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* Views expressed are those of the authors and do not necessarily reflect official positions of De Nederlandsche Bank.

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Drivers of market liquidity - Regulation, monetary policy or new players?*

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Abstract

Using transaction level data of Dutch fixed income markets, we analyze the drivers of market liquidity between 2014 and 2016. Our results differ significantly across asset classes and during more volatile periods. Policy interventions, such as favourable treatment in liquidity regulation increases the liquidity of bonds. The effects of un- conventional monetary policy are mixed. On the whole it seems to reduce liquidity during normal times but supports it during more volatile periods. Market structure, i.e. the presence of High Frequency Traders (HFT), affects liquidity of sovereign but not of other bonds with reversed effects in more volatile periods. Bond specifics such as shorter maturity and higher ratings are consistently associated with higher liquidity.

Keywords*:* Liquidity, Financial Markets, Monetary Policy, Regulation.
JEL classifications: G18, G21, E42.

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1 Introduction

Bond markets play a crucial role in the conduct of monetary policy and achieving a stable and efficient financial system. Recently, there have been increasing concerns among policymakers regarding a possible shortage of liquidity in fixed income markets. International Monetary Fund (2015), for instance, shows evidence that the level of market liquidity has remained stable in most asset classes, but warned that there may be risks to its resilience in periods of market stress. In line with this, Dick-Nielsen et al. (2012) find that liquidity in corporate bond markets significantly decreased since the onset of the subprime crisis but also that there is divergence according to asset quality. Financial Stability Board (2016), European Commission (2017), and Anderson et al. (2015) come to similar conclusions. In contrast, Aquilina and Suntheim (2016) find that UK bond markets appear to have become more liquid in recent years. The empirical evidence is thus mixed.

Focusing more on the drivers of market liquidity, CGFS (2014,2016) argue that dealer deleveraging, business model adjustments in response to the financial crisis and changes in market microstructure (especially the rise of algorithmic and high-frequency trading) have reduced trading and thus market liquidity. Exceptionally accommodative monetary policy may support market liquidity in the short term but hollow out the investor base in the long run. Among the regulatory drivers, the CGFS reports argue that the post-crisis overhaul of the Basel framework and initiatives like derivatives reform or structural bank regulation have changed the relative costs of banks' asset allocation and funding choices.

Due to data limitations, empirical research on the development of market liquidity and the drivers thereof is scarce. Using high quality transaction data from banks and other financial institutions in the Netherlands between 2014 and 2016, we add to the literature along two dimensions.[1] First, we attempt to shed light on the key drivers of market liquidity in Dutch bond markets. We specifically focus on the effects of new regulation (i.e., Liquidity Coverage Ratio), unconventional monetary policy and the presence of High Frequency Traders (HFT). We control for a set of bond characteristics and general volatility in financial markets. In line with Dick-Nielsen et al. (2012), we use a variety of liquidity measures as well as a combination thereof. Second, we perform a case study to observe the relative presence of different types of investors in Dutch fixed income markets.

[1] We use data reported under the Markets in Financial Instruments Directive (MiFID).

Our results regarding the drivers of market liquidity significantly differ across asset classes and during stressed conditions. First, as for policy interventions, favourable treatment in liquidity regulation increases the liquidity of bonds. The effects of unconventional monetary policy are mixed. Very broadly speaking it seems to reduce liquidity during normal times but supports it during more volatile periods. Second, a market structure condition such as the presence of HFT affects liquidity of sovereign but not of other bonds. However, during stressed conditions the results are reversed. Finally, bond specific characteristics are important as well: Shorter maturity and higher ratings are consistently associated with higher liquidity while other bond specific characteristics are particularly important for non-financial bonds.

Our case study, focusing on the relative importance of banks compared to HFT, reveals that the inclusion of a particular type of bond in the central bank's purchase programmes leads to a relative increase in the presence of HFT. Regulation, such as the Liquidity Coverage Ratio, that makes certain bonds more attractive increases the share of those players covered by the regulation.

Our results suggest that unconventional monetary policy, regulation and the presence of new players all affect market liquidity. Those effects significantly differ across asset classes, which in turn depends on the design of the respective policy measure. Although not new, our results once again confirm that care needs to be taken when designing regulatory requirements.

2 Background on the possible drivers of market liquidity

The literature on the drivers of market liquidity is vast and providing even a condensed account of the state of play is beyond the scope of this paper. We refer to excellent overviews in, for instance, O'Hara (2003) and Menkveld (2017). Here we focus on three drivers, namely, unconventional monetary policy, the liquidity coverage ratio and the role of high frequency traders.

2.1 Unconventional monetary policy

As argued by Committee on the Global Financial System (2014, 2016), monetary policy actions significantly effect fixed income markets. Government bonds, for instance, are key securities for central bank operations but also in private markets. On 9 March 2015, the Eurosystem started to buy public sector securities under the Public Sector Purchase Programme (PSPP).[2] The securities covered by the PSPP include: 1) nominal and inflation-linked central government bonds, and 2) bonds issued by recognised agencies, regional and local governments, international organisations and multilateral development banks located in the euro area. From March 2015 until March 2016 the average monthly pace was 60 billion EUR, which was increased to 80 billion EUR in April 2016.

The Eurosystem started to buy corporate sector bonds as well under the Corporate Sector Purchase Programme (CSPP) on 8 June 2016. The measure was intended to further strengthen the pass-through of the Eurosystem's asset purchases to financing conditions in the real economy, and, in conjunction with the other non-standard monetary policy measures in place, increase monetary policy accommodation even further.

The Eurosystem allows the actual monthly purchase volumes under the programmes to reflect seasonal fluctuations in market liquidity. This means that the Eurosystem engages in moderate front- and back-loading of aggregate purchases in months with adequate market liquidity and allows the purchases to fall below the monthly average in periods of relatively low market activity, notably the summer and the immediate run-up to year-end. The front- and back-loading is not tied to a specific calendar but to the Eurosystem's judgment of market conditions. Additionally, the monthly purchase volumes of the different programmes under the Asset Purchase Programme (APP) will remain flexible to take into account prevailing market liquidity and activity at any time.

The ECB's purchase programmes are likely to be an important driver of market liquidity. According to CGFS (2014,2016), the measures have supported bond valuations, reduced volatility and supported bond issuance in many fixed income markets, which is likely to support market liquidity. There are various channels through which this happens. First, reliable interventions can reduce uncertainty and revive confidence.[3] Second, monetary policy

[2] This section is largely based on public information provided by the ECB.

[3] Also see Christensen and Gillan (2018).

eases funding conditions, lowering the cost of liquidity provision by market participants. Finally, by reducing the yields on sovereign bonds and other directly targeted assets, monetary policies can raise investor demand for less liquid instruments.

Recently several contributions have looked at the impact of Quantitative Easing or QE policies. Joyce and Tong (2012) look at the UK Gilt market while for the Euro area Albertazzi et al. (2018), Altavilla et al. (2015), Arrata and Nguyen (2017), D'Amico and King (2013), Doran et al. (2013), Fabian Eser and Bernd Schwaab (2016), Galema and Lugo (2017), and Koijen et al. (2017) have examined different angles of the effects of ECB's interventions. These papers look at how holding patterns are affected, whether there is a (permanent) price effect or spillover to other markets or the real economy. They find evidence of an effect of stock purchased on bond prices, while supplemental effects from flows remain generally small. Altavilla et al. (2015) notes that asset purchases also have a greater price impact in times of financial stress.

Accommodative monetary policy of this form might also entail challenges. Firstly, asset purchases reduces the availability of securities, reducing market liquidity by definition. Second, CGFS (2014,2016) argue that some market participants have raised concerns about increasing "one-sidedness" of markets, pointing to the risk of crowded trades and illiquidity if expectations were to change.[4]

2.2 Liquidity Coverage Ratio

In response to the liquidity problems encountered by many banks during the last financial crisis, the Basel Committee on Banking Supervision (BCBS) has drafted a new regulatory framework that specifies a short-term and a long-term liquidity requirement as key concepts to reinforce the resilience of banks against liquidity risks. The Liquidity Coverage Ratio (LCR) is the short-term ratio that requires financial institutions to hold high quality liquid assets at least equal to their net cash outflows over a 30-day stress scenario. There are various classes of assets, namely Level 1 and 2. Level 1 assets include cash, central bank reserves and all assets that are either explicitly guaranteed or issued by highly-rated governments. in contrast to the US, the EU LCR also includes covered bonds as Level

[4]See van Kralingen et al. (2018) for a discussion and evidence regarding the impact of one sided or crowded trading. Relatedly, Boermans et al. (2016) study the effect of concentrated holdings on price volatility.

1 assets, albeit with higher haircuts and concentration limits. Level 2 assets consist of lower-rated government bonds, certain types of securitisations and corporate bonds. In Europe, the LCR requirement came into effect in October 2015.

CGFS (2014) argues that while the LCR increased banks' resilience, it has increased funding costs and also made market making less attractive. Some market participants have also argued that the LCR requires banks to hold assets on their balance sheets instead of trading them, which negatively influences market making. On the other hand, making certain types of assets more attractive in regulation might also be liquidity increasing.

2.3 High Frequency Traders

High-frequency trading is a form of algorithmic trading utilized by High-Frequency Traders (HFT). HFT generally trade in instruments listed on regulated exchanges. The business model of HFT consists of executing a large volume of trades with a small profit margin and they are usually proprietary traders. As HFT use banking licenses, they are mandated to report under the MiFID regulation. This makes our data particularly relevant to research the impact of HFT since The Netherlands is home to some of the largest HFT world-wide, in particular Flow Traders, IMC, Optiver en All Options. Within high-frequency trading, two strategies can broadly be distinguished: arbitrage and market-making. In the arbitrage strategy small price differences between exchanges are exploited. In the market-making strategy, HFT quote prices continuously in order to probe market conditions, which can be used to their advantage.[5]

There remains much debate with regards to HFT's net effect on market liquidity. Various studies argue that HFT increase the efficiency and liquidity of financial markets (cf Menkveld (2017)). The rationale behind this is that (1) HFT arbitrage between instruments listed on different exchanges and this reduces fragmentation between exchanges; and (2) HFT increase the number of tradable buy and sell orders leading to more efficient pricing (i.e., lower bid-ask spreads). Others argue that HFT create an illusion of liquidity by increasing the number of quotes disproportionately relative to the actually tradable orders they place

[5] For an excellent overview of HFT strategies, see: `https://www.afm.nl/~/profmedia/files/rapporten/2016/case-analysis-critiques-high-frequency-trading.ashx`. In this study the Dutch Financial Market Authority (AFM) specifically analyzes the Dutch HFT. See Menkveld (2017) for a complementing survey of the academic literature.

(because HFT often close their quotes before they are traded). Another commonly raised argument is that HFT are highly pro-cyclical. While they may decrease bid-ask spreads during normal times, they also withdraw relatively quickly during stress as, in contrast to for instance banks, they cannot warehouse assets. In this scenario, their absence amplifies already introduced market stress and thus further propagates the cycle.

3 Data

3.1 Data sources

We use data that is collected as part of the Markets in Financial Instruments Directive (MiFID). MiFID came into effect in November 2007 and replaced the Investment Services Directive (ISD). MiFID creates a legislative framework for the European Economic Area (EEA) and is designed to provide a transparent and efficient stock exchange trading and investments market. Importantly, the dataset used in this paper contains all transactions of exchange-traded (ET) instruments traded on a regulated market where a Dutch investment firms or credit institutions is either the buyer or the seller. It therefore does not include bonds traded over-the-counter (OTC). In bond markets, in stark contrast to equity markets, the OTC market is much bigger than the ET market.

In interpreting our results, we should be mindful of the scope of our dataset. Since we observe exchange traded instruments only, we should be cautious in extrapolating our results to include OTC instruments. Moreover, we only observe the exchange traded instruments of Dutch financial institutions. Notwithstanding these caveats, our data is sufficiently rich to still merit further analysis. First, our dataset is sufficiently large to shed light on the direction and magnitude of the underlying relationships. There is no a priori reason to assume that the ET and OTC markets would differ in this respect. Second, our dataset is in fact uniquely suitable to answer our second question with regards to the presence of the types of players as it provides a complete overview of Dutch financial players over time, mitigating many of the concerns stated earlier. Specifically, many of the world's most prominent HFT are present in our data.

The dataset spans January 2014 to November 2016. Each observation provides us with the International Securities Identification Number (ISIN), trading date and time, unit price, quantity, currency, a buy/sell indicator, the trading capacity to understand if the reporting firm is acting as a principal or agent and the reporting firm ID. We follow similar cleaning procedures as in Dick-Nielsen et al. (2012). The appendix contains an overview of the MiFID variables, as well as an overview of the cleaning steps. We further complement the MiFID data with additional asset characteristics (matched on ISIN) from the ECB's Centralised Securities Database (CSDB) and Thomson Reuters Elite. This allows us to obtain data on the issuer sector (ESA-2010), rating, total outstanding amount and remaining maturity.

3.2 Descriptive statistics

Table 1 shows the summary statistics of our dataset. We can see that with almost 3 million transactions, government bonds are by far the most widely traded instrument. This is followed by financial bonds (900,000) while non-financial corporate bonds only show around 100,000 transactions in our sample period. On average, the values of the control variables are comparable across asset classes. However, there are also important differences. Unsurprisingly, government bonds show longer maturities and larger outstanding amounts. Ratings and prices, on the other hand, are fairly comparable. Especially the involvement of HFT show large differences. With 90% of volume on average, HFT mainly trade government bonds while their involvement in other asset classes is very limited. In contrast, when the reporting institution acts on behalf of clients, this almost never concerns government bonds.

Figure 1 shows the general pattern of the transactions in the different asset classes over time. The vertical lines represent (from left to right) the first unconventional policy measure, the introduction of the LCR and the extension of the purchase programme (which then also included corporate bonds). On the Y-axis, the number of transactions for the particular month is shown, while the size of the circle reflects the average size of transactions. We can see that most trading takes place in government bonds, while non-financial corporate bonds show fewer transactions than the other bonds. Overall, we can see a decline of both the number of transactions as well as average transaction size between 2014 and 2016. However, the exact developments differ across asset classes.

Looking at sovereign bonds, we can see a clear upwards trend in transactions and size between 2014 and 2015. The first significant drop occurs after the start of the purchase programme in March 2015. In the months *before* the introduction of the LCR in October

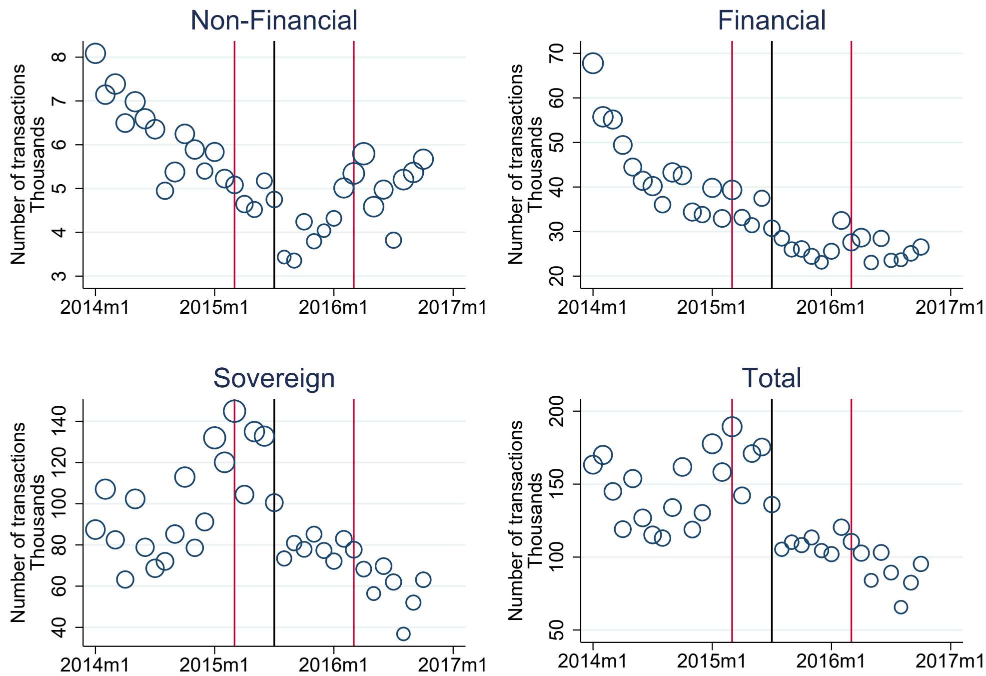
Table 1: Summary statistics

VARIABLES	N	Mean	Median	SD	Min	Max
Sovereign bonds						
Price of the asset	2.771e+06	113.5	110.3	14.45	5	300
Quantity of the transaction	2.771e+06	97.17	43	274.6	0.0200	4,000
Months to maturity	2.771e+06	16.09	15.42	9.683	0	99.92
Credit rating 1-5	2.654e+06	2.137	2	0.607	1	5
Notional Amount Issued in M	2.771e+06	19,872	20,565	5,568	2.842	43,185
HFT involved (%)	2.771e+06	90.57	100	29.23	0	100
Agent	2.771e+06	3.596	0	18.62	0	100
Financial corporate bonds						
Price of the asset	862,385	102.8	105.2	16.27	5	300
Quantity of the transaction	862,385	87.47	11.34	325.3	0.0200	4,000
Months to maturity	392,815	7.110	5.333	6.936	0	97.67
Credit rating 1-5	459,669	2.591	2	1.366	1	5
Notional Amount Issued in M	862,385	2,873	975	3,346	0.200	25,000
HFT involved (%)	862,385	0.319	0	5.635	0	100
Agent	862,385	42.40	0	49.42	0	100
Non-Financial corporate bonds						
Price of the asset	93,706	102.5	104.1	14.68	5	268
Quantity of the transaction	93,706	263.0	50	542.4	0.0200	4,000
Months to maturity	78,383	5.906	5	11.37	0	1,000
Credit rating 1-5	70,580	2.140	2	0.815	1	5
Notional Amount Issued in M	93,706	869.3	700	684.3	1.476	5,500
HFT involved (%)	93,706	0.257	0	5.065	0	100
Agent	93,706	28.89	0	45.33	0	100

2015, activity sharply increased again. This increase is immediately reversed *after* the introduction of the LCR when the number of transactions sharply reduces and eventually remains around this level. Also the size of the transactions remains low. The extension of the purchase programme falls together with a further reduction of the amount of transactions. This seems intuitive, as the majority of the purchase programme has been directed at sovereign debt.

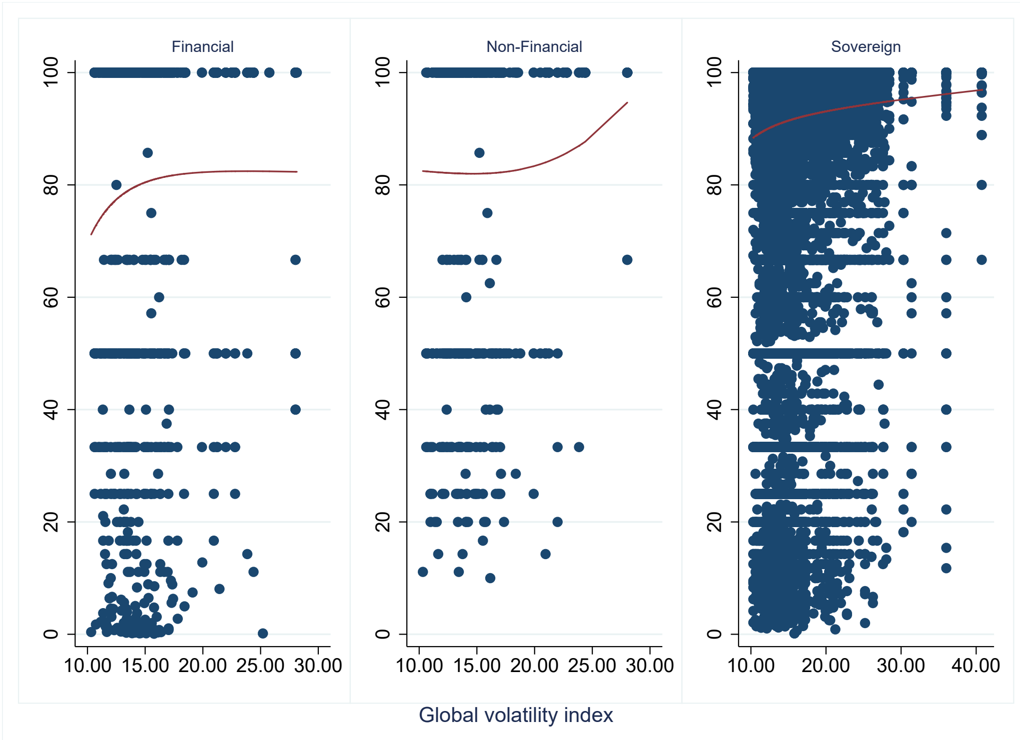
In broad terms, financial bonds show the opposite pattern from government bonds.

Figure 1: Number and size transactions per sector



Both, the number of transactions and their size, decline during 2014. The beginning of the purchase programme does not have a clear visual effect. Since the ECB did not buy financial bonds this seems plausible. However, one could have expected an indirect effect with financial bonds being pulled up by sovereign bond dynamics. Interestingly, the LCR also led to a sharp reduction of financial bonds. However, a few months after that liquidity increases again.

Figure 2: Volatility and HFT participation per sector



The panes show the VIX against the percentage of HFT involvement in each ISIN-period for financial, non-financial and sovereign bonds, respectively. The red line plots a fractional polynomial with degree 2 (i.e., a model with two power terms).

Non-financial bonds show the most consistent pattern with a steady reduction from 2014 to 2016. Nevertheless the pattern around the key events are similar: A very temporary increase of liquidity right before the introduction of the LCR, followed by a drop. The extension of the ECB purchase programme has a positive effect on non-financial bonds. This is straightforward as the additional programme was mainly targeted at corporate bonds.

To get a better sense of the activities of HFT in our sample we plot the level of market volatility against the percentage participation of these new players in Figure 2. The red line in the figure plots a fractional polynomial curve indicating the 'typical' relation. The figures do not prove causality but clearly indicate that the participation HFT varies with general market uncertainty.

In sum, it appears that our three variables of interest – unconventional monetary policy, regulation and new players – have had an effect on transaction size and volumes, which are both important determinants of liquidity. However, there is widespread agreement that liquidity is very complex and that no single measure captures all these complexities.[6] Against this background and in line with Dick-Nielsen et al. (2012), we use a variety of liquidity measures. Specifically, we use the *Price Impact*, *Amihud*, *Turnover*, *Price Impact over Turnover* and *Roll measure*. We will discuss these measures in turn.

4 Methodology

4.1 Liquidity measures

To address the complexity issue around liquidity, our baseline dependent variable is based on Principal Component Analysis (PCA) of five different liquidity measures. In line with convention, the liquidity measures we use are actually illiquidity measures, meaning a higher value indicates lower liquidity. The first measure, *Price Impact*, measures to what extent an individual transaction has impact on the price of the asset. Following Dick-Nielsen et al. (2012), we define *Price Impact* as daily average of absolute transaction returns:

$$PI_{t,i} = \frac{|p_{t,i} - p_{t,i-1}|}{p_{t,i-1}} \tag{1}$$

Amihud (2002) is the most widely used measures and is defined as the ratio of the absolute return (price impact) during time t (e.g. day or week) of an asset divided by its volume over the same period. The ratio therefore represents the absolute price change per dollar of trading volume during a specific time period:

$$Amihud_{t,i} = \frac{1}{N_t} \sum_{j=1}^{N_t} \frac{|r_j|}{T_j} = \frac{1}{N_t} \sum_{j=1}^{N_t} \frac{|\frac{P_j - P_{j-1}}{P_{j-1}}|}{T_j}. \tag{2}$$

Both, *Amihud* and *Price Impact* increase with decreasing liquidity and are therefore in fact illiquidity measures. The rationale is that for a liquid asset we do not expect to

[6]See, for instance, Vayanos and Wang (2012) or Dick-Nielsen et al. (2012).

observe a large price movement and hence a low $Price\ Impact$.

Our third measure captures the trading volume of a particular asset during a specific period. High trading volume and turnover imply high trading activity and the capability to liquidate portfolios within a short time period. $Turnover$ is therefore positively associated with liquidity. The inverse of the turnover ratio can be interpreted as the average holding time of the asset, e.g. a turnover ratio of 0.5 for monthly data implies an average holding period of 2 months. In order to make this variable easily comparable to the other liquidity variables, we multiply with minus one.

Our fourth measures is the ratio of $Price\ Impact\ over\ Turnover$ while the fifth one follows Roll (1984). Roll (1984) argues that under certain assumptions the bid-ask spread is equivalent to the square root of the negative covariance between two successive returns times two. The idea behind it is that a high bid-ask spread results in a high negative covariance between successive returns. The higher the bid-ask spread the more negative the covariance is. A high *Roll measure* means a high implied bid-ask spread and thus indicates an illiquid asset.

4.2 Model

To answer our question, we run two different sets of regressions. The first one aims at understanding the determinants of market liquidity, with a particular focus on monetary policy, regulation and new players. The second set of regressions aims at understanding the participation of HFTs in the market.

Our first regressions take the following form:

$$
\begin{aligned}
Illiquidity_{t,i} = {} & \alpha + \beta_1 UMP60_t + \beta_2 UMP80_t \\
& + \beta_3 LCR_t + \beta_4 HFT_t \\
& + \beta_5 (Bond\ Controls)_{t,i} + \beta_6 Volatility_t \\
& + \beta_7 (Interaction\ terms)_t + \epsilon_{t,i}
\end{aligned}
\tag{3}
$$

where $Illiquidity_{t,i}$ refers to the set of illiquidity measures as described in Section 4.1. In our baseline specification, we calculate all measures over a 1-week period while we also run sensitivity tests for day and month. This means that we compute weekly averages of the different liquidity measures. An exception is turnover for which the total traded weekly amount is summed up (and then divided by the total outstanding amount). $UMP60_t$ and $UMP80_t$ are dummies that capture the ECB's purchase programmes with daily purchase volumes of 60 EUR and 80 EUR billion, respectively. Both dummies are 1 after the first month and 0 otherwise. LCR_t is a dummy that is 1 starting from 3 months before the introduction of the Liquidity Coverage Ratio in October 2015 and 0 before. HFT_t is the percentage of the trades in which at least one counterpart is a High Frequency Trader.

$(Bond\ Controls)_{t,i}$ is a set of bond-specific characteristics. Specifically, this includes a bond's remaining time to maturity and rating as well as total amount outstanding. $Volatility_t$ is a volatility index for the Netherlands (FSI), similar to the global volatility index (VIX). $(Interaction\ terms)_t$ includes interaction terms of FSI with $UMP60_t$, $UMP80_t$, LCR_t and HFT_t. $\epsilon_{t,i}$ are ISIN-clustered robust standard errors. We run Ordinary Least Squares (OLS) regressions.

The second set of regressions is defined as follows:

$$\begin{aligned} HFT_{xt} = \alpha &+ \beta_1 UMP60_{xt} + \beta_2 UMP80_{xt} \\ &+ \beta_3 LCR_{xt} + \beta_4 Volatility_{xt} + \beta_5 liquidity_{xt} + \beta_6 week_{xt} \\ &+ \epsilon_{xt,i} \end{aligned} \tag{4}$$

where the subscript t refers to a particular week and the subscript x refers to a particular security (identified by ISIN). This set-up allows us to look at the within security effect of the structural changes on relative presence of HFT versus banks. As previously, the dependent variable is defined as the percentage of trades within each ISIN each week are conducted by HFT. We use the liquidity indicator of turnover computed earlier as one of the regressors. The volatility variable is again defined as a dummy equaling one in the tail (i.e., the weeks with the highest 5% volatility). We have added a week dummy that equals one in the last week of each quarter in order to capture any potential window dressing effects. The results for financial and non-financial corporate bonds are qualitatively similar, leading us to describe only sovereign bonds versus these corporate bonds together.

5 Results

5.1 Drivers

The following section discusses our results with respect to government, financial and non-financial bonds. Overall, our results suggest that drivers vary significantly across asset classes and during stressed conditions. As for policy interventions, unconventional monetary policy is associated with lower liquidity in sovereign bond markets. The inclusion of non-financial corporate bonds in the purchase programme has not had an overall effect on the liquidity of these bonds. The introduction of the Liquidity Coverage Ratio, which would affect the relative attractiveness of different types of bonds, increases the liquidity in non-financial bonds and sovereign bonds while it is associated with declined liquidity in financial bonds. As for market structure, we find that higher activity of High-Frequency Traders (HFT) increases liquidity in sovereign bonds while having no effect on liquidity in financial and non-financial bonds.

First, the first two columns of Table 2 show our baseline results for financial bonds. Overall, in line with expectations, we can see that shorter remaining time to maturity and larger outstanding amounts are associated with higher liquidity. Higher volatility does not have an effect on the liquidity of financial bonds. The monetary policy measures show mixed results. The first purchase programme is liquidity decreasing while the second one is liquidity increasing. The introduction of the LCR reduced liquidity in financial bonds and this effect is bigger during stressed conditions. This intuitively makes sense, as most financial bonds are not part of the LCR HQLA buffer and thus become relatively unattractive compared to for instance government bonds. A recurring methodological point in our results we note here, is that the magnitude and sign of the UMP and LCR variables are similar in magnitude and opposite in sign, effectively canceling each other out if taken together. We discuss the implications of this in the next Discussion section. The presence of HFT does not affect liquidity in financial bonds during normal times but does increase it during stressed conditions.

Next, we turn to Column 2, where interaction terms are added to observe how market liquidity of financial bonds is affected by our key variables in times of stress. We define stress here as those weeks that belong to the top 5% in terms of volatility as defined by

Table 2: PCA of liquidity factors, week

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Financial		Non-Financial		Sovereign	
Months to maturity	3.99**	3.99**	0.03	0.03	0.87**	0.87**
	(0.000)	(0.000)	(0.460)	(0.460)	(0.009)	(0.008)
Credit rating 1-5	2.92	2.92	-3.41**	-3.41**	-8.05	-8.04
	(0.242)	(0.242)	(0.006)	(0.006)	(0.076)	(0.077)
Notional amount issued	-0.00**	-0.00**	0.00	0.00	-0.00**	-0.00**
	(0.007)	(0.007)	(0.783)	(0.791)	(0.007)	(0.007)
Share of trades with HFT	0.05	0.06	0.01	0.01	-0.31**	-0.32**
	(0.381)	(0.270)	(0.883)	(0.851)	(0.004)	(0.004)
Dummy var. for UMP 60	3.64*	3.62*	2.28	2.35	0.09	0.24
	(0.024)	(0.025)	(0.065)	(0.059)	(0.979)	(0.942)
Dummy var. for UMP 80	-21.96**	-21.80**	-0.06	-0.31	15.17**	15.05**
	(0.000)	(0.000)	(0.965)	(0.826)	(0.000)	(0.000)
Dummy 3 mo. around LCR	23.11**	22.98**	-6.52**	-6.29**	-7.76*	-7.56*
	(0.001)	(0.001)	(0.000)	(0.000)	(0.020)	(0.024)
VIX	0.44	-3.66	5.09*	12.28	5.35	27.66
	(0.963)	(0.502)	(0.012)	(0.135)	(0.097)	(0.324)
ump1_vix		4.77		-8.28		-30.76
		(0.693)		(0.336)		(0.262)
ump2_vix		-7.30		3.37		-31.84**
		(0.568)		(0.806)		(0.004)
hft_vix		-0.55		-0.07		0.15**
		(0.123)		(0.274)		(0.001)
lcr_vix = o,		-		-		-
Constant	-47.06**	-47.04**	-4.10	-4.16	39.51	39.54
	(0.001)	(0.001)	(0.151)	(0.144)	(0.069)	(0.071)
Observations	17,567	17,567	5,781	5,781	18,340	18,340
Adjusted R-squared	0.022	0.022	0.019	0.019	0.018	0.018

Robust pval in parentheses ** p<0.01, * p<0.05

the VIX index. In general, we see no statistically significant effects on any of our key variables. Note that the interaction effect between the LCR and VIX variable drops out of the equation due to the perfect multicollinearity between this variable and the interaction between $UMP2$ and VIX. The reason for this is that these variables are closely related, as they are both defined as a dummy from a given date not so far apart and in the period between the inception of the LCR and the start of the increase of the QE programme there were no weeks with high volatility.

Columns 3 and 4 of Table 2 shows our baseline and stressed results for non-financial corporate bonds, which are rather different from the other bonds. While Maturity is an important factor for the other types of bonds, it does not play a role for corporate bonds. The Rating on the other hand is very important for the liquidity of these bonds. Also, in contrast to the other bond categories volatility has a significantly negative effect on non-financial bond liquidity, suggesting that these bonds are the first ones that stop trading when volatility increases. Interestingly, the purchase programmes do not have a statistically significant effect on the liquidity of these bonds. The introduction of the LCR is the only one of our key variables with a statistically significant effect on liquidity. Specifically, the introduction of the LCR increased the liquidity of corporate bonds by 0.05 standard deviation, which is also economically meaningful. Intuitively this seems plausible as many investment-grade rated corporate bonds are part of the LCR HQLA buffer. This is an interesting finding, as it suggests that inclusion in the HQLA actually led to these bonds becoming *more* liquid, as opposed to less liquid. The latter, reduced liquidity, could have resulted from banks warehousing these bonds rather than trading them prompted by the regulation. Similar to the case of financial bonds, there is no statistically significant effect of severe volatility on the effects of our key variables.

Columns 5 and 6 of Table 2 show our baseline results for sovereign bonds. Overall, we can see that shorter remaining time to maturity and larger issue sizes are associated with higher liquidity. Interestingly, higher ratings are not significantly related to liquidity in this bond category. A possible explanation for this is the fact that within the sovereign bond class, there is relatively little variation in terms of bonds (i.e., almost all sovereign bonds traded in our sample are rated A or higher). The variables measuring our key topics of interest – unconventional monetary policy, regulation and the presence of HFT

– have different effects. While unconventional monetary policy is associated with lower liquidity, higher activity of HFTs raises liquidity. Interestingly, during stress, the impact of unconventional monetary policy is reversed while the presence of HFT is reduced.

When looking at the effects of unconventional monetary policy, an interesting picture emerges. The first round of QE purchases has had no particular effect on the liquidity in bond markets. In contrast, when the amount of purchases was increased to 80 EUR billion per month, there has been a significant impact on market liquidity. Specifically, holding the other factors constant, this programme coincides with a decrease in market liquidity of 0.15. In economic terms this is also significant, as it means that during this programme market liquidity decreased by 0.15 standard deviation. Second, looking at the impact of high-frequency trading, we can see that an increase in HFT of 1% leads to an increase of 0.0032 standard deviations in market liquidity. While this may seem small, recall that the standard deviation of HFT is around 22%. This means that a standard deviation increase in the presence of HFT leads to approximately a 0.07 standard deviation increase in liquidity which is also economically meaningful. Third, we can see that the introduction of the LCR coincides with a 0.08 standard deviation increase in liquidity. Again, following the same reason as before with the non-financial bonds, this indicates that inclusion in the LCR actually increased the liquidity of these bonds.

Next, we turn to times of stress again. In the case of government bonds, there is a significant impact of the interaction variables on our key variables. First, we observe that during times of significant stress the sign of $UMP2$ reverses, meaning that in times of stress the impact of the unconventional monetary policy programme becomes positive (i.e., increases liquidity), relative to the situation of no unconventional policy. This result is also economically significant, as the programme then leads to an increase of liquidity of about 0.17 standard deviation. One interpretation of this result is that the purchases of the central banks provide a sort of 'minimum demand', through which there is always some liquidity available to willing participants even under stress. Conversely, the impact of stress situations on the impact of HFT on liquidity decreases (but not quite reverses). As a result a standard deviation increase in HFT only leads to approximately a 0.03 increase in liquidity in times of stress.

5.2 New players

We now take a closer look at any changes that have occurred in terms of market participation. While in the previous section the assertion is that the changes in business models drive changes in liquidity, we now test whether the structural changes that have occurred drive the relative presence of market players.

Table 4 differentiates the results along the different types of bonds. Starting with the effects of the first phase of unconventional monetary policy – mainly targeting sovereign bonds – we can see that this led to a reduced presence of HFT in financial (Column 1) and corporate bonds (Column 2) while it did not affect their presence in sovereign bond markets. The second phase on the other hand – targeting non-financial corporate bonds and asset-backed securities – led to more activity of HFT in financial (Column 1) and non-financial corporate bond markets while, again, it did not affect their activity regarding sovereigns. Those results broadly suggest that the inclusion of a particular type of bond in the central bank's purchase programmes leads to a relative increase in the presence of HFT. Ranging from 0.5% to 1% are economically significant but small.

The introduction of the LCR – arguably making government bonds relatively more attractive for banks – led to a decrease of HFT activity in sovereign bond markets but increased their role in other markets. A likely explanation for this result is that during the introduction period, banks built up their liquidity buffers and were hence relatively more active in these markets. A similar explanation can be given for the days at the end of the quarter. Since those are reporting dates for banks, they are probably more active on markets, decreasing the relative activity of HFT. Periods of significant volatility captured by the VIX index do not appear to have an effect on the relative presence of players.

5.3 Sensitivity Analysis

To test the robustness of our results, we run several sensitivity tests. Firstly, to ensure that our results are not driven by the particular frequency (i.e., weekly) that we chose for our baseline regressions, we conducted the same analyses for daily and monthly periods. While there are some differences, the results are qualitatively similar. Secondly, we changed the definition of our key variables. Specifically, we included the unconventional monetary policy measures as continuous variables instead of dummy variables, we adjusted the introduction

Table 4: Relative change in players

	(1)	(2)	(3)
Variables	Financial	Non-Financial	Sovereign
Dummy variable for UMP 60	-0.49**	-0.56**	0.09
	(0.000)	(0.000)	(0.889)
Dummy variable for UMP 80	0.75**	1.04**	0.10
	(0.000)	(0.000)	(0.859)
Dummy=1 three months around LCR	0.20**	0.38**	-6.18**
	(0.000)	(0.000)	(0.000)
vix2	0.01	0.12	0.99*
	(0.853)	(0.271)	(0.033)
week_dummy	-0.11*	-0.50**	-2.35**
	(0.041)	(0.000)	(0.000)
Constant	0.54**	0.63**	26.36**
	(0.000)	(0.000)	(0.000)
Observations	150,329	50,833	60,529
Number of unique ISIN	5,859	1,745	1,303
Adjusted R-squared	0.002	0.004	0.018

Robust pval in parentheses ** p<0.01, * p<0.05

date of the LCR to reflect implementation lags and defined the activity of HFT per unique bond as opposed to on aggregate. Again, while these changes affect our results, the overall pattern is consistent across all specifications. Thirdly, we run all our regressions also with the individual liquidity measures as opposed to the PCA. The results of these alternative specifications can be found in the appendices.

6 Conclusion

Making use of a unique dataset with trade level information on Dutch fixed income markets, we take a comprehensive look at the liquidity of bonds traded by Dutch financial institutions. This allows us to compare the liquidity of all traded bonds on a high frequency over a long time period. We contribute to the literature along two dimensions. First, we analyze the impact of new regulation, unconventional monetary policy and the presence of High Frequency Traders (HFTs) on market liquidity. Our results regarding the drivers of market liquidity significantly differ across asset classes and during stressed conditions. The first thing to note is that policy interventions affect markets. For instance, favourable treatment in liquidity regulation increases the liquidity of bonds. The effects of unconventional monetary policy are mixed. Very broadly speaking it seems to reduce liquidity during normal times but supports it during more volatile periods. The presence of HFT affects liquidity of sovereign but not of other bonds. Interestingly, during stressed conditions the results are reversed. Bond specifics also matter: shorter maturity and higher ratings are consistently associated with higher liquidity while other bond specific characteristics are particularly important for non-financial bonds.

Second, we also analyze whether new regulation and unconventional monetary policy had an impact on the presence of HFT compared to banks. In combination with our other results, we conclude that the effects of various policy measures significantly differ based on their specific design. While this finding is not new, our results once again confirm that great care needs to be taken when designing policies as small differences can change their effects.

References

Albertazzi, U., B. Becker, and M. Boucinha (2018): "Portfolio Rebalancing and the Transmission of Large-Scale Asset Programmes: Evidence from the Euro Area," *ECB Working Paper*, 2125.

Altavilla, C., G. Carboni, and R. Motto (2015): "Asset Purchase Programmes and Financial Markets: Lessons from the Euro Area," *ECB Working Paper*, 1864.

Amihud, Y. (2002): "Illiquidity and Stock Returns: Cross-Section and Time-Series Effects," *Journal of Financial Markets*, 5, 31–56.

Anderson, N., L. Webber, J. Noss, D. Beale, and L. Crowley-Reidy (2015): "The Resilience of Financial Market Liquidity," *Bank of England Financial Stability Paper*, 34.

Aquilina, M. and F. Suntheim (2016): "Liquidity in the U.K. Corporate Bond Market: Evidence from Trade Data," *FCA Occasional Paper*, 14.

Arrata, W. and B. Nguyen (2017): "Price impact of bond supply shocks: Evidence from the Eurosystem's asset purchase program," *Banque de France Working Paper*, 623.

Boermans, M., J. Frost, and S. Steins Bisschop (2016): "European Bond Markets: Do Illiquidity and Concentration Aggravate Price Shocks?" *Economics Letters*, 141, 143–146.

Christensen, J. H. E. and J. M. Gillan (2018): "Does Quantitative Easing Affect Market Liquidity?" *Federal Reserve Bank of San Francisco Working Paper*, 2013-26.

Committee on the Global Financial System (2014): "Market-Making and Proprietary Trading: Industry Trends, Drivers and Policy Implications," *CGFS Papers*, 52.

——— (2016): "Fixed Income Market Liquidity," *CGFS Papers*, 41.

D'Amico, S. and T. B. King (2013): "Flow and Stock Effects of Large-Scale Treasury Purchases: Evidence on the Importance of Local Supply," *Journal of Financial Economics*, 108, 425–448.

Dick-Nielsen, J., J. Gyntelberg, and T. Sangill (2012): "Liquidity in Government versus Covered Bond Markets," *BIS Working Paper*, 392.

Doran, D., P. Dunne, A. Monks, and G. O'Reilly (2013): "Was the Securities Markets Programme Effective in Stabilizing Irish Sovereign Yields?" *Research Technical Papers*.

European Commission (2017): *Drivers of Corporate Bond Market Liquidity in the European Union*.

Fabian Eser and Bernd Schwaab (2016): "Evaluating the Impact of Unconventional Monetary Policy Measures: Empirical evidence from the ECB's Securities Markets Programme," *Journal of Financial Economics*, 119, 147–167.

Financial Stability Board (2016): *Implementation and Effects of the G20 Financial Regulatory Reforms*.

Galema, R. and S. Lugo (2017): "When Central Banks Buy Corporate Bonds: Target Selection and Impact of the European Corporate Sector Purchase Program," *USE Working Paper*, 16.

International Monetary Fund (2015): *Global Financial Stability Report*.

Joyce, M. A. and M. Tong (2012): "QE and the Gilt Market: a Disaggregated Analysis," *The Economic Journal*, 122, F348–F384.

Koijen, R. S. J., F. Koulischer, B. Nguyen, and M. Yogo (2017): "Euro-Area Quantitative Easing and Portfolio Rebalancing," *American Economic Review*, 107, 621–627.

Menkveld, A. J. (2017): "The Economics of High-Frequency Trading: Taking Stock," *Annual Review of Financial Economics*, 8, 1–47.

O'Hara, M. (2003): "Liquidity and Price Discovery," *Journal of Finance*, 58, 1335–1354.

Roll, R. (1984): "A Simple Implicit Measure of the Effective Bid-Ask Spread in an Efficient Market," *Journal of Finance*, 39, 1127–1139.

van Kralingen, M., D. Garlaschelli, K. Scholtus, and I. van Lelyveld (2018): "Crowded Trades, Market Clustering and Price Instability," *DNB Working Paper*.

Vayanos, D. and J. Wang (2012): "Market Liquidity - Theory and Empirical Evidence," *LSE Financial Markets Group Discussion Paper*, 709.

Appendices

MiFID data

Article 25(3) and (4) of Directive 2004/39/EC require investment firms and credit institutions to report transactions when trading a financial instrument admitted to trading on a regulated market. These transaction reports are to be passed on to the competent authority of the most relevant market in terms of liquidity. The so-called MiFID transaction reports are clarified further in Commission Regulation (EC) 1287/2006. The requirement has applied since November 1st, 2007 but we focus on more recent years. Our dataset should thus include all transactions in Dutch bonds and equities by an investment firm or credit institution in the EU as one of the counterparties. The fields in the transaction report used in our analysis are shown in Table 6.

Cleaning steps

We have adjusted and cleaned the data mostly following Dick-Nielsen et al. (2012).

1. Only trades reported in *euro* are used.

2. The variable 'Trading capacity' is used to adjust the buy/sell indicator so that for all reports the buy/sell indicator reflects the perspective of the reporting firm. If the 'Trading capacity' variable indicates that the reporting firm is acting as an agent and therefore reports the transaction as seen from the perspective of the counterparty we change the buy/sell indicator from buy (sell) to sell (buy). This ensures that the indicator reflects the perspective of the reporting firm.

3. A large number of errors were identified in the counterparty identifiers. Therefore, this variable was deemed unusable.

4. Although repo transactions should not be reported, some firms nevertheless report repo transactions. We were able to detect and remove repo transactions cases where we found two transactions in opposite direction (buy/sell) and different prices, with the same counterparty in the same bond and of the same amount at exactly the same point in time.

Table 6: Transaction report variables

Variable	Description
Instrument	The International Securities Identification Number (ISIN) that uniquely identifies the transacted bond
Trading date time	The date, time and time zone when the trade was executed. Unit Price Price per bond excluding commission and accrued interest (clean price).
Quantity	The total nominal value of bonds included in the transaction.
Currency	Currency in which the price is expressed.
Buy/sell indicator	Identification whether the transaction was a buy or a sell from the perspective of the reporting investment firm if acting as a principal, or of the client if acting as an agent.
Trading capacity	Identification whether the reporting firm executed the transaction "on its own account, either on its own behalf or on behalf of a client" (principal) or "for the account, and on behalf, of a client" (agent).
Reporter identification	A unique code to identify the firm which executed the transaction. An 11 characters ISO 9362 SWIFT/Bank Identifier Code (BIC).
Counterparty ID	The BIC code if the counterparty is a MiFID investment firm. The MIC code of the trading venue if the counterparty is a regulated market or a multilateral trading facility (MTF). Otherwise an internal code for the customer/client is used.
Client name	The name of the client/customer. This field is optional.

5. We have removed outliers by deleting all trades at prices below */euro* 1. We also delete trades involving a higher volume than the outstanding amount of the bond. Finally, deleted all trades with a price impact (see section 3) of more than 100 basis points. In most cases we found that the high price impact is due to a single transaction reported at a very odd price compared to other transactions at that time.

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