Liquidity Patterns in the U.S. Corporate Bond Market

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Abstract

Liquidity commonality exists and empirical evidence (e.g. Lin et al., 2011) indicates that exposure to this common liquidity factor is priced in the cross-section of corporate bonds. The existence of commonality implies that part of a bond's illiquidity is left as idiosyncratic. In this paper, we study how illiquidity components explain the cross-section of bond yields and how this relationship varies over time and across bond categories. We use a factor decomposition to break down total illiquidity into a common and an idiosyncratic component and analyze how yields relate differentially to each of these two components. We find that a bond's idiosyncratic illiquidity is important, which might reflect informational asymmetries compounded by the lack of diversification in the institutional investors' portfolios. Moreover, the relation between idiosyncratic illiquidity and yield spreads appears to become stronger after the recent financial crisis.

1. Introduction

The recent global financial crisis has seen a deterioration of market-wide liquidity across all asset classes, which has been especially detrimental to markets for fixed income securities and their derivatives, including the corporate bond market.

Furthermore, despite the large volumes traded on this market, the demand for corporate bonds on the secondary market, especially for those of shorter maturities, remains scarce.[1] Managing this illiquidity risk constitutes a big challenge for investors, as the ease with which they will be able to trade and at what cost, is a centrepiece of the investment decision. In light of these challenges posed by liquidity we intend to provide a deeper understanding of the interactions between liquidity and bond yield spreads. In particular, we focus in this paper, on the relation between corporate bonds yield spreads and a bond's idiosyncratic level of liquidity.

There is large empirical evidence for the existence of commonality in liquidity (Chordia et al., 2000; Hasbrouck and Seppi, 2001, among others) and for the existence of a premium for systematic liquidity risk (Pastor and Staumbaugh, 2003; Sadka, 2006) in the equity market, and similarly in the corporate bond market (Lin et al., 2011; Bao et al. 2011; Dick-Nielsen et al. 2012). In addition, Rösch and Kaserer (2013) provide evidence that commonality is time-varying and that it peaks during major crisis events.

When looking at the pricing implications of liquidity and liquidity risk, most studies focus on the total level of liquidity or on the sensitivity to a common liquidity factor, respectively. Expected corporate bond returns are related to systematic risk associated with a common liquidity factor. Given the specific institutional settings of the corporate bond market, it is reasonable to believe that an important part of the bond's liquidity may remain idiosyncratic or bond specific. In fact, trading on the corporate bond market is generally dominated by a small group of institutional investors and the market remains very opaque to the general public. Unlike equities there is a large diversity in the securities provided, the bonds trade very infrequently and there is rarely a constant supply of buyers and sellers looking to trade sufficiently to sustain a central pool of investor provided liquidity. In such a setting we argue that some bonds

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[1] Stricter post-crisis regulations on banks as well as increases in their risk aversion in conjunction with ongoing bouts of market volatility have put further pressure on bond market liquidity with dealers' inventories shrinking by more than 75% since mid-2007, according to data published by the Federal Reserve Bank of New York. Asset managers now hold more than 99% of corporate bond inventory and while dealers continue to play an important role in the price discovery process the balance is starting to tilt with big buy-side players having more pricing information and influence than before.

potentially exhibit higher idiosyncratic illiquidity because they are less accessible or less known by the investor.

Liquidity has many facets and generally encompasses the time, cost and volume of a trade. It can notably be defined as the ability to trade large quantities of an asset at a low cost and with negligible price impact. Therefore it is reflected in trading costs, which are arguably well proxied by bid-ask spreads, or in the impact of a single trade on prices. In our study we use several liquidity measures that capture different liquidity dimensions. We use Amihud's (2002) measure and the standard deviation thereof to capture the price impact of a trade. We use the imputed roundtrip cost, its standard deviation, and Roll's (1984) measure as a proxy of trading cost. Finally we use the ratio of a bond's zero trading days within a period to capture trading activity.

In a view of increased transparency in this market, FINRA (the U.S. Financial Industry Regulatory Authority) has, since 2003, been gradually releasing transaction data of the secondary corporate bond market. Since 2005 almost 99% of the transactions in this market have been reported in TRACE (Trade Reporting and Compliance Engine) under SEC approved rules. The availability of this data has created a new avenue for research in corporate bond market, with a focus on investigating the effects of liquidity in the cross-section of bond returns.

Using this dataset we aim to make a contribution to the literature in the following way. We decompose a bond's individual liquidity into a common and an idiosyncratic component and study how these two components interact in driving bond yields. We start by measuring the magnitude of liquidity commonality of this market and define the residual as the idiosyncratic bond liquidity. The commonality in liquidity can be seen as the part that is driven by common factors of the market and which is common to all bonds. The idiosyncratic liquidity is seen as the order flows related to bond specific components or characteristics. We test whether only commonality exhibits a relation to yield spread, whether idiosyncratic liquidity can have some explanatory power, and how the prevalence between both varies over time. We expect that in stressed financial markets, spreads are more sensitive to commonality in liquidity, while under normal times, the sensitivity to idiosyncratic liquidity might be important as well. However, even in stressed times exposure to systematic liquidity risk may account for no more than little of returns, especially anomalous returns of bonds with high idiosyncratic illiquidity. We do have some anomalous findings and hence decided to investigate further. By disentangling commonality from the idiosyncratic part we are able to provide evidence on the specific relationship of yield spreads in relation to these measures.

We use factor decomposition to derive the common liquidity part of each bond. The common part based on 3 factors accounts for 13% of the liquidity variation on average, which leaves and important part of liquidity defined as the idiosyncratic component. We then use cross-sectional regressions to measure the extent of the sensitivity of yield spreads to commonality and idiosyncratic liquidity and look at the time series behavior of the coefficients on these measures. We find that a significant relationship exists between yield spreads and both common and idiosyncratic illiquidity. The finding that the idiosyncratic part is important may result from the fact that in such a very opaque market some bonds might not be available or known to all investors.

The remainder of the paper is organized as follows. In section 2 we present a survey of the relevant literature. In section 3 we describe our dataset and the methodology. In section 4 we discuss the empirical results. Section 5 concludes.

2. Literature review

Since Amihud and Mendelson (1986) liquidity has been considered as an important element in asset pricing. A number of studies, especially on stock markets, investigate the pricing implications and provide evidence of a premium for systematic liquidity risk (see for example, Amihud 2002; Pastor and Stambaugh, 2003; Acharya and Pedersen, 2005; Chen, 2005; Sadka, 2006). Pastor and Stambaugh (2003) consider market liquidity as a state variable. They find that expected stock returns are related cross-sectionally to the sensitivities of returns to fluctuations in aggregate liquidity.

Liquidity has many facets and there is not one single measure that has been accepted unanimously. Several proxies have emerged in the literature and are usually considered as reliably measuring transaction related costs. Roll's (1984) measure essentially relates to transaction costs and bid-ask spreads. The idea behind is that the price bounces back and forth between bid and ask prices and higher percentage bid-ask spreads lead to higher negative covariance between consecutive returns. This measure is indeed able to capture liquidity dynamics above and beyond the effect of bid-ask bounce as shown in Bao et al. (2011). Amihud (2002) develops a measure that relates the price impact of a trade to the trade volume. Pastor and Stambaugh (2003) build their illiquidity measure as the temporary price changes induced by trading volume. Mahanti et al. (2008) derive a "latent liquidity" measure from custodian banks' turnover, which is defined as the weighted average turnover of investors who hold a bond, in which the weights are the fractional investor holdings. Jankowitsch et al. (2011) propose a price dispersion measure, based on the dispersion of market transaction prices of an asset around the consensus valuation by market participants.

Corporate bonds and liquidity

Recent papers in the finance literature show that liquidity and liquidity risk are important components in explaining the credit spread puzzle exhibited in corporate bond returns. Bao et al. (2011) use a modified version of Roll's measure as a proxy for liquidity and show that this measure relates to other bond characteristics that are commonly used as liquidity proxies. This measure exhibits commonality across bonds, which tends to go up during periods of market crisis. Illiquidity is found to have pricing implications, to the extent that it is an important factor in explaining the time variation in bond indices and the cross-section of individual yield spreads. Dick-Nielsen et al. (2012) use a principal component analysis of eight liquidity measures to define a factor, which is used as a new liquidity proxy. They find that illiquidity contributes to spreads and does so even more for speculative bonds. The contribution is only small before the crisis but increases strongly at the onset of the crisis for all bonds except AAA-rated bonds. This finding underscores the flight-to-quality effect that occurred in AAA bonds. Friewald et al. (2012) study the pricing of liquidity in the US corporate bond market in periods of financial crises using a comprehensive dataset. Their liquidity measures are derived from standard liquidity measures such as Roll and Amihud, bond characteristics, trading activity variables and price dispersion. Liquidity is found to account for 14% of the explained time-series variation in corporate bond yields and its economic impact is almost doubled in crises periods.

Liquidity risk implications are analyzed in De Jong and Driessen (2012) and Lin et al. (2011). De Jong and Driessen (2012) use a linear factor models in which corporate bond returns are exposed to market risk factors and a liquidity risk factor. Yields are measured at the index level and liquidity risk factors are derived from shocks to equity market and government bond market liquidity, respectively. Expected corporate bond returns are found exposed to fluctuations in both treasury market and equity market liquidity. Lin et al. (2011) focus instead on liquidity risk, which is measured by bond returns' sensitivity to changes in aggregate liquidity rather than by the absolute liquidity level. Using the Fama and French (1993) five factor model for bond returns, augmented by a liquidity factor, they find that liquidity risk is priced in expected corporate bond returns and this result is robust to the inclusion of default, term and stock market risk factors, bond characteristics, the level of liquidity and the rating. Acharya et al. (2013) study the exposure of US corporate bond returns to liquidity shocks on the stock market and the Treasury bond market over more than 30 years. They find a conditional impact of liquidity shocks on bond prices defined over two regimes. In the first regime, characterized by normal times, liquidity shocks do not affect bond prices. However in the second regime, which is characterized by macroeconomic and financial distress, there is a differential impact of liquidity on investment grade bonds versus speculative bonds. Junk

bond returns respond negatively to illiquidity shocks, while investment grade bond returns respond in a positive and significant way.

Finally, a number of studies demonstrate that liquidity exhibits a systematic common component and that this commonality is time-varying and especially strong during crisis periods. Chordia, Roll and Subrahmanyam (2000) are the first ones to show that individual liquidity measures of stocks co-move. Hasbrouck and Seppi (2001) provide evidence of common factors in returns and order flows. Kamara et al. (2008) look at the cross-sectional variation of liquidity commonality and show how it has increased over time and how it depends on institutional ownership. The presence of this commonality implies that part of a security's liquidity remains idiosyncratic or unexplained by the market. The literature so far does not account for this component when studying pricing implications. Nevertheless in a very opaque market, with a large number of different securities and a large number of small dealers this idiosyncratic component may remain important.

There are several important differences between the prior papers and our own research. We go further into the analysis of liquidity by decomposing it into two parts, a common and an idiosyncratic component. We look at the pricing implications of these two measures over time and whether these relations change substantially over different periods. To our knowledge, no study so far has investigated the impact of idiosyncratic illiquidity, which in turn may be quite important in such an opaque market. Indeed the large diversity of products confronted by a large number of dealers with small market shares does not offer optimal transparency on choices of bonds that may be available to investors. In this context, we conjecture that some bonds might exhibit a stronger idiosyncratic illiquidity simply because they are not broadly available or known to all investors. Further, while previous studies look at monthly or quarterly liquidity series, by constructing weekly liquidity measures, we are able to analyze finer variations in the relationship between yield spreads and bond liquidity. Finally, our sample allows us to conduct a thorough analysis of the relation pre- and post- financial crisis as we have equal-length periods of data before and after the crisis at our disposal.

3. Data and methodology

3.1. *Liquidity measures*

We build weekly series of 6 liquidity measures that have been used in recent studies, notably in Dionne and Chun (2011) and in Dick-Nielsen et al. (2012). Our weekly measures are computed over weeks starting on Wednesday and ending on Tuesday, to avoid weekend effects.

1. Amihud price impact

Amihud (2002) measures the price impact of a trade per unit traded and takes the absolute value of the return over the trading volume. We follow Dionne and Chun (2011) by constructing this measure on all days, when at least 3 transactions of the bond are observed. For each individual bond i, we construct a daily Amihud measure, which is then aggregated weekly by taking the mean:

$$Ami_{i,d} = \frac{1}{N} \sum_{j=1}^{N} \frac{|return^i{}_{j,d}|}{volume^i{}_{j,d}}$$

where N is the number of returns during each day d, $return^i{}_{j,d}$ is the return on the j-th transaction during day d and $volume^i{}_{j,d}$ is the volume of this j-th transaction. The measure thus reflects how much the price moves due to a given volume of a trade.

2. Imputed roundtrip cost

The measure is developed by Feldhüter (2009) and is based on the observation that bonds might trade 2 or 3 times within a short interval, after a long interval without any trade. This is likely to occur because a dealer matches a buyer and a seller and collects the bid–ask spread as a fee. The dealer buys the bond from a seller, and further sells it to the buyer. The price difference can be seen as the transaction fee or the bid ask spread. The imputed roundtrip cost (IRC) is therefore defined as

$$\frac{P_{max} - P_{min}}{P_{max}}$$

where P_{max} and P_{min} are the largest and smallest prices in the set of transactions with the same volume, within a day. For each bond we obtain the daily IRC as the average of roundtrip costs on that day for different sizes and we then take averages of daily estimates to obtain weekly estimates.

3. Amihud and IRC risk

As in Dick-Nielsen et al. (2012) and in Dionne and Chun (2011), we use the standard deviations of the measures defined above as additional liquidity proxies. The measures capture the variation of liquidity and therefore offer another dimension to the liquidity level. The daily estimates of these measures are calculated as the standard deviation of daily Amihud and IRC values over a rolling window of 21 days. Weekly estimates are obtained as averages of daily values.

4. Roll bid-ask spread

Roll (1984) shows that the bid-ask spread can be approximated as follows:

$$Roll_t = -\sqrt{cov\left(\Delta\, p_t, \Delta p_{t-1}\right)}$$

The idea behind this measure is that adjacent price movements can be interpreted as bid-ask bounces and this results in a negative correlation between transitory price movements. A higher negative covariance therefore indicates higher bid-ask spreads and hence higher transaction costs. We compute this measure daily for each bond, using a rolling window of 21 days in which we require at least 4 transactions.

5. Bond's zero trading days

Another indicator of liquidity is the frequency at which the bonds trade. Many studies therefore compute the ratio of the number of zero trading days over the total number of trading days during a period. Less trading days indicate less liquidity of the bond. We compute this ratio rolling over every day for each bond, using a period of 21 trading days.

$$Bond\ zero = \frac{number\ of\ bond\ zero\ trades\ within\ the\ rolling\ window}{number\ of\ days\ in\ the\ rolling\ window}$$

All liquidity measures are built in such a way that higher positive values reflect higher illiquidity. In the remainder of the paper we will thus stick to this interpretation of an increasing measure –be it the measure of price impact, of transaction costs or trade frequency- as higher illiquidity or equivalently as lower liquidity.

3.2. *Sample construction*

We obtain detailed transaction data of the OTC US corporate bond market from TRACE. This systematic reporting of OTC corporate bond transactions is being maintained by FINRA in a view to increase price transparency on the corporate debt market. The database contains detailed trade-by-trade records with the timestamp of the transaction, the clean price and the par value traded, although the par value traded is truncated at $1 million for speculative grade bonds and at $5 million for investment grade bonds. All FINRA members are responsible for reporting all OTC corporate bond transactions in the secondary market to the system. The information is disseminated in TRACE and makes it a most valuable tool for microstructure research of bond market liquidity. Even if the reporting requirements are well specified, the database nevertheless contains many erroneous and cancelled reports. We follow Dick-Nielsen (2009) to manually filter out error reports, cancelation, reversals and agency transactions. For our

analysis we require the bonds to have frequent enough trading to be able to construct a liquidity measure at a weekly frequency.

We operate our selection in two steps. First, we include only bonds that are present in the sample for more than a year and are traded on at least 30 business days each year. Second, once liquidity measures are computed we operate a further selection of bonds to be able to obtain a time series of liquidity measures for a specific bond. Since Amihud's measure requires most transactions in order to be built, it is the most restrictive one and has fewest observations. By selecting on this measure we make sure that we have more frequent observations of other liquidity measures. We require that Amihud's liquidity measure be observed for an individual bond on a least 20% of the weeks of its presence in the sample. [2] This selection criterion leaves us with a sample of 9,670 bonds and still allows for large heterogeneity across bonds despite the fact of being slightly biased towards 'the most observed' and hence more liquid bonds. We use this bond list to retrieve bond characteristics from Bloomberg. Based on this information we retain only dollar denominated bonds with a bullet or callable repayment structure, without any other option features. We also require having information available on bond characteristics such as its issue size and date, its rating and its coupon. We end up with a selection of 7,535 bonds for which we have obtained the complete transaction data in TRACE and constructed weekly liquidity measures. In Table 1 we report summary statistics on the bonds' characteristics of our final sample and provide information about their trading activity. In our sample we have 519 weeks, starting on 21 January 2004 and ending on 31 December 2013. Since the number of bonds in the sample is not fixed, we obtain an unbalanced panel for each of the illiquidity measures, depending on the weeks and for which bond a given liquidity measure is observed.

Table 1: Summary statistics

Our sample consists of 7,535 unique bonds and we obtain trades over a period of ten years, from 2004 to 2013 included. The number of bonds in the sample gradually increases over the years, from 1,251 in 2004 to 5,635 in 2013. Average issue size of the bonds increases slightly over the years. In all years, average maturity is close to 15 years. The gradual decrease in maturity can be explained by our sample selection, as a bond usually stays in the sample once it is selected. We can see from the table that these bonds trade very little. Median number of trades a week ranges from 11 to 20, while the mean lies between 20 and 40. Both values are highest in 2009. Overall mean and median number of trades increases considerably towards the end of the sample. Turnover, measured as the total

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[2] We admit that our selection is arbitrary but it is the choice we make facing a tradeoff between obtaining a large cross-section of bonds and being able to compute liquidity measures, since some bonds have so few trades.

monthly trading volume over issue size has been decreasing between 2004 and 2008, where it attains 4.7%. It was higher in 2009 but then experienced a steady decrease until the end of the sample, which might also be related to the fact that average issue size has been increasing. The number of trading days is higher in the second half of the sample, which comes along with a higher activity on this market and with the fact that over the years more and more bonds have become subject to reporting. Average daily and weekly returns have alternated from positive to negative. The strongest negative values have been observed in 2008, which corresponds to the onset of the financial crisis in the US.

3.3. *Liquidity decomposition*

We would like to gain a deeper insight into liquidity dynamics and their pricing implications. Knowing that these bonds are usually held in largely undiversified portfolios, we expect that there remains an important part of idiosyncratic component, which may affect bond yields. Since the focus of this paper is on liquidity, we propose to decompose our liquidity measure into a common part and an idiosyncratic part. The common part is assumed to reflect liquidity shocks that are common to all bonds, while the idiosyncratic part is assumed to reflect shocks that are specific to the individual bond. To identify those distinct components, one option is to extract common factors in liquidity series and to treat the remaining part as idiosyncratic. We follow the approach already used in Korajczyk and Sadka (2008) to identify a systematic liquidity component. It assumes that an approximate factor model explains liquidity in the following way:

$$L^i = \beta^i F^i + \varepsilon^i$$

where L^i is the n*T matrix of liquidity observations of measure i (i=1,...6) on the n assets over T time periods, F^i is the k*T matrix of common liquidity factors and β^i is the n*k matrix of exposure to those factors for all individual assets n. Connor and Korajczyk (1986) show that for a balanced panel, the *n* latent factors of this approximate factor model can be obtained by calculating the eigenvectors corresponding to the k largest eigenvalues of:

$$\Omega^i = \frac{L^{i\prime} L^i}{n}$$

They show that the eigenvector analysis of the T×T covariance matrix of asset returns is asymptotically equivalent to traditional factor analysis. The estimates of those factors are referred to as asymptotic principal components. The main advantage of the asymptotic principal component analysis is that it overcomes the problems that are inherent to factor estimations in large cross-sections. The matrix Ω^i has dimension T*T and allows for a much easier factor decomposition

than an n*n matrix, when n is large. Connor and Korajczyk (1987) further show how this estimation procedure can be extended to unbalanced panels. Elements of Ω^i are obtained by averaging over observed data only. To this end, let L^i be the matrix with liquidity measures where missing values are replaced by 0 and let N^i be an n×T matrix where $N^i_{j,t}$ is equal to one if liquidity measure i of bond j at time t is observed and zero otherwise. We build the matrix Ω that accommodates missing data as follows:

$$\Omega^{i,u}_{t,\tau} = \frac{(L^{i\prime}L^i)_{t,\tau}}{(N^{i\prime}N^i)_{t,\tau}}$$

Element *(t, τ)* of matrix Ω *(T×T)* is defined over the cross-sectional averages of the observed liquidity values only. The factors used for the approximate factor model are then obtained by calculating the eigenvectors for the k largest eigenvalues of Ω.

We apply this asymptotic principal component analysis to our sets of liquidity measures since the number of assets n, is much greater than the number of time periods. We obtain factor estimates for each liquidity measure i and we run time series regressions of individual liquidity series on the identified common factors, alternatively using one, two or three factors. The choice of three factors is arbitrary and follows Korajczyk and Sadka (2008). Furthermore, the three first factors are able to capture between 44% and 98% of the variance in the data. Adding more factors increases the amount of variance captured by 1% only for each factor. Next we define the fitted and residual values obtained with three factors in these regressions as our common and idiosyncratic illiquidity measures, respectively. Hence for each bond we obtain weekly time series of common and idiosyncratic illiquidity over the time period a bond is in the sample. Table 2 reports the average R-squared and adjusted R-squared that we obtain by fitting our weekly illiquidity measures to one, two or three latent factors.

Table 2: Factor decomposition

Results in Table 2 indicate that there is evidence for commonality within individual bond liquidity measures. Most of the commonality seems to be captured by the first factor, as evidenced in the percentage of significant t-statistics of factor 1. Using the 3 factors model, we are able to explain between 4% and 16% for Amihud and zero trade bond measures, respectively. This leaves an important part that can be attributed to idiosyncratic components. The aggregate series of commonality and idiosyncratic illiquidity are plotted in

Figure 1.[3] We see from this graph that aggregate illiquidity exhibits a large spike towards the end of 2008. Hence along with the general market illiquidity induced by the financial crisis, we find corporate bonds have also experienced higher illiquidity, which peaked shortly after the fall of Lehman Brothers. We further see that aggregate illiquidity is composed of a positive common part and a negative idiosyncratic. The large spike is caused by liquidity commonality as expected, as all assets were hit by this event. At the aggregate level the idiosyncratic component is very low and very close to zero after the financial crisis. While the idiosyncratic component may be large at the individual level, it is largely canceled out when looking at aggregate series.

Figure 1: Aggregate series of the two liquidity components

Table 3 reports descriptive information on liquidity measures.[4] We know from previous research that illiquidity contributed to the widening of credit spreads during the financial crisis (Friewald et al. 2012, Dick-Nielsen et al. 2012). To disentangle the behavior of liquidity in crisis periods, we decompose the sample period into three parts pre-, during and post-crisis. We focus on the most tormented period of the crisis in the US market, which is usually assumed to be the fall of Lehman Brothers. We therefore define the crisis period for our purposes as starting in September 2008 and lasting until December 2008.

We further look at our illiquidity measures in different subgroups of bonds, designated according to the maturity, the rating, the issuance size and the industry of the bond. Most groups and sub-periods contain a few hundred bonds on which means and standard deviations of weekly liquidity measures are computed. For ratings AAA and C and for maturities around 2Y however, we obtain only a few observations, at least at the beginning of the sample, and results should therefore be interpreted with care. Notice that all liquidity proxies are built with a positive sign and hence higher values refer to higher illiquidity. As expected, illiquidity, and in particular commonality, are highest during the crisis while post-crisis fall below their pre-crisis level. This relation is verified throughout all liquidity proxies. Rösch and Kaserer (2013) among others also show that liquidity commonality increases during market downturns and peaks in periods of major crisis events. Better liquidity conditions after the crisis might be the result of the stimulus program initiated by the Fed starting in May 2009. Note that this pattern appears for our aggregate liquidity measure and for the commonality measure but not for idiosyncratic illiquidity. Idiosyncratic illiquidity instead has been increasing over time and gets very close to zero towards the end of the sample. In the pre-crisis sample idiosyncratic illiquidity

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[3] To save space we provide the graphs with IRC and Roll measures only.
[4] We only report the tables for Amihud and IRC liquidity measures as the results are usually very similar across different measures.

as measured by Amihud, IRC, IRC risk and Roll is negative indicating that all illiquidity of the bonds in the sample stemmed from the market and that individual bond characteristics might instead improve a bond's liquidity.

Next we look at the values of these liquidity components across several bond groups. Starting with the rating classification, we surprisingly find that in the pre-crisis period, the lowest illiquidity levels are exhibited by junk bonds (rating C or below). This finding is confirmed by all measures except the *zero bond* measure. Before the crisis, the lowest graded bonds are the ones with the lowest trading frequency. Price impact and round trip costs are however low for those bonds. We observe the same behavior for the common part in each liquidity measure. During the crisis period, the bonds with best liquidity measures are AAA rated bonds, interestingly followed by C rated bonds. When we look at the decomposition of liquidity values, we find that both bond categories exhibit around the same values of liquidity commonality but that for the best rated bonds, idiosyncratic illiquidity reduces the total illiquidity level, while for the lowest rated bonds, idiosyncratic illiquidity adds up to the common part. Hence idiosyncratic illiquidity is positive essentially for lower graded bonds, which might have undergone the strongest selling pressure during the crisis, as investors start by selling the least credit-worthy assets. Hence illiquidity generated by bond intrinsic features is important as well. After the crisis, we observe that the liquidity measures are gradually increasing when the bond's rating decreases. However C rated bonds still exhibit the lowest levels of both total illiquidity and commonality. On the other hand, idiosyncratic illiquidity is highest for the lower rated bonds. Hence all bonds are exposed to common liquidity shocks but illiquidity of lower rated bonds has an additional idiosyncratic part, due to a bond's characteristics and notably its credit quality.

We then group bonds according to their maturity, where we distinguish between bonds with time to maturity between 1 and 2 years (2Y), between 2 and 7 years (5Y), between 7 and 17 years (10Y) and above 17 years (30Y). All liquidity measures indicate lower liquidity for bonds with a longer time to maturity. As time to maturity increases the bonds experience higher illiquidity in terms of trading costs as well as in terms of trade frequency. This is in line with the buy and hold phenomenon of many long-term bonds. The relation is verified throughout the three sub-periods and illiquidity levels after the crisis fall below their pre-crisis levels. Idiosyncratic components are quite volatile in the sample but overall idiosyncratic illiquidity is positive in the post-crisis sample and it generally increases as the time to maturity of the bond increases. This holds for all liquidity measures expect for the trading frequency where we find that most part of the non-trading frequency is idiosyncratic to the bond before the crisis while after the crisis it is driven by commonality.

Further we look at liquidity behavior by sorting bonds according to their issuance size, where we distinguish between three categories: the bonds with an issue size below 500 Mln (small issuance), an issue size between 500 Mln and 1 Billion (Medium issuance) and an issue size above 1 Bln (large issuance). We find that liquidity usually increases with the issue size or is lowest for small issue sizes. Indeed large issues are usually expected to be more liquid. Again, the illiquidity levels post-crisis are below their pre-crisis levels. Idiosyncratic illiquidity is positive for Amihud's price impact and risk measure and is always highest for the small issue sizes.

Finally, we show that financial bonds exhibit highest illiquidity and the magnitude is even higher during the crisis period.

Table 3: Summary statistics of liquidity components

3.4. *Correlations*

Before turning to the regression analysis we report the correlations between the various liquidity measures in Table 4. The correlations between two measures are computed first within each week using pairwise complete observations and then averaging over the sample. As expected there is some correlation across the different measures. Amihud and IRC are most strongly correlated with their corresponding liquidity risk measures. The correlation between Amihud and IRC level is also lower than that between their standard deviations. The Roll measure is mostly correlated with the standard deviations of Amihud and IRC. Quite naturally the correlation between measures computed over a 21 days window is stronger than for measures that are computed on one day. We also find that the correlation with other explanatory variables is moderate, which will allow us to include these variables in the same cross-sectional regression.

We further look at the correlations between the two liquidity components. For all measures the common and idiosyncratic parts exhibit an important negative correlation. Individual common components of all measures also exhibit an important correlation, which is higher than the correlation observed between the total measures. Hence there is a large common dimension observed through all liquidity measures that becomes apparent with this decomposition. These measures are subject to common dynamics captured in their commonality component but each of them exhibits some noise that is specific to the measure.

Table 4: Correlations

4. Yield spreads and liquidity components

4.1. *Regression analysis*

In this section we investigate whether a bond's yield spread is related to our two liquidity components and how this relation evolves over time. We follow the Fama-MacBeth (1973) methodology applied to panel data and perform weekly cross-sectional regressions of individual yield spreads on a bond's illiquidity measure – common and idiosyncratic- and some control variables. A bond's yield spread is defined with respect to Treasury yields, matched according to their respective maturities. More specifically, we adopt the following cross-sectional regression:

$$yield\ spread_{i,t} = \alpha + \beta\gamma_{i,y} + \partial Z_{i,t} + \varepsilon_{i,t}$$

where i refers to a bond, $\gamma_{i,t}$ is the individual illiquidity measure – either aggregate or decomposed - and $Z_{i,t}$ contains the control variables. In all specifications, we systematically include a bond's credit rating to control for credit risk, a callable dummy, which is one if the bond is redeemable at maturity and zero if it is callable, the average transaction volume during the week and the bond's remaining time to maturity. Most of these variables have been used in previous literature, e.g. Dick-Nielsen et al., Houweling et al., Bao et al., as proxies for a bond's liquidity as they are thought to have an impact on spreads. A bond that is traded more frequently or that has lower trading costs is expected to be more liquid. While there is some overlapping in the different measures, we expect that they capture different aspects of liquidity. In our first set of regressions we consider a bond's aggregate liquidity measure only, while in the second set we consider the two liquidity components to see whether the relation stems from commonality in liquidity only or whether idiosyncratic illiquidity matters as well.

4.2. *Aggregate results*

Table 5 reports the results of alternative specifications of the regression model. In a first step we analyze each liquidity measure individually along with other explanatory variables. The table presents four different specifications. In model 1, we use a specification without liquidity measures, our baseline model, where individual bond yields are regressed on a bond's rating, time to maturity, average trading volume per day and a maturity type dummy. This baseline model is already able to explain a substantial part of yield spread variation, as the R-squared attains a value of 39%. Rating is measured on a numerical scale, where higher values represent less creditworthy bonds. The coefficient estimate is positive suggesting that less creditworthy bonds obtain higher yields. If the rating of a bond increases by one, its yield is expected to increase by almost 50

points. The coefficient on time to maturity is -0.01 meaning that bonds with longer time to maturity have slightly lower yields. The effect of maturity is surprising as bonds with long maturities are generally considered to be less liquid since they are often detained in "buy-and-hold" portfolios and therefore trade less regularly. This contrasts Bao et al. (2011) who find a positive coefficient on maturity. Our finding can however be the result of our sample selection in which we have a large fraction of bonds with a small maturity towards the end of the sample period. In any case, results should not be compared in a strict sense, as the sample selection and the time period covered are quite different.

In model 2 we add each liquidity variable and this increases the explanatory power of the model. The R-squared values increase to 40% when *bond zero* measure is added and up to 44% when the *Amihud* measure is added. These results confirm previous findings that liquidity variables contribute to the explanation of yield spreads, as has been shown in Bao et al. (2011) and Dick-Nielsen et al. (2012). We find statistically significant results for the coefficients of our liquidity proxies. The magnitude of the effect depends on the measure used and the sign is always positive indicating that illiquidity contributes to higher yield spreads. Illiquidity as reflected by Amihud's price impact involves higher yields and an increase of the price impact by one, increases the yield spread by 0.15. If the cost per 100K dollars of a round-trip transaction increases by 1 dollar, yields increase by 0.87.

Table 5: Yield spread regressions on liquidity variables

4.3. *Decomposition*

We now turn to the analysis of our liquidity decomposition and the impact of both components on yield spreads. In the cross-sectional regressions, we analyze each component separately along with other explanatory variables. In the table we report time-series averages of the coefficients and their Fama-MacBeth t-statistics. From Table 5 we can see that in all regression specifications both liquidity components are significant. The coefficients on the common components are usually stronger, but idiosyncratic liquidity remains important and has a statistically significant impact on yield spreads. This finding is important and indicates that the relation between liquidity and yield spreads does not only stem from common market dynamics. The signs of the coefficients are most of the time positive and bonds with higher idiosyncratic illiquidity have higher yield spreads. Investors are thus compensated for holding securities that are less liquid due to their idiosyncratic illiquidity. Especially in this over-the-counter and quite opaque market it is not surprising that idiosyncratic illiquidity still plays a role and those investors, who largely hold undiversified portfolios get remunerated or can buy these securities at a lower price than otherwise

equivalent ones. Interestingly, when liquidity is proxied by the *IRC risk* measure, we find a negative coefficient on idiosyncratic illiquidity. The positive relation between illiquidity and yield spreads does entirely stem from liquidity commonality and the idiosyncratic part of illiquidity does not require any compensation and investors holding these bonds accept to obtain lower yields. This finding could be rationalized if we consider that a bond with higher IRC risk is a bond that has exhibited more price variation in its imputed round-trip cost, beyond the variations stemming from the market, and that this bond therefore exhibits a higher chance of obtaining low round-trip costs in the future, which will decrease its yield.

4.4. *Time series analysis*

To gain further insights into the differential relation between liquidity and yield spreads over time, we propose to look at the time-series behavior of the coefficients in individual cross-sections and we plot the time series of the betas in Figure 2. We expect that liquidity effects, and especially liquidity commonality impacts are more important in times of distress. In the figure we already see that most of the variation in yield spreads can be attributed to commonality, hence the systemic part of illiquidity. The sensitivity is mostly positive and very large around the crisis period. The sensitivity of yields to the idiosyncratic part is lower and exhibits much variation during the crisis period. It seems also that it has been increasing over time for most of the liquidity proxies, except the zero bond measure.

Figure 2: Coefficients on liquidity components in cross-sectional regressions

In those graphs, we clearly see that the relation between liquidity and yield spreads is time varying and that taking simple averages of cross-sectional betas remains imprecise. To focus on the role of liquidity in financial crises, we therefore consider our cross-sectional regressions in three different periods: As before, we define the crisis period as going from mid-September 2008 to end of December 2008. The periods before and after are assumed to correspond to more normal market conditions. In Table 5 we report the results of several model specifications. Control variables are always included. We report the coefficients on these variables in the three distinct time periods. In all specifications we find a statistically significant effect of liquidity commonality on yield spread, and this impact is much stronger during the crisis period. This finding confirms our expectations and previous findings of Dick-Nielsen et al. (2012) that liquidity commonality gets more important in distress times. All bonds are exposed to same liquidity shocks and all yields are affected by this increased illiquidity. At the same time we see that idiosyncratic liquidity is not significant at all, or much less significant than in the two other periods. Results

are usually valid throughout any liquidity measure. The coefficient on liquidity commonality stays positive in all three periods, indicating that common liquidity shocks, that affect all securities and therefore cannot be diversified away, will always increase yield spreads. Idiosyncratic illiquidity on the other hand has a differential impact on yield spreads and we find that its coefficient is sometimes negative. Hence the liquidity shock that is specific to the bond is not necessarily compensated in the yield spread. Investors may have perceived it safer to hold their bonds rather than selling them in a hurry at a discounted price. This might especially be true for investors with a long-term investment horizon, which is the case of insurance companies or pension funds. In particular, a large part of bond investors are insurance companies, who given their long-term investment strategy usually adopt a "buy-and-hold" strategy for a bond rather than selling it on the secondary market. Therefore if the bond is detained in a buy and hold portfolio investors are not affected by its idiosyncratic illiquidity as they do not expect to sell it quickly. After the crisis however, the coefficient on idiosyncratic illiquidity turns positive as well. Hence investors might have changed their attitude since they and now require a compensation for holding bonds with higher idiosyncratic illiquidity.

All in all we thus confirm that during the distress period only liquidity commonality matters. We observe an important and reversed impact of idiosyncratic illiquidity on yield spreads, before and after the crisis. Before the crisis investors did not require any compensation for detaining bonds with high idiosyncratic illiquidity but this has changed after this period.

4.5. *Bond portfolios*

To further understand the time series behavior of the illiquidity coefficient, we propose to analyze it in subgroups of bonds formed on the characteristics of the bond. We divide our sample into two rating groups, investment grade and high yield, and into three maturity groups – 1-7y, 7-17y, 17-30y. We run the cross-sectional regressions in each bond group and focus our attention on the coefficients of the liquidity variable. We consider the regression model where yield spreads are regressed on each liquidity component, rating, maturity, volume and call dummy. We discuss the behavior of the coefficient on liquidity variables in the different groups below, as presented in Table 6. The time series of the betas are plotted in the graphs in Figure 3 and Figure 4.

Figure 3: Coefficients on liquidity components in rating groups

Figure 4: Coefficients on liquidity components in maturity groups

Table 6: Cross-sectional regressions in bond groups

Rating

The common trends that we identified before are confirmed. However the magnitude of the impact changes considerably from one rating group to the other. Overall, there is still a strong sensitivity of yield spreads to liquidity commonality, which peaks during the crisis. In terms of magnitude this impact is much stronger for high yield bonds. This finding is in line with previous studies showing that the contribution of illiquidity to yield spreads is much stronger for speculative grade bonds (Dick-Nielsen et al. 2012). For instance, if we consider the results with IRC as liquidity proxy, we find that if the IRC increases by 0.001 for instance (its average value is around 0,003 and its standard deviation at 0,001), yields of investment grade bonds will increase by 0,019 and those of high yield bonds by 0,18. Only for the zero bond measure we find that high yield bonds exhibit a strong negative sensitivity to the number of trades over the past 21 days interval. A higher zero bond measure implies a higher ratio of days without trade on the bond, and this ratio is negatively related to spreads. Hence if the ratio increases, this comes along with lower yield spreads. As we have seen this bond category is most sensible to liquidity shocks and this finding would imply that if the number of trades decreases (ratio increases) this is not seen as a bad signal and prices can still increase. This is reasonable in a setting where bonds are held until maturity or at a long horizon and where decreasing number of trades are not followed by selling pressures.

Overall, even if statistically significant, the impact of idiosyncratic liquidity on investment grade bond spreads remains low. The coefficient is very low, exhibiting more volatility around the crisis period. Hence for investment grade bonds, we can say that essentially the common liquidity shocks are compensated in yield spreads. For high yield bonds instead, both liquidity components are reflected in spreads, essentially in the post-crisis period.

Maturity

We consider three maturity groups, the first one, abbreviated by MAT5, includes bonds with a time to maturity ranging from 1 to 7 years, the second one, MAT10 contains bonds with time to maturity from 7 to 17 years and the last one MAT30, those with time to maturity above 17 years. Bonds with a very short time to maturity are discarded from the sample. Further our sample does not allow for enough cross-sectional variation for bonds of the MAT5 group and the time series therefore start in November 2004. The picture is different according to which liquidity measure is considered. We find that commonality of Amihud's price impact and of its risk has a significant effect on long term bonds; while it's idiosyncratic part is important for short-term bonds. All long term yields will be affected by liquidity shocks, while short-term yields are only affected by bond specific liquidity shocks that are not necessarily common to all bonds. For other measures we do not necessarily find a monotonic pattern throughout the

maturity spectrum. We find nevertheless that there is a negative sensitivity of yield spreads to the idiosyncratic component.

5. Conclusion

In this paper we provide evidence on the relation between corporate bond spreads and two illiquidity components, common and idiosyncratic. Illiquidity is priced in corporate bond yields (Bao et al. 2012, Dick-Nielsen et al. 2012, among others). We extend these studies in two ways. First, we use the trade reports provided in TRACE to compute weekly illiquidity measures for each bond. By computing weekly measures we are able to provide a finer analysis of liquidity as previous studies usually provide monthly or quarterly measures. Second, we decompose liquidity into two parts: a common part and an idiosyncratic part. Liquidity commonality prevails between assets and is time-varying. By disentangling the commonality from the idiosyncratic part we are able to provide evidence on the specific relationship of yield spreads to these two measures. We find that a significant relationship exists between yield spreads and both common and idiosyncratic illiquidity. The finding that the idiosyncratic part is important may result from the fact that in such a very opaque market some bonds might not be available or known to all investors. Our data also allows for a finer analysis between bond groups, where we find that high yield bonds and bonds with a shorter time to maturity are more sensitive to idiosyncratic illiquidity.

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