuation less difficult. Harris (1991) contends that traders use discrete price sets when underlying security values are well known.

Price is the average daily stock price during a particular month. Nominal share price will likely be positively related to clustering, because as the price increases, the minimum tick size becomes a smaller percentage of the trade value (Ball et al., 1985; Harris, 1991). Traders should be less concerned with placing frivolous bids when the marginal benefit is trivial. *Turn* is the ratio of monthly volume to total shares outstanding. We expect share turnover to be inversely correlated with clustering, because more information is likely to be impounded into stock prices as trading frequency increases. Higher trading frequency is inherently associated with greater return volatility.

Spread is the daily closing bid/ask spread averaged over each month. Both Chung and Zhang (2014) and Roll and Subrahmanyam (2010) suggest that daily closing spreads are a good approximation for transactions-level spreads.[7] Christie and Schultz (1994) argue that spreads and clustering are positively related because dealers prefer to transact on even-eights in order to maintain wider spreads. Chung et al. (2004) also find a direct correlation between spreads and clustering but attribute their findings to the unintentional outcome of investors preferring to transact on nickels and quarters. Huang and Stoll (1996) find no relation between quoted spreads and clustering and conclude that the relation is absorbed by differences in economic factors.

Illiq is Amihud's (2002) illiquidity measure, calculated as the absolute value of returns divided by dollar volume. This measurement is a reliable low-frequency proxy for price impact.[8] Alexander and Peterson (2007) examine the price impact of trade size clustering. They find that medium sized, rounded trades have the largest price impact. We therefore expect to find a positive relation between illiquidity and clustering. We control for exchange listing even though Ikenberry and Weston (2008) find that price clustering is similar between the NASDAQ and NYSE markets, holding other firm-characteristics constant. In contrast however, Grossman, Miller, Cone, Fischel, and Ross (1997) argue that market structure plays a substantial role in explaining stock price clustering. *NYSE* is an indicator variable set equal to one if the firm trades on the New York Stock Exchange and zero for the NASDAQ.

Table 1 reports the statistics that describe our sample. Panel A displays the summary statistics for the entire sample period, while panels B and C present the results for the pre-decimalization and post-decimalization periods, respectively. As shown in Panel A, the average firm's closing price clusters on round increments over 38% of the days in each month. The average firm in the sample has a return volatility of 3.14% and price volatility of 17.36%. Similar results are reported in Ikenberry and Weston (2008), in terms of return volatility and clustering. Furthermore, we find that the average sample firm has a market capitalization of $3.09 billion, a share price of $44.80, turnover of 1.5338, spread of 0.0165, and an illiquidity measure of 0.4484. We also note that approximately 36% of the sample firms are listed on the NYSE.

Panel B reports the results for the pre-decimalization period. We highlight that the average stock has a *Cluster%* of 0.4611. To the extent that prices are uniformly distributed across all pre-decimalization pricing increments, the percent of clustering should be in the vicinity of 37%.[9] The observed clustering percentage of 46% suggests that prices are not uniformly distributed across all pricing increments for the pre-decimalization period. In unreported binomial z-tests, we find that the difference between the observed level of clustering and the predicted (uniform) level of clustering is reliably different from zero at the 0.01 level. We discover a similar result in the post-decimalization period. In panel C, we find that the average stock has a clustering frequency of 32.16% during the post-decimalization period. Again, to the extent that prices are uniformly distributed, *Cluster%* for the average stock should be 0.20.[10] Therefore, we find a much higher level of price clustering during the post-decimalization period than what is expected under a uniform price distribution. Overall, these results are consistent with prior literature that document significant round increment clustering in trade prices in a variety of markets (see Wyckoff, 1963; Niederhoffer and Osborne, 1966; Harris, 1991; Aitken, Brown, Buckland, Izan, and Walter, 1996; Schwartz, Van Ness, and Van Ness, 2004; Davis, Van Ness, and Van Ness, 2014).

There are several clear differences between the two sub-periods. We find that price clustering decreases as we move from the eighths/sixteenths regime to the decimal regime – although this is to be expected given the decrease in the expected levels of baseline clustering (i.e. 37% pre-decimal to 20% post-decimal). Consistent with prior literature documenting liquidity improvements when moving across tick-size regimes (Chung and Hrazdil, 2010; Chordia, Roll, and Subrahmanyam, 2008a, 2008b), we find that spreads are

[6] Harris (1991) shows that the level of price clustering using transaction data and CRSP closing prices is almost identical.

[7] In other unreported tests, we use Corwin and Schultz (2012) estimate of bid-ask spread using daily high and daily low prices. Corwin and Schultz argue that the range between high and low prices represent both volatility and bid-ask spreads. They then decompose the ratio into the volatility component and the spread component. In general, the findings using Corwin and Schultz' spreads are similar to those reported in this paper.

[8] In a study testing whether measures of liquidity indeed measure liquidity (Goyenko, Holden, & Trzcinka, 2009), the Amihud (2002) measure is the top performer in a horse race between numerous price impact proxies.

[9] Recall that in 1997, tick sizes were reduced from 1/8th to 1/16th of dollars. Therefore, uniformity across pricing increments pre-1997 should result in a Cluster% of 0.50. Uniformity from 1997 to 2000 should result in Cluster% of 0.25. Given that this tick size reduction occurred almost directly in between 1995 and 2000, Cluster% should be somewhere in between these two values.

[10] Since *Cluster%* is determined by the number of days that prices cluster on round increments of $0.05, this would suggest that prices have an unconditional probability of closing on round numbers of 0.20.

Table 1
Summary statistics.

	Cluster%	*Rvolt*	*Pvolt*	*MktCap*	*Price*	*Turn*	*Spread*	*Illiq*	*NYSE*
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Panel A. All observations									
Mean	0.3806	0.0314	0.1736	3,099,289,035	44.80	1.5338	0.0165	0.4484	0.3600
Std. Dev.	0.1847	0.0217	0.2030	15,042,553,191	1435.40	2.4655	0.0225	4.9046	0.4800
25th Perc.	0.2381	0.0173	0.0846	101,187,896	8.00	0.4169	0.0020	0.0049	0.0000
Median	0.3500	0.0259	0.1308	335,680,794	16.52	0.9147	0.0086	0.0252	0.0000
75th Perc.	0.4783	0.0392	0.2008	1,296,466,769	29.75	1.8741	0.0225	0.1551	1.0000
Panel B. Pre-decimalization									
Mean	0.4611	0.0355	0.1944	2,041,933,302	31.53	1.2797	0.0296	0.4437	0.3271
Std. Dev.	0.1916	0.0243	0.2252	11,730,928,966	753.79	2.2079	0.0265	1.2722	0.4691
25th Perc.	0.3182	0.0194	0.0930	65,029,188	7.63	0.3529	0.0125	0.0154	0.0000
Median	0.4500	0.0299	0.1462	197,909,125	15.50	0.7007	0.0223	0.0664	0.0000
75th Perc.	0.5789	0.0450	0.2246	752,263,125	27.88	1.4409	0.0382	0.3169	1.0000
Panel C. Post-decimalization									
Mean	0.3216	0.0284	0.1584	3,875,866,916	54.54	1.7204	0.0069	0.4518	0.3841
Std. Dev.	0.1548	0.0190	0.1836	17,028,621,848	1776.54	2.6232	0.0119	6.3666	0.4864
25th Perc.	0.2105	0.0162	0.0798	152,249,726	8.38	0.5012	0.0011	0.0026	0.0000
Median	0.3000	0.0236	0.1212	486,083,666	17.40	1.1217	0.0026	0.0113	0.0000
75th Perc.	0.4091	0.0349	0.1837	1,764,793,743	31.19	2.1528	0.0079	0.0696	1.0000

The table reports statistics that summarize the pooled firm-month data used in the analysis. The sample consists of all common CRSP stocks (i.e. Share Codes 10 & 11) for which there are 200 daily closing prices reported each year and prices greater than $2 for the period between 1995 and 2012. There are 10,195 unique firm observations and 801,030 firm-month observations. Panel A reports the summary statistics for all observations used throughout the analysis. Panels B and C report the results for the pre-decimalization period (pre 2001) and the post-decimalization period (post 2001), respectively. *Cluster%* is the total number of daily CRSP closing prices that clustered on either $0.25 in the pre-decimalization period (1995–2000) or $0.05 in the post-decimalization period (2001 − 2012), divided by the total number of days traded in that month. *Rvolt* is the standard deviation of daily returns for each stock in each month. *Pvolt* is the difference between the highest price during the month and the lowest price during the month scaled by the high price. *MktCap* is the market capitalization. *Price* is the closing price obtained from CRSP. *Turn* is the ratio of monthly volume scaled by shares outstanding. *Spread* is average daily spread, which is calculated using closing bid/ask spreads available on CRSP, divided by the midpoint. *Illiq* is Amihud's (2002) illiquidity measure. *NYSE* is an indicator variable capturing stocks that are listed on the New York Stock Exchange.

substantially lower in the post-decimalization period, relative to the pre-decimalization period. Furthermore, the average market capitalization and share price for a firm in the post-decimalization era are dramatically higher, relative to the pre-decimal period. Finally, we find that both return volatility and price volatility are slightly lower in the post-decimalization period, implicating that the reduction in minimum price increment may have improved price stability.

3. Empirical results

In this section, we begin exploring our hypothesis that price clustering destabilizes stock prices. In the first subsection below, we examine whether the contemporaneous volatility-clustering relation exists within our sample. In the following subsection, we conduct a series of tests to explore the causal relation between volatility and clustering in both univariate and multivariate analyses.

3.1. Price clustering and volatility - correlation

We begin by estimating Pearson correlations between the variables reported in Table 1. These correlations are reported in Table 2 with *p*-values displayed in parentheses. We find that our two approximations for volatility are positively correlated with stock price clustering. The correlation coefficient between return volatility and clustering is 0.027 which is statistically significant at the 0.01 level. Similarly, price volatility is directly correlated with clustering with a reported coefficient of 0.0495, which is significant at the 0.01 level. The remaining correlation coefficients are generally consistent with our expectations. For instance, we find that firm size is negatively correlated with both clustering percentage and volatility. In addition, both spreads and illiquidity are positively related to clustering and volatility. Fig. 1 plots the level of price clustering and both measures of volatility across our sample time period.

The contemporaneous relation between volatility and clustering has been shown to hold in a multivariate setting. We therefore acknowledge the need to perform an analysis that controls for firm-specific characteristics, to ensure that this relation indeed exists within our sample. We estimate the following linear regression equation using least squares.

$$Volatility_{i,t} = \beta_0 + \beta_1 Cluster\%_{i,t} + \beta_2 NYSE_i + \beta_3 \ln(MktCap)_{i,t} + \beta_4 \ln(Price)_{i,t} + \beta_5 Turn_{i,t} + \beta_6 Spread_{i,t} + \beta_7 Illiq_{i,t} + \varepsilon_{i,t} \quad (1)$$

The dependent variable is one of two volatility measures, return volatility (*Rvolt*) or price volatility (*Pvolt*). We include the following as independent variables: *Cluster%* is the proportion of closing prices that are divisible by round increments.[11] *NYSE* is a categorical variable equal to one if the firm is listed on the NYSE and zero otherwise. Ln(*MktCap*) is the natural logarithm of market capitalization. Ln(*Price*) is the natural log of closing prices obtained from CRSP. *Turn* is the share turnover or the ratio of volume to shares outstanding. *Spread* is the average difference between the closing bid and ask prices, divided by the midpoint. *Illiq* is Amihud's (2002) measure of price impact, calculated as the absolute value of returns divided by dollar volume. We report *p*-values in parentheses that are obtained from robust standard errors that account for two-dimensional clustering (stock and month). We observe differences across years using a Hausman test, and *F*-tests, and therefore include year fixed effects. We estimate variance inflation factors and find no evidence of multicollinearity as factors are less than two in all cases.

Table 3 reports the results from estimating Eq. (1). In column [2], we report the results from the full sample specification with return volatility (*Rvolt*) as the dependent variable. In general, the control variables have their expected signs, consistent with prior literature (see e.g. Brandt, Brav, Graham, and Kumar, 2009). For instance, volatility is decreasing with share price and increasing with turnover, spread, and illiquidity. We therefore focus on the variable of interest *Cluster%*. The results suggest that clustering is indeed positively correlated with return volatility. In economic terms, a one unit increase in *Cluster%* is

[11] Round increments are defined as multiples of $0.25 in the pre-decimalization period (1995–2000) or multiples of $0.05 in the post-decimalization period (2001 − 2012).

Table 2
Correlation.

	Cluster%	*Rvolt*	*Pvolt*	*MktCap*	*Price*	*Turn*	*Spread*	*Illiq*
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Cluster%	1.0000	0.0270***	0.0495***	−0.0776***	0.0501***	−0.1359***	0.3258***	0.0489***
		(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Rvolt		1.0000	0.3887***	−0.1023***	−0.0171***	0.3355***	0.3174***	0.0379***
			(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Pvolt			1.0000	−0.0611***	−0.0100***	0.1188***	0.1974***	0.0771***
				(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
MktCap				1.0000	0.1081***	0.0024**	−0.1154***	−0.0172***
					(<0.0001)	(0.035)	(<0.0001)	(<0.0001)
Price					1.0000	−0.0076***	−0.0143***	0.0081***
						(<0.0001)	(<0.0001)	(<0.0001)
Turn						1.0000	−0.1849***	−0.0454***
							(<0.0001)	(<0.0001)
Spread							1.0000	0.1418***
								(<0.0001)
Illiq								1.0000

The table reports Pearson Correlation coefficients for the variables used throughout the analysis. *Cluster%* is the total number of daily CRSP closing prices that clustered on either $0.25 in the pre-decimalization period (1995–2000) or $0.05 in the post-decimalization period (2001–2012), divided by the total number of days traded in that month. *Rvolt* is the standard deviation of daily returns for each stock in each month. *Pvolt* is the difference between the highest price during the month and the lowest price during the month scaled by the high price. *MktCap* is the market capitalization. *Price* is the closing price obtained from CRSP. *Turn* is the ratio of monthly volume scaled by shares outstanding. *Spread* is average daily spread, which is calculated using closing bid/ask spreads available on CRSP, divided by the midpoint. *Illiq* is Amihud's (2002) illiquidity measure. *NYSE* is an indicator variable capturing stocks that are listed on the New York Stock Exchange. *, **, and *** denote statistical significance at the 0.10, 0.05, and the 0.01 levels, respectively.

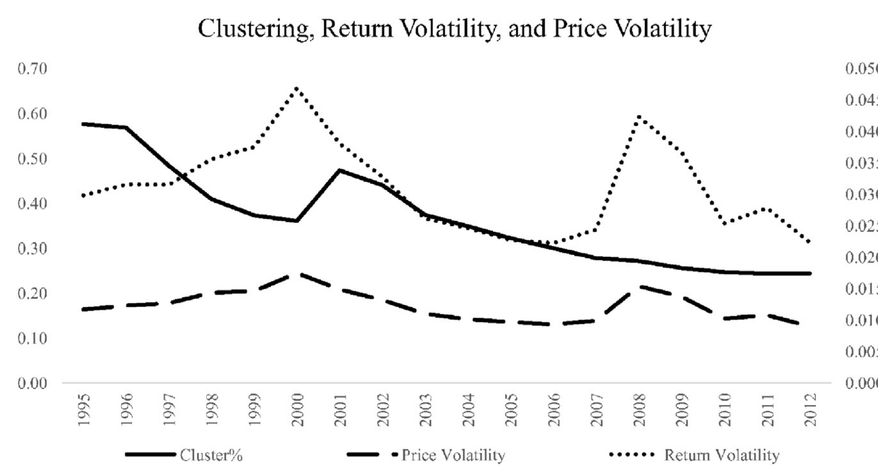

Fig. 1. The figure reports the price clustering (*Cluster%*), price volatility (*Pvolt*), and return volatility (*Rvolt*) in each year across our sample time period.

associated with a 0.0031 increase in return volatility, which represents approximately 10% of the mean return volatility.

In column [4], we report the results from estimating Eq. (1) with price volatility (*Pvolt*) as the dependent variable. We find further evidence of a positive relation between volatility and clustering. The coefficient on *Cluster%* is statistically significant at the 1% level and economically meaningful, as a 1% increase in clustering is associated with a 3% increase in price volatility, which represents nearly 18% of the mean price volatility.[12] Collectively, the results in Tables 2 and 3 confirm the findings in prior literature that there exists a positive relation between volatility and price clustering (see e.g. Harris, 1991; Chung et al., 2004; Ikenberry and Weston, 2008).

[12] In unreported tests, we estimate alternative specifications of Eq. (1) where we include relative short interest – or the ratio of monthly short interest to shares outstanding – as an additional control variable under the idea that short interest proxies for hedge fund trading activity and hedge funds have been purported to increase the volatility of stock prices. We note that including relative short interest as an additional control does not meaningfully influence the conclusions that we are able to draw in Table 3 as our unreported results are very similar to findings reported here.

3.2. Lagged price clustering and volatility

In this next section, we investigate the causal relation between price clustering and volatility by implementing linear Granger-like causality tests. Granger (1969) proposed a method for testing for causality between two economic variables in a time series, which attempts to determine whether lagged information on a variable X provides statistically significant information on a variable Y, while controlling for lagged Y. If not, then X does not Granger-cause Y. We examine whether lagged price clustering directly affects volatility by estimating the following equation.

$$\begin{aligned} Volatility_{i,t} = {} & \beta_0 + \beta_1 Cluster\%_{i,t-1} + \beta_2 Volatility_{i,t-1} + \beta_3 NYSE_i \\ & + \beta_4 \ln(MktCap)_{i,t} + \beta_5 \ln(Price)_{i,t} + \beta_6 Turn_{i,t} \\ & + \beta_7 Spread_{i,t} + \beta_8 Illiq_{i,t} + \varepsilon_{i,t} \end{aligned} \quad (2)$$

The dependent variable is either price volatility (*Pvolt*) or return volatility (*Rvolt*). The independent variable of interest, *Cluster%*, is lagged one month. We also include lagged values of each volatility measure

Table 3
Volatility and price clustering – multivariate tests.

	$Rvolt_{i,t}$		$Pvolt_{i,t}$	
	[1]	[2]	[3]	[4]
Intercept	0.0403***	0.0249***	0.3927***	0.2831***
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
$Cluster\%_{i,t}$	0.0010***	0.0031***	0.0291***	0.0307***
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
$NYSE_i$	−0.0071***	−0.0056***	−0.0252***	−0.0209***
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
$Ln(MktCap)_{i,t}$	0.0008***	0.0008***	−0.0087***	−0.0067***
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
$Ln(Price)_{i,t}$	−0.0089***	−0.0079***	−0.0273***	−0.0218***
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
$Turn_{i,t}$		0.0034***		0.0131***
		(<0.0001)		(<0.0001)
$Spread_{i,t}$		0.2082***		1.1463***
		(<0.0001)		(<0.0001)
$Illiq_{i,t}$		0.0097*		2.0446***
		(0.056)		(<0.0001)
Adj. R^2	0.2682	0.4257	0.0756	0.1082
Year FE	Yes	Yes	Yes	Yes
Robust SEs	Yes	Yes	Yes	Yes

The table reports the results from estimating the following equation using pooled stock-month data.

$Volatility_{i,t} = \beta_0 + \beta_1 Cluster\%_{i,t} + \beta_2 NYSE_i + \beta_3 ln(MktCap)_{i,t} + \beta_4 ln(Price)_{i,t} + \beta_5 Turn_{i,t} + \beta_6 Spread_{i,t} + \beta_7 Illiq_{i,t} + \varepsilon_{i,t}$.

The dependent variable is either return volatility (*Rvolt*) or price volatility (*Pvolt*). The independent variables include the following. *Cluster%* is the total number of daily CRSP closing prices that clustered on either \$0.25 in the pre-decimalization period (1995–2000) or \$0.05 in the post-decimalization period (2001–2012), divided by the total number of days traded in that month. *NYSE* is an indicator variable capturing stocks that are listed on the New York Stock Exchange. *Ln*(*MktCap*) is the natural log of market capitalization. *Ln*(*Price*) is the natural log of the closing price obtained from CRSP. *Turn* is the ratio of monthly volume scaled by shares outstanding. *Spread* is average daily spread, which is calculated using closing bid/ask spreads available on CRSP, divided by the midpoint. *Illiq* is Amihud's (2002) illiquidity measure. *P-values* are reported in parentheses and obtained using robust standard errors that account for two dimensional clustering. In response to results from a Hausman test and F-tests, we find observed differences across years so we include year fixed effects. *, **, and *** denote statistical significance at the 0.10, 0.05, and the 0.01 levels, respectively.

in their respective regressions. The other independent variables have been defined previously. Again, in response to significant results on a Hausman test and *F*-tests for time-series differences, we include year fixed effects. We report *p*-values in parentheses that are obtained from robust standard errors that account for two dimensional clustering (stock and month).

Table 4 reports the results from estimating Eq. (2). In columns [1] and [2] the dependent variable is return volatility. In full specification (in column [2]) we find that the coefficient on lagged *Cluster%* is positive and significant at the 0.01 level, even after controlling for the presence of the lagged dependent variable. This result seems to suggest that price clustering directly affects return volatility. The magnitude of the coefficient is also economically meaningful. For instance, a one unit increase in clustering in the previous month is associated with a 0.0012 unit increase in return volatility in the current month, holding constant all other independent variables. This increase represents nearly 4% of the mean return volatility. In columns [3] and [4] we report the results of estimating Eq. (2) and using price volatility as the dependent variable. Similar to the finding on return volatility, we report evidence consistent with the notion that clustering leads to greater price volatility. *Cluster%* in month $t-1$ is positive and significant, after controlling for the lagged value of price volatility and all other independent variables. These results suggest that the impact of clustering in the previous month is a significant indicator of both future price volatility and future return volatility.

In unreported tests, we estimate the "reverse" model and see if there exists a feedback effect from volatility to clustering. In particular, the dependent variable is clustering levels for a particular stock during a particular month and the independent variables of interest are our measures of volatility, which are lagged one month. The

Table 4
Volatility and lagged clustering.

	$Rvolt_{i,t}$		$Pvolt_{i,t}$	
	[1]	[2]	[3]	[4]
Intercept	0.0260***	0.0151***	0.2860***	0.2574***
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
$Cluster\%_{i,t-1}$	0.0022***	0.0012***	0.0327***	0.0304***
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
$Volt_{i,t-1}$		0.3648***		0.0952***
		(<0.0001)		(<0.0001)
$NYSE_i$	−0.0055***	−0.0033***	−0.0207***	−0.0184***
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
$Ln(MktCap)_{i,t}$	0.0007***	0.0005***	−0.0064***	−0.0058***
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
$Ln(Price)_{i,t}$	−0.0078***	−0.0049***	−0.0227***	−0.0206***
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
$Turn_{i,t}$	0.0034***	0.0026***	0.0131***	0.0122***
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
$Spread_{i,t}$	0.2077***	0.1596***	1.1049***	1.0144***
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
$Illiq_{i,t}$	0.0084*	0.0138***	2.0409***	1.8930***
	(0.094)	(0.004)	(<0.0001)	(<0.0001)
Adj. R^2	0.4255	0.5134	0.1088	0.1171
Year FE	Yes	Yes	Yes	Yes
Robust SEs	Yes	Yes	Yes	Yes

The table reports the results from estimating the following equation using pooled stock-month data.

$Volatility_{i,t} = \beta_0 + \beta_1 Cluster\%_{i,t-1} + \beta_2 Volatility_{i,t-1} + \beta_3 NYSE_i + \beta_4 ln(MktCap)_{i,t} + \beta_5 ln(Price)_{i,t} + \beta_6 Turn_{i,t} + \beta_7 Spread_{i,t} + \beta_8 Illiq_{i,t} + \varepsilon_{i,t}$.

The dependent variable is either return volatility (*Rvolt*) or price volatility (*Pvolt*) for each stock *i* in each month *t*. The independent variables include the following. $Cluster\%_{i,t-1}$ is the total number of daily CRSP closing prices that clustered on either \$0.25 in the pre-decimalization period (1995–2000) or \$0.05 in the post-decimalization period (2001–2012), divided by the total number of days traded in that month. $Rvolt_{i,t-1}$ is the standard deviation of daily returns during a particular month. We note that these first two independent variables are measured during the prior month. *NYSE* is an indicator variable capturing stocks that are listed on the New York Stock Exchange. *Ln*(*MktCap*) is the natural log of market capitalization. *Ln*(*Price*) is the natural log of the closing price obtained from CRSP. *Turn* is the ratio of monthly volume scaled by shares outstanding. *Spread* is average daily spread, which is calculated using closing bid/ask spreads available on CRSP, divided by the midpoint. *Illiq* is Amihud's (2002) illiquidity measure. *P-values* are reported in parentheses and obtained using robust standard errors that account for two dimensional clustering. In response to results from a Hausman test and F-tests, we find observed differences across years so we include year fixed effects. *, **, and *** denote statistical significance at the 0.10, 0.05, and the 0.01 levels, respectively.

other independent variables are similar to those in Eq. (2). While we find some evidence that lagged return volatility directly predicts current clustering levels, these results do not hold when we control for lagged clustering levels. Combined with our findings in columns [1] and [2] of Table 4, these results seem to indicate that causation flows from clustering to volatility instead of the other way around. We note, however, that when we examine the effect of lagged price volatility on clustering levels, we find a positive association whether or not we control for lagged clustering. The magnitude of the relationship between lagged price volatility and contemporaneous clustering decreases by >40% when we include lagged clustering. Regardless, these unreported results are only able to provide weak evidence of the direction of causation.[13]

Our findings in this section seem to suggest that price clustering directly influences volatility, instead of the other way around. Next, we attempt to address the identification problem by examining changes in the variables of interest surrounding exogenous shocks to the stability of stock prices.

[13] As mentioned in the introduction, we conduct some similar tests using intraday data. These unreported tests show that the level of price clustering during the previous 15-minute interval is directly associated with both return and price volatility during the current 15-minute interval – even after controlling for volatility during the previous 15 min. However, we do not find that price volatility during the previous 15 minute interval predicts the level of contemporaneous clustering, particularly when we control for previous clustering levels. These results support our findings using more high-frequency data.

3.3. Price clustering and volatility - regulation SHO

Our first natural experiment is to examine a sample of 1000 pilot stocks randomly selected by the Securities and Exchange Commission (SEC) for which Reg SHO was enacted. Reg SHO, implemented by the SEC in May of 2005, relaxed the uptick rule or the rule that restricted short selling on down ticks (or even ticks). The uptick rule had been enforced since the Securities and Exchange Act of 1934. As mentioned above, Alexander and Peterson (2008) and Diether et al. (2009) show that pilot stocks experienced a significant decrease in both return volatility and price volatility during the period surrounding the Reg SHO.

We begin by confirming that the volatility for the group of randomly selected pilot stocks is significantly different pre- and post-SHO enactment. Table 5 provides a univariate analysis of the effects of Regulation SHO on volatility and price clustering. Using a simple t-test in means we report that return volatility significantly decreases from before the price test to after (0.0025, p-value $=$ 0.0001). We find similar results in our price volatility measure (0.0112, p-value $=$ 0.001). To examine the degree to which Reg SHO affected pilot stock volatility, we calculate abnormal return and price volatility, by taking raw volatility values for the pilot stocks and subtracting the average for all control stocks that were not part of the pilot program (non-pilot stocks).

In Panel B of Table 5, we find that both abnormal volatility measures are significantly higher in the pre-SHO period. These results indicate that the pilot stocks selected to participate in this short-sale restriction test, exhibit a shock to volatility. Thus, Reg SHO provides a conducive setting in which we can test for the causal relation between volatility and price clustering. If indeed volatility drives price clustering, we should find that clustering moves in the same direction as volatility during the shock. We are unable to find evidence of such a relation. In fact, in Panel A we find that, if anything, the difference in *Cluster%* between the pre- and post-SHO periods is negative. Similar to volatility, we calculate abnormal clustering by taking the raw values of clustering for the treatment group of pilot stocks and subtracting the average clustering for the control group of non-pilot stocks. In Panel B, we find that clustering moves in the opposite direction of volatility surrounding regulation SHO. These univariate findings are compelling, in the sense that volatility does not seem to drive clustering. However, we recognize the need to control for other factors that may influence volatility and clustering.

We estimate the following equation using the random sample of pilot stocks for the testing period April and May of 2005.

$$\begin{aligned} Volatility_{i,t} \text{ or } Cluster\%_{i,t} = \beta_0 + \beta_1 NYSE_i + \beta_2 \ln(MktCap)_{i,t} \\ +\beta_3 \ln(Price)_{i,t} + \beta_4 Turn_{i,t} + \beta_5 Spread_{i,t} \\ +\beta_6 Illiq_{i,t} + \beta_7 SHO_t + \varepsilon_{i,t} \end{aligned} \tag{3}$$

The dependent variable is either return volatility (*Rvolt*), price volatility (*Pvolt*), or clustering (*Cluster%*). All independent variables have been defined previously with the exception of SHO_t, which is an indicator variable set equal to one in the month of May, and zero in the month of April. We do not include year fixed effects since doing so would avoid violating the full rank condition required for consistent and unbiased estimates. We again report p-values in parentheses that are obtained from robust standard errors that account for two-dimensional clustering (stock and month).

The results of estimating Eq. (3) are reported in Table 6. In columns [1] and [2] we find that the coefficient on the indicator variable *SHO* is negative and significant at the 1% level. These estimates suggest that, after holding other factors constant, both price and return volatility significantly decreased from the pre-SHO period to the post-SHO period. We test for the extent to which the pilot stocks experienced a volatility shock by estimating abnormal values of price and return volatility. As before, the abnormal values are simply the raw measures of volatility and clustering for the treatment stocks less the average values for the control stocks in the sample. In columns [4] and [5], we document that the categorical variable *SHO* is negative and significantly related to both abnormal return volatility and abnormal price volatility. These findings support our univariate results in Table 5, and indicate that the Regulation SHO test significantly impacted the volatility of the selected pilot stocks.

We now turn our attention to the regressions with *Cluster%* and *Abnormal Cluster%* as the dependent variables, which are also reported in Table 6. If volatility indeed affects the level of clustering in closing stock prices, then we should again observe a negative and significant coefficient on *SHO*. In column [3], however, we find that the indicator *SHO* is insignificantly different from zero. This suggests that the level of clustering for the pilot stocks did not change surrounding the enactment of Regulation *SHO*. Additionally, in column [6] we show that *SHO* is positively related with abnormal clustering (0.0131, p-value $=$ 0.022). We therefore conclude that volatility does not appear to directly affect price clustering. The results from this natural experiment provide strong evidence that volatility is not causing price clustering. The results may, however, be isolated to this one experiment. Therefore, in the following section we analyze an alternative event which is mutually exclusive from the first.

Table 5
Volatility and price clustering surrounding Regulation SHO.

	April 2005	*May 2005*	*Difference*
	[1]	[2]	[2] − [1]
Panel A. Rvolt, Pvolt, and Cluster% for pilot stocks			
Rvolt	0.0232	0.0207	−0.0025***
			(<0.0001)
Pvolt	0.1245	0.1132	−0.0112***
			(0.001)
Cluster%	0.2930	0.3032	0.0102*
			(0.086)
Panel B. Abnormal measures of Rvolt, Pvolt, and Cluster% for pilot stocks			
AB_Rvolt	−0.0031	−0.0042	0.0010*
			(0.073)
AB_Pvolt	−0.0326	−0.0416	0.0090**
			(0.010)
AB_Cluster%	−0.0441	−0.0282	−0.0159***
			(0.007)

The table reports the return volatility (*Rvolt*), price volatility (*Pvolt*), and our measure of price clustering (*Cluster%*) during the month prior and the month after Regulation SHO. Regulation SHO was enacted for a group of 1000 randomly selected pilot stocks on May 2nd, 2005. Panel A shows the mean measures of volatility and price clustering before and after for those pilot stocks. Panel B shows abnormal measures of volatility and price clustering (*AB_Rvolt*, *AB_Pvolt*, and *AB_Cluster%*) surrounding Regulation SHO. In this panel, these abnormal measures of volatility and price clustering are calculated by taking the raw measures of volatility and price clustering for pilot stocks and subtracting the average measures of volatility and price clustering for the stocks not included in the pilot sample. Column [3] reports the difference between the pre-SHO (April 2005) and Post-SHO period (May 2005). *, **, and *** denote statistical significance at the 0.10, 0.05, and the 0.01 levels, respectively.

3.4. Price clustering and volatility - September 11th, 2001

Our second natural experiment is to analyze volatility and clustering around the tragic events which occurred on September 11th, 2001. The terrorist attacks took place on the 11th of September which resulted in all U.S. financial markets closing until September 17th. Maillet and Michel (2005) provide evidence that markets were extremely volatile surrounding these events. We analyze the difference in volatility and clustering during the two months surrounding September 2001 (i.e. August and October).

As predicted, in Table 7 we find that both return volatility and price volatility significantly increase in the post-attack period. For instance,

Table 6
Volatility and clustering surrounding regulation SHO.

	$Rvolt_{i,t}$	$Pvolt_{i,t}$	$Cluster\%_{i,t}$	$AB\_Rvolt_{i,t}$	$AB\_Pvolt_{i,t}$	$AB\_Cluster\%_{i,t}$
	[1]	[2]	[3]	[4]	[5]	[6]
Intercept	0.0497***	0.2484***	0.4761***	0.0234***	0.0913***	0.1389**
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.001)	(0.021)
$NYSE_i$	−0.0013**	−0.0015	0.0423***	−0.0013**	−0.0015	0.0422***
	(0.016)	(0.676)	(<0.0001)	(0.016)	(0.676)	(<0.0001)
$Ln(MktCap)_{i,t}$	−0.0011***	−0.0047***	−0.0167***	−0.0011***	−0.0047***	−0.0167***
	(<0.0001)	(0.0004)	(<0.0001)	(<0.0001)	(0.001)	(<0.0001)
$Ln(Price)_{i,t}$	−0.0035***	−0.0214***	0.0425***	−0.0035***	−0.0214***	0.0425***
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
$Turn_{i,t}$	0.0029***	0.0161***	−0.0015	0.0029***	0.0161***	−0.0015
	(<0.0001)	(<0.0001)	(0.308)	(<0.0001)	(<0.0001)	(0.308)
$Spread_{i,t}$	1.7146***	6.2676***	8.9612***	1.7146***	6.2676***	8.9612***
	(<0.0001)	(0.0001)	(0.003)	(<0.0001)	(0.0001)	(0.003)
$Illiq_{i,t}$	−0.1731**	−0.5469	−0.0554	−0.1731**	−0.5469	−0.0554
	(0.036)	(0.161)	(0.947)	(0.036)	(0.161)	(0.947)
SHO_t	−0.0022***	−0.0091***	0.0074	−0.0008*	−0.0068**	0.0131**
	(<0.0001)	(0.002)	(0.197)	(0.072)	(0.020)	(0.022)
Adj. R^2	0.4308	0.2980	0.0993	0.4254	0.2964	0.1016
Year FE	No	No	No	No	No	No
Robust SEs	Yes	Yes	Yes	Yes	Yes	Yes
N	1590	1590	1590	1590	1590	1590

The table reports the results from estimating the following equation using pooled stock-month data.
$Volatility_{i,t}$ or $Cluster\%_{i,t} = \beta_0 + \beta_1 NYSE_i + \beta_2 ln(MktCap)_{i,t} + \beta_3 ln(Price)_{i,t} + \beta_4 Turn_{i,t} + \beta_5 Spread_{i,t} + \beta_6 Illiq_{i,t} + \beta_7 SHO_t + \varepsilon_{i,t}$.
We only include April 2005 and May 2005 in the analysis. The dependent variable is either *Rvolt*, *Pvolt* or *Cluster%* for each pilot stock *i* in each month *t*. We also include abnormal measures of the dependent variable, which are calculated by subtracting the mean measure of say *Cluster%* for non-pilot stocks from the *Cluster%* for each pilot stock *i*. The independent variables include the following. *NYSE* is an indicator variable capturing stocks that are listed on the New York Stock Exchange. *Ln*(*MktCap*) is the natural log of market capitalization. *Ln*(*Price*) is the natural log of the closing price obtained from CRSP. *Turn* is the ratio of monthly volume scaled by shares outstanding. *Spread* is average daily spread, which is calculated using closing bid/ask spreads available on CRSP, divided by the midpoint. *Illiq* is Amihud's (2002) illiquidity measure. The independent variable of interest is the indicator variable *SHO*, which is equal to unity in the month of May – zero in the month of April. *P-values* are reported in parentheses and obtained using robust standard errors that account for two dimensional clustering. In order to avoid violating the full rank condition required for consistent estimates, we do not include year fixed effects. *, **, and *** denote statistical significance at the 0.10, 0.05, and the 0.01 levels, respectively.

the difference in return volatility between the pre-attack period and the post-attack period is −0.0116. This is both economically and statistically significant. We test for statistical significance using a two-tailed *t*-test and report a *p*-value of <0.001, which indicates that we reject the hypotheses that the values are the same between the two periods at the 0.01 level. As far as univariate evidence is concerned, we report that volatility increased substantially surrounding the events of 9/11. Therefore, if volatility causes price clustering we expect to find a significant negative difference in clustering between the post-attack period and the pre-attack period. We do not find such evidence. In fact, the difference in clustering percentage between the periods is not significantly different from zero. The results indicate that volatility does not cause direct changes in clustering.

Table 7
Volatility and clustering surrounding September 11th, 2001.

	August 2001	October 2001	Difference
	[1]	[2]	[2] − [1]
Rvolt	0.0293	0.0409	0.0116***
			(<0.0001)
Pvolt	0.1790	0.2200	0.0410***
			(<0.0001)
Cluster%	0.4973	0.4954	−0.0019
			(0.626)

The table reports the return volatility (*Rvolt*), price volatility (*Pvolt*), and our measure of price clustering (*Cluster%*) during the month prior and the month after the Terror Attacks of September 11th, 2001. The terrorist attacks occurred on the 11th of September and U.S. financial markets were closed until September 17th. We therefore analyze our measures of volatility and price clustering during the month prior to September and the month after September. As before, column [3] reports the difference between the pre-attack period (August 2001) and post-attack period (October 2001). *, **, and *** denote statistical significance at the 0.10, 0.05, and the 0.01 levels, respectively.

As in previous sections, we control for other factors that may influence volatility and clustering by estimating the following regression equation.

$$\begin{aligned} Volatility_{i,t} or \ Cluster\%_{i,t} = {} & \beta_0 + \beta_1 NYSE_i + \beta_2 \ln(MktCap)_{i,t} \\ & + \beta_3 \ln(Price)_{i,t} + \beta_4 Turn_{i,t} + \beta_5 Spread_{i,t} \\ & + \beta_6 Illiq_{i,t} + \beta_7 SEPT11th_t + \varepsilon_{i,t} \end{aligned} \quad (4)$$

The dependent variable is one of the following measures: return volatility, price volatility or clustering. *SEPT*11*th* is an indicator variable equal to unity in the month of October and zero in the month of August. The control variables have been defined in previous sections. We include only observations for August 2001 and October 2001 in the analysis. As before, we do not include year fixed effects as to avoid violating the full-rank condition and we report *p*-values that are obtained from robust standard errors that account for two dimensional clustering (stock and month).

The results from estimating Eq. (4) are displayed in Table 8. In the first column, we find that the coefficient on the indicator variable *SEPT*11*th* is positive, 0.0079, and highly significant. This is indicative of a positive return volatility shock surrounding the events of 9/11. We find a similar result in our regression on price volatility. The coefficient on *SEPT*11*th* is again positive and significant (0.0236, *p*-value = 0.001). Therefore, we feel confident that we have isolated an alternative event in which the market experienced a significant shock to volatility. We can now analyze the causal relation between volatility and clustering. In column [3] we report that the dummy variable *SEPT*11*th* is not significantly related to clustering. This implies that the level of clustering did not seem to be impacted by the shock in volatility. Therefore, to the extent that the events of September 11th, 2001 created an exogenous shock to volatility, we find no evidence that volatility is driving clustering. Thus, causation does not appear to run from volatility to clustering.

Table 8
Volatility and clustering surrounding September 11th, 2001.

	$Rvolt_{i,t}$	$Pvolt_{i,t}$	$Cluster\%_{i,t}$
	[1]	[2]	[3]
Intercept	−0.0005	0.2310***	1.4137***
	(0.868)	(<0.0001)	(<0.0001)
$NYSE_i$	−0.0089***	−0.0326***	0.0361***
	(<0.0001)	(<0.0001)	(<0.0001)
$Ln(MktCap)_{i,t}$	0.0025***	0.0014	−0.0593***
	(<0.0001)	(0.571)	(<0.0001)
$Ln(Price)_{i,t}$	−0.0105***	−0.0439***	0.0848***
	(<0.0001)	(<0.0001)	(<0.0001)
$Turn_{i,t}$	0.0045***	0.0211***	−0.0077***
	(<0.0001)	(<0.0001)	(<0.0001)
$Spread_{i,t}$	0.4645***	1.5759***	2.3231***
	(<0.0001)	(0.001)	(<0.0001)
$Illiq_{i,t}$	−0.0126***	0.0932*	−0.0258
	(0.004)	(0.096)	(0.374)
$SEPT11th_t$	0.0079***	0.0236***	−0.0038
	(<0.0001)	(<0.0001)	(0.266)
Adj. R^2	0.5319	0.1297	0.2756
Year FE	No	No	No
Robust SEs	Yes	Yes	Yes
N	7268	7268	7268

The table reports the results from estimating the following equation using pooled stock-month data. $Volatility_{\ i,t}\ or\ Cluster\%_{i,t} = \beta_0 + \beta_1 NYSE_i + \beta_2 ln(MktCap)_{i,t} + \beta_3 ln(Price)_{i,t} + \beta_4 Turn_{i,t} + \beta_5 Spread_{i,t} + \beta_6 Illiq_{i,t} + \beta_7 SEPT11th_t + \varepsilon_{i,t}$.
We only include August 2001 and October 2001 in the analysis. The dependent variable is either *Rvolt*, *Pvolt* or *Cluster%* for each pilot stock *i* in each month *t*. We also include abnormal measures of the dependent variable, which are calculated by subtracting the mean measure of say *Cluster%* for non-pilot stocks from the *Cluster%* for each pilot stock *i*. The independent variables include the following. *NYSE* is an indicator variable capturing stocks that are listed on the New York Stock Exchange. *Ln*(*MktCap*) is the natural log of market capitalization. *Ln*(*Price*) is the natural log of the closing price obtained from CRSP. *Turn* is the ratio of monthly volume scaled by shares outstanding. *Spread* is average daily spread, which is calculated using closing bid/ask spreads available on CRSP, divided by the midpoint. *Illiq* is Amihud's (2002) illiquidity measure. The independent variable of interest is the indicator variable *SEPT*11*th*, which is equal to unity in the month of October – zero in the month of August. *P-values* are reported in parentheses and obtained using robust standard errors that account for two dimensional clustering. In order to avoid violating the full rank condition required for consistent estimates, we do not include year fixed effects. *, **, and *** denote statistical significance at the 0.10, 0.05, and the 0.01 levels, respectively.

We recognize that the natural experiments in these last two sections do not perfectly test our hypothesis that clustering destabilizes stock prices. However, these experiments allow us to conclude that the relation between clustering and volatility, which has been documented both in this analysis and in other studies (Harris, 1991; Chung et al., 2004; Ikenberry and Weston, 2008), does not seem to flow from volatility to clustering. Given the evidence from our Granger-like causality tests, the findings from these natural experiments seem to suggest that, indeed, investor preferences for round pricing increments may adversely affect the stability of financial markets.

4. Conclusion

In this study, we develop and test the hypothesis that clustering on round pricing increments can lead to greater volatility and less stable financial markets. The motivation for this analysis is based on the traditional idea that prices are an important information mechanism for market participants. In the presence of clustering, the lack of granularity might result in less informative prices, which can create uncertainty and lead to greater volatility.

We document a strong contemporaneous relation between price clustering and volatility that is robust to both univariate and multivariate tests and various measures of volatility. However, observing a contemporaneous correlation between clustering and volatility is not tantamount to determining causality. Therefore, we set out to conduct a series of tests to identify the direction of this relation. Results from Granger-like causality tests show that while lagged clustering predicts higher return volatility, lagged return volatility does not necessarily predict higher clustering. These results suggest that, to some extent, causation flows from clustering to return volatility instead of the other way around.

Admittedly, the evidence from our Granger-like tests only provides weak support for our hypothesis. To overcome this weakness, we examine volatility and clustering surrounding two exogenous events that affected volatility. In particular, we examine our variables of interest surrounding a regulatory change in the microstructure of financial markets that has been shown to decrease the level of volatility (Regulation SHO). We also examine clustering and volatility surrounding the September 11th, 2001 terrorist attacks, which lead to the closure of financial markets and a dramatic shock to volatility. Results from these two natural experiments show that while volatility changes, the level of price clustering does not, suggesting that, at a minimum, we are able to infer that exogenous shocks to volatility do not cause changes in the level of clustering.

Combined with our earlier findings, these results support the idea that investor preferences for round price increments can lead to destabilized stock prices. These conclusions have broad implications as they first contribute to the extensive literature that attempts to identify the determinants of volatility in financial markets. Our findings suggest that price clustering is indeed an important factor in determining the level of volatility. Second, and perhaps more importantly, our results have important implications regarding the formation of equilibrium prices and efficiency of financial markets. Much of asset pricing theory, and to a lesser extent corporate finance theory, is concerned with volatility levels. Our findings introduce the possibility that less informative prices caused by cognitive biases, and/or negotiation aversion, can create excess volatility and lead to less stable stock prices.

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