Trade price clustering in the corporate bond market

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Abstract

Purpose – In this paper, the authors document the existence of price clustering in the US corporate bond market.

Design/methodology/approach – Using a sample of 8,422,593 corporate bond trades in 2014, the authors find that over 18% (1,522,284 trades) of all bond trades end in a clustered price, defined as a price ending in 00, 25, 50, or 75.

Findings – Overall, the authors find that both bond rating category and risk, as measured by standard deviation of prices, play a role in price clustering; speculative grade bonds account for the majority of clustered prices. Clustered prices are more likely to have higher coupon rates, higher prices, and higher standard deviations of price than bonds with non-clustered prices. Regardless of size, both buy and sell dealer trades with customers (relative to interdealer trading) lead to an increase in price clustering. Dealers appear to use clustered prices when purchasing from and selling to institutions and, therefore, may use a clustered price to insulate themselves from the risk of asymmetric information. Additionally, the prevalence of clustered prices for retail-sized dealer sell trades suggests that dealers exercise dealer power over retail-sized traders.

Originality/value – This paper contributes to the literature on price clustering by examining trade price clustering of corporate bonds. It is different from previous papers on price clustering in equities. Given that bonds tend to be priced off of yield, it is unusual that trade prices cluster. It also demonstrates what kind of bonds cluster and with which customers dealers trade at clustered prices. It parallels other research in demonstrating dealer power over retail-sized traders.

Keywords Clustered prices, Corporate bond market, Trade price clustering

Paper type Research paper

1. Introduction

Many financial economists would agree that while price matters, the actual numerical digits of the price do not. Even so, humans tend to transact at certain prices more frequently than others in a world of almost infinite prices [1]. The corporate bond market seems like a perfect place to investigate price clustering, since the market is economically large and generally dominated by institutions and dealers which have sophisticated market technology, such as Bloomberg terminals, that are generally out of reach for retail-sized investors and thus provide a large informational advantage [2]. The corporate bond market is also a dealer market and is generally illiquid. This illiquidity enhances both informational asymmetry and dealer power, creating search and negotiation costs (Li, 2007; Holden, 2009; Goyenko *et al.*, 2009; Woodley *et al.*, 2020; Goldstein and Hotchkiss, 2020). Collectively, these advantages in the corporate bond market can lead to dealers quoting spreads on a wider pricing grid than the minimum price increment, which can result in price clustering (Harris, 1991; Christie and Schultz, 1994). Despite this, while price clustering has been studied in both equity and municipal bond markets, there is no examination to date of price clustering in the corporate bond market [3].

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In this paper, we examine price clustering in the corporate bond market. Using a sample of 8,422,593 bond trades from TRACE in 2014, we find that prices cluster in the corporate bond market, and they do so at predictable prices *ex ante*. Despite bond prices being quoted in decimals (which provides 100 possible price points), we find over 18% (1,552,284 trades) of all bond trades in 2014 end in a clustered price, defined as prices ending in 0.00, 0.25, 0.50, and 0.75 [4]. Figure 1 provides a breakdown of clustered prices versus non-clustered prices. Price clustering on these four prices is surprising as bonds tend to be priced using yields to maturity, coupon rates, and time to maturity. It seems highly unlikely that these yields would more often match four of the 100 possible price points.

The extent of clustering varies by rating and risk. While clustering appears in both investment grade and high-yield bonds, price clustering is much more prevalent in high-yield bonds. About 63.55% of all clustered prices are in high-yield bonds, while investment grade bonds account for just 36.45% of all clustered prices, consistent with the predictions of Harris (1991) and, given the higher asymmetric information with high-yield bonds, also consistent with Li (2007) and Green *et al.* (2007a, b) [5]. Trades at clustered prices (0.00, 0.25, 0.50, and 0.75) are more likely at higher prices and for bonds with higher coupon rates and higher standard deviation (Table 1).

We find that retail-sized trades (or small trades) account for a significant portion of clustered prices. 63.95% of clustered bond prices are associated with a retail-sized trade [6]. The prevalence of price clustering in small trades is consistent with the suggestions in Green *et al.* (2007a, b) and Li (2007) that dealers use their power to price discriminate, resulting in higher search and price discrimination costs for retail-sized clients for all bond grades. It is unlikely dealers would waste professional capital giving institutional clients inferior or clustered prices when a better execution price exists.

The secondary market for US corporate bonds is ripe with the possibility for large search and negotiation costs. The US corporate bond market is a dealer-to-dealer, over-the-counter market with post-trade reporting only. In stark contrast to the very active US equity markets with deep limit order books, the corporate bond market is generally illiquid and has no active limit order book. The median bond trades only a few times a day, and many bonds see no trades for a month or more (Goldstein and Hotchkiss, 2020). In an illiquid market like the corporate bond market, traders may be exposed to large search costs and exposed to large levels of dealer power. The corporate bond market thus provides an opportunity to study a market with ample ability to create wide pricing grids and large trading costs.

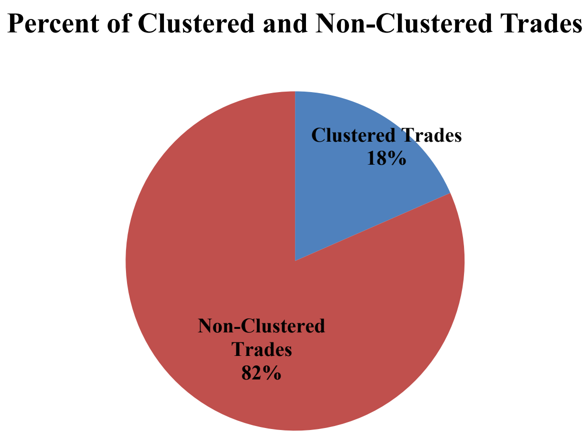

Figure 1.
Percent of clustered and non-clustered prices

Variable	All trades	Trades that cluster	Trades that do not cluster
Panel A: All Bonds			
Investment Grade	67.08%	36.45%	73.99%*
Speculative Grade	32.92%	63.55%	26.01%*
Coupon	4.16%	4.21%	4.11%*
Median	*4.25%*	*4.25%*	*4.25%*
Average Price	102.16%	102.45%	101.88%
Median	*101.38%*	*101.31%*	*101.44%*
Std. Dev. of Price	0.34	0.37	0.30*
Median	*0.26*	*0.30*	*0.23*
Buy	28.20%	28.93%	28.03%
Sell	35.01%	36.30%	34.72%*
Interdealer	36.79%	34.77%	37.25%*
Institutional Sized	32.32%	36.05%	31.48%*
Retail Sized	67.68%	63.95%	68.52%*
Years to Maturity	20.86	21.44	20.31
Median	*5.34*	*5.59*	*5.11*
Trades per Day	4.98	5.55	4.45*
Median	*3.14*	*3.50*	*2.95*
Bonds in Family	300.02	295.75	304.06*
Median	*70.00*	*67.00*	*84.00*
Panel B: Bonds with Active CDS Trading			
Investment Grade	68.87%	39.08%	75.27%*
Speculative Grade	31.13%	60.92%	24.73%*
Average Price	101.89%	102.22%	101.58%
Median	*101.25%*	*101.20%*	*101.30%*
Std. Dev. of Price	0.34	0.37	0.30
Median	*0.26*	*0.30*	*0.23*
Buy	28.16%	28.63%	28.05%
Sell	34.83%	35.95%	34.59%
Interdealer	37.01%	35.41%	37.36%*
Institutional	31.37%	34.31%	30.74%*
Retail-sized	68.63%	65.69%	69.26%*
Trades per Day	4.95	5.52	4.42*
Median	*3.11*	*3.47*	*2.92*
Bonds in Family	320.74	316.54	324.70*
Median	*109.00*	*96.00*	*116.00*

Note(s): Table 1 provides summary statistics for 8,422,593 bond trades in 2014. Trades are classified as clustered if the execution price after rounding to two decimals ends in 0.00, 0.25, 0.50, or 0.75. Investment Grade bonds have an investment quality credit rating. Speculative grade bonds are junk bonds. Coupon is the bond's coupon rate. Average price is the average of transaction prices, and standard deviation of price is the daily standard deviation of bond transaction prices. Buy is a dealer reported buy trade; sell is a dealer reported sell trade. Interdealer are trades executed between dealers. Institutional trades are greater than or equal to $100,000 in value, and retail-sized trades are less than $100,000 in value. Years to maturity is the time, in years, until a bond reaches its maturity. Trades per day is the average number of trades each day per bond. Bonds in Family is the average number of bonds issued by each firm in the sample. A * in the 'Trades that do not cluster' column indicates a significant difference at the 1% level between the values for trades that cluster and trades that do not cluster

Table 1.
Summary statistics

There are several reasons price clustering occurs in financial markets. First, price clustering may be a function of higher information costs in a market. Harris (1991) finds that securities with higher levels of uncertainty are more likely to trade at clustered prices. If a dealer is at an information disadvantage relative to a customer, the dealer may widen the bid/ask spread to rounded (or clustered) numbers. Another explanation for price clustering explored by Li

(2007) is dealer market power. If a dealer faces little competition from other dealers, he can afford to raise (lower) his ask (bid) to the nearest rounded number.

Second, Green *et al.* (2007a, b) suggest dealers are able to price discriminate against uninformed buyers. As a result, the models in Green *et al.* (2007a, b) and Li (2007) suggest that dealers may price discriminate based on the financial sophistication of customers. If a retail-sized customer does a poor job of assessing a bond's intrinsic value (and the dealer knows this), the dealer could take advantage of the situation by offering less sophisticated customers more rounded prices, in which case retail-sized trades would cluster more [7]. Less clustering of institutional trades also supports Duffie *et al.* (2005), who show theoretically that more sophisticated investors receive tighter bid-ask spreads from market-makers because they are more likely to seek out other market-makers.

In addition, Harris (1991) posits that within a negotiated market (like the corporate bond market) clustering increases as a result of reduced negotiation. Interdealer trades likely result from extensive negotiation; therefore, interdealer trades have fewer clustered prices than trades between dealers and customers. These trades may have a wider pricing grid, though, because dealers want to protect themselves against what other dealers may know as oppose to simply trading for inventory rebalancing.

Overall, our finding of price clustering suggests that the corporate bond market is imperfect and imposes larger search costs, negotiation costs, dealer power, and bid-ask spreads on customers. Our results are consistent with lower asymmetric information between dealers and institutional investors for investment grade bonds, but investment grade bonds cluster more in trades involving less sophisticated investors. However, it is possible that institutional investors have more information than dealers for speculative bonds, so the asymmetric information risk could outweigh the search costs. In this case, while conditional on being clustered, more of the clustered prices in speculative grade bonds are retail-sized trades than institutional trades (although less so than for investment grade bonds), the probability or likelihood of clustering is higher for trades with institutional investors, which presumably have higher levels of sophistication.

2. Data and summary statistics

The TRACE system has evolved over time, and it has operated under a variety of dissemination regimes [8]. TRACE requires public dissemination of all bonds' post-trade price and volume information, and currently covers nearly 100% of OTC activity, representing over 99% of total US corporate bond market activity. Corporate bond trades may also execute on the NYSE Bonds platform (previously called NYSE ABS). The majority of bond trades on the NYSE Bonds system are small, retail-sized in nature and represent a small portion of the overall corporate bond trading market. The NYSE Bonds platform offers firm bond prices, whereas TRACE trading allows for dealer negotiation. In recent years, the NYSE has taken strides towards increasing its market share in the corporate bond market, but currently most bond trades occur in the over the counter market [9].

The National Association of Securities Dealers (NASD) began collecting over the counter corporate bond trades in July 2002 using the Trade Reporting and Compliance Engine (TRACE) [10]. Bonds were gradually phased into TRACE reporting requirements under different dissemination regimes until all corporate bonds trades included post-trade transparency. We utilize TRACE reported trades from January 2014 to December 2014 (twelve calendar months). The TRACE data include all bond trades in the over the counter market. Each data observation includes the CUSIP number, trade date, price, time of trade, and whether the trade is a buy, sell, or interdealer trade. The TRACE master file includes bond-level information. We also utilize CRSP to identify financial firms.

We provide information about our sample construction in Appendix 1. Our initial sample includes 10,473,119 trades in non-convertible corporate bonds. We delete trades that are missing CUSIP information, canceled, corrected, late-reported trades, and trades reported outside normal trading hours. After doing so, our sample includes 10,023,374 corporate bond trades. We also delete trades without identifying ticker information, with missing master file information, and missing trade-reporting side information, along with all 144A bonds. After these data deletions, the sample includes 10,007,955 individual bond trades. After merging the data with SIC information from CRSP to control for financial firms and removing bonds that trade less than ten times, our final sample includes 8,422,593 bonds trades [11].

In TRACE, bond trades are reported within 15 minutes of execution, and are reported as a percentage of par, i.e. 105.000 or 98.625 [12]. These prices can be converted to reflect the value of a typical par value bond, i.e. $1,000. We define clustering as any quoted bond price ending with the two-digits 00, 25, 50, or 75 after the decimal point, i.e. 0.00, 0.25, 0.50, and 0.75. Prices with more than two decimals are rounded to two digits to determine if they are a clustered price [13]. We provide a graph of the decimal pricing increments in our sample using Figure 2. All price points ranging from 0.00 to 0.99 are represented in our sample. The four highest spikes on the graph correspond to prices ending in 0.00, 0.25, 0.50, or 0.75 [14]. While the remainder of the paper treats these four price points similarly as equal "cluster" prices. Prices ending in 0.00 account for 6.51% of all trades in our sample, while prices ending in 0.50 make up 4.72% of trades in our sample, showing the strong major number tendencies for round numbers and halves. The two-quarter numbers (0.25 and 0.75) have relatively similar amounts: prices ending in 0.25 (0.75) make up 3.68% (3.52%) of trades.

Summary statistics are provided in Table 1, which shows overall statistics for all trades, for trades that cluster on our four price points (0.00, 0.25, 0.50, and 0.75), and trades that do not cluster. Of the 8,422,593 bond trades in our sample, about 18% (1,552,284) of the trades end in one of our four clustered price increments. Over 67% of the trades in our sample involve an investment grade bond. Following Edwards *et al.* (2007), we define retail-sized trades as trades less than $100,000 in size. Other papers use different cutoffs to determine a retail-sized trade versus an institutional sized trade. For example, Ronen and Zhou (2013) utilize $500,000 as their breaking point between the two types of trades. We replicate our results using the cutoff from Ronen and Zhou (2013) and our results are similar in magnitude and direction.

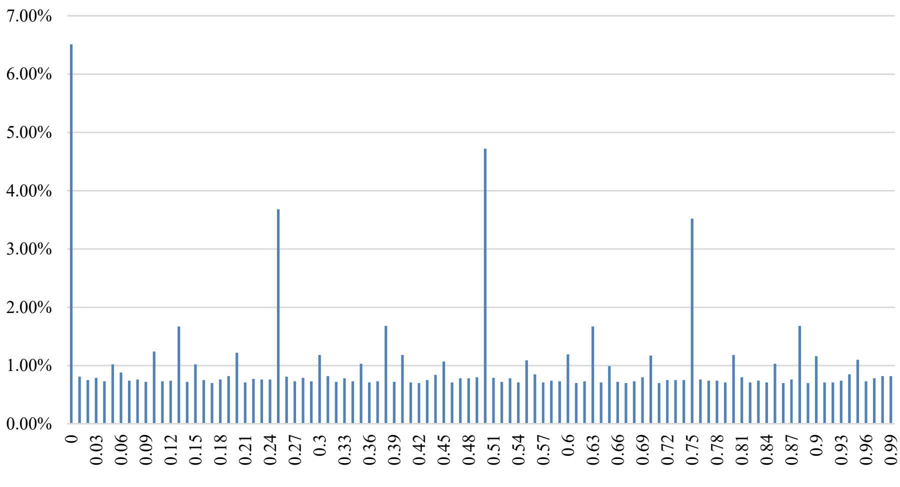

Figure 2.
Percent of trades by decimal increment

We choose to follow Edwards *et al.* (2007) in using $100,000 because the methods used have been validated multiple times, and it is also one of the seminal papers in corporate bonds. Edwards *et al.* use $100,000 not as a function of their time period or research question, but as a representation of the corporate bond market that still holds today. We find that retail-sized trades make up over 67% of the sample trades. The average bond in our sample trades an average of nearly five times per day [15]. Bonds with clustered prices trade slightly more frequently than both the full sample of bonds and the bonds without a clustered price.

Table 1 provides the first evidence that bond credit quality is a factor in price clustering. Over 63% of clustered prices involve a speculative grade bond, while roughly 74% of non-clustered prices involve an investment grade bond. So, clustering occurs more with speculative bonds than with investment grade bonds. This notable increase in the clustering of speculative bonds is consistent with Harris (1991) who shows that riskier stocks are more apt to cluster.

Table 1 also indicates that the average trade-weighted coupon in our sample is 4.16%. Transactions that cluster have a similar coupon rate (4.21%) to transactions that do not cluster (4.11%). The average price of trades in our sample is 102.16% of par and does not vary much for trades that cluster (102.45%) than those that do not (101.88%). The standard deviation of the average price in our entire sample is 0.35, but there is some variation by clustering: For trades that cluster, the standard deviation of the average price appears higher (0.37) that those that do not (0.30) [16].

As previously mentioned, the bond market is illiquid when compared to the equity market, so we divide our sample into activity level quartiles based on the total number of trades for each bond during our sample period in Table 2, to better access differences in activity. Quartile 1 represents the least active bonds in the sample, and Quartile 4 represents the most

Table 2.
Summary statistics by activity level

	Quartile 1	Quartile 2	Quartile 3	Quartile 4
% Cluster	27.63%	22.29%	17.50%	18.28%
% Non-Cluster	72.37%	77.71%	82.50%	81.72%
% Investment Grade	44.65%	63.57%	75.67%	66.26%
% Speculative Grade	55.35%	36.43%	24.33%	33.74%
% Buy	34.11%	33.25%	31.97%	27.35%
% Sell	29.31%	31.61%	33.82%	35.40%
% Interdealer	36.59%	35.14%	34.20%	37.24%
% Institutional Sized	21.81%	27.56%	36.94%	31.99%
% Retail Sized	78.19%	72.44%	63.06%	68.01%
Coupon Rate	3.01%	3.90%	4.58%	4.76%
Price	104.23%	96.63%	101.71%	105.28%
Std. Dev. Of Price	0.26	0.24	0.26	0.38
Years to Maturity	12.50	14.20	17.46	37.10
Trades per Day	3.07	3.35	3.49	7.99
Bonds in Family	469.98	375.58	249.59	133.58

Note(s): Table 2 provides summary statistics for 8,422,593 bond trades in 2014. Trades are classified as clustered if the execution price after rounding to two decimals ends in 0.00, 0.25, 0.50, or 0.75. Investment Grade bonds have an investment quality credit rating. Speculative grade bonds are junk bonds. Coupon is the bond's coupon rate. Average price is the average of transaction prices, and standard deviation of price is the daily standard deviation of bond transaction prices. Buy is a dealer reported buy trade; sell is a dealer reported sell trade. Interdealer are trades executed between dealers. Institutional sized trades are greater than or equal to $100,000 in value, and retail-sized sized trades are less than $100,000 in value. Years to maturity is the time, in years, until a bond reaches its maturity. Trades per day is the average number of trades each day per bond. Bonds in Family is the average number of bonds issued by each firm in the sample. Quartile 1 is the least active bonds in the sample, and Quartile 4 is the most active bonds in the sample. Active is measured by the number of trades over the course of the sample period, January 2014 to December 2014 active bonds in the sample. It appears that the most price clustering occurs in the least actively traded bonds. The least actively traded bonds also appear to include a higher portion of speculative bond trades. Speculative grade bonds are harder to value than investment grade bonds, which leads to more price clustering. Overall, the least active bonds appear to have the most price clustering, the most speculative grade bond trades, the most retail sized trades, and the most bonds in their bond issue families. All of these characteristics are conducive to an environment that fosters clustered trade prices. The most active bonds appear to have fewer clustered prices, more trades in investment grade bonds, a higher price volatility, and fewer bonds in their families. Again, all of these qualities make intuitive sense for the most active bonds.

We further examine the role activity plays in clustering by dividing the sample by both activity and whether a trade ends in a clustered price. Table 3 provides these results. We are

Table 3. Summary statistics by activity level, clustered versus non-clustered prices

	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Panel A: Clustered prices				
% Investment Grade	44.13%	56.52%	52.78%	32.96%
% Speculative Grade	55.87%	43.48%	47.22%	67.04%
% Buy	28.71%	26.71%	30.59%	28.83%
% Sell	35.36%	36.70%	35.85%	36.36%
% Interdealer	35.92%	36.60%	33.55%	34.81%
% Institutional Sized	24.11%	24.14%	36.09%	36.90%
% Retail Sized	75.89%	75.86%	63.91%	63.10%
Coupon Rate	3.18%	3.99%	4.59%	4.76%
Price	106.57%	97.10%	101.69%	105.10%
Std. Dev. Of Price	0.34	0.33	0.36	0.45
Years to Maturity	14.73	14.71	17.51	37.11
Trades per Day	3.28	3.91	4.66	9.80
Bonds in Family	465.63	373.22	249.21	133.52
Panel B: Non-Clustered prices				
% Investment Grade	44.85%	65.60%	80.52%	73.71%
% Speculative Grade	55.15%	34.40%	19.48%	26.29%
% Buy	36.16%	35.13%	32.27%	27.03%
% Sell	26.99%	30.15%	33.39%	35.19%
% Interdealer	36.84%	34.72%	34.34%	37.79%
% Institutional Sized	20.93%	28.54%	37.13%	30.90%
% Retail Sized	79.07%	71.46%	62.87%	69.10%
Coupon Rate	3.02%	3.91%	4.58%	4.76%
Price	104.03%	96.54%	101.72%	105.30%
Std. Dev. Of Price	0.28	0.26	0.28	0.40
Years to Maturity	12.13	14.27	17.47	37.10
Trades per Day	2.91	3.16	3.43	8.25
Bonds in Family	465.18	373.47	249.33	133.58

Note(s): Table 3 provides summary statistics for 8,422,593 bond trades in 2014. Trades are classified as clustered if the execution price after rounding to two decimals ends in 0.00, 0.25, 0.50, or 0.75. Investment Grade bonds have an investment quality credit rating. Speculative grade bonds are junk bonds. Coupon is the bond's coupon rate. Average price is the average of transaction prices, and standard deviation of price is the daily standard deviation of bond transaction prices. Buy is a dealer reported buy trade; sell is a dealer reported sell trade. Interdealer are trades executed between dealers. Institutional sized trades are greater than or equal to \$100,000 in value, and retail sized trades are less than \$100,000 in value. Years to maturity is the time, in years, until a bond reaches its maturity. Trades per day is the average number of trades each day per bond. Bonds in Family is the average number of bonds issued by each firm in the sample. Quartile 1 is the least active bonds in the sample, and Quartile 4 is the most active bonds in the sample. Active is measured by the number of trades over the course of the sample period, January 2014 to December 2014 most interested in the least active (Quartile 1) and the most active (Quartile 4) bonds, as well as any trends or patterns shown by activity level. Panel A includes only clustered prices. For the least and most active bonds, speculative grade bonds account for a large portion of clustered prices (55.87 and 67.04%). For non-clustered prices, the exact opposite is shown for Quartile 4. Results are similar for clustered and non-clustered prices for the other variables shown in Table 3. Table 3 provides further evidence that bond rating categories play a role in price clustering.

We further divide our sample by two other metrics. We provide this information Appendix 2. First, it is possible that industry plays a role in price clustering. Financial firms specifically are highly regulated, and as such, their bonds may be easier to value than bonds issued by other firms. We compare the percentage of price clustering in each type of firm in Panel A of Appendix 2 to examine if there are differences in clustering between financial firms and non-financial firms. Overall, price clustering between financial and non-financial firms is similar. We find that prices of bonds issued by financial firms appear to cluster slightly less than prices of non-financial firm bonds. Roughly 19% of non-financial firm bond prices are clustered, while roughly 17% of financial firm bonds have a clustered price. We further compare the percentage of price clustering by separating the sample by clustering digit (00, 25, 50, and 75). The results are similar regardless of clustering category or firm type. Overall, it appears that industry does not influence price clustering.

Second, the credit default swap market may play a role in bond price clustering. Bonds with active CDS trading may offer more or better available information about the issuing firm, which could lead to more accurate pricing. As such, bonds with CDS's may cluster less than bonds without CDS's. To determine what relation, if any, the CDS market with bond price clustering, we divide our sample into firms with CDS's and firms without CDS's. Our findings in Panel B of Appendix 2 indicate substantial less clustering in bond prices when CDS trading is also present. Over 26% of bond prices cluster for firms without CDS's trading, while over 17% of bond prices cluster when CDS trading is present. Similar to Panel A, we also separate our sample by clustering digit (00, 25, 50, 75). Regardless of the clustering digit, bonds with no CDS trading cluster more than bonds with CDS trading.

3. Relations of bond price clustering

We initially focus on the factors that influence bond price clustering, which could be different than findings of previous papers regarding equities for several reasons. First, bonds are highly illiquid, especially compared to equities. The average bond in our sample trades less than five times per day. Second, bonds are more expensive to trade than equities on a percentage basis (Edwards *et al.*, 2007; Goldstein *et al.*, 2007). Third, trade transparency in the bond market differs from that in the equity market. There is no exchange fostering pre-trade transparency for corporate bonds, no organized limit order book, and an ineffective best execution rule for trading guidelines. As such, clustering in the bond market (and the factors that influence clustering) could be different than clustering in the equity market.

Credit quality could also influence price clustering. Investment grade bonds are easier to value than speculative grade bonds, so we expect investment grade bond trades to cluster less than speculative grade bond trades. Price level may also correlate with price clustering, following Harris (1991), we expect more price clustering for higher priced bonds. Volatility should also lead to more price clustering because as prices change quickly due to trading, it may become harder to value the bond.

In our regressions, we control for the above factors as well as other factors. For example, we also control for the trade type with an institution dummy variable. The institution dummy is equal to one if the trade size is greater than or equal to $100,000, and zero otherwise. In our data, trades are classified as dealer buys, dealer sells, and interdealer trades: we similarly control for whether a trade is a dealer buy or dealer sell with dummy variables for each, but hold the interdealer variable out of the regression so as not to span the set (so it is included in the intercept).

We also control for the transaction frequency of each bond, following Harris (1991). We proxy for frequency with the number of trades, and we expect the number of trades to be inversely related to price clustering. Trading activity should incorporate information into prices, thus reducing the amount of clustering. Additionally, we control for financial firms and CDS trading activity with a CDS dummy variable. Lastly, we control for several bond specific factors, including coupon rate, time to maturity, number of bonds outstanding by the firm, and top bond status.

We provide estimates from logit regressions for factors that influence bond price clustering in Table 4. A trade is classified as clustered if the price ends in 00, 25, 50, or 75 [17]. The dependent variable is equal to one if the price clusters and zero otherwise in all Table 4 regressions. The first model provides estimates for the full sample of trades. Overall, we find that both rating (investment grade vs speculative grade) and bond price negatively influence price clustering. Specifically, the regression shows that investment grade bonds cluster less than speculative grade bonds, supporting the findings in Table 1. We also find that trade size influences clustering. Specifically, the regression indicates that trades greater than or equal to $100,000 (Institution variable in Table 2) cluster more than smaller trades. Prevalent clustering of institutional trades could indicate that dealers believe institutions possess superior information, or could indicate either negotiating costs or, surprisingly, dealer power issues, which may be related to the size of the transaction. Dealer reported buy and dealer reported sell trades cluster more than interdealer trades, which would be consistent with dealers providing needed liquidity to their clients, while their search costs are lower among their established dealer networks. A lower price clustering frequency in interdealer trades provides support for interdealer trading due to inventory maintenance by dealers. Bonds that are more volatile are more likely to cluster, which is consistent with riskier assets being harder to value. More bonds in a bond's family lead to more price clustering; more bonds outstanding may make valuing bonds difficult by overwhelming the investor with information that is difficult to absorb.

Our initial summary statistics in Table 1 along with the overall findings in the first column of Table 4 indicate that credit quality plays a role in clustering. We separate the sample into investment and speculative grade speculative grade bonds. The majority of the findings for the two bond grades are similar to those for the full sample with a few exceptions. Trading activity, measured as the number of trades, positively influences price clustering of investment grade bonds, while more trading activity leads to less price clustering in speculative grade bonds. Increased trading activity in speculative grade bonds may lead to more known information about a bond's true value, which could make speculative grade bonds easier to price (thus reducing the amount of clustering).

Last, top bonds with poor credit ratings (i.e. speculative grade bonds) have more clustered prices than top bonds with good credit ratings (i.e. investment grade bonds). The higher levels of clustering for low credit quality top bonds is likely due to two reasons. First, speculative grade bonds are harder to value than investment grade bonds. Second, dealers may quote higher or rounded prices on speculative grade bond trades as a way to guard themselves against superior information on the other side of the trade.

4. Differences in bond clustering analysis

4.1 Investment vs speculative grade

Speculative grade bond trades account for over 63% (see Table 1) of all clustered prices in our sample. Table 5 provides differences between the types of bonds in our sample and the types

	All bond trades	Investment grade trades	Speculative grade trades
Intercept	−1.34***	−1.89***	−1.39***
	0.00	0.00	0.00
Investment Grade	−1.36***		
	0.00		
Price (10^3)	−0.51***	−7.94***	−0.10***
	0.00	0.00	0.001
Volatility	0.31***	0.47***	0.16***
	0.00	0.00	0.00
Institution	0.27***	−0.06***	0.52***
	0.00	0.00	0.00
Buy	0.10***	0.10***	0.11***
	0.00	0.00	0.00
Sell	0.07***	0.07***	0.06***
	0.00	0.00	0.00
Number_Trades (10^3)	0.21***	1.53***	−0.22***
	0.00	0.00	0.00
Coupon Rate	0.11***	0.09***	0.11***
	0.00	0.00	0.00
Maturity (10^3)	0.44***	0.80***	0.30***
	0.00	0.00	0.00
Family (10^3)	0.25***	0.34***	0.03***
	0.00	0.00	0.00
Top Bond	−0.16***	−0.35***	0.04***
	0.00	0.00	0.00
CDS	−0.21***	−0.07***	−0.22***
	0.00	0.00	0.00
Financial	−0.04***	0.11***	−0.24***
	0.00	0.00	0.00

Note(s): Table 4 provides logit regression estimates for clustered bond trades during 2014 (8,422,593 trades). A trade is classified as executing at a clustered price if the reported price after rounding to two decimals ends in 0.00, 0.25, 0.50, or 0.75. 1,552,284 trades have a clustered price. The dependent variable is equal to one if the trade price clusters and zero otherwise. Investment grade is equal to one if the bond if rated as investment quality and zero otherwise. Price is the trade reported price. Volatility is the bond's daily price volatility. Institution is equal to one if the trade size is greater than or equal to $100,000 (Edwards *et al.*, 2007). Buy is equal to one if the trade is a dealer reported buy trade, and sell is equal to one if the trade is a dealer reported sell trade (and zero otherwise). The number of trades is the daily number of trades for each bond. The coupon rate is the bond's reported coupon. Maturity is the bond's years to maturity, and family is the number of the bonds issued by the parent firm. Top bond is equal to one if the bond has the most institutional trading on a given trading day and zero otherwise. Financial is equal to one if the firm's SIC code is 6000–6700. CDS is equal to one if the firm has active credit default swap trading. *p*-values are reported below the coefficients, and significance is indicated at the 1%, 5%, and 10% levels by ***,**, and *

Table 4.
Logit regressions by bond rating category

of clustered prices. Table 5 first shows differences in institutional sized trades and retail sized trades for both investment grade and speculative grade bonds. We find that retail-sized, or small trades, cluster significantly more than larger, institutional sized trades, particularly in investment grade bonds. Retail-sized trades account for roughly 70% of all clustered prices in investment grade bonds, while large trades make up the corresponding 30% of clustered prices in investment grade bonds. Because investment grade bonds bear little default risk, their prices are not as difficult to determine and are mainly a function of years to maturity and market interest rates. Institutions have easy access to this data, along with strong bargaining power. A sophisticated financial institution, therefore, likely has a good idea of a fair price and has the ability to shop around before trading. Search-based models such as Duffie *et al.* (2005)

	Investment grade	t-stat	Speculative grade	t-stat
Panel A: All Clustered prices				
Institutions	30.60%		34.66%	
-Retail-sized	69.40%		65.34%	
Difference	−38.80%***	−67.18	−30.69%***	−34.24
Top Bond	45.33%		46.99%	
-Not Top Bond	54.67%		53.01%	
Difference	−9.34%***	−13.27	−6.01%***	−5.98
Panel B: Clustered prices in Bonds with CDS Trading				
Institutions	29.54%		31.06%	
-Retail-sized	70.46%		68.94%	
Difference	−40.91%***	−69.90	−37.89%***	−41.45
Top Bond	44.13%		43.35%	
-Not Top Bond	55.87%		56.65%	
Difference	−11.74%***	−16.28	−13.30%***	−12.60

Note(s): Table 5 provides results for the differences in investment grade and speculative grade bond clustering. The percentages are based on 1,552,284 trades with clustered prices in the sample. Trades are classified as clustered if the execution price after rounding to two decimals ends in 0.00, 0.25, 0.50, or 0.75. Investment Grade bonds have an investment quality credit rating. Speculative grade bonds are junk bonds. Institutions are trades greater than or equal to $100,000, and retail-sized is trades less than $100,000 in value. Top bonds are the bonds with the most institutional trade each day for each bond (Ronen and Zhou, 2013). Significance is indicated at the 1%, 5%, and 10% levels with ***,**, and *

Table 5. Differences in clustering

and Li (2007) predict that these institutions (or large traders) investors receive tighter bid-ask spreads because of their wider opportunity set in terms of market makers.

Market makers have less incentive to offer narrow bid-ask spreads to retail-sized customers given that retail-sized traders (or small trades) may not have the resources to shop around before trading. The higher clustering we see with retail-sized customers of investment grade bonds is consistent with this notion, and as Li (2007) suggests, is consistent with higher bid-ask spreads. More price clustering is also suggestive of higher bid-ask spreads as per the models in Holden (2009) and Goyenko *et al.* (2009). Smaller bid-ask spreads for institutional size trades than for retail-sized trades is also consistent with the findings in other papers, such as Edwards *et al.* (2007) and Goldstein *et al.* (2007).

Speculative grade bonds are more difficult to value than investment grade bonds, so it is possible for clustering to differ for speculative grade bonds (for both retail-sized and institutional-sized trades). Consistent with the findings for investment grade bonds, we find that retail-sized trades cluster significantly more than institutional sized trades for speculative grade bonds, albeit to what appears to be a slightly lower level than investment grade bonds. Our findings are consistent with the suggestions in Duffie *et al.* (2005), Green *et al.* (2007a, b), and Li (2007) regarding dealer power and search costs. Our finding that speculative grade bonds cluster more for retail-sized trades is consistent with market makers taking advantage of constrained retail-sized or small traders.

We now examine liquidity. Over time, there is a debate in the literature on the efficiency and liquidity of bond markets. Bond markets are historically considered to be less efficient and less liquid than equity markets [18]. Ronen and Zhou (2013) suggest that informed trading may be concentrated in each firm's top bond, or the bond for each firm with the most institutional trading activity. Ronen and Zhou find little to no difference between information absorption between top bonds and equities. In our sample, it is possible for top bonds to cluster less than other bond trades. Top bonds are the bonds with the largest amount of institutional or large trading, and are easiest to price. However, it is also possible for top bonds to cluster more than other trades, especially if dealers think the large traders are using information to guide their decisions. We find that roughly 45% of clustered prices involve a top bond for investment grade bonds, but the majority of clustered prices in investment grade bonds are not in trades of top bonds (54.67%).

We find similar for speculative grade bonds. Top bonds make up 47% of clustered prices for speculative grade bonds, and non-top bonds account for the corresponding 53%. Even though institutional trades cluster less than retail-sized trades (and top bonds have the most institutional trading), it is not unexpected for top bonds to cluster in similar percentages for speculative grade bonds. Dealers are likely concerned that their large traders have superior information about the speculative grade bonds, and in turn prices of these bonds cluster as a source of protection for the dealer.

In Panel B of Table 5, we include only trades for bonds that also have actively traded credit default swaps. We find similar results to those in Panel A, showing that CDS trading is not driving the results. Retail-sized trading accounts for the majority of price clustering in both investment grade and speculative grade bonds, and non-top bonds make up the majority of clustered prices, regardless of rating.

4.2 Clustering by trade size and trade type

Table 6 provides an analysis of trade size and trade type clustering. We divide our sample into two broad groups to analyze the potential differences in clustering among trades. First, we divide the sample by trade size in Table 6 Panel A. We classify trade sizes in the following four ways: retail-sized trades are less than \$100,000 in size; odd lot trades are \$100,000 to \$999,999 in size; round lot trades are \$1,000,000 to \$4,999,999 in size; block trades are \$5,000,000 or larger in size. We also divide the sample between investment grade and speculative grade bond trades.

Overall, retail-sized trades appear to cluster the most of any trade size, regardless of the bond rating category. Investment grade retail-sized trades cluster 69.40% of the time, and speculative grade retail-sized trades cluster 65.34% of the time. For both odd lot and round lot trades, we find significant differences between investment grade and speculative grade bond trades, with the speculative grade showing higher levels of clustering in prices. In Panel B, we examine price by trade size for bonds with CDS trading. The results are qualitatively similar to Panel A.

Trade size	Investment grade	Speculative grade	Difference
Panel A: All Clustered prices			
Retail-sized	69.40%	65.34%	4.06%***
Odd Lot	20.08%	22.98%	−2.90%***
Round Lot	8.01%	11.53%	−3.52%***
Block	2.50%	0.15%	2.35%***
Panel B: Clustered prices in Bonds with CDS Trading			
Retail-sized	70.46%	68.94%	1.52%***
Odd Lot	19.54%	21.32%	−1.78%***
Round Lot	7.58%	9.59%	−2.01%***
Block	2.42%	0.15%	2.27%***

Note(s): Table 6 provides differences between the average percentage of trades that cluster between bond credit grade (investment grade versus speculative grade) for both trade size and trade type. The percentages are based on 1,552,284 trades with clustered prices in the sample. Prices are classified as clustered if they end in 00, 25, 50, or 75. Retail-sized trades are less than \$100,000 in value. Odd lot trades are \$100,000 to \$999,999 in value. Round lot trades are \$1,000,000 to \$4,999,999 in value. Block trades are \$5,000,000 or greater in value. Significance is indicated at the 1%, 5%, and 10% levels by ***,**, and *

Table 6.
Clustering by trade size and bond grade

5. Multivariate clustering analysis

Our univariate and regression results in Tables 1–6 document several findings. First, we show that credit quality plays a role in price clustering. Second, we find that the majority of price clustering is driven by retail-sized trades, regardless of the bond rating category. Third, we find that CDS trading influences price clustering. We now turn to a multivariate framework to further analyze price clustering.

Our first regression analysis revolves around activity. The dependent variable is the percent of daily clustered prices in each bond. We control for the same variables in our regression models that we detail in Section 3. In Table 7, we divide our sample into activity quartiles. Quartile 1 is the least active bonds, and Quartile 4 is the most active bonds. For all

	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Intercept	18.16***	4.65**	12.10***	30.25***
	6.17	2.47	5.41	11.85
Investment Grade	0.41	−4.61***	−20.47***	−21.96***
	0.46	−5.93	−23.80	−28.40
Price (10^3)	−4.36	24.20***	53.76**	−53.86**
	−1.12	2.65	2.04	−2.04
Volatility	3.63***	0.27	4.14***	4.20***
	3.78	1.14	12.89	12.63
Institution	−7.91***	−5.58***	−0.79**	1.97***
	−4.78	−6.52	−1.97	9.98
Buy	−1.78***	−2.93***	−0.41*	1.83***
	−3.66	−8.63	−1.79	12.47
Sell	6.53***	4.76***	2.83***	1.53***
	11.80	15.43	12.49	11.46
Number_Trades (10^3)	0.85***	0.46***	0.14***	0.00
	5.08	7.63	4.99	0.11
Coupon Rate	1.11***	2.21***	2.28***	1.43***
	5.67	14.29	13.32	10.79
Maturity (10^3)	27.26***	20.47***	10.97***	10.10***
	5.49	6.35	5.89	9.17
Family (10^3)	7.83***	15.37***	13.06***	−0.70
	6.29	14.83	12.91	−0.97
Top Bond	11.29***	6.33***	3.54***	0.18
	6.43	7.10	7.96	0.60
CDS	−5.44*	−2.70	−3.58***	−3.54***
	−2.03	−1.80	−4.07	−5.28
Financial	−0.83	3.30***	−0.08	−0.95**
	−0.89	4.65	−0.14	−1.98

Note(s): Table 7 provides OLS regression estimates for bond trades during 2014 (8,422,593 total trades). 1,552,284 trades have a clustered price. A trade is classified as executing at a clustered price if the reported price, after rounding to two decimals, ends in 0.00, 0.25, 0.50, or 0.75. The dependent variable is equal to the percentage of trades that cluster daily for each bond. Investment grade is equal to one if the bond if rated as investment quality and zero otherwise. Price is the trade reported price. Volatility is the bond's daily price volatility. Institution is equal to one if the trade size is greater than or equal to $100,000 (Edwards *et al.*, 2007). Buy is equal to one if the trade is a dealer reported buy trade, and sell is equal to one if the trade is a dealer reported sell trade (and zero otherwise). The number of trades is the daily number of trades for each bond. The coupon rate is the bond's reported coupon. Maturity is the bond's years to maturity, and family is the number of the bonds issued by the parent firm. Top bond is equal to one if the bond has the most institutional trading on a given trading day and zero otherwise. Financial is equal to one if the firm's SIC code is 6000–6700. CDS is equal to one if the firm has active credit default swap trading. *T*-statistics are reported below the coefficients, and significance is indicated at the 1%, 5%, and 10% levels by ***,**, and *. Standard errors are clustered by CUSIP

Table 7.
OLS regressions by activity level

activity levels except Quartile 1, we find that bond rating categories matter for price clustering. For the most active bonds, a bond having an investment grade credit rating reduces price clustering by nearly 22%. More volatile bonds tends to cluster more (for all activity levels except Quartile 2), and large, institutional sized trades tend to cluster less than retail sized trades. This evidence further supports our claim that dealers exercise power over small traders. Dealer buys tend to cluster more than interdealer trades for the most active bonds, which could indicate dealers are trying to protect themselves from unknown information. Regardless of activity level, bonds with more time to maturity cluster more than shorter term bonds, which is consistent with these bonds being more difficult to value. For Quartiles 1 to 3, bonds with larger bond families cluster more. Bonds with larger families may also be harder to value due to the large number of securities outstanding for one firm. Top bonds tend to cluster more than non-top bonds for all quartiles except the most active; this could be because dealers are trying to protect themselves from informed trading by institutions when a large volume of large trading occurs. Lastly, both financial firms and CDS issuance could influence clustering. We find that outstanding CDS's reduce clustering, particularly for Quartiles 3 and 4, but we only document weak evidence that financials and clustering are related, and the relation is strongest in Quartile 2.

Table 8 is similar to that of Table 7, but includes only top bonds. Top bonds are the bonds with the most institutional trading activity and are the bonds mostly closely related to equities on an informational level. The results in Table 8 are consistent with those shown in Table 7. Regardless whether we are looking at the full sample of bonds or the top bonds, our results are consistent.

We provide regressions of price clustering activity in Table 9. The dependent variable is the percent of daily clustered prices in each bond. We show regression estimates for the whole sample, investment grade bonds, speculative grade bonds, institutional sized trades, and retail-sized trades. We control for the same variables in our regression models that we detail in Section 3. In Table 9, we provide traditional *t*-stats for inferences of significance. In addition, we note that *t*-statistics of over 4.75 suggest a posterior odds ratio of better than 1:20 and *t*-statistics over 5.08 suggest a posterior odds ratio of better than 1:100 based on Zellner (1984); *t*-statistics larger than these cut-offs are also noted in Table 9 [19].

In Table 9, the first specification includes the entire sample. The most immediate observation is the negative coefficient for Investment Grade (−21.40), indicating investment grade bonds cluster roughly 21% less than speculative grade bonds, holding all else constant. Investment grade bonds have far less uncertainty than speculative grade bonds in terms of valuation, so it is not surprising those trades cluster less. Both dealer buy and dealer sell trades cluster more than interdealer trades, holding all else constant. The regression shows that institutional sized trades cluster more than retail-sized trades; when a trade is large (institutional), clustering increases by 1.28%. This conflicts with previous univariate results, but could be an indication of large trades that are difficult to value or of dealers protecting themselves against informed trading. The coefficients on the investment grade, institution, buy, and sell dummies all have *t*-statistics of greater than 5, so they are significant at the 1% level and have posterior odds ratios of better than 1:100 [20]. We control for activity level with dummy variables equal to one for their corresponding quartile and zero otherwise. We hold out the dummy variable for Quartile 4 (most active) for comparison. We find strong evidence that the bonds in Quartiles 1 through 3 cluster more than the most active bonds in our sample. The least active bonds cluster 9.80% more than the most active bonds.

Since bond rating is a strong explanatory factor, we separate speculative grade bond observations from investment grade observations in the next two columns of Table 9. Large trades in investment grade bonds cluster 0.58% less than retail-sized trades, but institutional sized trading in speculative grade bonds increases price clustering by 5.23%. This could be

	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Intercept	20.57***	12.22***	22.97***	32.83***
	5.39	5.17	10.90	9.90
Investment Grade	2.68	−9.10***	−25.26***	−22.00***
	1.61	−7.79	−27.06	−25.05
Price (10^3)	−11.09**	−5.04	−16.33	−83.21**
	−2.37	−0.59	−0.92	−2.45
Volatility	3.53**	0.15*	4.00***	3.83***
	2.40	1.65	7.87	9.35
Institution	−4.92***	−4.09***	−0.29	1.94***
	−2.99	−5.04	−0.78	9.94
Buy	−6.18***	−3.37***	−0.07	2.07***
	−5.22	−5.65	−0.25	12.35
Sell	6.93***	6.11***	3.47***	1.79***
	5.56	10.55	9.69	11.85
Number_Trades (10^3)	1.08***	0.41***	0.12***	0.00
	5.42	6.18	3.83	0.29
Coupon Rate	2.09***	3.10***	2.77***	1.66***
	6.66	14.99	16.98	11.04
Maturity (10^3)	25.33***	20.15***	8.64***	10.07***
	4.12	5.16	3.75	8.84
Family (10^3)	14.99***	22.93***	14.22***	−2.03***
	6.20	12.73	8.09	−2.76
CDS	−4.21	−4.41**	−2.96***	−3.80***
	−1.38	−2.52	−3.11	−5.15
Financial	−0.39	3.01***	0.34	−0.71
	−0.23	2.58	0.44	−1.40

Note(s): Table 8 provides OLS regression estimates for top bond trades during 2014. Top bond is classified if the bond has the most institutional trading on a given trading day. A trade is classified as executing at a clustered price if the reported price, after rounding to two decimals, ends in 0.00, 0.25, 0.50, or 0.75. The dependent variable is equal to the percentage of trades that cluster daily for each bond. Investment grade is equal to one if the bond if rated as investment quality and zero otherwise. Price is the trade reported price. Volatility is the bond's daily price volatility. Institution is equal to one if the trade size is greater than or equal to $100,000 (Edwards *et al.*, 2007). Buy is equal to one if the trade is a dealer reported buy trade, and sell is equal to one if the trade is a dealer reported sell trade (and zero otherwise). The number of trades is the daily number of trades for each bond. The coupon rate is the bond's reported coupon. Maturity is the bond's years to maturity, and family is the number of the bonds issued by the parent firm. Financial is equal to one if the firm's SIC code is 6000–6700. CDS is equal to one if the firm has active credit default swap trading. *T*-statistics are reported below the coefficients, and significance is indicated at the 1%, 5%, and 10% levels by ***,**, and *. Standard errors are clustered by CUSIP

Table 8.
OLS regressions by activity level (top bonds)

due to the signal that large trading activity does (or does not) send to dealers. It is likely that dealers will suspect information motivated trading if they observe large trading activity in high-yield bonds, but will exhibit less self-protecting behavior (i.e. widening spreads) if the same behavior is observed in investment grade bonds. Volatility appears to have a larger impact on clustering in investment grade bonds (5.60%) than speculative grade bonds (1.21%). Dealer buys and dealer sells increase price clustering compared to interdealer trades, and the effect is stronger for speculative grade bonds, consistent with an information-based model like Duffie *et al.* (2005) that predicts that bid-ask spreads will be widened by market makers when they believe their customers possess superior information. CDS trading has no influence on investment grade trades, but does reduce price clustering by 5.67% in speculative grade bond trades. For investment grade bonds, the least actively traded bonds cluster 18.13% more than the most actively traded bonds. The bonds in Quartile 2 and 3 also

	All trades	Investment grade trades	Speculative grade trades	Institutional trades	Retail-sized trades
Intercept	24.25***[b]	8.66*	19.56***[b]	34.85***[b]	19.73***[b]
	23.02	1.90	13.47	28.24	17.19
Investment Grade	−21.40***[b]			−26.90***[b]	−18.80***[b]
	−35.11[b]			−44.88	−28.69
Price (10^3)	−8.35	−48.71	−1.33	−52.86***[a]	10.89
	−1.03	−0.99	−0.26	−4.91	1.21
Volatility	2.71**	5.60***[b]	1.21*	1.65***	3.24**
	2.43	17.04	1.76	2.53	2.39
Institution	1.28***[b]	−0.58***[a]	5.23***[b]		
	5.65	−4.83	11.65		
Buy	0.91***[b]	0.56***[b]	3.06***[b]	1.50***[b]	0.62***
	6.27	5.25	9.16	12.18	3.45
Sell	1.86***[b]	0.82***[b]	3.59	1.68***[b]	1.96***[b]
	15.85	7.96	0.28	14.85	11.48
Number_Trades (10^3)	1.64	21.65***	−9.17	−3.90	3.98
	0.37	3.99	−1.27	−0.74	0.84
Coupon Rate	1.71***[b]	0.59***	2.34***[b]	1.83***[b]	1.58***[b]
	16.33	2.83	13.06	20.11	12.73
Maturity	9.93***[b]	15.70***[b]	7.34***[b]	7.84***[b]	11.11***[b]
	9.10	18.13	8.81	7.53	9.31
Family (10^3)	2.00***	2.60***	0.29	−0.15	2.39***
	3.25	4.66	0.15	−0.25	3.56
Top Bond	0.43*	−1.56***[b]	3.60***		1.01***
	1.71	−7.45	5.49		3.70
CDS	−3.48***[b]	−0.52	−5.67***[b]	−3.26***[b]	−3.14***
	−5.85	−0.73	−6.16	−5.20	−4.56
Financial	−1.12***	0.87**	−5.19***[a]	−1.22***	−1.09**
	−2.74	2.32	−5.06	−2.90	−2.43
Quartile 1	9.80***[b]	18.13***[b]	5.05***	7.40***[b]	11.11***[b]
	16.13	30.46	4.38	7.52	17.88
Quartile 2	6.17***[b]	11.02***[b]	0.87	1.31**	8.53***[b]
	13.81	27.80	0.84	2.47	17.55
Quartile 3	2.67***[b]	3.84***[b]	2.72***	0.55	4.02***[b]
	8.19	13.85	3.13	1.57	11.02

Note(s): Table 9 provides OLS regression estimates for clustered bond trades during 2014 (8,422,593 total trades). 1,552,284 trades have a clustered price. A trade is classified as executing at a clustered price if the reported price, after rounding to two decimals, ends in 0.00, 0.25, 0.50, or 0.75. The dependent variable is equal to the percentage of trades that cluster daily for each bond. Investment grade is equal to one if the bond if rated as investment quality and zero otherwise. Price is the trade reported price. Volatility is the bond's daily price volatility. Institution is equal to one if the trade size is greater than or equal to $100,000 (Edwards *et al.*, 2007). Buy is equal to one if the trade is a dealer reported buy trade, and sell is equal to one if the trade is a dealer reported sell trade (and zero otherwise). The number of trades is the daily number of trades for each bond. The coupon rate is the bond's reported coupon. Maturity is the bond's years to maturity, and family is the number of the bonds issued by the parent firm. Top bond is equal to one if the bond has the most institutional trading on a given trading day and zero otherwise. Financial is equal to one if the firm's SIC code is 6000–6700. CDS is equal to one if the firm has active credit default swap trading. *T*-statistics are reported below the coefficients, and significance is indicated at the 1%, 5%, and 10% levels by ***,**, and *. Standard errors are clustered by CUSIP. Significance using the posterior odds ratio is indicated by a for 5% significance and b for 1% significance

Table 9.
OLS regressions by bond rating category and trade type

cluster more than those in Quartile 4. While we find no significant results for Quartile 2 and speculative grade trades, we do find that the least active bonds continue to cluster more than the most active bonds for speculative trades.

Table 9 also divides the trading sample into institutional versus retail-sized trades. Institutional trades are inherently different than retail-sized trades in terms of both size and cost, and as such, the clustering effects may be different as well. Investment grade bonds cluster substantially less than speculative grade bond trades for both institutions and retail-sized trades. Investment grade large trades cluster 27% less than speculative grade bond trades, and investment grade retail-sized trades cluster 19% less. Dealer buys (1.50%) and sells (1.68%) cluster more than interdealer trades for institutions. The same is true for retail-sized trades, although dealer buys increase clustering by only 0.62% even though dealer sells in retail sizes increase clustering by 2%. As noted in Goldstein and Hotchkiss (2020), dealers may break up purchases they make from institutions into more retail-sized trades, so dealers may be able to have more power on dealer sales than buys in retail-sized units. CDS trading reduces clustering in institutional sized trades by 3.26%, and CDS activity reduces clustering in retail-sized trades by 3.14%. We find that the least actively traded bonds cluster more (7.40 and 11.11%) than the most actively traded bonds (institutional and retail-sized).

We extend our analysis in Table 10 by dividing our sample into investment grade (speculative) bonds for both institutions and retail-sized trades. The first two columns in Table 10 are for investment grade trades. For both large and small investment grade trades, volatility is correlated with an increase in price clustering, and the magnitude of the coefficient is similar between the two trade size groups. Dealer buys and sells increase clustering more than interdealer trades for both institution and retail sized trades. Prices appear to cluster more when dealers sell to retail-sized traders than when dealers buy from retail-sized traders, consistent with dealers taking advantage of retail-sized traders and exhibiting dealer power. CDS trading reduces price clustering by 1.84% for investment grade large trades, but CDS trading has no relation with retail-sized trades.

The second two columns in Table 10 are for speculative grade bond trades. Volatility increases the amount of price clustering for both institutions and retail traders, but the effect is diminished from that for investment grade bonds. For institutions, the magnitude of price clustering is similar for both dealer buys and sells. Dealer sells appear to cluster slightly more than buys for speculative grade bonds, which is consistent with dealers exerting power over retail-sized traders. CDS trading reduces price clustering for both institution and retail-sized speculative trades.

5.1 Robustness check – top bonds only

Unlike equities, one firm can have multiple bond issues and types (convertible, callable, etc.) outstanding and trading at one time. Ronen and Zhou (2013) show that informational differences exist between what they call a firm's top bond and all other firm bonds. For robustness, we verify that our results hold for both the full sample and for top bonds. Top bonds are designated by the number of large, institutional sized trades. The bond with the largest number of institutional sized trades is the firm's top bond.

The first set of top bond results are presented in Table 11. Table 11 follows a setup similar to Table 9, except the sample is limited to top bonds only. Consistent with previous results (Table 9) investment grade bonds cluster notably less than speculative grade bonds. The magnitude of the coefficients ranges from −19% to −27%. For all specifications, both buys and sells continue to lead to more price clustering than interdealer trades, regardless of trade size or bond grade. We also consistently find that the most actively traded bonds cluster less than the bonds in the other three quartiles. In Table 12, we replicate the regression models from Table 10 for top bonds only and find similar, consistent results. Collectively, the results in Tables 11 and 12 for only top bonds confirms the overall results and the results found in Tables 9 and 10 for all bonds.

	Investment grade trades		Speculative grade trades	
	Institution sized	Retail-sized	Institution sized	Retail-sized
Intercept	5.71**	9.24	29.49***[b]	22.53***[b]
	2.13	1.58	22.39	12.51
Price	−0.00	−0.07	−0.05***[b]	0.03***
	−0.10	−1.17	−7.56	3.82
Volatility	4.20***[b]	5.55***[b]	0.53**	1.64
	12.98	14.51	2.17	1.64
Buy	0.26***	0.46***	4.74***[b]	2.28***[a]
	2.87	3.20	17.45	5.07
Sell	0.11	1.05***[b]	5.14***[b]	3.06***[b]
	1.48	7.32	19.07	7.13
Number of Trades	0.02***	0.01**	−0.02***	−0.01
	4.72	2.12	−2.66	−0.72
Coupon Rate	0.49***	0.82***	2.867***[b]	1.97***[b]
	3.60	3.16	18.64	9.54
Maturity	0.016***[b]	0.02***[b]	0.01***[b]	0.01***[b]
	27.34	13.61	7.08	9.51
Family (10^3)	0.36	4.29***[b]	−2.48	1.83
	0.72	5.91	−1.18	0.89
CDS	−1.84**	0.42	−4.72***[b]	−6.51***[b]
	−2.12	0.60	−5.36	−5.56
Financial	0.62*	1.27***	−5.28***[a]	−5.43***
	1.84	2.79	−4.84	−4.65
R-Squared	8.20%	7.30%	7.61%	6.81%
F-Stat	140.70	88.74	105.55	84.29

Note(s): Table 10 provides OLS regression estimates for clustered bond trades during 2014 (8,422,593 total trades). 1,552,284trades have a clustered price. A trade is classified as executing at a clustered price if the reported price after rounding to two decimals ends in 0.00, 0.25, 0.50, or 0.75. The dependent variable is equal to the percentage of trades that cluster daily for each bond. Investment grade is equal to one if the bond if rated as investment quality and zero otherwise. Price is the trade reported price. Volatility is the bond's daily price volatility. Institution is equal to one if the trade size is greater than or equal to $100,000 (Edwards *et al.*, 2007). Buy is equal to one if the trade is a dealer reported buy trade, and sell is equal to one if the trade is a dealer reported sell trade (and zero otherwise). The number of trades is the daily number of trades for each bond. The coupon rate is the bond's reported coupon. Maturity is the bond's years to maturity, and family is the number of the bonds issued by the parent firm. Top bond is equal to one if the bond has the most institutional trading on a given trading day and zero otherwise. Financial is equal to one if the firm's SIC code is 6000–6700. CDS is equal to one if the firm has active credit default swap trading. *T*-statistics are reported below the coefficients, and significance is indicated at the 1%, 5%, and 10% levels by ***,**, and *. Standard errors are clustered by CUSIP. Significance using the posterior odds ratio is indicated by a for 5% significance and b for 1% significance

Table 10.
OLS regressions by bond rating category and trade type

6. Conclusion

We find price clustering in the corporate bond market, an economically large market notably different than the market for equities. We document substantial corporate bond market price clustering; over 18% of all bond trades end in prices of 0.00, 0.25, 0.50, and 0.75. We find differences in clustering between investment grade and speculative grade bonds; in particular, we find a remarkable amount of clustering in the speculative grade bond market, with speculative grade bonds accounting for over 63% of clustered prices. Using univariate and multivariate tests, we show that bond rating categories (investment vs speculative grade) is a key factor that influences price clustering: investment grade bonds cluster less frequently than speculative grade bonds. Bond activity level also plays a role in price clustering; bonds with lower liquidity have higher levels of price clustering than the more active bonds in our sample.

	All trades	Investment grade trades	Speculative trades	Institutional trades	Retail-sized trades
Intercept	29.87***[b]	4.86	25.76***[b]	34.85***[b]	26.70***[b]
	19.04	1.21	14.44	28.24	13.04
Investment Grade	−22.71***[b]			−26.90***[b]	−19.49***[b]
	−29.78			−44.88	−21.14
Price	−49.64***[b]	−27.62	−41.69***[b]	−52.86***[a]	−48.42***
	−3.68	−0.65	−5.98	−4.91	−2.59
Volatility	2.08**	5.65***[b]	0.91*	1.65***	2.38*
	2.11	13.92	1.82	2.53	1.86
Institution	1.19***[b]	−0.56***	5.19***[b]		
	5.45	−4.63	11.95		
Buy	1.50***[b]	0.52***	3.77***[b]	1.50***[b]	1.32***[b]
	8.97	4.09	9.76	12.18	5.56
Sell	2.03***[b]	0.73***[b]	4.15***[b]	1.68***[b]	2.21***[b]
	14.50	6.01	12.85	14.85	9.83
Number_Trades	0.03	21.06***	−9.64	−3.90	2.29
(10^3)	0.01	4.07	−1.35	−0.74	0.49
Coupon Rate	1.82***[b]	0.81***	2.52***[b]	1.83***[b]	1.86***[b]
	14.65	4.20	11.83	20.11	11.14
Maturity (10^3)	9.90***[b]	15.80***[b]	6.44***[b]	7.84***[b]	11.38***[b]
	8.43	17.72	6.98	7.53	8.89
Family (10^3)	0.00	−0.18	1.64	−0.15	−0.65
	0.00	−0.30	0.64	−0.25	−0.79
CDS	−3.63***[b]	−0.74	−5.77***[b]	−3.26***[b]	−3.45***
	−5.50	−0.89	−5.80	−5.20	−4.05
Financial	−0.08*	0.70	−4.14***	−1.22***	−0.69
	−1.74	1.69	−3.50	−2.90	−1.21
Quartile 1	12.56***[b]	26.49***[b]	3.82**	7.40***[b]	26.29***[b]
	10.97	19.18	2.16	7.52	11.83
Quartile 2	5.34***[b]	10.17***[b]	0.65	1.31	16.90***[b]
	8.21	15.94	0.45	2.47**	12.74
Quartile 3	2.34***[b]	3.03***[b]	4.13***	0.55	6.40***[b]
	5.69	8.34	3.99	1.57	9.48

Note(s): Table 11 provides OLS regression estimates for clustered bond trades during 2014 for top bonds only. A trade is classified as executing at a clustered price if the reported price ends in 0.00, 0.25, 0.50, or 0.75. The dependent variable is equal to the percentage of trades that cluster daily for each bond. Investment grade is equal to one if the bond if rated as investment quality and zero otherwise. Price is the trade reported price. Volatility is the bond's daily price volatility. Institution is equal to one if the trade size is greater than or equal to \$100,000 (Edwards *et al.*, 2007). Buy is equal to one if the trade is a dealer reported buy trade, and sell is equal to one if the trade is a dealer reported sell trade (and zero otherwise). The number of trades is the daily number of trades for each bond. The coupon rate is the bond's reported coupon. Maturity is the bond's years to maturity, and family is the number of the bonds issued by the parent firm. Top bond is equal to one if the bond has the most institutional trading on a given trading day and zero otherwise. Financial is equal to one if the firm's SIC code is 6000–6700. CDS is equal to one if the firm has active credit default swap trading. *T*-statistics are reported below the coefficients, and significance is indicated at the 1%, 5%, and 10% levels by ***,**, and *. Standard errors are clustered by CUSIP. Significance using the posterior odds ratio is indicated by a for 5% significance and b for 1% significance

Table 11. OLS regressions by bond rating category and trade type (top bonds only)

We also find that trade size is also an important factor in price clustering for corporate bonds. In univariate tests, retail-sized trades account for a larger portion of clustered prices. However, large trades appear to cluster more in multivariate tests. This is perhaps a manifestation of dealers protecting themselves against knowledgeable institutions. Duffie *et al.* (2005) would argue that investors' outside options would dictate the bid-ask spread, particularly for large, investment grade bonds. We do indeed see, in univariate

	Investment grade trades		Speculative grade trades	
	Institution sized	Retail-sized	Institution sized	Retail-sized
Intercept	5.71**	3.81	29.48***b	28.68***b
	2.13	0.75	22.39	12.34
Price	−0.00	−0.04	−0.05***b	−0.04***
	−0.10	−0.71	−7.56	−3.03
Volatility	4.20***b	6.25***b	0.53**	1.11
	12.98	11.94	2.17	1.61
Buy	0.26***	0.80***	4.74***	3.09***a
	2.87	4.06	17.45	5.00
Sell	0.11	1.28***b	5.14***b	3.44***b
	1.48	6.63	19.07	7.01
Number of Trades	0.02***	0.020***	−0.02***	−0.01
	4.72	3.26	−2.66	−1.10
Coupon Rate	0.49***	1.08***	2.87***b	2.10***b
	3.60	4.51	18.64	7.50
Maturity	0.02***b	0.02***	0.01***b	0.01***a
	27.34	13.82	7.08	5.03
Family (10^3)	0.36	0.90	2.48	6.26*
	0.72	−1.28	−1.18	1.90
CDS	−1.84**	0.11	−4.72***b	−7.19***b
	−2.12	0.12	−5.36	−5.23
Financial	0.62*	0.94*	−5.28***a	−3.04**
	1.84	1.81	−4.84	−2.07
R-Squared	8.20%	14.24%	7.61%	5.38%
F-Stat	140.70	73.65	105.55	30.97

Note(s): Table 12 provides OLS regression estimates for clustered bond trades during 2014 for top bonds only. A trade is classified as executing at a clustered price if the reported price ends in 0.00, 0.25, 0.50, or 0.75. The dependent variable is equal to the percentage of trades that cluster daily for each bond. Investment grade is equal to one if the bond if rated as investment quality and zero otherwise. Price is the trade reported price. Volatility is the bond's daily price volatility. Institution is equal to one if the trade size is greater than or equal to $100,000 (Edwards *et al.*, 2007). Buy is equal to one if the trade is a dealer reported buy trade, and sell is equal to one if the trade is a dealer reported sell trade (and zero otherwise). The number of trades is the daily number of trades for each bond. The coupon rate is the bond's reported coupon. Maturity is the bond's years to maturity, and family is the number of the bonds issued by the parent firm. Top bond is equal to one if the bond has the most institutional trading on a given trading day and zero otherwise. Financial is equal to one if the firm's SIC code is 6000–6700. CDS is equal to one if the firm has active credit default swap trading. *T*-statistics are reported below the coefficients, and significance is indicated at the 1%, 5%, and 10% levels by ***,**, and *. Standard errors are clustered by CUSIP. Significance using the posterior odds ratio is indicated by a for 5% significance and b for 1% significance

Table 12.
OLS regressions by bond rating category and trade type (top bonds only)

testing, that institutional trades cluster less. It seems they are offered narrower bid-ask spreads than retail-sized customers because institutional traders have more outside options, i.e. knowledge of market makers. But for large trades of speculative grade bonds, dealers are presented with an adverse selection problem as in Glosten and Milgrom (1985). If they believe that their customers have superior information, they will increase their bid-ask spreads. This is somewhat consistent with our findings, more clustering for large trades of speculative grade bonds than investment grade bonds.

Our study sheds light on market quality in the corporate bond market. The prevalence of price clustering, especially for retail-sized traders, could be of particular interest to bond market regulators. The behavior of dealers and their ability to exert power over retail-sized traders could serve as a deterrent to market participation and could influence market liquidity.

The recent establishment of electronic markets such as MarketAxess in the corporate bond market is a potential solution to manage dealer behavior. MarketAxess's electronic request-for-quote (RFQ) corporate bond trading platform has helped provide more information to the market, resulting reduced search costs for both customers and dealers and increased dealer competition, ultimately lowering execution costs, particularly for retail traders (O'Hara and Zhou, 2021). However, most of the trading are small trades in investment grade bonds; the low liquidity of corporate bonds and other issues may provide significant impediments to further increases in electronic trading (O'Hara and Zhou, 2021). Thus, while MarketAxess has at times captured 20% of corporate bond trading volume, the larger dealer structure remains for most of the market, suggesting that while electronic trading may be helpful, regulators cannot rely solely on this competitive innovation to change market structure rapidly.

Notes

1. Clustering remains a conundrum. In a world of perfect competition, prices should be uniform across a pricing grid, yet this is not the case even in markets that are considered very competitive and "rational" such as U.S. equity markets, where price clustering – i.e. when all price increments are not used with similar frequency, such as the overuse of whole dollars, half dollars, dimes, or nickels – is prevalent both in transaction prices (Harris, 1991; Christie and Schultz, 1994) and trade sizes (Alexander and Peterson, 2007).

2. Total corporate bond issuances for 2014 are valued at $1.44 trillion; see Securities Industry and Financial Markets Association (SIFMA) website at: https://www.sifma.org/resources/?aq=corporate%20bond&hPP=10&idx=prod_wp_searchable_posts&ap=0&is_v=1

3. There is no current study of price clustering in the corporate bond market, even though as far back as Harris (1991), it was noted that "no studies have been made of clustering in bond markets". Most previous clustering studies examine the clustering of stock prices, some from as early as the 1960s (Osborne, 1962; Niederhoffer, 1966). A number of more recent studies show price clustering in equity markets (Cooney *et al.*, 2003; Ascioglu *et al.*, 2007; Chiao and Wang, 2009), as well as trade size clustering in equity markets (Alexander and Peterson, 2007; Blau *et al.*, 2012) and in the foreign exchange market (Moulton, 2005). Edwards *et al.* (2007) note that bond trades are clustered, but do not make any inferences about bond trade prices being clustered. Clustering of transaction prices is shown in a number of other financial markets. Ball *et al.* (1985) document the clustering of gold prices, while Schwartz *et al.* (2004) show transaction price clustering in the futures market. Sopranzetti and Datar (2002) detail price clustering in the foreign exchange spot market, and Liu and Witte (2013) show price clustering in the foreign exchange swap market.

4. Prices in TRACE are quoted in three to six decimals, with a $1,000 par value quoted as 100.000 or 100.000000. To define clustering, we capture the first two decimals from every price quotation in our sample (the tenths and hundredths decimal places). We classify a price as clustered if the first two decimals of the price after the decimal point are 0.00, 0.25, 0.50, or 0.75. Prices with more than two decimals are rounded to two digits to determine if they are a clustered price.

5. Our finding of increased price clustering is consistent with the implications in Li (2007), Holden (2009), and Goyenko *et al.* (2009) that more price clustering is indicative of higher bid-ask spreads.

6. In unreported results, we also find significant clustering of bond prices in 2012 (similar to those reported for the 2014 sample in this paper).

7. Another but unlikely possibility is that price clustering could stem from dealer collusion. Christie and Schultz (1994) hypothesize collusion as an explanation in a study of NASDAQ stock clustering. Like corporate bonds, NASDAQ stocks at that time traded over-the-counter in a dealer market. Christie *et al.* (1994) show that dealer behavior changed (and clustering diminished) once news of the price clustering was published in *The Wall Street Journal*, lending credence to the original dealer collusion hypothesis from Christie and Schultz (1994).

8. On July 1, 2002 the National Association of Securities Dealers, or NASD (now FINRA), began a dissemination service called the Trade Reporting and Compliance Engine (TRACE) to bring transparency to the OTC corporate bond market. For further information, see Table 1 in Goldstein and Hotchkiss (2012) for a timeline of dissemination.
9. For information on the NYSE's efforts to improve its market share, you can visit: https://www.nyse.com/markets/bonds.
10. The NASD merged with the Financial Industry Regulatory Authority (FINRA) in 2007.
11. While Appendix 1 details each sample deletion, it is worth nothing that the most trades are lost when we add the Financial Industry variable into our sample.
12. From FINRA (2017), page 22: "Price (Required) Enter the price at which the trade was executed as a percentage of par. Valid entry format is 9,999.999999. For example, a security traded at 98.625 should be reported as "98.625". For principal trades, the price must include any markups or markdowns. For agent trades, the price field should NOT include the commission charged, since commission is reported in a separate field. For ELNs, price is reported as a dollar amount (price per share)."
13. We also estimate price clustering without rounding prices, and the results are qualitatively similar regardless of rounding prices.
14. While the larger clustering is on the quarters (0.00, 0.25, 0.50, 0.75) on which we focus, it is also apparent from Figure 2 that the pattern of price clustering repeats on a smaller scale at the eighths (such as 0.125 and 0.375 and 0.875, rounded in this graph) and also decimals (0.10, 0.20, 0.30, 0.40 . . .) and to a lesser extent the fives (0.05, 0.15, 35, etc.). Therefore, we are conservatively considering the amount of clustering by limiting our definition of clustering to just the four-quarter (0.00, 0.25, 0.50 and 0.75) numbers; clearly clustering percentages would be higher if other patterns of clustering were also included.
15. While we restrict our sample to bonds that trade at least ten times over our sample period, we do not require the bonds to trade ten times per day. Therefore, it is possible to have an average number of trades below ten. We require bonds to trade ten times over the course of the sample (not per day) to avoid biasing our results with the most illiquid bonds in the trading universe. Bonds are illiquid, especially compared to equities, and many bonds trade only a handful of times each year. By focusing on the more liquid bonds in our sample, we are better able to study the informational effects that price clustering may have.
16. Of course, this result may be an artifact of clustering: clustering causes a coarser price grid, resulting in mechanically higher measured price standard deviation, similar to the bid-ask bounce effect in Blume and Stambaugh (1983).
17. We also run logit regressions on each cluster price (0.00, 0.25, 0.50 and 0.75) individually to examine clustering at each cluster pricing grid. These regression results qualitatively similar to those for the full sample are presented in Table 4.
18. See Kwan (1996) and Downing *et al.* (2009).
19. Some feel that in large data sets traditional t-statistics can be misleading: due to the large number of observations, rejection of the null is likely. One alternative is to use a posterior odds ratio. Using the sharp null test in equation 3.11 of Zellner (1984) and 8,422,593 observations, we can generate posterior odds ratios for each coefficient using the t-statistics listed in Table 5. Using Equation 3.11, we can also generate "cut-off" t-statistic values for different values of K_{12} as in Table 3 on page 287 of Zellner (1984). Using our 8,422,593 observations, we find that the cut-off t-statistic to generate a posterior odds ratio of 1:20 is 4.75, and the cut-off t-statistic to generate a posterior odds ratio of 1:100 is 5.08. We note these in Table 9.
20. For example, the posterior odds ratio for the Buy dummy with a t-statistic of 10.05 is 1:2.16 $\times 10^{18}$ as calculated by the inverse of the K_{12} value (4.63×10^{-19}) calculated by equation 3.11 in Zellner (1984).

References

Alexander, G. and Peterson, M. (2007), "An analysis of trade size clustering and its relation to stealth trading", *Journal of Financial Economics*, Vol. 84, pp. 435-471.

Ascioglu, A., Comerton-Forde, C. and McInish, T. (2007), "Price clustering on the Tokyo stock exchange", *The Financial Review*, Vol. 42, pp. 289-301.

Ball, C., Torous, W. and Tschoegl, A. (1985), "The degree of price resolution: the case of the gold market", *The Journal of Futures Markets*, Vol. 5, pp. 29-43.

Blau, B., Van Ness, B. and Van Ness, R. (2012), "Trade size and price clustering: the case of short sales and the suspension of price tests", *The Journal of Financial Research*, Vol. 35, pp. 159-182.

Blume, M.E. and Stambaugh, R.F. (1983), "Biases in computed returns: an application to the size effect", *Journal of Financial Economics*, Vol. 12, pp. 387-404.

Chiao, C. and Wang, Z. (2009), "Price clustering: evidence using comprehensive limit-order data", *The Financial Review*, Vol. 44, pp. 1-29.

Christie, W. and Schultz, P. (1994), "Why do NASDAQ market makers avoid odd-eighth quotes?", *The Journal of Finance*, Vol. 49, pp. 1813-1840.

Christie, W., Harris, J. and Schultz, P. (1994), "Why did NASDAQ market makers stop avoiding odd-eighth quotes?", *The Journal of Finance*, Vol. 49, pp. 1841-1860.

Cooney, J., Van Ness, B. and Van Ness, R. (2003), "Do investors prefer even-eighth prices? Evidence from NYSE limit orders", *Journal of Banking and Finance*, Vol. 27, pp. 719-748.

Downing, C., Underwood, S. and Xing, Y. (2009), "The relative informational efficiency of stocks and bonds: an intraday analysis", *Journal of Financial and Quantitative Analysis*, Vol. 44, pp. 1081-1102.

Duffie, D., Gârleanu, N. and Pedersen, L.H. (2005), "Over-the-counter markets", *Econometrica*, Vol. 73, pp. 1815-1847.

Edwards, A., Harris, L. and Piwowar, M. (2007), "Corporate bond market transparency and transaction costs", *Journal of Finance*, Vol. 62, pp. 1421-1451.

FINRA (2017), TRACE™ Reporting and Quotation Service OTC Corporate Bonds and Agency Debt USER GUIDE Reference Manual, Version 4.6, Financial Industry Regulatory Authority, available at: http://www.finra.org/sites/default/files/TRAQS-CA-user-guide-v4.6.pdf (25 January 2017).

Glosten, L.R. and Milgrom, P.R. (1985), "Bid, ask, and transaction prices in a specialist market with heterogeneously informed traders", *Journal of Financial Economics*, Vol. 14, pp. 71-100.

Goldstein, M. and Hotchkiss, E. (2012), "Dealer behavior and the trading of newly issued corporate bonds", Babson College working paper, Babson Park, MA.

Goldstein, M. and Hotchkiss, E. (2020), "Providing liquidity in an illiquid market: dealer behavior in U.S. Corporate bonds", *Journal of Financial Economics*, Vol. 135, pp. 16-40.

Goldstein, M., Hotchkiss, E. and Sirri, E. (2007), "Transparency and liquidity: a controlled experiment on corporate bonds", *Review of Financial Studies*, Vol. 20, pp. 235-273.

Goyenko, R., Holden, C. and Trzcinka, C. (2009), "Do liquidity measures measure liquidity?", *Journal of Financial Economics*, Vol. 92, pp. 153-181.

Green, R., Hollifield, B. and Schürhoff, N. (2007a), "Dealer intermediation and price behavior in the aftermarket for new bond issues", *Journal of Financial Economics*, Vol. 86, pp. 643-682.

Green, R., Hollifield, B. and Schürhoff, N. (2007b), "Financial intermediation and the costs of trading in an opaque market", *The Review of Financial Studies*, Vol. 20, pp. 275-314.

Harris, L. (1991), "Stock price clustering and discreteness", *The Review of Financial Studies*, Vol. 4, pp. 389-415.

Holden, C. (2009), "New low-frequency spread measures", *Journal of Financial Markets*, Vol. 12, pp. 778-813.

Kwan, S. (1996), "Firm-specific information and the correlation between individual stocks and bonds", *Journal of Financial Economics*, Vol. 40, pp. 63-80.

Li, D. (2007), *Rounding as Discrimination: Price Clustering in the OTC Tax-Exempt Bond Market*, Working paper, Federal Reserve.

Liu, H. and Witte, M. (2013), "Price clustering in the U.S. Dollar/Taiwan dollar swap market", *The Financial Review*, Vol. 48, pp. 77-96.

Moulton, P. (2005), "You can't always get what you want: trade-size clustering and quantity choice in liquidity", *Journal of Financial Economics*, Vol. 78, pp. 89-119.

Niederhoffer, V. (1966), "Clustering of stock prices", *Operations Research*, Vol. 13, pp. 258-265.

O'Hara, M. and Zhou, X.A. (2021), "The electronic evolution of corporate bond dealers", *Journal of Financial Economics*, Vol. 140, pp. 368-390.

Osborne, M. (1962), "Periodic structure in the Brownian motion of stock prices", *Operations Research*, Vol. 10, pp. 345-379.

Ronen, T. and Zhou, X. (2013), "Trade and information in the corporate bond market", *Journal of Financial Markets*, Vol. 16, pp. 61-103.

Schwartz, A., Van Ness, B. and Van Ness, R. (2004), "Clustering in the futures market: evidence from S&P 500 futures contracts", *The Journal of Futures Markets*, Vol. 24, pp. 413-428.

Sopranzetti, B.J. and Datar, V. (2002), "Price clustering in foreign exchange spot markets", *Journal of Financial Markets*, Vol. 5 No. 4, pp. 411-417, doi: 10.1016/S1386-4181(01)00032-5.

Woodley, M., DaDalt, P. and Wingender, J. (2020), "The price and volume response to earnings announcements in the corporate bond market", *The Financial Review*, Vol. 55, pp. 669-696.

Zellner, A. (1984), "Posterior odds ratios for regression hypotheses: general considerations and some specific results", in Zellner, A. (Ed.), *Basic Issues in Econometrics*, University of Chicago Press, Chicago, pp. 275-305.

Appendix 1

Data deletions

Appendix 1 includes information about data filters used. The left-hand column provides information about the criteria used to create the bond trade sample, and the right-hand column provides the number of observations remaining after data deletions.

Data filter	Remaining observations
Initial Observations	10,473,119 trades
Missing CUSIP Information	10,463,731 trades
Cancelled/Corrected Trades	10,194,033 trades
Late-Reported Trades	10,062,324 trades
Trades Reported Outside Regular Trading Hours	10,023,374 trades
Missing Ticker Information	10,021,643 trades
Missing Bond-Level Information (From Master File)	10,008,351 trades
144A Bonds	10,007,967 trades
Missing Trade Reporting-Side Information	10,007,955 trades
Missing Information for Financial/Non-Financial Indicator	8,447,471 trades
Bonds with less than ten trades	8,422,593 trades
Final Sample	*8,422,593 trades*

Appendix 2

Price clustering division

Appendix 2 provides detailed price clustering information for a breakdown of the sample. Panel A divides the sample into non-financial and financial firms. Panel B divides the sample in firms without credit default swaps and firms with credit default swaps. % Clustered prices is the portion of all trades with a clustered price, and % non-clustered prices is the portion of all trades without a clustered price. % Cluster_00 is the portion of clustered prices ending in 0.00. % Cluster_25 is the portion of clustered prices ending in 0.25. % Cluster_50 is the portion of clustered prices ending in 0.50. % Cluster_75 is the portion of clustered prices ending in 0.75.

Panel A: Financials versus non-financials				
	Non-financial firms	Financial firms	Difference	*N*
% Clustered prices	18.94%	17.15%	1.79%**	410,980
% Non-Clustered prices	81.06%	82.85%	−1.79%**	1,985,799
% Cluster_00	6.57%	6.36%	0.21%	152,349
% Cluster_25	3.82%	3.33%	0.49%	79,846
% Cluster_50	4.88%	4.31%	0.57%	103,214
% Cluster_75	3.67%	3.15%	0.53%	75,571

Panel B: CDS firms versus Non-CDS firms				
	No credit default swap	Credit default swap	Difference	*N*
% Clustered prices	26.18%	17.69%	8.49%***	1,360,867
% Non-Clustered prices	73.82%	82.31%	−8.49%***	6,331,135
% Cluster_00	8.87%	6.28%	2.59%***	483,415
% Cluster_25	5.25%	3.53%	1.72%**	271,863
% Cluster_50	6.69%	4.53%	2.16**	348,275
% Cluster_75	5.36%	3.35%	2.01%**	257,314

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