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Have Stock Prices become more Uniformly Distributed?

Ahmed Baig
Lahore University of Management Science

Nasim Sabah
Framingham State University

Drew Winters
Texas Tech University

Abstract

We find that: (1) prices cluster on 0¢ and 5¢, (2) prices cluster at the close and intraday, (3) intraday prices cluster more than closing prices with the difference increasing through time, and (4) price clustering declines with time. Our results suggest several paths for future research.

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Contact: Ahmed Baig - ahmed.baig@ttu.edu, Nasim Sabah - nasim.sabah@ttu.edu, Drew Winters - drew.winters@ttu.edu.
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1. Introduction

The value of an asset is the present value of the future cash flows that the asset will generate for the owner. With all the various inputs to the valuation process there is no reason to expect the true price of assets to cluster on a subset of price increments, yet Harris (1991) states that security prices have clustered for decades.[1]

Harris (1991) says that price clusters occur due to regulation and convention. Harris (1991) suggests that coarse price increments (which appear as clustering) reduce negotiation costs. Christie and Schultz (1994) examine price clustering on NASDAQ in 1991 when market regulations required price increments of 1/8 dollar (12.5¢). They find prices clustered on even 1/8, which results in 25¢ price increments. Christie, Harris and Schultz (1994) find that after public reports of even 1/8 clustering NASDAQ market makers moved to using odd 1/8 quotes, which reduced the even 1/8 clustering. These results demonstrate that market regulations and human decisions have a role in price clustering.

In the first half of 2001, the US stock markets switched to decimal (1¢ price increments) pricing. Ikenberry and Weston (2007) examine price clustering following the switch to decimalization using data from the last six months of 2002. They find that about 40% of closing prices cluster on 0¢ and 5¢ where an even distribution across all prices would have 20% of closing prices on 0¢ and 5¢. They conclude "… that market participants share a common bias towards certain prominent prices that psychologists have identified as natural cluster points." (p. 33)

Stock market decimalization has coincides with: substantial growth in institutional investment, improved market liquidity, decreased trading costs and the advent of the internet, which improved the flow of information. Bai, Philippon and Savov (2016) use stock market data from 1960 through 2014 and find that stock prices have become more informative each decade. We posit that with more informative prices there should be less price clustering.

We find that: (1) prices cluster on 0¢ and 5¢, (2) prices cluster at the close and intraday, (3) intraday prices cluster more than closing prices with the difference increasing through time, and (4) price clustering declines with time. Our results suggest several paths for future research, which we discuss in the final section of the paper.

2. Data

We obtain stock-level information for all common stocks from CRSP and TAQ.[2] Our sample period is from May 2001 to September 2016. Our sample starts in May 2001 because NASDAQ decimalization takes place in April of 2001. We end our sample in September 2016 because the SEC implemented the 'Tick Size Pilot Program' in October 2016.[3] Our intra-day sample ends in December 2015 due to data limitations.

We collect daily closing prices from CRSP. Using closing prices, we calculate the percentage of prices at each price increment and average the results monthly. Using the transaction-level data from TAQ, we calculate the percent of prices at each price increment daily.

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[1] Price clustering has been documented in various markets including stock markets, bond markets, commodity markets, derivative markets, and the (crypto) currency markets across the globe (Harris, 1991; Ap Gwilym, Clare, and Thomas, 1998; Blau and Griffith, 2016; Urquhart, 2017).

[2] We delete stocks with prices less than two dollars.

[3] Under the tick size pilot program the SEC changed the minimum tick sizes (de-decimalization) for three groups of stocks (about 1200 stocks) for a period of two years.

We use these calculations of the percent of prices at each price increment to determine if price clustering has declined through time.

3. Summary Statistics

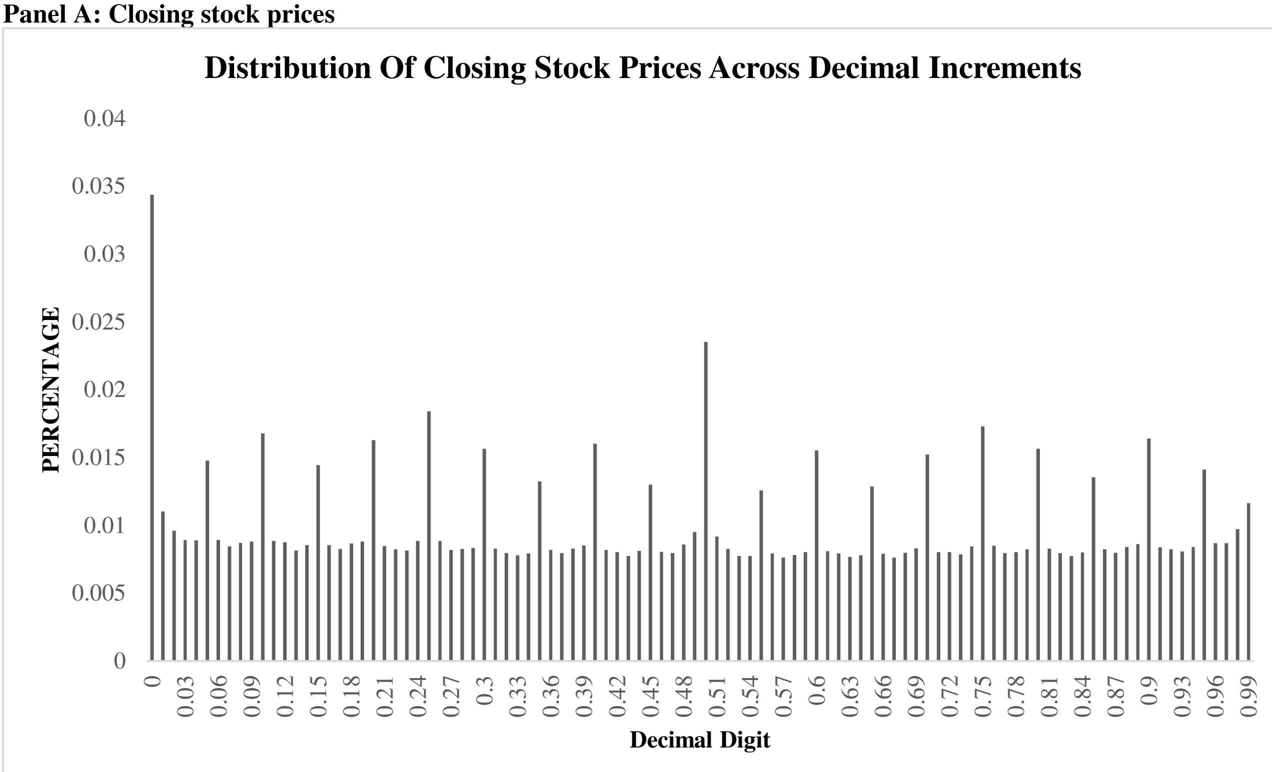
Current literature defines price clustering as prices ending on 0¢ and 5¢.[4] Accordingly, we begin our analysis with plots across the available 1¢ price increments (decimal pricing). Figure 1 presents the distribution of stock prices. Panel A presents the distribution of closing prices and Panel B presents the distribution of intraday transaction prices.

Consistent with the prior literature we observe that there is a high instance of clustering on 5¢ increments in both closing prices and intraday prices. Additionally, there is a clear preference for $1 and 50¢ prices. Interestingly, the clusters at $1, 25¢, 50¢ and 75¢ are all slightly larger intraday than at the close.

Prices ending in 0¢ and 5¢ represent 20% of the available prices. Figure 1 shows that prices ending in 0¢ and 5¢ are over-represented. Specifically, we find that 31% of the closing prices end in 0¢ or 5¢ while 33% of the intra-day prices 0¢ or 5¢. These results suggest that price clustering is present in both of our samples.

Figure 1: Distribution of stock prices across decimal increments

Panel A: Closing stock prices



[4] See, for example: Blau and Griffith (2016) and Das and Kadapakkam (2018).

Panel B: Intraday stock prices

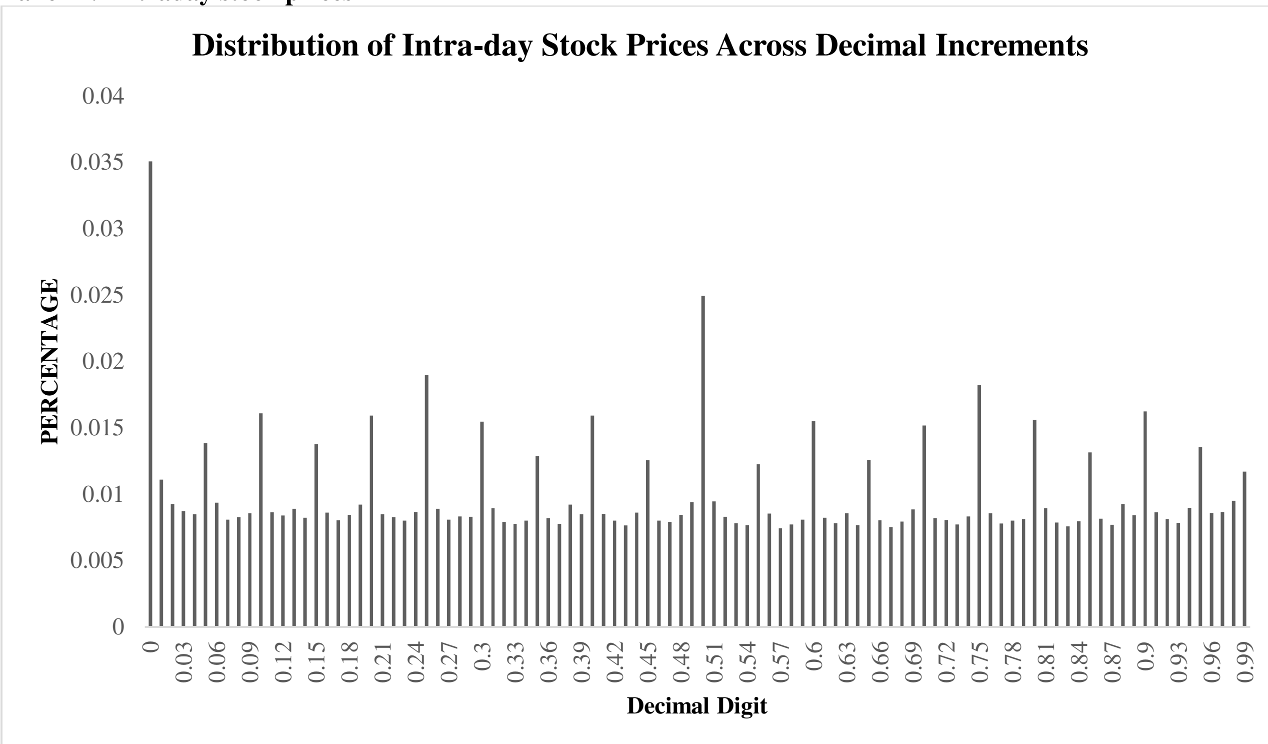


Table I presents the summary statistics with Panel A providing statistics for the monthly summaries of closing prices and Panel B providing statistics for the daily summaries of intraday prices. The overall conclusion from the summary statistics is that the two samples are similar. The only characteristic where our two samples appear to differ is in volatility with higher volatility in our intraday sample than in the closing price sample. However, we note that this is the only sample characteristic reported in Table I where different methods of calculation are used for the two samples and therefore, the volatility measures are not directly comparable.

Table I: Summary Statistics

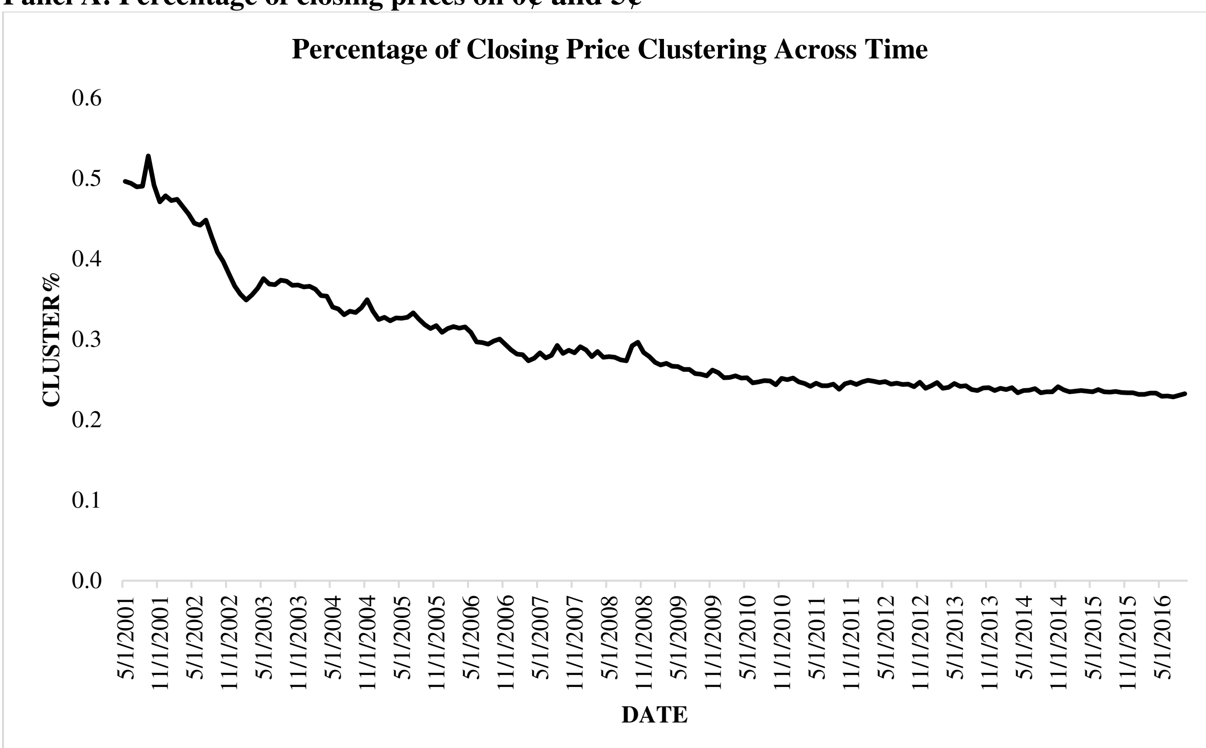
	Mean	Standard deviation	25th Percentile	Median	75th percentile
Panel A: Closing Prices: Monthly Analysis (n=724,929)					
CLUSTER%	0.312	0.158	0.200	0.286	0.391
PRICE	56.907	2093.538	7.690	16.660	31.340
LNSIZE	13.074	1.944	11.658	12.949	14.343
IDIO_VOLATILITY	0.023	0.020	0.011	0.018	0.028
TURNOVER	0.008	0.016	0.002	0.005	0.010
SPREAD	0.009	0.018	0.001	0.003	0.010
NASDAQ	0.589				

Panel B: Intraday Prices: Daily Analysis (n=14,086,106)					
CLUSTER_RATIO	0.328	0.186	0.224	0.274	0.373
PRICE	55.270	2007.858	7.670	16.740	31.370
LNSIZE	13.128	1.909	11.754	12.998	14.364
RANGE_VOLATILITY	0.039	0.040	0.018	0.029	0.048
TURNOVER	0.008	0.026	0.002	0.004	0.009
SPREAD	0.008	0.019	0.001	0.002	0.007
NASDAQ	0.586				

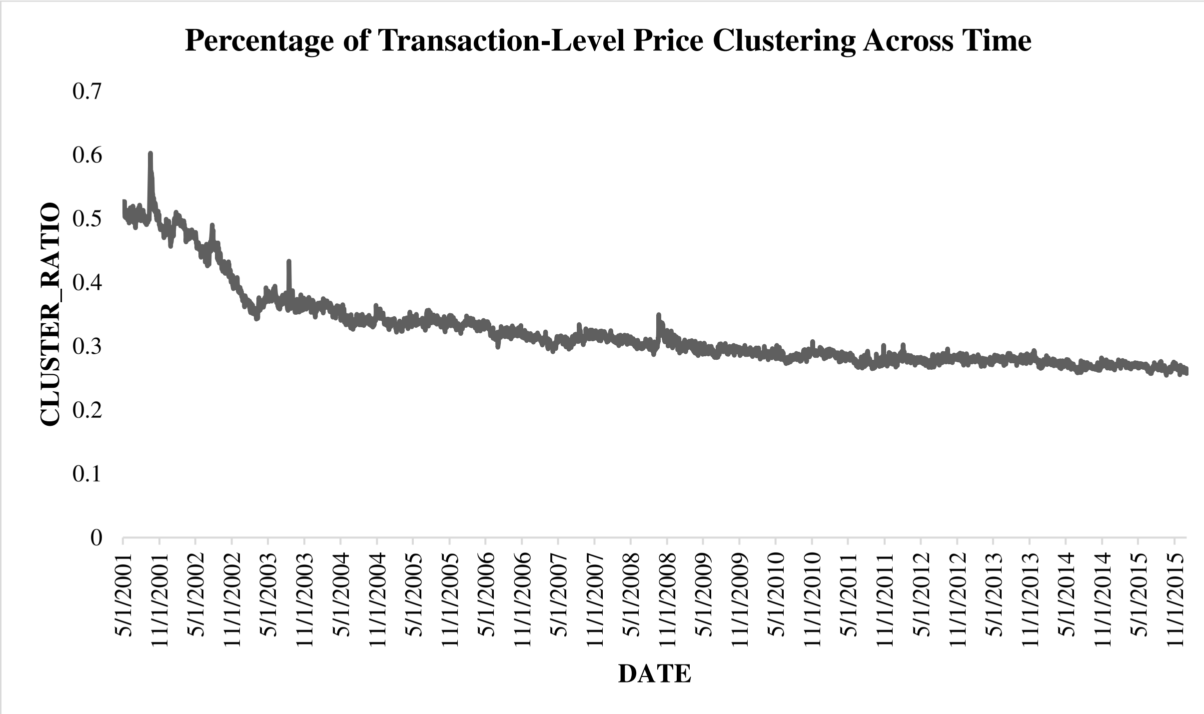
Our research question is whether price clustering declines through time as Bai, Philippon and Savov (2016) find that prices become more efficient through time. Figure 2 plots the percentage of prices ending in 0¢ and 5¢ across our sample period. Panel A plots monthly clustering in closing prices and Panel B plots daily clustering in intraday transaction prices.

Figure 2 Price clustering across time

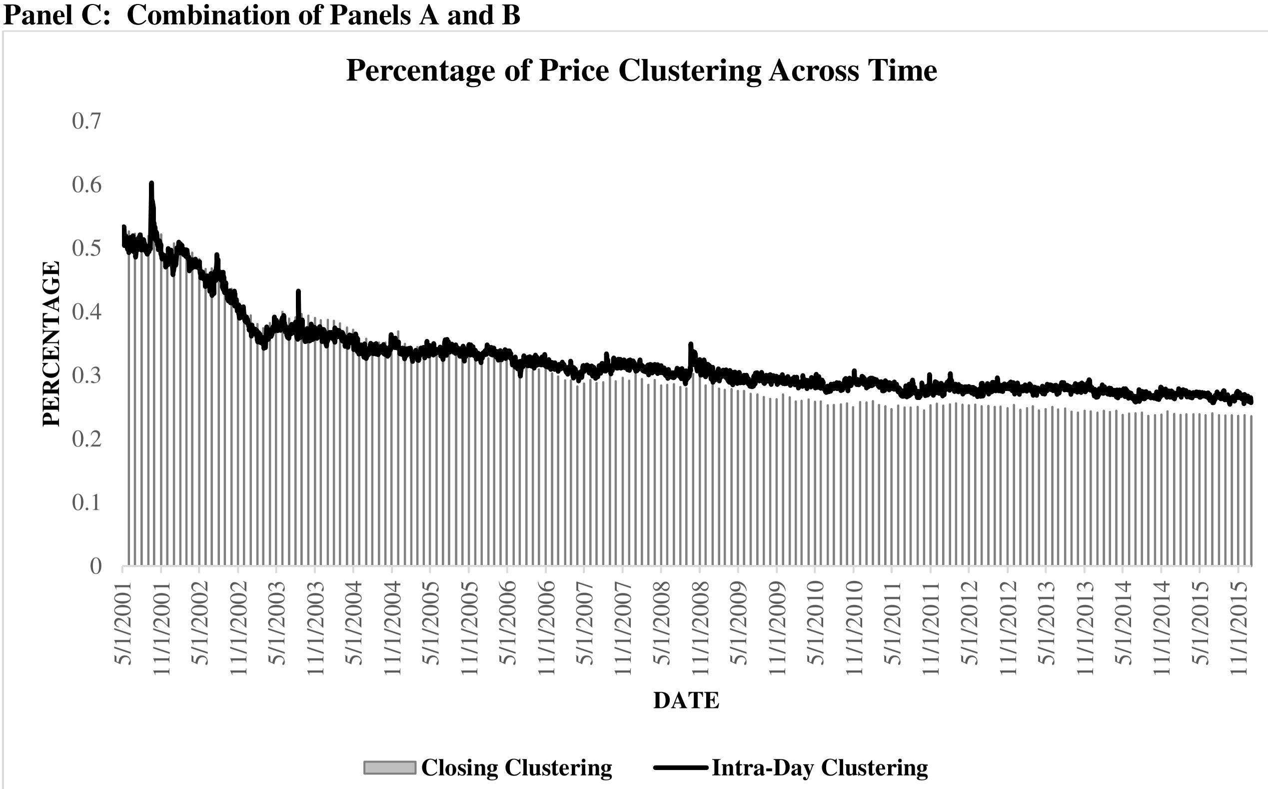
Panel A: Percentage of closing prices on 0¢ and 5¢



Panel B: Percentage of intraday transaction prices on 0¢ and 5¢



Panel C: Combination of Panels A and B



Panel A shows closing price clustering declines rapidly under decimalization from May 2001 through December 2002 with a notable spike for September 2001.[5] The decline in clustering stops in early 2003, which Hendershott, Jones and Menkveld (2011) note coincides with the NYSE implementation of their Autoquote software from January 2003 through May 2003. Autoquote provides a liquidity quote with a firm bid and a firm offer for 15,000 shares. After the implementation of Autoquote we see a slow and steady decline in 0¢ and 5¢ clustering through the end of our sample with a notable spike in clustering for September and October of 2008. Panel B plots intraday transaction price clustering and shows the same basic pattern as Panel A including the September 2001 and September/October of 2008 spikes in 0¢ and 5¢ clustering.

Panel C of Figure 2 combines Panels A and B, for ease of comparison. The plot line is intraday clustering while the vertical bars are closing clustering. Prior to the beginning of the financial crisis (mid 2007), closing price clustering on 0¢ and 5¢ is about the same as intraday transaction price cluster with the notable exception of the second half of 2003. However, following the financial crisis closing price clustering is less than intraday transaction price clustering and the difference appears to widen through time.

Finally, we calculate the correlation between closing price clustering and intraday transaction price clustering. To do this we move from CRSP closing prices to TAQ closing prices and calculate the average daily closing price clustering across all TAQ common stocks.[6] This provides two daily time-series of price clustering for all TAQ common stocks. The correlation between the two time-series is about 92%.

4. Clustering Regressions

Our analysis to this point shows: (1) closing and intraday prices cluster on 0¢ and 5¢, (2) there is more 0¢ and 5¢ clustering intraday, and (3) clustering declines with time. However, the decline through time may be due to stock-specific or exchange characteristics. To control for these factors we estimate a series of OLS regressions using our monthly and daily panel datasets. We use firm fixed effects in some specifications and all specifications have robust standard errors clustered at the firm level. Our regression model is:

$$CLUSTERING_{i,t} = \beta_0 + \beta_1 TIME\_TREND_{i,t} + Controls_{i,t} + \epsilon_{i,t} \qquad (1)$$

The dependent variable for the regressions on average monthly closing price clustering is CLUSTER%, which is defined as the number of days each month that share prices close on a round increment of $0.05 scaled by the number of trading days of the stock in the month. The dependent variable for the regressions on average intraday transaction price clustering is CL_RATIO, which is defined as the number of daily trades that occur at prices on round increments of $0.05 scaled by total number of daily trades for the stock.

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[5] Ikenbery and Weston (2007) find closing price clustering at about 40% in the last six months of 2002. Panel A of Figure 2 shows closing price clustering around 40% in the last half of 2002 suggesting that our empirical results are consistent with Ikenberry and Weston.

[6] Plots of the CRSP monthly closing price clustering and the TAQ daily average closing price clustering follow the same basic pattern with more noise in the daily average plot.

Our test variable is TIME_TREND. It is a simple time counter that starts at 1 for the first observation in a time-series and increments by 1 for each subsequent observation in the time-series (monthly or daily) until the end of the sample.

Following the literature, we also compute various other stock-level measures at monthly and daily horizons and use them as our control variables. LNPRICE represents the natural log of monthly (daily) price. LNSIZE represents the natural log of month (day) end market capitalization. SPREAD represents the average monthly (daily) percentage spread calculated as the difference between the closing ask and bid scaled by spread midpoint. TURNOVER represents the monthly (daily) shares traded scaled by shares outstanding at the end of the month (day). We have separate volatility measures for closing and intraday regressions. IDIO_VOLATILITY is used for the monthly sample, which is the standard deviation of daily residual returns, where residual returns are obtained from estimating a Fama and French 3-factor model using daily returns. RANGE VOLATILITY for daily data is calculated as the LN(intraday high price) – LN(intraday low price). NASDAQ is an indicator variable taking 1 if a stock is listed on NASDAQ and 0 otherwise.

Regression results are reported in Table II. The first two columns use the firm-month panel dataset and CLUSTER% is the dependent variable, while the last two columns use the firm-day panel dataset and CLUSTER_RATIO is the dependent variable. Our test variable is TIME_TREND, which allows us to study whether price clustering decreases across time after controlling for stock specific characteristics.[7]

Table II: OLS Regressions

	(1)	(2)	(3)	(4)
	CLUSTER%	CLUSTER%	CLUSTER_RATIO	CLUSTER_RATIO
TIME_TREND	-0.001***	-0.001***	-0.000***	-0.000***
	(-99.565)	(-96.325)	(-98.744)	(-84.928)
LNPRICE	0.046***	0.046***	0.050***	0.051***
	(21.403)	(22.061)	(24.150)	(25.741)
LNSIZE	-0.032***	-0.036***	-0.042***	-0.049***
	(-35.549)	(-19.352)	(-44.316)	(-27.287)
SPREAD	1.498***	1.136***	1.311***	0.633***
	(16.986)	(15.114)	(37.767)	(26.145)
TURNOVER	-0.442***	-0.123***	-0.053***	0.049***
	(-10.018)	(-6.205)	(-7.010)	(7.781)
VOLATILITY	-0.167***	-0.031**	-0.200***	-0.058***
	(-5.090)	(-1.966)	(-17.802)	(-11.850)
NASDAQ	-0.051***	-0.074***	-0.014***	-0.047***
	(-32.378)	(-13.604)	(-8.929)	(-8.961)
CONSTANT	0.697***	0.775***	0.802***	0.910***
	(70.508)	(38.536)	(81.870)	(48.039)

[7] We reach similar conclusions when we use date dummy variables such as year and year-months. However, to make our results more presentable we report the regression results with time trend variable.

Firm FE	No	Yes	No	Yes
Robust SE	Yes	Yes	Yes	Yes
Observations	724,929	724,929	14,086,106	14,086,106
R-squared	0.282	0.410	0.216	0.297

Across all specifications, TIME_TREND is highly significant and negative. This supports that across time price clustering has declined both at the close and intraday after some basic controls. In other words, prices become more uniformly distributed through time. For our basic control variables, we find that SPREAD and LNPRICE is positively associated price clustering, while TURNOVER, LNSIZE, VOLATILITY and NASDAQ is negatively associated with price clustering.[8]

5. Discussion and Implications for Future Research

We find that: (1) prices cluster on 0¢ and 5¢, (2) prices cluster at the close and intraday, (3) intraday prices cluster more than closing prices with the difference increasing through time, and (4) price clustering declines with time. Our results suggest several paths for future research.

First, how much of the decline in clustering is due to algorithmic trading (also referred to as high frequency trading (HFT)). Hendershott, Jones and Menkveld (2011) report that 73% of trading volume in 2009 is algorithmic trading. Das and Kadapakkam (2018) examine the decline in pricing clustering for three benchmark ETFs from 2001 through 2010 and find that in 2010 that prices clustering is: 20.6% for SPY, 20.4% for QQQ, and DIA is 22.1%. They assume that the decline must be the result of algorithmic trading. Davis, Van Ness and Van Ness (2014) use a special NASDAQ sample of 120 stocks trading in 2009 by 26 HFTs and find that HFTs cluster less than humans. Figure 2 Panel C shows that price clustering at about 25% by the end of our sample in 2016. This suggests a path of future research that separates algorithmic trading (HFTs) from human trading to determine the rate of clustering for humans. Ikenberry and Weston (2007) conclude that their results are consistent with a behavioral bias contributing to price clustering. There is no reason to expect that a behavioral bias for specific prices declines through time. Separating human trades from algorithmic trading would provide a direct test of the role of behavioral bias in price clustering observed in market wide data.

Second, we find less price clustering at the close than intraday as we move through time. This suggests that the mix of trade types may differ at the close from intraday. This suggests an analysis of how different trade types relate to price clustering. Limit orders are liquidity providing while market orders are liquidity demanding based on information, so it seems reasonable that limit orders may cluster more than market orders.

Third, the NYSE Autoquote system began in the first half of 2003 and was created to ensure liquidity. Figure 2 shows that as Autoquote started the rapid decline in price clustering slowed. This suggests that liquidity trades may cluster more than information trades. Admati and Pfleiderer (1988) suggest that liquidity traders trade for reasons unrelated to information. This suggests more clustering to reduce transaction costs (Harris (1991)). This suggests an

[8] The signs on our controls are generally consistent with the signs on similar variables in cross-sectional regressions reported by Ikenberry and Weston (2007) in their Table 4.

analysis of the limit order book to determine if the best bid and ask cluster differently than the remainder of the limit order book.

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