(In)frequently Traded Corporate Bonds*

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ABSTRACT

We study a large group of bonds that experience substantial and long-lasting swings in trading activity. We call these bonds (in)frequently traded. They are similar to other bonds in primary bond characteristics, and publicly observed changes in these characteristics do not explain the swings in trading activity. We link jumps in trading activity of (in)frequently traded bonds to mutual fund rebalancing and document that more active trading in these bonds is associated with positive abnormal returns, but only after the 2008 crisis. Our results suggest that returns are due to growing mutual fund demand for (in)frequently traded bonds amid limited post-crisis secondary market supply, but the exact forces behind abnormal returns largely remain a puzzle.

JEL classification: G12, G14.

Keywords: corporate bond returns, trading frequency, mutual fund rebalancing, over-the-counter markets.

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I. Introduction

Corporate bonds tend to trade actively on the secondary market for the first few months up to two years after issuance while they settle into the most-desired portfolios, and afterward, the trading thins out as many bonds are held to maturity, redemption, or a credit-default event. The early empirical literature on corporate bonds, e.g., Alexander, Edwards, and Ferri (2000) documented this anecdotal evidence. Nowadays, as the comprehensive TRACE data on corporate bonds trading has been available for more than a decade, it turns out not all bonds follow the conventional wisdom and there are notable and numerous exceptions from that rule above. Figure 1 shows a corporate bond that experiences substantial and long-lasting swings in trading activity sufficiently long after its issuance. We document that roughly 25% of all plain-vanilla fixed-coupon bonds stand out from the conventional wisdom and experience swings in trading activity in our sample period from January 2005 to July 2017. We call these bonds (in)frequently traded or the (I)TBs.

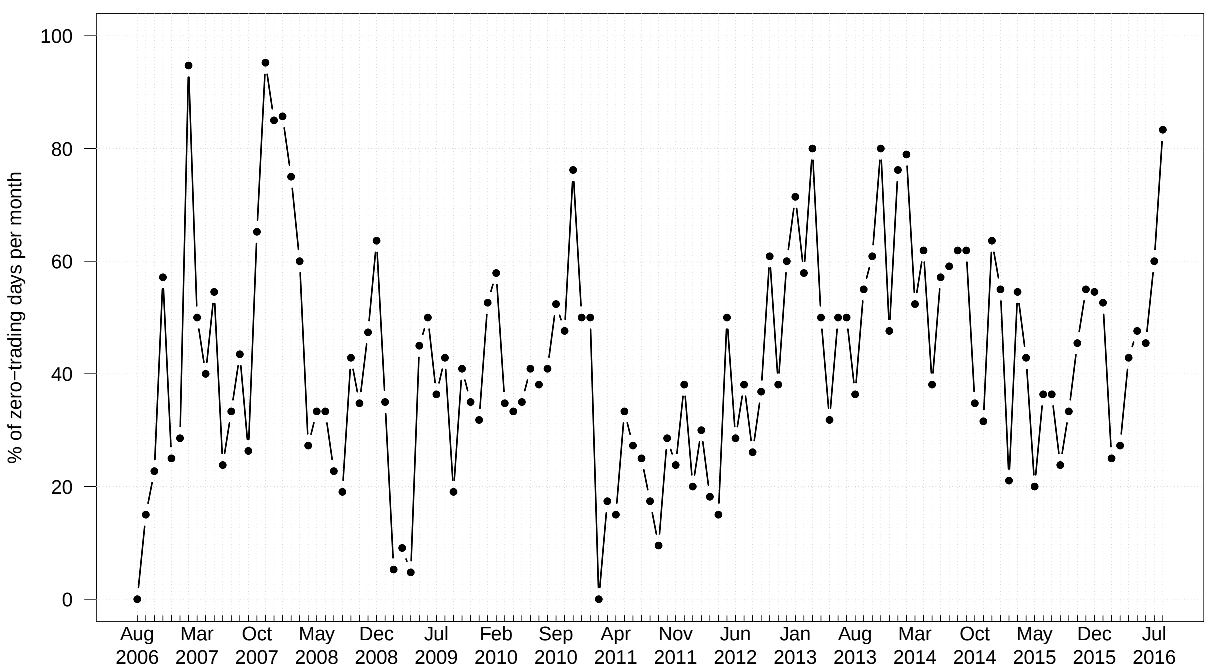

Figure 1. Fraction of zero-trading days per month for the Credit Suisse senior unsecured USD-denominated 500 mln USD 10Y 5.85% bond issued in Aug'06; CUSIP: 225434CJ6.

Surprisingly, the (in)frequently traded bonds are almost indistinguishable from all other plain-vanilla fixed-coupon bonds in major bond characteristics, including the issue size, average age, credit quality, etc. One cannot recover the information contained in the trading activity waves from headline bond characteristics.

Moreover, we find substantial excess returns associated with changes in bond trading frequency, but only post-crisis and only for the subsample of (in)frequently traded bonds. Figure 2 compares excess returns for (in)frequently traded bonds and all other bonds in our sample. The returns of the (I)TBs that move to states with higher trading frequency are about 12 basis points per month higher compared to the (I)TBs that stay in the same trading frequency state. We show that the exposure to Bai, Bali, and Wen (2018) risk factors does not explain these returns. Abnormal excess returns of the (I)TBs jumping to higher trading frequency states are of the same magnitude and statistically significant.

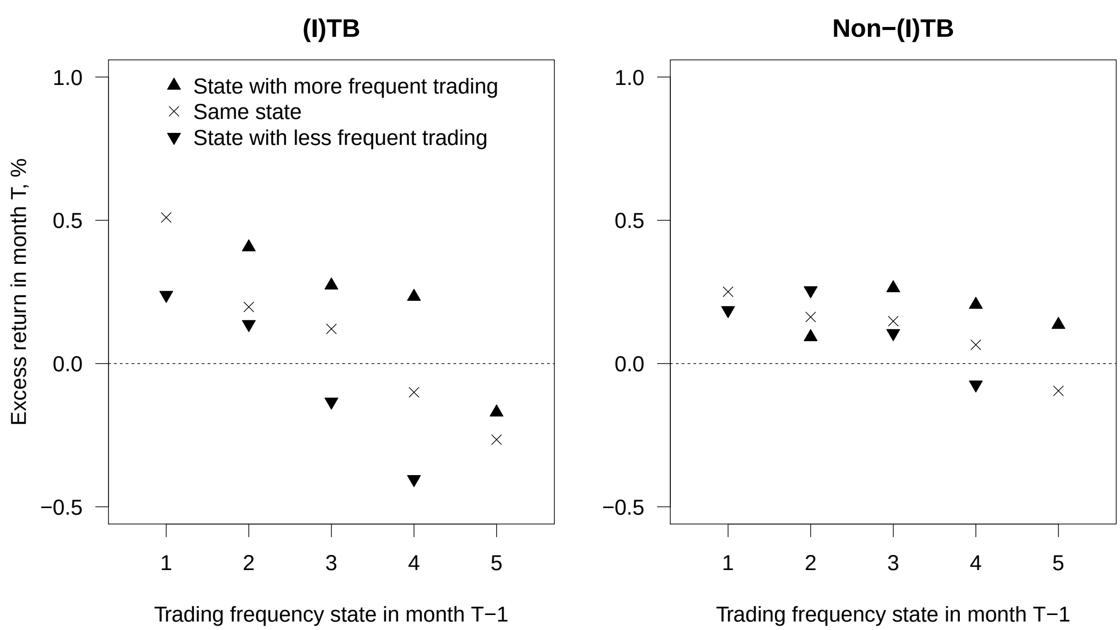

Figure 2. Mean excess returns and jumps between trading frequency states. State 1 is the state with the most frequent trading, and state 5 is the state with the least frequent trading. The cross represents the case when the bond stays in the same trading frequency state, the triangle pointed up represents a jump to a more frequent trading state (from 3 to 2, for example), and the triangle pointed down represents a jump towards less frequent trading (from 3 to 4, for example). Excess returns are returns above the 3-month T-Bill rate.

We document substantial differences between the (I)TBs and all other bonds in the structure of their trade flow and institutional ownership which as well sheds light on the nature of trading frequency changes of the (I)TBs. We found that the (I)TBs are more likely to be owned by mutual funds. Remarkably, there's a relatively constant number of funds that hold an (I)TB in any trading frequency state, unlike a Non-(I)TB that is held by substantially fewer funds when it trades infrequently. We also demonstrate that in the (I)TBs, compared to the rest of the sample, higher volumes are traded via small trades (less than 100'000 USD), and it takes more days to trade the same additional volume in small trades in the (I)TBs. It turns out that (I)TBs trading frequency goes up simultaneously with increases in net *purchases* by mutual funds and higher *sell* volumes in small trades by some investors. So, we link the waves of trading activity in the (I)TBs to mutual fund rebalancing. We also show that time-varying issue and issuer characteristics explain only a tiny portion of the variation of changes in corporate bond trading frequencies. From this, we conclude that mutual funds rebalancing that drives changes in trading activity is arguably not due to public corporate news.

Given that trading activity of (in)frequently traded bonds is related to demand from mutual funds, especially in the post-crisis period, one might expect that the link between trading frequency jumps and excess returns is due to the market impact of mutual fund purchases. We find some support for this view in the data, but institutional flows per se do not fully explain excess returns of the (I)TBs; the latter remains a puzzle.

We tend to think that the impact of trading frequency jumps on returns emerges from the interplay of higher demand from mutual funds, lower bond inventories among broker-dealers, and the desire of some smaller investors (supposedly, hedge funds) to take profit from cash corporate bond positions they have established in the wake of crisis sell-off. As documented in Dick-Nielsen and Rossi (2018), dealers prefer to keep low bond inventories post-crisis. So, the demand from mutual funds for the (I)TBs is not satisfied immediately as it takes time for dealers to accumulate positions and for investors to trade to their desired allocations.

Smaller investors, who sell the (I)TBs, are likely to sell in small volumes, precisely as we observe in the data. Smaller trades tend to have the highest price impact in corporate bonds, as shown by Edwards, Harris, and Piwowar (2007), and they contribute to excess returns of the (I)TBs. Since we do not observe dealer inventories and hedge funds positions in corporate bonds, we cannot test the described mechanism directly. However, much indirect evidence we present in this paper is consistent with such an explanation.

To our knowledge, we are the first paper to look closely at the bond-by-bond variation in trading activity. Most empirical studies of corporate bond markets document that bonds trade only several times per day, and most bonds trade less than once a month (e.g., Edwards et al. (2007), Bessembinder, Maxwell, and Venkataraman (2006)). We focus on sudden changes in trading activity. Our trading frequency measure is weakly correlated with changes in trading volume. Trading in corporate bonds is often pre-arranged. Harris (2015) documents that more than 40% of all trades in corporate bonds are riskless-principal trades. Large volumes may be traded within one business day and will not affect the waves of trading activity we analyze. Trading frequency is only weakly related to illiquidity measures either (e.g., the Bao, Pan, and Wang (2011) measure), and the relationship is weaker for the (I)TBs than for other bonds in our sample. Hence, our paper extends beyond the existing discussion of corporate bond illiquidity and its impact on bond prices.

The paper is organized as follows. Section II describes the data and the measure of trading frequency we use. In Section III we define (in)frequently traded bonds, document the differences between the (I)TBs and the rest of the sample in trade flows and mutual fund holdings, and attempt to explain monthly changes in trading frequency with institutional flows into the (I)TBs. In Section IV we demonstrate that public news about issuers and issues do not drive changes in bond trading frequencies. Section V explores the relationship between bond trading frequency, returns, mutual fund holdings, trade flows, and exposure to corporate bond risk factors. Section VI concludes.

II. Data and measurements

Corporate bonds in the U.S. are traded primarily on the OTC market, and trades are reported to the FINRA's Trade Reporting and Compliance Engine (TRACE). We use Enhanced TRACE data (contain uncapped volume records) available through WRDS in our study. Our sample consists of 'plain vanilla' corporate bonds only: unsecured fixed-coupon or zero-coupon bonds nominated in USD with the most typical coupon schedules and quoting conventions. We aggregate tick-by-tick TRACE data to the monthly frequency keeping in the sample all months when an outstanding bond *was not traded*. Volume is assumed 0 and prices missing (`NA`) for such bond-months. The sample consists of about 940 thousand bond-month observations covering approximately 14 thousand bonds issued by 2.6 thousand firms and traded for at least two days between Jan 1, 2005, and Jun 30, 2017. Roughly 25% of bond-month observations refer to months when the bonds were not traded at all. We present the details on sample selection and data cleaning in Appendix A.

We obtain individual bond characteristics from the Mergent Fixed Income Securities Database (FISD) also available through WRDS. Besides, we use two pieces of data on institutional trading of corporate bonds. The transactions of insurance companies are reported to NAIC and are also available via Mergent FISD. For mutual fund transactions, we scrape the data from the SEC N-Q forms submitted by SEC-registered funds and available through SECs Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system. N-Q forms contain all mutual fund holdings; we focus on corporate bond holdings only. Changes in holdings represent net purchases by mutual funds in the reporting period. We describe the recovery of holdings from scraped textual data in Appendix B. As Table I shows, we recover mutual fund holdings for about 12 thousand out of 14 thousand bonds of the original sample; they cover about 740 thousand out of 940 thousand initial bond-month observations.

In Chapter V we work with bond returns that are recognized using Bai et al. (2018) approach. First, we calculate volume-weighted daily (dirty) prices from the tick-by-tick TRACE data. Then, we calculate monthly returns if there are days with trades within five

	Full sample	Subsample (SEC NQ)
Bond issues		
Unique securities	14,234	11,796
of them, identified as (I)TB	3,884	3,721
Bond-month observations		
Bond-month obs. (incl. non-traded)	938,229	736,514
of them, with identified returns	362,358	347,812
of them, identified as (I)TB	170,803	164,590

Table I. Full sample and subsamples with identified mutual fund holdings and returns. For details on sample construction see Appendix A and B.

last business days of two consecutive months, or (if the first condition is false) in the first five and in the last five business days of a given month. In the first case, we use the latest volume-weighted daily prices of consecutive months to compute returns; in the second case, we use the earliest and the latest volume-weighted daily prices of a given month. Monthly returns in this study are total returns and contain coupon payments if there are any. Our return recognition approach results in about 360 thousand bond-month observations with recognized returns, which is roughly 40% of the original bond-month sample. Remarkably, about 96% of observations with recognized returns have identified mutual fund holdings.

In this paper, we focus on the frequency of corporate bond trading. To measure the trading infrequency of bond i in month t we construct the fraction of zero-trading business days within that month, Z_{it}. Assume there are D_t trading days in a month t, and the bond i was only traded $\bar{D}_t \leqslant D_t$ of them.[1] Then

$$Z_{it} = 100 \cdot \left(1 - \frac{\bar{D}_t}{D_t}\right).$$

Hence, if the bond is traded every business day in month t, then $Z_t = 0$; if the bond is not traded at all in month t, then $Z_t = 100$. Z_t is the measure of trading infrequency we use throughout this paper.

In a detailed study of trading cost and price impact proxies for corporate bonds Schestag, Schuster, and Uhrig-Homburg (2016) document that Z measure does not relate strongly to

[1]We count a day in $\bar{D}_t$ if there is at least one trade of the bond on that day, regardless of the total trading volume.

trading cost and price impact proxies both in the cross-section and in the time series. We find a similar pattern in our sample. In the pooled data the correlation coefficient between Z_{it} and, for instance, Bao et al. (2011) illiquidity measure is significant but small: pre-2008 crisis it stands at 0.08, post-crisis – at 0.13; the R^2 is less than 1.5%. In first differences, the correlation coefficients are twice smaller. Trading infrequency measure Z provides a different perspective on bond trading properties than typical illiquidity measures. In the next chapter, we also demonstrate that the relationship between illiquidity and trading infrequency differs across subsamples of the data.

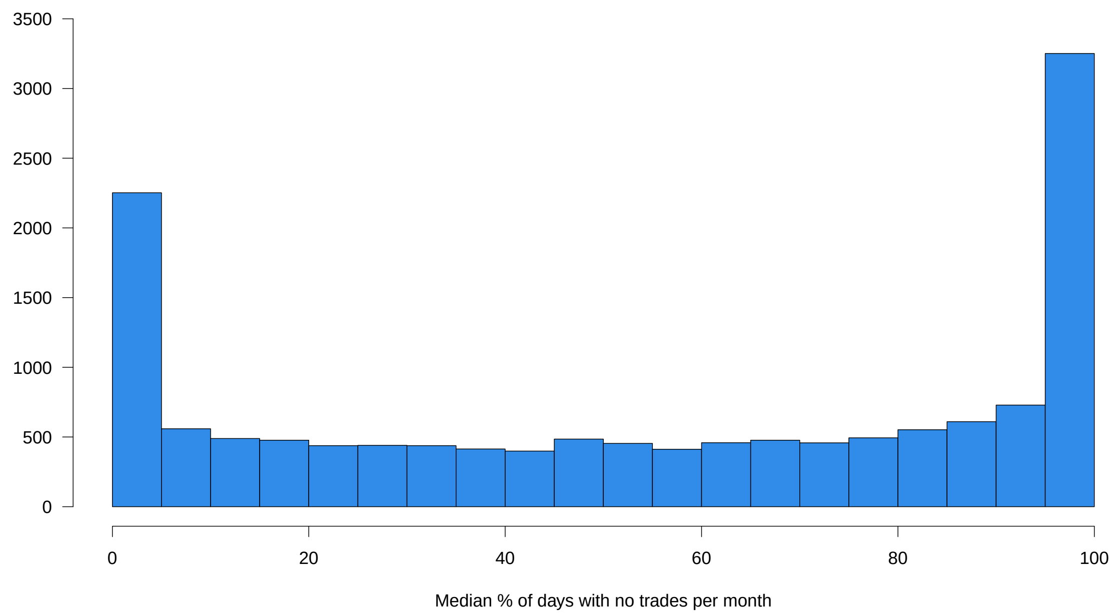

Figure 3. Distribution of bonds by a median fraction of zero trading days per month. The vertical axis counts bond issues in each bin. There are 14287 bonds in the sample. For each bond, the median is taken over its lifespan (defined as the time between dated date and maturity) that falls between Jan 1, 2005, and Jun 30, 2017.

Z is not correlated with total trading volume in levels: in the pooled data the correlation coefficient is statistically indifferent from zero. It comes as no surprise given the extent of pre-arranged trading in the corporate bond market. According to market participants, it takes time to discuss and prepare big trades, but once everything is set the execution occurs within one day. In the data, we indeed observe a high number of bond-months with very high volumes but very few trading days (hence, high Z). The relationship between *changes* in Z and the trading volume is more pronounced: volume increases are associated with decreases in Z. Interestingly, this relationship has different numerical properties in different subsamples of the data, we discuss it in more details in the next chapter.

Figure 3 plots the histogram of Z_i^{median} across bonds. It has two pronounced modes in the tails: there are about 2300 issues in the sample with Z^{median} below 5% (less than 5% non-trading days in the median month) and a thousand more issues with Z^{median} above 95%. The remaining mass of issues is almost uniformly distributed between the two tails.

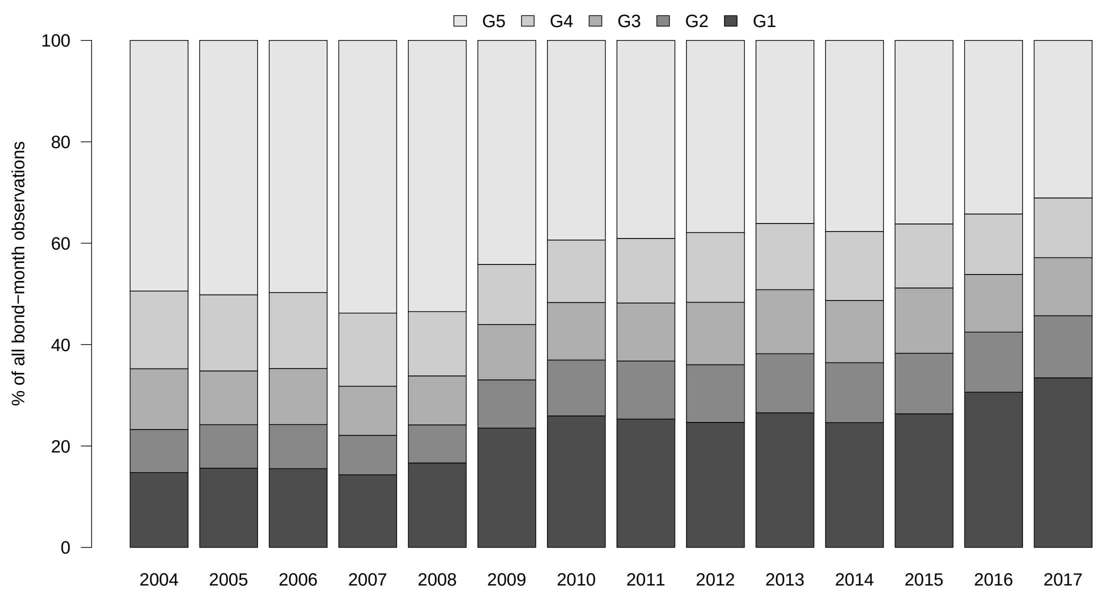

Figure 4. Distribution of bonds by trading frequency groups, per year. The histogram presents the number of bond-month observations in a given trading frequency group in a given year as % of the total number of bond-month observations in that year.

To study how the distribution of Z across bonds changes over time, we partition the domain of Z (from 0 to 100%) into five intervals of equal length: 0 to 20% being the first one, 80 to 100% – the fifth one. We refer to these intervals as 'trading frequency groups'. The first group, we call it G1 (Z between 0 and 20), consists of the bonds that traded *at least four out of five trading days* in each week on average in a month. These are frequently traded bonds. The last group, G5 (Z between 80 and 100), consists of the bonds that traded *at most one out of five trading days* in each week on average in a month. These are rarely traded bonds.[2] Figure 4 plots the distribution of bonds across trading frequency groups over time. Intermediate groups, G2–G4, contain about 35% of bond-month observations both pre- and post-2008 crisis. The mass in high trading frequency group G1 almost doubles in the post-crisis decade and stands at around 30% in 2017; the mass in low trading frequency group G1 shrunk accordingly. In the next chapters, we show that many bonds 'travel' across trading frequency groups during their lifetime in a non-intuitive way and have a puzzling relationship between changes in trading frequencies and prices.

III. (In)frequently traded bonds

A. Main characteristics

A widespread view links trading frequencies of corporate bonds with their maturity: right after issuance bonds trade actively on the secondary market, but after desired allocations are achieved trading activity slows down, and the closer the maturity is the less trading we observe. Such a pattern is indeed present in our data, but yet there is a large share of bonds whose trading activity evolves differently.

For every bond in our sample, we record a sequence of trading frequency groups (as defined in the previous chapter) that it belonged to. We are interested in the instances when bonds that presently trade rarely but were traded actively in the past start trading actively again. Table II counts the bonds that experienced this transition from frequent to infrequent trading, *and back*. There are about 3.9 thousand bonds in the entire sample, roughly 25% of all considered bonds, that make a trip from G1 (active trading) to G3-5 (inactive trading), and back to G1 at least once during the observed part of their lifetime. We call these bonds *(in)frequently traded bonds* or the (I)TBs. Roughly 2 out of 3 (I)TBs make the same trip, G1–G3-5–G1, at least twice in their life.

[2] Our partition of Z into five intervals is immune to occasional distortions and short-lived jumps in trading activity. It would take roughly 4-5 additional business days with non-zero trading per month to take a particular bond to a higher trading frequency group.

	Full sample	Pre-crisis	Post-crisis
.. 1 .. 5 .. 1 ..	808	72	441
.. 1 .. 4 .. 1 ..	2,150	399	1,515
.. 1 .. 4 or 5 .. 1 ..	2,172	404	1,529
.. 1 .. 3 or 4 or 5 .. 1 ..	3,886	1,058	2,985
.. 1 .. 3 or 4 or 5 .. 1 .. x2	2,487	481	1,861
Total no. of issues	14,287	8,348	11,462

Table II. Number of bonds that travelled from a frequently traded category (G1) to infrequently traded categories (G3/4/5) and back (to G1). The sequences in rows indicate trip types. The first line is a trip from G1 to G5 and back to G1. The number of months spent in the intermediate states is unlimited. The second line is a trip from G1 to G4 and back to G1, etc. Columns represent bond subsamples. The last line is the total number of issues in the subsamples. The pre-crisis period is from Jan 2005 to Jun 2008; the post-crisis period is from Jan 2009 to Jun 2017.

Table II also shows how the fraction of bonds classified into the (I)TB subsample changes in pre- and post-crisis data treated separately. Throughout the paper we define the pre-crisis period as Jan 2005 to Jun 2008 and the post-crisis period as Jan 2009 to Jun 2017.[3] In pre-crisis data, only 13% of bonds are the (I)TBs, in post-crisis data this fraction doubles. There is a substantially smaller fraction of the (I)TBs that make a G1–G3-5–G1 trip at least twice pre-crisis than post-crisis.

To formally describe these 'waves' in trading activity we estimate a Markov model of the evolution of trading activity across five previously defined trading frequency states. The five-state Markov chain is defined in continuous time and instantaneous transitions are allowed to neighboring states only. Once we have the estimates of transition intensities, we compute monthly transition probabilities and average 'sojourn' times in each trading frequency states. Figure 5 presents the latter, Table XVII in Appendix C gives the former. Figure 5 shows that the (I)TBs stay in the active trading state G1 for about two months and in the inactive trading state G5 for three months on average. Both numbers are higher post-crisis than pre-crisis. The (I)TBs leave intermediate states within one month. The Non-(I)TBs stay in the boundary states for longer. For them, the average sojourn time is about fifteen months in the active trading state and twice less in the inactive trading state.

[3]We remove the fall of 2008 from this data split to make sure that extreme crisis observations do not drive our results.

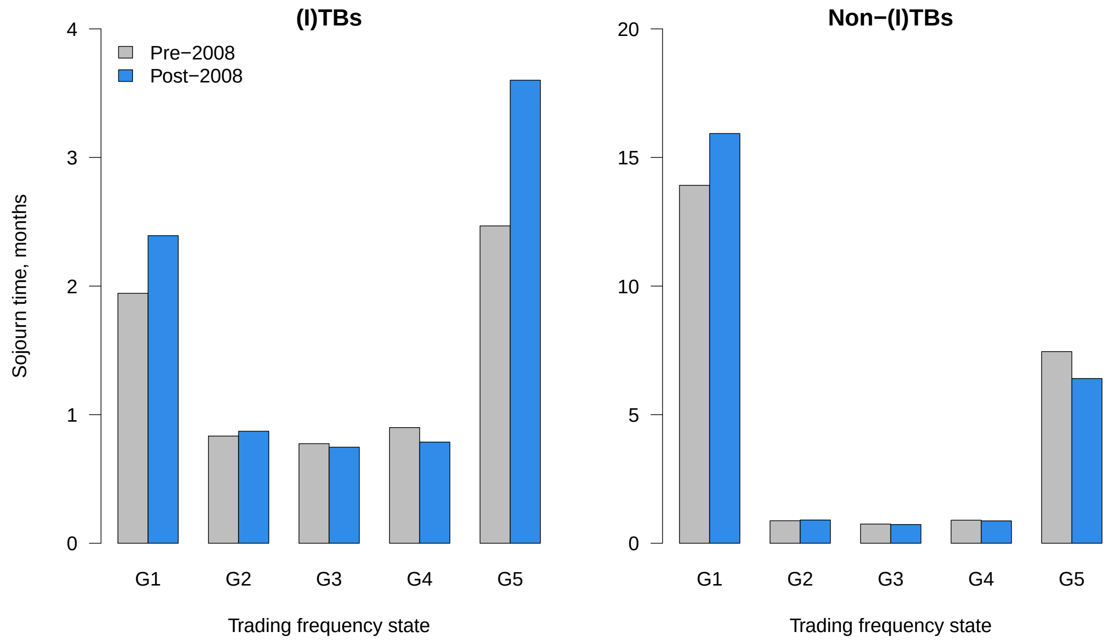

Figure 5. Number of months an average bond stays in a given trading frequency state (sojourn time). The underlying model is a five-state continuous time Markov chain with constant generator and instantaneous jumps to neighbouring states only.

Surprisingly, we find very little difference between the (I)TBs and the Non-(I)TBs in primary bond characteristics. Table III presents means, medians, and inter-quartile range for the number of indicators. An average (I)TB bond in our sample has between 400 and 500 million USD outstanding amount, a credit rating between BBB+ and BBB (investment grade), it still has between 9 and 10 years to maturity (between 40% and 50% of its maturity at issuance has already elapsed), it is traded between 3 and 4 times a day (when traded at all) with an average volume per trade around 700 thousand USD, and in the same month we observe about 8 other outstanding bonds issued by the same firm. This description remains unchanged for an average Non-(I)TB bond except it has two more other outstanding bonds of the same issuer. There are more pronounced differences in the median outstanding amounts, relative age, and the number of trades between the (I)TBs and the Non-(I)TBs. The former tend to be 'younger', have higher outstanding amounts, and the number of trades per day. We experimented with different classification algorithms, including traditional logit regressions as well as boosted trees with random forests and more modern methods, to try to recover the classification into the (I)TBs and the Non-(I)TBs using primary bond characteristics only to conclude that it does not work. The information contained in sequences of trading frequency groups cannot be recovered from headline bond characteristics.

	Mean		Median		IQR	
	(I)TB	Other	(I)TB	Other	(I)TB	Other
Amount outstanding, mln USD	465.4	411.5	400.0	200.0	350.0	358.1
Credit rating	8.7	8.1	8.0	8.0	4.0	3.0
Time since issuance, years	5.9	7.3	4.7	5.9	6.1	7.6
Time to maturity, years	9.5	9.8	6.2	6.1	9.6	10.8
Relative age, % of lifetime	43.6	48.2	40.8	47.6	45.5	49.2
Number of trades per business day	3.8	3.5	2.8	1.7	2.1	3.1
Average volume per trade, th USD	657.4	738.4	287.8	266.0	727.7	768.3
Number of bonds of the same issuer	9.2	11.2	7.0	6.0	9.0	10.0

Table III. Descriptive statistics for (in)frequently traded bonds and all the other bonds. (In)frequently traded bonds are the bonds that made a trip G1–G3/4/5–G1. Credit rating is in conventional numerical score from 1 to 21: 1 corresponds to AAA, 8 to BBB+, 21 to C. IQR is the inter-quartile range.

B. Trading volume and frequency

To give a better statistical description of the differences between the (I)TBs and the Non-(I)TBs we analyze in more details their trading records. Table IV compares retail-size (trades $\leqslant$ 100'000 USD in volume) to institutional size (trades $>$ 100'000 USD in volume) trading volume in the (I)TBs and the Non-(I)TBs across trading frequency states. In all states, both pre-crisis and post-crisis, aggregate monthly retail-size volume measured in % to institutional-size trading volume is substantially higher in the (I)TBs. The difference is the largest in the active trading state G1: here the average aggregate volume in small trades is roughly one-third of that in big trades for the (I)TBs and almost twice less in all other bonds.

To link the extent of retail-size trading to changes in trading frequencies ΔZ_{it} (which leads to jumps between trading frequency states) we regress ΔZ_{it} on changes in trading volume split by size, direction, and counterparty. Using TRACE counterparty marker we classify every trade as either a buy transaction by a client from a dealer, or a sale by a client

	G1	G2	G3	G4	G5
Pre-crisis					
(I)TB	31.43	24.05	19.58	12.77	6.36
Non-(I)TB	18.76	19.98	15.45	11.04	4.30
Post-crisis					
(I)TB	31.69	23.84	20.77	17.46	9.27
Non-(I)TB	17.47	19.24	17.87	13.90	7.13

Table IV. Mean retail-size to institutional-size trading volume ratio, %. Institutional-size trades are above 100k USD. The sample is restricted to bond-month observations with positive institutional volume.

to a dealer, or an inter-dealer trade.[4] Each of the three categories is further split into two depending on the size of the trade.

	Dependent variable: $\Delta(Z_{it})$			
	(I)TB	Non-(I)TB	(I)TB	Non-(I)TB
	Pre-crisis		Post-crisis	
Δ(Client sell volume in big trades)$_{it}$	-0.24^{***}	-0.21^{***}	-0.24^{***}	-0.24^{***}
Δ(Client sell volume in small trades)$_{it}$	-11.14^{***}	-5.05^{***}	-11.60^{***}	-3.06^{***}
Δ(Client buy volume in big trades)$_{it}$	-0.28^{***}	-0.29^{***}	-0.48^{***}	-0.33^{***}
Δ(Client buy volume in small trades)$_{it}$	-13.09^{***}	-6.66^{***}	-7.86^{***}	-3.76^{***}
Δ(Inter-dealer volume in big trades)$_{it}$	-0.22^{***}	-0.19^{***}	-0.15^{***}	-0.14^{***}
Δ(Inter-dealer volume in small trades)$_{it}$	-6.23^{***}	-1.95^{***}	-7.42^{***}	-2.57^{***}
Month FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Observations	37,552	221,951	194,326	441,579
Adjusted R^2	0.14	0.11	0.11	0.08
Note:	*p<0.1; **p<0.05; ***p<0.01			
	Standard errors are clustered by the bond CUSIP.			

Table V. Panel regressions of monthly changes in trading frequency ΔZ_{it} on trading volume split by size and type. Volumes are in % of the outstanding amount.

The sign of the relationship between changes in volume and ΔZ is straightforward: the bigger is the change in volume the more trading days we likely observe (hence, the lower ΔZ is). What matters more is how different this relationship is in the (I)TBs and the Non-(I)TBs. Table V shows that coefficients on trading volume in small trades are substantially higher in absolute value for the (I)TBs both pre-crisis and post-crisis. Z falls by 7 to 12 p.p. (percentage points) when an additional 1 p.p. of the bond outstanding amount is traded in

[4]TRACE contains trade reports by broker-dealers, hence every inter-dealer trade must appear twice in TRACE records. Only one such record remains in our sample after cleaning as in Dick-Nielsen (2014).

small trades in a given month for an (I)TB compared to only 2 to 4 p.p. drop in Z for a Non-(I)TB. There is no such difference for big trades except for big trades that are client buy transactions. From Tables IV and V we conclude that it takes more days to trade in small chunks the same volume of the (I)TBs than the Non-(I)TBs.

C. *Mutual fund holdings, trading frequency, and illiquidity*

We find differences between the (I)TBs and the Non-(I)TBs in mutual fund ownership and in the reaction of their ΔZ on changes in mutual fund holdings. Table VI compares average mutual fund holdings of bonds in different trading frequency states (Table XIX in Appendix C presents additional descriptive statistics of mutual fund holdings). We find that mutual fund ownership ratios are higher for the (I)TBs both pre-crisis and post-crisis. The difference is especially pronounced in the least active trading state G5: on average 19% of the outstanding amount of a rarely traded (I)TB bond is held by mutual funds, 7 p.p. more than for an average Non-(I)TB bond.

	G1	G2	G3	G4	G5
			Pre-crisis		
(I)TB	8.18	8.90	9.91	10.87	18.27
Non-(I)TB	7.17	9.44	9.22	8.63	9.81
			Post-crisis		
(I)TB	12.08	12.29	12.63	12.92	19.11
Non-(I)TB	11.49	11.86	11.20	10.68	12.59

Table VI. Mean mutual fund holdings of bonds in different trading frequency states, % of the outstanding amount. Holdings are winsorized at 5% and 95%.

The difference between the (I)TBs and the Non-(I)TBs in the dispersion of fund ownership is even more striking. In Figure 6 we use a simple indicator: we count how many funds have non-zero holdings of a given bond in a given month depending on the trading frequency state. It turns out that for the (I)TBs this number is relatively constant across states. For instance, there are on average about 30 funds that own an (I)TB post-crisis (this number is close to 20 pre-crisis) regardless of whether the bond trades actively or not. This relationship is different for the Non-(I)TBs both pre- and post-crisis. Many more funds own a Non-(I)TB if it trades actively: there are more than 50 fund owners in G1 (more than for an (I)TB) compared to less than 20 in G5 (less than for an (I)TB).

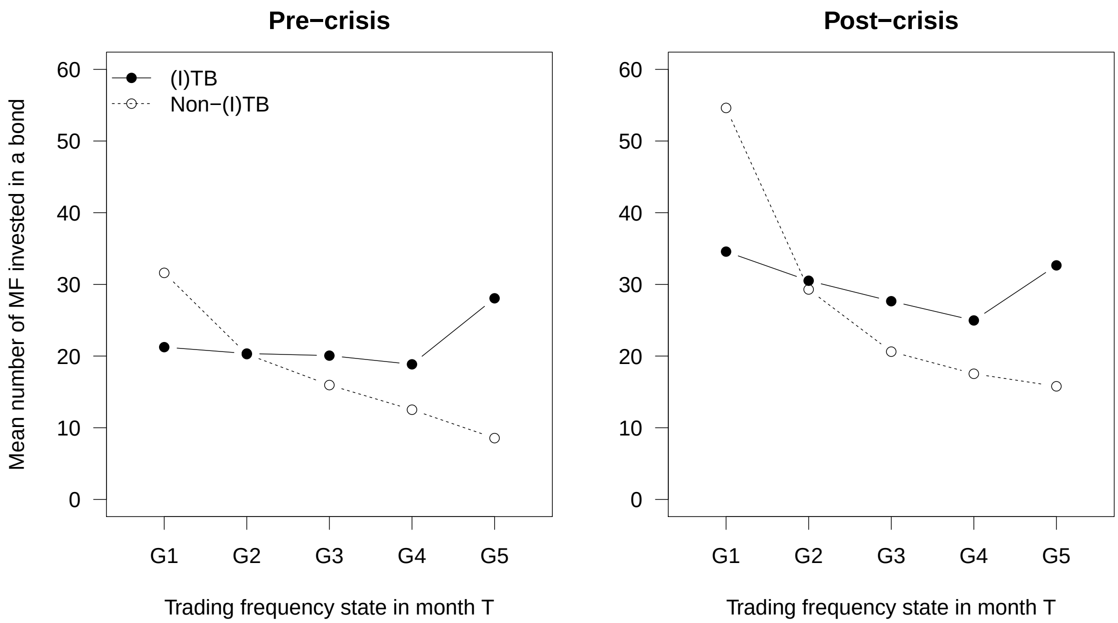

Figure 6. Mean number of mutual funds that hold the bond in different trading frequency states.

If one assumes that the dispersion of mutual fund ownership is associated with information asymmetry in a given security (broader ownership arguably implies lower information asymmetry), than it should also be related to the autocovariance in returns which is a measure of illiquidity. For instance, Llorente, Michaely, Saar, and Wang (2002) show that return autocovariance is more negative in stocks with higher information asymmetry (they are 'more illiquid'). In Table VII we present the Bao et al. (2011) bond illiquidity measure (negative log return autocovariance), for bonds in our sample in different trading frequency states. For the Non-(I)TBs, illiquidity grows strongly with trading infrequency, which is in line with lower dispersion in fund ownership and higher information asymmetry in lower trading frequency states. For the (I)TBs, the dispersion of fund ownership is flatter across trading frequency states, so is the illiquidity. Post-crisis, the (I)TBs are more liquid than the Non-(I)TBs in states G3 and G4 according to the results in Table VII.

	G1	G2	G3	G4
Pre-crisis				
(I)TB	0.25	0.21	0.26	0.50
Non-(I)TB	0.14	0.24	0.27	0.37
Post-crisis				
(I)TB	0.26	0.27	0.36	0.50
Non-(I)TB	0.11	0.28	0.43	0.60

Table VII. Mean Bao et al. (2011) illiquidity measure for bonds in different trading frequency states. The illiquidity measure is a negative covariance of daily changes in volume-weighted average log-prices for months with at least 5 trading days. The illiquidity measure is winsorized at 0.1% and 99.9% in the entire sample. There are no observations in G5 because of the way the illiquidity measure is calculated.

D. Changes in mutual fund demand and trading frequency

Changes in mutual fund net demand for corporate bonds significantly affect bond trading frequencies. Moreover, trading frequency tends to increase more when mutual funds are increasing their net demand for the (I)TBs rather than the Non-(I)TBs. Table VIII presents the regressions of changes in the trading frequency ΔZ_{it} of both types of bonds on changes in net purchases by mutual funds, insurance companies, and all other investors.[5] Among three types of investors considered, changes in net demand of mutual funds have the most substantial impact on changes in trading frequency. The effect is also stronger for the (I)TBs than for the Non-(I)TBs post-crisis. When mutual funds are buying 10 percentage points of the outstanding amount of a given bond more in a current month than in a previous month, Z falls by 2 percentage points for an (I)TB and by 1.4 percentage points for a Non-(I)TB.

So far we have established that similar changes in small trading volume (especially in client sell trades) and in net mutual fund demand tend to have a stronger impact on changes in the trading frequency of the (I)TBs compared to the Non-(I)TBs. Now we ask, is there a relationship between changes in trading volume and net mutual fund demand at the first place? Table IX regresses the latter on the former splitting volume by size and type as

[5] We use interchangeably the terms 'net purchases' and 'net demand', both represent the difference between total buy and sell transactions. Mutual funds net demand is simply the change in total mutual fund holdings of a given bond. Net purchases by all other investors are the residual category. We know total net demand from TRACE, net mutual fund demand from processed SEC N-Q forms and net insurance companies demand from the NAIC data. Subtracting the last two from the first gives us net demand by investors other than U.S. mutual funds or insurance companies.

	Dependent variable: $\Delta(Z_{it})$			
	(I)TB	Non-(I)TB	(I)TB	Non-(I)TB
	Pre-crisis		Post-crisis	
ΔMF net purchase$_{it}$	-0.10	-0.12^{**}	-0.20^{***}	-0.14^{***}
ΔIC net purchase$_{it}$	0.06	0.06^{***}	-0.004	0.01
ΔOther net purchase$_{it}$	-0.003^{**}	0.0005	-0.004^{**}	0.001
Month FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Observations	29,024	114,320	154,859	283,703
Adjusted R^2	0.02	0.004	0.02	0.01
Note:	*p<0.1; **p<0.05; ***p<0.01 Standard errors are clustered by the bond CUSIP.			

Table VIII. Panel regressions of monthly changes in trading frequency ΔZ_{it} on changes in net purchases by mutual funds, insurance companies, and other investors. Changes in net purchases are in % of the outstanding amount.

before. It turns out that post-crisis changes in net mutual fund demand are associated with changes in sell volume in small trades rather than any other type of volume, and more so for the (I)TBs. When *some clients* are selling 1 p.p. of the outstanding amount of an (I)TB more in a current month, we observe a significant increase in net mutual fund demand of 0.2 p.p. The effect is three times smaller and statistically insignificant for the Non-(I)TBs.

	Dependent variable: Δ(Net MF purchase)$_{it}$			
	(I)TB	Non-(I)TB	(I)TB	Non-(I)TB
	Pre-crisis		Post-crisis	
Δ(Client sell volume in big trades)$_{it}$	0.01	0.01^{***}	0.01^{***}	0.003
Δ(Client sell volume in small trades)$_{it}$	0.45	0.49^{**}	0.20^{**}	0.07
Δ(Client buy volume in big trades)$_{it}$	0.01^{***}	0.01^{***}	0.01^{***}	0.01^{***}
Δ(Client buy volume in small trades)$_{it}$	-0.03	-0.06	-0.04	-0.02
Δ(Inter-dealer volume in big trades)$_{it}$	0.01	0.01	-0.002	0.01^{*}
Δ(Inter-dealer volume in small trades)$_{it}$	-0.07	-0.04	0.08	0.03
Month FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Observations	29,024	114,320	154,859	283,703
Adjusted R^2	0.05	0.04	0.02	0.02
Note:	*p<0.1; **p<0.05; ***p<0.01 Standard errors are clustered by the bond CUSIP.			

Table IX. Panel regressions of monthly changes in net mutual fund purchases on the trading volume split by size and type. Changes in net purchases and changes in volume are in % of the outstanding amount.

IV. Trading frequency and public information about bond issuers and issues

There is a long list of potential issuer-level factors that might drive changes in bond trading frequencies. In this section, we first investigate how much variation in trading frequency changes is due to time-varying firm-level factors that we broadly refer to as 'corporate news' or simply 'news'. Corporate disclosures and public corporate events, media coverage, updates by equity analysts, spillovers from the equity market or the CDS market, etc. – any piece of information that is relevant for *all bonds of the same firm* we call the 'news'. Instead of trying to measure the news directly (which would be problematic given our broad definition of the news), we employ a modern econometric technique to select among time-varying firm-level dummies that proxy for the news and find that they explain only a small part of the variation in trading frequency changes. Then we demonstrate that the remaining *within-firm within-month* variation of bond trading frequencies is not well explained by bond-level characteristics either.

We start with a simple observation about correlations of changes in trading frequency $\Delta Z_{jt}(k)$ between bonds j of the same firm k. For all pairs of bonds of firm k we compute correlations $\rho_{\Delta Z_i(k),\Delta Z_j(k)}$ in trading frequency changes (we require at least 12 monthly observations per bond), then take the median pairwise correlation per firm $\rho(k)^{\text{median}}$, and plot the distribution of this number across firms on Figure 7. If changes in trading frequencies were mostly driven by firm-level factors, we would expect $\rho(k)^{\text{median}}$ to be positive and relatively high.[6] Instead, we observe on Figure 7 that the distributions are concentrated around zero with a small and insignificantly positive mean of 0.06–0.08 for both types of bonds considered. One should not expect high explanatory power of firm-level factors on changes in bond trading frequencies in such case.

To formally measure the explanatory power of corporate news and bond-level factors

[6] We assume here that corporate news should affect different bonds of the same firm similarly, but do not test this assumption formally.

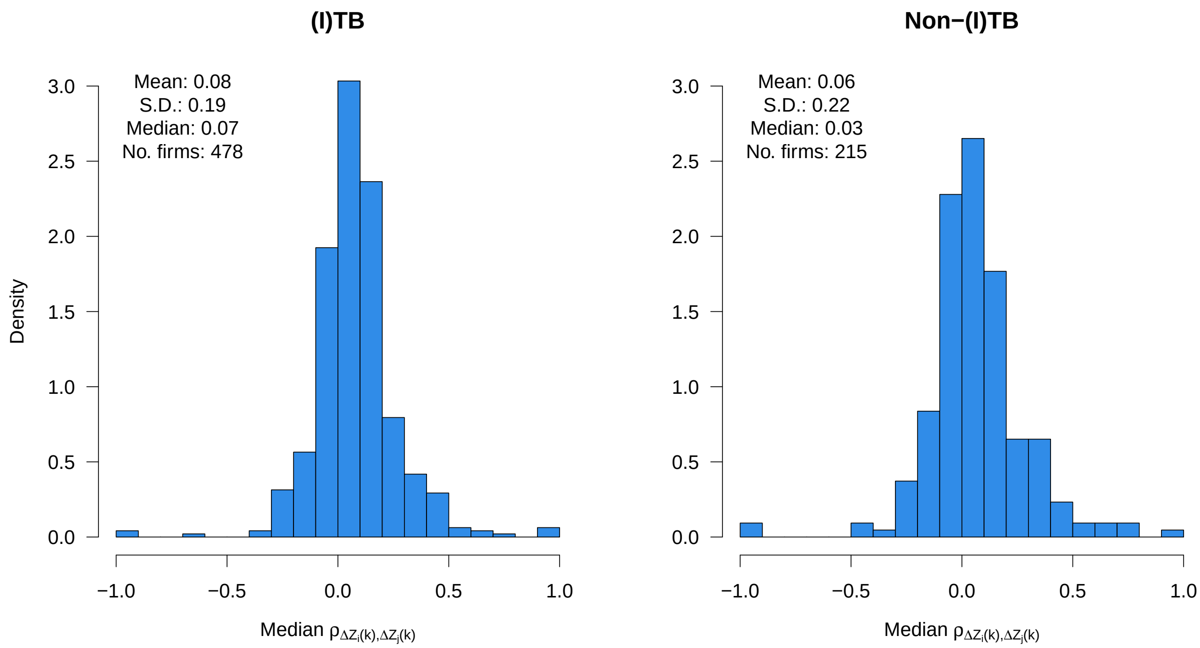

Figure 7. Cross-firm distribution of median pairwise correlation in ΔZ between different bonds of the same firm. We require at least 2 bonds of a given type of the same firm and at least 12 observation months per bond to compute correlations.

for changes in bond trading frequencies, we are using an econometric technique of double partialling-out introduced in Belloni, Chernozhukov, and Hansen (2014). Here is how we adapt it to our problem. Define ΔZ_i as the cross-sectional extract from $\{\Delta Z_{it}\}$ for any given month t. We will fit the models for ΔZ_i in the cross-section of bonds *independently for each month* t. The effect of firm-level news in month t will be captured by firm dummies D_f (where $f = 1, \ldots, F$; F being the total number of issuers) multiplied by respective coefficients γ_f to be estimated. The model for ΔZ_i at any given month is:

$$\Delta Z_i = (\beta_1 \Delta X_{1,i} + \cdots + \beta_P \Delta X_{P,i}) + (\gamma_1 D_1 + \cdots + \gamma_F D_F) + \epsilon_i,$$

where $\Delta X_1, \ldots, \Delta X_P$ are changes in bond-specific covariates of interest, and ϵ is orthogonal to both $\Delta X = (\Delta X_p)$ and $D = (D_f)$. There are *no restrictions* on the relationship among estimated coefficients in different months, the month-by-month cross-sectional estimations are fully independent from each other. The collection of estimates $\hat{\gamma}(t) = (\hat{\gamma}_1(t), \ldots, \hat{\gamma}_F(t))$ captures the total impact of time-varying firm-level factors on changes in bond trading frequencies. Our primary interest here is the joint explanatory power of firm dummies for ΔZ and the coefficients β, we have no interest in particular values of γ coefficients.

The cross-sectional model can be estimated with the OLS. But the OLS regression would suffer from over-fitting due to a relatively small number of bonds issued by each firm. We observe a median of 7 and 6 bonds per firm in the (I)TB and Non-(I)TB subsamples respectively. Firm dummies D_f would over-fit the data in the OLS regression, R^2 would be inflated and the estimates of β would be biased. To overcome the problem of too many explanatory variables relative to the sample size, Belloni et al. (2014) propose the following two-step procedure:

1. Project ΔZ and ΔX on D using some high-quality penalized regression procedure (we use LASSO here), compute the residuals $\Delta\tilde{Z} = \Delta Z - \Delta\hat{Z}$ and $\Delta\tilde{X} = \Delta X - \Delta\hat{X}$;
2. Run the OLS regression $\Delta\tilde{Z} = \Delta\tilde{X}\beta + u$, the estimate $\hat{\beta}_{OLS}$ is the consistent estimate of β of the original model.

In our case, the first stage projection of ΔZ on D is interesting per se. LASSO selects firms dummies and shrinks coefficients towards zero to avoid over-fitting. The intensity of shrinkage (LASSO penalty parameter) is chosen by 10-fold cross-validation. Each LASSO regression is run 30 times every month to explore the stability of the results. The explanatory power of this LASSO regression indicates what portion of the variation of ΔZ is due to corporate news. The second stage OLS regression of $\Delta\tilde{Z}$ on $\Delta\tilde{X}$ investigates how the residuals of bond-level covariates unexplained by firm dummies affect the residuals of changes in trading frequencies.

Figure 8 presents the R^2 from the first stage Ridge regressions of ΔZ on D for (in)frequently traded bonds (the results for the Non-(I)TBs are similar). The R^2 varies over time from 0 to about 20% (shaded area), with the smoothed median value being close to 5% before 2010 and even lower after that. It means that the impact of time-varying firm characteristics on the

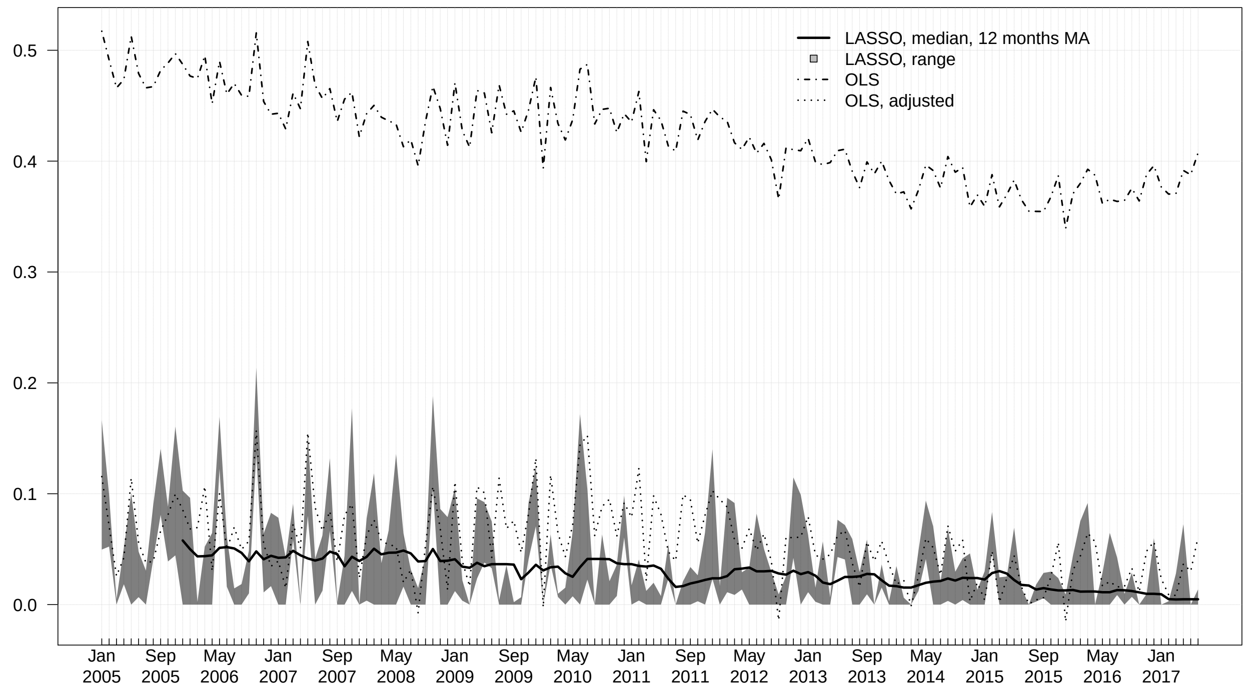

Figure 8. R^2 **of the first stage cross-section regressions of** ΔZ_i **on firm dummies**. The penalty parameter for the first stage LASSO regression is chosen by 10-fold cross-validation. Each regression is estimated 30 times to investigate the stability of the results. The range of R^2 generated by these 30 runs is the shaded grey area on this plot. The solid black line is the median value of that range after smoothing with 12-month backwards-looking moving average. Dashed and dashed-dotted lines are respectively adjusted R^2 and simple R^2 from (over-fitted) cross-section OLS-regressions. The sample is the (I)TBs.

frequency of bond trading is very limited. Even if we run a plain OLS regression of ΔZ on D on the first-stage, the over-fitted R^2 is around 40% in the post-crisis period (dashed-dotted line on Figure 8). Observe also that the adjusted R^2 of the OLS regression (dotted line) is of the same order of magnitude as the R^2 from the LASSO first-stage regression. Hence, changes in trading frequency of the (I)TBs remain largely unexplained by corporate news, broadly defined.

The second stage regression of $\Delta\tilde{Z}$ on $\Delta\tilde{X}$ is presented on Figure 9. We consider three explanatory variables: changes in outstanding amount (size), credit rating, and relative age (% of bond lifetime that has already passed at the measurement date). These variables were pre-selected by running multiple panel models of ΔZ on bond- and firm-level covariates with independent firm and time fixed effects; they turned out to be the most significant ones across

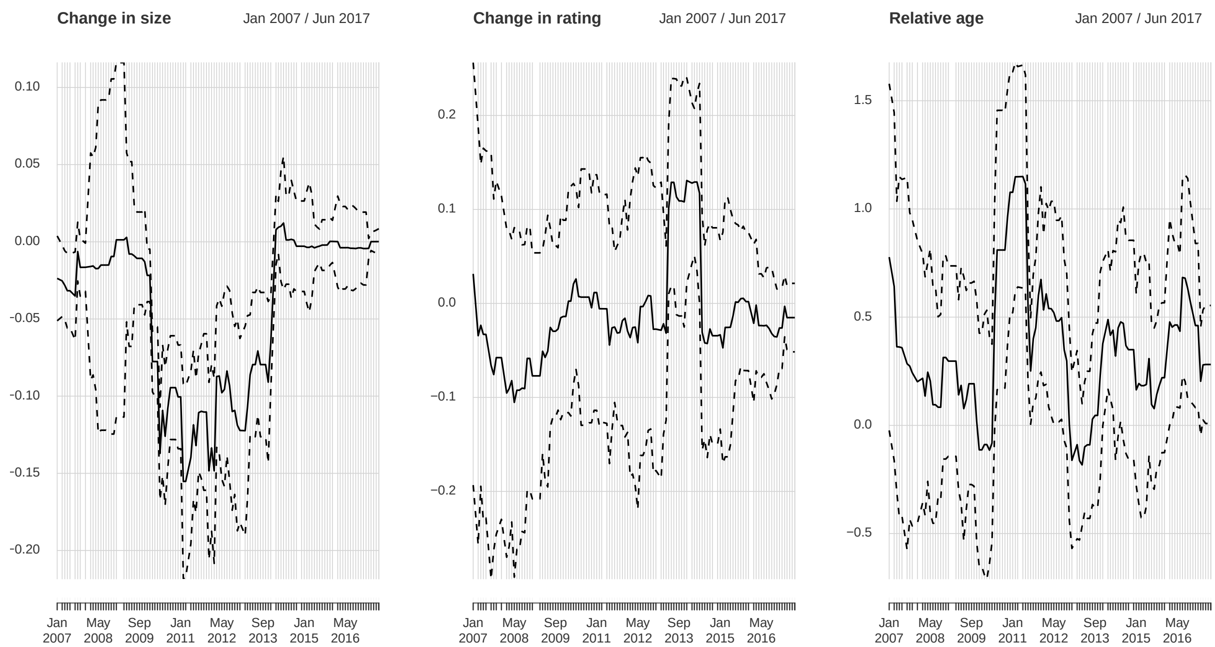

Figure 9. Coefficients on candidate covariates in cross-section second stage OLS regressions of $\Delta\tilde{Z}$. Solid lines are 12-month moving-average point estimates. Dashed lines are 12-month moving averages of 2 standard error bounds around point estimates. Some months have no variability in covariates; they are excluded from estimation. Change in size is the % change in the outstanding amount month-on-month. Age is the time elapsed since issuance as a fraction of total maturity at issuance. Credit rating is on the conventional numerical scale from 1 (AAA) to 21 (D), a unit change represents an upgrade or a downgrade by one notch. The sample is the (I)TBs.

different specifications. Solid lines on Figure 9 present point estimates of the coefficients on corresponding covariates. The signs of coefficients on Figure 9 are similar to a simple panel model with independent firm and time fixed effects (see Table XX in Appendix C): bond redemptions and bond ageing are associated with lower trading frequencies. Yet, Figure 9 says that these effects are not stable over time and the statistical significance is often absent. The effect of credit rating changes on trading frequencies is small and nowhere significant (unlike in the panel model with independent firm and time fixed effects). The explanatory power of $\Delta\tilde{X}$ for $\Delta\tilde{Z}$ in the second-stage regressions is small either: mean R^2 is close to 5%. So, the evidence presented on Figures 7–9 suggests that corporate news and major bond characteristics can explain only a small portion of changes in bond trading frequencies ΔZ.

We further explore within-firm within-month variation in bond trading frequencies in the subsample of issuers with many outstanding bonds (over-fitting with firm-dummies is less likely here) to confirm our previous findings. We require at least 10 bonds per firm to be observed for at least 12 months each for the issuer to be included in the sample. There are 50 and 150 firms that satisfy these criteria for the (I)TBs and non-(I)TBs respectively. For each of these firms k we run *separately* a fixed-effects panel model:

$$\Delta Z_{jt}(k) = (\beta_1 \Delta X_{1,jt}(k) + \cdots + \beta_P \Delta X_{P,jt}(k)) + (\tau_1 D_1 + \cdots + \tau_T D_T) + u_{jt},$$

where $\Delta Z_{jt}(k)$ is the change in trading frequency of bond j of firm k in month t, ΔX are bond-specific factors, and month dummies D capture time fixed effects for all bonds of firm k. Under the assumption that news affect changes in trading frequencies of all bonds of the same firm similarly, time fixed effects in the regression above capture the effect of corporate news on firm's k bond trading frequencies.

	Mean	Med.	Min.	Max.	No. firms
	R^2				
(I)TB	0.15	0.14	0.09	0.30	50
Non-(I)TB	0.20	0.17	0.04	0.95	150
	Adjusted R^2				
(I)TB	0.06	0.05	-0.06	0.20	50
Non-(I)TB	0.06	0.05	-0.43	0.77	150

Table X. Explanatory power of firm-level regressions for ΔZ_{it} in the subsample of issuers with many outstanding bonds. The estimated model includes changes in amount outstanding and credit rating, relative age, changes in the number of outstanding bonds of the same issuer, coupon dummy, and month fixed effects as explanatory variables. The model is estimated separately for each firm, hence, the dataset in each estimation consists of different bonds of the same firm observed in different months. We require at least 10 bonds of certain type to be observed in at least 12 months for a firm to be included in the sample. The number of firms in the last column shows how many firms satisfy these criteria for two types of bonds considered.

We estimate the firm-level models with the OLS. The OLS still over-fits the data, but now we have around 10 observations per estimated coefficient (if the panel is balanced). Table X presents R^2 and adjusted R^2 from firm-level regressions. These numbers show the percentage of variation in changes in trading frequency that is explained by corporate news and bond-specific factors *combined*. The average R^2 in Table X is around 15% for (in)frequently traded bonds and 20% for all other bonds. Median R^2 is a bit lower than the mean, adjusted R^2 are around 5-6% on average. These adjusted R^2 values are in line with the evidence provided earlier in this chapter. About 5% – this is how much variance of changes in bond trading frequency we can credibly explain with corporate news and bond-specific factors. We believe that this number is quite low, and conclude that changes in bond trading frequency are mostly due to factors unrelated to bond- or firm-level characteristics and corporate news. Hence, spikes and dry-ups in bond trading activity are probably more related to *who* trades the bonds rather than to *what* bonds are traded.

V. Trading frequency and returns

This chapter describes a puzzling observation: when the (I)TBs jump to states with more (less) frequent trading, they generate positive (negative) returns that are not explained by institutional trading flows and exposure to risk factors. There is no such effects for the Non-(I)TBs.

We have already presented the phenomenon briefly in the introduction. Figure 2 shows that the effect is two-fold. The states with more active trading in month $T-1$ are associated with higher returns in month T, and these returns are higher or lower if trading frequency increases or decreases in month T. Table XXI presents the same result in a more elaborate form comparing returns across 25 possible combinations of trading frequency states in months $T-1$ and T. In the rest of the chapter, we demonstrate that the effect appears only after the 2008 crisis and is not subsumed by the exposure of the (I)TBs to main risk factors and institutional flows.

We start with Figure 10, the analog of Figure 2, where instead of mean returns we plot bond alphas. Here we first compute value-weighted return time series for 25 bond

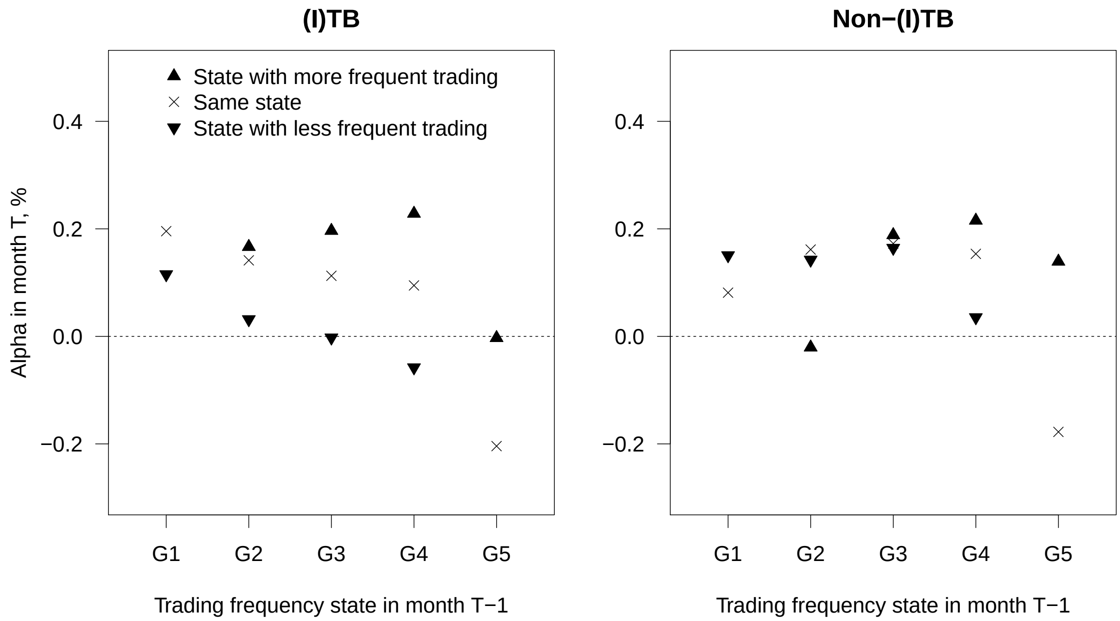

Figure 10. Estimated alphas and trading frequency jumps. The underlying model is the Bai et al. (2018) model. Bond baskets here are not investable since the trading frequency state in month T is not known apriori. Returns are computed by weighting individual bond returns in excess of the 3-month T-Bill rate by the market value of issues.

baskets based on all combinations of five trading frequency states in the previous and in the current month.[7] We regress each of these 25 time series on 4 time series of Bai et al. (2018) pricing factors and extract alphas.[8] All 25 estimated alphas are presented in Table XXII in Appendix C, Figure 10 presents the same result in a more intuitive form. We observe the same relationship between alphas and trading frequency states as before and, again, only for the (I)TBs. States with higher trading frequency in month $T-1$ are associated with higher abnormal returns in month T, and if an (I)TB jumps to a higher trading frequency state in month T this abnormal return is even higher (lower if trading frequency falls).

It turns out that the relationship between trading frequency jumps and returns appears only after the 2008 crisis. To demonstrate it formally we run panel regressions for excess

[7]These bond baskets are not investable since the trading frequency state in month T is not know apriori. Switching from value-weighted to equally-weighted returns does not change the results.

[8]These are the market, default, liquidity, and credit factors. The last 3 are constructed by double sorting on 36-month 5% VaR, Bao et al. (2011) illiquidity measure, and credit rating in different combinations.

	Dependent variable: R_{it}			
	(I)TB	Non-(I)TB	(I)TB	Non-(I)TB
	Pre crisis		Post crisis	
$\text{State}_{i,t-1} = \text{G2}$	−0.050	−0.103**	−0.106***	−0.058*
$\text{State}_{i,t-1} = \text{G3}$	−0.230***	−0.245***	−0.151***	−0.032
$\text{State}_{i,t-1} = \text{G4}$	−0.249**	−0.301***	−0.271***	−0.035
$\text{State}_{i,t-1} = \text{G5}$	−0.517	−0.482***	−0.651***	−0.106*
$(\text{State}_{i,t-1} = \text{G1}) \times \text{Jump}_{it}$	0.160***	0.084	0.148***	0.002
$(\text{State}_{i,t-1} = \text{G2}) \times \text{Jump}_{it}$	0.066*	0.012	0.077***	0.056
$(\text{State}_{i,t-1} = \text{G3}) \times \text{Jump}_{it}$	0.115**	0.090***	0.077***	0.088**
$(\text{State}_{i,t-1} = \text{G4}) \times \text{Jump}_{it}$	0.108	0.153***	0.172***	0.060**
$(\text{State}_{i,t-1} = \text{G5}) \times \text{Jump}_{it}$	0.264	0.120**	0.479***	0.109**
Month FE	YES	YES	YES	YES
Issuer FE	YES	YES	YES	YES
Observations	22,446	54,548	113,598	148,280
Adjusted R^2	0.097	0.122	0.191	0.205
Note:	*p<0.1; **p<0.05; ***p<0.01			
	SEs are clustered by bond CUSIP.			

Table XI. Regressions of excess returns on trading frequency characteristics. 'Jump' is the integer variable that equals the difference in trading frequency state numbers in months $t-1$ and t. For instance, if the bond jumps from state G3 to state G1, the $\text{Jump}_{it} = 2$. The reverse jump has the value of -2.

returns pre- and post-crisis separately. Our basic regression has the following form:

$$R_{it} = \sum_{s=2}^{5} \left(\beta_s \cdot D_{i,t-1}^{\text{State = s}}\right) + \sum_{s=1}^{5} \left(\gamma_s \cdot D_{i,t-1}^{\text{State = s}} \cdot \text{Jump}_{it}\right) + \text{Month FE} + \text{Issuer FE} + \epsilon_{it}.$$

Here $D_{i,t-1}^{\text{State = s}}$ is a dummy variable that takes the value of 1 if the bond i is in the trading frequency state $s \in 1, 2, \ldots, 5$ in month $t-1$. Coefficients β_s capture the relationship between past trading frequency states and current excess returns relative to excess returns in the most active trading state G1. Jump_{it} is the integer variable that equals the difference in trading frequency state numbers in months $t-1$ and t. For instance, if the bond jumps from state G3 to state G1, the $\text{Jump}_{it} = 2$. The reverse jump has the value of -2. If the bond stays in the same trading frequency state then $\text{Jump}_{it} = 0$. Hence, coefficients γ_s capture additional returns associated with trading frequency jumps in month t relative to returns in the case when trading frequency state does not change.[9]

Table XI shows that only for the (I)TBs and only post-crisis all $\hat{\beta}_s$ and $\hat{\gamma}_s$ are highly

[9]We could also tell the same story with 25 estimated dummies for all the combinations of trading frequency states in months $t-1$ and t. We prefer this form with jump variables for its concise presentation.

significant. Coefficients $\hat{\beta}_s$ monotonically decrease with s from -10 b.p. to -65 b.p. For instance, average returns in month t of the bonds that were in state G2 in month $t-1$ are 10 b.p. lower than of the bonds that were in state G1 in month $t-1$. Coefficients $\hat{\gamma}_s$ are positive suggesting that that jumps towards more active trading yield additional positive returns and jumps towards less active trading result in lower returns. The absolute value of these additional returns is around 12 b.p. for jumps from states G1–4. Observe that pre-crisis the effect is less significant or absent.[10]

	Dependent variable: R_{it}			
	(I)TB	Non-(I)TB	(I)TB	Non-(I)TB
	Before Jun 2008		After Jan 2009	
ΔNet purchase in big trades$_{i,t}$	0.005	0.004	0.012***	0.008**
ΔNet purchase in small trades$_{i,t}$	−0.824***	−0.259	−0.240***	−0.159**
State$_{i,t-1}$ = G2	−0.038	−0.100**	−0.102***	−0.057
State$_{i,t-1}$ = G3	−0.223***	−0.243***	−0.147***	−0.031
State$_{i,t-1}$ = G4	−0.257**	−0.299***	−0.270***	−0.035
State$_{i,t-1}$ = G5	−0.579*	−0.485***	−0.669***	−0.108*
(State$_{i,t-1}$ = G1) × Jump$_{it}$	0.176***	0.092	0.152***	0.003
(State$_{i,t-1}$ = G2) × Jump$_{it}$	0.084**	0.018	0.081***	0.058
(State$_{i,t-1}$ = G3) × Jump$_{it}$	0.137***	0.095***	0.082***	0.090***
(State$_{i,t-1}$ = G4) × Jump$_{it}$	0.131	0.157***	0.179***	0.063**
(State$_{i,t-1}$ = G5) × Jump$_{it}$	0.338*	0.128**	0.501***	0.114**
Month FE	YES	YES	YES	YES
Issuer FE	YES	YES	YES	YES
Observations	22,446	54,548	113,598	148,280
Adjusted R^2	0.100	0.122	0.191	0.206
Note:	*p<0.1; **p<0.05; ***p<0.01 SEs are clustered by bond CUSIP.			

Table XII. Regressions of returns on changes in net purchases grouped by size and trading frequency characteristics. Trades with less than 100k volume are small trades. 'Jump' is the integer variable that equals the difference in trading frequency state numbers in months $t-1$ and t. For instance, if the bond jumps from state G3 to state G1, the Jump$_{it} = 2$. The reverse jump has the value of -2.

In Tables XII and XIII we add either changes in net buy volume in big and small trades or changes in net demand by institutional investors to the baseline regression specification. Changes in volume in small trades and changes in net mutual fund purchases are related to jumps in trading frequency. Hence, one might expect them to explain some of the effects of trading frequency jumps on returns. It does not happen, at least for the (I)TBs post-crisis.

[10] Figure 11 in Appendix C plots cumulative returns on some of the 25 bond baskets described above. These graphs also demonstrate that returns associated with trading frequency jumps accrue only after 2008.

	Dependent variable: R_{it}			
	(I)TB	Non-(I)TB	(I)TB	Non-(I)TB
	Before Jun 2008		After Jan 2009	
ΔMF net purchase$_{i,t}$	0.030**	0.015	0.001	0.014
ΔIC net purchase$_{i,t}$	0.007	0.003	0.008	0.011*
ΔOther net purchase$_{i,t}$	−0.001	0.0003	−0.0005	0.00003
State$_{i,t-1}$ = G2	−0.061	−0.152***	−0.105***	−0.045
State$_{i,t-1}$ = G3	−0.246***	−0.297***	−0.152***	0.00001
State$_{i,t-1}$ = G4	−0.181	−0.351***	−0.289***	0.019
State$_{i,t-1}$ = G5	−0.747	−0.621***	−0.846***	0.048
(State$_{i,t-1}$ = G1) × Jump$_{it}$	0.175***	0.102	0.147***	0.025
(State$_{i,t-1}$ = G2) × Jump$_{it}$	0.059	0.041	0.075***	0.057
(State$_{i,t-1}$ = G3) × Jump$_{it}$	0.140**	0.111***	0.090***	0.082**
(State$_{i,t-1}$ = G4) × Jump$_{it}$	0.023	0.161***	0.227***	0.064*
(State$_{i,t-1}$ = G5) × Jump$_{it}$	0.552	0.122*	0.656***	0.054
Month FE	YES	YES	YES	YES
Issuer FE	YES	YES	YES	YES
Observations	19,221	44,182	98,324	131,236
Adjusted R^2	0.100	0.122	0.191	0.204

Note: *p<0.1; **p<0.05; ***p<0.01
SEs are clustered by bond CUSIP.

Table XIII. Regressions of returns on changes in net institutional demand and trading frequency characteristics. 'MF' stand for mutual funds, 'IC' for insurance companies. 'Jump' is the integer variable that equals the difference in trading frequency state numbers in months $t-1$ and t. For instance, if the bond jumps from state G3 to state G1, the Jump$_{it} = 2$. The reverse jump has the value of -2.

Remarkable though that the signs at changes in net buy volume in big and small trades in Table XII are opposite. Increases in net buy volume in big trades are associated with higher returns while increases in net buy volume in small trades are associated with lower returns (equivalently, increases in net sell volume in small trades occur in bond-months with higher returns). A rise of net sales in small trades of 1 p.p. of the outstanding amount translates into 25 b.p. of excess return in the (I)TBs and 16 b.p. in the Non-(I)TBs.

We like the following explanation for the positive impact of changes in big net buys and small net sells on returns, especially in ITBs. We have established before that when mutual funds increase their net purchases of the (I)TBs (arguably for non-informational reasons), some other agents sell more of these bonds in small trades. Now we know that it also pushes prices up. Given the time frame we are looking at, we tend to think that increases in sell volumes in small trades represent profit-taking by hedge funds that were entering the corporate bond market actively in 2008 and 2009 and closing positions several years later.

The fact that trading frequency jumps still affect returns even when we control for changes in volumes and institutional flows suggests that there was potentially some friction in the reallocation of bonds from hedge funds to mutual funds that pushed prices even further up. It might be lower dealer inventory levels and longer intermediation chains post-crisis.

	Dependent variable: R_{it}	
	(I)TB	Non-(I)TB
$\text{VaR}_{i,t-1}$	0.084***	0.098***
$\text{Rating}_{i,t-1}$	0.204***	0.128***
$\text{Illiquidity}_{i,t-1}$	0.090**	0.078
$\text{State}_{i,t-1} = \text{G2}$	−0.071*	−0.007
$\text{State}_{i,t-1} = \text{G3}$	−0.139***	−0.061
$\text{State}_{i,t-1} = \text{G4}$	−0.297**	−0.156
$\text{State}_{i,t-1} = \text{G5}$	0.167***	0.090
$(\text{State}_{i,t-1} = \text{G1}) \times \text{Jump}_{it}$	0.107***	0.128
$(\text{State}_{i,t-1} = \text{G2}) \times \text{Jump}_{it}$	0.100**	0.163**
$(\text{State}_{i,t-1} = \text{G3}) \times \text{Jump}_{it}$	0.061	0.062
Month FE	YES	YES
Issuer FE	YES	YES
Observations	42,792	47,441
Adjusted R^2	0.197	0.201
Note:	*p<0.1; **p<0.05; ***p<0.01 SEs are clustered by bond CUSIP.	

Table XIV. Regressions of post-crisis returns on riskiness and trading frequency characteristics. VaR is the 36-month rolling 5% value at risk (second smallest return). Rating is the numerical score from 1 to 21. Illiquidity is the Bao et al. (2011) measure. 'Jump' is the integer variable that equals the difference in trading frequency state numbers in months $t-1$ and t. For instance, if the bond jumps from state G3 to state G1, the $\text{Jump}_{it} = 2$. The reverse jump has the value of -2.

Indirectly supporting this point of view, we present in Table XIV the baseline regression for returns extended with corporate bond risk proxies from Bai et al. (2018): bond-level Value at Risk, Bao et al. (2011) illiquidity, and credit rating, all lagged one period. If the effect of trading frequency jumps on returns was due to the exposure of the (I)TBs to these risk factors rather than to a complicated interplay of institutional liquidity trading and low inventory issues, then we would not observe significant coefficients at trading frequency levels and jumps in the extended regression. Table XIV shows that it happens only to a minimal extent. For the (I)TBs, all $\hat{\beta}_s$ and $\hat{\gamma}_s$ except for one are still significant.

VI. Concluding Remarks

In this paper, we analyzed a large subset of plain-vanilla fixed coupon corporate bonds that experience prolonged swings in trading activity long after issuance. We called these bonds that 'travel' from active to inactive trading *and back* (in)frequently traded, or the (I)TBs, and attempted to describe statistically the dimensions along which the (I)TBs are different from the Non-(I)TBs. It turned out that headline bond characteristics like size, maturity, and credit rating are not much different in our two subsamples of bonds. We found substantial differences between the (I)TBs and the Non-(I)TBs in the structure of their trade flow and institutional ownership.

First, we demonstrated that in the (I)TBs higher volumes are traded via small trades, and it takes more days to trade the same additional volume in small trades in the (I)TBs than in the Non-(I)TBs. The latter might indicate that intermediation chains are longer in the (I)TBs. Second, we found that the (I)TBs are more likely to be owned by mutual funds. Remarkably, there's a relatively constant number of funds that hold an (I)TB in any trading frequency state, unlike a Non-(I)TB that is held by substantially fewer funds when it trades infrequently. Related to that, the illiquidity of the (I)TBs grows very moderately with trading infrequency compared to the Non-(I)TBs. Third, we showed that positive changes in mutual fund net demand are associated with positive changes in sell volume in small trades and more frequent trading. Next, we argued that time-varying firm-level and bond-level characteristics were able to explain only a minor fraction of variation of changes in trading frequency, and so the long-lasting waves of trading activity we documented were not attributed to public news about the issuers or the issues.

Finally, we documented that the (I)TBs yield abnormal returns that relate to the swings of trading activity in a way unexplained by common bond-risk factors and institutional flows. When the (I)TBs jumped to states with more (less) frequent trading, they generated positive (negative) returns in the after-crisis period. There were no such effects for the Non-(I)TBs.

Overall, it seems that the (I)TBs happened to be the bonds that were in high demand among mutual funds, especially in the post-crisis period. We tend to think that the sell volume in small trades that goes up together with the (I)TBs trading frequency suggests that mutual funds were ultimately purchasing these bonds from smaller investors like hedge funds that populated the market in the aftermath of the 2008 crisis. Given dealers' preferences for low inventory levels after 2008, the intermediation between selling small investors and buying mutual funds was relatively slow and contributed to abnormal returns of the (I)TBs.

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Appendix A. Sample selection

We apply the number of filters to the TRACE database *after* cleaning it as in Dick-Nielsen (2014) (we *do not* remove agency trades). Here are the criteria we use to select the sample:

- The trade was executed between Oct 4, 2004 and Dec 31, 2014;
- The bond is nominated in USD;
- Fixed coupon (including zero-coupon), non-asset backed, non-convertible, non-enhanced bond;
- Of one of the following types according to the Mergent FISD classification: CMTN (US Corporate MTN), CDEB (US Corporate Debentures), CMTZ (US Corporate MTN Zero), CZ (US Corporate Zero), USBN (US Corporate Bank Note), PS (Preferred Security), UCID (US Corporate Insured Debenture);
- The interest is paid 1, 2, 4, or 12 times a year;
- The quoting convention is 30/360;
- The trades are executed at eligible times (time stamps of the trades are between 00:00:00 and 23:59:59; there is a small number of trades in TRACE with misreported times that don't fall into this range, they are removed from the sample);
- The trades are executed on NYSE business days;
- The bond was traded for at least two days in the sample period;
- The trade was executed on or after the dated date of the bond (the date when the interest starts to accrue).

Appendix B. SEC N-Q forms and holdings data

Mutual fund N-Q forms are available online through the SEC EDGAR system. We machine-read these forms and recover holdings from this scraped textual data. Mutual funds have a lot of discretion in how they fill their N-Q forms which makes the recovery of holdings difficult. We discuss the main steps we take below.

First and foremost, funds normally do not report bond CUSIP numbers in N-Q forms. Bond holdings in N-Q forms are identified by the issuer name, maturity, and coupon rate. Instead of trying to fill CUSIP numbers for all N-Q records we find N-Q records matching the CUSIPs we are interested in. We start with a list of CUSIPs from our sample (about 14 thousand as stated in Table I), take their maturity, coupon rate, and issuer name; and match this dataset with N-Q records by maturity and coupon rate. Several possibilities arise. If there is no match, we remove such CUSIP from our 'NQ-matched subsample' (column 2 of Table I).[11] If there is a match it may or may not be unique. Even if the match is unique (which is the dominant case observed for about 9 thousand bonds of interest), there is no guarantee that it is not some other bond, not from our plain-vanilla USD-denominated corporate bond sample, with the same coupon rate and maturity. To check that we compute a cosine text similarity measure between the true issuer name from the FISD database and an issuer name we recover from N-Q forms.[12] Table XV provides some examples. Table XVa shows a record with a uniquely identified bond while Table XVb shows a record with double matching: one bond is the true bond we are looking for, another bond is a mortgage-backed security with the same coupon and maturity. Regardless of whether the match is unique or not, we keep a record in our sample only if the similarity measure is above 0.45.

On the next step, we recover dollar holdings of the matched securities for every combination of bond–fund–reporting date. The raw data we have for every such observation is a string of dollar-like values, see an example in Table XVI. The most frequent case is when the

[11] An alternative way would be to assign the value of zero to mutual fund holdings of such bonds. Since funds rebalance infrequently, we do not want to overpopulate our sample with 0 changes in fund holdings.

[12] We experimented with different similarity measures and did not observe much difference in results.

cusip_id	issuer	maturity	rate	report	CIK	what	similarity
22541LAL7	credit suisse first boston (usa) inc	2009-01-15	3.88	2005-01-31	0000933996	credit suisse fb usa inc	0.67

(a) Unique maturity and coupon rate pair

cusip_id	issuer	maturity	rate	report	CIK	what	similarity
36158FAA8	ge global ins hldg corp	2026-02-15	7.00	2005-01-31	0000933996	ge global insurance holding	0.56
36158FAA8	ge global ins hldg corp	2026-02-15	7.00	2005-01-31	0000933996	fhlmc pool	0.17

(b) Non-unique maturity and coupon rate pair

Table XV. Examples of records with unique and non-unique combination of maturity and coupon rate. First four columns (CUSIP number, issuer name, maturity, and coupon rate) are the data from Mergent FISD. The next three columns (report date, investment fund identifier CIK, and 'what') are the data from an N-Q filing matched to the FISD data by maturity and coupon rate. 'Similarity' is a cosine similarity between 'issuer' and 'what' fields.

par value and the market value are reported. We attempt to recover the par value, which is usually a number with a string of zeroes in the end. Sometimes funds also report the number of securities held (which is the par value divided by 1000 in almost all cases), together with the dollar par value or instead of it. Another complication comes from the fact that funds often scale dollar values in their reports by 1,000 or 1,000,000. In this case, the string that captures the table header contains a scaling unit, in numerical or textual form. We develop an algorithm that takes into account these and some other less frequent reporting patterns and recovers a dollar par value for every bond–fund–reporting date observation.

cusip_id	issuer	maturity	rate	report	CIK	dollars
22541LAL7	credit suisse first boston (usa) inc	2009-01-15	3.88	2005-01-31	0000933996	[365000, 362038]

Table XVI. An entry with dollar fields. Same entry as in Table XVa. 'Dollar' field is a text string that contains all dollar values found in the row corresponding to the entry.

Given the nature of the data, we can not be sure that the algorithm recovers all holdings correctly. Because of that, we apply some additional checks and adjustments once we obtain all candidate holding values. For instance, we track the holdings that are 'too high' relative to the outstanding amounts and scale them down assuming that we did not capture the scaling unit correctly at the previous step. Similarly, we scale down holdings that are unrealistically high relative to the average fund ownership in a given bond in a given month. We also truncate holdings at 1% and 99% in the entire bond–fund–reporting date sample; the tails are removed from the data.

In this paper, we are interested in aggregated fund holdings per bond per month. Before aggregating holdings across funds we need to make an additional assumption about how funds rebalance their holdings. N-Q forms are submitted twice every fiscal year, which is fund-specific. So, funds report their holdings asynchronously. We test several ways of interpolating these data to the monthly frequency: 'last observation carried forward' (all rebalancing happens in the reporting month), linear interpolation (rebalancing in equal portions throughout six months), and exponential interpolation (more rebalancing in months right before the reporting months). In the paper we present the results with the 'last observation carried forward' approach, they are qualitatively similar to the two other methods.

Appendix C. Additional tables and charts

	State 1	State 2	State 3	State 4	State 5
State 1	0.609	0.285	0.089	0.015	0.001
State 2	0.227	0.442	0.257	0.065	0.009
State 3	0.075	0.271	0.424	0.189	0.040
State 4	0.018	0.098	0.272	0.430	0.182
State 5	0.002	0.017	0.070	0.220	0.691

(a) (I)TB, pre-crisis

	State 1	State 2	State 3	State 4	State 5
State 1	0.674	0.246	0.070	0.010	0.001
State 2	0.249	0.454	0.239	0.052	0.006
State 3	0.093	0.314	0.414	0.153	0.027
State 4	0.029	0.149	0.334	0.352	0.136
State 5	0.002	0.018	0.064	0.145	0.770

(b) (I)TB, post-crisis

	State 1	State 2	State 3	State 4	State 5
State 1	0.900	0.071	0.022	0.006	0.001
State 2	0.199	0.395	0.263	0.113	0.030
State 3	0.032	0.139	0.391	0.306	0.132
State 4	0.004	0.031	0.158	0.426	0.381
State 5	0.000	0.002	0.015	0.083	0.900

(c) Non-(I)TB, pre-crisis

	State 1	State 2	State 3	State 4	State 5
State 1	0.920	0.059	0.016	0.004	0.001
State 2	0.228	0.403	0.240	0.104	0.025
State 3	0.035	0.134	0.396	0.314	0.121
State 4	0.006	0.036	0.192	0.430	0.336
State 5	0.000	0.002	0.021	0.097	0.879

(d) Non-(I)TB, post-crisis

Table XVII. Estimated monthly transition probabilities. State 1 is G1 of trading frequency ($Z \in [0, 20)$), state 2 is G2 ($Z \in [20, 40)$), etc. The underlying model is a five-state continuous time Markov chain with constant generator and instantaneous jumps to neighbouring states only.

	Mean	Median	S.D.	Min	5th	25th	75th	95th	Max	N.Obs.
					(I)TB					
Big trades	-0.03	0.00	2.19	-17.98	-2.78	-0.37	0.30	2.72	15.30	305763
Small trades	0.04	0.00	0.27	-5.72	-0.09	-0.02	0.04	0.26	9.49	305763
					Non-(I)TB					
Big trades	-0.02	0.00	1.81	-17.98	-1.88	0.00	0.00	1.80	15.30	651880
Small trades	0.02	0.00	0.32	-5.72	-0.06	0.00	0.01	0.16	9.49	651880

(a) Levels

	Mean	Median	S.D.	Min	5th	25th	75th	95th	Max	N.Obs.
					(I)TB					
Big trades	-0.01	0.00	3.18	-33.28	-4.22	-0.72	0.58	4.38	33.28	301877
Small trades	-0.00	0.00	0.27	-10.15	-0.18	-0.03	0.03	0.18	9.51	301877
					Non-(I)TB					
Big trades	-0.00	0.00	2.64	-33.28	-3.06	-0.11	0.02	3.05	33.28	641479
Small trades	-0.00	0.00	0.40	-15.20	-0.12	-0.01	0.01	0.11	15.20	641479

(b) Changes

Table XVIII. Distribution of monthly levels and changes in net client buy volume conditional on trade size, in % of outstanding amounts. Volumes are winsorized at 0.001% and 0.999%.

Bond type	Mean	Median	S.D.	Min	5th	25th	75th	95th	Max	N.Obs.
					Mutual fund holdings					
(I)TB	12.29	9.20	10.78	0.00	0.66	4.41	16.78	40.29	42.08	280748
Non-(I)TB	10.78	7.28	11.00	0.00	0.34	2.82	14.29	42.08	42.08	455766
					Net purchases by mutual funds					
(I)TB	0.11	0.00	0.84	-19.98	-0.30	0.00	0.01	0.99	37.62	255010
Non-(I)TB	0.09	0.00	0.76	-26.12	-0.19	0.00	0.00	0.84	40.93	406569
					Net purchases by insurance companies					
(I)TB	-0.03	0.00	3.47	-70.35	-1.48	0.00	0.00	1.32	39.89	301874
Non-(I)TB	-0.17	0.00	4.45	-70.35	-0.82	0.00	0.00	0.69	39.89	636355

Table XIX. Distribution of mutual fund holdings, changes in holdings, and net purchases of insurance companies. Mutual fund (MF) holdings are analyzed for the subset of data that contains only bonds matched in SEC NQ filings. MF holdings are winsorized at 5% and 95%, changes in holdings are computed on the winsorized data. Insurance companies' (IC) net purchases are analyzed in the entire sample (all bond-month observations with no recorded purchases by insurance companies are filled with zeros). IC net purchases are winsorized at 0.1% and 99.9%.

	Dependent variable: ΔZ_{it}					
	(1)-(3) = (I)TB			(4)-(6) = Non-(I)TB		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.09***			−0.40***		
Δ(Amount outstanding)$_{it}$, %	−0.001	−0.001	−0.001	−0.05**	−0.05**	−0.04**
Δ(Credit rating)$_{it}$, notch	−0.28***	−0.20**	−0.20**	−0.28***	−0.25***	−0.26***
Age$_{it}$, % of maturity at issuance	0.01***	0.01***	0.01***	−0.003***	−0.002***	0.004***
Δ(No. bonds of same issuer)$_{it}$	−0.43***	−0.41***	−0.45***	−0.18***	−0.18***	−0.17***
Coupon month dummy$_{it}$	−2.57***	−2.78***	−2.84***	−1.48***	−1.62***	−2.15***
Month FE	NO	YES	YES	NO	YES	YES
Firm FE	NO	NO	YES	NO	NO	YES
Observations	283,532	283,532	283,532	422,353	422,353	422,353
Adjusted R^2	0.002	0.03	0.02	0.001	0.01	0.02

Note: *p<0.1; **p<0.05; ***p<0.01
Standard errors are clustered by the bond CUSIP.

Table XX. Panel models for monthly changes in trading frequency ΔZ_{it}. Models (1) and (4) are pooled OLS, the rest are fixed-effect panel models.

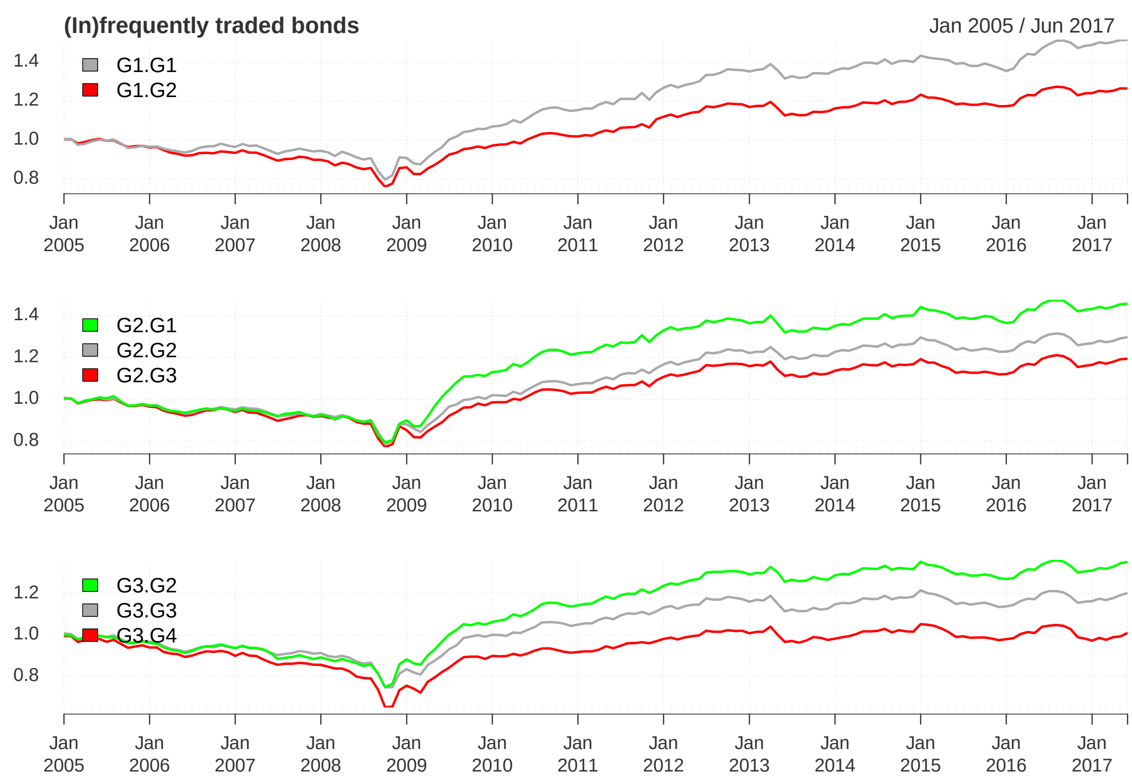

Figure 11. Cumulative excess returns on (I)TB baskets based on the pairs of trading frequency. Excess returns are value-weighted returns in excess of the 3-month T-Bill rate. Baskets here are not investable since the trading frequency state in month T is not known apriori.

		(I)TB		Non-(I)TB	
GR_{t-1}	GR_t	R_t	$Diff$	R_t	$Diff$
G1	G1	0.51**		0.25**	
G1	G2	0.23**	-0.28**	0.18**	-0.08*
G1	G3	0.24**	-0.26**	0.66**	0.41
G1	G4	-0.12	-0.63**	-0.64	-0.89*
G1	G5	0.41	-0.09	0.67	0.42
G2	G1	0.42**	0.22**	0.10*	-0.05
G2	G2	0.20**		0.15**	
G2	G3	0.15**	-0.06	0.24**	0.09
G2	G4	-0.03	-0.23**	0.10	-0.05
G2	G5	0.29	0.09	-0.02	-0.17
G3	G1	0.44**	0.32**	0.54*	0.38
G3	G2	0.27**	0.14**	0.27**	0.11*
G3	G3	0.13**		0.16**	
G3	G4	-0.13*	-0.26**	0.10**	-0.05
G3	G5	-0.28	-0.41	-0.12	-0.27**
G4	G1	1.06**	1.16**	0.49*	0.41*
G4	G2	0.47**	0.57**	0.35**	0.27**
G4	G3	0.21**	0.31**	0.21**	0.12**
G4	G4	-0.10		0.08**	
G4	G5	-0.38*	-0.28*	-0.10	-0.18**
G5	G1	1.28*	1.55**	1.48*	1.56**
G5	G2	1.83**	2.10**	0.79**	0.87**
G5	G3	0.87**	1.14**	0.32**	0.39**
G5	G4	-0.13	0.14	0.14**	0.22**
G5	G5	-0.27		-0.08	

Table XXI. Mean excess returns for the pairs of trading frequency groups in months $t-1$ and t. R_t is the mean return above the 3-month T-Bill rate in month t, $Diff$ is the difference in mean excess return relative to the case when a bond stays in the same trading frequency state in both months $t-1$ and t. **, and * correspond to 1%, and 5% significance.

	(I)TB	Non-(I)TB
G1-G1	0.196**	0.081
G1-G2	0.115	0.151
G1-G3	0.021	0.516**
G1-G4	-0.187	0.014
G1-G5	-0.202	1.242
G2-G1	0.167**	-0.020
G2-G2	0.141*	0.161
G2-G3	0.032	0.142
G2-G4	-0.003	0.193
G2-G5	0.288	-0.219
G3-G1	0.150*	0.500
G3-G2	0.197*	0.189
G3-G3	0.113	0.172*
G3-G4	-0.002	0.164
G3-G5	-0.414	0.368*
G4-G1	0.391	-0.019
G4-G2	0.272**	0.131
G4-G3	0.228*	0.215*
G4-G4	0.095	0.153
G4-G5	-0.058	0.035
G5-G1	0.378	0.695
G5-G2	2.075**	0.523*
G5-G3	0.454*	0.189
G5-G4	-0.003	0.139
G5-G5	-0.204	-0.178

Table XXII. Estimated alphas for bond portfolios formed by the pairs of trading frequencies in months $T-1$ and T. The underlying model is the Bai et al. (2018) corporate bond pricing model. 'Portfolios' here are not investable since the trading frequency state in month T is not known a-priori. Portfolio returns are computed by weighting individual bond excess returns by the market value of issues.