# Illiquidity or credit deterioration: A study of liquidity in the US corporate bond market during financial crises ☆

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## ARTICLE INFO

## ABSTRACT

We investigate whether liquidity is an important price factor in the US corporate bond market. In particular, we focus on whether liquidity effects are more pronounced in periods of financial crises, especially for bonds with high credit risk, using a unique data set covering more than 20,000 bonds, between October 2004 and December 2008. We employ a wide range of liquidity measures and find that liquidity effects account for approximately 14% of the explained market-wide corporate yield spread changes. We conclude that the economic impact of the liquidity measures is significantly larger in periods of crisis, and for speculative grade bonds.

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## 1. Introduction

The global financial crisis had its origins in the US subprime mortgage market in 2006–2007, but has since spread to virtually every financial market around the world. The most important aspect of this crisis, which sharply distinguishes it from previous crises, is the rapidity and degree to which both the liquidity and credit quality of several asset classes deteriorated. While clearly both liquidity and credit risk are key determinants of asset prices, in general, it is important to quantify their relative effects and, particularly, how much they changed during the crisis. It is also relevant to ask if there are interactions between these factors, and whether these relations changed substantially in magnitude and quality from prior periods. In this paper, we study liquidity effects in the US corporate bond market for the period October 2004 to December 2008, including the GM/Ford

downgrades and the subprime crisis, using a unique data set covering basically the whole US corporate bond market. We employ a wide range of liquidity measures to quantify the liquidity effects in corporate bond yield spreads.

Our analysis explores the time-series and cross-sectional aspects of liquidity for the whole market, as well as various important segments, using panel and Fama-MacBeth regressions, respectively.

Most major financial markets, including those for equity, foreign exchange, credit, and commodities, were severely affected in terms of price and liquidity in the subprime crisis. However, the impact has been disproportionately felt in the fixed income markets, including the markets for collateralized debt obligations (CDO), credit default swaps (CDS), and corporate bonds. An important point to note is that these securities are usually traded in over-the-counter (OTC) markets, where there is no central market place, or even a clearing house. Indeed, this aspect has come under regulatory scrutiny since the near collapse of the CDS market, which was an opaque OTC market. It is the OTC structure of fixed income markets that makes research, especially on liquidity effects, difficult as traded prices and volumes are not readily available, and important aspects of the markets can only be analyzed based on quotations from individual dealers, which are not necessarily representative of the market as a whole.

US corporate bonds trade in an important OTC market. This market is an ideal laboratory to examine liquidity and credit factors because of the following reasons: First, in contrast to most other OTC markets, detailed transaction data are available on prices, volumes, and other market variables since 2004, through an effort of the Financial Industry Regulatory Agency (FINRA), known as the Trade Reporting and Compliance Engine (TRACE). This database aggregates virtually all transactions in the US corporate bond market, which is unusual for any OTC market. Second, the US corporate bond market bore the brunt of the subprime crisis in terms of credit deterioration, almost to the same extent as the credit derivatives market, to which it is linked by arbitrage and hedging activities. Third, there is considerable variation in credit quality as well as liquidity in this market, both over time and across bonds, providing researchers with the opportunity to examine the differences arising out of changes in liquidity.

For our empirical analysis, we use all traded prices from TRACE, along with market valuations from Markit, bond characteristics from Bloomberg, and credit ratings from Standard & Poor's. Our combined data set is perhaps the most comprehensive one of the US corporate bond market that has been assembled to date, covering 23,703 bonds and 3,261 firms. This data set enables us to study liquidity effects for virtually the whole bond market, including bond segments that show very low trading activity.

The main focus of our research in this paper is to determine the quantitative impact of liquidity factors, while controlling for credit risk, based on credit ratings and other risk characteristics. In our analysis, we focus on the yield spread of a corporate bond, defined as its yield differential relative to that of a risk-free benchmark of similar duration. The benchmark could be either the Treasury bond or the swap rate curve.

To measure liquidity, we consider several alternative proxies for liquidity. We employ *bond characteristics* that have been used as liquidity proxies in many studies. We use directly observable *trading activity variables* (e.g., the number of trades) and, most important, we employ several alternative *liquidity measures* proposed in the literature, i.e., the Amihud, Roll, zero-return, and price dispersion measure.

First, we explore the hypothesis that liquidity is priced in the US corporate bond market. We find that the liquidity proxies account for about 14% of the explained time-series variation of the yield spread changes over time for individual bonds, while controlling for credit quality. Most of the liquidity proxies exhibit statistically as well as economically significant results. While the trading activity variables are important in explaining the bond yield spread changes, the liquidity measures exhibit even stronger effects in terms of economic impact. In particular, measures estimating trading costs based on transaction data show the strongest effects.

Second, our main research question is whether the effect of liquidity is stronger in times of crises. Our hypothesis is that in crises, when capital constraints become binding and inventory holding costs and search costs rise dramatically, liquidity effects are more pronounced. Therefore, we analyze credit and liquidity effects for three different regimes during our sample period, i.e., the GM/Ford crisis, the subprime crisis, and the period in between, when market conditions were more normal. Based on time-series analysis, we find that the effect of the liquidity measures is far stronger in both the GM/Ford crisis and the subprime crisis: the economic significance of the liquidity proxies increased by 30% in the GM/Ford crisis compared to the normal period, and more than doubled in the subprime crisis. We also examine the cross-sectional behavior of the yield spread using Fama-MacBeth regressions in the three different time periods. In general, the cross-sectional results paint a picture similar to the time-series analysis. Moreover, we find in the cross-section that time-invariant bond characteristics, e.g., amount issued, show significant effects as well.

Third, we analyze the interaction between credit and liquidity risk. We expect to find higher liquidity in the investment grade sector if liquidity concerns cause investors to abandon the junk bond market in favor of investment grade bonds in a *flight-to-quality*. We present descriptive statistics providing evidence for a flight-to-quality during financial distress and the regression analysis indeed shows lower liquidity for speculative grade bonds as well as a stronger reaction to changes in liquidity. In general, these results indicate that the liquidity component is far more important in explaining the change in the yield spread for bonds with high credit risk.

The remainder of the paper is organized as follows: we present a survey of the relevant literature in Section 2 of the paper, focusing mainly on papers relating to liquidity effects in corporate bond markets. Section 3 discusses the hypotheses being tested in the paper and the economic

motivation behind them. In Section 4, we explain, in detail, the composition of our data set and the filters and matching procedures we employ in combining data from four different data sources. Section 5 discusses the alternative measures of liquidity that have been proposed and used in the literature and their pros and cons. We focus, in particular, on the relevance of these measures for a relatively illiquid OTC market. In Section 6 we outline the methodology. Section 7 presents the time-series results, based on panel regressions, and the results for the cross-sectional analysis based on the Fama-Mac-Beth procedure, used to test our hypotheses. Section 8 concludes.

## 2. Literature survey

The academic literature on liquidity effects on asset prices is vast. An early paper was by Amihud and Mendelson (1986), who first made the conceptual argument that transaction costs result in liquidity premiums in asset prices in equilibrium, due to different trading horizons of investors. This conclusion has been extended and modified in different directions and also been tested in a host of asset markets. This literature, focusing mainly on equity markets, is surveyed by Amihud, Mendelson, and Pedersen (2006). In the context of OTC markets, Duffie, Garleanu, and Pedersen (2007) show that transaction costs are driven by search frictions, inventory holding costs, and bargaining power in this particular market structure. A related argument is presented in Jankowitsch, Nashikkar, and Subrahmanyam (2011). In a recent paper, Acharya, Amihud, and Bharath (2009) argue that these frictions change over time and are higher in times of financial crises, due to binding capital constraints and increased holding and search costs.

The literature on credit risk modeling provides evidence of liquidity effects in the corporate bond market and shows that risk-free interest rates and credit risk are not the only factors that drive corporate bond prices. This result has been established based on reduced-form models (see, for example, Longstaff, Mithal, and Neis, 2005; Nashikkar, Subrahmanyam, and Mahanti, 2011), and structural models (see, for example, Huang and Huang, 2003), i.e., neither credit risk measured by the prices of CDS contracts nor asset value information from the equity market, can fully explain corporate bond yields.

Several authors study the impact of liquidity, based on corporate bond yields or yield spreads over a risk-free benchmark. Most of these papers rely on indirect proxies based on *bond characteristics* such as the coupon, age, amount issued, industry, and bond covenants; some papers additionally use market-related proxies based on *trading activity* such as trade volume, number of trades, number of dealers, and the bid-ask spread, see, e.g., Elton, Gruber, Agrawal, and Mann (2001), Collin-Dufresne, Goldstein, and Martin (2001), Perraudin and Taylor (2003), Eom, Helwege, and Huang (2004), Liu, Longstaff, and Mandell (2004), Houweling, Mentink, and Vorst (2005), Longstaff, Mithal, and Neis (2005), De Jong and Driessen (2006), Edwards, Harris, and Piwowar (2007), and Acharya, Amihud, and Bharath (2009). Essentially, all

these papers find that liquidity is priced in bond yields. However, they find different magnitudes and varying importance of these basic liquidity proxies, but mostly at the market-wide level.

In the more recent literature, several alternative *liquidity measures* that are estimators of transaction costs, market impact, or turnover, have been proposed and applied to analyze liquidity in the corporate bond market at the level of individual bonds. The *Roll measure* (see Roll, 1984; Bao, Pan, and Wang, 2011) interprets the subsequent prices as arising from the "bid–ask bounce": thus, the autocovariance in price changes provides a simple liquidity measure. A similar idea to measure transaction costs is proposed and implemented in the *LOT measure* proposed by Lesmond, Ogden, and Trzcinka (1999). The *Amihud measure* (see Amihud, 2002) relates the price impact of a trade to the trade volume. Trading activity itself is used in the *zero-return measure* based on the number of unchanged sequential prices and the *no-trade measure* based on time periods without trading activity (see, e.g., Chen, Lesmond, and Wei, 2007). Mahanti, Nashikkar, Subrahmanyam, Chacko, and Mallik (2008) propose another measure known as *latent liquidity* that is based on the institutional holdings of corporate bonds, which can be used even in the absence of transaction data. Jankowitsch, Nashikkar, and Subrahmanyam (2011) develop the *price dispersion measure*, which is based on the dispersion of market transaction prices of an asset around its consensus valuation by market participants.

Most of the early papers on bond market liquidity are based only on quotation data as reasonably complete transaction data were not available until a few years ago. However, some papers use restricted samples of the transaction data for certain parts of the corporate bond market to analyze liquidity, including Chakravarty and Sarkar (1999), Hong and Warga (2000), Schultz (2001), and Hotchkiss and Ronen (2002). Many more researchers focused on the issue of liquidity in the corporate bond market since the TRACE data on US corporate bond transactions started to become available in 2002. This new source of bond price information allows researchers to analyze many different aspects of the US corporate bond market; see, e.g., Edwards, Harris, and Piwowar (2007), Goldstein and Hotchkiss (2007), Mahanti, Nashikkar, Subrahmanyam, Chacko, and Mallik (2008), Ronen and Zhou (2009), Nashikkar, Subrahmanyam, and Mahanti (2011), Lin, Wang, and Wu (2011), and Jankowitsch, Nashikkar, and Subrahmanyam (2011).

It is especially interesting to examine how liquidity affects the corporate bond market in times of financial crisis. While much of the research on the current financial crisis is probably in progress, two recent papers do provide some early evidence on the impact of liquidity in the US corporate bond market. These include Bao, Pan, and Wang (2011) and Dick-Nielsen, Feldhütter, and Lando (2012).

Bao, Pan, and Wang (2011) use the TRACE data to construct the Roll measure as a proxy for liquidity. Using a sample of around 1,000 bonds that existed prior to October 2004, they show that illiquidity measured by the Roll measure is quite significant in this market and

much larger than would be predicted by the bid–ask bounce. They also show that their measure exhibits commonality across bonds, which tends to go up during periods of market crisis. Further, they relate the Roll measure to bond yield spreads in a cross-sectional regression setup and provide evidence that part of the yield spread differences across bonds is due to illiquidity.

Dick-Nielsen, Feldhütter, and Lando (2012) combine the TRACE data using straight bullet bonds (around 4,000 bonds), with accounting data and equity volatility, as proxies for credit risk. They use a panel regression based on quarterly data to study the effects of five different liquidity measures and the defined credit risk variables. In general, they find a significant effect of liquidity, which increased with the onset of the subprime crisis. However, their multivariate regression results show somewhat mixed results for different rating classes.

There are several important differences between these prior papers and our own research in this paper. First, we employ a much larger data set on transaction data on US corporate bonds than any prior papers, as our sample of 23,703 bonds basically covers the whole traded market. This is a major difference even compared with the recent work of Bao, Pan, and Wang (2011) and Dick-Nielsen, Feldhütter, and Lando (2012), who focus only on a certain, generally the more liquid, subsegment of the market. Second, our research explicitly covers two crisis periods, which are analyzed separately: the broader subprime crisis and the earlier, GM/Ford crisis, which affected particular segments of the US corporate bond market. We contrast the behavior of liquidity and its pricing in bond yield spreads during periods of crisis with more normal periods and analyze the interaction of credit and liquidity risk. Third, we include the additional information on the market's consensus valuation of bonds provided by Markit. These data permit us to estimate the price dispersion measure for the bonds in our sample and, thus, include an important additional measure of transaction costs. This liquidity proxy is particularly relevant for our research question, as transaction cost measures appear to be especially important in explaining liquidity in OTC markets.

## 3. Hypotheses

In this section, we provide an overview of the research questions we pose and the hypotheses we test in our research. Our approach is to examine the validity of specific arguments regarding the effect of liquidity in the US corporate bond market.

*H1: Liquidity is an important price factor in the US corporate bond market.*

As argued by Amihud and Mendelson (1986), investors with different trading horizons have different expected returns, after taking into account the transactions costs they will incur over their respective horizons. This phenomenon translates into a clientele effect (for securities in positive net supply) by which the more illiquid assets are cheaper and are held by investors with longer horizons relative to their liquid counterparts, which are held by those with shorter horizons. Duffie, Garleanu, and Pedersen (2007) and

Jankowitsch, Nashikkar, and Subrahmanyam (2011) argue that in OTC markets the liquidity premium is driven by transaction costs due to search frictions, inventory holding costs, and bargaining power. In the corporate bond market context, these frictions are reflected in the bond prices, whereby liquid bonds earn a lower expected return than illiquid bonds which are similar on other dimensions, such as bond features and risk characteristics.

The US corporate bond market is especially interesting in this respect, as liquidity differences across individual bonds seem to be rather pronounced: very few bonds are traded frequently, while most other bonds are hardly ever traded at all (see Mahanti, Nashikkar, Subrahmanyam, Chacko, and Mallik, 2008 for details of a cross-sectional comparison for the US corporate bond market). Moreover, trading in the US corporate bond market involves much higher transaction costs compared to related markets such as the stock market. Thus, we would expect a significant liquidity premium, as argued in Amihud and Mendelson (1986), and expect that our liquidity proxies can explain a significant part of bond yield spreads. Our aim is to quantify these liquidity effects as a priced factor.

*H2: Liquidity effects are more important in periods of financial distress.*

The liquidity premium in the corporate bond market can be expected to change over time depending on market conditions, especially during a financial crisis. Several arguments have been proposed in the literature regarding the behavior of agents in a crisis. For example, Duffie, Garleanu, and Pedersen (2007) propose that liquidity is more important in crisis periods, since inventory holding costs and search costs are higher, and also asymmetric information is a more important issue. Acharya, Amihud, and Bharath (2009) provide empirical support for this hypothesis arguing that banks face more stringent capital requirements when they hold illiquid assets and could find it more difficult to access liquidity during a crisis. Moreover, a greater proportion of investors could have shorter horizons in a crisis. For example, bond mutual funds and hedge funds could face the possibility of redemptions or are forced to meet value-at-risk requirements and margin calls and, therefore, wish to hold more liquid assets to address this eventuality; see, e.g., Sadka (2010). Individual investors could shift more of their portfolios from illiquid to liquid assets as they turn more risk averse. For all these reasons, the gap in pricing between liquid and illiquid bonds, that are otherwise similar, may widen, resulting in a higher liquidity premium.

Thus, the second and main research question of this paper is whether the effect of liquidity is stronger during times of financial crises. We expect a particularly strong effect in the subprime crisis, when capital constraints became binding and inventory holding costs and search costs rose dramatically for all market participants.

*H3: Liquidity effects are more important for bonds with high credit risk.*

We study whether a bond's credit rating is related to liquidity effects by focusing on the difference between investment grade and speculative grade bonds. Acharya, Amihud, and Bharath (2009) show that liquidity is

substantially different between investment grade and speculative grade bonds using a regime switching model. They argue that in periods of financial crisis, all bond prices decline due to an increase of illiquidity. At the same time, a *flight-to-quality* effect is expected, which leads to lower price reactions among investment grade bonds. Chen, Lesmond, and Wei (2007) also provide empirical support for this argument. Thus, we expect stronger liquidity effects for speculative grade bonds and to find flight-to-quality effects in periods of crisis.

## 4. Data description

In this section, we present the unique data set we have at hand for this liquidity study covering basically the whole US corporate bond market. Our data are drawn from several different sources:

1. Transaction data from the Trade Reporting and Compliance Engine (TRACE).
2. Consensus market valuations from Markit.
3. Credit ratings from Standard & Poor's.
4. Bond characteristics from Bloomberg.
5. Treasury and swap data from Bloomberg.

Our time period starts with the date when TRACE was fully implemented on October 1, 2004, and covers the period until December 31, 2008. TRACE provides detailed information about all transactions in the US corporate bond market, i.e., the actual trade price, the yield based on this price, as well as the trade volume measured in US dollars for each transaction.[1] Phase I of TRACE was launched by the Financial Industry Regulatory Agency (FINRA) in July 2002, with the aim of improving transparency in the US corporate bond market. This phase covered only the larger and generally higher credit quality issues. Phase II expanded the coverage and dissemination of information to smaller investment grade issues. Since the final Phase III was implemented on October 1, 2004, transactions of essentially all US corporate bonds have been reported. Hence, the TRACE database has been reasonably complete since its final implementation. This data source is almost unique for an OTC market, since in many other cases, price information usually must be obtained either from an individual dealer's trading book, which provides a very limited view of the market, or by using bid–ask quotations instead. In the US corporate bond market, reporting of any transaction to TRACE is obligatory for broker-dealers and follows a set of rules approved by the Securities and Exchange Commission (SEC), whereby all transactions must be reported within a time frame of 15 minutes.

We use the filters proposed by Dick-Nielsen (2009) for the TRACE data to eliminate potentially erroneous data points.[2] In addition, we follow Edwards, Harris, and Piwowar (2007) and apply a *median filter* and a *reversal filter* to eliminate further potential data errors. While the median filter identifies potential outliers in reported prices within a certain time period, the reversal filter identifies unusual price movements.[3] Eliminating any potential errors in the reported transactions reduces the number of reported trades by roughly 5.5% to 23.5 million trades. This results in a TRACE data sample consisting of 34,822 bonds from 4,631 issuers.

An important additional source for the market's valuation of a bond is obtained from Markit Group Limited, a leading data provider, specialized in security and derivatives pricing. One of its services is to gather, validate, and distribute end-of-day composite bond prices from dealer polls. Up to 30 contributors provide data from their books of record and from feeds to automated trading systems (see Markit Group Limited, 2006). These reported valuations are averaged for each bond after eliminating outliers, using their proprietary methodology. Hence, this price information can be considered as a market-wide average of a particular bond price, reflecting the market consensus. The Markit valuations are used by many financial institutions to mark their portfolios to market and have credibility among practitioners. In total, we have 5,522,735 Markit quotes, covering 28,145 bonds in our database.

To control for default risk, we use credit ratings from Standard & Poor's (S&P). We focus on long-term, issue credit ratings as the market's current judgment of the obligor's creditworthiness with respect to a specific financial obligation. It should be noted, that in our descriptive statistics of the rating variable, we assign integer numbers to ratings, i.e., AAA=1, AA+=2, etc., to measure the "average" rating of certain groups of bonds or time periods. Our time period contains 25,464 bonds, which have at least one S&P credit rating each. Note that credit risk could be measured using alternative approaches. Two prominent examples come to mind: using CDS spreads in the context of a reduced-form credit risk model, as in Longstaff, Mithal, and Neis (2005) and Nashikkar, Subrahmanyam, and Mahanti (2011), or using accounting-based and equity-related data in a structural model context, as in Huang and Huang (2003). We do not incorporate such proxies as this information is generally only available for a very small (presumably more liquid) segment of the market and our intention is to explicitly analyze liquidity effects for the whole market. In addition, the impact of the liquidity on these data inputs would also have to be taken into account, rendering the analysis far more complex, and hence, prone to additional error. This issue is particularly true during periods of crisis when liquidity and counterparty risk considerations are exacerbated in the pricing of CDS as well as equity contracts. Hence, we apply the more parsimonious approach of using only the credit ratings, with their admitted

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[1] The reported trade volume is capped at $1 million for high yield and unrated bonds and at $5 million for investment grade bonds.

[2] As pointed out by Dick-Nielsen (2009), care should be exercised when accounting for order cancelations or corrections in the TRACE data. To mitigate the errors that result from these issues, Dick-Nielsen (2009) suggests that the trade data need to be "cleaned up" using error filters.

[3] The median filter eliminates any transaction where the price deviates by more than 10% from the daily median or from a nine-trading-day median centered at the trading day. The reversal filter eliminates any transaction with an absolute price change deviating from the lead, lag, and average lead/lag price change by at least 10%.

shortcomings, in terms of their own error and failure to anticipate changes in credit risk.

For each of the bonds available in TRACE, we additionally obtain bond characteristics from Bloomberg. These bond characteristics include the issue date, maturity, age, coupon, amount issued, industry sector, and bond covenants. Most of these characteristics have been considered as simple liquidity proxies by previous studies. Furthermore, we use swap rates and Treasury rates for various maturities retrieved from Bloomberg as the benchmark for the risk-free interest rate curve to compute the corporate bond yield spreads.

Given these data sets, we generate a sample that is representative of the whole market by merging the daily trade observations from TRACE with end-of-day Markit-quotations, the available S&P ratings, and the bond characteristics. This sample covers 23,703 bonds of 3,261 firms. On average per day, we observe 5,423 traded bonds, 21,254 trades, and $7.563 billion in volume. Thus, our panel data set covers approximately 80% of the overall trading activity in the US corporate bond market. We find that the market coverage is at this high level throughout the observation period and, hence, is highly representative of the whole US corporate bond market including bonds with very low trading activity, which is a major difference compared to most other studies. Nevertheless, a considerable number of bonds is traded only very rarely. However, data limitations caused by this lack of trading activity should actually bias us against finding any clear liquidity effects at all.

## 5. Liquidity proxies

This section presents the various liquidity proxies that we use in the regression analysis as explanatory variables. A number of liquidity proxies have been proposed in the literature (see Section 2) which are not all equally viable, given the challenges of obtaining detailed and sufficiently frequent data in the relatively illiquid corporate bond market. Our data set allows us to compare the efficiency of most of these proposed proxies in this empirical study. We classify the available proxies into three groups: *bond characteristics*, *trading activity variables*, and *liquidity measures*.

Bond characteristics, such as the amount issued, are simple liquidity proxies which provide a rough indication about the potential liquidity of a bond. Trading activity variables, such as the number of trades, provide bond-specific information based on transaction data. Liquidity measures, such as the price dispersion and Amihud measure, are alternative estimators of transaction costs or market impact.[4]

All these liquidity proxies can either be calculated on a daily basis, if price information is observable for a particular bond, or are time-invariant (e.g., coupon), or change linearly with time (e.g., age). In the following subsections, we present the definitions of the various liquidity proxies that we use in our analysis and discuss the details of their computation.

### 5.1. Bond characteristics

The bond characteristics we consider as liquidity proxies are the *amount issued*, *coupon*, *maturity*, and *age*. These proxies, while admittedly crude measures, make intuitive sense. In general, we expect bonds with a larger amount issued to be more liquid and bonds with a larger coupon to be less liquid.[5] Bonds with long maturities (over 10 years) are generally considered to be less liquid since they are often bought by "buy-and-hold" investors, who trade infrequently. Similarly, we expect recently issued (on-the-run) bonds to be more liquid. We consider these measures to be important only for our cross-sectional analysis, as most of these are either constant (e.g., coupon) or change linearly (e.g., maturity) over time.

### 5.2. Trading activity variables

A bond's trading activity provides information about liquidity. In this sense, higher trading activity generally indicates higher liquidity. We consider the following trading activity variables: *number of trades*, *trade volume*, and *trading interval*. We compute the number of trades and the trade volume of a particular bond on each day from the trading information given by TRACE. The trading interval is the elapsed time (measured in days) since the last day a given bond was traded. Longer trade intervals indicate less trading activity and, thus, lower liquidity. Therefore, we expect liquidity to be higher for bonds with shorter time intervals between trading days.

### 5.3. Liquidity measures

#### 5.3.1. Amihud measure

This liquidity proxy is a well-known measure originally proposed for the equity market by Amihud (2002), which is conceptually based on Kyle (1985). It relates the price impact of trades, i.e., the price change measured as a return, to the trade volume measured in US dollars. The Amihud measure at day $t$ for a certain bond over a particular time period with $N_t$ observed returns is defined as the average ratio between the absolute value of these returns $r_j$ and its trading volumes $v_j$, i.e.,

$$\text{Amihud}_t = \frac{1}{N_t} \sum_{j=1}^{N_t} \frac{|r_j|}{v_j}. \tag{1}$$

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[4] We are aware that many studies without access to transaction data use the quoted bid–ask spread as a liquidity proxy. However, bid–ask spreads are, in general, only available for a small subsample representing the relatively larger issues. In a robustness check we find that bid–ask spreads from Bloomberg are of minor importance once transaction-based measures are considered, in the empirical specifications we investigate below. These results are not reported in this paper, but are available from the authors upon request.

[5] Note that the coupon *per se* is rather a crude proxy for credit risk. Once we adjust for credit risk (e.g., by using ratings), bonds with different coupons but with identical credit risk exhibit different levels of liquidity. However, as we are certainly not able to perfectly adjust for credit risk, the coupon cannot be viewed as a pure liquidity proxy.

A larger Amihud measure implies that trading a bond causes its price to move more in response to a given volume of trading, in turn, reflecting lower liquidity. We use the daily volume-weighted average TRACE prices to generate the returns $r_j$ and calculate the Amihud measure on a day-by-day basis.

### 5.3.2. Price dispersion measure

A new liquidity measure recently introduced for the OTC market is the price dispersion measure of Jankowitsch, Nashikkar, and Subrahmanyam (2011). This measure is based on the dispersion of traded prices around the market-wide consensus valuation. A low dispersion around the valuation indicates that the bond can be bought close to its fair value and, therefore, represents low trading costs and high liquidity, whereas high dispersion implies high transaction costs, and hence, low liquidity. This measure is derived from a market microstructure model and shows that price dispersion is the result of market frictions such as inventory risk for dealers and search costs for investors. It presents a direct estimate of trading costs based on transaction data. As in Jankowitsch, Nashikkar, and Subrahmanyam (2011), the traded prices are obtained from TRACE and the market valuations from Markit. The price dispersion measure is defined as the root mean squared difference between the traded prices and the respective market-wide valuation weighted by volume, i.e., for each day $t$ and a particular bond, it is given by

$$\text{Price dispersion}_t = \sqrt{\frac{1}{\sum_{k=1}^{K_t} \nu_k} \sum_{k=1}^{K_t} (p_k - m_t)^2 \nu_k}, \qquad (2)$$

where $p_k$ and $\nu_k$ represent the $K_t$ observed traded prices and their trade volumes on date $t$ and $m_t$ is the market-wide valuation for that day. Hence, the price dispersion indicates the potential transaction cost for a trade.

### 5.3.3. Roll measure

This measure developed by Roll (1984) shows that, under certain assumptions, adjacent price movements can be interpreted as a bid–ask bounce which, therefore, allows us to estimate the effective bid–ask spread. This bid-ask bounce results in transitory price movements that are serially negatively correlated and the strength of this covariation is a proxy for the round-trip costs for a particular bond, and hence, a measure of liquidity. More precisely, the Roll measure is defined as

$$\text{Roll}_t = 2\sqrt{-\text{Cov}(\Delta p_t, \Delta p_{t-1})}, \qquad (3)$$

where $\Delta p_t$ is the change in prices from $t-1$ to $t$. We compute the Roll measure based on the daily volume-weighted bond prices $p_t$ from the TRACE data set, where we use a rolling window of 60 days and require at least eight observations to determine the covariance.[6]

### 5.3.4. Zero-return measure

The zero-return measure indicates whether we observe a zero price movement between trading days. The zero-return measure is set to one, if we find an unchanged price, and is set to zero, otherwise. Bond prices that stay constant over long time periods are likely to be less liquid, as the information could be stale. Obviously, such a measure can only be based on price quotations or valuations, such as Markit quotes in our case. Constant price information in these data sources reveal illiquidity as unchanged quotations could indicate an incomplete coverage of the bond.

## 6. Methodology

This section outlines our general approach to measuring the impact of liquidity and credit risk on pricing in the US corporate bond market. We present here our definitions of the bond yield spread and define the subperiods of interest to test our hypotheses about financial crises. We then present the specifications for our panel data regressions to explore the time-series properties, and the Fama-MacBeth regressions to explore the cross-sectional properties of our data. We use these specifications to study market-wide liquidity effects and analyze subsegments of the market, where we compare investment grade and speculative grade bonds.

### 6.1. Bond yield spread

The dependent variable in our setup is the corporate bond yield spread, represented by the yield differential relative to that of a risk-free benchmark. We define this benchmark as the yield of a risk-free zero-coupon bond with a maturity equal to the duration of the corporate bond. We compute this duration based on the reported yield in the TRACE database and the corporate bond's cash flow structure. Note that we do not incorporate adjustments for optionalities or covenants included in the bond structure to determine the duration. Overall, yield spreads based on this duration adjustment can be considered as a proxy for the zero-coupon yield spread taken from a more complete pricing model.[7]

We use both the Treasury yield curve and the swap curve as risk-free benchmarks to calculate the bond yield spreads. We find that the general structure of the resulting yield spread is basically identical for both benchmarks. However, as expected, the yield spread based on the swap curve is shifted downwards compared to the spread based on the Treasury curve, indicating that the swap curve represents market participants with AA

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[6] If positive covariances occur, we set the Roll measure to zero. Since we interpret the Roll measure as a transaction cost metric, we think it is quite reasonable to bound this measure at zero. However, we also compared the results with two alternatives: preserving the sign in the spirit of Roll (1984) (i.e., positive covariance translates into a negative

(footnote continued)

Roll measure) and not using these observations at all. Neither of these changes affects the qualitative nature of our results.

[7] Given the complexity of these models and the limited information available for their calibration, we presume that the resulting zero-coupon yield spread would not improve the economic interpretation of our results, in general. To test this assumption, we have employed regression analyses for a subsample of straight coupon, bullet bonds without any option features. For this subsample, we find similar results, confirming our conjecture.
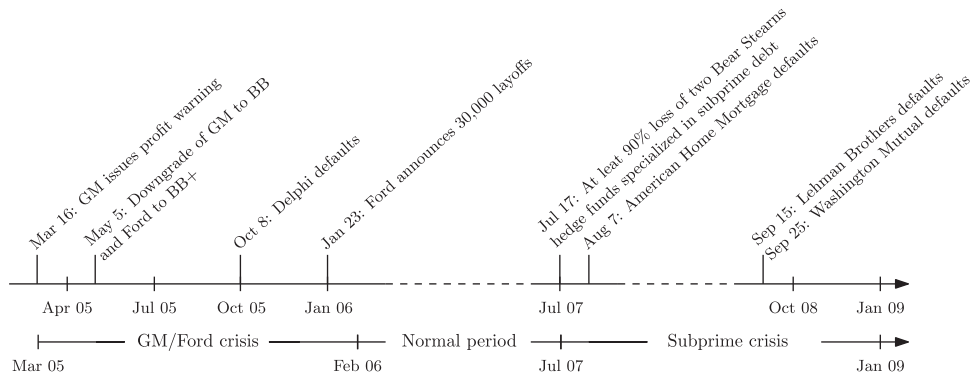
**Fig. 1.** Timeline showing important events in the US corporate bond market, since March 2005. Based on these events, we identified three different regimes: the GM/Ford crisis between March 2005 and January 2006, the normal period from February 2006 to June 2007, with no exceptional events, and the subprime crisis that started in July 2007.

ratings with greater credit risk, while the Treasury curve represents lower credit risk. We conduct all our regression analysis on both spread series; however, as the results are basically identical, we report only the results for the spreads against the Treasury benchmark in the empirical results section.

We calculate the bond yield spread for every price observation in the TRACE data set. Thus, we can have more than one spread observation for a given bond on a particular day, since there can be multiple trades for the bond on that day. Hence, to get a single value for the yield spread for each day, we estimate the bond spread from the individual observations by calculating a volume-weighted average for the day, i.e., we implicitly assume that the spread information is reflected more strongly in large trades.

### 6.2. Subperiods of interest

We are interested in how the explanatory power of the independent variables differs in financial crises compared to normal market environments. Therefore, we define the following three subperiods: The *GM/Ford crisis* (March 2005–January 2006) when a segment of the corporate bond market was affected, the *subprime crisis* (July 2007–December 2008), which was much more pervasive across the corporate bond market, and the *normal period* in between (February 2006–June 2007). We choose the start and end dates of the subperiods based on exceptional events that are believed to have affected market conditions (see Fig. 1).[8]

### 6.3. Panel data regression

We rely on a panel data regression approach to analyze bond yield spread changes. We use first differences, as we observe that yield spreads are integrated. Since we observe autocorrelated yield spread changes, we add one

autoregressive parameter to our specifications.[9] Of course, in this difference specification, the static bond characteristic variables drop out. Thus, our panel consists of the pooled time-series of the first differences of the bond yield spread as the dependent variable and the trading activity variables and liquidity measures as the explanatory variables. Furthermore, we add changes in rating class dummies to the regression to consider credit risk-related effects on the yield spread:

$$\Delta(\text{Yield spread})_{i,t} = a_0 + a_1 \cdot \Delta(\text{Yield spread})_{i,t-1}$$
$$+ \boldsymbol{a_2} \cdot \Delta(\text{Trading activity variables})_{i,t}$$
$$+ \boldsymbol{a_3} \cdot \Delta(\text{Liquidity measures})_{i,t}$$
$$+ \boldsymbol{a_4} \cdot \Delta(\text{Rating dummies})_{i,t} + \epsilon_{i,t}. \quad (4)$$

Our basic time-series data are at a daily frequency. However, because of computational restrictions due to the large sample size, we create weekly averages of all variables from the daily data for each bond. Thus, all the time-series regression results presented in the empirical results section below are based on weekly data. Note that we use logarithmic values of the traded volume in the regressions, as is common practice.

### 6.4. Fama-MacBeth cross-sectional regression

These regressions are in levels rather than in changes and, therefore, allow a cross-sectional analysis. In particular, we can test for the importance of static bond characteristics in explaining the cross-sectional differences in yield spread. The regressions are performed with the following structure:

$$(\text{Yield spread})_{i,t} = a_0 + \boldsymbol{a_1} \cdot (\text{Bond characteristics})_{i,t}$$
$$+ \boldsymbol{a_2} \cdot (\text{Trading activity variables})_{i,t}$$
$$+ \boldsymbol{a_3} \cdot (\text{Liquidity measures})_{i,t}$$
$$+ \boldsymbol{a_4} \cdot (\text{Rating dummies})_{i,t} + \epsilon_{i,t}. \quad (5)$$

We run this regression based on weekly averages from the daily data of all variables. Thus, we have the

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[8] Alternative definitions of these subperiods could have been used. Therefore, as a stability test, we varied the start and end dates of the subperiods by up to one month. However, we find similar results, and hence, report only results for the three subperiods defined above.

[9] We investigated alternative specifications of the time-series model, including different lags of the autoregressive parameters, and find that the results are very similar for these specifications.

**Table 1**
This table reports the cross-sectional descriptives statistics (5th, 25th, 50th, 75th, and 95th quantiles, mean, and standard deviation) for the yield spread, credit rating, bond characteristics, and liquidity proxies. The corporate bond yield spread is measured relative to the US Treasury bond yield curve and given in percentage points. We use credit ratings from Standard & Poor's where we assign integer numbers to ratings, i.e., AAA=1, AA+=2, etc., to measure the average rating. The liquidity proxies are classified into three groups: bond characteristics (amount issued, coupon, maturity, and age), trading activity variables (traded volume, number of trades, and time interval between trades), and liquidity measures (Amihud, price dispersion, Roll, and zero-return measure). For time-varying variables, the statistics are first averaged across time for each individual bond. The data set consists of 23,703 US corporate bonds traded over the period October 2004 to December 2008.

|  |  | $Q_{0.05}$ | $Q_{0.25}$ | $Q_{0.50}$ | $Q_{0.75}$ | $Q_{0.95}$ | Mean | Std. dev. |
|---|---|---|---|---|---|---|---|---|
|  | Yield spread (%) | 0.52 | 1.17 | 1.92 | 3.67 | 7.67 | 2.87 | 2.95 |
|  | Rating | 1.30 | 5.00 | 7.03 | 11.50 | 15.46 | 8.00 | 4.14 |
| Bond characteristics | Amount issued (bln) | 0.00 | 0.01 | 0.20 | 0.40 | 1.25 | 0.32 | 0.50 |
|  | Coupon (%) | 3.03 | 5.00 | 5.97 | 7.00 | 9.13 | 5.98 | 1.87 |
|  | Maturity (yr) | 0.45 | 1.83 | 5.20 | 9.74 | 24.87 | 7.62 | 7.63 |
|  | Age (yr) | 0.47 | 1.52 | 2.77 | 4.53 | 10.36 | 3.80 | 3.61 |
| Trading activity variables | Volume (mln) | 0.02 | 0.05 | 0.39 | 1.74 | 5.23 | 1.35 | 2.53 |
|  | Trades | 1.45 | 2.00 | 2.46 | 3.25 | 8.44 | 3.47 | 4.50 |
|  | Trading interval (dy) | 1.50 | 2.72 | 4.48 | 5.72 | 7.80 | 4.46 | 2.18 |
| Liquidity measures | Amihud (bp per mln) | 0.68 | 9.99 | 38.33 | 103.01 | 260.68 | 78.38 | 137.21 |
|  | Price dispersion (bp) | 1.69 | 16.08 | 33.64 | 58.00 | 106.84 | 41.53 | 35.56 |
|  | Roll (bp) | 24.48 | 82.99 | 155.98 | 259.69 | 420.86 | 185.12 | 144.69 |
|  | Zero-return (%) | 0.00 | 0.00 | 0.01 | 0.02 | 0.16 | 0.03 | 0.08 |

cross-sectional regression result for each week and we use the Fama-MacBeth procedure to report the regression parameters and *t*-statistics. We present the results of this procedure for the subperiods defined earlier. This approach allows us to analyze liquidity effects in times of regular market conditions and financial crises, across bonds. Again, we use logarithmic values of the traded volume and the amount issued in the regressions.

## 7. Results

### 7.1. Descriptive statistics

This section provides summary statistics for the US corporate bond market based on our matched data sample of 23,703 bonds for the period October 2004 to December 2008 (see Section 4). Table 1 reports the cross-sectional variation of the main variables used in our empirical analysis, i.e., the yield spread, the credit rating, and the liquidity proxies (bond characteristics, trading activity variables, and liquidity measures). For time-varying explanatory variables, the statistics are computed as the time averages for each individual bond. The table reports the 5th, 25th, 50th, 75th, and 95th percentiles, as well as the mean and standard deviation of each variable. It provides an aggregate picture of the substantial cross-sectional variation of the variables.

The yield spread between the 5th and 95th percentiles ranges from 52 to 767 basis points (bp) with a mean of 287 bp. Part of this enormous variation is obviously due to credit risk given that our sample contains bonds with credit ratings all the way from AAA (=1) to C (=21). The average credit rating is roughly eight which corresponds to BBB+ and a standard deviation of approximately four rating notches.

As is to be expected, there is a reasonable variation in the bond characteristics of amount issued, coupon,

maturity, and age across bonds, e.g., the amount issued varies from just below $5 million to $1.25 billion between the 5th and 95th percentiles. Regarding trading activity variables, we find that the average frequency of bond trading is every 4.5 days. For a bond that is traded on a particular day, we observe an average of 3.5 trades with an average trade size of roughly $1.4 million dollars, with substantial cross-sectional variation.

Regarding the liquidity measures, the mean value of the Amihud measure is 78.4 bp per million, which indicates that trading one million dollars in a particular bond shifts the price by 78.4 bp, on average. The variation in liquidity across bonds is remarkably high and ranges between 0.7 and 260.7 bp, a factor of around 400 for the 5th and the 95th percentiles. The price dispersion indicates the trading cost of a single transaction for which we observe a mean of around 41.5 bp with high variation across bonds as well. For the Roll measure, which corresponds to the round-trip costs, we observe an average value of 185.1 bp. Interestingly, this mean value is more than twice as large as the mean value of the price dispersion measure. Considering the zero-return measure, we find that these are mostly zero, indicating only very few observations of stale prices or quotations.

Table 2 presents the correlations between the various liquidity proxies within our panel data. Overall, we find the expected patterns: in general, there is positive correlation among the trading activity variables (e.g., the correlation between volume and number of trades is 0.51) and among the liquidity measures estimating trading costs (e.g., the correlation between Amihud, Roll, and price dispersion measure is between 0.02 and 0.2). However, the general level of correlation appears to be relatively low, especially for the liquidity measures. Thus, correlation measured at the individual bond level over time shows that the liquidity proxies have substantial idiosyncratic movements. This result suggests that the

**Table 2**

This table presents the correlation matrix of bond characteristics (amount issued, coupon, maturity, and age), trading activity variables (traded volume, number of trades, and time interval between trades), and liquidity measures (Amihud, price dispersion, Roll, and zero-return measure) based on the panel data for pairwise complete observations. The data set consists of weekly averages of all variables and consists of 23,703 US corporate bonds traded over the period October 2004 to December 2008.

| | Amount issued | Coupon | Maturity | Age | Volume | Trades | Trading interval | Amihud | Price dispersion | Roll | Zero-return |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Amount issued | 1.00 | | | | | | | | | | |
| Coupon | −0.01 | 1.00 | | | | | | | | | |
| Maturity | −0.05 | 0.14 | 1.00 | | | | | | | | |
| Age | −0.12 | 0.20 | −0.03 | 1.00 | | | | | | | |
| Volume | 0.46 | 0.03 | 0.05 | −0.13 | 1.00 | | | | | | |
| Trades | 0.46 | −0.02 | −0.03 | −0.01 | 0.51 | 1.00 | | | | | |
| Trading interval | −0.28 | −0.02 | 0.03 | 0.03 | −0.15 | −0.17 | 1.00 | | | | |
| Amihud | −0.13 | −0.01 | 0.09 | 0.03 | −0.09 | −0.07 | 0.11 | 1.00 | | | |
| Price dispersion | 0.06 | 0.08 | 0.28 | 0.01 | 0.01 | 0.14 | −0.11 | 0.02 | 1.00 | | |
| Roll | −0.29 | 0.03 | 0.29 | 0.08 | −0.21 | −0.13 | 0.15 | 0.19 | 0.20 | 1.00 | |
| Zero-return | −0.04 | 0.14 | −0.01 | −0.04 | −0.02 | −0.06 | −0.01 | −0.03 | −0.01 | −0.05 | 1.00 |

various liquidity proxies are measuring somewhat different aspects of liquidity empirically, although at a conceptual level they are related.[10] Therefore, for our empirical work, the issues of multicollinearity may not be as severe as one may suspect, at first glance. Note that once correlations in our sample are measured at a more aggregate level (e.g., averaging across time or across bonds), the correlations are much higher. Thus, it is important not to analyze the bond market based solely on aggregated data, but also at the level of individual bonds, as we do here, to distinguish between the effects of the various liquidity proxies.

To gain a better understanding of the time-series behavior of the bond yield spread over the whole time period, we compute the count-weighted average of the daily yield spreads over all bonds in our sample.[11] Fig. 2 shows this time-series of the market-wide average corporate bond yield spread, indicating the dramatic increase of the spread during the two crisis periods. Especially during the subprime crisis, we observe a sharp increase in the yield spread, which rose, on average, from around 2% to 10%, most likely indicating a far higher risk premium for illiquidity and credit risk.

### 7.2. Liquidity effects in corporate bond yield spreads

In this section, we examine whether liquidity effects are priced in the US corporate bond market. As argued in Section 3, we expect to find a significant liquidity premium in bond yield spreads. We base our conclusions in this section on our overall sample covering the whole market for the time period of our sample. We present the empirical results explaining the time-series properties of the bond yield spread changes with the credit ratings and the liquidity proxies introduced in Section 5, and using
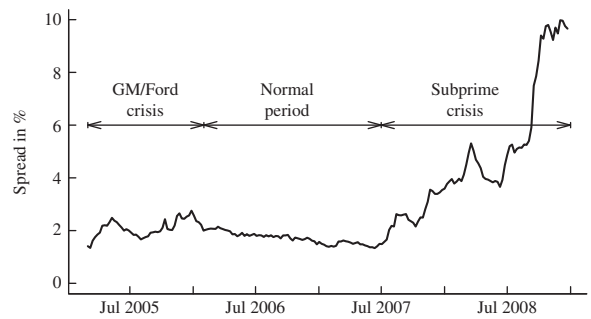
**Fig. 2.** This figure shows the market-wide corporate bond yield spread between October 2004 and December 2008 computed by averaging the bond yield spreads across bonds traded. The corporate bond yield spread is measured relative to the US Treasury bond yield curve and given in percentage points. The data set consists of 23,703 US corporate bonds traded over the period October 2004 to December 2008.

the panel data regression methodology presented in Section 6.

The regressions are based on a sample of data consisting of 691,016 bond-week observations. The results are shown in Table 3. This table presents four different specifications. In Regression 1, we use a specification without the liquidity proxies, which is a base case that can be compared to the other specifications, allowing us to explore the increase in explanatory power after including liquidity proxies. Note that there is reasonable explanatory power even in this specification, which includes the information contained in the dummy variables based on the credit ratings and the persistence of bond yield spreads in terms of first differences measured by the lagged term. The next three specifications present the results of the panel regressions using the liquidity proxies (i.e., trading activity variables and liquidity measures).[12] Regression 2 reports the results with the trading activity

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[10] Along the same lines, a principal component analysis (not reported here) shows that the liquidity proxies can only be represented by a relatively large number of components.

[11] We also examine the behavior of bond yield spreads, weighted by the volume of trading and by the amount outstanding of the individual bonds, both of which show a similar pattern.

[12] Since the regressions are based on the *change* in the bond yield spread, the static bond characteristics, such as coupon, drop out of the specification since they are fixed effects. Others, such as age, vary linearly with time and are absorbed in the constant term.

**Table 3**

This table reports the panel data regression models explaining the yield spread changes based on weekly averages of all variables:

$$\Delta(\text{Yield spread})_{i,t} = \alpha_0 + \alpha_1 \cdot \Delta(\text{Yield spread})_{i,t-1} + \alpha_2 \cdot \Delta(\text{Volume})_{i,t} + \alpha_3 \cdot \Delta(\text{Trades})_{i,t} + \alpha_4 \cdot \Delta(\text{Trading interval})_{i,t}$$

$$+ \alpha_5 \cdot \Delta(\text{Amihud})_{i,t} + \alpha_6 \cdot \Delta(\text{Price dispersion})_{i,t} + \alpha_7 \cdot \Delta(\text{Roll})_{i,t} + \alpha_8 \cdot \Delta(\text{Zero-return})_{i,t} + \sum_{k=1}^{21} \beta_k \cdot \Delta(\text{Rating dummy})_{i,t,k} + \epsilon_{i,t}.$$

The yield spread change is explained by the change in the lagged yield spread, trading activity variables (traded volume, number of trades, and time interval between trades), liquidity measures (Amihud, price dispersion, Roll, and zero-return measure), and rating dummies to control for credit risk. The corporate bond yield spread is measured relative to the US Treasury bond yield curve. In Regression (1) we use a specification without the liquidity proxies. Regression (2) reports the results with the trading activity variables only, while Regression (3) reports them with the liquidity measures only. In Regression (4) we add both types of liquidity proxies. The $t$-statistics are given in parentheses and are calculated from Newey and West (1987) standard errors, which are corrected for heteroskedasticity and serial correlation. In addition, the table also reports each model's $R^2$ and the number of observations. The data set consists of 23,703 US corporate bonds traded over the period October 2004–December 2008.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Intercept | 0.0731*** | 0.0726*** | 0.0721*** | 0.0717*** |
| | (73.6195) | (76.4741) | (76.0680) | (77.1532) |
| $\Delta(\text{Yield spread})_{i,t-1}$ | −0.2853*** | −0.2825*** | −0.2816*** | −0.2797*** |
| | (73.6195) | (−44.1891) | (−43.7139) | (−44.0573) |
| $\Delta(\text{Volume})_{i,t}$ | | −0.0204*** | | −0.0108*** |
| | | (−23.2748) | | (−12.9274) |
| $\Delta(\text{Trades})_{i,t}$ | | 0.0067*** | | 0.0054*** |
| | | (16.0245) | | (12.8891) |
| $\Delta(\text{Trading interval})_{i,t}$ | | 0.0068*** | | 0.0070*** |
| | | (19.4614) | | (20.2071) |
| $\Delta(\text{Amihud})_{i,t}$ | | | 0.0502*** | 0.0477*** |
| | | | (35.0938) | (33.8126) |
| $\Delta(\text{Price dispersion})_{i,t}$ | | | 0.0744*** | 0.0702*** |
| | | | (26.7098) | (25.4506) |
| $\Delta(\text{Roll})_{i,t}$ | | | 0.0510*** | 0.0512*** |
| | | | (16.0256) | (16.1036) |
| $\Delta(\text{Zero-return})_{i,t}$ | | | −0.0774*** | −0.0696*** |
| | | | (−8.4762) | (−7.6153) |
| $\Delta(\text{Rating dummies})$ | Yes | Yes | Yes | Yes |
| $R^2$ | 0.0735 | 0.0766 | 0.0839 | 0.0856 |
| Observations | 691,016 | 691,016 | 691,016 | 691,016 |

variables only, while Regression 3 reports them with the liquidity measures only. Regression 4 includes both types of liquidity proxies.

Focusing on the model that includes both types of proxies, the results of Regression 4 show that all the liquidity proxies are statistically significant in explaining the changes in the bond yield spreads. Among the trading activity variables, changes in the volume and trading interval have the highest $t$-statistics, while among the liquidity measures, changes in the Amihud measure and the price dispersion measure are most important. Interestingly, despite the correlation across the liquidity measures, they are sufficiently different across bonds and time that they are all incrementally relevant in explaining the changes in the bond yield spreads. All variables have the expected signs except for two liquidity proxies: the number of trades and the zero-return measure. Regarding the zero-return measure, the economic significance of this measure is very low, as discussed below. Thus, we assume that this measure might not be meaningful. As for the number of trades, we find that an increase in the number of trades increases the yield spread. This result can arise if, in times of crisis, regular trades are split up in smaller trades due to a general reduction in trade size or sellside

pressure, as more institutional orders are broken up to be placed in the market. This aspect will be analyzed in the next section.

In terms of $R^2$, we find a relative improvement of about 4.2% when the trading activity variables are added to Regression 1. When we add the liquidity measures to Regression 1, we find an additional relative improvement of 9.5% in the $R^2$, showing that liquidity measures are more important compared to the trading activity variables. Overall, we find that liquidity effects account for approximately 14% of the explained market-wide corporate yield spread changes.

The Amihud measure turns out to be the most important explanatory variable in these regressions in economic terms. A one standard deviation change in the Amihud measure explains about 6.1 basis points of the change in the bond yield spread in Regression 4.[13] Similar statistics for the price dispersion measure and the Roll measure are 3.4 bp and 3.1 bp, respectively. The impact of the trading

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[13] Note that the calculation of the economic significance is based on the standard deviation of the first differences of the variables. Due to space limitations we do not report details concerning these statistics for the first differences.

interval, volume, and number of trades are 2.5, 1.8, and 1.5 bp, respectively. The smallest impact is provided by the zero-return measure (0.8 bp), which seems not to be particularly relevant given its low economic significance. Considering all liquidity proxies together, a one standard deviation move in the direction of greater illiquidity in all proxies would increase the yield spread by 19.2 bp. This effect is important when compared with the volatility of the yield spread changes of 75.6 bp.[14,15]

Overall, we find in this analysis that liquidity is an important factor driving yield spread changes. Liquidity measures as well as trading activity variables can explain a fair proportion of bond yield spread changes; in particular, liquidity measures estimating trading costs seem to be more important than pure trading activity measures.

### 7.3. Liquidity effects in periods of financial distress

In this section, we explore whether the effect of liquidity is stronger during times of financial crises. As argued in Section 3, we expect that liquidity is an even more important factor in times of distress. To focus on the role of liquidity in financial crises, we analyze three different subperiods of our overall sample. We present the results for the two different crisis periods (the GM/Ford crisis and the subprime crisis) and compare them with those for the period in between, which can be considered as a period with more normal market conditions. We first provide evidence on the descriptive statistics of the key variables for the three subperiods, and then draw our main conclusions based on the panel data and Fama-MacBeth regressions introduced in Section 6.

The analysis of the averages of the variables in these three subperiods allows us to gain some important insights into the causes of the variation (see Table 4). The top panel of the table presents the average yield

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[14] Since credit ratings might adjust slowly compared to changes in credit risk, part of the explanatory power of the liquidity variables in our regressions could result because these variables might be proxies for changes in credit risk. As a robustness check, we test whether adding future rating changes (i.e., assuming perfect foresight) to the regressions affects the coefficients of the liquidity variables. In our tests (the results of which are not reported here to conserve space), we add weekly rating changes for each of the next 12 weeks to the regression equation in column 4 of Table 3. We find that future rating changes are statistically significant, i.e., ratings indeed change slowly. More importantly, however, we find the same results as in the original regression for the liquidity variables, i.e., "perfect-foresight" rating information does *not* take explanatory power away from the liquidity variables. Thus, our original results are confirmed and there is no evidence that the liquidity variables are proxies for credit risk information. Rather, future rating changes explain part of the current changes in yield spreads, *in addition to* changes in the liquidity variables. Furthermore, we test whether the liquidity variables can forecast future rating changes. Again, we find no evidence for this conjecture.

[15] As a robustness check for the use of ratings as a credit risk proxy, we instead use CDS spreads. We are able to match a small sample (representing the rather more liquid issues) with 5-year CDS spreads obtained from Markit. We then repeat our regression analysis using this CDS spread variable. The $R^2$ is only marginally improved in these regressions and for our liquidity measures, we find essentially the same results as in the analysis based on ratings, i.e., the coefficients and statistical significance stay at the same levels, thus strengthening the robustness of our results.

spread and the credit rating as well as information about the average daily market-wide trading activity (i.e., number of traded bonds, trades, and volume). The bottom panel provides the liquidity proxies computed for each subperiod.

The average yield spread in the normal period of 1.9% is less than in the GM/Ford crisis with 2.3%, and even less so than in the subprime crisis with 5.0%, documenting the strong impact of this crisis on yield spreads for the whole market. This evidence is also visible in Fig. 2. The averages of the market-wide trading activity variables are also illustrative. During both crises, trading activity is lower, in terms of the number of traded bonds and trade volume, than in the normal period. This reduction is more severe in the subprime crisis. For example, the number of bonds traded each day dropped during the subprime crisis, from roughly 6,000 on average, to a little under 5,200. The volume of trading showed a similar decline. Interestingly, during the subprime crisis, we find a larger number of trades indicating relatively smaller trade sizes for this period. Overall, the impact on trading activity is more severe in the subprime crisis, indicating that the liquidity changes that occurred during the two crisis periods were different. During the GM/Ford crisis, there was some shuffling of bond portfolios to account for the shifts in credit ratings, particularly in the automobile sector, resulting only in a minor reduction of trading activity. In contrast, during the subprime crisis, overall market liquidity was affected. This point is also evidenced by the changes in the average credit rating in the different subperiods. The credit rating of the average bond traded during the GM/Ford crisis was somewhat worse than during normal times. In contrast, the credit rating of the average bond traded during the subprime crisis was better than during normal times, indicating a *flight-to-quality* during the subprime crisis: the average rating is 8.8 (close to BBB) for the GM/Ford crisis, 8.4 (between BBB and BBB+) for the normal period, and 7.6 (between BBB+ and A−) for the subprime crisis.

The bottom panel of Table 4 presents similar evidence for the averages of the daily bond-level liquidity proxies. All liquidity measures indicate lower liquidity in times of crisis, especially for the subprime crisis. Considering the average price dispersion measure, as one example, we find that the average value is higher in both crises (46.4 bp in the GM/Ford crisis and 70.0 bp in the subprime crisis) compared to the normal period (39.8 bp). With regard to the trading activity variables, we find that the average daily volume and the trade interval at the bond-level stay approximately at the same level. However, the number of trades increases in both crises. These results are consistent with the level of market-wide trading activity, where we find that, in crises, trading takes place in fewer bonds, with a larger number of smaller size trades.

We next analyze the behavior of the changes in the yield spreads in the different subperiods, using the panel data regression, as in the previous section, incorporating dummy variables for the subperiods. More importantly, we include interaction terms between the liquidity proxies with the dummy variables for the two crisis subperiods. This setup allows us to analyze whether the

**Table 4**

Panel A shows the mean and standard deviation for the yield spread, credit rating, and daily market-wide trading activity in the three regimes (GM/Ford crisis, normal period, and subprime crisis). The corporate bond yield spread is measured relative to the US Treasury bond yield curve and given in percentage points. We use credit ratings from Standard & Poor's where we assign integer numbers to ratings, i.e., AAA=1, AA+=2, etc., to measure the average rating. The market-wide trading activity variables represent the number of traded bonds and trades, and the total trading volume per day. Panel B shows the mean and the standard deviation for the bond characteristics (amount issued, coupon, maturity, and age), trading activity variables (traded volume, number of trades, and time interval between trades), and liquidity measures (Amihud, price dispersion, Roll, and zero-return measure). The data set consists of 23,703 US corporate bonds traded over the period October 2004–December 2008.

*Panel A: Yield-spread, rating, and market-wide trading activity*

| | Mean | | | Standard deviation | | |
|---|---|---|---|---|---|---|
| | GM/Ford crisis | Normal period | Subprime crisis | GM/Ford crisis | Normal period | Subprime crisis |
| Yield spread (%) | 2.34 | 1.88 | 5.00 | 0.43 | 0.25 | 2.38 |
| Rating | 8.82 | 8.38 | 7.63 | 0.15 | 0.36 | 0.28 |
| Traded bonds (thd) | 5.23 | 5.92 | 5.19 | 0.54 | 0.42 | 0.53 |
| Market-wide trades (thd) | 20.43 | 20.71 | 22.77 | 2.34 | 2.05 | 4.67 |
| Market-wide volume (bln) | 7.65 | 8.06 | 6.99 | 1.32 | 1.41 | 1.56 |

*Panel B: Liquidity proxies*

| | Mean | | | Standard deviation | | |
|---|---|---|---|---|---|---|
| | GM/Ford crisis | Normal period | Subprime crisis | GM/Ford crisis | Normal period | Subprime crisis |
| Amount issued (bln) | 0.43 | 0.45 | 0.54 | 0.01 | 0.03 | 0.06 |
| Coupon (%) | 6.26 | 6.24 | 6.23 | 0.06 | 0.05 | 0.05 |
| Maturity (yr) | 7.57 | 7.75 | 8.31 | 0.13 | 0.20 | 0.18 |
| Age (yr) | 3.91 | 4.36 | 4.76 | 0.09 | 0.12 | 0.14 |
| Volume (mln) | 1.51 | 1.44 | 1.53 | 0.26 | 0.22 | 0.32 |
| Trades | 4.48 | 4.06 | 5.33 | 0.48 | 0.24 | 1.31 |
| Trading interval (dy) | 3.31 | 3.38 | 3.37 | 0.44 | 0.49 | 0.48 |
| Amihud (bp per mln) | 66.48 | 53.21 | 89.20 | 6.13 | 7.42 | 35.75 |
| Price dispersion (bp) | 46.36 | 39.75 | 70.02 | 4.33 | 1.83 | 21.84 |
| Roll (bp) | 164.28 | 142.82 | 209.77 | 9.57 | 10.57 | 52.34 |
| Zero-return (%) | 0.02 | 0.02 | 0.03 | 0.01 | 0.01 | 0.01 |

yield spread changes are more sensitive to liquidity changes in times of crisis. The results are presented in Table 5.

Overall, we find that liquidity is far more important in times of crisis. During the subprime crisis period, we find that nearly all the liquidity proxies have a statistically significantly higher impact on the changes in the bond yield spreads. Again, this result suggests that the various liquidity proxies are measuring somewhat different aspects of liquidity, as already indicated by the low level of correlation (see Section 7.1). The most important ones are the price dispersion and the Amihud measure, where both coefficients basically increase by around 100%. A similar result can be found for the GM/Ford period, although the effects are not quite as strong. We do not observe a statistically significant increase in all of the proxies for the GM/Ford period, and also, the magnitude of the increase seems to be smaller. However, an F-test shows that we can reject at a 1% level the hypothesis that the interaction terms for each period of crisis are jointly zero.

In terms of the improvement in $R^2$, we find that the inclusion of the interaction terms leads to an increase from 8.56% to 10.14%, compared to the analysis for the whole time-series, highlighting the importance of adding these terms. Considering the economic significance, a one standard deviation move in all proxies in the direction of

greater illiquidity would increase the spread by 11.6 bp in the normal period compared to 15.2 bp and 25.9 bp in the GM/Ford and subprime crisis periods, respectively. Thus, we find a far higher impact of the liquidity proxies in the crisis periods: the economic significance more than doubles during the subprime crisis and increases by approximately 30% in the GM/Ford crisis. The ranking of the economic importance of the individual liquidity proxies in the different time periods stays approximately the same, with the Amihud measure showing the highest impact in all periods (4.3 bp in the normal period, 5.2 bp in the GM/Ford period, and 7.7 bp in the subprime period). In sum, we find a significant increase, in both statistical and economic terms, of the liquidity component in the crisis periods.

To widen the scope of the analysis, we explore the cross-sectional differences in explaining the bond yield spreads considering all liquidity proxies using the Fama-MacBeth procedure to report the results for the three subperiods.[16] Again, rating class dummies are used to explain credit risk-related differences in spreads across bonds.

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[16] Since the t-statistics of the Fama-MacBeth regression could potentially be biased due to serial correlation, we additionally calculate results for a cross-sectional regression on time-series averages. This robustness check (not presented here) shows that the variables are, again, statistically significant.

**Table 5**

This table reports the panel data regression model explaining the yield spread changes based on weekly averages of all variables:

$$\Delta(\text{Yield spread})_{i,t} = \alpha_0 + \alpha_1 \cdot \Delta(\text{Yield spread})_{i,t-1} + \alpha_2 \cdot \Delta(\text{Volume})_{i,t} + \alpha_3 \cdot \Delta(\text{Trades})_{i,t} + \alpha_4 \cdot \Delta(\text{Trading interval})_{i,t}$$
$$+ \alpha_5 \cdot \Delta(\text{Amihud})_{i,t} + \alpha_6 \cdot \Delta(\text{Price dispersion})_{i,t} + \alpha_7 \cdot \Delta(\text{Roll})_{i,t} + \alpha_8 \cdot \Delta(\text{Zero-return})_{i,t} + (\text{GM/Ford dummy})_t \times [\beta_1 \cdot \Delta(\text{Yield spread})_{i,t-1}$$
$$+ \beta_2 \cdot \Delta(\text{Volume})_{i,t} + \beta_3 \cdot \Delta(\text{Trades})_{i,t} + \beta_4 \cdot \Delta(\text{Trading interval})_{i,t} + \beta_5 \cdot \Delta(\text{Amihud})_{i,t} + \beta_6 \cdot \Delta(\text{Price dispersion})_{i,t}$$
$$+ \beta_7 \cdot \Delta(\text{Roll})_{i,t} + \beta_8 \cdot \Delta(\text{Zero-return})_{i,t}] + (\text{Subprime dummy})_t \times [\gamma_1 \cdot \Delta(\text{Yield spread})_{i,t-1} + \gamma_2 \cdot \Delta(\text{Volume})_{i,t} + \gamma_3 \cdot \Delta(\text{Trades})_{i,t}$$
$$+ \gamma_4 \cdot \Delta(\text{Trading interval})_{i,t} + \gamma_5 \cdot \Delta(\text{Amihud})_{i,t} + \gamma_6 \cdot \Delta(\text{Price dispersion})_{i,t} + \gamma_7 \cdot \Delta(\text{Roll})_{i,t} + \gamma_8 \cdot \Delta(\text{Zero-return})_{i,t}]$$
$$+ \sum_{k=1}^{21} \delta_k \cdot \Delta(\text{Rating dummy})_{i,t,k} + \epsilon_{i,t}.$$

The yield spread change is explained by the change in the lagged yield spread, trading activity variables (traded volume, number of trades, and time interval between trades), liquidity measures (Amihud, price dispersion, Roll, and zero-return measure), and rating dummies to control for credit risk. Additionally, we add interaction terms between the subperiod dummies and the liquidity proxies. The corporate bond yield spread is measured relative to the US Treasury bond yield curve. The $t$-statistics are given in parentheses and are calculated from Newey and West (1987) standard errors, which are corrected for heteroskedasticity and serial correlation. We provide an $F$-test to test whether the interaction terms of the dummy variable with the liquidity proxies are jointly zero. The standard errors of the $F$-statistics are also Newey and West (1987) corrected. In addition, the table also reports the model's $R^2$ and the number of observations. The data set consists of 23,703 US corporate bonds traded over the period October 2004–December 2008.

| | | |
|---|---|---|
| Intercept | 0.0644*** | (70.5469) |
| $\Delta(\text{Yield spread})_{i,t-1}$ | −0.4318*** | (−47.6400) |
| $\Delta(\text{Volume})_{i,t}$ | −0.0137*** | (−15.8406) |
| $\Delta(\text{Trades})_{i,t}$ | 0.0030*** | (7.3703) |
| $\Delta(\text{Trading interval})_{i,t}$ | 0.0032*** | (7.8087) |
| $\Delta(\text{Amihud})_{i,t}$ | 0.0332*** | (19.7728) |
| $\Delta(\text{Price dispersion})_{i,t}$ | 0.0417*** | (13.0552) |
| $\Delta(\text{Roll})_{i,t}$ | 0.0080*** | (2.7972) |
| $\Delta(\text{Zero-return})_{i,t}$ | −0.0495*** | (−4.5916) |
| $(\text{GM/Ford dummy})_t \times \Delta(\text{Yield spread})_{i,t-1}$ | 0.0366*** | (3.6263) |
| $(\text{GM/Ford dummy})_t \times \Delta(\text{Volume})_{i,t}$ | −0.0028** | (−1.9884) |
| $(\text{GM/Ford dummy})_t \times \Delta(\text{Trades})_{i,t}$ | 0.0019*** | (2.6333) |
| $(\text{GM/Ford dummy})_t \times \Delta(\text{Trading interval})_{i,t}$ | −0.0040*** | (−6.1069) |
| $(\text{GM/Ford dummy})_t \times \Delta(\text{Amihud})_{i,t}$ | 0.0069*** | (2.6422) |
| $(\text{GM/Ford dummy})_t \times \Delta(\text{Price dispersion})_{i,t}$ | 0.0046 | (0.9846) |
| $(\text{GM/Ford dummy})_t \times \Delta(\text{Roll})_{i,t}$ | −0.0029 | (−0.7340) |
| $(\text{GM/Ford dummy})_t \times \Delta(\text{Zero-return})_{i,t}$ | 0.0239 | (1.3503) |
| $(\text{Subprime dummy})_t \times \Delta(\text{Yield spread})_{i,t-1}$ | 0.2260*** | (19.5475) |
| $(\text{Subprime dummy})_t \times \Delta(\text{Volume})_{i,t}$ | 0.0135*** | (6.5583) |
| $(\text{Subprime dummy})_t \times \Delta(\text{Trades})_{i,t}$ | 0.0039*** | (4.4352) |
| $(\text{Subprime dummy})_t \times \Delta(\text{Trading interval})_{i,t}$ | −0.0070*** | (−8.2507) |
| $(\text{Subprime dummy})_t \times \Delta(\text{Amihud})_{i,t}$ | 0.0266*** | (9.4860) |
| $(\text{Subprime dummy})_t \times \Delta(\text{Price dispersion})_{i,t}$ | 0.0529*** | (9.4447) |
| $(\text{Subprime dummy})_t \times \Delta(\text{Roll})_{i,t}$ | 0.0777*** | (13.6655) |
| $(\text{Subprime dummy})_t \times \Delta(\text{Zero-return})_{i,t}$ | −0.0824*** | (−3.5895) |
| $\Delta(\text{Rating dummies})$ | Yes | |
| $F$-stat. $\mathcal{H}_0$: (GM/Ford dummy) $\times \Delta$(Liquidity proxies) $= 0$ | | 7.8864 |
| $F$-stat. $\mathcal{H}_0$: (Subprime dummy) $\times \Delta$(Liquidity proxies) $= 0$ | | 64.3814 |
| Observations | | 691,016 |
| $R^2$ | | 0.1014 |

Table 6 provides the detailed results. The findings for the individual measures basically confirm the results of the panel data analysis, i.e., based on the $t$-statistics, liquidity measures are more important than trading activity variables; among the liquidity measures, the Amihud measure and the price dispersion measures are the most important proxies. As in the panel data analysis, we find an unexpected sign for the number of trades. Interestingly, the bond characteristics are important liquidity proxies in explaining the cross-section, as well. The most important one is the amount issued with a high overall $t$-statistic. Thus, high outstanding amounts

indicate higher liquidity. The coefficient of the coupon variable indicates higher liquidity for bonds with lower coupons. As expected, a longer time-to-maturity indicates lower liquidity for bonds in the normal period and in the GM/Ford crisis. However, the effect is negative for the subprime period. This result could indicate that, for "buy-and-hold" bonds with long maturities, the selling pressure was not as high as for bonds with shorter maturities resulting in lower spreads.

We find that a large part of the cross-sectional differences in the yield spread across bonds can be explained by our specification, indicated by an $R^2$ ranging between

**Table 6**
This table reports the cross-sectional regression models explaining the weekly averages of yield spreads based on the Fama-MacBeth procedure, estimated for the three regimes (GM/Ford crisis, normal period, and subprime crisis):

$$(\text{Yield spread})_{i,t} = \alpha_0 + \alpha_1 \cdot (\text{Amount issued})_{i,t} + \alpha_2 \cdot (\text{Coupon})_{i,t}$$
$$+ \alpha_3 \cdot (\text{Maturity})_{i,t} + \alpha_4 \cdot (\text{Age})_{i,t} + \alpha_5 \cdot (\text{Volume})_{i,t}$$
$$+ \alpha_6 \cdot (\text{Trades})_{i,t} + \alpha_7 \cdot (\text{Trading interval})_{i,t}$$
$$+ \alpha_8 \cdot (\text{Amihud})_{i,t} + \alpha_9 \cdot (\text{Price dispersion})_{i,t}$$
$$+ \alpha_{10} \cdot (\text{Roll})_{i,t} + \alpha_{11} \cdot (\text{Zero-return})_{i,t}$$
$$+ \sum_{k=1}^{21} \beta_k \cdot (\text{Rating dummy})_{i,t,k} + \epsilon_{i,t}.$$

The level of the yield spread is explained by bond characteristics (amount issued, coupon, maturity, and age), trading activity variables (traded volume, number of trades, and time interval between trades), liquidity measures (Amihud, price dispersion, Roll, and zero-return measure), and rating dummies to control for credit risk. The corporate bond yield spread is measured relative to the US Treasury bond yield curve. The $t$-statistics are given in parentheses and are calculated from Newey and West (1987) standard errors, which are corrected for heteroskedasticity and serial correlation. The table also reports each model's $R^2$, and the number of observations, representing the average number of bonds in the weekly cross-sectional regressions. The data set consists of 23,703 US corporate bonds traded over the period October 2004–April 2008.

| | GM/Ford crisis | Normal period | Subprime crisis |
|---|---|---|---|
| Intercept | 1.8476*** | 1.4437*** | 4.4413*** |
| | (16.2425) | (24.7543) | (3.7724) |
| $(\text{Amount issued})_{i,t}$ | −0.2539*** | −0.1824*** | −0.3250*** |
| | (−27.2371) | (−14.5819) | (−10.0361) |
| $(\text{Coupon})_{i,t}$ | 0.1567*** | 0.1142*** | 0.3506** |
| | (5.8644) | (27.9038) | (2.3741) |
| $(\text{Maturity})_{i,t}$ | 0.0110*** | 0.0177*** | −0.0599*** |
| | (3.6594) | (11.6510) | (−3.6648) |
| $(\text{Age})_{i,t}$ | 0.0053** | −0.0038 | −0.0430*** |
| | (2.4118) | (−0.8124) | (−3.2945) |
| $(\text{Volume})_{i,t}$ | 0.0013 | −0.0113** | 0.0432** |
| | (0.2851) | (−2.4204) | (2.4711) |
| $(\text{Trades})_{i,t}$ | 0.0452*** | 0.0316*** | 0.0335* |
| | (16.7888) | (13.4338) | (1.8092) |
| $(\text{Trading interval})_{i,t}$ | 0.0073*** | 0.0025** | 0.0062 |
| | (6.0842) | (1.9338) | (1.0638) |
| $(\text{Amihud})_{i,t}$ | 0.0864*** | 0.0718*** | 0.1696*** |
| | (28.4551) | (29.4427) | (12.5740) |
| $(\text{Price dispersion})_{i,t}$ | 0.3496*** | 0.2742*** | 0.4523*** |
| | (14.0045) | (18.8816) | (7.8913) |
| $(\text{Roll})_{i,t}$ | 0.0721*** | 0.0808*** | 0.1133* |
| | (8.2594) | (23.4407) | (1.9265) |
| $(\text{Zero-return})_{i,t}$ | 0.2371*** | 0.0387 | 0.6128 |
| | (4.1320) | (0.7780) | (1.5735) |
| $(\text{Rating dummies})$ | Yes | Yes | Yes |
| $R^2$ | 0.5905 | 0.6016 | 0.4966 |
| Observations | 3,815 | 3,845 | 3,187 |

49.7% and 60.2% in the three subperiods. The relative improvement in $R^2$ when considering the liquidity proxies (not presented in the tables) is around 10%. Interestingly, this ratio stays at the same level in all three subperiods. Thus, we cannot observe an increase of explanatory power due to liquidity proxies in the crisis periods. It seems that especially in the subprime crisis, the spread levels of *all* bonds increased, and thus, the cross-sectional variation did not change dramatically. Considering the

credit risk component of the yield spreads, the results clearly show the importance of the rating class dummies in the cross-section, as the remaining 90% of the explanatory power stems from this credit risk proxy. However, the lower $R^2$ in the subprime crisis results from a decrease in the explanatory power of the credit ratings, indicating that ratings could have become stale and reacted rather slowly to the increase in credit risk.

When analyzing the economic effect, we find that the cross-sectional variation of the yield spread measured by the standard deviation is 200.5 bp. With regard to the economic effect of the liquidity proxies based on the Fama-MacBeth regressions, we find statistically significant results, in terms of the coefficients of the relevant dummy variables: e.g., the Amihud measure and the price dispersion measure show strong effects; a one standard deviation change explains around 12.1 bp and 17.1 bp, respectively. The effects are more pronounced in the crisis periods compared to the normal period, e.g., for the price dispersion measure, the economic significance is 11.3 bp in the normal period vs. 15.4 bp and 24.4 bp in the GM/Ford and subprime crisis, respectively. Again, the zero-return measure shows the lowest economic effect of around 2.5 bp. A one standard deviation move in all the liquidity proxies in the direction of greater illiquidity would increase the spread by 98.9 bp in the normal period, compared to 111.9 bp and 153.1 bp, respectively, in the GM/Ford and subprime crisis periods. Thus, we find a higher impact of the liquidity proxies in the crises periods.[17]

Overall, the panel data and Fama-MacBeth regressions show a significant increase, in both statistical and economic terms, of the liquidity component in the crisis periods. We observe a dramatic increase in the liquidity premium, especially during the subprime crisis. Furthermore, we find that beyond liquidity measures and trading activity variables, simple bond characteristics, such as the amount issued, are also of importance in explaining liquidity.

### 7.4. Interaction effects between liquidity and credit ratings

In this section, we explore whether the effect of liquidity is related to credit risk measured by credit ratings. We divide the bonds into investment grade (AAA to BBB−) and speculative grade (BB+ to C/CCC), expecting the liquidity effects of speculative grade bonds to be more pronounced. This analysis allows us to explore the interaction between credit and liquidity risk. We expect to find lower liquidity effects for investment grade bonds compared to speculative grade bonds, as argued in Section 3.

Fig. 3 shows the yield spreads for the two time-series at the market-wide level. As expected, the bond yield

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[17] As a robustness test for causality between liquidity proxies and yield spreads, we estimated all cross-sectional regressions using liquidity variables lagged by one week instead of contemporaneous ones. We find that the lagged liquidity proxies show basically the same explanatory power as the contemporaneous proxies in the cross-sectional regressions.

spread for investment grade bonds is always lower than that for speculative bonds. However, we stress three important points here: First, the GM/Ford crisis is mainly reflected in the speculative grade yield spreads, as the GM/Ford bonds were downgraded to junk bond status and probably had spillover effects in the whole corporate bond market. Second, in the normal period, the difference between the spreads of investment and speculative grade bonds systematically shrank over time reflecting decreasing risk premiums, a phenomenon that has received widespread attention in the popular press. Third, in the
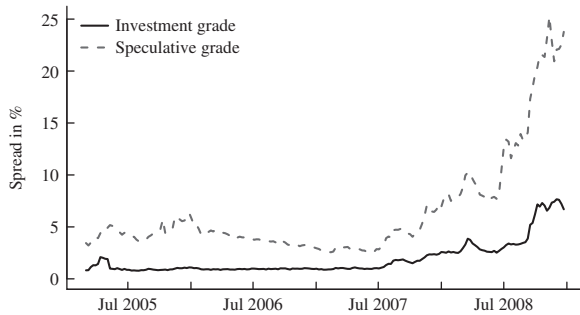


**Fig. 3.** This figure shows the corporate bond yield spread of investment grade and speculative grade bonds computed by averaging the bond yield spreads across bonds traded. The corporate bond yield spread is measured relative to the US Treasury bond yield curve and given in percentage points. The data set consists of 23,703 US corporate bonds traded over the period October 2004 to December 2008.

subprime crisis, the spread series for both investment and speculative grade bonds increased dramatically.

Table 7 (Panel A) presents the descriptive statistics of the yield spread, credit rating, and market-wide trading activity for the two subsegments in the three different time periods. We find that, in general, trading is focused on the investment grade segment. In the GM/Ford crisis, we observe a higher level of trading activity for the speculative grade segment compared with the normal period, perhaps due to the trade volume caused by a shuffling of bonds, due to clientele preferences in anticipation of, and as a consequence of, the downgrades. In the subprime crisis, we observe a lower market-wide volume for both segments. Furthermore, we find a significant reduction in the number of traded bonds and trades for the speculative grade segment, whereas we observe approximately the same number of bonds and more trades in the case of investment grade bonds. Thus, we find a flight-to-quality indicated by trading in better rated bonds compared to the normal period.

Table 7 (Panel B) presents the descriptive statistics of the liquidity proxies for the two subsegments. In general, we find that the liquidity proxies clearly indicate lower liquidity for speculative grade bonds, e.g., the price dispersion measure is 44.1 bp vs. 38.8 bp for investment grade bonds in the normal period. In the crisis periods, the liquidity of bonds in both groups deteriorates, e.g., the price dispersion measure for speculative grade bonds is 55.8 bp and 68.2 bp in the GM/Ford and the subprime crisis, respectively. Interestingly, the difference in the liquidity proxies between the two groups is less

**Table 7**
This table reports the mean of the yield spread, the credit rating, and the daily market-wide trading activity in Panel A for investment grade and speculative grade bonds for the three different regimes (GM/Ford crisis, normal period, and subprime crisis). The corporate bond yield spread is measured relative to the US Treasury bond yield curve and given in percentage points. We use credit ratings from Standard & Poor's where we assign integer numbers to ratings, i.e., AAA=1, AA+=2, etc., to measure the average rating. The market-wide trading activity variables represent the number of traded bonds and trades, and the total trading volume per day. Panel B provides the averages for the trading activity variables (traded volume, number of trades, and time interval between trades) and liquidity measures (Amihud, price dispersion, Roll, and zero-return measure). The data set consists of 23,703 US corporate bonds traded over the period October 2004–December 2008.

*Panel A: Yield-spread, rating, and market-wide trading activity*

|  | Investment grade | | | Speculative grade | | |
|---|---|---|---|---|---|---|
|  | GM/Ford crisis | Normal period | Subprime crisis | GM/Ford crisis | Normal period | Subprime crisis |
| Yield spread (%) | 1.19 | 0.97 | 3.21 | 4.41 | 3.48 | 10.82 |
| Rating | 6.50 | 6.01 | 5.88 | 13.10 | 13.44 | 14.12 |
| Traded bonds (thd) | 3.23 | 3.90 | 3.96 | 1.99 | 2.02 | 1.22 |
| Market-wide trades (thd) | 11.53 | 13.10 | 18.11 | 8.90 | 7.61 | 4.66 |
| Market-wide volume (bln) | 5.26 | 6.01 | 5.66 | 2.38 | 2.04 | 1.33 |

*Panel B: Liquidity proxies*

|  | Investment grade | | | Speculative grade | | |
|---|---|---|---|---|---|---|
|  | GM/Ford crisis | Normal period | Subprime crisis | GM/Ford crisis | Normal period | Subprime crisis |
| Volume (mln) | 1.99 | 1.91 | 1.77 | 1.29 | 0.96 | 1.08 |
| Trades | 4.37 | 4.12 | 5.86 | 4.77 | 3.94 | 4.24 |
| Trading interval (dy) | 3.28 | 3.30 | 3.28 | 3.18 | 3.37 | 3.49 |
| Amihud (bp per mln) | 61.27 | 50.47 | 75.14 | 68.76 | 54.69 | 147.94 |
| Price dispersion (bp) | 44.74 | 38.78 | 72.72 | 55.79 | 44.09 | 68.22 |
| Roll (bp) | 154.70 | 128.83 | 206.68 | 183.47 | 164.95 | 215.64 |
| Zero-return (%) | 0.01 | 0.01 | 0.01 | 0.04 | 0.04 | 0.06 |

**Table 8**

This table reports the panel data regression model explaining the yield spread changes based on weekly averages of all variables:

$$\Delta(\text{Yield spread})_{i,t} = \alpha_0 + \alpha_1 \cdot \Delta(\text{Yield spread})_{i,t-1} + \alpha_2 \cdot \Delta(\text{Volume})_{i,t} + \alpha_3 \cdot \Delta(\text{Trades})_{i,t} + \alpha_4 \cdot \Delta(\text{Trading interval})_{i,t}$$
$$+ \alpha_5 \cdot \Delta(\text{Amihud})_{i,t} + \alpha_6 \cdot \Delta(\text{Price dispersion})_{i,t} + \alpha_7 \cdot \Delta(\text{Roll})_{i,t} + \alpha_8 \cdot \Delta(\text{Zero-return})_{i,t} + (\text{Speculative grade dummy})_t \cdot [\beta_1 \cdot \Delta(\text{Yield spread})_{i,t-1}$$
$$+ \beta_2 \cdot \Delta(\text{Volume})_{i,t} + \beta_3 \cdot \Delta(\text{Trades})_{i,t} + \beta_4 \cdot \Delta(\text{Trading interval})_{i,t} + \beta_5 \cdot \Delta(\text{Amihud})_{i,t} + \beta_6 \cdot \Delta(\text{Price dispersion})_{i,t}$$
$$+ \beta_7 \cdot \Delta(\text{Roll})_{i,t} + \beta_8 \cdot \Delta(\text{Zero-return})_{i,t}] + \sum_{k=1}^{21} \delta_k \cdot \Delta(\text{Rating dummy})_{i,t,k} + \epsilon_{i,t}.$$

The yield spread change is explained by the change in the lagged yield spread, trading activity variables (traded volume, number of trades, and time interval between trades), liquidity measures (Amihud, price dispersion, Roll, and zero-return measure), and rating dummies to control for credit risk. Additionally, we add interaction terms between the subsegment of speculative grade bonds and the liquidity proxies. The corporate bond yield spread is measured relative to the US Treasury bond yield curve. The $t$-statistics are given in parentheses and are calculated from Newey and West (1987) standard errors, which are corrected for heteroskedasticity and serial correlation. We provide an $F$-test to test whether the interaction terms of the dummy variable with the liquidity proxies are jointly zero. The standard errors of the $F$-statistics are also Newey and West (1987) corrected. In addition, the table also reports the model's $R^2$ and the number of observations. The data set consists of 23,703 US corporate bonds traded over the period October 2004–December 2008.

| | | |
|---|---|---|
| Intercept | 0.0757*** | (73.5243) |
| $\Delta(\text{Yield spread})_{i,t-1}$ | −0.3034*** | (−35.2591) |
| $\Delta(\text{Volume})_{i,t}$ | −0.0038*** | (−3.6157) |
| $\Delta(\text{Trades})_{i,t}$ | 0.0057*** | (8.9298) |
| $\Delta(\text{Trading interval})_{i,t}$ | 0.0070*** | (15.1603) |
| $\Delta(\text{Amihud})_{i,t}$ | 0.0458*** | (25.4481) |
| $\Delta(\text{Price dispersion})_{i,t}$ | 0.0803*** | (20.8335) |
| $\Delta(\text{Roll})_{i,t}$ | 0.0602*** | (13.5645) |
| $\Delta(\text{Zero-return})_{i,t}$ | −0.0833*** | (−3.5542) |
| $(\text{Speculative grade dummy})_t \times \Delta(\text{Yield spread})_{i,t-1}$ | 0.0377*** | (3.2552) |
| $(\text{Speculative grade dummy})_t \times \Delta(\text{Volume})_{i,t}$ | −0.0122*** | (−4.9216) |
| $(\text{Speculative grade dummy})_t \times \Delta(\text{Trades})_{i,t}$ | 0.0015 | (1.3913) |
| $(\text{Speculative grade dummy})_t \times \Delta(\text{Trading interval})_{i,t}$ | −0.0097*** | (−9.5900) |
| $(\text{Speculative grade dummy})_t \times \Delta(\text{Amihud})_{i,t}$ | 0.0246*** | (7.6564) |
| $(\text{Speculative grade dummy})_t \times \Delta(\text{Price dispersion})_{i,t}$ | 0.0315*** | (4.5624) |
| $(\text{Speculative grade dummy})_t \times \Delta(\text{Roll})_{i,t}$ | −0.0010 | (−0.1301) |
| $(\text{Speculative grade dummy})_t \times \Delta(\text{Zero-return})_{i,t}$ | −0.0085 | (−0.3184) |
| $\Delta(\text{Rating dummies})$ | Yes | |
| $F$-stat. $\mathcal{H}_0$: (Speculative grade dummy) $\times \Delta$(Liquidity proxies) $= 0$ | 28.8800 | |
| Observations | 637,814 | |
| $R^2$ | 0.0954 | |

pronounced in the subprime crises for the price dispersion and Roll measure, i.e., the average trading cost increases relatively more for the investment grade segment. However, for the Amihud measure we find a large difference between investment and speculative grade bonds in the subprime crisis (i.e., 75.1 bp vs. 147.9 bp) indicating that large trades in speculative grade bonds have a high price impact.

Table 8 presents the results for the panel data regressions using a dummy variable for speculative grade bonds and, more important, including interaction terms between this dummy and the liquidity proxies. Overall, we find that speculative grade bonds react more strongly to changes in liquidity. The Amihud measure, the price dispersion measure, and the trading activity parameters are significantly higher (in absolute terms) for speculative grade bonds. Thus, we find a significant interaction between credit and liquidity risk. On average, bonds with higher credit risk are less liquid and react more strongly to liquidity changes. The most important ones are the Amihud and the price dispersion measure, for which both coefficients basically increase by 50%. An $F$-test reveals that we can reject at a

1% level the hypothesis that the interaction terms between credit and liquidity risk are jointly zero.

As for the improvement in $R^2$, we find that the inclusion of the interaction terms leads to an increase from 8.56% to 9.54% compared to the analysis for the whole time-series, highlighting the importance of adding these terms. Considering the economic significance, a one standard deviation move in all proxies in the direction of greater illiquidity would increase the spread by 13.8 bp for investment grade bonds, compared to 37.6 bp for speculative grade bonds, respectively. Thus, we find a higher impact of the liquidity proxies for bonds with high credit risk. The ranking of the economic importance of the individual liquidity proxies for investment grade and speculative grade bonds stays approximately the same, with the Amihud measure showing the highest impact (4.6 bp for investment grade bonds and 10.4 bp for speculative grade bonds).[18]

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[18] In other tests, not reported here due to space constraints, we also estimated a panel data regression separately for each subsegment using

Overall, we find that the liquidity effects are far more pronounced for speculative grade bonds and, thus, indicating an interaction between credit and liquidity risk. This effect is particularly important for the subprime crisis, when we observe a clear flight-to-quality effect.

## 8. Conclusion

Financial economists have been concerned with the impact of liquidity and liquidity risk on the pricing of assets for at least two decades. During this period, several issues relating to liquidity effects in asset prices have been analyzed at a theoretical and empirical level by academic researchers, particularly in the context of US equity markets. More recently, the focus on liquidity has been broadened to include a wider class of assets such as derivatives and fixed income securities. This trend has accelerated since the onset of the subprime crisis, as the discussion of liquidity has attracted much interest among academics, practitioners, and regulators. While the crisis has manifested itself in almost every financial market in the world, the most stressed markets, by far, have been those for fixed income securities and their derivatives, particularly those with credit risk, including corporate bonds, CDSs, and CDOs. These developments require that the scope of the discussion of liquidity be extended to include the interplay between liquidity and credit.

Corporate bond markets are far less liquid than related equity markets, since only a very small proportion of the universe of corporate bonds trades even as often as once a day. In addition, corporate bonds trade in an over-the-counter market, where there is no central market place. Hence, conventional transaction metrics of liquidity such as bid-offer quotes do not have the same meaning in this market compared to exchange traded markets. The issue of liquidity in this relatively illiquid, OTC market is fundamentally different from that in exchange traded markets: Thus, it is necessary to use measures of liquidity that go beyond the standard transaction-based measures common in research in more liquid, exchange traded markets.

We employ a wide range of liquidity measures to quantify the liquidity effects in corporate bond yield spreads. Our analysis explores the time-series and cross-sectional aspects of liquidity using panel and Fama-MacBeth regressions, respectively. We find that the liquidity proxies in the specified regression models account for about 14% of the explained time-series variation of the yield spread changes. Furthermore, we find that the effect of the liquidity measures is far stronger in both the GM/Ford crisis and the subprime crisis, most remarkably the economic effect more than doubles in the subprime crisis. All the liquidity proxies considered exhibit statistically as well as economically significant results.

In particular, measures estimating trading costs based on transaction data show the strongest effects.

Comparing investment grade to speculative grade bonds, we find lower liquidity for speculative grade bonds as well as a stronger reaction to changes in liquidity. These results show that bonds with higher credit risk also are more exposed to liquidity risk.

These results are useful for many practical applications, particularly pricing and risk management, and also have implications for regulatory policy. They also highlight the importance of transparency of trades for OTC markets, with reporting to a central authority being a crucial element for price discovery.

## References

Acharya, V.V., Amihud, Y., Bharath, S., 2009. Liquidity risk of corporate bond returns. Unpublished working paper. New York University and Arizona State University.

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. Journal of Financial Markets 5, 31–56.

Amihud, Y., Mendelson, H., 1986. Asset pricing and the bid–ask spread. Journal of Financial Economics 17, 223–249.

Amihud, Y., Mendelson, H., Pedersen, L.H., 2006. Liquidity and asset prices. Foundations and Trends in Finance 1, 269–364.

Bao, J., Pan, J., Wang, J., 2011. Liquidity and corporate bonds. Journal of Finance 66, 911–946.

Chakravarty, S., Sarkar, A., 1999. Liquidity in US fixed income markets: a comparison of the bid–ask spread in corporate, government and municipal bond markets. Federal Reserve Bank of New York Staff Report No. 73.

Chen, L., Lesmond, D.A., Wei, J., 2007. Corporate yield spreads and bond liquidity. Journal of Finance 62, 119–149.

Collin-Dufresne, P., Goldstein, R.S., Martin, J.S., 2001. The determinants of credit spread changes. Journal of Finance 56, 2177–2207.

De Jong, F., Driessen, J., 2006. Liquidity risk premia in corporate bond markets. Unpublished working paper. University of Tilburg.

Dick-Nielsen, J., 2009. Liquidity biases in TRACE. Journal of Fixed Income 19, 43–55.

Dick-Nielsen, J., Feldhütter, P., Lando, D., 2012. Corporate bond liquidity before and after the onset of the subprime crisis. Journal of Financial Economics 103, 471–492.

Duffie, D., Garleanu, N., Pedersen, L.H., 2007. Valuation in over the counter markets. Review of Financial Studies 20, 1865–1900.

Edwards, A., Harris, L., Piwowar, M., 2007. Corporate bond market transaction costs and transparency. Journal of Finance 62, 1421–1451.

Elton, E.J., Gruber, M., Agrawal, D., Mann, C., 2001. Explaining the rate spread on corporate bonds. Journal of Finance 56, 247–277.

Eom, Y., Helwege, H.J., Huang, J.Z., 2004. Structural models of corporate bond pricing: an empirical investigation. Review of Financial Studies 17, 499–544.

Goldstein, M.A., Hotchkiss, E.S., 2007. Dealer behavior and the trading of newly issued corporate bonds. Unpublished working paper. Babson College and Boston College.

Hong, G., Warga, A., 2000. An empirical study of bond market transactions. Financial Analysts Journal 56, 32–46.

Hotchkiss, E.S., Ronen, T., 2002. The informational efficiency of the corporate bond market: an intraday analysis. Review of Financial Studies 15, 1325–1354.

Houweling, P., Mentink, A., Vorst, T., 2005. Comparing possible proxies of corporate bond liquidity. Journal of Banking and Finance 29, 1331–1358.

Huang, J., Huang, M., 2003. How much of the corporate-treasury yield spread is due to credit risk? Unpublished working paper. Pennsylvania State University and Cornell University.

Jankowitsch, R., Nashikkar, A., Subrahmanyam, M., 2011. Price dispersion in OTC markets: a new measure of liquidity. Journal of Banking and Finance 35, 343–357.

Kyle, A.S., 1985. Continuous auctions and insider trading. Econometrica 53, 1315–1335.

Lesmond, D.A., Ogden, J., Trzcinka, C., 1999. A new estimate of transaction costs. Review of Financial Studies 12, 1113–1141.

Lin, H., Wang, J., Wu, C., 2011. Liquidity risk and expected corporate bond returns. Journal of Financial Economics 99, 628–650.

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(footnote continued)

dummy variables with interaction terms for the subperiods. This allows us to compare liquidity effects in different time periods between the investment grade and speculative grade bonds. For the subprime crisis, we find a significant increase in the liquidity proxies for both subsegments, where the increase is particularly strong for speculative grade bonds. This result reinforces the findings of the previous analysis.

Liu, J., Longstaff, F.A., Mandell, R.E., 2004. The market price of credit risk: an empirical analysis of interest rate swap spreads. Journal of Business 79, 2337–2359.

Longstaff, F., Mithal, S., Neis, E., 2005. Corporate yield spreads: default risk or liquidity? New evidence from the credit-default swap market. Journal of Finance 60, 2213–2253.

Mahanti, S., Nashikkar, A., Subrahmanyam, M., Chacko, G., Mallik, G., 2008. Latent liquidity: a new measure of liquidity, with an application to corporate bonds. Journal of Financial Economics 88, 272–298.

Markit Group Limited, 2006. Markit.com User Guide—Version 8.0 March 2006. User guide, Markit Group Limited.

Nashikkar, A., Subrahmanyam, M., Mahanti, S., 2011. Liquidity and arbitrage in the market for credit risk. Journal of Financial and Quantitative Analysis 46, 627–656.

Newey, W., West, K., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703–708.

Perraudin, W., Taylor, A., 2003. Liquidity and bond market spreads. Unpublished working paper. Bank of England.

Roll, R., 1984. A simple implicit measure of the effective bid–ask spread in an efficient market. Journal of Finance 39, 1127–1139.

Ronen, T., Zhou, X., 2009. Where did all the information go? Trade in the corporate bond market. Unpublished working paper. Rutgers University.

Sadka, R., 2010. Liquidity risk and the cross-section of hedge-fund returns. Journal of Financial Economics 98, 54–71.

Schultz, P., 2001. Corporate bond trading costs and practices: a peek behind the curtain. Journal of Finance 56, 677–698.