Essays on the Determinants of Corporate Bond Yield Spreads

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Diplom-Wirtschaftsmathematiker Sebastian Bethke

aus

Bergisch Gladbach

Referent: Univ.-Prof. Dr. Alexander Kempf, Universität zu Köln

Korreferent: Univ.-Prof. Dr. Thomas Hartmann-Wendels, Universität zu Köln

Vorsitz: Univ.-Prof. Dr. Dieter Hess, Universität zu Köln

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Chapter 1

Introduction

This thesis consists of three essays on the determinants of corporate bond yield spreads. Specifically, it focuses on (1) the impact of investor sentiment on the correlation between corporate bond yield spreads through the correlation between credit risk and liquidity, (2) the impact of consumer sentiment on issuers' credit risk, and (3) the comovement of individual corporate bonds' liquidity with market liquidity.[1]

Several studies document the rise in corporate bond yield spreads during times of financial stress (e.g., Driessen, 2005; Friewald et al., 2012; Dick-Nielsen et al., 2012; Chun et al., 2014). For instance, the collapse of Long-Term Capital Management in 1998, the downgrades of the General Motors Corporation and the Ford Motor Company to junk status in 2005, or the US subprime crisis in 2008 are examples of severe financial stress events that have highlighted the importance of credit risk, liquidity, and the influence of sentiment for the US corporate bond market. Corporate bonds' simultaneously falling credit quality and liquidity lead to rising yield spreads, decreasing investors' portfolio values, and increasing issuers' financing costs. The overall impact likely has been reinforced through investors' fear of even larger future losses leading to flight-to-quality behavior (e.g., Longstaff et al., 2005; Dick-Nielsen et al., 2012). This raises several questions: What are the risk factors affecting corporate bond yield spreads? What are the determinants of credit risk and liquidity, and how

[1] A corporate bond's yield spread is defined as the difference between a bond's yield and a benchmark risk-free rate. The yield spread compensates investors for bearing risks (e.g., Fisher, 1959; Collin-Dufresne et al. (2001); Longstaff et al., 2005; Dick-Nielsen et al., 2012). As such, credit risk describes the risk that the issuer of a bond may default or its default probability changes (e.g., Fisher, 1959; Merton, 1974). Liquidity has several meanings. This thesis focuses on bonds' trading liquidity. Bonds are liquid, if they can be traded quickly and in large quantities without significant deviations from their fundamental value (e.g., Fisher, 1959; Amihud and Mendelson, 1986).

do both affect corporate bond yield spreads? Does investor or consumer sentiment have an impact on corporate bond yield spreads? What determines diversification opportunities among corporate bonds? These questions are of vital interest for researchers, investors, issuers, and policy makers, especially when considering the growth in the outstanding amount of US corporate bonds. It steadily increased over the last two decades from 2 trillion USD in 1995 to 8 trillion USD in 2015 accounting, on average, to more than 30% of the US stock market capitalization.[2] In providing answers to these questions, this thesis contributes to the literature analyzing the determinants of corporate bond yield spreads.

The academic literature on the determinants of corporate bond yield spreads can be broadly separated into three strands. The first strand of the literature analyzes the risk factors affecting corporate bond yield spreads. By corporate bonds' nature of being debt capital, the issuers' credit risk should be the main risk factor driving yield spreads (Merton, 1974). However, the literature documents that credit risk models are not able to fully explain empirically observed yield spreads.[3] More precisely, the literature shows that corporate bond yield spreads have both a credit risk as well as a non-credit risk component with a large fraction of the latter being often attributed to liquidity.[4] More recent research documents that also the correlation between credit risk and liquidity influences corporate bond yield spreads.[5] This underlines the importance of understanding the determinants of corporate bond credit risk and liquidity.

Hence, the second strand of the literature focuses on the analysis of issuers' credit risk. For this purpose, the literature analyzes the determinants of credit ratings and credit default swap[6] (CDS) premiums.[7] By definition, credit ratings measure issuers' credit risk and CDS

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[2] See Securities Industry and Financial Markets Association (SIFMA) (2016) and World Bank (2016).

[3] Examples of studies that document the existence of the so called "credit spread puzzle" are Collin-Dufresne et al. (2001), Elton et al. (2001), and Huang and Huang (2012).

[4] Examples of studies that document liquidity to be an important risk factor influencing corporate bond yield spreads are Longstaff et al. (2005), Nashikkar et al. (2011), Dick-Nielsen et al. (2012), and Friewald et al. (2012).

[5] In this context, Longstaff et al. (2005) find a negative correlation between credit risk and liquidity premiums for corporate bonds while Ericsson and Renault (2006) motivate and document a positive correlation. Bühler and Trapp (2009), Dick-Nielsen et al. (2012), and Friewald et al. (2012) find risk factor correlation to be positive. For stocks, Rösch and Kaserer (2013) document a positive relation between credit risk and liquidity.

[6] A credit default swap is a credit derivative designed as an insurance contract whose payoff is linked to the credit risk of an underlying reference bond or issuer.

[7] The determinants of credit ratings are analyzed by, e.g., Pottier and Sommer (1999), Jorion et al. (2005); Güttler and Wahrenburg (2007), Cheng and Neamtiu (2009), Becker and Milbourn (2011), and Jiang et al. (2012) who, for instance, document differences between the credit ratings of different agencies and an impact of credit rating market competition on rating quality. Among others, Ericsson et al. (2009), Zhang et al. (2009), Cao et al. (2010), Tang and Yan (2013), and Wang et al. (2013) analyze the determinants of CDS premiums and document that firm value information, either accounting-based or from the equity market, determines CDS premiums.

premiums reflect the market price of issuers' credit risk (e.g., Hull et al., 2004; Norden and Weber, 2004). The literature documents that both are linked while CDS premiums are the more efficient credit risk measure summarizing firm value and credit rating information.[8] However, neither credit risk measured by CDS premiums, credit ratings, nor additional firm value information, can fully explain corporate bond yield spreads. This finally underlines the importance of the non-credit risk component in corporate bond yield spreads.

Thus, the third strand of the literature focuses on the analysis of corporate bonds' non-credit risk component which has been mainly linked to liquidity. Given the over-the-counter (OTC) market structure of the corporate bond market, it is not possible to observe a limit order book as for centralized markets such as the New York Stock Exchange. Thus, measuring liquidity for corporate bonds is even more challenging. Therefore, on the one hand, this strand of the literature focuses on the measurement of corporate bond liquidity.[9] On the other hand, it investigates the determinants of liquidity and its influence on corporate bond yield spreads.[10]

The essays in this thesis contribute to the previous three strands of the literature on the determinants of corporate bond yield spreads. The first essay (Bethke et al., 2015) adds to the strand of the literature on the risk factors affecting corporate bond yield spreads by identifying an economic mechanism of investor sentiment driving the correlation between yield spreads through the correlation between credit risk and liquidity. While the risk factors affecting corporate bond yield spreads are already extensively studied, the literature on the correlation between yield spreads is scarce.[11] This is surprising as correlations are crucial when managing

[8] In this context, e.g., Hull et al. (2004) and Norden and Weber (2004) provide evidence of the predictive power of CDS premiums for credit rating downgrades. Examples of studies showing that CDS lead corporate bonds are, e.g., Blanco et al. (2005), Forte and Peña (2009) , Norden and Weber (2009), and Coudert and Gex (2010).

[9] An overview of existing studies with respect to the used liquidity proxies is given by Friewald et al. (2012). Several studies exist that use bond characteristics as liquidity proxies, e.g., issuance volume, issuers' industries, or trading activity variables such as trade volume or number of trades. Examples are, e.g., Collin-Dufresne et al. (2001), Houweling et al. (2005), Longstaff et al. (2005), and Friewald et al. (2012). In addition, several studies exist that develop liquidity proxies or apply liquidity proxies already used in studies for other asset classes. For instance, the Roll measure and the inter-quartile range are proxies for bid-ask spreads (e.g., Han and Zhou, 2007; Pu, 2009; Bao et al., 2011) while the Amihud measure proxies for the price impact of a trade (e.g., Dick-Nielsen et al., 2012; Friewald et al., 2012).

[10] Studies that analyze corporate bond liquidity are, among others, Alexander et al. (2000), Schultz (2001), Longstaff et al. (2005), Chacko et al. (2005), Houweling et al. (2005), Bessembinder et al. (2006), Edwards et al. (2007), Chen et al. (2007), Bao et al. (2011), Dick-Nielsen et al. (2012), Friewald et al. (2012), Acharya et al. (2013), and Schestag et al. (2016). Overall, the studies show that liquidity influences corporate bond yield spreads and its magnitude varies over time and across bonds.

[11] Examples of studies that analyze correlations for other asset classes are, e.g., Ang and Chen (2002), Connolly et al. (2007), and Christiansen and Ranaldo (2009) for stocks, Abad et al. (2010), Piljak (2013), and Abad et al. (2014) for sovereign bonds, and Connolly et al. (2005), Baele et al. (2010), Bansal et al. (2014), and Nieto and Rodriguez (2015) between asset classes.

portfolios. Moreover, economic mechanisms known from the stock market are not easily transferable. This is because studies related to the stock market often document retail investors’ herding behavior to determine higher correlations in market downturns. However, this explanation is unlikely to apply for the corporate bond market due to a higher fraction of institutional investors who are less prone to herding behavior in market downturns (e.g., Kumar and Lee, 2006; Borensztein and Gelos, 2003). As a consequence, we develop a theoretical model that proposes an economic mechanism for bond correlations that takes two main effects of investor sentiment induced behavior into account. First, investors with low sentiment avoid risky assets (e.g., Baker and Wurgler, 2006; Ben-Rephael et al., 2012; Da et al., 2015). Second, investors react more to negative information than to positive information (e.g., Mian and Sankaraguruswamy, 2012; Kaplanski and Levy, forthcoming). Thus, low sentiment makes investors less willing to invest in bonds with high credit risk and these bonds are less liquid than when sentiment is good due to investors’ stronger reactions. As a result of these two effects, liquidity premiums increase more with credit risk premiums when sentiment is low. This higher correlation between the two main corporate bond risk factors is consistent with investors’ flight-to-quality into safer assets, e.g., Treasury bonds or cash. Finally, high risk factor correlation translates into high correlation between corporate bond yield spreads. In particular, our model predicts that investors’ sentiment influences bond correlation through risk factor correlation.

In our empirical analyses we focus on a sample of US corporate bond transaction data from October 2004 to September 2010. We first document that bond correlation varies heavily over time. Second, consistent with our model’s predictions, our main results confirm that the correlation between risk factors is high when investor sentiment is low and high risk factor correlation translates into high bond correlation. Investor sentiment has a significant indirect impact on bond correlation via risk factor correlation even after controlling for a possible direct impact of sentiment, herding behavior, and the state of the economy.

Taken together, this essay documents the importance of risk factor correlation for corporate bond yield spreads. Our results are consistent with investor sentiment driving investors’ flight-to-quality behavior and thereby influencing corporate bond investors’ diversification opportunities. Thus, the findings of this essay are highly important for portfolio and risk managers.

Having shown that investor sentiment plays an important role in the corporate bond market, it is of further interest whether the sentiment of consumers, i.e. investors and all other individuals acting in an economy, also has an impact on corporate bond yield spreads. Consumer sentiment might influence corporate bond yield spreads through their credit risk component. This is because consumer sentiment drives economic output (e.g., Ludvigson, 2004; Golinelli and Parigi, 2004; Gelper et al., 2007; Fornell et al., 2010). Thus, consumer sentiment should impact firms' credit risk as firms' economic success depends on the willingness to consume (e.g., Ittner and Larcker, 1998; Anderson et al., 2004).

Adhering to this idea, in the second essay (Bethke and Gehde-Trapp, 2016) we add to the strand of the literature analyzing the determinants of credit risk by investigating whether aggregated volume of Google search queries possesses fundamental value for the CDS market. Today, Google is one of the major internet search engines.[12] It is likely that individuals' also use Google to gather information for their consumer decisions. Thereby they reveal their sentiment through their search queries (Demartini and Siersdorfer, 2010) which, in the end, influences their consumption. Consistent with this view, the aggregated volume of Google search queries contains consumption information before other financial variables or economic indicators (e.g., McLaren and Shanbhogue, 2011; Vosen and Schmidt, 2011; Choi and Varian, 2012). However, it is still an open issue whether aggregated Google search volume contains fundamental information for capital markets (e.g., Da et al., 2011b; Da et al., 2015; Dimpfl and Jank, 2016). In this context, the CDS market is an ideal laboratory to further analyze this open issue. This is because only institutional investors are active in the CDS market which reduces the influence of uninformed noise trading (e.g., Piotroski and Roulstone, 2004; Boehmer and Kelley, 2009). In line with this view, the literature documents that information is priced efficiently (e.g., Norden and Weber, 2004; Acharya and Johnson, 2007). Finally, Tang and Yan (2010) show that monthly measured consumer sentiment is a determinant of CDS premiums while Google allows us to capture daily consumer sentiment before any other financial variable. If aggregated volume of Google search queries possesses fundamental value for the CDS market, we expect it to improve CDS premium change forecasts. If it even contains fundamental information not yet reflected in CDS premiums, we expect the Google indices to predict trends in CDS premium changes.

[12] Nearly 80% of US households had access to the internet and 64% of US citizens used Google for their internet searches in 2015 (e.g., eMarketer, 2016; Comscore, 2016).

Our analyses focus on the Markit CDX Investment Grade Index.[13] Additionally, we use time series of aggregated volume of Google search queries from January 2004 to December 2013 for a large set of positive and negative connoted terms. These terms are used to compute two Google indices, one based on all positive and negative connoted terms and one based on positive and negative connoted economic terms. In line with the existing literature, we find the contemporaneous Google indices to positively determine CDS premium changes (e.g., Tang and Yan, 2010; Tang and Yan, 2013). We then document in-sample predictive power for both Google indices. However, the Google indices predict CDS premium change reversals. Thus, our results show that the Google indices contain no new fundamental information for the CDS market. Instead, the results are consistent with shocks in overall risk aversion temporarily influencing CDS premiums (e.g., Tetlock, 2007, Tang and Yan, 2010, and Tang and Yan, 2013). However, as indicated by the predictive power of both indices, analyzing Google search volume is valuable. In support of this result, we find that both Google indices improve out-of-sample forecasts especially in times when forecasts are more demanding. Overall, although both indices contain no new fundamental information, their in- and out-of-sample predictive power documents their fundamental value for the CDS market and its market participants.

The first two essays look at different aspects of sentiment and its influence on credit markets. Thereby the first essay identifies investor sentiment to be a driver of flight-to-quality behavior which is related to decreasing corporate bond liquidity. In this context, the question arises which corporate bonds are most affected by sharp decreases of corporate bond market liquidity.

For this reason, the third essay (Bethke, 2016) contributes to the strand of the literature that analyzes the determinants of corporate bond liquidity. While liquidity as a risk factor affecting individual corporate bond yield spreads has already been extensively analyzed, the literature on the comovement of individual bonds' liquidity with market liquidity, commonality in liquidity, is scarce.[14] This is surprising as commonality in liquidity influences investors' opportunities to benefit from diversification (Domowitz et al., 2005). This is even more surprising given the size of the US corporate bond market and the fact that liquidity

[13] A CDS index is designed as a credit insurance contract whose payoff is linked to the credit risk of a basket of firms.

[14] Among others, Chordia et al. (2000), Hasbrouck and Seppi (2001), Huberman and Halka (2001), Kempf and Mayston (2008), and Karolyi et al. (2012) study commonality in liquidity among stocks, Chordia et al. (2005) between sovereign bonds and stocks, and Cao and Wei (2010), Marshall et al. (2013), and Frino et al. (2014) for derivative markets.

significantly dropped for all US corporate bonds during the financial crisis in 2008 (e.g., Dick-Nielsen et al., 2012; Friewald et al., 2012). This suggests that the liquidity of individual corporate bonds depends on the overall market liquidity leading to commonality in liquidity.

My empirical analyses base on a sample of US corporate bond transaction data from July 2002 to December 2012. First, I document that commonality in liquidity exists among US corporate bonds. Given this result, it is then essential to get a better understanding of the determinants of commonality in liquidity. The theoretical literature suggests comovement in liquidity supply and demand to determine the degree of commonality in liquidity.[15]

For the cross-section of corporate bonds, my analyses reveal that the degree of commonality in liquidity is higher for bonds with an investment grade credit rating, with longer time to maturity, with higher amount outstanding, and for bonds issued by financial firms. In multivariate analyses that consider a broader set of possible bond, firm, and industry characteristics, I find support for supply- and demand-side effects both influencing individual bonds' comovement with market liquidity.

For the time series of market-wide commonality in liquidity, I document that it varies heavily over time and peaks in months with more financial stress events. As for the cross-sectional results, I find supply- and demand-side effects to determine market-wide commonality in liquidity while the results provide evidence on supply-side effects, such as funding liquidity, being more important. In summary, my results contribute to the literature by providing a detailed picture of commonality in liquidity among corporate bonds.

Overall, the three essays provide new insights into the determinants of corporate bond risk factors and their impact on corporate bond yield spreads. First, the correlation between corporate bonds is higher when sentiment is low. This effect arises through higher risk factor correlation which is consistent with investors' flight-to-quality behavior. Thus, risk factor correlation is important to consider when pricing corporate bonds. Second, not only investor sentiment but also consumer sentiment measured by aggregated volume of Google search queries is important as it determines and forecasts CDS premium changes. The results are consistent with a temporary impact of overall risk aversion on CDS premiums and show that

[15] Regarding liquidity supply, higher inventory risk (e.g., Kyle and Xiong, 2001; Gromb and Vayanos, 2002), tighter risk management (Gârleanu and Pedersen, 2007), or lower funding liquidity (Brunnermeier and Pedersen, 2009) of liquidity suppliers may induce higher commonality in liquidity. Correlated demand for liquidity may arise through investors' correlated selling activities arising through initial losses that raise the fear of even larger future losses (e.g., Bernardo and Welch, 2004; Morris and Shin, 2004), increased demand for more liquid assets (Vayanos, 2004), or preference for cheap information resulting in a common subset of information that is used to price different assets (Veldkamp, 2006).

Google search volume is valuable for forecasting CDS premium changes especially in times when forecasts are more demanding. Finally, this thesis documents that investors' demand and supply for corporate bonds influences the relation of individual corporate bonds' liquidity to market liquidity. In summary, the results are highly relevant for investors' diversification benefits across corporate bonds, firms' financing costs, and policy makers' basis for decision-making.

Chapter 2*

Investor Sentiment, Flight-to-Quality, and Corporate Bond Comovement

2.1. Introduction

Correlations are crucial when setting up efficient portfolios, taking appropriate hedging decisions, and managing risks. Thus, it is not surprising that correlations are widely studied in the financial literature (e.g., Ang and Chen, 2002; Connolly et al., 2007; Baele et al., 2010; Abad et al., 2014; Nieto and Rodriguez, 2015). This evidence is based on correlations between equity markets, government bond markets, individual stocks and bonds, and common factors in asset prices and returns. Our paper contributes to this literature by identifying an economic mechanism of correlated risk factors driving corporate bond correlations.

Using a sample of US corporate bonds, we document that bond correlation varies heavily over time. Correlation between high-yield and investment-grade bonds is, for example, about three times higher in the financial crisis beginning in July 2007 than it was before.

Why does bond correlation display this time-series behavior? One possible explanation, typically adopted to explain correlations in equity markets, is investors' herding. Kumar and Lee (2006) show that trading is correlated across retail investors and influences stock comovements. However, it is unlikely that retail investor herding is as important in bond markets as in equity markets since bond markets are dominated by institutional investors less prone to herding in market downturns (Borensztein and Gelos, 2003).

* This chapter is based on Bethke et al. (2015).

We propose an alternative explanation. In a nutshell, our theoretical model is based on the idea that investor sentiment has two main effects on investor behavior: Investors with low sentiment avoid risky assets (Baker and Wurgler, 2006) and react more to negative information (e.g., Mian and Sankaraguruswamy, 2012; Kaplanski and Levy, forthcoming). Thus, when sentiment is low, investors are less prone to invest in bonds with high credit risk and these bonds are less liquid than when sentiment is high. Consequently, liquidity premiums increase more with credit risk premiums when sentiment is low, i.e., correlation between these two main risk factors in corporate bonds is higher. High risk factor correlation translates into high correlation between corporate bonds. Thus, low investor sentiment ultimately goes along with high bond correlation.

In the empirical part of our paper, we use TRACE (Trade Reporting and Compliance Engine) data from October 2004 to September 2010. We document how bond correlation evolves over time and test our model that links bond correlation to risk factor correlation and risk factor correlation to investor sentiment. We find strong support for the predictions of our model. Correlation between risk factors in the corporate bond market is high when investor sentiment is low and high risk factor correlation translates into high bond correlation. Investor sentiment has a significant indirect impact on bond correlation via risk factor correlation even after controlling for a possible direct impact of sentiment, herding behavior, and state of the economy. Our results are stable over time and remain stable when we dig deeper into the cross-section by analyzing correlations between more detailed credit rating buckets.

After establishing our main results, we run several tests to determine robustness of our findings. We show that our main findings depend neither on how we measure credit risk and liquidity premiums nor on how we proxy investor sentiment. They remain robust when we adjust correlations for interest rate risk and unexpected inflation, use the swap rate as proxy for the risk-free rate, or split the sample into a pre-crisis and crisis interval.

Our study is related to several strands of the literature. First, we contribute to the large body of literature measuring asset correlations across countries and asset classes. Inter-market studies for sovereign bonds (for Europe, e.g., Kim et al., 2006; Abad et al., 2010; Abad et al., 2014; for Europe and the US, e.g., Skintzi and Refenes, 2006; Christiansen, 2007; for developed countries, Driessen et al., 2003; for emerging and frontier countries, Nowak et al., 2011; and Piljak, 2013) and equities (Connolly et al., 2007; Christiansen and Ranaldo, 2009) focus on increasing financial integration at the international level. Studies that span asset classes such as sovereign bond and equity markets (e.g., Connolly et al., 2005; Yang et al., 2009; Baele et al., 2010; Baker and Wurgler, 2012; and Bansal et al., 2014) or sovereign bond, corporate bond and equity markets at the aggregate level (e.g., Baur and Lucey, 2009; Brière et al., 2012) document the evolution of financial integration and flight to low-risk sovereign bonds in market downturns. At the individual security level, Acharya et al. (2013) find higher inter-market correlation between distressed stocks and corporate bonds in times of market downturns; Nieto and Rodriguez (2015) document common factors driving correlation between US stocks and corporate bonds of the same issuer. Correlations within asset classes are assessed either directly (e.g., Steeley, 2006 for different maturity segments of the UK sovereign bond market) or via common risk factors (e.g., Steeley, 1990; Litterman and Scheinkman, 1991 for UK and US sovereign bonds; Fama and French, 1993; Collin-Dufresne et al., 2001; Elton et al., 2001; Gebhardt et al., 2005; and Lin et al., 2011 for US corporate bonds; Klein and Stellner, 2014 and Aussenegg et al., 2015 for European corporate bonds). We add to this literature by analyzing correlations within the US corporate bond market, determining and analyzing the correlation of systematic credit risk and liquidity, and interpreting this correlation as a flight-to-quality phenomenon.

Second, our paper is related to the literature that analyzes the economic mechanisms leading to higher correlation between asset returns. King and Wadhwani (1990) suggest that investors infer asset values in one market from values in another market to a larger degree when the information environment becomes more complex, which leads to higher correlations. Connolly et al. (2007) trace high correlation back to high market uncertainty. In Brunnermeier and Pedersen (2009), a sudden drying up of investors' funding ability leads to low market liquidity and high correlation. Barberis et al. (2005) argue that groups of investors are prone to "investment habitats". Investors within one habitat trade more similarly. Kumar and Lee (2006) show that such herding is caused by investor sentiment. Chordia et al. (2011) find that market downturns lead to retail investors' herding and to higher stock correlations. We add to this literature by showing that low investor sentiment increases risk factor correlation, and high risk factor correlation leads to high bond correlation.

Third, we contribute to the literature analyzing the relation between liquidity and credit risk. Vayanos (2004) argues that investors attach a higher value to liquidity when markets are volatile. Ericsson and Renault (2006) motivate and document a positive correlation between credit risk and liquidity premiums for corporate bonds. Dick-Nielsen et al. (2012) and Friewald et al. (2012) show that – consistent with flight-to-quality behavior – liquidity premiums increase more for low-rated than for high-rated corporate bonds during the recent financial crisis. In contrast, Longstaff et al. (2005) find a negative correlation between credit risk and liquidity premiums for corporate bonds. Our paper reconciles this contradictory evidence by showing that risk factor correlation varies over time and depends on investor sentiment. In addition, we show that stronger flight-to-quality increases the comovement within corporate bond markets.

Finally, our results extend the growing literature on the influence of investor sentiment in the US corporate bond market. Nayak (2010) finds that corporate bond spreads are affected by investor sentiment. Tang and Yan (2010) show that market-wide credit spreads negatively depend on investor sentiment. We add to this literature by showing that low investor sentiment leads to high risk factor correlation and, ultimately, high bond correlation.

The remainder of the paper is organized as follows. In Section 2.2, we document how bond correlation evolves over time. In Section 2.3, we develop our model to explain varying bond correlation and state our main hypotheses linking bond correlation to risk factor correlation and risk factor correlation to investor sentiment. Our hypotheses are tested in Section 2.4. In Section 2.5, we provide various robustness tests and Section 2.6 concludes.

2.2. Bond correlation over time

2.2.1. Bond sample

We calculate bond correlations based on bond transaction data (actual trade price, yield resulting from this price, trade size, trade time, and trade date) from TRACE (Trade Reporting and Compliance Engine). We filter out erroneous trades with the algorithm described in Dick-Nielsen (2009) and use only plain vanilla bonds with fixed coupons. We exclude bonds without S&P rating (obtained from Thomson Reuters Datastream) and initial time to maturity of more than 30 years. Additionally, we exclude bonds for which Thomson Reuters Datastream does not provide 5-year credit default swap (CDS) mid quotes, since we use these to calculate credit risk premiums.

As TRACE does not cover BBB-rated and high yield bonds before October 2004 (Goldstein and Hotchkiss, 2012), our sample starts on October 1, 2004. It ends on September 30, 2010, since Thomson Reuters Datastream provides CDS data only until that date. We exclude federal holidays as only sparse trading occurs on these days. The final sample consists of 4,266 corporate bonds of 426 companies. Table 2.1 displays summary statistics.

Table 2.1: Summary statistics of the TRACE sample

	All	IG	HY	AAA&AA	A	BBB	IG – HY	
#Firms	302.44	245.01	65.04	35.69	97.21	140.47	179.97	***
#Bonds	1,531.61	1,364.13	169.79	333.00	626.93	412.25	1,194.34	***
Volume	453.16	463.64	368.19	598.38	450.81	382.26	95.45	***
Time to maturity	5.32	5.24	5.87	5.24	4.92	5.81	-0.63	***
Coupon	6.10	5.92	7.54	5.05	5.87	6.66	-1.62	***
S&P rating	6.88	6.03	13.59	2.40	5.61	8.56	-7.56	***
#Trades	78.87	81.86	53.81	97.57	93.33	50.23	28.05	***
Trade Size	360.20	365.54	319.68	243.79	281.07	591.27	45.86	***
Turnover	0.04	0.04	0.04	0.05	0.04	0.04	0.00	

Notes: The table reports characteristics of the TRACE corporate bond sample. We report the mean of these characteristics for the full sample, the investment grade (IG) sample and high yield (HY) sample. The IG sample is further split into three subsamples consisting of all bonds belonging to specific credit rating buckets. The buckets are AAA and AA, A, and BBB. #Firms is the average number of companies with actively traded bonds, #Bonds is the average number of actively traded bonds per month. Volume is the average outstanding volume per actively traded bond in million USD. Time to maturity is the average time to maturity in years. Coupon is the average per annum coupon rate in percentage points. S&P rating is the average S&P rating expressed as a number (AAA=1, …, C=21). #Trades is the average number of trades per bond per month. Trade size is the average trade size per bond in thousand USD. Turnover is the average monthly trading volume per bond as a percentage of issue volume. In the last column, we report the difference between the IG and HY sample ***, **, and * denote significance of a t-test for differences from zero at the 1%, 5%, and 10% significance level, respectively.

Table 2.1 shows that the mean number of companies with actively traded bonds per month is 302, the majority with an investment grade (IG) rating (245 companies). The mean number of actively traded bonds per month (1,531) indicates that five bonds per issuing company are traded. Again, most bonds are in the IG segment, but even the high yield (HY) segment contains a broad bond portfolio (170 bonds). Mean outstanding volume is 453.64 m USD. It is significantly higher in the IG segment than in the HY segment (IG: 463.64 m USD; HY: 368.79 m USD). Mean time to maturity roughly equals 5 years and is significantly higher in the HY segment (IG: 5.24 years; HY: 5.87 years). The mean S&P rating for IG bonds is 6 (=A), the mean HY rating is almost 14 (=B+). Regarding trading activity, IG bonds trade significantly more frequently: 82 trades per bond per month, on average, compared to 54 trades of HY bonds. Mean trade size is 14% larger for IG bonds than for HY bonds. Despite the higher trading frequency and trading size, mean turnover is not larger for IG bonds than for HY bonds due to higher issuance volume in the IG segment.

An analysis of the specific credit rating buckets shows most bonds are rated A or BBB, but average bond volumes and number of trades (but not trade size) are larger in the AAA&AA bucket.[16] Time to maturity equals roughly five years in all buckets, and turnover is also similar in all buckets. As expected, coupon rates are larger for lower credit rating buckets.

2.2.2. Bond correlation

To calculate bond correlation, we first aggregate corporate bonds into two portfolios: an investment grade and a high yield corporate bond portfolio. Like Longstaff et al. (2005), we focus on bond spreads as the difference between the yield and the maturity-matched risk-free rate (obtained by interpolating US Treasury yields).[17] For each trading day, we compute one IG and one HY portfolio yield spread as the average yield spread across all traded bonds in the respective segment. We then calculate bond correlation as the 22-day rolling Pearson's correlation between the two portfolios' daily yield spread changes.[18] We focus on changes instead of levels to ensure stationarity. Figure 2.1 shows how bond correlation evolves over time.

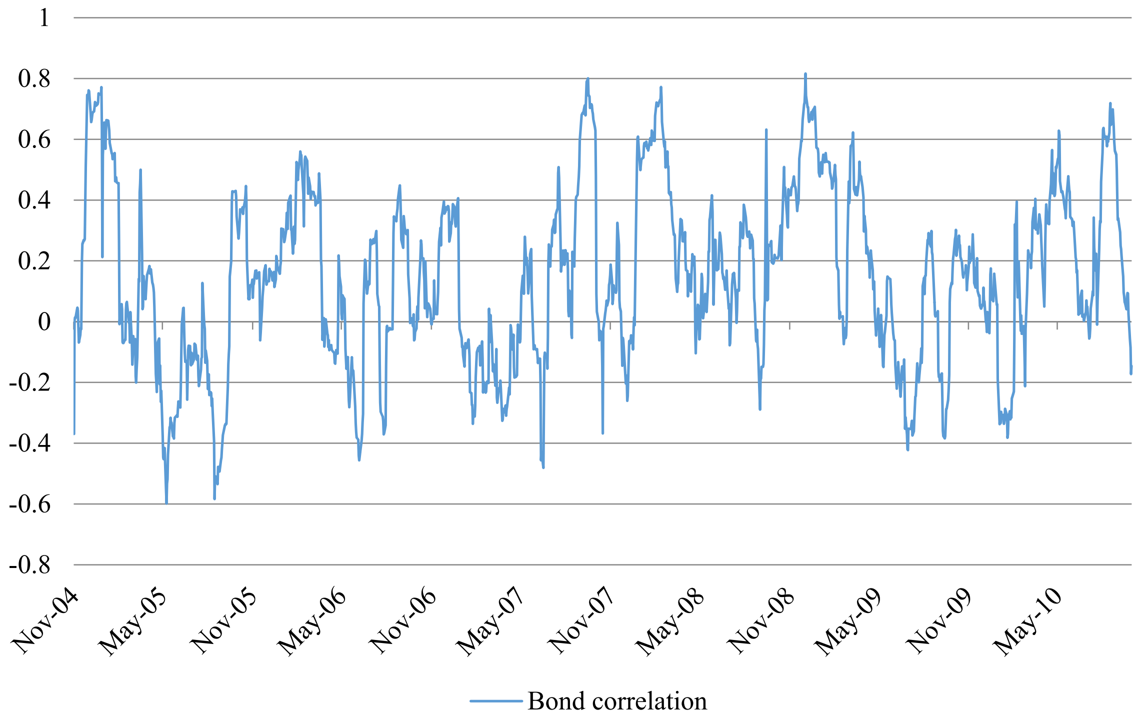
Figure 2.1 clearly shows that bond correlation varies strongly over time. It exhibits spikes around the acquisition of Bear Stearns by JPMorgan (March 16, 2008) and the September 2008 turmoil (federal takeover of Fannie Mae and Freddie Mac on September 7, the acquisition of Merrill Lynch by Bank of America on September 14, and the Lehman default on September 15). It is easy to see that bond correlation is much higher at the start of the financial crisis (July 2007). A numerical analysis shows that it is about three times as large,

[16] Like Wang and Wu (2015), we split the IG segment into three credit rating buckets and do not split the HY segment due to its much lower number of bonds and trading frequency. The first IG bucket (AAA&AA) consists of all bonds rated AAA or AA. The second and third IG buckets consist of bonds rated A and BBB, respectively.

[17] More specifically, on each trading day we collect constant maturity US Treasury yields from Thomson Reuters Datastream of maturities between one month and 30 years. We then fit a cubic function with maturity as the independent variable to the observed yields, and use the interpolated yield as a proxy for the maturity-matched risk-free rate at this date.

[18] As an alternative, we could measure time-varying correlation via a dynamic conditional correlation (DCC)-GARCH model, as Nieto and Rodriguez (2015) and Bartram and Wang (2015), or a smooth transition Markov-switching model, as Yang et al. (2009). We choose the conventional rolling window estimation as in Connolly et al. (2007); Panchenko and Wu (2009); Chordia et al. (2011); and Bansal et al. (2014) because it is more parsimonious with respect to the number of parameters that need to be estimated, does not depend on a specific distribution assumption or a specific functional form for the transition function, and is less likely to be dominated by past dynamics, and thus overstate persistence, if the data contains structural breaks.

Figure 2.1: Bond correlation time series



Notes: The figure displays bond correlation time series. The depicted time period lasts from November 2, 2004 to September 30, 2010. Bond correlation is computed as the 22-day rolling Pearson's correlation between the average investment grade and the average high yield bond yield spread changes.

with 21.3% after July 2007 but only 6.3% before, and the difference is statistically significant at the 1% level. This increase in correlation mirrors the higher correlation between equities in crises widely documented in the empirical literature (King and Wadhwani, 1990; Longin and Solnik, 1995; De Santis and Gerard, 1997; Longin and Solnik, 2001; Connolly et al., 2007; Chordia et al., 2011).

Next we analyze bond correlations in the ratings cross-section. We use the same buckets as before, and compute correlation between two credit rating buckets using the same portfolio approach as for Figure 2.1 and Table 2.1. Table 2.2 reports summary statistics.

Table 2.2 shows that correlations between the different buckets are positive on average. However, average correlation is much lower (around 0.15) and only significant at the 5% level when the HY segment is involved, compared to correlations between the IG buckets (0.70 at least, always significant at the 1% level). This difference is consistent with empirical evidence in Brière et al. (2012) that cross-country correlations across the IG and HY segment are lower than correlations within the IG and the HY segment. The standard deviation and the 5th and

95^{th} percentile indicate high variation over time in all correlations, in line with the visual impression obtained from Figure 2.1.

Table 2.2: Summary statistics of bond correlations

Bond correlation	Mean	Std. Dev.	5^{th} Percentile	95^{th} Percentile
IG with HY	0.15 **	0.29	-0.33	0.66
AAA&AA with A	0.91 ***	0.12	0.62	0.99
AAA&AA with BBB	0.70 ***	0.18	0.35	0.92
AAA&AA with HY	0.14 **	0.28	-0.34	0.62
A with BBB	0.70 ***	0.18	0.35	0.94
A with HY	0.15 **	0.30	-0.35	0.66
BBB with HY	0.15 **	0.31	-0.38	0.67

Notes: This table reports the mean, standard deviation, 5^{th}, and 95^{th} percentile of bond correlations. Bond correlations are determined as described in Section 2.2.2. We report correlations between investment grade (IG) and high yield (HY) bonds. The IG sample is further split into three subsamples consisting of all bonds belonging to specific credit rating buckets. The buckets are AAA and AA, A, and BBB. ***, **, and * denote significance of a t-test for differences from zero at the 1%, 5%, and 10% significance level, respectively. Significance is determined using Newey-West standard errors.

2.3. Explaining bond and risk factor correlation

In this section, we propose a model to explain the evolution of bond correlation. The model uses the fact that the main risk factors priced in bond yield spreads are credit risk and liquidity. Therefore, higher correlation between these risk factors translates into higher bond correlation. This raises the question: What drives risk factor correlation? We show that low sentiment translates into high risk factor correlation and, thus, high bond correlation.

Our model consists of two basic ingredients: First, correlation between risk factors (credit risk premiums, liquidity premiums) depends crucially on investor sentiment. Second, bond correlation is determined by this correlation between credit risk premiums and liquidity premiums. We focus on the economic intuition in this section. In the appendix, we formally derive our hypotheses in a reduced-form model based on a discrete two-factor Hull and White (1994) term structure model.

2.3.1. Risk factor correlation and investor sentiment

We first derive the impact of investor sentiment on risk factor correlation. Consider a corporate bond whose credit risk and liquidity vary over time. For simplicity, consider a zero bond maturing at date t=2 with notional value 1 and assume that the risk-free interest rate is r=0 and the recovery rate is R=0 as well. We can express the bond's risk-neutral price at time t=1 as

$$\mathrm{B}(1,2)=\exp(-\lambda_1-\gamma_1), \tag{2.1}$$

where λ_1 is the bond's risk-neutral default intensity and γ_1 is the bond's risk-neutral illiquidity intensity, both known at $t=1$. From the perspective of time $t=0$, the default and illiquidity intensities at $t=1$ are unknown, and the price at time $t=0$ is

$$\mathrm{B}(0,2)=\exp(-\lambda_0-\gamma_0)\cdot E_0\left[\exp\left(-\tilde{\lambda}_1-\tilde{\gamma}_1\right)\right], \tag{2.2}$$

where expectations are computed under the risk-neutral measure. The corresponding per-period log yields at time $t=0$ and time $t=1$ are $ys_0=\frac{1}{2}\left\{(\lambda_0+\gamma_0)-\log\left(E_0\left[\exp\left(-\tilde{\lambda}_1-\tilde{\gamma}_1\right)\right]\right)\right\}$ and $ys_1=\lambda_1+\gamma_1$, and the corresponding credit risk and liquidity premiums[19] are

$$\begin{aligned} cr_0 &= \frac{1}{2}\left\{\lambda_0-\log\left(E_0\left[\exp\left(-\tilde{\lambda}_1\right)\right]\right)\right\}, \\ cr_1 &= \lambda_1, \end{aligned} \tag{2.3}$$

$$\begin{aligned} liq_0 &= ys_0-cr_0=\frac{1}{2}\left\{\gamma_0-\log\left(E_0\left[\exp\left(-\tilde{\lambda}_1-\tilde{\gamma}_1\right)\right]\right)+\log\left(E_0\left[\exp\left(-\tilde{\lambda}_1\right)\right]\right)\right\}, \\ liq_1 &= ys_1-cr_1=\gamma_1. \end{aligned} \tag{2.4}$$

Equations (2.3) and (2.4) show that in this model, the covariance between credit risk and liquidity premium changes $Covar_0\left(\Delta\widetilde{cr},\Delta\widetilde{liq}\right)$ equals the covariance between the intensities $Covar_0\left(\tilde{\lambda}_1,\tilde{\gamma}_1\right)$.

In the empirical literature (e.g., Ericsson and Renault, 2006 or Dick-Nielsen et al., 2012), credit risk and liquidity premiums are usually assumed to be positively correlated, which corresponds to positively correlated intensities in our model (as in Schönbucher, 2002). Economically, this positive correlation reflects the pricing effect of the well-known flight-to-quality behavior of investors: bonds become less liquid when their credit quality deteriorates

[19] Since we consider a risk-neutral investor, we use the term "risk premium" for the compensation this investor requires for expected losses. As Equations (2.2) to (2.4) show, the investor does not demand additional compensation for possible variations in the credit quality or liquidity of the bond.

(e.g., Dick-Nielsen et al., 2012; Friewald et al., 2012; and Acharya et al., 2013) as investors shift their portfolios towards risk-free bonds or cash.

The novel mechanism we suggest is that the extent of flight-to-quality depends on investor sentiment. The economic rationale is twofold. First, low investor sentiment reduces an investor's propensity to invest in risky assets (Baker and Wurgler, 2006). Hence, the overall bond liquidity premium level is high when investor sentiment is low. We therefore link sentiment to liquidity premium levels. Second, the extent to which liquidity premiums change as a reaction to shocks in credit quality depends on sentiment. Investors perceive risks more severely when their sentiment is low (e.g., Kaplanski and Levy, forthcoming), and low sentiment affects an investor's reaction to negative information about firm fundamentals more than her reaction to positive information (e.g., Mian and Sankaraguruswamy, 2012). Therefore, we make the impact of credit risk shocks on liquidity premiums dependent on the sentiment level.

We model both effects in our setting by introducing a general investor sentiment parameter *x* and an impact variable $\tilde{a}_t$ which depends on the default intensity $\tilde{\lambda}_t$. Both *x* and $\tilde{a}_t$ jointly determine the magnitude of the flight-to-quality effect that investors exhibit as a reaction to a credit risk shock.[20] Larger values of *x* ($-1<x<1$, where $x=0$ corresponds to neutral sentiment) indicate lower investor sentiment; $\tilde{a}_t$ depends on whether the fundamental information is negative (then, $\tilde{a}_t = a_t^u$), neutral ($\tilde{a}_t = a_t^m$), or positive ($\tilde{a}_t = a_t^d$ with $a_1^d < a_1^m < a_1^u$). To illustrate the sentiment impact, consider a negative fundamental information ($\tilde{a}_t = a_t^u$) about the firm implying a credit risk shock at *t=1* ($\lambda_1 > \lambda_0$). If investor sentiment is low, i.e., *x* is positive, investors react more strongly to this information, which leads to a higher flight-to-quality effect compared to the case of neutral sentiment (x=0). Conversely, positive sentiment (x<0) reduces the flight-to-quality effect compared to the case of neutral sentiment. We model this sentiment-dependent flight-to-quality effect by multiplying the liquidity intensity $\tilde{\gamma}_1$ with $\left(1 + a_1^u \cdot x\right)$.[21] Therefore, the liquidity risk premium depends on sentiment:

[20] Conceivably, causality could also run in the opposite direction: a liquidity shock could be the fundamental information, and this could affect credit risk. In our model, we choose credit risk as the fundamental information for two reasons: First, only this direction of the effect is consistent with the economic intuition of Baker and Wurgler (2006), Kaplanski and Levy (forthcoming), and Mian and Sankaraguruswamy (2012). Second, this is consistent with empirical evidence of Kalimipalli and Nayak (2012) and Kalimipalli et al. (2013) that liquidity shocks have a second-order effect on corporate bond spreads compared to credit risk shocks.

[21] Positive sentiment (x<0) can generate negative risk factor correlation in our model, leading to a flight-from-quality effect. Longstaff et al. (2005) and Ericsson and Renault (2006) have empirically documented that

$$liq_0 = \frac{1}{2}\left\{\gamma_0\left(1+a_0\cdot x\right)-\log\left(E_0\left[\exp\left(-\tilde{\lambda}_1-\tilde{\gamma}_1\cdot\left(1+\tilde{a}_1\cdot x\right)\right)\right]\right)+\log\left(E_0\left[\exp\left(-\tilde{\lambda}_1\right)\right]\right)\right\},$$
$$liq_1 = \gamma_1\cdot\left(1+a_1\cdot x\right), \tag{2.5}$$

and the covariance between credit risk and liquidity premium changes $Covar_0\left(\Delta\widetilde{cr},\Delta\widetilde{liq}\right)$ equals the covariance between the credit risk intensity and the sentiment-adjusted liquidity intensities $Covar_0\left(\tilde{\lambda}_1,\tilde{\gamma}_1\cdot\left(1+\tilde{a}_1\cdot x\right)\right)$.[22] This covariance as well as the corresponding correlation both increase in the sentiment parameter x as shown in the appendix. This leads to our first hypothesis: risk factor correlation increases when investor sentiment decreases.

2.3.2. Bond correlation and risk factor correlation

Second, we link risk factor correlation and bond correlation. Consider two corporate bonds, for example, one investment grade bond i and one high yield bond h with positive default and liquidity intensities $\tilde{\lambda}_{i/h,t}$ and $\tilde{\gamma}_{i/h,t}\cdot\left(1+\tilde{a}_t\cdot x\right)$. Without loss of generality, the default (liquidity) intensity of a bond can be split into a systematic part $\tilde{\lambda}_{m,t}\cdot\beta_{i/h,\lambda}$ ($\tilde{\gamma}_{m,t}\cdot\left(1+\tilde{a}_t\cdot x\right)\cdot\beta_{i/h,\gamma}$) and an idiosyncratic part, $\tilde{\varepsilon}_{i/h}$ ($\tilde{\eta}_{i/h}$). Under the standard assumption that idiosyncratic factors are uncorrelated with systematic risk factors and across bonds, the covariance between yield spread changes of the two bonds results solely from covariance between systematic credit risk and systematic liquidity:[23]

$$\begin{aligned}Covar_0\left(\Delta\widetilde{ys}_i,\Delta\widetilde{ys}_h\right) &= \beta_{i,\lambda}\beta_{h,\lambda}\cdot Var\left(\tilde{\lambda}_{m,1}\right)+\beta_{i,\gamma}\beta_{h,\gamma}\cdot Var\left(\tilde{\gamma}_{m,1}\cdot\left(1+\tilde{a}_1\cdot x\right)\right)\\ &\quad+\left(\beta_{i,\lambda}\beta_{h,\gamma}+\beta_{i,\gamma}\beta_{h,\lambda}\right)\cdot Covar\left(\tilde{\lambda}_{m,1},\tilde{\gamma}_{m,1}\cdot\left(1+\tilde{a}_1\cdot x\right)\right).\end{aligned} \tag{2.6}$$

negative and positive correlations alternate in corporate bond markets. However, models that can explain both positive and negative risk factor correlations are scarce: for example, Ericsson and Renault (2006) can only generate consistently positive risk factor correlations. Beber et al. (2009), on the other hand, document average negative correlations between credit risk and liquidity premiums, and Chan et al. (2011) find flight-from-quality episodes in equity and commodity markets.

22 Alternatively, one could interpret $\tilde{a}_t x$ as the time-varying market price of liquidity risk, which could be caused by variations in the risk-free interest rate or in unexpected inflation. Since our model is derived from the perspective of a risk-neutral investor, we only account for these effects in our empirical analysis. In Section 2.5.2, we show that sentiment remains significant as a determinant of risk factor correlation even after adjusting credit risk and liquidity premiums for interest rate risk and unexpected inflation.

23 There is a large body of literature on correlated defaults and systematic credit risk: see, e.g., Das et al. (2007) or Duffie et al. (2009). Among others, Chacko (2006) and Lin et al. (2011) show that systematic liquidity is priced for corporate bonds. Bao et al. (2011) document a positive relation between systematic credit risk and systematic illiquidity in corporate bond markets.

In the appendix, we formally show that this relation also holds for correlations.[24] Thus, higher risk factor correlation (resulting from correlation between the systematic credit risk and liquidity) translates into higher bond correlation. This leads to our second hypothesis: bond correlation increases when risk factor correlation increases.

2.4. Hypotheses tests

2.4.1. Measuring investor sentiment and risk factor correlation

We use the Chicago Board Options Exchange (CBOE) daily market volatility index (VIX) to capture investor sentiment.[25] It measures the implied volatility of options on the S&P 500 and, thus, reflects investors' expectation about future market volatility. VIX is said to measure investor fear (e.g., Whaley, 2000, Baker and Wurgler, 2007) and is widely used as investor sentiment proxy (e.g., Kurov, 2010; Kaplanski and Levy, 2010; Da et al., 2015; and Smales, 2015). A high value of VIX corresponds to low investor sentiment. In our sample, VIX has an average value of 21.42 and a standard deviation of 11.61. A possible concern is that VIX will not reflect pure investor sentiment, but mainly the state of the economy. To ensure that we do not capture this effect, we orthogonalize VIX to macroeconomic factors as in Baker and Wurgler (2006) and use the residual of this orthogonalization as our measure of sentiment in the remainder of the paper.[26] The residual has mean zero and its standard deviation is 6.40.

To determine risk factor correlation, we first calculate credit risk premiums and liquidity premiums at the bond level. We use daily 5-year CDS mid quotes from Thomson Reuters Datastream as a proxy for the bond's credit risk premium. As a proxy for the liquidity premium, we use the non-credit risk portion of the bond yield spread (see, e.g., Longstaff et al., 2005; Chen et al., 2007). To compute this, we subtract the CDS mid quote from the yield spread to obtain the bond's liquidity premium.[27] On average, the credit risk premium equals

[24] Note that our model can generate negative bond correlation. The intuition is that if the systematic credit risk and liquidity intensity are sufficiently negatively correlated, bond covariance and thus bond correlation is also negative.

[25] In the robustness section, we use alternative measures of investor sentiment and show that the qualitative results of this paper do not depend on the investor sentiment proxy.

[26] The factors used in the orthogonalization are the growth rate of the 12-month moving averages of growth in durable, nondurable, and services consumption, growth in employment, growth in industrial production, and a dummy for NBER recessions We obtain the time series from the Federal Reserve Economic Database: http://research.stlouisfed.org/fred2/

[27] Arguably, the CDS mid premium and the non-credit risk portion on the bond yield spread may also reflect factors other than credit risk and liquidity. In Section 2.5.1, we show that our empirical results are robust

0.85% for IG bonds and 3.59% for HY bonds. The difference in the liquidity premiums is less pronounced: The mean liquidity premium is 1.44% in the IG and 2.21% in the HY segment. Both differences are statistically significant at the 1% level.

To calculate risk factor correlation, we aggregate corporate bonds into an IG and a HY portfolio as in Section 2.2.2. For each portfolio, we determine daily credit risk premiums and liquidity premiums as the average across all traded bonds in the respective segment. We then compute 22-day rolling Pearson's correlation between credit risk and liquidity premium changes. The average of the IG and the HY correlation is our measure of risk factor correlation. To obtain an unbounded variable, we transform Pearson's correlation using the Fisher z-transformation from Section 2.4.2 onwards. We proceed in the same way when we calculate risk factor correlation for bonds belonging to specific credit rating buckets (e.g., A and BBB): We first form two portfolios (consisting of A and BBB bonds, respectively), then calculate the correlation between credit risk and liquidity premium changes in each portfolio, and finally average the two correlation estimates to come up with risk factor correlation. Table 2.3 reports summary statistics on risk factor correlations.

Table 2.3: Summary statistics of risk factor correlations

Risk factor correlation	Mean	Std. Dev.	5th Percentile	95th Percentile
IG and HY	0.03	0.20	-0.27	0.37
AAA&AA and A	0.07	0.23	-0.30	0.46
AAA&AA and BBB	0.05	0.22	-0.33	0.40
AAA&AA and HY	0.04	0.21	-0.30	0.39
A and BBB	0.04	0.20	-0.26	0.41
A and HY	0.03	0.24	-0.35	0.45
BBB and HY	0.01	0.24	-0.36	0.42

Notes: This table reports the mean, standard deviation, 5th, and 95th percentile of risk factor correlations. Risk factor correlations are determined as described in Section 2.4.1. We report risk factor correlations calculated for the investment grade (IG) and high yield (HY) segment. The IG sample is further split into three subsamples consisting of all bonds belonging to specific credit rating buckets. The buckets are AAA and AA, A, and BBB. ***, **, and * denote significance of a t-test for differences from zero at the 1%, 5%, and 10% significance level, respectively. Significance is determined using Newey-West standard errors.

Table 2.3 documents that the average risk factor correlation is small in economic terms. The positive values, though not significant, indicate a moderate flight-to-quality effect in all

against the use of alternative credit risk and liquidity premium specifications. Section 2.5.2 adjusts correlations for additional risk factors.

credit ratings buckets. This finding is in line with evidence by Dick-Nielsen et al. (2012) that flight-to-quality affects both investment grade and speculative corporate bonds. Interestingly, the maximum value of 0.07 is attained for the highest credit rating buckets (AAA&AA with A), suggesting that even highly rated corporate bonds suffered from the flight-to-quality effect during our observation interval. However, differences between the average risk factor correlations are not statistically significant as indicated by the high standard deviations ($\geq$ 0.20) and the values of the 5th and 95th percentile.

We conclude the descriptive analysis of risk factor correlation by comparing the cross-sectional results of Table 2.2 and Table 2.3. Consistent with the lower risk factor correlation when the HY segment is involved, Table 2.2 indicates lower bond correlation in these cases. Economically, this implies that diversification across the IG and HY segments decreases portfolio risk because risk factor correlation is low. However, if risk factor correlation increases, this diversification benefit is reduced. In the next section, we therefore turn to our analysis of sentiment as a driver of risk factor correlation.

2.4.2. The link between sentiment and risk factor correlation

In this section, we test our first main hypothesis: Risk factor correlation increases when sentiment decreases. To do so, we run the following time-series regression:

$$\text{Corr}_t^{Risk} = \alpha + \beta \cdot \text{Sentiment}_t + \Gamma \cdot \text{Controls}_t + \varepsilon_t. \tag{2.7}$$

Risk factor correlation Corr_t^{Risk} and sentiment are measured as described in Section 2.4.1. We use the Fisher z-transformations of risk factor correlations to obtain an unbounded variable. Controls_t is the vector of variables controlling for market-wide risk and for market downturns. We include these variables since equity market correlation is higher when market risk is high (e.g., King and Wadhwani, 1990; Longin and Solnik, 1995) and during market downturns (e.g., Longin and Solnik, 2001). To measure market-wide risk, we determine the market-wide yield spread as the sum of the credit risk premium and liquidity premium. We then compute its 22-day rolling standard deviation as a proxy for market-wide risk. The average value of this standard deviation is 0.33 with a standard deviation of 0.30. To indicate market downturns, we define a dummy variable that takes on a value of one if the yield spread at time *t* is above a one-sigma band compared to the previous month.

Table 2.4: Risk factor correlation and investor sentiment

	Dependent variable: Risk factor correlation						
Explanatory variables	IG and HY	AAA&AA and A	AAA&AA and BBB	AAA&AA and HY	A and BBB	A and HY	BBB and HY
Sentiment	0.0037 ***	0.0058 ***	0.0033 **	0.0024 **	0.0066 ***	0.0059 ***	0.0034 **
	(0.0001)	(0.0000)	(0.0321)	(0.0444)	(0.0000)	(0.0000)	(0.0171)
Market-wide risk	0.2967 ***	-0.0410 *	-0.0484	0.3044 ***	-0.0532 **	0.3007 ***	0.2915 ***
	(0.0000)	(0.0891)	(0.1021)	(0.0000)	(0.0171)	(0.0000)	(0.0000)
Market downturn	0.0070	0.1288 ***	-0.0741 **	-0.1214 ***	0.0734 **	0.0325	-0.1813 ***
	(0.8161)	(0.0019)	(0.0452)	(0.0004)	(0.0265)	(0.3879)	(0.0003)
Constant	-0.0713 ***	0.0866 ***	0.0705 ***	-0.0503 ***	0.0585 ***	-0.0634 ***	-0.0766 ***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Adj. R^2	21.86	4.36	1.20	14.27	4.62	18.58	10.39

Notes: The table reports the results of the regression of risk factor correlation on sentiment and control variables. Risk factor correlation is the Fisher z-transformation of Pearson's correlation coefficients, determined as described in the main text in Section 2.4.1. Sentiment is measured as CBOE VIX index orthogonalized to macroeconomic factors. The control variables are market-wide risk and a market downturn dummy. Market-wide risk is measured as the 22-day rolling standard deviation of the sum of the credit risk premium and liquidity premium. The market downturn dummy takes on a value of one if the yield spread at time t is above a one-sigma band compared to the previous month. Columns 1 to 7 provide the results for the investment grade (IG) and high yield (HY) segment The IG sample is further split into three subsamples consisting of all bonds belonging to specific credit rating buckets. The buckets are AAA and AA, A, and BBB. P-values are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Significance is determined using Newey-West standard errors. Adjusted R^2 are in percentage points. The number of observations is 1,456 in all regressions.

Table 2.4 shows the regression results. In the first column, we present results for the overall risk factor correlation calculated using all IG and HY bonds. Columns 2 to 7 present results for the more detailed credit rating buckets used above.

Table 2.4 provides strong support for our first hypothesis: Irrespective of whether we consider the overall (IG&HY) or the bucket-specific risk factor correlations, risk factor correlation is significantly (at least at the 5% level) related to sentiment with the hypothesized positive coefficient sign. Thus, risk factor correlation, and hence flight-to-quality, increases when investor sentiment decreases. With respect to the different credit rating buckets, the lower intercept when the HY segment is involved is consistent with the lower average values in Table 2.3. In contrast, the control variables have no consistent impact on risk factor correlation across the buckets.

2.4.3. The link between risk factor correlation and bond correlation

We now test our second hypothesis: Bond correlation increases with risk factor correlation. We run the following time-series regression:

$$\mathrm{Corr}_t^{Bond} = \alpha + \beta \cdot \mathrm{Corr}_t^{Risk} + \gamma \cdot \mathrm{Sentiment}_t + \delta \cdot \mathrm{Herding}_t + \Gamma \cdot \mathrm{Controls}_t + \varepsilon_t. \tag{2.8}$$

The main variables are bond correlation Corr_t^{Bond} and risk factor correlation Corr_t^{Risk}. We use Fisher z-transformations of both correlations to obtain unbounded variables. We add the same vector of controls, $\mathrm{Controls}_t$, as in Table 2.4 to capture possible effects of the state of the economy on bond correlation. Furthermore, we add sentiment (captured by VIX) to control for the direct impact of investor sentiment on bond correlation. Since empirical studies (e.g., Kumar and Lee, 2006) have documented a link between investors' herding behavior and equity market correlations and a similar link might exist in the bond market, we also control for herding in the bond market.[28] We calculate the herding measure of Lakonishok et al. (1992) for each traded bond *i* on each day *t* as:

$$\mathrm{LSV}_{i,t} = \left|\mathrm{br}_{i,t} - \overline{\mathrm{br}}_t\right| - E_t\left(\left|\mathrm{br}_{i,t} - \overline{\mathrm{br}}_t\right|\right). \tag{2.9}$$

The buyer ratio $\mathrm{br}_{i,t}$ denotes the fraction of buys relative to the total number of trades of bond *i* on day *t*. $\overline{\mathrm{br}}_t$ is the buyer ratio on day *t* averaged across bonds, and $E_t\left(\left|\mathrm{br}_{i,t} - \overline{\mathrm{br}}_t\right|\right)$ is the bias

[28] Cai et al. (2012) document herding behavior among bond mutual fund managers.

correction suggested by Bellando (2012). The resulting LSV measure has a mean of 0.09 and a standard deviation of 0.02. Table 2.5 reports the regression results.

Table 2.5 provides strong support for our second hypothesis. We find a positive and significant impact of risk factor correlation on bond correlation, no matter whether we consider the overall market or specific credit rating buckets. The A and HY credit rating bucket exhibits the highest sensitivity, but all coefficient estimates are of a similar order of magnitude. We also find a significant direct impact of sentiment on bond correlation, except for the highest credit rating buckets (AAA&AA and A). The herding variable and the remaining control variables have no consistent impact on bond correlation.

A possible concern with our empirical analysis in Equation (2.8) is that we cannot formally test whether sentiment affects bond correlation only directly, or also indirectly via the risk factor correlation channel we propose. To address this concern, we test for significance of this indirect impact using a causal mediation analysis as in Imai et al. (2010b). The mediation model is based on Equations (2.7) and (2.8), and allows us to quantify the indirect impact of sentiment on bond correlation via risk factor correlation.[29] We report the indirect impact of sentiment on bond correlation, measured via the average causal mediation effect, in the last row of Table 2.5. Significance is computed using bootstrapped standard errors from 10,000 simulation runs. The last row of Table 2.5 shows that investor sentiment has a statistically significant indirect impact on bond correlation via risk factor correlation, which amounts to up to 18% of the total impact of investor sentiment (for the A and HY credit rating buckets). Hence, sentiment affects bond correlation not only directly, but also indirectly via risk factor correlation.

Overall, the results of Section 2.4 clearly support the economic rationale developed in Section 2.3: When investor sentiment decreases, risk factor correlation increases, translating into increasing bond correlation.

[29] Specifically, Equation (2.7) represents the mediator model and specifies the conditional distribution of the mediator risk factor correlation given the treatment sentiment, and the control variables. Equation (2.8) represents the outcome model and specifies the conditional distribution of the outcome bond correlation given the mediator risk factor correlation, the treatment sentiment, and the control variables. We fit both models sequentially, using standard errors with a Newey-West correction. We then estimate the average causal mediation effect (the indirect impact) using the algorithm in Imai et al. (2010a) for parametric inference, and determine its significance using bootstrapped standard errors.

Table 2.5: Bond correlation and risk factor correlation

	Dependent variable: Bond correlation						
Explanatory variables	IG and HY	AAA&AA and A	AAA&AA and BBB	AAA&AA and HY	A and BBB	A and HY	BBB and HY
Risk factor correlation	0.2461 ***	0.2753 ***	0.2738 ***	0.2500 ***	0.1277 *	0.3490 ***	0.2394 ***
	(0.0001)	(0.0000)	(0.0000)	(0.0006)	(0.0758)	(0.0000)	(0.0011)
Sentiment	0.0094 ***	-0.0050	0.0131 ***	0.0095 ***	0.0143 ***	0.0099 ***	0.0072 ***
	(0.0000)	(0.1096)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0012)
Herding	0.8971	-1.7728 **	1.8381 **	-0.2783	3.3710 ***	1.2131 *	0.2824
	(0.1276)	(0.0467)	(0.0182)	(0.6804)	(0.0001)	(0.0626)	(0.6928)
Market-wide risk	0.0279	-0.5279 ***	-0.3777 ***	0.0254	-0.4206 ***	-0.0291	-0.1364 **
	(0.4744)	(0.0000)	(0.0000)	(0.6693)	(0.0000)	(0.5675)	(0.0186)
Market downturn	0.1124 **	0.1542	-0.0170	0.2081 ***	-0.1259	0.1443 **	0.2310 ***
	(0.0406)	(0.1585)	(0.8058)	(0.0077)	(0.1073)	(0.0271)	(0.0023)
Constant	0.0610	2.0890 ***	0.9095 ***	0.1456 **	0.8114 ***	0.0501	0.1723 ***
	(0.2519)	(0.0000)	(0.0000)	(0.0268)	(0.0000)	(0.4028)	(0.0070)
Adj. R^2	11.22	11.31	14.38	13.16	14.61	16.67	6.78
Indirect impact	0.0009 ***	0.0016 ***	0.0009 ***	0.0006 **	0.0008 ***	0.0021 ***	0.0008 ***
	(0.0000)	(0.0000)	(0.0000)	(0.0100)	(0.0000)	(0.0000)	(0.0000)

Notes: The table reports results of the regression of bond correlation on risk factor correlation, sentiment, herding, market-wide risk, and market downturn. Both bond correlation and risk factor correlation are the Fisher z-transformation of Pearson's correlation coefficients, determined as described in the main text in Section 2.2.2 and 2.4.1. Herding is measured using the approach of Lakonishok et al. (1992) as described in Section 2.4.3. Sentiment, market-wide risk, and market downturn are as in Table 2.4. We report correlations between investment grade (IG) and high yield (HY) bonds. The IG sample is further split into three subsamples consisting of all bonds belonging to specific credit rating buckets. The buckets are AAA and AA, A, and BBB. P-values are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level. Significance is determined using Newey-West standard errors. Adjusted R^2 are in percentage points. In the last row, we report the indirect impact of sentiment on bond correlation, measured by the average causal mediation effect using the approach of Imai et al. (2010b) as described in Section 2.4.3. The corresponding standard errors are bootstrapped. The number of observations is 1,456 in all regressions.

2.5. Robustness

In this section, we perform various robustness tests. In Section 2.5.1, we check for the robustness of our results when we use alternative proxies for credit risk and liquidity premium. The motivation for this robustness analysis is that CDS mid quotes may not be pure measures of credit risk, but may also reflect CDS illiquidity (e.g., Tang and Yan, 2008; Bongaerts et al., 2011), and bond yield spreads may reflect other time-varying factors than credit risk and liquidity (e.g., Collin-Dufresne et al., 2001). In Section 2.5.2, we adjust correlations for interest rate risk and unexpected inflation. The reason is that both may affect both credit risk premiums and liquidity premiums, and we might erroneously identify this impact as risk factor correlation. In Section 2.5.3 we, use alternative proxies for investor sentiment and in Section 2.5.4 we use the swap-rate as an alternative proxy for the risk-free rate. Finally, we test the temporal stability of our results in Section 2.5.5. For the sake of brevity, we report only results for the overall market (HY and IG) in the robustness tests.

2.5.1. Alternative credit risk and liquidity premium

We first control for the impact of CDS illiquidity on CDS mid premiums: correlation between CDS mid quotes and bond yield spreads minus CDS mid quotes (which we use as a proxy for liquidity premiums) may also reflect CDS illiquidity. Like Tang and Yan (2008), we use the CDS bid-ask spread as the independent variable to identify the liquidity component in the CDS mid quote. We run a time-series regression of CDS mid quotes on CDS bid-ask spreads for each CDS contract, and then compute risk factor correlation and bond correlation as in Section 2.2.2 and 2.4.1, this time using the unexplained part instead of the original CDS mid quotes. The first two columns of Table 2.6 present the results we obtain when repeating our analyses from Section 2.4 for these adjusted correlation measures.

All our main results remain valid when we use the alternative credit risk premium: sentiment explains risk factor correlation, and risk factor correlation explains bond correlation. We can therefore exclude CDS illiquidity as an alternative explanation for our effect.

In Columns 3 and 4 of Table 2.6 we use an alternative measure for the liquidity premium. Arguably, part of the non-credit yield spread may be due to factors other than illiquidity. Empirically, taxes (Elton et al., 2001), equity volatility and accounting variables (Campbell and Taksler, 2003), and an unexplained systematic factor (Collin-Dufresne et al., 2001) have

Table 2.6: Alternative credit risk and liquidity premium

	Alternative credit risk premium				Alternative liquidity premium			
Explanatory variables	RFC		BC		RFC		BC	
Risk factor correlation			0.1920	***			0.1728	**
			(0.0076)				(0.0357)	
Sentiment	0.0028	**	0.0096	***	0.0068	***	0.0082	***
	(0.0354)		(0.0000)		(0.0000)		(0.0011)	
Herding			1.9002	**			1.8942	**
			(0.0139)				(0.0136)	
Market-wide risk	0.1716	***	-0.1693	***	0.0624	**	-0.0939	*
	(0.0000)		(0.0007)		(0.0228)		(0.0680)	
Market downturn	-0.0806	*	0.2564	***	0.1247	***	0.2369	***
	(0.0636)		(0.0001)		(0.0092)		(0.0006)	
Constant	-0.0418	***	0.1402	**	0.0363	***	0.0899	
	(0.0029)		(0.0418)		(0.0020)		(0.1735)	
Adj. R^2	4.80		9.27		11.90		8.49	
Indirect impact			0.0005	***			0.0012	***
			(0.0000)				(0.0000)	

Notes: The table replicates Table 2.4 and 2.5 using only the investment grade and high yield segment. In Columns 1 and 2, risk factor correlation (RFC) and bond correlation (BC) are computed using CDS mid quotes adjusted for CDS illiquidity as the credit risk measure as described in Section 2.5.1. In Columns 3 and 4, RFC and BC are computed using price dispersion as the liquidity measure as described in Section 2.5.1. ***, **, and * denote significance at the 1%, 5%, and 10% level. Significance is determined using Newey-West standard errors for the regression analyses, and bootstrapped standard errors for the indirect impact. Adjusted R^2 are in percentage points. The number of observations is 1,456 in all regressions.

been shown to affect bond yield spreads. Directly adjusting for these effects, however, is difficult since they differ across bonds but are basically constant over time (taxes, accounting variables), unavailable for some bonds (equity volatility), or impossible to proxy for (unexplained systematic factors).

We therefore compute an alternative liquidity measure not derived from yield spreads. Jankowitsch et al. (2011) introduce a price dispersion measure that reflects transaction costs as well as dealers' inventory risk and investors' search costs. Friewald et al. (2012) show that this measure is a major liquidity proxy in the corporate bond market. Hence, we focus on price dispersion as an alternative measure of bond illiquidity using the modified version of Schestag et al. (2016) and compute for each bond *i* on each trading day t the average price dispersion as

$$\text{PriceDispersion}_{\text{i,t}} = 2\sqrt{\frac{1}{\sum_{n=1}^{N} Q_n} \sum_{n=1}^{N} Q_n \left(\frac{P_n - \bar{P}}{\bar{P}}\right)^2} \tag{2.10}$$

where N denotes the number of trades on day t, Q_n is the trading volume of trade n on day t, P_n is the transaction price of trade n on day t, and $\bar{P}$ is the average across all transaction prices on day t. This relative dispersion measure gives us an estimate of the effective relative spread.

We then compute risk factor correlation and bond correlation, using price dispersion as the liquidity premium measure. Columns 3 and 4 of Table 2.6 present the results when we repeat the analyses from Section 2.4, using the new risk factor correlation and bond correlation. The results clearly show that the main results still hold. Investor sentiment drives risk factor correlation and risk factor correlation determines bond correlation. Thus, we can reject the hypothesis that our results are driven by our use of the non-credit risk component of the yield spread as the liquidity premium.

2.5.2. Correlations adjusted for interest rate risk and unexpected inflation

In this section, we control for the impact of interest rate risk and unexpected inflation by adjusting our correlation measures. The reason is that interest rate risk might affect both credit risk premiums (due to the link between a firm's default risk and the risk-free rate (see, e.g., Duffee, 1999)) and liquidity premiums (because of the flight-to-quality effect). Hence, we might erroneously identify interest rate risk as risk factor correlation, leading to spurious results in the estimation of Equations (2.7) and (2.8). Similarly, unexpected inflation has been proposed as an explanation for time-varying risk aversion (Brandt and Wang, 2003), leading to higher market prices of risk for all risk sources, and thus also an increased comovement of credit risk and liquidity premiums.

To control for interest rate risk, we first regress yield spread, credit risk premium, and liquidity premium changes on changes in the 5-year constant-maturity Treasury yield. Then, we compute risk factor correlation and bond correlation as before, but now use the residuals of the first-step regression instead of the original observations. We then repeat the analyses from Section 2.4. The results are presented in the first two columns of Table 2.7.

The first two columns of Table 2.7 show that our main results remain valid when we use interest rate risk-adjusted correlations: sentiment explains risk factor correlation, and risk factor correlation explains bond correlation. Thus, interest rate risk does not drive our results.

Table 2.7: Correlations adjusted for interest rate risk and unexpected inflation

	Adjustment for interest rate risk		Adjustment for unexpected inflation	
Explanatory variables	RCF	BC	RFC	BC
Risk factor correlation		0.3172 ***		0.2787 ***
		(0.0000)		(0.0015)
Sentiment	0.0034 ***	0.0089 ***	0.0031 ***	0.0100 ***
	(0.0003)	(0.0000)	(0.0013)	(0.0000)
Herding		0.7771		0.8897
		(0.2241)		(0.2170)
Market-wide risk	0.2687 ***	0.0045	0.3049 ***	0.0512
	(0.0000)	(0.9213)	(0.0000)	(0.3712)
Market downturn	0.0034	0.0971	0.0372	0.0748
	(0.9006)	(0.1461)	(0.1947)	(0.3475)
Constant	-0.0628 ***	0.0722	-0.0810 ***	0.0562
	(0.0000)	(0.2109)	(0.0000)	(0.3942)
Adj. R^2	18.42	12.00	24.20	12.58
Indirect impact		0.0011 ***		0.0009 ***
		(0.0000)		(0.0000)

Notes: The table replicates Table 2.4 and 2.5 using only the investment grade and high yield segment. In Columns 1 and 2, risk factor correlation (RFC) and bond correlation (BC) are adjusted for interest rate risk as described in Section 2.5.2. In Columns 3 and 4, both RFC and BC are adjusted for unexpected inflation as described in Section 2.5.2. ***, **, and * denote significance at the 1%, 5%, and 10% level. Significance is determined using Newey-West standard errors for the regression analyses, and bootstrapped standard errors for the indirect impact. Adjusted R^2 are in percentage points. The number of observations is 1,456 in all regressions.

We next control for the impact of unexpected inflation. We compute unexpected inflation as the difference between the realized inflation rate and its forecast using the following regression:

$$\text{Inflation}_t = \alpha + \beta_1 \cdot \text{Inflation}_{t-1} + \beta_2 \cdot \text{Inflation}_{t-2} + \varepsilon_t\,. \tag{2.11}$$

Inflation_t denotes the monthly inflation rate based on the Consumer Price Index (CPI) provided by the Federal Reserve Economic Database. We use the residuals from the above regression as the monthly unexpected inflation, and interpolate between monthly estimates to obtain a daily estimate.

To adjust our correlation measures for unexpected inflation, we use the same approach as before. We first regress yield spread, credit risk premium, and liquidity premium changes on changes in unexpected inflation. Then, we use the residuals from this regression to compute correlations and test our two hypotheses. The results, presented in Columns 3 and 4 of Table

2.7, document that our results still hold when we use inflation-adjusted correlations: When investor sentiment decreases, risk factor correlation increases, translating into increasing bond correlation. Thus, our proposed mechanism remains valid when using inflation-adjusted correlations, ruling out the possibility that unexpected inflation drives our results.

2.5.3. Alternative proxies for investor sentiment

In this section, we use five alternative proxies for investor sentiment: Individual Investor Sentiment Index (AAII) from Thomson Reuters Datastream (weekly) as in Brown and Cliff (2004); Economic Cycle Research Institute United States Leading Index (ECRI) (weekly); Daily Economic Policy Uncertainty Index (EPU) (daily) suggested by Baker et al. (forthcoming)[30]; St. Louis Fed Financial Stress Index (FSI) from the St. Louis Fed (weekly) which is similar to the Kansas City Financial Stress Index described in Hakkio and Keeton (2009); and the SENTIX World Economic Sentiment Index (SENTIX) (monthly). If necessary, we interpolate the indices to a daily frequency.

The indices offer different ways of capturing sentiment: They are based on surveys of investors' expectations in the US (AAII) and worldwide (SENTIX), screen US newspaper articles for positive and negative terms (EPU), are constructed from market variables capturing financial stress (FSI), or anticipate turns in the economic cycle (ECRI). Given the index construction, high sentiment is associated with high values for AAII, ECRI, and SENTIX and low values for EPU and FSI. To assure that all proxies have the same expected sign as our main sentiment proxy (VIX), we redefine AAII, ECRI, and SENTIX by multiplying them with -1. We again orthogonalize each sentiment index to the macroeconomic factors as in Baker and Wurgler (2006) to ensure that they do not capture the state of the economy.

Table 2.8 shows that our main results also hold when we use alternative proxies for investor sentiment. Sentiment drives risk factor correlation, and risk factor correlation drives bond correlation, no matter which proxy we use for investor sentiment.

[30] http://www.policyuncertainty.com/us_daily.html

Table 2.8: Alternative proxies for investor sentiment

Panel A: Risk factor correlation as dependent variable										
Explanatory variables	AAII		ECRI		EPU		FSI		SENTIX	
Sentiment	0.0023	***	0.0103	***	0.0004	***	0.0386	***	0.0016	*
	(0.0000)		(0.0000)		(0.0000)		(0.0002)		(0.0989)	
Market-wide risk	0.3046	***	0.2639	***	0.2961	***	0.2911	***	0.2990	***
	(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)	
Market downturn	0.0535	**	0.0285		0.0239		0.0068		0.0369	
	(0.0464)		(0.3674)		(0.3778)		(0.8313)		(0.1971)	
Constant	-0.0770	***	-0.0613	***	-0.0718	***	-0.0695	***	-0.0736	***
	(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)	
Adj. R^2	23.59		26.87		22.18		21.85		21.01	

Panel B: Bond correlation as dependent variable										
Explanatory variables	AAII		ECRI		EPU		FSI		SENTIX	
Risk factor correlation	0.2933	***	0.2249	***	0.2758	***	0.2361	***	0.2720	***
	(0.0008)		(0.0052)		(0.0003)		(0.0018)		(0.0016)	
Sentiment	-0.0010		0.0075	***	0.0001		0.1296	***	0.0045	*
	(0.2952)		(0.0038)		(0.7378)		(0.0000)		(0.0758)	
Herding	1.4351	**	0.7133		1.3624	**	0.8424		1.0865	
	(0.0402)		(0.2485)		(0.0338)		(0.1814)		(0.1176)	
Market-wide risk	0.0342		0.0274		0.0382		0.0056		0.0234	
	(0.5664)		(0.5841)		(0.4535)		(0.9016)		(0.6743)	
Market downturn	0.1922	**	0.1933	***	0.1960	***	0.0840		0.1852	**
	(0.0175)		(0.0032)		(0.0064)		(0.1237)		(0.0155)	
Constant	0.0064		0.0742		0.0115		0.0749		0.0413	
	(0.9206)		(0.1889)		(0.8450)		(0.1905)		(0.5205)	
Adj. R^2	8.64		9.56		8.43		13.24		9.09	
Indirect impact	0.0007	***	0.0023	***	0.0001	***	0.0091	***	0.0004	**
	(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0200)	

Notes: The table replicates Table 2.4 (Panel A) and 2.5 (Panel B) for alternative proxies for investor sentiment using only the investment grade and high yield segment. AAII is the Individual Investor Sentiment Index, ECRI the Economic Cycle Research Institute United States Leading Index, EPU the Daily Economic Policy Uncertainty Index, FSI the St. Louis Fed Financial Stress Index, and SENTIX the SENTIX World Economic Sentiment Index. ***, **, and * denote significance at the 1%, 5%, and 10% level. Significance is determined using Newey-West standard errors for the regression analyses, and bootstrapped standard errors for the indirect impact. Adjusted R^2 are in percentage points. The number of observations is 1,456 in all regressions.

2.5.4. Alternative proxy for the risk-free rate

In Section 2.4 we use maturity-matched constant maturity US-Treasury bonds to approximate risk-free rates. We now show that our results are robust when we use swap rates as a proxy for the risk-free rates, as in, e.g., Friewald et al. (2012).[31,32] The results are presented in Table 2.9.

Table 2.9: Swap rate as proxy for the risk-free rate

Explanatory variables	RCF		BC	
Risk factor correlation			0.1460	*
			(0.0667)	
Sentiment	0.0029	***	0.0078	***
	(0.0022)		(0.0002)	
Herding			0.4830	
			(0.4578)	
Market-wide risk	0.3429	***	0.0203	
	(0.0000)		(0.7134)	
Market downturn	-0.0433		0.1087	*
	(0.1589)		(0.0770)	
Constant	-0.0935	***	0.1141	*
	(0.0000)		(0.0590)	
Adj. R^2	8.63		6.01	
Indirect impact			0.0004	***
			(0.0000)	

Notes: The table replicates Table 2.4 and 2.5 using only the investment grade and high yield segment. Instead of calculating the risk-free rate from US Treasuries, we now use swap rates. Risk factor correlation (RFC) and bond correlation (BC) are computed based on yield spreads computed from swap rates. ***, **, and * denote significance at the 1%, 5%, and 10% level. Significance is determined using Newey-West standard errors for the regression analyses, and bootstrapped standard errors for the indirect impact. Adjusted R^2 are in percentage points. The number of observations is 1,456 in all regressions.

Table 2.9 shows that our results do not change when we use the swap rate to proxy the risk-free rate. The impact of sentiment on risk factor correlation remains significant as does the impact of risk factor correlation on bond correlation.

[31] More specifically, on each trading day we collect US swap rates from Thomson Reuters Datastream of maturities between one week and 30 years. We then fit a cubic function with maturity as the independent variable to the observed yields, and use the interpolated yield as a proxy for the maturity-matched risk-free rate at this date.

[32] Alternatively, one could use Overnight Index Swap rates (Michaud and Upper, 2008), the general collateral rate (Longstaff, 2000) or risk-free rates implied by derivatives prices (Brenner and Galai, 1986; Brenner et al., 1990). However, these rates are either not available for longer maturities, or empirically lie between Treasury rates and swap rates (Naranjo, 2009). We therefore focus on plain-vanilla interest rate swap rates.

2.5.5. Stability over time

In this section, we test the stability of our main results over time. We use two time splits. First, we split our sample period into two subperiods of equal size. Second, we spilt our sample at the beginning of the financial crisis (July 1, 2007 as in Friewald et al., 2012). For each subperiod we repeat the analyses from Section 2.4. The results are presented in Table 2.10.

Table 2.10: Temporal stability

Panel A: Risk factor correlation as dependent variable								
Explanatory variables	First half of sample period		Second half of sample period		Before July 2007		From July 2007	
Sentiment	0.0059	**	0.0020	*	0.0094	***	0.0023	**
	(0.0124)		(0.0625)		(0.0001)		(0.0251)	
Market-wide risk	0.3372	***	0.3203	***	0.3009	***	0.3351	***
	(0.0000)		(0.0000)		(0.0000)		(0.0000)	
Market downturn	0.0145		0.0675	**	0.0422		0.0611	**
	(0.5872)		(0.0154)		(0.1161)		(0.0265)	
Constant	-0.0352	**	-0.1359	***	-0.0068		-0.1461	***
	(0.0126)		(0.0000)		(0.6188)		(0.0000)	
Adj. R^2	17.57		34.90		20.23		34.33	

Panel B: Bond correlation as dependent variable								
Explanatory variables	First half of sample period		Second half of sample period		Before July 2007		From July 2007	
Risk factor correlation	0.3148	***	0.4125	***	0.4003	***	0.5227	***
	(0.0004)		(0.0001)		(0.0003)		(0.0000)	
Sentiment	0.0227	***	0.0101	***	0.0116	**	0.0110	***
	(0.0000)		(0.0000)		(0.0400)		(0.0000)	
Herding	-0.7876		-0.5408		0.0053		-1.7016	**
	(0.3967)		(0.5720)		(0.9956)		(0.0255)	
Market-wide risk	0.1489	**	-0.0100		0.1437	**	-0.0769	
	(0.0198)		(0.8784)		(0.0201)		(0.1532)	
Market downturn	-0.3764	***	0.0236		-0.3952	***	0.0065	
	(0.0000)		(0.7332)		(0.0000)		(0.9116)	
Constant	0.1823	**	0.2728	***	0.0707		0.4254	***
	(0.0232)		(0.0036)		(0.3818)		(0.0000)	
Adj. R^2	18.28		20.68		20.82		21.69	
Indirect impact	0.0019	***	0.0008	**	0.0037	***	0.0012	***
	(0.0000)		(0.0100)		(0.0000)		(0.0000)	

Notes: The table replicates Table 2.4 (Panel A) and 2.5 (Panel B) using only the investment grade and high yield segment. In Columns 1 and 2, we report results for the first and second half of the sample period. The number of observations is 728 in each subsample. In Columns 3 and 4, we cut the sample at July 1st, 2007 as in Friewald et al. (2012) to capture the beginning of the financial crisis. The number of observations is 644 in the first and 812 in the second subsample. ***, **, and * denote significance at the 1%, 5%, and 10% level. Significance is determined using Newey-West standard errors for the regression analyses, and bootstrapped standard errors for the indirect impact. Adjusted R^2 are in percentage points.

Table 2.10 shows that our results are stable when splitting our sample in the middle or at the beginning at the financial crisis. In both subperiods, we find a significant impact of sentiment on risk factor correlation and of risk factor correlation on bond correlation. Since the effects seem to be so stable over time, we expect our findings to remain valid in the years following our sample period.

2.6. Conclusion

In this paper, we theoretically and empirically explore the link between investor sentiment, risk factor correlation, and bond correlation. We set up a simple theoretical model that shows that investors exhibit a stronger flight-to-quality when sentiment is low. This in turn leads to higher risk factor correlation between the two main risk factors in corporate bond markets: credit risk and liquidity. As a consequence of this higher risk factor correlation when sentiment is low, bonds exhibit a higher comovement. Thus, sentiment-induced flight-to-quality effectively reduces diversification benefits across corporate bonds.

We test our model predictions using data on US corporate bonds and find strong and robust empirical support for our hypotheses: (i) When investor sentiment decreases, risk factor correlation increases. (ii) This increasing risk factor correlation translates into increasing bond correlation. We rule out several alternative explanations for our findings and show that they are stable over time and in the cross-section.

2.A. Model relating investor sentiment to bond correlation

In Section 2.3, we outline the economic intuition of how risk factor correlation is linked to investor sentiment and how bond correlation is linked to risk factor correlation. We formalize this intuition in a discrete two-factor model in this appendix. We first provide a detailed model description and then derive our hypotheses.

2.A.1. Model setup

Our model is based on a discrete two-factor Hull and White (1994) term structure model. We consider a single default-risky zero bond with two periods to maturity. The bond can default after one period (t=1) or after two periods (t=2). Default occurs at the end of a period, and in default the bond holder is paid a fraction R (recovery rate) of the bond's notional value. For simplicity, we set the default-free interest rate r and the bond's recovery rate to zero (r=0, R=0). The credit risk of this bond is described by the risk-neutral survival probability $\tilde{P}$:

$$\tilde{P}\left(t_1,t_2\right)=\exp\left(-\sum_{t=t_1}^{t_2}\tilde{\lambda}_t\right), \tag{2.12}$$

where $\tilde{\lambda}_t$ is the discrete stochastic default intensity at time t. We model the default intensity evolution from λ_0 (which is known at t=0) to $\tilde{\lambda}_1$ (conditional on no default in t=1, which occurs with probability $1-PD=\exp(-\lambda_0)$). The default intensity can increase or decrease by a constant factor $\Delta\lambda$ or remain the same $\left(\tilde{\lambda}_1\in\left\{\lambda_1^u,\lambda_1^m,\lambda_1^d\right\}=\left\{\lambda_0+\Delta\lambda,\lambda_0,\lambda_0-\Delta\lambda\right\}\right)$ and the unconditional probability of the states are $(1-PD)\cdot p_u^\lambda$, $(1-PD)\cdot p_m^\lambda$, and $(1-PD)\cdot p_d^\lambda$, respectively. The conditional probabilities for each state are derived via the following moment conditions of Schönbucher (2002):

$$p_u^\lambda+p_m^\lambda+p_d^\lambda=1$$

$$E_0\left[\tilde{\lambda}_1-\lambda_0\right]=p_u^\lambda\cdot\Delta\lambda+p_m^\lambda\cdot 0-p_d^\lambda\cdot\Delta\lambda=0 \tag{2.13}$$

$$E_0\left[\left(\tilde{\lambda}_1-\lambda_0\right)^2\right]=p_u^\lambda\cdot\Delta\lambda^2+p_m^\lambda\cdot 0^2+p_d^\lambda\cdot\Delta\lambda^2.$$

The first condition implies that there are no other states for the default intensity in t=1. The second condition ensures that there is no drift in the default intensity. The third condition links the conditional probabilities to the conditional variance.

Now consider a bond affected by illiquidity. The price impact of illiquidity is described by a liquidity discount factor $\tilde{L}$:

$$\tilde{L}(t_1, t_2) = \exp\left(-\sum_{t=t_1}^{t_2} \tilde{\gamma}_t\right), \tag{2.14}$$

where $\tilde{\gamma}_t$ is a non-negative, discrete stochastic liquidity intensity process. We model the evolution of $\tilde{\gamma}_t$ in a similar trinomial tree model as the evolution of $\tilde{\lambda}_t$. In Figure 2.2, we describe the common dynamics of the credit risk and liquidity intensity.

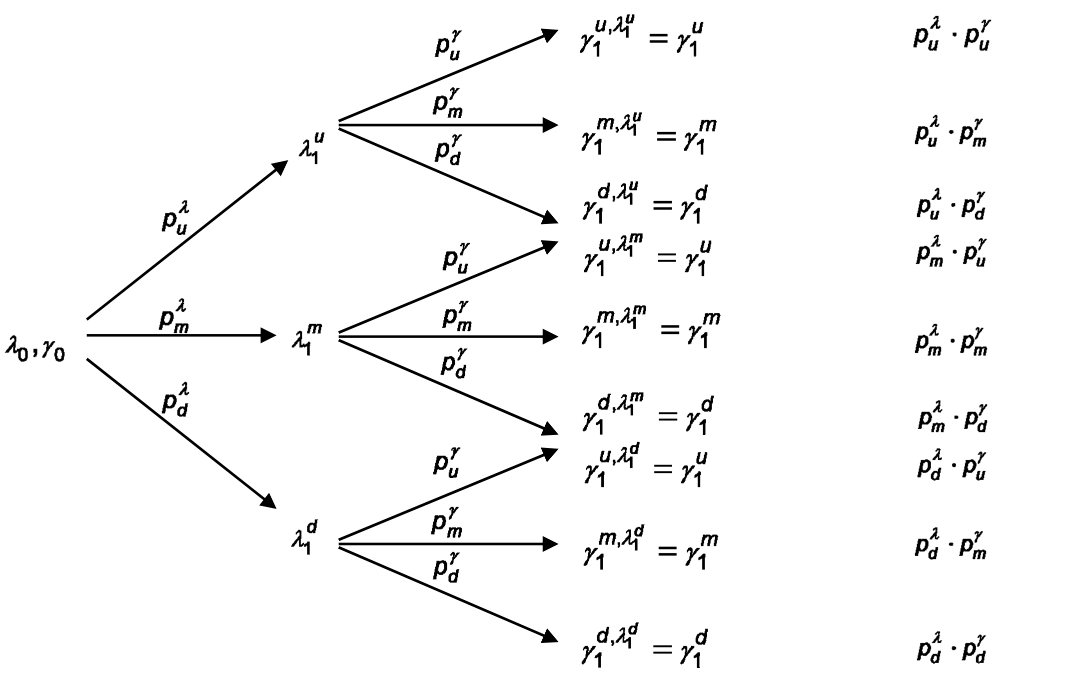
Panel A of Figure 2.2 shows the base case where the credit risk and liquidity intensity are independent. In Panel B of Figure 2.2, we introduce the well-known flight-to-quality by allowing for a positive correlation between both intensities without taking investor sentiment into account. We model this as Schönbucher (2002) and introduce a parameter ε that ranges from zero to one. This parameter affects the joint probabilities of the credit risk and liquidity intensity. For $\varepsilon > 0$, it increases the joint probabilities for states where both intensities move in the same direction: higher ε indicates higher correlation between the two intensities. Hence, positive values of ε model the price effect of investors' flight-to-quality behavior not due to investor sentiment.

Panel C of Figure 2.2 displays our full model, which also takes investor sentiment and its impact on flight-to-quality into account. We capture investor sentiment in the parameter x. Larger values of x $(-1 \le x \le 1)$ indicate lower investor sentiment. The non-negative random variable $\tilde{a}_t$ captures fundamental news about the firm. Thus, our full model extends the model in Panel B of Figure 2.2 by allowing an additional sentiment-driven flight-to-quality. We assume (consistent with the empirical evidence of Mian and Sankaraguruswamy, 2012) that investors react more to negative information than to neutral or positive information when investor sentiment is low. Thus, $\tilde{a}_t$ takes on a value of a_1^u for λ_1^u, a_1^m for λ_1^m, and a_1^d for λ_1^d with $0 \le a_1^d < a_1^m < a_1^u$. Consistent with the assumption that $\lambda_0 = \lambda_1^m$, we choose $a_0 = a_1^m$.

Figure 2.2: Reduced-form credit risk and liquidity model

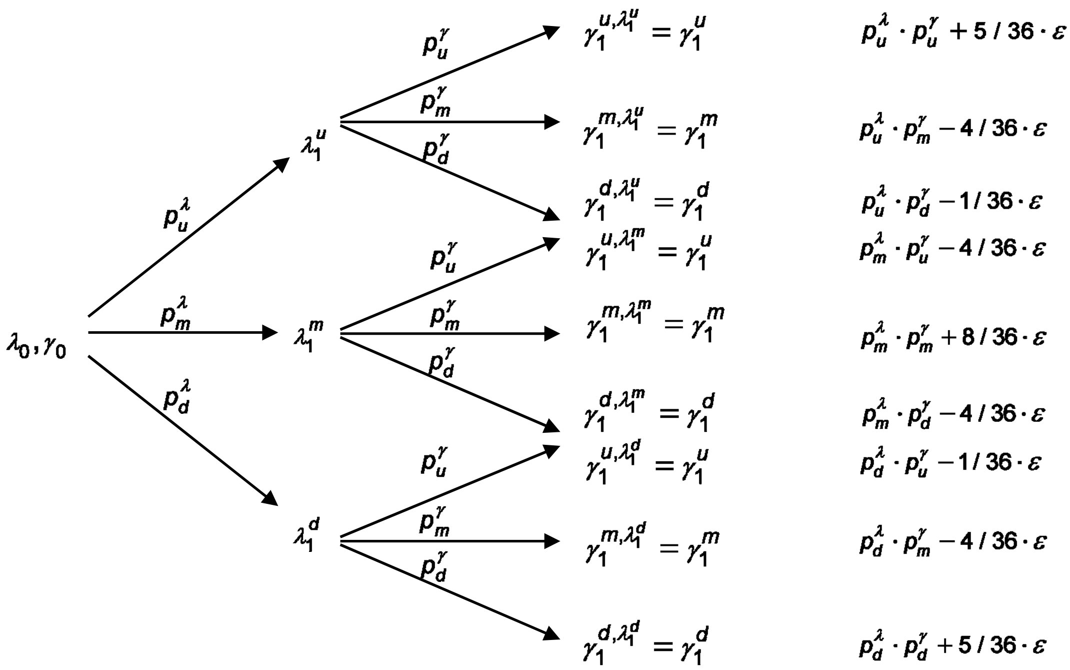
Panel A:

Joint probabilities



Panel B:

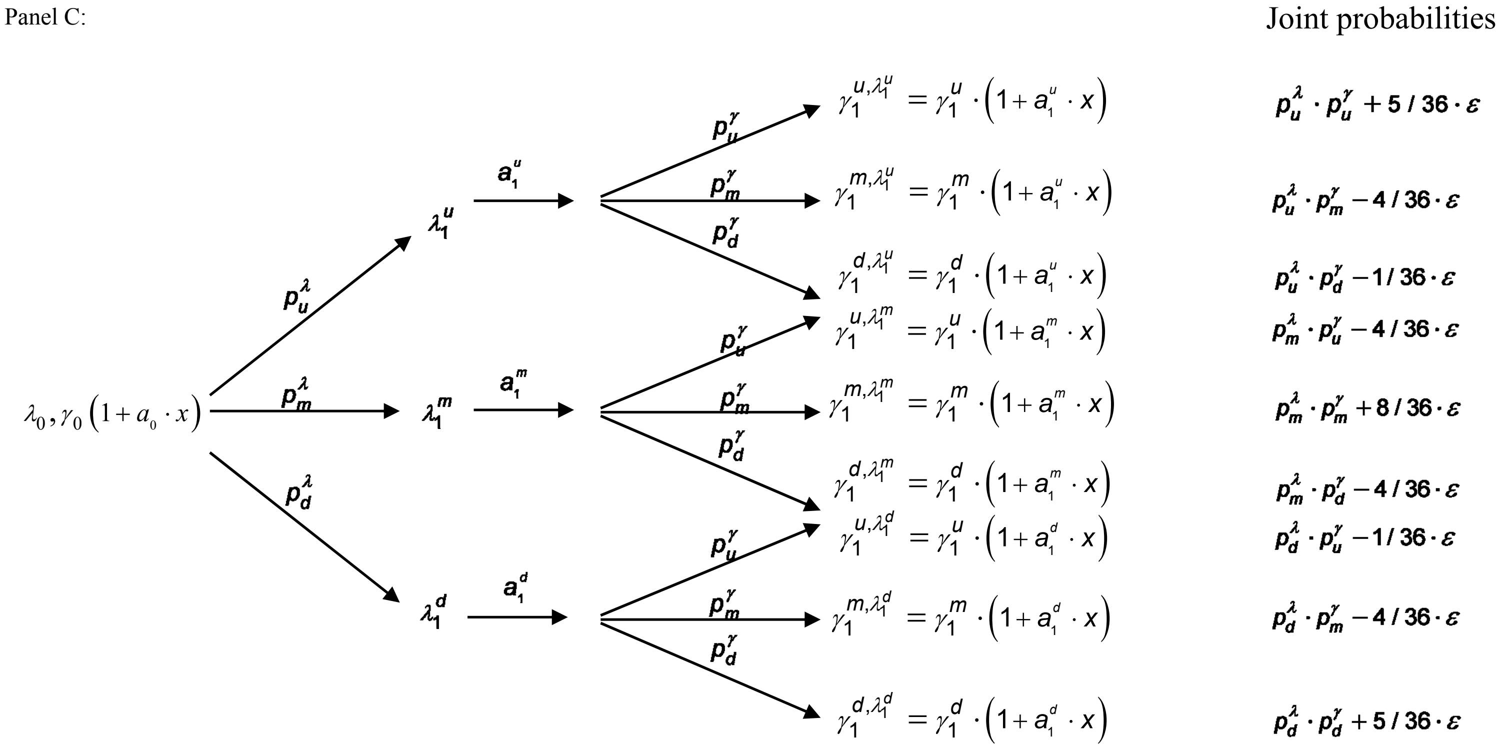
Joint probabilities



(Continued)

Figure 1.2 (Continued): Reduced-form credit risk and liquidity model

Panel C:



Notes: The figure displays the joint dynamics of default and liquidity intensities, conditional on no default at time 1. At time 0, λ and γ equal λ_0 and γ_0. At time 1, the default intensity may increase ($\lambda_1^u = \lambda_0 + \Delta\lambda$) with probability p_u^λ, decrease ($\lambda_1^d = \lambda_0 - \Delta\lambda$) with probability p_d^λ, or remain the same ($\lambda_1^m = \lambda_0$) with probability p_m^λ. $\Delta\lambda$ is defined as $\Delta\lambda = \sigma_\lambda \cdot \sqrt{3} \cdot \sqrt{\Delta t}$. Also, the liquidity intensity may increase ($\gamma_1^u = \gamma_0 + \Delta\gamma$) with probability p_u^γ, decrease ($\gamma_1^d = \gamma_0 - \Delta\gamma$) with probability p_d^γ, or remain the same ($\gamma_1^m = \gamma_0$) with probability p_m^γ. $\Delta\gamma$ is defined as $\Delta\gamma = \sigma_\gamma \cdot \sqrt{3} \cdot \sqrt{\Delta t}$. Panel A displays the tree for uncorrelated intensities. Panel B shows the tree for correlated intensities. Panel C presents our final model. There, the liquidity intensity level depends on the default intensity level. This is modeled by the random variable $\tilde{a}_1 \in \left\{a_1^u, a_1^m, a_1^d\right\}$. Furthermore the influence of investor sentiment on liquidity intensities is modeled by the parameter x where high values of x indicate low investor sentiment.

2.A.2. Impact of investor sentiment on risk factor correlation

Based on the model described above, we now derive the correlation between changes in a corporate bond's credit risk premium and liquidity premium, and show that this correlation increases when investor sentiment decreases.

We start by considering a zero bond with maturity in t=2 which is only subject to credit risk. From the perspective of time t=1 and conditional on no default at t=1, the risk-neutral price of such a zero bond is $\exp(-\lambda_1)$ and the log yield a risk-neutral investor requires for investing in this bond equals:

$$cr_1 = \log\left(\frac{1}{\exp(-\lambda_1)}\right) = \lambda_1. \tag{2.15}$$

At time t=0, the bond price is $\exp(-\lambda_0)\cdot E_0\left[\exp(-\tilde{\lambda}_1)\right]$, and the per-period log yield required by a risk-neutral investor is:

$$\begin{aligned} cr_0 &= \log\left(\left(\frac{1}{\exp(-\lambda_0)\cdot E_0\left[\exp\left(-\tilde{\lambda}_1\right)\right]}\right)^{\frac{1}{2}}\right) \\ &= \frac{1}{2}\left\{\lambda_0 - \log\left(E_0\left[\exp\left(-\tilde{\lambda}_1\right)\right]\right)\right\} \end{aligned} \tag{2.16}$$

with $E_0\left[\exp\left(-\tilde{\lambda}_1\right)\right] = \mathrm{p}_u^\lambda \cdot \exp\left(-\lambda_1^u\right) + \mathrm{p}_m^\lambda \cdot \exp\left(-\lambda_1^m\right) + \mathrm{p}_d^\lambda \cdot \exp\left(-\lambda_1^d\right)$. Since the bond price is determined solely by credit risk, the change in its log yield equals the change in the credit risk premium:

$$\Delta\widetilde{cr} = \widetilde{cr}_1 - cr_0 = \tilde{\lambda}_1 - \frac{1}{2}\cdot\left\{\lambda_0 - \log\left(E_0\left[\exp\left(-\tilde{\lambda}_1\right)\right]\right)\right\}. \tag{2.17}$$

Now consider a bond that is subject to both credit risk and illiquidity. From the perspective of time t=1 and conditional on no default in t=1, this bond has a risk-neutral price of $\exp\left(-\lambda_1 - \gamma_1\cdot\left(1+a_1\cdot x\right)\right)$ and a log yield of $ys_1 = \lambda_1 + \gamma_1\cdot\left(1+a_1\cdot x\right)$. At time t=0, the price is $\exp\left(-\lambda_0 - \gamma_0\cdot\left(1+a_0\cdot x\right)\right)\cdot E_0\left[\exp\left(-\tilde{\lambda}_1 - \tilde{\gamma}_1\cdot\left(1+\tilde{a}_1\cdot x\right)\right)\right]$, and the corresponding per-period log yield is

$$ys_0 = \frac{1}{2}\left\{\left(\lambda_0 + \gamma_0 \cdot \left(1 + a_0 \cdot x\right)\right) - \log\left(E_0\left[\exp\left(-\tilde{\lambda}_1 - \tilde{\gamma}_1 \cdot \left(1 + \tilde{a}_1 \cdot x\right)\right)\right]\right)\right\} \tag{2.18}$$

with:

$$\begin{aligned}
E_0\left[\exp\left(-\tilde{\lambda}_1 - \tilde{\gamma}_1 \cdot (1 + \tilde{a}_1 \cdot x)\right)\right] = &\left(\mathrm{p}_u^\lambda \mathrm{p}_u^\gamma + \tfrac{5}{36}\varepsilon\right) \cdot \exp\left(-\lambda_1^u - \gamma_1^u \cdot \left(1 + a_1^u \cdot x\right)\right) \\
&+ \left(\mathrm{p}_u^\lambda \mathrm{p}_m^\gamma - \tfrac{4}{36}\varepsilon\right) \cdot \exp\left(-\lambda_1^u - \gamma_1^m \cdot \left(1 + a_1^u \cdot x\right)\right) \\
&+ \left(\mathrm{p}_u^\lambda \mathrm{p}_d^\gamma - \tfrac{1}{36}\varepsilon\right) \cdot \exp\left(-\lambda_1^u - \gamma_1^d \cdot \left(1 + a_1^u \cdot x\right)\right) \\
&+ \left(\mathrm{p}_m^\lambda \mathrm{p}_u^\gamma - \tfrac{4}{36}\varepsilon\right) \cdot \exp\left(-\lambda_1^m - \gamma_1^u \cdot \left(1 + a_1^m \cdot x\right)\right) \\
&+ \left(\mathrm{p}_m^\lambda \mathrm{p}_m^\gamma + \tfrac{8}{36}\varepsilon\right) \cdot \exp\left(-\lambda_1^m - \gamma_1^m \cdot \left(1 + a_1^m \cdot x\right)\right) \\
&+ \left(\mathrm{p}_m^\lambda \mathrm{p}_d^\gamma - \tfrac{4}{36}\varepsilon\right) \cdot \exp\left(-\lambda_1^m - \gamma_1^d \cdot \left(1 + a_1^m \cdot x\right)\right) \\
&+ \left(\mathrm{p}_d^\lambda \mathrm{p}_u^\gamma - \tfrac{1}{36}\varepsilon\right) \cdot \exp\left(-\lambda_1^d - \gamma_1^u \cdot \left(1 + a_1^d \cdot x\right)\right) \\
&+ \left(\mathrm{p}_d^\lambda \mathrm{p}_m^\gamma - \tfrac{4}{36}\varepsilon\right) \cdot \exp\left(-\lambda_1^d - \gamma_1^m \cdot \left(1 + a_1^d \cdot x\right)\right) \\
&+ \left(\mathrm{p}_d^\lambda \mathrm{p}_d^\gamma + \tfrac{5}{36}\varepsilon\right) \cdot \exp\left(-\lambda_1^d - \gamma_1^d \cdot \left(1 + a_1^d \cdot x\right)\right).
\end{aligned} \tag{2.19}$$

Since the yield of this zero bond consists of the credit risk premium (which is known from Equations (2.15) and (2.16)) and the liquidity premium, the latter equals:

$$liq_1 = ys_1 - cr_1 = \gamma_1 \cdot \left(1 + a_1 \cdot x\right), \tag{2.20}$$

$$\begin{aligned}
liq_0 &= ys_0 - cr_0 \\
&= \frac{1}{2}\left\{\begin{aligned}&\gamma_0\left(1 + a_0 \cdot x\right) - \log\left(E_0\left[\exp\left(-\tilde{\lambda}_1 - \tilde{\gamma}_1 \cdot \left(1 + \tilde{a}_1 \cdot x\right)\right)\right]\right) \\ &+ \log\left(E_0\left[\exp\left(-\tilde{\lambda}_1\right)\right]\right)\end{aligned}\right\}.
\end{aligned} \tag{2.21}$$

The liquidity premium change is:

$$\begin{aligned}
\Delta\widetilde{liq} &= \widetilde{liq}_1 - liq_0 \\
&= \tilde{\gamma}_1 \cdot \left(1 + \tilde{a}_1 \cdot x\right) - \frac{1}{2}\left\{\begin{aligned}&\gamma_0\left(1 + a_0 \cdot x\right) \\ &- \log\left(E_0\left[\exp\left(-\tilde{\lambda}_1 - \tilde{\gamma}_1 \cdot \left(1 + \tilde{a}_1 \cdot x\right)\right)\right]\right) \\ &+ \log\left(E_0\left[\exp\left(-\tilde{\lambda}_1\right)\right]\right)\end{aligned}\right\}.
\end{aligned} \tag{2.22}$$

The correlation between credit risk and liquidity premium changes can now be easily derived. Since the terms in brackets are constants in Equations (2.17) and (2.22), the covariance between credit risk and liquidity premium changes is given by:

$$\begin{aligned} Covar_0\left(\Delta\widetilde{cr},\Delta\widetilde{liq}\right) &= Covar_0\left(\tilde{\lambda}_1,\tilde{\gamma}_1\cdot\left(1+\tilde{a}_1\cdot x\right)\right) \\ &= E_0\left[\tilde{\lambda}_1\cdot\tilde{\gamma}_1\cdot\left(1+\tilde{a}_1\cdot x\right)\right]-E_0\left[\tilde{\lambda}_1\right]\cdot E_0\left[\tilde{\gamma}_1\cdot\left(1+\tilde{a}_1\cdot x\right)\right]. \end{aligned} \tag{2.23}$$

The expected values are

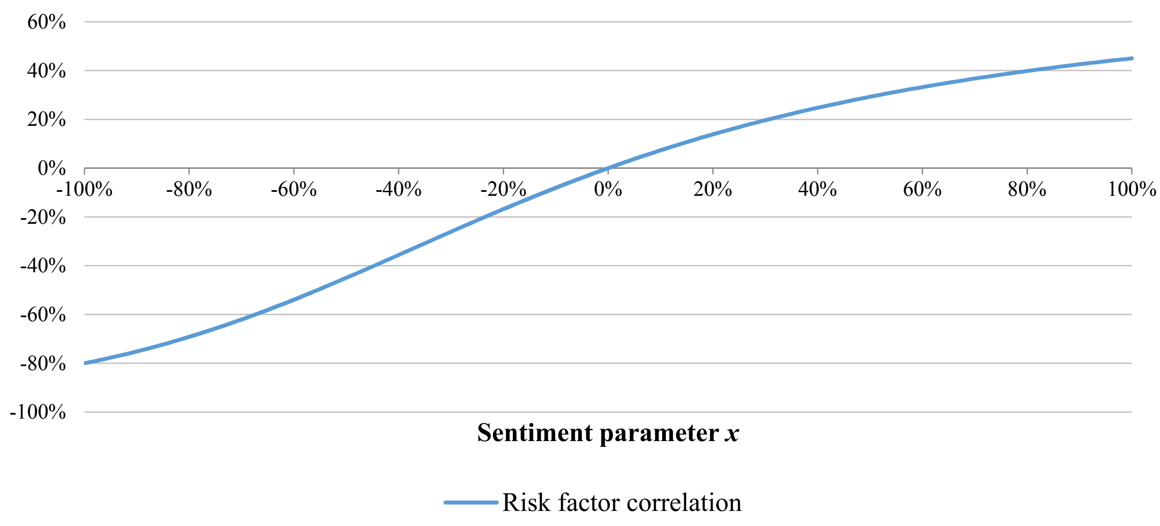
$$E_0\left[\tilde{\lambda}_1\right]=p_u^{\lambda}\cdot\lambda_1^u+p_m^{\lambda}\cdot\lambda_1^m+p_d^{\lambda}\cdot\lambda_1^d, \tag{2.24}$$

$$\begin{aligned} E_0\left[\tilde{\gamma}_1\cdot\left(1+\tilde{a}_1\cdot x\right)\right] &= (p_u^{\lambda}\cdot p_u^{\gamma}+\frac{5}{36}\varepsilon)\cdot\gamma_1^u\cdot\left(1+a_1^u\cdot x\right) \\ &\quad +\ldots+(p_d^{\lambda}\cdot p_d^{\gamma}+\frac{5}{36}\varepsilon)\cdot\gamma_1^d\cdot\left(1+a_1^d\cdot x\right), \end{aligned} \tag{2.25}$$

$$\begin{aligned} E_0\left[\tilde{\lambda}_1\cdot\tilde{\gamma}_1\cdot\left(1+\tilde{a}_1\cdot x\right)\right] &= (p_u^{\lambda}\cdot p_u^{\gamma}+\frac{5}{36}\varepsilon)\cdot\lambda_1^u\cdot\gamma_1^u\cdot\left(1+a_1^u\cdot x\right) \\ &\quad +\ldots+(p_d^{\lambda}\cdot p_d^{\gamma}+\frac{5}{36}\varepsilon)\cdot\lambda_1^d\cdot\gamma_1^d\cdot\left(1+a_1^d\cdot x\right). \end{aligned} \tag{2.26}$$

The correlation between credit risk and liquidity premium changes directly follows from these expressions. Note that the correlation depends on investor sentiment x. Figure 2.3 illustrates the impact of investor sentiment on risk factor correlation. More specifically, it shows that risk factor correlation increases when investor sentiment decreases, the first hypothesis stated in Section 2.3.

Figure 2.3: Risk factor correlation and sentiment



Notes: The figure displays correlation between credit risk and liquidity premium changes as a function of investor sentiment x. High values of x indicate low investor sentiment. The plot is based on the following parameter values: $\Delta t=1$, $\lambda_0=3.00\%$, $\gamma_0=2.00\%$, $\Delta\lambda=1.73\%$, $\Delta\gamma=1.30\%$, $a_u=1.00$, $a_m=0.50$, $a_d=0.00$.

To prove this relation formally, we show that the first derivative of the correlation with respect to x is larger than zero. We assume that the usual regularity conditions apply for all random variables, i.e., the first and second moment exist and are finite, and the variance is positive. For ease of exposition, we consider the case $\varepsilon = 0$, i.e., the flight-to-quality effect is purely driven by sentiment. However, the relation also holds in the more general case $\varepsilon > 0$.

We start by showing how the numerator of the correlation, the covariance between credit risk and liquidity premium changes, depends on investor sentiment. For $\varepsilon = 0$, $\tilde{\lambda}_1$ and $\tilde{\gamma}_1$ are independent. Therefore, the covariance summands given in Equation (2.23) can be written as

$$\begin{aligned} E_0\left[\tilde{\lambda}_1 \cdot \tilde{\gamma}_1 \cdot \left(1+\tilde{a}_1 \cdot x\right)\right] &= E_0\left[\tilde{\gamma}_1\right] \cdot E_0\left[\tilde{\lambda}_1 + x \cdot \tilde{\lambda}_1 \cdot \tilde{a}_1\right] \\ &= E_0\left[\tilde{\gamma}_1\right] \cdot \left\{E_0\left[\tilde{\lambda}_1\right] + x \cdot E_0\left[\tilde{\lambda}_1 \cdot \tilde{a}_1\right]\right\}, \end{aligned} \tag{2.27}$$

$$E_0\left[\tilde{\lambda}_1\right] \cdot E_0\left[\tilde{\gamma}_1 \cdot \left(1+\tilde{a}_1 \cdot x\right)\right] = E_0\left[\tilde{\lambda}_1\right] \cdot E_0\left[\tilde{\gamma}_1\right] \cdot \left(1 + x \cdot E_0\left[\tilde{a}_1\right]\right). \tag{2.28}$$

Consequently, the covariance between the premium changes becomes

$$\begin{aligned} Covar_0\left(\Delta\widetilde{cr}, \Delta\widetilde{liq}\right) &= E_0\left[\tilde{\gamma}_1\right] \cdot E_0\left[\tilde{\lambda}_1\right] + x \cdot E_0\left[\tilde{\gamma}_1\right] \cdot E_0\left[\tilde{\lambda}_1 \cdot \tilde{a}_1\right] \\ &\quad - E_0\left[\tilde{\gamma}_1\right] \cdot E_0\left[\tilde{\lambda}_1\right] - x \cdot E_0\left[\tilde{\gamma}_1\right] \cdot E_0\left[\tilde{\lambda}_1\right] \cdot E_0\left[\tilde{a}_1\right] \\ &= x \cdot E_0\left[\tilde{\gamma}_1\right] \cdot \left(E_0\left[\tilde{\lambda}_1 \cdot \tilde{a}_1\right] - E_0\left[\tilde{\lambda}_1\right] \cdot E_0\left[\tilde{a}_1\right]\right) \\ &= x \cdot E_0\left[\tilde{\gamma}_1\right] \cdot Covar_0\left(\tilde{\lambda}_1, \tilde{a}_1\right). \end{aligned} \tag{2.29}$$

Equation (2.29) shows two properties of our model. First, the covariance between the premium changes increases when investor sentiment decreases, since

$$\begin{aligned} Covar_0\left(\tilde{\lambda}_1, \tilde{a}_1\right) &= E_0\left[(\tilde{\lambda}_1 - E_0\left[\tilde{\lambda}_1\right]) \cdot (\tilde{a}_1 - E_0\left[\tilde{a}_1\right])\right] \\ &= p_u^{\lambda} \cdot (\lambda_1^u - E_0\left[\tilde{\lambda}_1\right]) \cdot (a_1^u - E_0\left[\tilde{a}_1\right]) \\ &\quad + p_m^{\lambda} \cdot (\lambda_1^m - E_0\left[\tilde{\lambda}_1\right]) \cdot (a_1^m - E_0\left[\tilde{a}_1\right]) \\ &\quad + p_d^{\lambda} \cdot (\lambda_1^d - E_0\left[\tilde{\lambda}_1\right]) \cdot (a_1^d - E_0\left[\tilde{a}_1\right]) \end{aligned} \tag{2.30}$$

is always positive. This follows from the fact that by construction (i) $\tilde{\lambda}_1$ has no drift $\left(\lambda_1^m - E\left[\tilde{\lambda}_1\right] = 0\right)$, and (ii) the following inequalities hold:

$$\begin{aligned} &a_1^u - E_0\left[\tilde{a}_1\right] > 0, \\ &a_1^d - E_0\left[\tilde{a}_1\right] < 0, \\ &\lambda_1^u - E_0\left[\tilde{\lambda}_1\right] > 0, \\ &\lambda_1^d - E_0\left[\tilde{\lambda}_1\right] < 0. \end{aligned} \tag{2.31}$$

Second, since the second and third factor in (2.29) are positive, the covariance between the premium changes is positive if $x > 0$ (bad sentiment) and negative if $x < 0$ (good sentiment). Thus, our model can generate both positive and negative risk factor correlations.

The denominator of the bond correlation equals the square root of the product of the variances of premium changes. The credit risk premium, and hence its change, is independent of investor sentiment x. Hence, its variance is also independent of x. The variance of the liquidity premium, however, depends on x:

$$\begin{aligned} Var\left(\Delta\widetilde{liq}\right) &= Var\left(\tilde{\gamma}_1\left(1+\tilde{a}_1\cdot x\right) - \frac{1}{2}\underbrace{\left\{\begin{array}{l} \gamma_0\left(1+a_0\cdot x\right) \\ -\log\left(E_0\left[\exp\left(-\tilde{\lambda}_1-\tilde{\gamma}_1\left(1+\tilde{a}_1\cdot x\right)\right)\right]\right) \\ +\log\left(E_0\left[\exp\left(-\tilde{\lambda}_1\right)\right]\right) \end{array}\right\}}_{=:const}\right) \\ &= Var\left(\tilde{\gamma}_1\left(1+\tilde{a}_1\cdot x\right)\right) \\ &= Var\left(\tilde{\gamma}_1\right) + x^2\cdot Var\left(\tilde{a}_1\cdot\tilde{\gamma}_1\right) + 2\cdot Covar_0\left(\tilde{\gamma}_1, x\cdot\tilde{a}_1\cdot\tilde{\gamma}_1\right) \\ &= Var\left(\tilde{\gamma}_1\right) + x^2\cdot\left\{E_0\left[\tilde{a}_1^2\tilde{\gamma}_1^2\right] - E_0\left[\tilde{a}_1\tilde{\gamma}_1\right]^2\right\} \\ &\quad +2\cdot\left\{E_0\left[x\tilde{a}_1\tilde{\gamma}_1^2\right] - E_0\left[\tilde{\gamma}_1\right]E_0\left[x\tilde{a}_1\tilde{\gamma}_1\right]\right\} \\ &= Var\left(\tilde{\gamma}_1\right) + x^2\cdot E_0\left[\tilde{a}_1^2\right]E_0\left[\tilde{\gamma}_1^2\right] - x^2\cdot E_0\left[\tilde{a}_1\right]^2 E_0\left[\tilde{\gamma}_1\right]^2 \\ &\quad +2\cdot x\cdot E_0\left[\tilde{a}_1\right]\cdot E_0\left[\tilde{\gamma}_1^2\right] - 2\cdot x\cdot E_0\left[\tilde{a}_1\right]\cdot E_0\left[\tilde{\gamma}_1\right]^2 \\ &= Var\left(\tilde{\gamma}_1\right) + 2\cdot x\cdot E_0\left[\tilde{a}_1\right]\cdot Var\left(\tilde{\gamma}_1\right) \\ &\quad + x^2\cdot\left\{E_0\left[\tilde{a}_1^2\right]E_0\left[\tilde{\gamma}_1^2\right] - E_0\left[\tilde{a}_1\right]^2 E_0\left[\tilde{\gamma}_1\right]^2\right\}. \end{aligned} \tag{2.32}$$

Using Equations (2.29) and (2.32) and taking the first derivative of the correlation with respect to x yields:

$$\begin{aligned}
\frac{\partial Corr_0\left(\Delta\widetilde{cr},\Delta\widetilde{liq}\right)}{\partial x} &= \frac{Var(\Delta\widetilde{cr})^{\frac{1}{2}}}{Var(\Delta\widetilde{cr})\cdot Var(\Delta\widetilde{liq})} \\
&\quad\cdot\left\{\frac{\partial Covar_0\left(\Delta\widetilde{cr},\Delta\widetilde{liq}\right)}{\partial x}Var(\Delta\widetilde{liq})^{\frac{1}{2}}-Covar_0\left(\Delta\widetilde{cr},\Delta\widetilde{liq}\right)\cdot\frac{\partial Var(\Delta\widetilde{liq})^{\frac{1}{2}}}{\partial x}\right\} \\
&= \underbrace{\frac{Var(\Delta\widetilde{cr})^{\frac{1}{2}}}{2\cdot Var(\Delta\widetilde{cr})\cdot Var(\Delta\widetilde{liq})^{3/2}}}_{>0}\underbrace{Covar_0\left(\tilde{\lambda}_1,\tilde{a}_1\right)}_{>0} \\
&\quad\cdot E_0\left[\tilde{\gamma}_1\cdot\left(1+\tilde{a}_1\cdot x\right)\right]\cdot\left\{2\cdot Var(\Delta\widetilde{liq})-x\cdot\frac{\partial Var(\Delta\widetilde{liq})}{\partial x}\right\}.
\end{aligned} \tag{2.33}$$

The usual regularity conditions for random variables and the fact that $Covar_0\left(\tilde{\lambda}_1,\tilde{a}_1\right)>0$ ensure that the first two terms after the second equal sign in Equation (2.33) are positive.

To show that the product of the last two terms in Equation (2.33) is also positive, we re-write the third term in Equation (2.33) using the independence of $\tilde{\gamma}_1$ and $\tilde{a}_1$:

$$E_0\left[\tilde{\gamma}_1\cdot\left(1+\tilde{a}_1\cdot x\right)\right]=E_0\left[\tilde{\gamma}_1\right]\cdot\left(1+x\cdot E_0\left[\tilde{a}_1\right]\right). \tag{2.34}$$

We further use (2.32) and re-write the last term in brackets in Equation (2.33) as

$$\begin{aligned}
\left\{2\cdot Var(\Delta\widetilde{liq})-x\cdot\frac{\partial Var(\Delta\widetilde{liq})}{\partial x}\right\} &= 2\cdot Var(\tilde{\gamma}_1)+2\cdot x\cdot E_0\left[\tilde{a}_1\right]Var(\tilde{\gamma}_1) \\
&= 2\cdot Var(\tilde{\gamma}_1)\cdot\left(1+x\cdot E_0\left[\tilde{a}_1\right]\right).
\end{aligned} \tag{2.35}$$

Multiplying Equation (2.35) with Equation (2.34) results in:

$$\begin{aligned}
&E_0\left[\tilde{\gamma}_1\right]\cdot\left(1+x\cdot E_0\left[\tilde{a}_1\right]\right)\cdot 2\cdot Var(\tilde{\gamma}_1)\cdot\left(1+x\cdot E_0\left[\tilde{a}_1\right]\right) \\
&\qquad = 2\cdot E_0\left[\tilde{\gamma}_1\right]\cdot Var(\tilde{\gamma}_1)\cdot\left(1+x\cdot E_0\left[\tilde{a}_1\right]\right)^2
\end{aligned} \tag{2.36}$$

Consequently, the product of the last two terms in Equation (2.33) is always positive. This proves that risk factor correlation increases when investor sentiment decreases – the first hypothesis tested in the empirical part of our paper.

2.A.3. Bond correlation and risk factor correlation

In this section, we provide a formal proof that higher risk factor correlation translates into higher bond correlation. We consider two bonds, e.g., one investment grade bond *i* and one high yield bond *h* with positive default and liquidity intensities $\tilde{\lambda}_{i/h,t}$ and $\tilde{\gamma}_{i/h,t}$. Both intensities contain a systematic credit risk and a systematic liquidity intensity, $\tilde{\lambda}_{m,t}$ and $\tilde{\gamma}_{m,t}$, as well as idiosyncratic credit risk and liquidity intensities, $\tilde{\varepsilon}_{i/h}$ and $\tilde{\eta}_{i/h}$. For ease of exposition, we use the notation $\tilde{\gamma}^x_{i/h/m,t} := \tilde{\gamma}_{i/h/m,t} \cdot \left(1 + \tilde{a}_t \cdot x\right)$ in the following. We define the default and liquidity intensities for bonds i and h as follows:

$$
\begin{aligned}
\tilde{\lambda}_{i,t} &= \tilde{\lambda}_{m,t} \cdot \beta_{i,\lambda} + \tilde{\varepsilon}_i, \\
\tilde{\lambda}_{h,t} &= \tilde{\lambda}_{m,t} \cdot \beta_{h,\lambda} + \tilde{\varepsilon}_h, \\
\tilde{\gamma}^x_{i,t} &= \tilde{\gamma}^x_{m,t} \cdot \beta_{i,\gamma} + \tilde{\eta}_i, \\
\tilde{\gamma}^x_{h,t} &= \tilde{\gamma}^x_{m,t} \cdot \beta_{h,\gamma} + \tilde{\eta}_h.
\end{aligned}
\tag{2.37}
$$

We assume that the systematic factors are positively correlated, the idiosyncratic risk factors are uncorrelated with the systematic risk factors and across bonds, and that both bonds have positive loadings on the systematic factors ($\beta_{i,\gamma} > 0$, $\beta_{i,\lambda} > 0$, $\beta_{h,\gamma} > 0$, $\beta_{h,\lambda} > 0$).

The covariance between the yield spread changes of bond *i* and *h* is given by

$$
\begin{aligned}
Covar_0\left(\Delta\widetilde{ys}_i, \Delta\widetilde{ys}_h\right) &= Covar_0\left(\tilde{\lambda}_{i,1} + \tilde{\gamma}^x_{i,1}, \tilde{\lambda}_{h,1} + \tilde{\gamma}^x_{h,1}\right) \\
&= \beta_{i,\lambda}\beta_{h,\lambda} \cdot Var\left(\tilde{\lambda}_{m,1}\right) + \beta_{i,\gamma}\beta_{h,\gamma} \cdot Var\left(\tilde{\gamma}^x_{m,1}\right) \\
&\quad + \left(\beta_{i,\lambda}\beta_{h,\gamma} + \beta_{i,\gamma}\beta_{h,\lambda}\right) \cdot Var\left(\tilde{\lambda}_{m,1}\right)^{1/2} Var\left(\tilde{\gamma}^x_{m,1}\right)^{1/2} Corr_0\left(\tilde{\lambda}_{m,1}, \tilde{\gamma}^x_{m,1}\right)
\end{aligned}
\tag{2.38}
$$

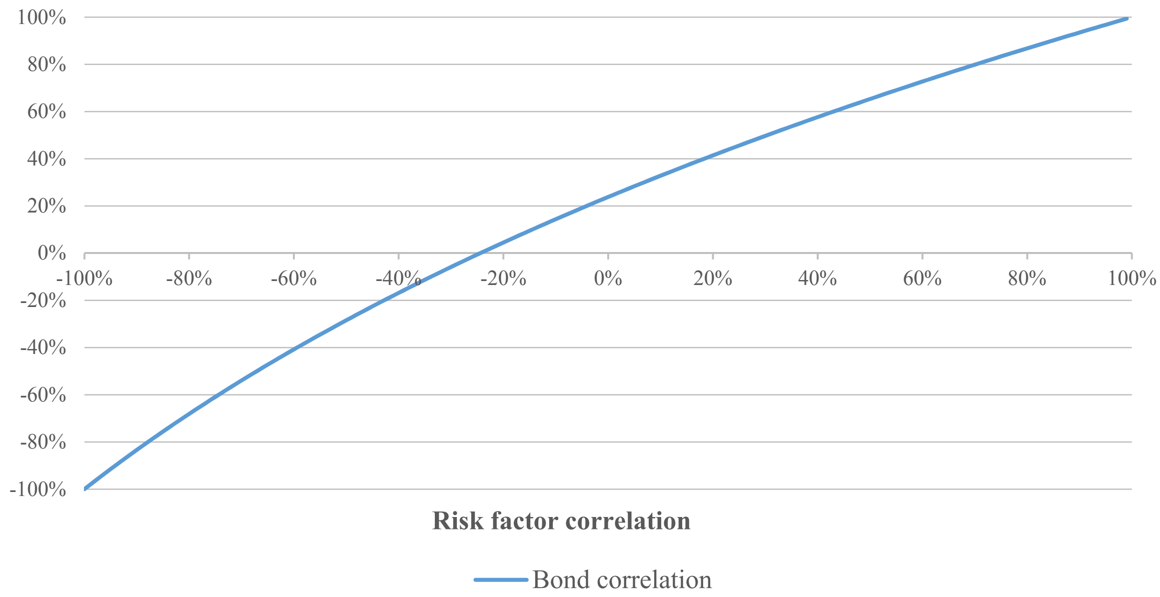
since the constants in brackets in (2.17) and (2.22) drop out of the covariance. Equation (2.38) shows three properties of our model: first, the covariance between the two bonds increases when the correlation between the systematic intensities $\tilde{\lambda}_{m,1}$ and $\tilde{\gamma}^x_{m,1}$ increases. Second, bond correlation is strictly positive if risk factor correlation is positive. Third, for sufficiently negative correlation between $\tilde{\lambda}_{m,1}$ and $\tilde{\gamma}^x_{m,1}$, the covariance between the two bonds (and thus bond correlation) can become negative. Whether bond correlation is negative depends on the standard deviation ratios of $\tilde{\lambda}_{m,1}$ and $\tilde{\gamma}^x_{m,1}$ and on the systematic risk factor loadings $\beta_{i,\gamma}$, $\beta_{i,\lambda}$, $\beta_{h,\gamma}$, and $\beta_{h,\lambda}$:

$$Covar_0\left(\Delta\widetilde{ys}_i,\Delta\widetilde{ys}_h\right)<0$$

$$\Leftrightarrow Corr_0\left(\tilde{\lambda}_{m,1},\tilde{\gamma}^x_{m,1}\right)<-\frac{Var\left(\tilde{\lambda}_{m,1}\right)^{1/2}}{Var\left(\tilde{\gamma}^x_{m,1}\right)^{1/2}}\frac{\beta_{i,\lambda}\beta_{h,\lambda}}{\beta_{i,\lambda}\beta_{h,\gamma}+\beta_{i,\gamma}\beta_{h,\lambda}}-\frac{Var\left(\tilde{\gamma}^x_{m,1}\right)^{1/2}}{Var\left(\tilde{\lambda}_{m,1}\right)^{1/2}}\frac{\beta_{i,\gamma}\beta_{h,\gamma}}{\beta_{i,\lambda}\beta_{h,\gamma}+\beta_{i,\gamma}\beta_{h,\lambda}}. \tag{2.39}$$

Equation (2.39) shows that bond correlation can become negative for sufficiently negative risk factor correlation. This is the case whenever either $\frac{\beta_{i,\lambda}}{\beta_{i,\gamma}}$ or $\frac{\beta_{\mathrm{h},\lambda}}{\beta_{\mathrm{h},\gamma}}$ (but not both) are smaller than $\frac{Var\left(\tilde{\gamma}^x_{m,1}\right)^{1/2}}{Var\left(\tilde{\lambda}_{m,1}\right)^{1/2}}$. We illustrate this relation in Figure 2.4.

Figure 2.4: Bond correlation and risk factor correlation



Notes: The figure displays correlation between bond yield spread changes as a function of investor sentiment risk factor correlation. The plot is based on the following parameter values: $\beta_{i,\lambda}=1.13$ $\beta_{h,\lambda}=0.60$, $\beta_{i,\gamma}=0.01$, $\beta_{h,\gamma}=2.72$, $Var\left(\lambda_m\right)=0.15$, $Var\left(\gamma_m\right)=0.14$.

Figure 2.4 shows that bond correlation monotonously increases in risk factor correlation and becomes positive for risk factor correlations higher than -0.24.

We now turn to the formal analysis of the relation between bond correlation and risk factor correlation. The denominator of the correlation between the yield spread changes equals the square root of the product of the variances of the yield spread change of bonds i and h. The variance of $\Delta\widetilde{ys}_{i/h}$ can be expressed as follows:

$$\begin{aligned}Var\left(\Delta\widetilde{ys}_{i/h}\right) &= Var\left(\tilde{\lambda}_{i/h,1} + \tilde{\gamma}^{x}_{i/h,1}\right)\\ &= Var\left(\tilde{\lambda}_{m,1}\cdot\beta_{i/h,\lambda} + \tilde{\varepsilon}_{i/h} + \tilde{\gamma}^{x}_{m,1}\cdot\beta_{i/h,\gamma} + \tilde{\eta}_{i/h}\right)\\ &= Var\left(\tilde{\varepsilon}_{i/h}\right) + Var\left(\tilde{\eta}_{i/h}\right) + \beta^{2}_{i/h,\lambda}Var\left(\tilde{\lambda}_{m,1}\right)\\ &\quad + \beta^{2}_{i/h,\gamma}Var\left(\tilde{\gamma}^{x}_{m,1}\right) + 2\beta_{i/h,\lambda}\beta_{i/h,\gamma}Covar_{0}\left(\tilde{\lambda}_{m,1},\tilde{\gamma}^{x}_{m,1}\right).\end{aligned} \tag{2.40}$$

We now use Equations (2.38) and (2.40) to calculate the first derivative of the correlation between $\Delta\widetilde{ys}_{i}$ and $\Delta\widetilde{ys}_{h}$:

$$Corr_{0}\left(\Delta\widetilde{ys}_{i},\Delta\widetilde{ys}_{h}\right) = \frac{Covar_{0}\left(\Delta\widetilde{ys}_{i},\Delta\widetilde{ys}_{h}\right)}{\mathrm{Var}\left(\Delta\widetilde{ys}_{i}\right)^{1/2}\,\mathrm{Var}\left(\Delta\widetilde{ys}_{h}\right)^{1/2}} \tag{2.41}$$

with respect to risk factor correlation $Corr_{0}\left(\tilde{\lambda}_{m,1},\tilde{\gamma}^{x}_{m,1}\right)$:

$$\begin{aligned}\frac{\partial Corr_{0}\left(\Delta\widetilde{\mathrm{ys}}_{i},\Delta\widetilde{\mathrm{ys}}_{h}\right)}{\partial Corr_{0}\left(\tilde{\lambda}_{m,1},\tilde{\gamma}^{x}_{m,1}\right)} &= \underbrace{\frac{Var\left(\tilde{\lambda}_{m,1}\right)^{1/2}Var\left(\tilde{\gamma}^{x}_{m,1}\right)^{1/2}}{\mathrm{Var}\left(\Delta\widetilde{ys}_{h}\right)^{3/2}\,\mathrm{Var}\left(\Delta\widetilde{ys}_{i}\right)^{3/2}}}_{>0}\\ &\quad\cdot\left(\begin{aligned}&\left(\beta_{i,\lambda}\beta_{h,\gamma} + \beta_{i,\gamma}\beta_{h,\lambda}\right)\cdot\mathrm{Var}\left(\Delta\widetilde{ys}_{h}\right)\mathrm{Var}\left(\Delta\widetilde{ys}_{i}\right)\\ &-Covar_{0}\left(\Delta\widetilde{\mathrm{ys}}_{i},\Delta\widetilde{\mathrm{ys}}_{h}\right)\cdot\left(\beta_{i,\lambda}\beta_{i,\gamma}\mathrm{Var}\left(\Delta\widetilde{ys}_{h}\right) + \beta_{h,\lambda}\beta_{h,\gamma}\mathrm{Var}\left(\Delta\widetilde{ys}_{i}\right)\right)\end{aligned}\right).\end{aligned} \tag{2.42}$$

The first factor is a function of the variances of the yield spread changes, systematic credit risk, and liquidity intensities. Due to the regularity conditions, all variances are larger than zero. Hence, we consider the second factor and show that it is larger than zero. We first show this for $0 \leq Corr_{0}\left(\tilde{\lambda}_{m,1},\tilde{\gamma}^{x}_{m,1}\right) \leq 1$ and address negative risk factor correlation below.

Expanding the second factor results in:

$$
\begin{aligned}
&\left\{Var\left(\tilde{\varepsilon}_h\right)+Var\left(\tilde{\eta}_h\right)\right\} \\
&\quad\cdot\left\{\begin{aligned}&\left(\beta_{h,\lambda}\beta_{i,\gamma}+\beta_{i,\lambda}\beta_{h,\gamma}\right)\cdot\left(Var\left(\tilde{\varepsilon}_i\right)+Var\left(\tilde{\eta}_i\right)+\beta_{i,\lambda}\beta_{i,\gamma}Covar_0\left(\tilde{\lambda}_{m,1},\tilde{\gamma}^x_{m,1}\right)\right)\\&+\beta_{h,\lambda}\beta^3_{i,\gamma}+\beta_{h,\gamma}\beta^3_{i,\lambda}\end{aligned}\right\} \\
&\underbrace{\begin{aligned}&+\left\{Var\left(\tilde{\varepsilon}_i\right)+Var\left(\tilde{\eta}_i\right)\right\}\\&\quad\cdot\left\{\beta^3_{h,\gamma}\beta_{i,\lambda}+\beta^3_{h,\lambda}\beta_{i,\gamma}+\left(\beta_{h,\gamma}\beta^2_{h,\lambda}\beta_{i,\gamma}+\beta^2_{h,\gamma}\beta_{h,\lambda}\beta_{i,\lambda}\right)Covar_0\left(\tilde{\lambda}_{m,1},\tilde{\gamma}^x_{m,1}\right)\right\}\end{aligned}}_{=:summand_1} \\
&\underbrace{+Var\left(\tilde{\lambda}_{m,1}\right)Var\left(\tilde{\gamma}^x_{m,1}\right)\cdot\left(\beta^3_{h,\lambda}\beta^3_{i,\gamma}-\beta_{h,\gamma}\beta^2_{h,\lambda}\beta^2_{i,\gamma}\beta_{i,\lambda}-\beta^2_{h,\gamma}\beta_{h,\lambda}\beta_{i,\gamma}\beta^2_{i,\lambda}+\beta^3_{h,\gamma}\beta^3_{i,\lambda}\right)}_{=:summand_2} \\
&\underbrace{\begin{aligned}&+Corr_0\left(\tilde{\lambda}_{m,1},\tilde{\gamma}^x_{m,1}\right)\\&\quad\cdot\left(\beta_{h,\gamma}\beta_{i,\gamma}Var\left(\tilde{\lambda}_{m,1}\right)^{1/2}Var\left(\tilde{\gamma}^x_{m,1}\right)^{3/2}+\beta_{h,\lambda}\beta_{i,\lambda}Var\left(\tilde{\lambda}_{m,1}\right)^{3/2}Var\left(\tilde{\gamma}^x_{m,1}\right)^{1/2}\right)\cdot\\&\quad\cdot\left(\beta^2_{h,\lambda}\beta^2_{i,\gamma}-2\beta_{h,\gamma}\beta_{h,\lambda}\beta_{i,\gamma}\beta_{i,\lambda}+\beta^2_{h,\gamma}\beta^2_{i,\lambda}\right)\end{aligned}}_{=:summand_3}
\end{aligned}
\tag{2.43}
$$

Due to our assumptions ($\beta_{i,\gamma}>0$, $\beta_{i,\lambda}>0$, $\beta_{h,\gamma}>0$, $\beta_{h,\lambda}>0$, $0\le Corr_0\left(\tilde{\lambda}_{m,1},\tilde{\gamma}^x_{m,1}\right)\le 1$) and the fact that all variances are larger than zero, $summand_1$ is larger than zero. Hence, it only remains to show that $summand_2$ and $summand_3$ are larger than or equal to zero. Rearranging $summand_2$ gives:

$$
\begin{aligned}
&Var\left(\tilde{\lambda}_{m,1}\right)Var\left(\tilde{\gamma}^x_{m,1}\right)\cdot\left(\beta^3_{h,\lambda}\beta^3_{i,\gamma}-\beta_{h,\gamma}\beta^2_{h,\lambda}\beta^2_{i,\gamma}\beta_{i,\lambda}-\beta^2_{h,\gamma}\beta_{h,\lambda}\beta_{i,\gamma}\beta^2_{i,\lambda}+\beta^3_{h,\gamma}\beta^3_{i,\lambda}\right)\ge 0 \\
\Leftrightarrow\ &Var\left(\tilde{\lambda}_{m,1}\right)Var\left(\tilde{\gamma}^x_{m,1}\right)\cdot\left(\beta_{h,\lambda}\beta_{i,\gamma}-\beta_{h,\gamma}\beta_{i,\lambda}\right)\cdot\left(\beta^2_{h,\lambda}\beta^2_{i,\gamma}-\beta^2_{h,\gamma}\beta^2_{i,\lambda}\right)\ge 0.
\end{aligned}
\tag{2.44}
$$

Both terms in braces in Equation (2.44) always have the same sign. If $\beta_{h,\lambda}\beta_{i,\gamma}>\beta_{h,\gamma}\beta_{i,\lambda}$, it follows that $\beta^2_{h,\lambda}\beta^2_{i,\gamma}>\beta^2_{h,\gamma}\beta^2_{i,\lambda}$. Similarly this holds for $\beta_{h,\lambda}\beta_{i,\gamma}<\beta_{h,\gamma}\beta_{i,\lambda}$. If $\beta_{h,\lambda}\beta_{i,\gamma}=\beta_{h,\gamma}\beta_{i,\lambda}$, then the product is zero. Consequently Equation (2.44) is always larger than or equal to zero. Rearranging $summand_3$ gives:

$$
\begin{aligned}
&Corr_0\left(\tilde{\lambda}_{m,1},\tilde{\gamma}^x_{m,1}\right)\cdot\left(\beta_{h,\gamma}\beta_{i,\gamma}Var\left(\tilde{\lambda}_{m,1}\right)^{1/2}Var\left(\tilde{\gamma}^x_{m,1}\right)^{3/2}+\beta_{h,\lambda}\beta_{i,\lambda}Var\left(\tilde{\lambda}_{m,1}\right)^{3/2}Var\left(\tilde{\gamma}^x_{m,1}\right)^{1/2}\right)\\
&\quad\cdot\left(\beta^2_{h,\lambda}\beta^2_{i,\gamma}-2\beta_{h,\gamma}\beta_{h,\lambda}\beta_{i,\gamma}\beta_{i,\lambda}+\beta^2_{h,\gamma}\beta^2_{i,\lambda}\right)\geq 0\\
\Leftrightarrow\ &Corr_0\left(\tilde{\lambda}_{m,1},\tilde{\gamma}^x_{m,1}\right)\cdot\left(\beta_{h,\gamma}\beta_{i,\gamma}Var\left(\tilde{\lambda}_{m,1}\right)^{1/2}Var\left(\tilde{\gamma}^x_{m,1}\right)^{3/2}+\beta_{h,\lambda}\beta_{i,\lambda}Var\left(\tilde{\lambda}_{m,1}\right)^{3/2}Var\left(\tilde{\gamma}^x_{m,1}\right)^{1/2}\right)\\
&\quad\cdot\left(\beta_{h,\lambda}\beta_{i,\gamma}-\beta_{h,\gamma}\beta_{i,\lambda}\right)^2\geq 0.
\end{aligned}
\tag{2.45}
$$

Due to our assumptions ($\beta_{i,\gamma}>0$, $\beta_{i,\lambda}>0$, $\beta_{h,\gamma}>0$, $\beta_{h,\lambda}>0$, $0\leq Corr_0\left(\tilde{\lambda}_{m,1},\tilde{\gamma}^x_{m,1}\right)\leq 1$) and the fact that all variances are larger than zero, all factors in Equation (2.45) are larger than or equal to zero. Hence, we have shown that Equations (2.44) and (2.45) are larger than or equal to zero.

We now turn to negative risk factor correlation. As discussed above, negative risk factor correlation can result in negative bond correlation. Equation (2.42) directly shows that *negative* bond correlation always increases in risk factor correlation, since all terms in brackets are positive. It therefore remains to be shown whether bond correlation also increases in risk factor correlation when bond correlation is *positive* (and risk factor correlation is negative). This positive relation will not hold in general, and we therefore derive conditions under which it holds. From Equation (2.42), we know that bond correlation increases in risk factor correlation if and only if

$$
\frac{\mathrm{Var}\left(\Delta\widetilde{ys}_h\right)\mathrm{Var}\left(\Delta\widetilde{ys}_i\right)}{Covar_0\left(\Delta\widetilde{\mathrm{ys}}_i,\Delta\widetilde{\mathrm{ys}}_h\right)}\left(\beta_{i,\lambda}\beta_{h,\gamma}+\beta_{i,\gamma}\beta_{h,\lambda}\right)>\beta_{i,\lambda}\beta_{i,\gamma}\mathrm{Var}\left(\Delta\widetilde{ys}_h\right)+\beta_{h,\lambda}\beta_{h,\gamma}\mathrm{Var}\left(\Delta\widetilde{ys}_i\right)
\tag{2.46}
$$

Without loss of generality, we set $\mathrm{Var}\left(\Delta\widetilde{ys}_i\right)=\mathrm{z}_1\cdot\mathrm{Var}\left(\Delta\widetilde{ys}_h\right)$, $\beta_{i,\lambda}=z_2\cdot\beta_{h,\lambda}$, and $\beta_{i,\gamma}=z_3\cdot\beta_{h,\gamma}$. It is economically plausible that $z_1<1$, $z_2<1$, and $z_3<1$ since we consider two bonds with different credit and liquidity risk, e.g., one investment grade bond *i* and one high yield bond *h.* The condition therefore becomes

$$\frac{z_1 \mathrm{Var}\left(\Delta \widetilde{ys}_h\right)^2 \beta_{h,\lambda}\beta_{h,\gamma}\left(z_2+z_3\right)}{Corr_0\left(\Delta \widetilde{\mathrm{ys}}_i, \Delta \widetilde{\mathrm{ys}}_h\right) z_1 \mathrm{Var}\left(\Delta \widetilde{ys}_h\right)} > \left(z_2 z_3 + z_1\right)\beta_{h,\lambda}\beta_{h,\gamma}\mathrm{Var}\left(\Delta \widetilde{ys}_h\right)$$

$$\Leftrightarrow Corr_0\left(\Delta \widetilde{\mathrm{ys}}_i, \Delta \widetilde{\mathrm{ys}}_h\right) < \frac{z_2+z_3}{z_1+z_2 z_3}. \tag{2.47}$$

For the special case that $z_1 = z_3$, it is immediately clear that Equation (2.47) holds, since the correlation is positive but bounded from above by 1. Otherwise, Equation (2.47) holds when either $z_1 < z_2$ or $z_1 < z_3$.

This completes our analysis of the relation between bond correlation and risk factor correlation. This substantiates the economic rationale of our second hypothesis to be tested in the empirical part of our paper.

Chapter 3†

Forecasting Credit Default Swap Premiums with Google Search Volume

2.1. Introduction

Individuals' decisions are all based on a decision making process that weighs up several different alternatives resulting from a given subset of information (Simon, 1955). Today, Google is one of the major internet search engines for individuals to gather information for their decisions. Nearly 80% of US households had access to the internet and 64% of US citizens used Google for their internet searches in 2015 (e.g., eMarketer, 2016; Comscore, 2016). Thus, it is likely that individuals' also use Google to gather information for their consumer decisions. Thereby they reveal their sentiment through their search queries (Demartini and Siersdorfer, 2010). Finally, their sentiment influences their consumption and consequently economic output. Consistent with this view, the aggregated volume of Google search queries (Google search volume) contains valuable consumption information before other financial variables or economic indicators (e.g., McLaren and Shanbhogue, 2011; Vosen and Schmidt, 2011; Choi and Varian, 2012). However, it is still an open issue whether aggregated Google search volume contains fundamental information for capital markets (e.g., Da et al., 2011b; Da et al., 2015; Dimpfl and Jank, 2016). This paper adds to the literature by analyzing whether aggregated volume of Google search queries has fundamental value for capital markets by following a new approach based on the credit default swap (CDS) market.

† This chapter is based on Bethke and Gehde-Trapp (2016).

CDS simplified the tradability of credit risk since their introduction at the end of the twentieth century. A CDS is a credit derivative designed as a credit insurance contract. Its payoff is linked to the default or change in default probability of a certain issuer or bond. The contracts are solely traded by institutional investors who are well-informed (e.g., Piotroski and Roulstone, 2004; Boehmer and Kelley, 2009). This reduces the influence of uninformed noise trading often found for stocks (Baker and Wurgler, 2006) and leads to an efficient pricing of information for CDS (e.g., Norden and Weber, 2004; Acharya and Johnson, 2007). Finally, Tang and Yan (2010) show that monthly measured consumer sentiment is a determinant of CDS premiums while Google allows us to capture daily consumer sentiment before any other financial variable. Thus, the CDS market provides an ideal setting to analyze the fundamental value of Google search volume. If aggregated Google search volume possesses fundamental value for the CDS market, it should improve CDS premium forecasts. If it even contains fundamental information not yet reflected in CDS premiums, we expect it to predict trends in CDS premium changes. Given the characteristics of the CDS market, these findings would be strong evidence for the fundamental value of Google search volume also for other capital markets.

In this paper, we focus on the Markit CDX Investment Grade Index.[33] More precisely, our analyses focus on CDS premium changes due to stationarity reasons (e.g., Byström, 2006; Avino and Nneji, 2014). In addition, we use aggregated volume of Google search queries for the period from January 1, 2004 to December 27, 2013 for a large set of terms. These are positive and negative connoted terms within the General Inquirer's merged word list of the Harvard IV-4 dictionary and Lasswell value dictionary as well as the Loughran and McDonald (2011) word list. We are able to download the daily aggregated US search volume of 3,404 terms. In the following we use the method of Da et al. (2015) to construct a Google index capturing consumer sentiment. Every six months we identify the index constituents by regressing CDS premium changes on the contemporaneous search volume of each term. The literature documents terms with a negative market impact to be best in identifying sentiment (e.g., Tetlock, 2007; Da et al., 2015). Thus, those 30 terms with the highest positive t-statistic constitute our index for the next 6 months.

In advance, it is not obvious which terms should be considered in the index constituent computation, because we do not know whether all or only economic terms of our word list

[33] A CDS index is designed as a credit insurance contract whose payoff is linked to the credit risk of a basket of firms.

capture sentiment better. Furthermore, it is unknown beforehand which subset of terms contains additional information not already captured by other financial variables. Our large set of terms with Google search volume allows us to analyze subsets of terms. Thus, we first compute one daily Google index based on all 3,404 terms. Second, we limit the choice of terms to economic terms and again compute one daily Google index. Consistent with the findings of Tang and Yan (2010), our results show that both Google indices are significantly positively related to CDS premium changes. However, only the Google index based on our full set of terms remains significant after the inclusion of control variables. Thus, this index seems to contain contemporaneous information not already captured by well-established determinants of CDS premium changes.

Given the previous result, we know that our Google indices comove with CDS premium changes. In line with the above economic rationale of these indices containing information not yet reflected in CDS premium changes, we expect our Google indices to have predictive power for CDS premium changes. This expectation is supported by our in-sample forecast results. Both Google indices predict CDS premium change reversals. If Google search volume even contains fundamental information, we expect it to predict trends in CDS premium changes. However, the Google indices predict CDS premium change reversals. This result is in line with even the CDS market being temporarily influenced by shocks to overall risk aversion (e.g., Tetlock, 2007 ;Tang and Yan, 2010). Hence, our results show that the Google indices contain no new fundamental information for the CDS market. But, they possess fundamental value as indicated by their predictive power.

However, a model's better in-sample explanatory power does not necessarily translate into better out-of-sample forecast accuracy. Our results show that the overall out-of-sample predictive power of our Google indices is weak. Specifically, adding our Google indices in out-of-sample forecasts does not significantly enhance the forecasts' accuracy relative to models without them. In line with Avino and Nneji (2014), we document that a simple autoregressive model only considering lagged CDS premium changes has the highest forecast accuracy. Thus, these findings support that information is priced efficiently for CDS.

Nevertheless, analyzing Google search volume is valuable. We find that the Google index based on economic terms improves forecasts in times of high CDS volatility while its forecasts in low volatility regimes are not statistically different to those not considering this Google index. Thus, when precise forecasts are most needed information in Google search volume is valuable. Additionally, both Google indices statistically significantly improve forecasts for longer forecast horizons with low economic significance. Overall, these results reveal that Google search volume provides fundamental value especially in times when forecasts are more demanding. For CDS investors, it may be one source of information to maintain or even increase the informational efficiency of the CDS market.

Having established our main results, we run several robustness tests. First, we provide evidence for the assumption underlying all our analyses of the Google indices containing information before CDS premium changes and not vice versa. The results of Granger causality tests document the validity of this assumption. Second, we compare our indices to the FEARS index suggested by Da et al. (2015) by adding it as a further control variable to our regression models. We find that the impact of our indices does not evaporate. Third, our results hold when varying the number of index constituents. Finally, we limit the index construction to only negative connoted (economic) terms and show that it is important to consider positive and negative terms for the index not limited to economic terms.

Our paper is related to several strands of the literature. First, we contribute to the literature analyzing the determinants of firms' credit risk based on yield spreads or CDS premiums. A vast literature focuses on firm-specific determinants of CDS premiums (e.g., Benkert, 2004; Ericsson et al., 2009; Callen et al., 2009; Tang and Yan, 2013; Bai and Wu, 2014). However, we add to the literature analyzing the impact of market-wide variables. Theoretically, Tang and Yan (2006) propose a model in which macroeconomic variables determine firms' credit risk while Chen (2010) argues that firms adjust their financing policy to macroeconomic conditions leading to countercyclical behavior of their credit risk. Empirically, Carling et al. (2007) show the relevance of macroeconomic variables in explaining firms‘ credit risk. Huang and Kong (2008) find that the announcement of macroeconomic news has an impact on firms‘ yield spreads, especially for high yield firms. In addition, Baum and Chi (2010) and Wisniewski and Lambe (2015) find macroeconomic uncertainty to determine CDS premiums and CDS premium changes. Byström (2006) shows that the stock market return and volatility determine European CDS premium changes. Breitenfellner and Wagner (2012) extend this study by showing that stock returns and implied stock market volatility are determinants after the financial crisis in 2008 while global financial variables such as the gold price and the global stock market return are main drivers before and in the financial crisis. Additionally, there exists a scarce literature analyzing the impact of consumer sentiment on CDS premiums.

Carling et al. (2007), Tang and Yan (2010) and Tang and Yan (2013) show that consumer sentiment influences CDS premiums negatively. Thereby consumer sentiment is used as a proxy for overall risk aversion. We contribute to this literature by documenting that daily aggregated Google search volume determines CDS premiums. Overall, our results are in line with Google search volume being a proxy for overall risk aversion.

Second, our paper extends the literature on the predictability of credit risk. Krishnan et al. (2010) document that the shape of the risk-free yield curve improves yield spread forecasts. Gündüz and Uhrig-Homburg (2011) find predictive power of CDS premiums for CDS premiums of firms within the same credit rating bucket. Norden (2014) analyzes the CDS market efficiency and shows that CDS premiums contain public and private information. Finally, Avino and Nneji (2014) find simple autoregressive models with one lag to have the highest forecast accuracy for CDS premium changes. We add to this literature by providing additional evidence on the informational efficiency of the CDS market and by showing that Google search volume is a source of further valuable information as indicated by its predictive power for CDS premium changes.

Finally, we contribute to the literature analyzing the fundamental value of Google search volume. So far, the existing literature focuses on stock markets. Thereby the literature may be split into two strands: On the one hand, papers use Google search volume to capture sentiment (Da et al., 2015). On the other hand, studies use Google search volume to extract investor attention for specific stocks (Da et al., 2011a). A short-lived influence of Google search volume is documented by (e.g., Da et al., 2015; Dimpfl and Jank, 2016). Their findings are consistent with noise trader models (e.g., De Long et al., 1990; Subrahmanyam, 2005) or models where trades do not arise due to information, i.e. liquidity needs or changes in overall risk aversion (e.g., Campbell et al., 1993; Hendershott and Menkveld, 2014). Persistent influence of Google search volume on prices is documented by (Da et al., 2011b). We contribute to this literature by documenting a temporary impact of Google search volume on CDS premium changes being in line with shocks to overall risk aversion. Furthermore, we analyze different sets of terms and the difference in their fundamental value for the CDS market.

The remainder of the paper is organized as follows. In Section 3.2, we describe our sample and the construction of Google indices. The in-sample predictive power of our Google indices is tested in Section 3.3. In Section 3.4, we investigate the out-of-sample predictive power. Various robustness tests provides Section 3.5 and Section 3.6 concludes.

3.2. Data and Google index construction

The paper uses data from several sources. Section 3.2.1 describes the data of the basic sample of CDS premiums and control variables. Section 3.2.2 describes how we use aggregated volume of Google search queries to compute two Google indices.

3.2.1. CDS sample

The paper uses CDS mid quotes of the Markit CDX Investment Grade Index (CDS premiums) with five years to maturity downloaded from Bloomberg. Our sample period lasts from November 19, 2004 to December 30, 2013. The CDS index is a credit insurance contract whose payoff is linked to the credit risk of a basket of firms. Every six months a new series of the index is issued with an updated basket of firms. Our index values describe the mid quotes of the most recent series at a point in time. Figure 3.1 shows the time-series evolution of the CDS premiums.

Figure 3.1: Markit CDX Investment Grade Index time series

Notes: The figure displays the time series of CDS mid quotes in basis points of the Markit CDX Investment Grade Index. The depicted time period lasts from November 19, 2004 to December 30, 2013.

Figure 3.1 shows that the CDS premiums rose enormously with the onset of the financial crisis in 2008. Peaks are around the acquisition of Bear Stearns by JPMorgan (March 16, 2008) and the September 2008 turmoil (federal takeover of Fannie Mae and Freddie Mac on September 7, the acquisition of Merrill Lynch by Bank of America on September 14, and the Lehman default on September 15). After these events CDS premiums remained at higher levels as before. The figure indicates that the time series is not stationary. Thus, we analyze first differences of CDS premiums in the following (e.g., Byström, 2006; Breitenfellner and Wagner, 2012; Avino and Nneji, 2014).

Additionally, we obtain further market variables from Thomson Reuters Datastream and the Federal Reserve Economic Database[34]. The variables are the S&P 500 Index return, Chicago Board Options Exchange (CBOE) daily market volatility index (VIX), the 5-year USD Libor swap rate, and the term spread defined as the difference between the 10-year and 2-year US Treasury note rate. Finally, we download the Aruoba-Diebold-Scotti Business Conditions Index (ADS Index)[35] suggested by Aruoba et al. (2009) and the daily Economic Policy Uncertainty Index (EPU Index)[36] suggested by Baker et al. (forthcoming). Summing up, we use the same sets of control variables in our regressions in Section 3.3 to 3.5 as Avino and Nneji (2014) and Da et al. (2015). Consistent with the literature, we use the S&P 500 Index return and the CBOE VIX as proxies for stock market returns and volatility found to be determinants of CDS premium changes (Breitenfellner and Wagner, 2012). The 5-year USD Libor swap rate proxies for the risk-free rate (Houweling and Vorst, 2005). The term spread describes the steepness of the yield curve (Collin-Dufresne et al., 2001). The ADS Index measures the overall state of macroeconomic conditions (Aruoba et al., 2009) with higher values indicating better conditions. Baker et al. (forthcoming) show that their EPU Index measures policy-related economic uncertainty and has an impact on economic output. Wisniewski and Lambe (2015) find this index to be related to CDS premium changes.

Table 3.1 provides summary statistics of changes in CDS premiums and the control variables. The statistics are comparable to those reported by Avino and Nneji (2014). Overall, the variables are stationary as indicated by the augmented Dickey-Fuller test. Thus, the analyses in the following sections base on changes in CDS premiums and control variables.

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[34] http://research.stlouisfed.org/fred2
[35] https://www.philadelphiafed.org/research-and-data/real-time-center/business-conditions-index
[36] http://www.policyuncertainty.com/us_daily.html

Table 3.1: Summary statistics of sample variables

	Mean	Std. dev.	Skewness	Kurtosis	Jarque-Bera		ADF	
CDS	0.0062	3.8210	0.1046	19.9724	38072.4609	***	-32.1325	***
CBOEVIX	-0.0005	1.9049	0.6056	18.1176	31465.5094	***	-39.0817	***
S&P 500	0.0003	0.0132	-0.4271	10.5122	10613.4828	***	-37.101	***
Swap rate	-0.0010	0.0610	-0.0034	4.3479	1802.4493	***	-34.1983	***
Term spread	0.0006	0.0449	-0.0178	5.4717	2855.3591	***	-33.8151	***
ADS Index	0.0001	0.0278	1.3394	35.3271	119802.4130	***	-13.8814	***
EPU Index	-0.0142	58.3453	0.0152	3.8664	1425.1469	***	-54.5923	***

Notes: The table reports the summary statistics of the main variables in our sample. We report the mean, standard deviation (Std. dev.), skewness (Skewness), kurtosis (Kurtosis), Jarque-Bera test statistic (Jarque-Bera), and augmented Dickey-Fuller test statistic (ADF) of these variables for the full sample period from November 19, 2004 to December 30, 2013. CDS is the change in the Markit CDX Investment Grade Index. S&P 500 is the return of the S&P 500 Index. CBOEVIX is the change in the Chicago Board Options Exchange (CBOE) Volatility Index computed out of S&P 500 Index option prices. Swap rate is the change in the 5-year USD-Libor Swap rate. Term spread is the change in the difference between the 10-year and 2-year Treasury rate. ADS Index is the change in the Aruoba-Diebold-Scotti Business Conditions index. EPU Index is change in the daily Economic Policy Uncertainty index. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

3.2.2. *ALL-SVI* and *FIN-SVI* Google index construction

We obtain aggregated volume of Google search queries (Google search volume) from Google Trends.[37] For terms with enough searches, this Google product provides the aggregated search volume for these terms scaled by the maximum search volume within a pre-defined region and time period. We download the US search volume for all positive and negative connoted terms within the General Inquirer's merged word list of the Harvard IV-4 dictionary and Lasswell value dictionary as well as the Loughran and McDonald (2011) word list for the period from January 1, 2004 to December 27, 2013. In our analyses we only consider time series longer than one year. Based on this criterion, we get daily time series for 3,404 terms. Thus, our analyses base on an extremely large set of daily time series of Google search volume. In the appendix we provide a more detailed description on how we compute daily time series.

To construct Google indices, we mainly follow Da et al. (2015). First, we compute log differences of each search volume time series

$$\Delta SV_{i,t} = \log(SV_{i,t}) - \log(SV_{i,t-1}) \tag{3.1}$$

[37] http://www.google.com/trends

where $SV_{i,t}$ is the search volume for the *i*-th term at day *t*. Da et al. (2015) document seasonality effects and heteroscedasticity of search volume time series. Therefore, they adjust the time series of their sample once for the full sample period. Contrary, we adjust the time series in our sample on each day since we expect Google indices to have predictive power for CDS premium changes. Thus, we should only use the information up to a specific day to adjust our data. Specifically, for each log difference time series of search volume on each day we winsorize the 2.5% smallest and 2.5% largest observations in the period from January 1, 2004 to the specific day. Afterwards, we remove seasonality by regressing the log differences on weekday and month dummies and use the residuals in the following (Da et al., 2015). Finally, we standardize the residual time series by dividing by the time series' standard deviation resulting in adjusted log differences of search volume time series ($\Delta ASV_{i,t}$).

Having cleaned the search volume data, we are able to compute a Google index. Consistent with Tetlock (2007) and Da et al. (2015), we assume terms with a negative market impact to be best in identifying sentiment. Every 6 months, we separately regress the time series of adjusted search volume of all terms up to the index constituents' computation date on contemporaneous CDS premium changes.[38] Then, the constituents of our Google index are the 30 terms with the highest positive t-statistics. We finally compute the Google index on day *t* by using the most recent index constituents and summing up the most recent adjusted log differences of search volume ($\Delta ASV_{i,t}$) for day *t* of these terms as in Da et al. (2015) resulting in one Google index times series (SVI_t)

$$SVI_t = \sum_{i=1}^{30} \Delta ASV_{i,t}. \tag{3.2}$$

Our large set of terms with Google search volume allows us to analyze subsets of terms. Using the described procedure, we compute a Google index based on all positive and negative connoted terms ($ALL - SVI_t$) and a Google index based on all positive and negative connoted economic terms ($FIN - SVI_t$).[39] We choose these two sets of possible terms because Da et al. (2015) base their index construction on economic terms only. Thereby they assume that only

[38] Terms have to have at least half a year of available Google search volume to be considered as potential index constituents.

[39] Economic terms are those terms in the categories Econ@ or ECON of the General Inquirer's merged list of the Harvard IV-4 dictionary and Lasswell value dictionary. The analysis of economic terms is based on 120 Google search volume time series.

economic terms contain consumer sentiment information. However, ultimately this is not obvious. Consumers, i.e. individuals, reveal their sentiment in their daily searches irrespective of whether these are economic terms or not (Demartini and Siersdorfer, 2010). In advance, there is no reason to limit the choice of potential index constituents to economic terms.

Table 3.2: Google index constituents

	ALL-SVI Google index			*FIN-SVI* Google index		
Rank	Term	Coverage	*FIN-SVI Rank*	Term	Coverage	*ALL-SVI Rank*
1	agile	68.42%		charitable	100.00%	
2	crude	68.42%		gamble	94.74%	
3	cuddle	63.16%		crisis	89.47%	25
4	failing	63.16%		skill	89.47%	
5	crusade	57.89%		success	89.47%	
6	depression	57.89%	16	bankrupt	84.21%	16
7	enhancements	57.89%		benefit	84.21%	
8	gold	57.89%	13	colony	84.21%	
9	nervous	57.89%		compensation	84.21%	
10	recession	57.89%	18	poor	84.21%	169
11	risk	57.89%		expensive	78.95%	
12	robbery	57.89%		equity	73.68%	
13	associate	52.63%	14	gold	73.68%	8
14	deviation	52.63%		associate	68.42%	13
15	awkward	47.37%		profit	68.42%	
16	bankrupt	47.37%	6	depression	63.16%	6
17	expert	47.37%		expense	63.16%	
18	faint	47.37%		recession	63.16%	10
19	smooth	47.37%		bankruptcy	57.89%	
20	warp	47.37%		capitalize	57.89%	40
21	accused	42.11%		contribute	57.89%	
22	appears	42.11%		corrupt	57.89%	
23	visionary	42.11%		default	57.89%	
24	defaults	36.84%		successful	57.89%	
25	crisis	31.58%	3	unemployed	57.89%	
26	accept	26.32%		lay	52.63%	
27	allegiance	26.32%		backer	47.37%	
28	bait	26.32%		donate	47.37%	
29	brute	26.32%		jobless	47.37%	44
30	consider	26.32%		warfare	42.11%	188

Notes: The table reports the 30 most often Google index constituents resulting from the construction of Google indices based on all positive and negative connoted terms (*ALL-SVI*, Column 2 to Column 4) as well as all positive and negative connoted economic terms (*FIN-SVI*, Column 5 to Column 7) as explained in Section 3.2.2. The terms are reported in Column 2 and Column 5 (Term). They are sorted by their occurrence frequency (Coverage), reported in Column 3 and Column 6. The maximum number a term may be an index constituent is 19. Column 4 and Column 7 show, if possible, the rank of a term in the respective other Google index.

Table 3.2 lists the 30 most frequently used index constituents of both indices, the frequency of these terms being an index constituent (coverage ratio), and compares the frequency ranks of terms in both indices. The maximum frequency of terms to be an index constituent is 19. In case of the $ALL-SVI$ Google index no term is an index constituent for the full sample period. The highest coverage ratio equals 68.42%. Contrary, for the $FIN-SVI$ Google index "charitable" is an index constituent for the full sample period.[40] The comparison of coverage ratios reveals that those of the $ALL-SVI$ Google index are lower and thus fluctuation among index constituents is higher relative to the $FIN-SVI$ Google index. This effect is driven by the fact that the fraction of economic terms to all terms is only 3.5%. However, the list of terms and the rank comparison reveal that both indices are not fully distinct but consider similar terms (e.g., depression, gold, recession). Given that the correlation between both indices is 47%, this also documents that both indices differ to a certain degree. This is in line with our above rationale to compute two Google indices as, in advance, it is not obvious which index contains additional information for the CDS market.

Given that both indices contain different information, we first test whether both indices are determinants of CDS premium changes. For this purpose we use three regression models for each Google index. The first model is a basic model only considering lagged CDS premium changes and the contemporaneous Google indices

$$\Delta CDS_t = \alpha + \beta \cdot ALL\,/\,FIN - SVI_t + \gamma \cdot \Delta CDS_{t-1} + \varepsilon_t \tag{3.3}$$

where ΔCDS_t are the changes in CDS premiums and $ALL-SVI_t$ as well as $FIN-SVI_t$ are the contemporaneous Google indices. In line with Byström (2006) we consider lagged changes in CDS premiums to control for autocorrelation. We extend the first model in Equation (3.3) with two sets of control variables

$$\Delta CDS_t = \alpha + \beta \cdot ALL\,/\,\mathrm{FIN} - SVI_t + \gamma \cdot \Delta CDS_{t-1} + \delta_{1/2} \cdot Controls_{t,1/2} + \varepsilon_t \tag{3.4}$$

where the second model's set of control variables is $Controls_{t,1}$ and the third model's set of control variables is $Controls_{t,2}$. $Controls_{t,1}$ consists of the set of control variables used in Avino and Nneji (2014): the S&P 500 Index return, the change in the CBOE VIX, the change in the 5-year swap rate, and the change in the term spread. $Controls_{t,2}$ is the set of control

[40] Note, this does not mean that "charitable" is the term with the highest explanatory power for CDS premium changes throughout our sample period.

Table 3.3: Contemporaneous impact of Google indices on CDS premium changes

	Model 1		Model 2		Model 3	
			Panel A: *ALL-SVI* Google index			
Intercept	0.0072		0.0631		0.0709	
	(0.9254)		(0.2314)		(0.1762)	
ALL-SVI(t)	1.7574	***	0.5484	**	0.5830	**
	(0.0002)		(0.0464)		(0.0350)	
CDS(t-1)	0.0946	*	0.1613	***	0.1645	***
	(0.0965)		(0.0000)		(0.0000)	
S&P 500(t)			-172.8831	***	-176.6000	***
			(0.0000)		(0.0000)	
CBOE VIX(t)			0.2469	***	0.2502	***
			(0.0029)		(0.0034)	
5yr swap rate(t)			-4.2027	**		
			(0.0298)			
Term spread(t)			3.2590			
			(0.1650)			
ADS Index(t)					-4.2310	
					(0.1003)	
EPU Index(t)					-0.0005	
					(0.7113)	
Adj. R^2	1.69		52.56		52.21	
Obs.	2300		2299		2299	
			Panel B: *FIN-SVI* Google index			
Intercept	0.0058		0.0624		0.0701	
	(0.9393)		(0.2374)		(0.1809)	
FIN-SVI(t)	1.0097	**	0.1034		0.1198	
	(0.0142)		(0.6540)		(0.6058)	
CDS(t-1)	0.0931		0.1612	***	0.1644	***
	(0.1029)		(0.0000)		(0.0000)	
S&P 500(t)			-172.4829	***	-176.2000	***
			(0.0000)		(0.0000)	
CBOE VIX(t)			0.2545	***	0.2581	***
			(0.0020)		(0.0024)	
5yr swap rate(t)			-4.2432	**		
			(0.0281)			
Term spread(t)			3.3037			
			(0.1590)			
ADS Index(t)					-4.2550	*
					(0.0972)	
EPU Index(t)					-0.0004	
					(0.7589)	
Adj. R^2	1.20		52.47		52.12	
Obs.	2300		2299		2299	

(Continued)

Table 3.3 (Continued): Contemporaneous impact of Google indices on CDS premium changes

Notes: The table reports the results of the regression of CDS premium changes on lagged CDS premium changes (CDS), the Google indices (*ALL-SVI* and *FIN-SVI*), and control variables. The Google indices are described in the main text in Section 3.2.2. Panel A reports the results for the Google index based on all positive and negative connoted terms (*ALL-SVI*). Panel B reports the results for the Google index based on all positive and negative connoted economic terms (*FIN-SVI*). Model 1 is the basic model, regressing CDS premium changes on the Google indices and lagged CDS premium changes. For Model 2, the additional control variables are the S&P 500 Index return (S&P 500), the change in the CBOE VIX (CBOE VIX), the change in the 5-year swap rate (5yr swap rate), and the change in the term spread (Term spread). For Model 3, the additional control variables are the S&P 500 Index return (S&P 500), the change in the CBOE VIX (CBOE VIX), the change in the Aruoba-Diebold-Scotti Business Conditions Index (ADS Index), and the change in the Economic Policy Uncertainty Index (EPU Index). P-values are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Significance is determined using Newey-West standard errors. Adjusted R^2 are in percentage points.

variables used in Da et al. (2015). It consists of the S&P 500 Index return, the change in the CBOE VIX, the change in the Aruoba-Diebold-Scotti Business Conditions Index (ADS Index), and the change in the Economic Policy Uncertainty Index (EPU Index).

Table 3.3 shows the regression results of the regression models from Equation (3.3) and Equation (3.4). Panel A of Table 3.3 shows that the $ALL-SVI$ Google index is significantly positively related to CDS premium changes at least at the 5% level. Panel B of Table 3.3 reports that the $FIN-SVI$ Google index is only significantly positively related to CDS premium changes at the 5% level in case of the basic model in Column 1. Adding control variables leads to an insignificant coefficient. The positive coefficients are in line with the findings of Tang and Yan (2010) and Da et al. (2015). The results reveal that the index constituents' positive contemporaneous relation to CDS premium changes at the index constituents' computation dates remains robust on the other sample days. Higher Google indices, i.e. days with increases in searches for the respective index constituents, coincide with higher CDS premium changes.

Overall, we find that the contemporaneous Google indices $ALL-SVI$ and $FIN-SVI$ are positively related to CDS premium changes while the $ALL-SVI$ Google index determines CDS premium changes irrespective of the set of control variables. The difference in the significance of both Google indices reveals that the $FIN-SVI$ Google index contemporaneously seems to only contain information that is already captured by other financial variables.

3.3. In-sample predictive power of Google indices

Given our initial rationale of Google search volume containing information before any other financial variable, this section tests the in-sample predictive power of our Google indices described in Section 3.2. For this purpose we use the three regression models from Equation (3.3) and Equation (3.4) with lagged variables. The dependent variable is always the time series of CDS premium changes. The first model is the basic model considering lagged CDS premium changes and our lagged Google indices

$$\Delta CDS_t = \alpha + \beta \cdot ALL / FIN - SVI_{t-1} + \gamma \cdot \Delta CDS_{t-1} + \varepsilon_t \tag{3.5}$$

where ΔCDS_t are the changes in CDS premiums and $ALL - SVI_{t-1}$ as well as $FIN - SVI_{t-1}$ are the lagged Google indices. In line with Avino and Nneji (2014) we consider lagged changes in CDS premiums as the most important variable for CDS premium change forecasts. We extend the first model in Equation (3.5) with two sets of lagged control variables

$$\Delta CDS_t = \alpha + \beta \cdot ALL / FIN - SVI_{t-1} + \gamma \cdot \Delta CDS_{t-1} + \delta_{1/2} \cdot Controls_{t-1,1/2} + \varepsilon_t \tag{3.6}$$

where $Controls_{t-1,1}$ and $Controls_{t-1,2}$ are the same sets of control variables as defined in Section 3.2 based on Avino and Nneji (2014) and Da et al. (2015). If aggregated Google search volume possesses fundamental value for the CDS market, we expect it to improve CDS premium change forecasts. If it even contains fundamental information not yet reflected in CDS premiums, we expect the Google indices to predict trends in CDS premium changes.

Table 3.4 shows the regression results for the above three models based on the lagged Google indices and lagged control variables (Equation (3.5) and Equation (3.6)). The results document that both Google indices have in-sample predictive power at the 5% to 10% level. Relative to the other variables the Google indices have the highest p-values. Regarding the economic effect of both Google indices, a one standard deviation shock today seems to be temporary. Due to the negative loading, the positive shock to CDS premium changes reported in Table 3.3 is reversed the day after. This finding is similar to those of Tetlock (2007) and Da et al. (2015). Thus, our results provide evidence for our Google indices having fundamental value for the CDS market although they contain no fundamental information not yet priced in CDS premiums. This would be the case if the loadings of the Google indices in Table 3.3 and Table 3.4 would have the same signs.

Table 3.4: In-sample predictive power of Google indices for CDS premium changes

	Model 1		Model 2		Model 3	
Panel A: *ALL-SVI* Google index						
Intercept	0.0047		0.0136		0.0123	
	(0.9513)		(0.8593)		(0.8726)	
ALL-SVI (t-1)	-0.8535	**	-0.7370	*	-0.7698	*
	(0.0286)		(0.0711)		(0.0573)	
CDS(t-1)	0.0985	*	0.1284		0.1263	
	(0.0882)		(0.1311)		(0.1328)	
S&P 500(t-1)			-19.7428		-19.5534	
			(0.4151)		(0.4137)	
CBOE VIX(t-1)			-0.2432	*	-0.2414	*
			(0.0789)		(0.0821)	
5yr swap rate(t-1)			0.8261			
			(0.7197)			
Term spread(t-1)			-0.6565			
			(0.7745)			
ADS Index(t-1)					-0.3874	
					(0.9113)	
EPU Index(t-1)					0.0026	
					(0.1262)	
Adj. R^2	1.01		1.32		1.47	
Obs.	2300		2298		2298	
Panel B: *FIN-SVI* Google index						
Intercept	0.0054		0.0144		0.0131	
	(0.9442)		(0.8512)		(0.8647)	
FIN-SVI (t-1)	-0.6778	**	-0.5749	*	-0.5740	*
	(0.0352)		(0.0762)		(0.0743)	
CDS(t-1)	0.0969	*	0.1268		0.1246	
	(0.0903)		(0.1343)		(0.1364)	
S&P 500(t-1)			-19.9593		-19.7985	
			(0.4050)		(0.4031)	
CBOE VIX(t-1)			-0.2439	*	-0.2427	*
			(0.0746)		(0.0771)	
5yr swap rate(t-1)			0.8558			
			(0.7085)			
Term spread(t-1)			-0.6949			
			(0.7604)			
ADS Index(t-1)					-0.3203	
					(0.9262)	
EPU Index(t-1)					0.0025	
					(0.1428)	
Adj. R^2	0.98		1.30		1.43	
Obs.	2300		2298		2298	

(Continued)

Table 3.4 (Continued): In-sample predictive power of Google indices for CDS premium changes

Notes: The table reports the results of the regression of CDS premium changes on lagged CDS premium changes (CDS), the lagged Google indices (*ALL-SVI* and *FIN-SVI*), and lagged control variables. The Google indices are described in the main text in Section 3.2.2. Panel A reports the results for the Google index based on all positive and negative connoted terms (*ALL-SVI*). Panel B reports the results for the Google index based on all positive and negative connoted economic terms (*FIN-SVI*). Model 1 is the basic model, regressing CDS premium changes on the lagged Google indices and lagged CDS premium changes. For Model 2, the additional lagged control variables are the S&P 500 Index return (S&P 500), the change in the CBOE VIX (CBOE VIX), the change in the 5-year swap rate (5yr swap rate), and the change in the term spread (Term spread). For Model 3, the additional lagged control variables are the S&P 500 Index return (S&P 500), the change in the CBOE VIX (CBOE VIX), the change in the Aruoba-Diebold-Scotti Business Conditions Index (ADS Index), and the change in the Economic Policy Uncertainty Index (EPU Index). P-values are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Significance is determined using Newey-West standard errors. Adjusted R^2 are in percentage points.

Overall, our results are in line with two strands of theoretical models. These are noise trader models (e.g., De Long et al., 1990; Subrahmanyam, 2005) and models where trades are not based on information, but arise due to, e.g., liquidity needs or changes in overall risk aversion (e.g., Campbell et al., 1993; Chordia and Subrahmanyam, 2004; Hendershott and Menkveld, 2014). As summarized by Tetlock (2007), both types of theoretical models predict reversals. Since our analyses base on the institutional CDS market the influence of noise trading is unlikely. Thus, it is more likely that our results arise through sudden changes in overall risk aversion.

Summing up the findings reported in Table 3.4, we provide evidence for the predictive power and the fundamental value of Google search volume for the CDS market.

3.4. Out-of-sample predictive power of Google indices

The previous section documents in-sample predictive power of our Google indices indicating fundamental value of Google search volume for the CDS market. To find further support for this finding, this section analyzes the out-of-sample predictive power of our Google indices described in Section 3.2. In Section 3.4.1 we test whether our Google indices improve the one-day ahead forecast accuracy. Section 3.4.2 analyses one-day ahead forecast results for different times of CDS volatility. Finally, Section 3.4.3 compares results for different forecast horizons.

3.4.1. One-day ahead out-of-sample forecasts

In this section we perform one-day ahead out-of-sample forecasts to test the predictive power of our $ALL-SVI$ and $FIN-SVI$ Google index. For this purpose we use the three regression models from Section 3.3 with and without our Google indices. Based on these models and the Google indices we perform one-day ahead forecasts

$$\Delta CDS_{t+1}^{without\ SVI} = \alpha + \gamma \cdot \Delta CDS_t \left(+\delta_{1/2} \cdot Controls_{t,1/2} \right) + \varepsilon_t \tag{3.7}$$

and

$$\Delta CDS_{t+1}^{with\ SVI} = \alpha + \beta \cdot ALL/FIN - SVI_t + \gamma \cdot \Delta CDS_t \left(+\delta_{1/2} \cdot Controls_{t,1/2} \right) + \varepsilon_t \tag{3.8}$$

where ΔCDS_t are the changes in CDS premiums, $ALL-SVI_t$ as well as $FIN-SVI_t$ are our Google indices, $Controls_{t,1}$ as well as $Controls_{t,2}$ are the sets of control variables defined as in Section 3.2, and $\Delta CDS_{t+1}^{without/with\ SVI}$ are the CDS premium change forecasts without and with considering our Google indices. The models in Equation (3.7) and Equation (3.8) are first estimated based on an extending window of all known observations from the start of our sample to the current day *t*. The coefficient estimates are then used to compute forecasts for day *t+1*. We get daily forecasts for the period from May 26, 2005 to December 30, 2013.

Based on the forecasts and the actual realized CDS premium changes for the next day (ΔCDS_{t+1}), we are able to evaluate the predictive power of our Google indices. We test the forecast accuracy of the models in Equation (3.7) against the forecast accuracy of the same models additionally considering the $ALL-SVI$ or $FIN-SVI$ Google index in Equation (3.8).[41] For this purpose, we compare the mean absolute error (MAE), mean squared error (MSE), and the mean correct prediction (MCP) of these models. We test the null hypothesis of a model without and with the respective Google index ($ALL-SVI$ or $FIN-SVI$) generating equal forecasts. For the MAE and MSE, we test the null hypothesis using the modified Diebold and Mariano (1995) test and the weighted modified Diebold and Mariano (1995) test. For the MAE we additionally use the Giacomini and White (2006) test and for the MSE we additionally use the Clark and West (2007) test. For the MCP we use the 2-proportion z-test. A detailed description of the applied statistical tests can be found in Avino and Nneji (2014). This analysis reveals whether the inclusion of our Google indices provides additional value in forecasting CDS premium changes.

[41] Avino and Nneji (2014) also compare their basic model to a random walk model. Unreported results (available upon request from the authors) document that all models are superior to a random walk model as in Avino and Nneji (2014).

Table 3.5: Out-of-sample predictive power of Google indices for CDS premium changes

		ALL-SVI Google index		*FIN-SVI* Google index	
Model 1 without Google index	MAE	2.2082			
	MSE	15.2955			
	MCP	54.27%			
Model 1 with Google index	MAE	2.2205**	°°° ^^	2.2166	
	MSE	15.3031		15.2871	~
	MCP	53.45%		53.22%	
Model 2 without Google index	MAE	2.2298			
	MSE	15.4900			
	MCP	52.21%			
Model 2 with Google index	MAE	2.2425**	°°° ^^	2.2386*	° ^
	MSE	15.5064		15.4897	
	MCP	51.24%		52.02%	
Model 3 without Google index	MAE	2.2231			
	MSE	15.4263			
	MCP	53.72%			
Model 3 with Google index	MAE	2.2366***	°°° ^^^	2.2305	
	MSE	15.4404		15.4259	
	MCP	52.44%		52.94%	

Notes: The table reports the results of out-of-sample forecasts based on the models described in Equation (3.7) and Equation (3.8). For each model and Google index (*ALL-SVI* and *FIN-SVI*) a forecast without and with the respective Google index is computed. The *ALL-SVI* and *FIN-SVI* Google index are described in the main text in Section 3.2.2. Column 3 and Column 4 report the results for the *ALL-SVI* Google index. Column 5 and Column 6 report the results for the *FIN-SVI* Google index. Model 1 is the basic model only considering lagged CDS premium changes. Model 2 additionally considers the lagged S&P 500 Index return, the lagged change in the CBOE VIX, the lagged change in the 5-year swap rate, and the lagged change in the term spread. Model 3 additionally considers the lagged S&P 500 Index return, the change in the CBOE VIX, the change in the Aruoba-Diebold-Scotti Business Conditions Index, and the change in the Economic Policy Uncertainty Index. We report the mean absolute error (MAE), the mean squared error (MSE), and the mean correct prediction of the sign of the CDS premium changes (MCP). Additionally, we test the null hypothesis of a model without and with the respective Google index (*ALL-SVI* or *FIN-SVI*) generating equal forecasts. We test the null hypothesis for the MAE and MSE using the modified Diebold and Mariano (1995) test and the weighted modified Diebold and Mariano (1995) test. For the MAE we additionally use the Giacomini and White (2006) test and for the MSE we additionally use the Clark and West (2007) test. For the MCP we use the 2-proportion z-test. ***, **, and * denote significance at the 1%, 5%, and 10% level for the modified Diebold and Mariano (1995) test. °°°, °°, and ° denote significance at the 1%, 5%, and 10% level for the weighted modified Diebold and Mariano (1995) test. ^^^, ^^, and ^ denote significance at the 1%, 5%, and 10% level for the Giacomini and White (2006) test. ~~~, ~~, and ~ denote significance at the 1%, 5%, and 10% level for the Clark and West (2007) test. ###, ##, and # denote significance at the 1%, 5%, and 10% level for the 2-proportion z-test.

Table 3.5 provides the out-of-sample one-day ahead forecast results. Column 3 and Column 4 of Table 3.5 report the results for the $ALL-SVI$ Google index. The models considering this Google index are slightly worse regarding the values of the MAE and MSE, as well as the statistical significance for the MAE of the modified Diebold and Mariano (1995) test, weighted modified Diebold and Mariano (1995) test, and Giacomini and White (2006) test. Column 5 and Column 6 of Table 3.5 show the results for the $FIN-SVI$ Google index. Although the MAE and MSE are slightly higher for the models considering this Google index, the difference is not statistically significant.

To sum up, Table 3.5 shows that both indices do not improve out-of-sample forecasts. However, other financial variables also do not improve forecasts of CDS premium changes as the basic model only considering lagged CDS premium changes has the lowest MAE and MSE. Irrespective of the used set of variables, improving the CDS forecast accuracy is demanding which is evidence for the informational efficiency of the CDS market.

3.4.2. Out-of-sample forecasts for different periods

Given the previous section's findings, CDS volatility may be a parameter that decisively influences the forecast accuracy of the basic autoregressive model with lagged CDS premium changes. High CDS volatility might reduce the forecast accuracy when it is most needed (Dimpfl and Jank, 2016). In this section we analyze whether our two Google indices ($ALL-SVI$ and $FIN-SVI$) improve the forecast accuracy of the models explained in Section 3.4.1 in times of high CDS volatility.

First, we compute CDS volatility as the 20-day rolling standard deviation of CDS premium changes. Second, we sort the days in our forecasting period according to the computed CDS volatility. Finally, we compute the same statistics and statistical tests as in Table 3.5 for different quantiles of our sample. Table 3.6 reports the results.

Panel A of Table 3.6 shows the results for the 10% (low CDS volatility) and 90% (high CDS volatility) quantile for the $ALL-SVI$ and $FIN-SVI$ Google index. The results for the $ALL-SVI$ Google index show that it slightly improves the forecast accuracy in high volatile times for all models. But, it also reduces the forecast accuracy in times of low volatility. The results for the $FIN-SVI$ Google index are more convincing. It significantly improves the

Table 3.6: Out-of-sample predictive power of Google indices for different periods

Panel A: 10% and 90% quantile					
		ALL-SVI (10% quantile)	*ALL-SVI* (90% quantile)	*FIN-SVI* (10% quantile)	*FIN-SVI* (90% quantile)
Model 1 without Google index	MAE	0.3018	7.0108	0.3018	7.0108
	MSE	0.1569	95.7713	0.1569	95.7713
	MCP	62.39%	53.67%	62.39%	53.67%
Model 1 with Google index	MAE	0.3304***°° ^^^	6.9881 °	0.3020	6.9762** °° ^^
	MSE	0.1747*	95.4477	0.1574	95.2079** °° ~~
	MCP	53.21% #	51.38%	61.01%	50.92%
Model 2 without Google index	MAE	0.3108	7.1104	0.3108	7.1104
	MSE	0.1704	97.0702	0.1704	97.0702
	MCP	59.63%	53.67%	59.63%	53.67%
Model 2 with Google index	MAE	0.3427***°° ^^^	7.0913 °	0.3108	7.0816* ° ^
	MSE	0.1901*	96.8282	0.1707	96.6244** ° ~~
	MCP	52.29%	51.38%	58.26%	52.29%
Model 3 without Google index	MAE	0.3121	7.0792	0.3121	7.0792
	MSE	0.1741	96.6208	0.1741	96.6208
	MCP	58.26%	55.05%	58.26%	55.05%
Model 3 with Google index	MAE	0.3418***°° ^^^	7.0575 °°	0.3116	7.0511* ° ^
	MSE	0.1919*	96.3012	0.1743	96.1649** °° ~~
	MCP	53.21%	52.29%	59.17%	52.29%

(Continued)

Table 3.6 (Continued): Out-of-sample predictive power of Google indices for different periods

Panel B: 25% and 75% quantile					
		ALL-SVI (25% quantile)	*ALL-SVI* (75% quantile)	*FIN-SVI* (25% quantile)	*FIN-SVI* (75% quantile)
Model 1 without Google index	MAE	0.5374	4.7674	0.5374	4.7674
	MSE	0.6379	48.7575	0.6379	48.7575
	MCP	58.82%	53.49%	58.82%	53.49%
Model 1 with Google index	MAE	0.5647*** °° ^^^	4.7472** ^^	0.5460* °° ^	4.7397*** °°° ^^^
	MSE	0.6852*** °°	48.5646 ~	0.6640** °°	48.4268*** °°° ~~~
	MCP	55.33%	54.04%	58.46%	53.31%
Model 2 without Google index	MAE	0.5463	4.8193	0.5463	4.8193
	MSE	0.6485	49.3787	0.6485	49.3787
	MCP	57.17%	51.84%	57.17%	51.84%
Model 2 with Google index	MAE	0.5715*** °° ^^^	4.8064	0.5544* °° ^^	4.7982** °° ^^
	MSE	0.6963*** °°	49.2433	0.6733** °°	49.1136** °° ~~~
	MCP	54.04%	51.10%	55.70%	52.21%
Model 3 without Google index	MAE	0.5464	4.7928	0.5464	4.7928
	MSE	0.6501	49.1384	0.6501	49.1384
	MCP	56.80%	53.86%	56.80%	53.86%
Model 3 with Google index	MAE	0.5718*** °° ^^^	4.7796	0.5577*** °°° ^^^	4.7714** °° ^^
	MSE	0.7032*** °°	48.9775	0.6767** °°	48.8716*** °° ~~~
	MCP	54.23%	53.13%	55.88%	53.68%

(Continued)

Table 3.6 (Continued): Out-of-sample predictive power of Google indices for different periods

Notes: The table reports the results of out-of-sample forecasts based on the models described in Equation (3.7) and Equation (3.8) for different CDS premium volatility quantiles. CDS premium volatility is defined as the 20-day rolling standard deviation of CDS premium changes. For each model and Google index (*ALL-SVI* and *FIN-SVI*) a forecast without and with the respective Google index is computed. The *ALL-SVI* and *FIN-SVI* Google index are described in the main text in Section 3.2.2. Panel A reports the results for the 10% and 90% quantile of CDS premium volatility for the Google indices. Panel B reports the results for the 25% and 75% quantile of CDS premium volatility for the Google indices. In each panel, Column 3 to Column 6 report the results for the *ALL-SVI* Google index and Column 7 to Column 10 report the results for the *FIN-SVI* Google index. Model 1 is the basic model only considering lagged CDS premium changes. Model 2 additionally considers the lagged S&P 500 Index return, the lagged change in the CBOE VIX, the lagged change in the 5-year swap rate, and the lagged change in the term spread. Model 3 additionally considers the lagged S&P 500 Index return, the change in the CBOE VIX, the change in the Aruoba-Diebold-Scotti Business Conditions Index, and the change in the Economic Policy Uncertainty Index. We report the mean absolute error (MAE), the mean squared error (MSE), and the mean correct prediction of the sign of the CDS premium changes (MCP). Additionally, we test the null hypothesis of a model without and with the respective Google index (*ALL-SVI* or *FIN-SVI*) generating equal forecasts. We test the null hypothesis for the MAE and MSE using the modified Diebold and Mariano (1995) test and the weighted modified Diebold and Mariano (1995) test. For the MAE we additionally use the Giacomini and White (2006) test and for the MSE we additionally use the Clark and West (2007) test. For the MCP we use the 2-proportion z-test. ***, **, and * denote significance at the 1%, 5%, and 10% level for the modified Diebold and Mariano (1995) test. °°°, °°, and ° denote significance at the 1%, 5%, and 10% level for the weighted modified Diebold and Mariano (1995) test. ^^^, ^^, and ^ denote significance at the 1%, 5%, and 10% level for the Giacomini and White (2006) test. ~~~, ~~, and ~ denote significance at the 1%, 5%, and 10% level for the Clark and West (2007) test. ###, ##, and # denote significance at the 1%, 5%, and 10% level for the 2-proportion z-test.

forecast accuracy for all models in high volatile times while the difference in the forecast accuracy is not statistically significant in low volatile times. Panel B of Table 3.6 presents the results for the 25% and 75% quantile. For the $ALL-SVI$ Google index the forecast accuracy is no longer significantly higher in times of high CDS volatility while the reduced forecast accuracy in times of low CDS volatility has gained statistical significance. Contrary, for the $FIN-SVI$ Google index the statistical significance in volatile times has even improved while it only slightly worsens the forecasts accuracy in times of low CDS volatility. This is especially the case when considering the best performing model only based on lagged CDS premium changes in Row 3 to 5 of Table 3.6.

Overall, we see that our Google indices improve out-of-sample forecasts in times of high CDS volatility. Thus, when forecasts are more demanding, Google search volume improves the forecast accuracy. Again, the basic models only considering lagged CDS premium changes, or lagged CDS premium changes and the lagged Google indices have the lowest MAE and MSE.

3.4.3. Out-of sample forecasts for different forecasts horizons

Having seen that the predictive power depends on CDS volatility a second parameter related to uncertainty and thus possibly leading to differences in the forecast accuracy is the forecast horizon. In this section we test the forecast accuracy improvement of our Google indices for two-day, one-week, and two-week forecast horizons.

For this analysis we focus on the models only considering lagged CDS premium changes without our Google indices

$$\Delta CDS_{t+i}^{without\ SVI} = \alpha + \beta \cdot \Delta CDS_{t+i-1} + \varepsilon_t \tag{3.9}$$

and with our Google indices

$$\Delta CDS_{t+i}^{with\ SVI} = \alpha + \beta \cdot \Delta CDS_{t+i-1} + \gamma \cdot ALL / FIN - SVI_{t+i-1} + \varepsilon_t \tag{3.10}$$

where ΔCDS_t are the changes in CDS premiums, $ALL-SVI_t$ as well as $FIN-SVI_t$ are our Google indices, and *i* determines the forecast horizon. We focus on these models because they have the highest forecast accuracy in Section 3.4.1 and Section 3.4.2.

Due to the longer forecast horizon, we also have to forecast the Google indices themselves. Similar to Dimpfl and Jank (2016), we use an autoregressive model with the respective lagged Google index

Table 3.7: Out-of-sample predictive power for different forecasting horizons

		ALL-SVI Google index		*FIN-SVI* Google index	
Model 1: 2 day forecast without Google index	MAE	2.2080		2.2080	
	MSE	15.2942		15.2942	
	MCP	50.67%		50.67%	
Model 1: 2 day forecast with Google index	MAE	2.2091		2.2082	
	MSE	15.2987		15.2926	
	MCP	49.38%		49.15%	
Model 1: 1 week forecast without Google index	MAE	2.2095		2.2095	
	MSE	15.3054		15.3054	
	MCP	49.86%		49.86%	
Model 1: 1 week forecast with Google index	MAE	2.2095		2.2096	
	MSE	15.3053		15.3053	
	MCP	49.72%		49.82%	
Model 1: 2 weeks forecast without Google index	MAE	2.2108		2.2108	
	MSE	15.3313		15.3313	
	MCP	49.70%		49.70%	
Model 1: 2 weeks forecast with Google index	MAE	2.2107**	°° ^^	2.2108**	°°° ^^
	MSE	15.3311	°	15.3312**	°°° ~~
	MCP	50.16%		49.63%	

Notes: The table reports the results of out-of-sample forecasts based on the basic model without additional control variables described in described in Equation (3.7) and Equation (3.8) for different forecast horizons. The forecasts horizons are 2 days, 1 week, and 2 weeks. For each forecast horizon and each Google index (*ALL-SVI* and *FIN-SVI*) a forecast without and with the respective Google index is computed. The *ALL-SVI* and *FIN-SVI* Google index are described in the main text in Section 3.2.2. Column 3 and Column 4 report the results for the *ALL-SVI* Google index. Column 5 and Column 6 report the results for the *FIN-SVI* Google index. We report the mean absolute error (MAE), the mean squared error (MSE), and the mean correct prediction of the sign of the CDS premium changes (MCP). Additionally, we test the null hypothesis of a model without and with the respective Google index (*ALL-SVI* or *FIN-SVI*) generating equal forecasts. We test the null hypothesis for the MAE and MSE using the modified Diebold and Mariano (1995) test and the weighted modified Diebold and Mariano (1995) test. For the MAE we additionally use the Giacomini and White (2006) test and for the MSE we additionally use the Clark and West (2007) test. For the MCP we use the 2-proportion z-test. ***, **, and * denote significance at the 1%, 5%, and 10% level for the modified Diebold and Mariano (1995) test. °°°, °°, and ° denote significance at the 1%, 5%, and 10% level for the weighted modified Diebold and Mariano (1995) test. ^^^, ^^, and ^ denote significance at the 1%, 5%, and 10% level for the Giacomini and White (2006) test. ~~~, ~~, and ~ denote significance at the 1%, 5%, and 10% level for the Clark and West (2007) test. ###, ##, and # denote significance at the 1%, 5%, and 10% level for the 2-proportion z-test.

$$ALL / FIN - SVI_{t+i} = \alpha + \beta \cdot ALL / FIN - SVI_{t+i-1} + \varepsilon_t \tag{3.11}$$

where $ALL - SVI_t$ as well as $FIN - SVI_t$ are our Google indices. As in Section 3.4.1, the models in Equation (3.9), Equation (3.10), and Equation (3.11) are first estimated based on an extending window of all known observations from the start of our sample to the current day *t*. The coefficient estimates are then used to compute forecasts for day *t+i*. Table 3.7 reports the results for two-day, one-week, and two-week ahead forecasts.

Table 3.7 shows that the forecast accuracy of the models including the Google indices improves forecasts for longer horizons relative to the model not considering the Google indices. For the two-week horizon the results document that the forecast accuracy is statistically significantly higher for the models considering the Google indices. However, the economic significance is low.

In summary, both Google indices statistically significantly improve the forecasts for longer horizons. Hence, the results reveal that Google search volume contains fundamental value especially when forecasts are more demanding.

3.5. Robustness

This section provides results of several robustness analyses. In Section 3.5.1, we analyze the causal assumption underlying all our analyses of Google search volume containing information before CDS premium changes and not vice versa. We compare our indices to the FEARS index suggested by Da et al. (2015) in Section 3.5.2. Finally, Section 3.5.3 analyzes whether our results hold when varying the number of index constituents or when limiting the index construction to only negative connoted (economic) terms.

3.5.1. Granger causality

The previous sections' findings document that our Google indices have fundamental value for the CDS market. However, the previous sections' analyses are based on the assumption that the Google indices cause CDS premium changes and not vice versa. In this section we test this causal assumption by performing Granger causality tests. We first estimate vector autoregressive (VAR) models

$$\Delta CDS_t = \alpha + \sum_{l=1}^{5} \beta_l \cdot ALL/FIN-SVI_{t-l} + \sum_{k=1}^{5} \gamma \cdot \Delta CDS_{t-k} \left(+\delta_{1/2} \cdot Controls_{t-1,1/2} \right) + \varepsilon_t$$
$$ALL/FIN-SVI_t = \alpha + \sum_{l=1}^{5} \beta_l \cdot ALL/FIN-SVI_{t-l} + \sum_{k=1}^{5} \gamma \cdot \Delta CDS_{t-k} \left(+\delta_{1/2} \cdot Controls_{t-1,1/2} \right) + \varepsilon_t \quad (3.12)$$

where ΔCDS_t, $ALL/FIN-SVI_t$, and $Controls_{t-1,1/2}$ are defined as in Section 3.2 and then run Granger causality tests. The first VAR model separately consider our Google indices ($ALL-SVI$ and $FIN-SVI$) and CDS premium changes of up to 5 lags. In a second and third VAR model we add $Controls_{t-1,1}$ and $Controls_{t-1,2}$ from Equation (3.6) as control variables. Table 3.8 and Table 3.9 report the results of the Granger causality tests.

Table 3.8: *ALL-SVI* Google index and CDS premium changes: Granger causality test

Null hypothesis:	CDS premium changes do not Granger cause the *ALL-SVI* Google index	The *ALL-SVI* Google index does not Granger cause CDS premium changes
Lags	Panel A: No control variables	
1	0.5876	0.0275 **
2	0.8094	0.0782 *
3	0.3132	0.1336
4	0.3319	0.1856
5	0.4094	0.2213
	Panel B: S&P 500 Index return, CBOE VIX, 5yr swap rate, Term spread	
1	0.9240	0.0585 *
2	0.8361	0.1335
3	0.3464	0.2082
4	0.3941	0.2624
5	0.4389	0.3024
	Panel C: S&P 500 Index return, CBOE VIX, ADS Index, EPU Index	
1	0.9029	0.0481 **
2	0.8639	0.1184
3	0.4327	0.1860
4	0.4786	0.2425
5	0.5172	0.2703

Notes: The table reports the results of Granger causality tests of whether the CDS premium changes Granger cause the Google index based on all positive and negative connoted terms (*ALL-SVI*), or whether the *ALL-SVI* Google index Granger causes CDS premium changes. The *ALL-SVI* Google index is described in the main text in Section 3.2.2. The dependent variables of the underlying vector autoregressive (VAR) models are the CDS premium changes and the *ALL-SVI* Google index, the independent variables are the lagged CDS premium changes and the lagged *ALL-SVI* Google index in in Panel A. In Panel B additional lagged control variables are the S&P 500 Index return, the change in the CBOE VIX, the change in the 5-year swap rate, and the change in the term spread. In Panel C additional lagged control variables are variables are the S&P 500 Index return, the change in the CBOE VIX, the change in the Aruoba-Diebold-Scotti Business Conditions Index, and the change in the Economic Policy Uncertainty Index. We report up to 5 lags. A significant Chi-squared statistic suggests that the null hypothesis given in the column header can be rejected at the displayed significance level. ***, **, and * denote significance at the 1%, 5%, and 10% level.

Table 3.9: *FIN-SVI* Google index and CDS premium changes: Granger causality test

Null hypothesis:	CDS premium changes do not Granger cause the *FIN-SVI* Google index	The *FIN-SVI* Google index does not Granger cause CDS premium changes
Lags	Panel A: No control variables	
1	0.2685	0.0416 **
2	0.6129	0.1227
3	0.4572	0.2223
4	0.6455	0.2935
5	0.2631	0.3829
	Panel B: S&P 500 Index return, CBOE VIX, 5yr swap rate, Term spread	
1	0.5248	0.0853 *
2	0.7221	0.2298
3	0.5788	0.3825
4	0.7633	0.4560
5	0.2838	0.5624
	Panel C: S&P 500 Index return, CBOE VIX, ADS Index, EPU Index	
1	0.6105	0.0856 *
2	0.8317	0.2312
3	0.7226	0.3863
4	0.8741	0.4627
5	0.3274	0.5642

Notes: The table reports the results of Granger causality tests of whether the CDS premium changes Granger cause the Google index based on all positive and negative connoted economic terms (*FIN-SVI*), or whether the *FIN-SVI* Google index Granger causes CDS premium changes. The *FIN-SVI* Google index is described in the main text in Section 3.2.2. The dependent variables of the underlying vector autoregressive (VAR) models are the CDS premium changes and the *FIN-SVI* Google index, the independent variables are the lagged CDS premium changes and the lagged *FIN-SVI* Google index in in Panel A. In Panel B additional lagged control variables are the S&P 500 Index return, the change in the CBOE VIX, the change in the 5-year swap rate, and the change in the term spread. In Panel C additional lagged control variables are variables are the S&P 500 Index return, the change in the CBOE VIX, the change in the Aruoba-Diebold-Scotti Business Conditions Index, and the change in the Economic Policy Uncertainty Index. We report up to 5 lags. A significant Chi-squared statistic suggests that the null hypothesis given in the column header can be rejected at the displayed significance level. ***, **, and * denote significance at the 1%, 5%, and 10% level.

Table 3.8 and Table 3.9 show that the Google indices Granger cause CDS premium changes and the results are robust to the inclusion of control variables. Reversely, CDS premium changes do not Granger cause the Google indices. This supports our assumption and is further evidence that Google search volume has fundamental value for the CDS market.

3.5.2. *ALL-SVI* and *FIN-SVI* Google index vs. FEARS index

Finding only moderate predictive power may be due to the fact that our Google indices are inferior to existing ones. Thus, we compare our index to the FEARS index suggested by Da et al. (2015). Their search query selection is more advanced since they consider combinations of economic terms individuals' searched for. Thus, their index may be superior to our Google indices. The correlation of the FEARS index with the $ALL-SVI$ Google index is 33% and 52% with the $FIN-SVI$ Google. As expected, the correlation of the two indices based on economic terms is higher. Nevertheless, the correlation reveals that all three indices contain different information. We test the robustness of our results by replicating the results of Table 3.4 and adding the FEARS index as additional control variable. To be able to compare our Google indices to the FEARS index, we additionally run these regressions for the S&P 500 Index return as dependent variable as in Da et al. (2015). Table 3.10 reports the results.

Panel A of Table 3.10 presents the results for the $ALL-SVI$ Google index. The relation of the $ALL-SVI$ Google index to the respective dependent variable is significant in all models while the FEARS index is always insignificant. Panel B of Table 3.10 shows the results for the $FIN-SVI$ Google index. In the basic model for CDS premium changes as dependent variable, the $FIN-SVI$ Google index significantly determines future CDS premium changes. The significance disappears when adding control variables or when considering S&P 500 Index returns as dependent variable. However, the FEARS index is always insignificant and the level of statistical significance is always higher for the $FIN-SVI$ Google index. In addition to the results from Table 3.4, unreported results (available upon request from the authors) document that both indices statistically significantly predict S&P 500 Index returns when considered separately. Again, the level of statistical significance is higher for the $FIN-SVI$ Google index. Thus, our less advanced index construction is not inferior to Da et al. (2015). Both indices show similar results, while the findings indicate that due to the usage of the CDS premium changes to construct our Google indices noise may be reduced when capturing information in market data.

Table 3.10: *ALL-SVI* and *FIN-SVI* Google index vs. FEARS index

	Panel A: *ALL-SVI* Google index											
	CDS premium changes						S&P 500 Index return					
	Model 1		Model 2		Model 3		Model 1		Model 2		Model 3	
Intercept	0.0455		0.0512		0.0517		0.0002		0.0002		0.0002	
	(0.6313)		(0.5878)		(0.5879)		(0.4646)		(0.4534)		(0.4643)	
ALL-SVI (t-1)	-1.1385	**	-1.0364	*	-1.0853	*	0.0042	**	0.0041	**	0.0041	**
	(0.0468)		(0.0831)		(0.0670)		(0.0310)		(0.0439)		(0.0407)	
FEARS (t-1)	-0.4660		-0.3988		-0.3970		0.0014		0.0014		0.0014	
	(0.1778)		(0.2319)		(0.2371)		(0.2951)		(0.2832)		(0.2989)	
CDS (t-1)	0.1109	*	0.1402		0.1381				0.0000		-0.0000	
	(0.0734)		(0.1203)		(0.1193)				(0.9445)		(0.9090)	
S&P 500(t-1)			-20.8944		-20.5288		-0.1350	***	-0.0920		-0.0855	
			(0.4152)		(0.4174)		(0.0016)		(0.3383)		(0.3610)	
CBOE VIX(t-1)			-0.2518	*	-0.2482	*			0.0005		0.0005	
			(0.0929)		(0.0986)				(0.4573)		(0.4266)	
5yr swap rate(t-1)			0.5612						0.0130	*		
			(0.8203)						(0.0768)			
Term spread(t-1)			0.3864						0.0025			
			(0.8813)						(0.8039)			
ADS Index(t-1)					-0.9975						-0.0378	*
					(0.8085)						(0.0799)	
EPU Index(t-1)					0.0026						-0.0000	
					(0.2131)						(0.2323)	
Adj. R^2	1.37		1.65		1.78		2.48		2.74		3.02	
Obs.	1,773		1,772		1,772		1,772		1,772		1,772	

(Continued)

Table 3.10 (Continued): *ALL-SVI* and *FIN-SVI* Google index vs. FEARS index

	Panel B: *FIN-SVI* Google index					
	CDS premium changes			S&P 500 Index return		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Intercept	0.0485	0.0536	0.0541	0.0002	0.0002	0.0002
	(0.6110)	(0.5724)	(0.5735)	(0.4810)	(0.4706)	(0.4810)
FIN-SVI (t-1)	-0.8561 *	-0.7277	-0.7489	0.0028	0.0025	0.0025
	(0.0836)	(0.1583)	(0.1474)	(0.1207)	(0.1669)	(0.1698)
FEARS (t-1)	-0.4072	-0.3608	-0.3618	0.0013	0.0014	0.0014
	(0.2361)	(0.2827)	(0.2816)	(0.3257)	(0.3006)	(0.3179)
CDS (t-1)	0.1080 *	0.1376	0.1352		0.0000	-0.0000
	(0.0791)	(0.1265)	(0.1264)		(0.9167)	(0.9383)
S&P 500(t-1)		-21.4213	-21.0581	-0.1370 ***	-0.0897	-0.0833
		(0.3987)	(0.4011)	(0.0014)	(0.3500)	(0.3731)
CBOE VIX(t-1)		-0.2552 *	-0.2520 *		0.0005	0.0005
		(0.0859)	(0.0911)		(0.4435)	(0.4133)
5yr swap rate(t-1)		0.6217			0.0128 *	
		(0.8006)			(0.0810)	
Term spread(t-1)		0.3218			0.0027	
		(0.9005)			(0.7862)	
ADS Index(t-1)			-0.9987			-0.0378 *
			(0.8080)			(0.0798)
EPU Index(t-1)			0.0025			-0.0000
			(0.2393)			(0.2638)
Adj. R^2	1.25	1.54	1.65	2.31	2.56	2.84
Obs.	1,773	1,772	1,772	1,772	1,772	1,772

(Continued)

Table 3.10 (Continued): *ALL-SVI* and *FIN-SVI* Google index vs. FEARS index

Notes: The table reports the results of the regression of CDS premium changes and S&P 500 Index returns on lagged CDS premium changes (CDS), the lagged Google indices (*ALL-SVI* and *FIN-SVI*), the lagged FEARS index (FEARS) introduced by Da et al. (2015), and lagged control variables. The Google indices are described in the main text in Section 3.2.2. Panel A reports the results for the Google index based on all positive and negative connoted terms (*ALL-SVI*). Panel B reports the results for the Google index based on all positive and negative connoted economic terms (*FIN-SVI*). In each panel, Column 2 to Column 4 show results for the regressions with CDS premium changes as dependent variable and Column 5 to Column 7 show results for the regressions with S&P 500 Index returns as dependent variable. For Model 1 is the basic model, separately regressing CDS premium changes or S&P 500 Index returns on the lagged Google indices, the lagged FEARS index, and the lagged dependent variable. For Model 2, the additional lagged control variables are the S&P 500 Index return (S&P 500) or CDS premium changes (CDS), the change in the CBOE VIX (CBOE VIX), the change in the 5-year swap rate (5yr swap rate), and the change in the term spread (Term spread). For Model 3, the additional lagged control variables are the S&P 500 Index return (S&P 500) or CDS premium changes (CDS), the change in the CBOE VIX (CBOE VIX), the change in the Aruoba-Diebold-Scotti Business Conditions Index (ADS Index), and the change in the Economic Policy Uncertainty Index (EPU Index). P-values are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Significance is determined using Newey-West standard errors. Adjusted R^2 are in percentage points.

3.5.3. Modifications of the Google index construction

Finally, we analyze the robustness of our index construction. We vary the number of index constituents to be 25 or 35. Additionally, we base the construction of both Google indices on the respective set of negative connoted terms. Given the variations of Google indices, we replicate Table 3.4 and report the results in Table 3.11.

Table 3.11: In-sample predictive power of Google index modifications

	Model 1		Model 2		Model 3	
Panel A: *ALL-SVI* Google index based on 25 index constituents						
ALL-SVI (t-1)	-0.7596	**	-0.6544		-0.6895	*
	(0.0494)		(0.1060)		(0.0861)	
Panel B: *ALL-SVI* Google index based on 35 index constituents						
ALL-SVI (t-1)	-0.9444	**	-0.8246	*	-0.8507	*
	(0.0268)		(0.0608)		(0.0513)	
Panel C: *FIN-SVI* Google index based on 25 index constituents						
FIN-SVI (t-1)	-0.7025	**	-0.6147	*	-0.6160	*
	(0.0276)		(0.0560)		(0.0545)	
Panel D: *FIN-SVI* Google index based on 35 index constituents						
FIN-SVI (t-1)	-0.7320	**	-0.6293	*	-0.6255	*
	(0.0342)		(0.0705)		(0.0699)	
Panel E: Google index based on all negative connoted terms						
SVI (t-1)	-0.4000		-0.2829		-0.2782	
	(0.3262)		(0.5060)		(0.5089)	
Panel F: Google index based on all negative connoted economic terms						
SVI (t-1)	-0.6040	**	-0.5268	*	-0.5534	*
	(0.0291)		(0.0620)		(0.0501)	

Notes: The table reports the results of the regression of CDS premium changes on lagged CDS premium changes (CDS), lagged Google indices, and lagged control variables. The Google indices *ALL-SVI* and *FIN-SVI* are described in the main text in Section 3.2.2. This table replicates the analysis reported in Table 3.4 and varies the construction of both Google indices. Panel A reports the results for the *ALL-SVI* Google index based on 25 index constituents. Panel B reports the results for the *ALL-SVI* Google index based on 35 index constituents. Panel C reports the results for the *FIN-SVI* Google index based on 25 index constituents. Panel D reports the results for the *FIN-SVI* Google index based on 35 index constituents. Panel E reports the results for a Google index based on all negative connoted terms. Panel F reports the results for a Google index based on all negative connoted economic terms. Model 1 is the basic model, regressing CDS premium changes on the lagged Google indices and lagged CDS premium changes. For Model 2, the additional lagged control variables are the S&P 500 Index return (S&P 500), the change in the CBOE VIX (CBOE VIX), the change in the 5-year swap rate (5yr swap rate), and the change in the term spread (Term spread). For Model 3, the additional lagged control variables are the S&P 500 Index return (S&P 500), the change in the CBOE VIX (CBOE VIX), the change in the Aruoba-Diebold-Scotti Business Conditions Index (ADS Index), and the change in the Economic Policy Uncertainty Index (EPU Index). For brevity, we only report the coefficients and p-values of the respective Google indices. P-values are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Significance is determined using Newey-West standard errors. Adjusted R^2 are in percentage points.

Panel A to Panel D of Table 3.11 show that our results hold when varying the number of index constituents. Panel E and Panel F of Table 3.11 document that the Google index based on all negative connoted terms has no predictive power while our results hold when we base the index construction on negative connoted economic terms.

3.6. Conclusion

In this paper we use daily aggregated volume of Google search queries to measure consumers' sentiment based on the correlation of aggregated Google search volume with CDS premium changes. We compute two Google indices that have in-sample predictive power for CDS premium changes. Given this finding, we incorporate our Google indices in several out-of-sample forecasting models for CDS premium changes. The Google indices are most powerful when forecasts are more demanding.

Our results are highly relevant for researchers and practitioners. We add to the literature analyzing the fundamental value of Google search volume. In contrast to other studies, our analyses base on the CDS market. The forecast results underline the informational efficiency of the CDS market and that our Google indices provide no new fundamental information for the CDS market. Nevertheless, our findings also show that Google search volume contains fundamental value for the CDS market. Considering the vast number of possible search queries, our results also reveal that focusing on a relatively small number of economic terms keeps the data collection process manageable and provides the highest fundamental value.

3.A. Google Trends data processing

In Section 3.2 we shortly describe our Google search volume data. In this appendix we describe the data processing of Google Trends data in detail.

Google does not allow to download daily time series for periods longer than 3 months. For longer periods, Google Trends provides weekly time series. However, the respective time series do not provide the search volume for specific terms in absolute values, but are scaled by the maximum search volume within a pre-defined period to a range of 0 to 100. Thus, if daily search volume for longer periods than 3 months is required, one cannot simply append quarterly search volume.

In this paper, we use Google search volume from January 1, 2004 to December 27, 2013. To compute daily time series of each term for this period, we follow Risteski and Davcev (2014) and Johansson (2016). For each term, we download one time series of weekly search volume covering our full sample period and, if available, 40 quarterly subsets of our sample period with daily time series. To be able to compute log differences, we add one to each search volume time series. Finally, we combine all quarterly time series. To do so, we use the weekly time series of each term as reference values and adjust the respective daily time series based on these values. Therefore, we compute an adjustment factor as the ratio of search volume for a specific day to the search volume of the day's week. The daily values within this week are then adjusted by the week's average daily adjustment factor. Following this procedure we make the daily time series comparable across different quarters.

Chapter 4‡

Commonality in Liquidity in the US Corporate Bond Market

2.1. Introduction

Commonality in liquidity, the comovement of individual assets' liquidity with market liquidity, has been widely studied for stock, sovereign bond, and derivative markets (e.g., Chordia et al., 2000; Chordia et al., 2005; Cao and Wei, 2010; Karolyi et al., 2012). However, less attention has been paid to the US corporate bond market, although its outstanding volume amounted to more than 8 trillion USD in 2015 which was more than 30% of the US stock market capitalization.[42] This is even more surprising as for all US corporate bonds liquidity significantly dropped during the financial crisis in 2008 (e.g., Friewald et al., 2012; Dick-Nielsen et al., 2012). This suggests that the liquidity of individual corporate bonds depends on the overall market liquidity leading to commonality in liquidity. If commonality in liquidity exists, it influences investors' opportunities to benefit from diversification. Thus, knowing the determinants of individual bonds' comovement with market liquidity is highly relevant. This paper contributes to the literature by documenting the existence and analyzing the determinants of commonality in liquidity among US corporate bonds.

The analyses base on a TRACE (Trade Reporting and Compliance Engine) sample of US corporate bond transaction data from July 2002 to December 2012. Using a factor model that

‡ This chapter is based on Bethke (2016).

[42] See Securities Industry and Financial Markets Association (SIFMA) (2016) and World Bank (2016).

relates bonds' individual liquidity to market liquidity (Chordia et al., 2000), I document that commonality in liquidity exists among US corporate bonds.

This finding raises the question of what determines the degree of individual bonds' comovement with market liquidity. The theoretical literature suggests comovement in liquidity supply and demand to determine the degree of commonality in liquidity. Regarding liquidity supply, higher inventory risk (e.g., Kyle and Xiong, 2001; Gromb and Vayanos, 2002), tighter risk management (Gârleanu and Pedersen, 2007), or lower funding liquidity (Brunnermeier and Pedersen, 2009) of liquidity suppliers may induce higher commonality in liquidity. Correlated demand for liquidity may arise through investors' correlated selling activities arising through initial losses that raise the fear of even larger future losses (e.g., Bernardo and Welch, 2004; Morris and Shin, 2004), increased demand for more liquid assets (Vayanos, 2004), or preference for cheap information resulting in a common subset of information that is used to price different assets (Veldkamp, 2006). Empirically, it is found for stocks that supply- and demand-side effects both drive commonality in liquidity (e.g., Coughenour and Saad, 2004; Hameed et al., 2010; Karolyi et al., 2012; Koch et al., 2016).

For corporate bonds, obvious observable characteristics for which liquidity supply and demand differ are a bond's credit rating bucket (e.g., Edwards et al., 2007; Kisgen and Strahan, 2010; Friewald et al., 2012), time to maturity (Gehde-Trapp et al., 2016), amount outstanding (e.g., Edwards et al., 2007; Wang and Wu, 2015), and industry (e.g., Longstaff et al., 2005; Dick-Nielsen et al., 2012). These are basic and important characteristics for investors' investment and issuers' financing decisions (e.g., Hale and Santos, 2008; Gopalan et al., 2014). If comovement in liquidity supply and demand influences commonality in liquidity, I expect to find differences in the degree of commonality across these broad dimensions. For instance, high yield bonds should be exposed to high inventory risk and asymmetric information which should increase their dependence on market liquidity relative to investment grade bonds. However, dealers' supply of liquidity is more focused on investment grade bonds (Bessembinder et al., 2016) and institutional investors are often obliged to only invest into investment grade bonds (Kisgen and Strahan, 2010). Accordingly, liquidity suppliers and demanders of investment grade bonds are exposed to similar shocks which should overall translate into a higher dependence of investment grade bonds on market liquidity. To test the existence of differences in commonality in liquidity among the four characteristics, I repeat my initial analysis for different sample subsets. The results show that the degree of commonality in liquidity is higher for bonds with an investment grade rating, with longer time to maturity, with higher amount outstanding, and issued by financial firms.

However, the previous results do not reveal whether the analyzed characteristics proxy for the same or separate effects. For instance, investment grade bonds have, on average, a high amount outstanding (Wang and Wu, 2015). Thus, I dig deeper into the analysis of the cross-sectional determinants of individual bonds' comovement with market liquidity by running panel regressions. Motivated by the previous findings, I consider these bond characteristics (i.e., a bond's credit rating bucket, time to maturity, amount outstanding, and industry) as explanatory variables. Additionally, I add proxies for inventory risk (e.g., Stoll, 1978; Friewald and Nagler, 2016), dealer and customer trading activity (e.g., Ho and Stoll, 1980; Chordia et al., 2011), firm-specific profitability, riskiness, and information uncertainty (e.g., Zhang, 2006; Lu et al., 2010; Danis et al., 2014), as well as industry concentration and industry riskiness (Piotroski and Roulstone, 2004). All variables are potentially related to supply and demand of liquidity for corporate bonds. In summary, I find strong support for supply- and demand-side effects both determining individual bonds' comovement with market liquidity.

So far, the results base on the assumption that market liquidity is the only source of commonality in liquidity. However, determinants that are common to several bonds themselves may be sources of commonality in liquidity. For instance, the well-known flight-to-quality effect results in correlated demand for bonds in higher-quality credit rating buckets (Dick-Nielsen et al., 2012) suggesting rating bucket liquidity to be a source of comovement in liquidity itself. Thus, market liquidity may only be one out of several sources of corporate bonds' liquidity comovement. Again, I focus on the four basic bond characteristics to analyze the existence and importance of further sources of commonality in liquidity. I separately add credit rating bucket, time to maturity, amount outstanding, and industry liquidity to the baseline factor model that relates bonds' individual liquidity to market liquidity (Chordia et al., 2000). Thereby, I find all four sources to be significantly related to individual bond liquidity, but market liquidity to remain the most important source of commonality in liquidity.

The previous findings document a high cross-sectional variation in commonality in liquidity for corporate bonds. In addition, it is highly relevant to understand the time-series dynamics of commonality in liquidity. For instance, the Brunnermeier and Pedersen (2009) model implies that evaporating dealers' funding liquidity increases the commonality in liquidity for all bonds. Thus, I further analyze the determinants of the time-series variation in market-wide commonality in liquidity. Based on the empirical findings for stocks (e.g., Hameed et al., 2010, Rösch and Kaserer, 2013) and the high dependence on dealers' market making activities due to the over-the-counter (OTC) market structure of the corporate bond market, I expect market-wide commonality in liquidity to be higher in times of financial stress and funding liquidity to be a major determinant. The results show that market-wide commonality in liquidity varies heavily over time and peaks in months with more financial stress events. As for the cross-sectional results, I find that supply- and demand-side effects both determine market-wide commonality in liquidity. In contrast to the cross-sectional findings, the time-series results provide evidence on supply-side effects being more important. Commonality In liquidity is high, when funding liquidity is scarce. This relation is especially pronounced since the financial crisis in 2008.

Having established the main results, I run tests to determine the robustness of the main findings. First, I show that the cross-sectional findings do not depend on how I measure commonality in liquidity, how I construct the underlying bond sample, or on whether I consider a bond or firm sample. Second, time-series results remain robust when using alternative funding liquidity or market liquidity proxies, or when varying the method to measure commonality in liquidity.

This paper is related to several strands of the literature. First, it contributes to the literature documenting commonality in liquidity for US stocks (e.g., Chordia et al., 2000; Hasbrouck and Seppi, 2001; Huberman and Halka, 2001; Pastor and Stambaugh, 2003), for international stock markets (e.g., Galariotis and Giouvris, 2007; Kempf and Mayston, 2008; Karolyi et al., 2012; Rösch and Kaserer, 2013; Dang et al., 2015b), for derivative markets (e.g., Marshall et al., 2013; Frino et al., 2014), across international markets (e.g., Brockman et al., 2009; Syamala et al., 2014; Dang et al., 2015a), across US stocks and Treasury bonds (Chordia et al., 2005), and across US corporate bonds and credit default swaps (Pu, 2009). The paper adds to this literature by documenting the existence of commonality in liquidity among US corporate bonds.

Second, the paper is related to the literature that analyzes the economic mechanisms behind commonality in liquidity. Theoretical models link comovement in liquidity to liquidity supply effects (e.g., Kyle and Xiong, 2001; Gromb and Vayanos, 2002; Gârleanu and Pedersen, 2007; Brunnermeier and Pedersen, 2009; Cespa and Foucault, 2014) or liquidity demand effects (e.g., Bernardo and Welch, 2004; Morris and Shin, 2004; Vayanos, 2004;

Veldkamp, 2006). Empirically, Coughenour and Saad (2004), Comerton-Forde et al. (2010), Hameed et al. (2010), and Rösch and Kaserer (2013) present evidence for supply-side effects; Kamara et al. (2008), Koch et al. (2016), and Karolyi et al. (2012) find demand-side effects driving commonality in liquidity; and Domowitz et al. (2005) and Corwin and Lipson (2011) document that both effects determine commonality in liquidity. The paper adds to this literature by showing cross-sectional evidence for supply- and demand-side effects driving commonality in liquidity. Regarding the time-series determinants, the paper provides evidence for supply-side effects being more important in driving market-wide commonality in liquidity, especially in times of financial stress.

Third, the paper contributes to the literature analyzing corporate bond liquidity. For instance, Bao et al. (2011); Friewald et al. (2012); Dick-Nielsen et al. (2012), and Acharya et al. (2013) find corporate bond liquidity to vary in the cross-section and over time. The paper adds to this by showing cross-sectional determinants of individual bonds' liquidity dependence on market liquidity.

Finally, the paper's results extend the literature analyzing contagion within stock markets (e.g., Lang and Stulz, 1992; Hertzel et al., 2008; Boone and Ivanov, 2012; Helwege and Zhang, 2016), within the US corporate bond market (Theocharides, 2007), within derivative markets (e.g., Jorion and Zhang, 2007; Jorion and Zhang, 2009), and across different markets (e.g., Bekaert et al., 2005; Baur and Lucey, 2009; Longstaff, 2010; Chan et al., 2011; Claeys and Vašíček, 2014). I add to this literature as our results reveal that market liquidity is a potential contagion channel for corporate bonds.

The remainder of the paper is organized as follows. In Section 4.2, I describe my corporate bond sample and the used liquidity measures. The existence and cross-sectional determinants of corporate bonds' comovement with market liquidity as well as the existence of other sources of commonality in liquidity are tested in Section 4.3. In Section 4.4, I investigate the time-series variation of market-wide commonality in liquidity. Various robustness tests regarding the cross-sectional and time-series analyses provides Section 4.5 and Section 4.6 concludes.

4.2. Bond sample and liquidity measures

The paper uses US bond transaction data (i.e., actual trade price, yield resulting from this price, trade size, trade time, and trade date) from TRACE (Trade Reporting and Compliance Engine). The sample period lasts from July 1, 2002 until December 31, 2012. I filter out erroneous trades with the median and reversal filter introduced by Edwards et al. (2007) and the algorithm described in Dick-Nielsen (2009). The sample only consists of plain vanilla bonds with fixed coupons. I obtain bond characteristics such as S&P ratings, coupons, and maturity dates from Thomson Reuters Datastream and exclude bonds without S&P rating and initial time to maturity of more than 30 years. Defaulted bonds are only included up to three months before the default date to eliminate an impact of abnormal trading behavior around and after the default event (Jankowitsch et al., 2014). I further exclude federal holidays as only sparse trading occurs on these days.

I obtain accounting data from Compustat, historical stock and industry information from the Center for Research in Security Prices (CRSP), and US Treasury yields, swap rates, and market data from Thomson Reuters Datastream. The final sample consists of 3,177 corporate bonds of 736 firms.

Using the bond transaction data from TRACE, I compute seven daily liquidity measures for each bond: number of trades (Trades), trading volume (Volume), turnover (Turnover), realized depth (Depth), Amihud measure (Amihud), Roll measure (Roll), and the inter-quartile range (IQR). All measures are found to be related to liquidity (e.g., Han and Zhou, 2007; Bao et al., 2011; Friewald et al., 2012; Dick-Nielsen et al., 2012). In the appendix I provide a more detailed description of the computation of these measures. Table 4.1 presents summary statistics for the firms and bonds in the sample as well as for the liquidity measures.

Panel A of Table 4.1 shows summary statistics of firm characteristics. On average, a firm in the sample has a size of 32.06 bn USD, a leverage ratio of 28%, and exists for 32 years. Firm performance in terms of return on assets (ROA) is 12%. The outstanding and actively traded corporate bonds of the firms in the sample have, on average, 5 years to maturity and a rating of almost 9 (=BBB).

Panel B of Table 4.1 shows summary statistics of bond characteristics. The mean outstanding volume is 0.49 bn USD, the mean coupon rate is 6.53%, the mean maturity roughly equals 5 years, and the mean S&P rating equals 8 (=BBB+).

Panel C of Table 4.1 presents bond pricing variables. The average yield is 4.97%. I compute yield spreads as the difference between the yield and the maturity-matched US Treasury yields or maturity-matched US swap rates.[43] The average yield spreads based on US

[43] More specifically, on each trading day I collect constant maturity US Treasury yields from Thomson Reuters Datastream of maturities between one month and 30 years. Afterwards, I fit a cubic function with maturity as the independent variable to the observed yields, and use the interpolated yield as a proxy for the maturity-

Table 4.1: Summary statistics of the bond sample

Variable	Mean	Std. dev.	5th percentile	median	95th percentile
Panel A: Firm characteristics					
Firm size (bn USD)	32.06	50.05	1.62	11.36	165.68
Leverage ratio	0.28	0.14	0.06	0.27	0.52
Return on assets	0.12	0.07	0.02	0.11	0.23
Firm age (yrs)	31.98	22.73	5.76	26.50	80.42
Average time to maturity (yrs)	4.86	3.41	1.45	4.03	11.93
Average rating	8.89	2.99	4.67	8.87	14.59
Panel B: Bond characteristics					
Amount issued (bn USD)	0.49	0.55	0.10	0.30	1.50
Coupon (%)	6.53	1.68	3.63	6.65	9.13
Time to maturity (yrs)	4.98	5.47	0.90	3.11	19.07
Rating	8.00	3.13	3.51	7.83	14.20
Panel C: Bond pricing variables					
Yield (%)	4.97	3.13	2.04	4.47	9.28
Yield spread (Treasury, %)	2.32	2.95	0.51	1.51	6.42
Yield spread (Swap, %)	1.98	2.94	0.19	1.15	6.09
Panel D: Bond liquidity measures					
Trades	4.61	5.24	1.64	2.76	13.54
Volume (m USD)	2.96	3.44	0.32	2.06	8.35
Turnover (%)	1.10	6.67	0.19	0.55	2.41
Depth (m USD)	1.17	1.27	0.13	0.85	3.39
Amihud (bp per m USD)	77.98	74.38	9.13	56.40	220.06
Roll (bp)	136.44	93.29	24.61	114.15	331.95
Inter quartile range (bp)	0.40	0.36	0.06	0.29	1.09

Notes: The table reports characteristics of the corporate bond sample. The dataset consists of 3,177 US corporate bonds of 736 firms traded over the period July 2002 to December 2012. The table reports the mean, standard deviation, 5th percentile, median, and 95th percentile for firm and bond characteristics. The statistics are first averaged across time for each individual firm or bond. Panel A shows firm characteristics: Firm size is the book value of assets (at) in billion USD. Leverage ratio is the sum of long term debt and debt in current liabilities (dltt and dlc) relative to the book value of assets. Return on assets is the ratio of earnings before interest, taxes, depreciation and amortization (ebitda) to the book value of assets. Firm age is proxied by the first trade date of a firm in CRSP. Average time to maturity is the average time to maturity in years of a firm's actively traded bonds in the sample. Average rating is the average rating of a firm's actively traded bonds in the sample. Panel B shows bond characteristics: Amount issued is the outstanding volume per traded bond in billion USD. Coupon is the per annum coupon rate in percentage points. Time to maturity is the time to maturity per traded bond in years.

(Continued)

matched risk-free rate at this date. For swaps, on each trading day I collect US swap rates from Thomson Reuters Datastream of maturities between one week and 30 years. I then fit a cubic function with maturity as the independent variable to the observed yields, and use the interpolated yield as a proxy for the maturity-matched risk-free rate at this date.

Table 4.1 (Continued): Summary statistics of the bond sample

Rating is the S&P rating expressed as a number (AAA=1, ... , C=21). Panel C shows bond pricing variables: Yield is the yield to maturity in percentage points. Yield Spread is computed relative to the US Treasury yield curve (Treasury) and swap curve (Swap) in percentage points. Panel D shows bond liquidity measures: Trades is daily number of trades. Volume is the daily trading volume. Turnover is daily trading volume relative to outstanding volume in percentage points. Depth is the daily realized depth of a bond computed as its mean of daily buy and sell volume. Amihud is the Amihud measure in basis points per million USD. Roll is the roll measure in basis points. Inter quartile range is the inter quartile range in basis points. The liquidity measures (Amihud, Roll, inter quartile range) are computed as described in the main text in the Appendix.

Treasury yields and US swap rates are 2.32% and 1.98%, respectively. Overall, firm and bond characteristics as well as pricing variables are comparable to the literature (e.g., Friewald et al., 2012; Colla et al., 2013).

Panel D of Table 4.1 presents summary statistics for the liquidity measures. The average bond trades four to five times a day, with a trading volume of 2.96 m USD, a realized depth of 1.17 m USD, and a turnover of 1.10%. Considering relative (effective) bid-ask spread measures, the average Roll measure is 136.44 bp and the average IQR measure is 0.40 bp. Finally, the average price impact measured by the average Amihud measure is 77.98 bp per m USD. Overall, the summary statistics of the liquidity measures are comparable to the literature (e.g., Friewald et al., 2012; Dick-Nielsen et al., 2012; Schestag et al., 2016).

4.3. Commonality in liquidity and cross-sectional determinants

Commonality in liquidity is basically defined as the comovement of individual assets' liquidity with market liquidity (Chordia et al., 2000). In this section, I analyze the existence and determinants of commonality in liquidity among US corporate bonds. Specifically, I describe the approach used to compute commonality in liquidity and present empirical evidence on its existence in Section 4.3.1. I then analyze the determinants of commonality in liquidity in Section 4.3.2. Finally, I test for the existence of additional sources of comovement in liquidity while controlling for market liquidity in Section 4.3.3.

4.3.1. Existence of commonality in liquidity

I first test whether commonality in liquidity exists in the corporate bond market. The extensive empirical evidence on the existence of commonality in liquidity for different markets (e.g., Hasbrouck and Seppi, 2001; Chordia et al., 2005; Kempf and Mayston, 2008; Cao and Wei, 2010; Karolyi et al., 2012) and studies documenting the time-series variation and varying importance of corporate bond liquidity (e.g., Bao et al., 2011; Friewald et al., 2012; Dick-Nielsen et al., 2012) imply the existence of a common driver of corporate bond liquidity. Thus, I expect commonality in liquidity to exist also among US corporate bonds.

First, I adjust the liquidity measures for day-of-the-week and monthly effects in liquidity (e.g., Chordia et al., 2005; Nippani and Arize, 2008; Dbouk et al., 2013). To do so, I follow Hameed et al. (2010) and Karolyi et al. (2012) and run yearly bond-specific regressions for the natural logarithm of liquidity measures

$$\ln\left(Liquidity_t\right) = \beta \cdot \ln\left(Liquidity_{t-1}\right) + \sum_{d=1}^{5} \gamma \cdot Weekday_d + \sum_{m=2}^{12} \gamma \cdot Month_m + \varepsilon_{Liq,t}, \tag{4.1}$$

where $Liquidity_t$ are the different liquidity measures introduced in Section 4.2, $Weekday_d$ are day-of-the-week dummies, and $Month_m$ are month-dummies.[44] In the following I use the residuals $\varepsilon_{Liq,t}$ of these regressions. They can be interpreted as percentage innovations in the liquidity measures because I control for the respective lagged dependent variable in Equation (4.1). Analyzing liquidity innovations is sensible because commonality in liquidity describes common variation in liquidity over time.[45]

Second, I follow Chordia et al. (2000) to measure commonality in liquidity and use a factor model that relates individual bond liquidity to concurrent market liquidity. Specifically, the following yearly bond-specific time-series regression of liquidity innovations on market liquidity innovations of the respective liquidity measures determines the bond-specific degree of commonality in liquidity

$$\varepsilon_{Liq,t} = \alpha + \beta_{Liq}^{Mkt} \cdot \varepsilon_{Liq,t}^{Mkt} + \Gamma \cdot Controls_t + \varepsilon_t, \tag{4.2}$$

where $\varepsilon_{Liq,t}$ are the respective residuals from Equation (4.1), $\varepsilon_{Liq,t}^{Mkt}$ is the respective market average of $\varepsilon_{Liq,t}$ for all bonds excluding the dependent variable bond, and $Controls_t$ is a vector of further control variables. These are the one trading day leading and lagging values of $\varepsilon_{Liq,t}^{Mkt}$, the concurrent, one trading day leading and lagging market return, and the concurrent

[44] As in Karolyi et al. (2012), I add one to the Amihud measure and then take the natural logarithm to reduce the impact of outliers.

[45] I run yearly regressions because my general approach to analyze commonality in liquidity is based on yearly time-series regressions. The results also hold when adjusting the full time series of each bond. Therefore I add yearly dummies to the regression in Equation (4.1). Panel C and Panel D of Table 4.11 in the robustness section, Section 4.5, present the results.

percentage change in the dependent variable bond's squared return.[46] In line with the literature (e.g., Chordia et al., 2000; Karolyi et al., 2012; Rösch and Kaserer, 2013), adding leading and lagging values of market liquidity innovations controls for temporal differences in commonality in liquidity, market returns control for general market conditions, and the bond's squared return controls for changes in the riskiness of a bond.

Table 4.2: Commonality in liquidity among US corporate bonds

	Trades	Volume	Turnover	Depth	Amihud	Roll	IQR
Concurrent	1.0345 ***	0.9662 ***	0.9655 ***	0.8542 ***	0.7375 ***	0.9599 ***	1.3653 ***
	(41.19)	(34.36)	(34.33)	(25.42)	(11.87)	(30.97)	(20.83)
%positive	75.35	73.58	73.59	70.10	58.59	68.15	68.02
% + significant	21.13	15.51	15.50	14.20	7.86	14.52	13.20
Lag	0.0466 *	0.0627 **	0.0635 **	0.0878 ***	0.0690 *	0.0961 ***	0.2666 ***
	(1.96)	(2.37)	(2.40)	(2.79)	(1.90)	(3.31)	(4.23)
%positive	51.19	51.94	51.85	52.01	51.82	51.56	55.54
% + significant	3.34	3.02	2.99	3.41	4.31	3.62	4.59
Lead	0.0377	0.0477 *	0.0478 *	0.0393	0.0956 ***	0.0580 **	0.2453 ***
	(1.56)	(1.80)	(1.80)	(1.20)	(2.62)	(2.00)	(4.10)
%positive	51.32	52.33	52.33	51.63	50.04	51.27	54.40
% + significant	3.29	2.81	2.79	3.10	4.18	3.12	3.89
Sum	1.1189 ***	1.0766 ***	1.0768 ***	0.9814 ***	0.9021 ***	1.1139 ***	1.8773 ***
	(33.10)	(27.57)	(27.57)	(19.91)	(11.69)	(24.03)	(20.02)
Adj. R^2	1.90	1.59	1.58	1.04	2.62	1.22	1.95
N	8962	8962	8962	8962	8962	8582	4728

Notes: The table reports the results of time-series regressions that relate daily individual bond liquidity innovations to the respective market liquidity innovations for all bonds in the sample. In each individual regression, the market liquidity innovations are the averages of the respective liquidity measure for all bonds excluding the dependent variable bond. Column 1 to 7 provide the results for the different liquidity measures. Trades is daily number of trades. Volume is the daily trading volume. Depth is the daily realized depth of each bond computed as the mean of daily buy and sell volume. Turnover is daily trading volume as a percentage of outstanding volume. Amihud is the Amihud measure. Roll is the roll measure. IQR is the inter quartile range. The liquidity measures (Amihud, Roll, inter quartile range) are computed as described in the Appendix.
Cross-sectional averages of time-series slope coefficients are reported with t-statistics in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Concurrent, Lag, and Lead refer, respectively, to the same, previous, and next trading day observations of market liquidity innovations. "% positive" reports the percentage of positive slope coefficients, while "% + significant" gives the percentage of positive slope coefficients with p-values smaller than 5%.

(Continued)

[46] Following Chordia et al. (2000) who analyze one year of stock data, I use their approach to run yearly time-series regressions and exclude bonds with less than 20 trading days to reduce the influence of rarely traded bonds.

Table 4.2 (Continued): Commonality in liquidity among US corporate bonds

Sum is the average of the sum of the Concurrent, Lag, and Lead coefficients. Adj. R^2 mean are the cross-sectional averages of adjusted R^2 statistics in percentage points.
The concurrent, lagging, and leading values of the market return, and the proportional daily change in dependent variable bond's squared return (a measure of change in return volatility) are additional regressors; coefficients not reported.

Table 4.2 shows cross-sectional averages of concurrent coefficients β_{Liq}^{Mkt} (Concurrent) from these yearly bond-specific time-series regressions. Additionally, Table 4.2 shows the cross-sectional averages of the leading (Lead) and lagging (Lag) coefficients of market liquidity innovations, the average sum of all three coefficients, and the average adjusted R^2 statistics.

Table 4.2 provides strong support for the existence of commonality in liquidity. The concurrent coefficients β_{Liq}^{Mkt} for all liquidity measures are positive and significant at the 1% level. More precisely, the average concurrent coefficient ranges from 0.74 for the Amihud measure to 1.37 for the IQR measure.[47] For all liquidity measures a high fraction of coefficients is positive, ranging from 59% to 75%. Considering the percentage of positive and significant coefficients, the percentage ranges from 8% (for the Amihud measure) to 21% (for commonality in the number of trades). Comparing these percentages to the results for stock markets, they are slightly lower but in the range of Chordia et al. (2000) and lower compared to the results of Kamara et al. (2008). The latter may reflect the difference in the market structures (opaque OTC vs. transparent centralized market structure) or indicate that bond-specific liquidity is less related to systematic movements in market liquidity compared to stocks.

In line with other studies analyzing commonality in liquidity (e.g., Chordia et al., 2000; Kempf and Mayston, 2008), the average adjusted R^2 statistics are very low and range from 1.04% to 2.62%. This indicates that also for bonds a substantial part of bond-specific liquidity is not related to systematic movements in market liquidity, overall market conditions, and

[47] Considering the IQR measure, coefficients reflect only the most often traded bonds in the sample as this measure is based on bonds' trading days with at least three trades per bond.

bond-specific riskiness and/or bond-specific liquidity is substantially driven by noise (e.g., Chordia et al., 2000; Huberman and Halka, 2001).[48,49]

4.3.2. Cross-sectional determinants of commonality in liquidity

Having documented the existence of commonality in liquidity, it is essential to analyze its determinants. Commonality in liquidity can arise through comovement in liquidity supply or comovement in liquidity demand. Comovement in liquidity supply may theoretically be explained by systematic variation in inventory risk, asymmetric information, or funding liquidity (e.g., Kyle and Xiong (2001); Gromb and Vayanos (2002); Gârleanu and Pedersen (2007); Brunnermeier and Pedersen (2009)). Comovement in liquidity demand may theoretically arise through investors' correlated trading activities (e.g., Bernardo and Welch (2004); Morris and Shin (2004); Vayanos (2004); Veldkamp (2006)). The potential mechanisms imply that bond, firm (=issuer), and industry characteristics are potential determinants of the degree of commonality in liquidity.

In Section 4.3.2.1 to 4.3.2.4, I first test for obvious observable bond characteristics (rating, time to maturity, amount outstanding, and industry) that are related to supply and demand of liquidity to be determinants of commonality in liquidity. The analyses focus on these obvious observable characteristics because these are basic characteristics considered by investors and issuers. Investors tend to acquire cheap and easily accessible information (e.g., Dong and Ni, 2014; Dong et al., 2016) as well as information that is common to several assets (e.g., Veldkamp, 2006; Peng and Xiong, 2006). For issuers these basic characteristics are important to consider in their financing decisions as they decisively influence issuers' type of funding and financing costs (e.g., Hale and Santos, 2008; Gopalan et al., 2014). In Section 4.3.2.5, a more detailed set of bond, firm, and industry characteristics is analyzed.

[48] Noise and the opaque TRACE information setting might be reasons as shown in the robustness section. Panel E of Table 4.11 presents commonality in liquidity results based on aggregated firm time series. Noise is reduced and the adjusted R^2 statistics increase to roughly 10%.

[49] Regarding the yearly bond-specific time-series regression approach, one might have the concern that the results are driven by single years. Unreported results (available upon request from the author) of yearly cross-sectional averages document substantial coefficient averages for all sample years. The coefficients are higher in years of financial stress as in Rösch and Kaserer (2013), but these results do not imply that the main results in Table 4.2 are driven by single years. To account for the time-series variation in these coefficients, I use year fixed effects in the panel analyses in Table 4.7.

4.3.2.1. Commonality in liquidity by credit rating bucket

Liquidity supply and demand differs across credit rating buckets. Edwards et al. (2007) and Jankowitsch et al. (2011) find transaction costs to increase with corporate bond ratings, i.e. bonds with lower credit quality face higher transaction costs which might indicate higher dependence of high yield bonds on market liquidity relative to investment grade bonds. However, Bessembinder et al. (2016) document higher dealer trading activity for investment grade bonds indicating a higher likelihood of supply-side comovement among these bonds. Kisgen and Strahan (2010) relate the segmentation of the corporate bond market to higher demand for investment grade bonds due to constrained investors such as insurance companies. This also indicates a higher likelihood of demand-side comovement among investment grade bonds. Since the overall trading activity is also more focused on investment grade bonds (Wang and Wu, 2015), I expect commonality in liquidity to differ between credit rating buckets and to be higher among investment grade bonds relative to high yield bonds.

To test for credit rating buckets being a determinant of commonality in liquidity, I replicate Table 4.2 for different credit rating buckets. As in Dick-Nielsen et al. (2012), I consider six credit rating buckets (all investment grade (IG) bonds, AAA-, AA-, A-, BBB-rated bonds, and all high yield (HY) bonds).

Table 4.3 presents results for different credit rating buckets. For brevity, it only reports results for the average concurrent coefficient, the average sum of concurrent, leading, and lagging coefficients, and the average adjusted R^2 statistics. Panel A and Panel B of Table 4.3 show the results for all investment grade (IG) bonds, i.e. bonds rated between AAA and BBB-, and high yield (HY) bonds, i.e. bonds rated below BBB-. Panel C to Panel F of Table 4.3 present the results for the specific investment grade credit rating buckets AAA to BBB. The concurrent coefficients indicate that commonality in liquidity is higher among investment grade bonds. The difference between all IG and HY bonds is positive for all liquidity measures and significant in four out of seven cases as shown in Panel G of Table 4.3. Within the investment grade segment, commonality in liquidity is, on average, lowest for AAA-rated bonds and highest among AA-rated bonds. This pattern also holds for the sum of concurrent, leading, and lagging coefficients.[50]

[50] Compared to Table 4.2, the results in Table 4.3 to 4.6 are slightly upward-biased because the influence of extreme values increases when considering smaller sample subsets.

Table 4.3: Commonality in liquidity by credit rating bucket

	Trades	Volume	Turnover	Depth	Amihud	Roll	IQR
				Panel A: IG bonds			
Concurrent	1.0544 ***	0.9805 ***	0.9798 ***	0.8807 ***	0.7667 ***	1.0312 ***	1.4537 ***
Sum	1.1281 ***	1.0706 ***	1.0712 ***	0.9782 ***	0.8822 ***	1.1904 ***	1.9153 ***
Adj. R^2	4.02	3.66	3.66	3.37	4.59	3.61	4.11
				Panel B: HY bonds			
Concurrent	0.9067 ***	0.8743 ***	0.8732 ***	0.6842 ***	0.5493 ***	0.4977 ***	0.7059 ***
Sum	1.0599 ***	1.1151 ***	1.1129 ***	1.0018 ***	1.0294 ***	0.6189 ***	1.5935 ***
Adj. R^2	3.76	3.77	3.77	3.43	4.23	3.53	4.07
				Panel C: AAA bonds			
Concurrent	0.8727 ***	0.6388 ***	0.6411 ***	0.5008 ***	0.2825	1.5762 ***	0.6729
Sum	1.1697 ***	0.6813 **	0.6786 **	0.1190	0.6778	1.2934 ***	1.1476 *
Adj. R^2	4.33	3.80	3.80	3.20	4.42	4.25	4.11
				Panel D: AA bonds			
Concurrent	1.1611 ***	1.1208 ***	1.1195 ***	0.9229 ***	0.5272 ***	1.2739 ***	1.4467 ***
Sum	1.4094 ***	1.2420 ***	1.2404 ***	1.1090 ***	0.5757 ***	1.3646 ***	1.9515 ***
Adj. R^2	4.07	3.24	3.24	2.93	4.24	3.68	3.98
				Panel E: A bonds			
Concurrent	1.0873 ***	0.9229 ***	0.9209 ***	0.8460 ***	0.8602 ***	1.0795 ***	1.6518 ***
Sum	1.2424 ***	1.0613 ***	1.0618 ***	0.9644 ***	1.0107 ***	1.2174 ***	2.1255 ***
Adj. R^2	3.96	3.47	3.46	3.27	4.33	3.47	4.15
				Panel F: BBB bonds			
Concurrent	0.9634 ***	1.0310 ***	1.0327 ***	0.9409 ***	0.7528 ***	0.8039 ***	1.0880 ***
Sum	0.8117 ***	1.0314 ***	1.0333 ***	0.9930 ***	0.8249 ***	1.0573 ***	1.4889 ***
Adj. R^2	4.08	4.15	4.15	3.73	5.17	3.77	4.10
				Panel G: Differences in slope coefficients of IG and HY bonds			
IG-HY	0.1478 *	0.1062	0.1066	0.1965 *	0.2174	0.5335 ***	0.7479 ***

Notes: The table reports the results of time-series regressions that relate daily individual bond liquidity innovations to the respective market liquidity innovations for all bonds in the sample by credit rating bucket. In each individual regression, the market liquidity innovations are the averages of the respective liquidity measure for all bonds excluding the dependent variable bond. Column 1 to 7 provide the results for the different liquidity measures. Trades is daily number of trades. Volume is the daily trading volume. Depth is the daily realized depth of each bond computed as the mean of daily buy and sell volume. Turnover is daily trading volume as a percentage of outstanding volume. Amihud is the Amihud measure. Roll is the roll measure. IQR is the inter quartile range. The liquidity measures (Amihud, Roll, inter quartile range) are computed as described in the Appendix.

The concurrent, lagging, and leading values of market liquidity innovations; concurrent, lagging, and leading values of the market return, and the proportional daily change in dependent variable bond's squared return (a measure of change in return volatility) are regressors. Cross-sectional averages of the concurrent time-series slope coefficients of market liquidity innovations and the average sum of the concurrent, lagging, and leading coefficients of market liquidity innovations are reported. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Adj. R^2 is the cross-sectional average of adjusted R^2 statistics in percentage points.

(Continued)

Table 4.3 (Continued): Commonality in liquidity by credit rating bucket

Panel A shows the respective statistics for all investment grade (IG) bonds, i.e. bonds having a rating between AAA and BBB-. Panel B shows the respective statistics for all high yield (HY) bonds, i.e. bonds having a rating below BBB-. Panel C shows the respective statistics for all AAA-rated bonds. Panel D shows the respective statistics for all AA-rated bonds. Panel E shows the respective statistics for all A-rated bonds. Panel F shows the respective statistics for all BBB-rated bonds. Panel G shows differences between concurrent slope coefficients from Panel A and B. Significance of differences is determined by using a Welch test. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Summing up, Table 4.3 documents differences in commonality in liquidity across credit rating buckets, consistent with the expected positive difference between IG and HY bonds. Overall, the results indicate that credit rating buckets determine the degree of commonality in liquidity.

4.3.2.2. Commonality in liquidity by time to maturity

Bonds' time to maturity may also lead to differences in commonality in liquidity. Gehde-Trapp et al. (2016) develop a model in which investors' weigh up two sources of liquidity for their portfolio allocation of bonds with different maturities: transaction costs and maturity waiting costs. If investors are hit by a shock, short-term bonds are not sold due to low waiting costs implying less active trading for short-term bonds. A clientele effect arising from investors with different trading needs indicates that long-term bonds are also less actively traded. The two effects result in a hump-shaped relation between trading volume and time to maturity for corporate bonds. Shocks seem to have the largest impact for medium-term bonds increasing the likelihood of correlated supply- and demand-side trading activity in these bonds. Thus, I expect commonality in liquidity to differ with respect to bonds' time to maturity and to be highest among medium-term corporate bonds.

I test for this by replicating Table 4.2 for all bonds yearly grouped into three maturity groups: short-term bonds, i.e. bonds that have less than 3 years to maturity, medium-term bonds, i.e. bonds with maturities between 3 and 7 years, and long-term bonds, i.e. bonds with more than 7 years to maturity. Panel A to C of Table 4.4 report the results for short-term bonds, medium-term bonds, and long-term bonds. Panel D of Table 4.4 shows differences between concurrent slope coefficients from Panel A to C.

Panel A to C of Table 4.4 report that commonality in liquidity differs across maturity groups and is lowest within the maturity group of short-term bonds. The first and last row of Panel D of Table 4.4 support this finding. The differences are always positive and significant

Table 4.4: Commonality in liquidity by maturity group

	Trades	Volume	Turnover	Depth	Amihud	Roll	IQR
			Panel A: Maturity shorter than 3 years (short)				
Concurrent	0.9441 ***	0.8632 ***	0.8612 ***	0.7965 ***	0.5719 ***	0.5908 ***	1.2546 ***
Sum	1.0574 ***	0.9766 ***	0.9747 ***	0.8857 ***	0.7999 ***	0.7386 ***	1.7879 ***
Adj. R^2	3.75	3.65	3.64	3.43	5.09	3.17	4.36
			Panel B: Maturity between 3 and 7 years (medium)				
Concurrent	1.1744 ***	1.0407 ***	1.0394 ***	0.9422 ***	0.6862 ***	1.1877 ***	1.4297 ***
Sum	1.2566 ***	1.1734 ***	1.1739 ***	1.0701 ***	0.8855 ***	1.3500 ***	1.8979 ***
Adj. R^2	4.09	3.51	3.51	3.20	4.00	3.75	3.94
			Panel C: Maturity larger than 7 years (long)				
Concurrent	0.9880 ***	1.0398 ***	1.0423 ***	0.8265 ***	1.1104 ***	1.3001 ***	1.4500 ***
Sum	1.0238 ***	1.1116 ***	1.1150 ***	1.0207 ***	1.1097 ***	1.4535 ***	1.9989 ***
Adj. R^2	4.26	3.98	3.97	3.55	4.37	4.16	3.93
			Panel D: Differences in commonality in liquidity				
medium-short	0.2303 ***	0.1776 ***	0.1782 ***	0.1458 *	0.1143	0.5969 ***	0.1751
long-medium	-0.1864 ***	-0.0009	0.0029	-0.1157	0.4243 **	0.1124	0.0203
long-short	0.0439	0.1767 **	0.1811 **	0.0300	0.5385 ***	0.7093 ***	0.1953

Notes: The table reports the results of time-series regressions that relate daily individual bond liquidity innovations to the respective market liquidity innovations for all bonds in the sample by maturity groups. In each individual regression, the market liquidity innovations are the averages of the respective liquidity measure for all bonds excluding the dependent variable bond. Column 1 to 7 provide the results for the different liquidity measures. Trades is daily number of trades. Volume is the daily trading volume. Depth is the daily realized depth of each bond computed as the mean of daily buy and sell volume. Turnover is daily trading volume as a percentage of outstanding volume. Amihud is the Amihud measure. Roll is the roll measure. IQR is the inter quartile range. The liquidity measures (Amihud, Roll, inter quartile range) are computed as described in the Appendix.
The concurrent, lagging, and leading values of market liquidity innovations; concurrent, lagging, and leading values of the market return, and the proportional daily change in dependent variable bond's squared return (a measure of change in return volatility) are regressors. Cross-sectional averages of the concurrent time-series slope coefficients of market liquidity innovations and the average sum of the concurrent, lagging, and leading coefficients of market liquidity innovations are reported. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Adj. R^2 is the cross-sectional average of adjusted R^2 statistics in percentage points.
Panel A shows the respective statistics for all bonds with maturities shorter than 3 years (short). Panel B shows the respective statistics for all bonds with maturities between 3 and 7 years (medium). Panel C shows the respective statistics for all bonds with maturities larger than 7 years. Panel D shows differences between concurrent slope coefficients from Panel A to C. Significance of differences is determined by using a Welch test. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

in 9 out of 14 cases. There is no significant difference between the medium-term and long-term maturity group. The differences in the second row of Panel D of Table 4.4 are three times negative, four times positive, and only one negative and one positive difference are significant. The positive differences between short- and medium-term bonds are in line with the expectation based on Gehde-Trapp et al. (2016). Contrary to the above expectation, Table 4.4 documents similar commonality in liquidity for long-term bonds and medium-term bonds. One explanation might be that long-term bonds are more sensitive to yield changes compared to short- and medium-term bonds. Thus, market liquidity changes might have a stronger impact on the individual liquidity of these bonds as well, being in line with the findings of Acharya et al. (2013).

To sum up, Table 4.4 shows differences in commonality in liquidity between maturity groups and indicates that a time to maturity is a further determinant of a bond’s degree of commonality in liquidity.

4.3.2.3. Commonality in liquidity by amount outstanding

As a further characteristic, a bond’s amount outstanding decisively determines its degree of tradability. Edwards et al. (2007) document lower transaction costs for bonds with higher amount outstanding. Thus, the sum of potential determinants of transaction costs (e.g., inventory risk, asymmetric information, or funding liquidity risk) is lower. This should translate into lower commonality in liquidity. Contrary, the common component driving transaction costs in these bonds is expected to be larger. This is because dealers make markets if they have access to order flow and price information (Schultz, 2003). This is more likely for bonds with high amount outstanding which are, on average, investment grade bonds with higher trading activity (Wang and Wu, 2015). This implies that dealers’ market making activity is more focused on large issues leading to higher commonality in liquidity. Thus, I expect commonality in liquidity to differ with respect to bonds’ amount outstanding and to be highest among large issues.

To test for bonds’ amount outstanding being a determinant of commonality in liquidity, I repeat the analyses of Table 4.2 for all bonds grouped into amount outstanding quintiles on an annual basis. Panel A to E of Table 4.5 show the respective statistics for all bonds in amount outstanding quintile one (smallest) to five (largest). Panel F of Table 4.5 reports the differences between concurrent slope coefficients from Panel A and E.

Table 4.5: Commonality in liquidity by amount outstanding quintile

	Trades	Volume	Turnover	Depth	Amihud	Roll	IQR
Panel A: Amount outstanding quintile 1 (smallest amount outstanding)							
Concurrent	0.6690 ***	0.5547 ***	0.5534 ***	0.3808 ***	0.6313 ***	0.2724 ***	1.0147 ***
Sum	0.7434 ***	0.5668 ***	0.5673 ***	0.3813 ***	1.0372 ***	0.4047 ***	1.5600 ***
Adj. R^2	4.64	4.46	4.45	4.12	6.08	4.30	4.98
Panel B: Amount outstanding quintile 2							
Concurrent	0.7354 ***	0.7184 ***	0.7181 ***	0.7505 ***	0.4996 ***	0.4170 ***	1.5297 ***
Sum	0.7844 ***	0.7686 ***	0.7686 ***	0.8461 ***	0.5715 ***	0.6678 ***	2.1619 ***
Adj. R^2	4.12	4.25	4.25	3.94	5.44	4.19	4.83
Panel C: Amount outstanding quintile 3							
Concurrent	1.0576 ***	1.0189 ***	1.0171 ***	0.8528 ***	0.5967 ***	0.7793 ***	1.2224 ***
Sum	1.1998 ***	1.0597 ***	1.0596 ***	0.9355 ***	0.6597 ***	1.0164 ***	1.3311 ***
Adj. R^2	3.82	3.28	3.28	2.90	4.38	3.16	3.97
Panel D: Amount outstanding quintile 4							
Concurrent	1.1563 ***	1.1201 ***	1.1201 ***	1.0011 ***	0.9876 ***	1.1290 ***	1.5321 ***
Sum	1.2331 ***	1.3591 ***	1.3603 ***	1.2573 ***	1.1524 ***	1.3308 ***	1.8985 ***
Adj. R^2	2.92	2.87	2.87	2.66	3.50	2.73	3.43
Panel E: Amount outstanding quintile 5 (largest amount outstanding)							
Concurrent	1.5470 ***	1.4120 ***	1.4118 ***	1.2882 ***	0.9877 ***	2.1870 ***	1.4969 ***
Sum	1.6197 ***	1.6315 ***	1.6309 ***	1.4972 ***	1.1120 ***	2.1358 ***	2.3840 ***
Adj. R^2	4.41	3.54	3.52	3.30	3.32	3.60	3.32
Panel F: Differences in commonality in liquidity							
Q5-Q1	0.8780 ***	0.8573 ***	0.8584 ***	0.9074 ***	0.3564	1.9146 ***	0.4822 **

Notes: The table reports the results of time-series regressions that relate daily individual bond liquidity innovations to the respective market liquidity innovations for all bonds in the sample by amount outstanding quintiles. In each individual regression, the market liquidity innovations are the averages of the respective liquidity measure for all bonds excluding the dependent variable bond. Column 1 to 7 provide the results for the different liquidity measures. Trades is daily number of trades. Volume is the daily trading volume. Depth is the daily realized depth of each bond computed as the mean of daily buy and sell volume. Turnover is daily trading volume as a percentage of outstanding volume. Amihud is the Amihud measure. Roll is the roll measure. IQR is the inter quartile range. The liquidity measures (Amihud, Roll, inter quartile range) are computed as described in the Appendix.

The concurrent, lagging, and leading values of market liquidity innovations; concurrent, lagging, and leading values of the market return, and the proportional daily change in dependent variable bond's squared return (a measure of change in return volatility) are regressors. Cross-sectional averages of the concurrent time-series slope coefficients of market liquidity innovations and the average sum of the concurrent, lagging, and leading coefficients of market liquidity innovations are reported. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Adj. R^2 is the cross-sectional average of adjusted R^2 statistics in percentage points.

Panel A to E show the respective statistics for all bonds by amount outstanding quintile. Panel A shows the results for bonds with the lowest amount outstanding and Panel E shows the results for bonds with the highest amount outstanding. Quintiles are determined yearly. Panel F shows differences between concurrent slope coefficients from Panel A and E. Significance of differences is determined by using a Welch test. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Panel A to E of Table 4.5 show that commonality in liquidity is monotonously increasing across amount outstanding quintiles for all but two liquidity measures. For the Amihud measure the average concurrent coefficient and the sum of coefficients of the first quintile are higher compared to the second and third quintile. For the IQR measure a similar effect arises for the second quintile. Overall, Panel F of Table 4.5 confirms that commonality in liquidity is monotonously increasing across amount outstanding quintiles. The difference between the fifth and first quintile is positive in all cases and statistically significant in six out of seven cases.

Summing up, the results of Table 4.5 are in line with the expectation of supply- and demand-side trading activity being more focused on large issues and thus leading to higher commonality in liquidity. Hence, bonds' amount outstanding is a further determinant of commonality in liquidity.

4.3.2.4. Commonality in liquidity by industry

Finally, liquidity supply and demand may also be driven by a bond's industry. In the model of Cespa and Foucault (2014) dealers try to infer price information of assets for which they are liquidity suppliers from other assets linking the supply-side liquidity of these assets with each other. Regarding liquidity demand, in the model of Veldkamp (2006) comovement arises through investors' preference for cheap information resulting in a common subset of information that is used to price different assets. Relative to non-financial firms, financial firms as a group depend more on a common subset of information that is also related more to market-wide liquidity effects (Dick-Nielsen et al., 2012). Thus, I expect commonality in liquidity to be higher among financial firms relative to all non-financial firms.

To test the expectation of a bond's industry being a determinant of commonality in liquidity, I replicate Table 4.2 for financial and non-financial firms as in Dick-Nielsen et al. (2012). Firms with SIC codes ranging from 6000 to 6999 are classified as financial firms. Firms with other SIC codes are non-financial firms. Table 4.6 presents results for the respective sample subsets.

Panel A of Table 4.6 shows the respective statistics for bonds issued by financial firms, Panel B of Table 4.6 shows the respective statistics for bonds issued by non-financial firms, and Panel C of Table 4.6 reports the differences between concurrent slope coefficients from Panel A and B. Commonality in liquidity is higher among financial firms as documented in

Table 4.6: Commonality in liquidity – financial vs. non-financial firms

	Trades	Volume	Turnover	Depth	Amihud	Roll	IQR
			Panel A: Bonds of financial firms				
Concurrent	1.1504 ***	0.9771 ***	0.9759 ***	0.8581 ***	0.9028 ***	1.1277 ***	1.5812 ***
Sum	1.2908 ***	1.1507 ***	1.1511 ***	0.9592 ***	1.0976 ***	1.3049 ***	2.2439 ***
Adj. R^2	3.97	3.42	3.41	3.19	4.32	3.62	4.19
			Panel B: Bonds of non-financial firms				
Concurrent	0.9541 ***	0.9587 ***	0.9582 ***	0.8515 ***	0.6227 ***	0.8406 ***	1.1653 ***
Sum	0.9996 ***	1.0252 ***	1.0252 ***	0.9967 ***	0.7664 ***	0.9783 ***	1.5376 ***
Adj. R^2	4.00	3.86	3.85	3.51	4.69	3.58	4.02
			Panel C: Difference in commonality in liquidity				
FIN-NONFIN	0.1962 ***	0.0184	0.0177	0.0066	0.2801 **	0.2871 ***	0.4159 ***

Notes: The table reports the results of time-series regressions that relate daily individual bond liquidity innovations to the respective market liquidity innovations for all bonds in the sample by the issuers' type of industry (financial vs. non-financial firms). In each individual regression, the market liquidity innovations are the averages of the respective liquidity measure for all bonds excluding the dependent variable bond. Column 1 to 7 provide the results for the different liquidity measures. Trades is daily number of trades. Volume is the daily trading volume. Depth is the daily realized depth of each bond computed as the mean of daily buy and sell volume. Turnover is daily trading volume as a percentage of outstanding volume. Amihud is the Amihud measure. Roll is the roll measure. IQR is the inter quartile range. The liquidity measures (Amihud, Roll, inter quartile range) are computed as described in the Appendix.
The concurrent, lagging, and leading values of market liquidity innovations; concurrent, lagging, and leading values of the market return, and the proportional daily change in dependent variable bond's squared return (a measure of change in return volatility) are regressors. Cross-sectional averages of the concurrent time-series slope coefficients of market liquidity innovations and the average sum of the concurrent, lagging, and leading coefficients of market liquidity innovations are reported. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Adj. R^2 is the cross-sectional average of adjusted R^2 statistics in percentage points.
Panel A shows the respective statistics for bonds issued by financial firms. Panel B shows the respective statistics for bonds issued by non-financial firms. Panel C shows differences between concurrent slope coefficients from Panel A and B. Significance of differences is determined by using a Welch test. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Panel C of Table 4.6. The differences between concurrent slope coefficients are positive for all liquidity measures and significant in four out of seven cases.

In summary, Table 4.6 supports the expectation by documenting a positive difference in commonality in liquidity between financial and non-financial firms. This indicates that a bond's industry is a further determinant of commonality in liquidity.

4.3.2.5. Panel analysis of determinants of commonality in liquidity

Overall, the results from Section 4.3.2.1 to 4.3.2.4 suggest basic bond characteristics to be determinants of commonality in liquidity. However, the results do not reveal whether the analyzed determinants proxy for the same effects. For instance, bonds with high amount outstanding are, on average, investment grade bonds with higher trading activity (Wang and Wu, 2015). Moreover, several other bond, firm, and industry characteristics may determine individual bonds' comovement with market liquidity. To take this into account, this section analyses the cross-sectional determinants of commonality in liquidity using the panel structure of the bond-specific time-series regression results summarized in Table 4.2.

The coefficients β_{Liq}^{Mkt} of the time-series regressions in Equation (4.2) describe individual bonds' sensitivity to market liquidity (Kamara et al., 2008). A second measure are the R^2 statistics of these regressions (Karolyi et al., 2012). A higher R^2 statistic indicates a higher commonality in liquidity because a higher fraction of bonds' individual liquidity variation can be explained by market movements.[51] A higher slope coefficient does not necessarily coincide with a higher R^2 statistic. Thus, for the cross-section of bonds both measures are important in understanding commonality in liquidity as they identify which bonds react more strongly to market liquidity and which bonds' variation in liquidity is explained more by the variation in market liquidity.

I run the following panel regressions to test for the influence of bond, firm, and industry characteristics on the degree of commonality in liquidity

$$\begin{aligned}\beta_{Liq\ i,t}^{Mkt} = {} & \alpha + \mathrm{B}_{bond} \cdot \text{bond characteristics}_{i,t} + \mathrm{B}_{firm} \cdot \text{firm characteristics}_{i,t} \\ & + \mathrm{B}_{industry} \cdot \text{industry characteristics}_{i,t} + \text{Year}_t + \varepsilon_{i,t},\end{aligned} \tag{4.3}$$

$$\begin{aligned}\ln\left[\frac{R_{i,t}^2}{\left(1-R_{i,t}^2\right)}\right] = {} & \alpha + \mathrm{B}_{bond} \cdot \text{bond characteristics}_{i,t} + \mathrm{B}_{firm} \cdot \text{firm characteristics}_{i,t} \\ & + \mathrm{B}_{industry} \cdot \text{industry characteristics}_{i,t} + \text{Year}_t + \varepsilon_{i,t},\end{aligned} \tag{4.4}$$

where the dependent variable in Equation (4.3), $\beta_{Liq\ i,t}^{Mkt}$, are the bond-specific concurrent coefficients of market liquidity innovations from Equation (4.2) and the dependent variable in Equation (4.4), the logistic transformation of $R_{i,t}^2$, are the R^2 statistics of the bond-specific

[51] To be consistent with the previous analyses of Section 4.3, I use the R^2 statistics based on the regression model in Equation (4.2) using concurrent, one trading day leading and lagging values of market liquidity innovations, the concurrent, one trading day leading and lagging market return, and the concurrent percentage change in the dependent variable bond's squared return. Unreported regression results (available upon request from the author) using only concurrent, one trading day leading and lagging values of market liquidity innovations as in Karolyi et al. (2012) provide similar results. Hence, the results of Table 4.7 are not driven by the market return or individual bonds' squared returns.

regressions from Equation (4.2).[52] Both analyses consider the same rich set of explanatory variables covering yearly averages of bond, firm, and industry characteristics to some extent all being related to supply- and demand-side effects. The main explanatory variables are based on the previous sections, being a bond's rating expressed as a number, a bond's time to maturity, the logarithm of a bond's amount outstanding, and a dummy indicating whether a bond's issuer is a financial firm.[53] Additionally, I control for a bond's return and return standard deviation found to be related to inventory risk (e.g., Stoll, 1978; Hameed et al., 2010; Friewald and Nagler, 2016). Bonds with higher inventory risk are expected to depend more on market liquidity. Since trading activity also may be an important determinant of commonality in liquidity, I add the logarithm of dealer trading volume as a proxy for comovement in supply-side liquidity: high dealer trading volume might indicate higher market making activity and thus a higher relevance of funding liquidity (Brunnermeier and Pedersen, 2009) or stronger informational liquidity linkages (Cespa and Foucault, 2014). The logarithms of customer buys and customer sells are proxies for correlated demand-side trading activity: high buy or sell volume might indicate high correlated trading activity (Chordia et al., 2011). I further control for the aging effect of seasoned bonds being less actively traded by adding bonds' age (Hotchkiss and Jostova, 2007). A firm's leverage ratio and return on assets control for profitability and riskiness (Danis et al., 2014), and logarithmized firm size, firm age, and analyst coverage[54] proxy for the ease to gather firm-specific information and information uncertainty all likely to drive supply and demand of firms' outstanding bonds (e.g., Zhang, 2006; Lu et al., 2010; Zhao, 2012). Regarding the industry a firm is operating in, it is more likely that firms depend on a more similar subset of information in concentrated industries (Piotroski and Roulstone, 2004) leading to higher supply and demand-side commonality in liquidity according to the theoretical models of Cespa and Foucault (2014) and Veldkamp (2006). I proxy for concentration with an industry's Herfindahl Index computed as the sum of the squared fractions of each individual firm's sales over the total sales of the industry. Additionally, I control for the riskiness of industries potentially driving overall industry supply and demand by the average industry leverage ratio. Finally, I include year

[52] The values of the R^2 statistics are between zero and one by construction. The logistic transformation is used to obtain an unbounded variable (e.g., Hameed et al., 2010; Karolyi et al., 2012).

[53] Unreported results (available upon request from the author) show that the results are robust to the inclusion of industry fixed effects instead of the financial firm dummy where firms' three-digit SIC codes define industries.

[54] Analyst coverage is from Institutional Brokers' Estimate System (I/B/E/S) and is the number of analysts following a firm's stock.

Table 4.7: Cross-sectional determinants of commonality in liquidity

	Trades	Volume	Turnover	Depth	Amihud	Roll	IQR
Panel A: Dependent variables are concurrent market liquidity coefficients							
Return	3.2539	1.8432	2.0058	1.1289	0.1484	7.1226 **	-9.1751
	(0.1026)	(0.5167)	(0.4801)	(0.6974)	(0.9750)	(0.0106)	(0.2319)
Return std. dev.	0.1668	0.2840	0.2869	-0.1372	1.7166 ***	-0.6041 *	0.0556
	(0.5146)	(0.3204)	(0.3177)	(0.6792)	(0.0022)	(0.0574)	(0.9419)
Dealer volume	0.2586 ***	0.1201 **	0.1218 **	0.0559	0.1159 *	0.4761 ***	0.1387
	(0.0000)	(0.0153)	(0.0141)	(0.3258)	(0.0570)	(0.0000)	(0.3441)
Sell volume	0.1879	0.0089	0.0087	-0.0470	-0.4391 **	0.1219	-0.2353
	(0.1373)	(0.9430)	(0.9444)	(0.7547)	(0.0453)	(0.3983)	(0.5489)
Buy volume	-0.3583 ***	0.0854	0.0862	0.1256	0.1371	-0.3248 **	0.0928
	(0.0049)	(0.5028)	(0.4989)	(0.4044)	(0.5436)	(0.0246)	(0.8148)
Rating	-0.0012	0.0050	0.0051	0.0045	-0.0113	-0.0234 *	-0.0525 *
	(0.9188)	(0.7026)	(0.7003)	(0.7709)	(0.5380)	(0.0960)	(0.0934)
Time to maturity	-0.0143 ***	-0.0051	-0.0050	-0.0054	0.0126	0.0197 ***	-0.0148
	(0.0017)	(0.3174)	(0.3312)	(0.3824)	(0.1605)	(0.0024)	(0.2181)
Age	-0.0109	-0.0129 *	-0.0127 *	-0.0095	0.0118	-0.0235 ***	-0.0175
	(0.1422)	(0.0745)	(0.0798)	(0.3333)	(0.3593)	(0.0052)	(0.4193)
Amt. outstanding	0.2547 ***	0.1499 **	0.1497 **	0.2672 ***	0.4903 ***	0.4463 ***	0.0339
	(0.0000)	(0.0111)	(0.0113)	(0.0002)	(0.0000)	(0.0000)	(0.8310)
Leverage ratio	0.1021	0.1619	0.1618	-0.1301	-0.5432	0.3052	-0.3982
	(0.6701)	(0.5303)	(0.5314)	(0.6943)	(0.1447)	(0.3097)	(0.6134)
Return on assets	-0.8740	-0.6368	-0.6369	-0.8519	-0.9996	1.2884 *	1.7713
	(0.1259)	(0.3657)	(0.3659)	(0.3054)	(0.2060)	(0.0829)	(0.3144)
Firm size	0.0471	0.0428	0.0425	-0.0278	-0.1666 ***	0.0232	0.0366
	(0.2026)	(0.3105)	(0.3144)	(0.5680)	(0.0065)	(0.5819)	(0.7480)
Firm age	-0.0116	-0.0445	-0.0436	-0.0031	0.0007	0.0160	-0.0133
	(0.7036)	(0.1711)	(0.1808)	(0.9417)	(0.9900)	(0.6907)	(0.8766)
Analyst coverage	-0.0078	0.0338	0.0316	0.0732 **	-0.0660	-0.0354	0.0451
	(0.7831)	(0.2989)	(0.3302)	(0.0488)	(0.2504)	(0.3062)	(0.6031)
Financial firm	0.0123	-0.1608 **	-0.1612 **	-0.1724 **	0.1208	0.1171	0.3782 **
	(0.8485)	(0.0354)	(0.0351)	(0.0496)	(0.2543)	(0.1718)	(0.0208)
Industry HERF	0.2410 *	0.3353 **	0.3380 **	-0.1567	-0.1302	-0.0519	-0.2035
	(0.0988)	(0.0347)	(0.0333)	(0.4178)	(0.6013)	(0.7823)	(0.5947)
Industry leverage	0.1830	-0.3446	-0.3477	-0.1623	0.2121	0.0175	1.0958
	(0.5070)	(0.2636)	(0.2598)	(0.6578)	(0.6515)	(0.9603)	(0.1495)
N	8749	8749	8749	8749	8749	8384	4630
Adj. R^2	2.91	2.40	2.40	1.48	1.21	8.98	0.97

(Continued)

Table 4.7 (Continued): Cross-sectional determinants of commonality in liquidity

	Trades	Volume	Turnover	Depth	Amihud	Roll	IQR
	Panel B: Dependent variable are the logistic transformations of R^2 statistics						
Return	3.9876 ***	2.6262 ***	2.5937 ***	3.0297 ***	4.2350 ***	4.1429 ***	5.1158 ***
	(0.0000)	(0.0034)	(0.0039)	(0.0011)	(0.0000)	(0.0000)	(0.0050)
Return std. dev.	0.3043 ***	0.4050 ***	0.4026 ***	0.3994 ***	0.6905 ***	0.5098 ***	0.9096 ***
	(0.0034)	(0.0002)	(0.0002)	(0.0004)	(0.0000)	(0.0000)	(0.0000)
Dealer volume	-0.2017 ***	-0.2422 ***	-0.2426 ***	-0.2531 ***	-0.3350 ***	-0.2293 ***	-0.3998 ***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Sell volume	0.2031 ***	0.2233 ***	0.2243 ***	0.2774 ***	0.2101 ***	0.2044 ***	0.2149 **
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0112)
Buy volume	0.0683	0.1207 **	0.1189 **	0.0675	0.1487 ***	0.1262 **	0.1593 *
	(0.1396)	(0.0120)	(0.0133)	(0.1583)	(0.0037)	(0.0119)	(0.0706)
Rating	-0.0264 ***	-0.0266 ***	-0.0265 ***	-0.0238 ***	-0.0475 ***	-0.0338 ***	-0.0413 ***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Time to maturity	0.0014	0.0026	0.0026	0.0014	-0.0078 ***	0.0103 ***	-0.0053
	(0.5236)	(0.2911)	(0.2834)	(0.5826)	(0.0023)	(0.0002)	(0.1200)
Age	0.0058 *	0.0087 **	0.0087 **	0.0087 **	0.0082 **	0.0055 *	-0.0046
	(0.0750)	(0.0116)	(0.0119)	(0.0351)	(0.0256)	(0.0885)	(0.4306)
Amt. outstanding	-0.3573 ***	-0.4252 ***	-0.4247 ***	-0.4141 ***	-0.4236 ***	-0.3731 ***	-0.3930 ***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Leverage ratio	-0.5536 ***	-0.5329 ***	-0.5333 ***	-0.4652 ***	-0.6302 ***	-0.6054 ***	-0.3113 *
	(0.0000)	(0.0001)	(0.0001)	(0.0004)	(0.0000)	(0.0000)	(0.0673)
Return on assets	0.5612 **	0.6849 **	0.6829 **	0.7669 ***	0.2554	0.8511 ***	0.8795 **
	(0.0325)	(0.0106)	(0.0108)	(0.0052)	(0.3786)	(0.0056)	(0.0305)
Firm size	-0.1050 ***	-0.1150 ***	-0.1151 ***	-0.1046 ***	-0.1566 ***	-0.1225 ***	-0.0997 ***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
Firm age	0.0078	0.0140	0.0138	0.0099	0.0276 *	0.0031	0.0183
	(0.6205)	(0.3711)	(0.3768)	(0.5422)	(0.0971)	(0.8570)	(0.3739)
Analyst coverage	-0.0232 *	-0.0318 **	-0.0317 **	-0.0418 ***	-0.0279 **	-0.0324 **	-0.0240
	(0.0793)	(0.0192)	(0.0196)	(0.0036)	(0.0471)	(0.0276)	(0.2264)
Financial firm	0.0812 **	0.0625 *	0.0621 *	0.0651 *	0.0385	0.1109 ***	0.1333 ***
	(0.0137)	(0.0666)	(0.0684)	(0.0552)	(0.2750)	(0.0035)	(0.0021)
Industry HERF	-0.0216	-0.0021	-0.0023	0.0245	-0.0485	0.0435	-0.2525 **
	(0.7693)	(0.9784)	(0.9769)	(0.7481)	(0.5298)	(0.6118)	(0.0147)
Industry leverage	0.5083 ***	0.5485 ***	0.5490 ***	0.4901 ***	0.5895 ***	0.4447 ***	0.4957 ***
	(0.0002)	(0.0002)	(0.0002)	(0.0011)	(0.0000)	(0.0050)	(0.0062)
N	8749	8749	8749	8749	8749	8384	4630
Adj. R^2	16.28	19.76	19.77	18.71	24.64	16.59	17.92

Notes: The table reports the results of panel data regressions of commonality in liquidity on different cross-sectional explanatory variables. Commonality in liquidity is measured by the yearly bond-specific concurrent coefficient from Equation (4.2) as well as the R^2 statistic of these regressions that relate daily individual bond liquidity innovations to the respective market liquidity innovations for all bonds using concurrent, lagging, and leading values of market liquidity innovations as well as lagging, leading, and concurrent values of the market return, and the proportional daily change in dependent variable bond's squared return (a measure of change in return volatility) as explanatory variables. I use the logistic transformation of the yearly bond-specific R^2 statistics, determined as described in the main text in Section 4.3.2.5.

Column 1 to 7 provide the results for the different liquidity measures. Trades is daily number of trades. Volume is the daily trading volume. Depth is the daily realized depth of each bond computed as the mean of daily buy and sell volume. Turnover is daily trading volume as a percentage of outstanding volume. Amihud is the Amihud measure. Roll is the roll measure. IQR is the inter quartile range. The liquidity measures (Amihud, Roll, inter quartile range) are computed as described in the Appendix.

(Continued)

Table 4.7 (Continued): Cross-sectional determinants of commonality in liquidity

The explanatory variables are bond, firm, and industry variables as described in the main text in Section 4.3.2.5. Panel A shows results using the concurrent regression coefficients of yearly bond-specific regressions as dependent variable. Panel B shows results using the logistic transformation of the R^2 statistics of yearly bond-specific regressions as dependent variable. In all regressions I use year fixed-effects. P-values are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Significance is determined using robust standard errors clustered at the bond level. Adjusted R^2 statistics are in percentage points.

fixed effects, denoted by Year_t, to adjust for time-series variation in commonality in liquidity (e.g., Hameed et al., 2010; Rösch and Kaserer, 2013) and cluster standard errors at the bond level.

Panel A of Table 4.7 presents results of panel regressions from Equation (4.3). Only dealer volume and bonds' amount outstanding are systematically significant. The effect of further potential determinants of commonality in liquidity from Table 4.3 to 4.6 seems to be subsumed by these two variables. The sensitivity of individual bond liquidity to market liquidity is higher for bonds with higher dealer volume in 5 out of 7 cases. This finding is in line with the above argumentation of dealer volume being a proxy for market making activity. In addition, the liquidity of bonds with high amount outstanding is more sensitive to market liquidity being significant in 6 out 7 cases. Given that dealer volume controls for dealers' market making activity being more likely for large issues (Schultz, 2003), amount outstanding most likely captures demand-side effects. Bonds with high amount outstanding are more actively traded and, thus, likely to be in overall higher demand (Wang and Wu, 2015). Hence, supply- and demand-side effects both drive the sensitivity of individual bonds' liquidity to market liquidity.

Panel B of Table 4.7 shows results of panel regressions from Equation (4.4). Compared to the determinants of the sensitivity of individual bonds' liquidity to market liquidity from Panel A of Table 4.7, several more variables have an impact on individual bonds' liquidity variations being explained by market variations. Regarding the bond characteristics from Section 4.3.2.1 to 4.3.2.4, I find bonds with higher credit quality (= lower rating number) to have higher R^2 statistics, bonds' time to maturity to have no impact, bonds' with higher amount outstanding to have lower R^2 statistics, and bonds of financial firms to have higher R^2 statistics. Interestingly, bonds' amount outstanding and dealer volume have opposite signs in Panel A and Panel B of Table 4.7. Bonds with higher amount outstanding or higher dealer volume are more sensitive to variations in market liquidity, but are also influenced more by bond-specific or noise components according to the lower R^2 statistics. This finding underlines the importance of slope coefficients and R^2 statistics as measures of individuals bonds' degree of commonality in liquidity. Overall, the significant explanatory variables are to some extend all related to supply- and demand-side effects. Summing up, the results in Table 4.7 show that supply- or demand-side effects both influence individual bonds' comovement with market liquidity.

4.3.3. Alternative sources of individual bonds' comovement in liquidity

The analyses in Section 4.3.2 assume market liquidity to be the only source of individual bonds' comovement in liquidity. However, the determinants discussed in Section 4.3.2.1 to 4.3.2.4 are common to several bonds and, thus, themselves may be sources of commonality in liquidity. For instance, the well-known flight-to-quality effect results in correlated demand for less risky bonds, i.e. bonds in higher-quality credit rating buckets (e.g., Longstaff et al., 2005; Dick-Nielsen et al., 2012). Thus, market liquidity may only be one out of several sources of corporate bonds' liquidity comovement. This section tests for additional sources of commonality in liquidity while controlling for market liquidity. For the same reason as in Section 4.3.2, I focus on the bond characteristics discussed in Section 4.3.2.1 to 4.3.2.4: credit rating buckets, time to maturities, amounts outstanding, and industries.

To test for additional sources of commonality in liquidity, I extend the model in Equation (4.2) that relates bonds' individual liquidity to market liquidity. I separately add credit rating bucket, maturity group, amount outstanding quintile, and industry liquidity resulting in the following regression models:

$$\varepsilon_{Liq,t} = \alpha + \beta_{Liq}^{Mkt} \cdot \varepsilon_{Liq,t}^{Mkt} + \beta_{Liq}^{Rat} \cdot \varepsilon_{Liq,t}^{Rat} + \Gamma \cdot Controls_t + \varepsilon_t, \tag{4.5}$$

$$\varepsilon_{Liq,t} = \alpha + \beta_{Liq}^{Mkt} \cdot \varepsilon_{Liq,t}^{Mkt} + \beta_{Liq}^{Mat} \cdot \varepsilon_{Liq,t}^{Mat} + \Gamma \cdot Controls_t + \varepsilon_t, \tag{4.6}$$

$$\varepsilon_{Liq,t} = \alpha + \beta_{Liq}^{Mkt} \cdot \varepsilon_{Liq,t}^{Mkt} + \beta_{Liq}^{Amt} \cdot \varepsilon_{Liq,t}^{Amt} + \Gamma \cdot Controls_t + \varepsilon_t, \tag{4.7}$$

$$\varepsilon_{Liq,t} = \alpha + \beta_{Liq}^{Mkt} \cdot \varepsilon_{Liq,t}^{Mkt} + \beta_{Liq}^{Ind} \cdot \varepsilon_{Liq,t}^{Ind} + \Gamma \cdot Controls_t + \varepsilon_t. \tag{4.8}$$

The additional regressor $\varepsilon_{Liq,t}^{Rat}$ is the respective credit rating bucket average of $\varepsilon_{Liq,t}$, $\varepsilon_{Liq,t}^{Mat}$ is the respective monthly maturity group (short-, medium-, long-term bonds) average of $\varepsilon_{Liq,t}$, $\varepsilon_{Liq,t}^{Amt}$ is the respective monthly amount outstanding quintile average of $\varepsilon_{Liq,t}$, and $\varepsilon_{Liq,t}^{Ind}$ is the respective industry[55] average of $\varepsilon_{Liq,t}$. The averages consider all bonds excluding the respective dependent variable bond. $Controls_t$ is the same vector of control variables as in Equation (4.2) supplemented with one trading day leading and lagging values of $\varepsilon^{Rat}_{Liq,t}$, $\varepsilon^{Mat}_{Liq,t}$, $\varepsilon^{Amt}_{Liq,t}$, or $\varepsilon^{Ind}_{Liq,t}$.

Panel A of Table 4.8 presents the results for Equation (4.5). It shows that market liquidity and credit rating bucket liquidity determine individual bonds' liquidity as the average concurrent slope coefficients and the average sum of the concurrent, leading, and lagging slope coefficients are significantly positive. Similarly, Panel B to D of Table 4.8 present the results for Equation (4.6) to (4.8). They document that maturity group, amount outstanding quintile, and industry liquidity influence individual bond liquidity. Regarding the economic significance, a one standard deviation shock in market liquidity based on the roll measure, for instance, is 27%, 77%, and 39% larger than a one standard deviation shock in credit rating bucket, maturity group, and amount outstanding quintile liquidity, respectively. This relation also holds for the other six liquidity measures. For industry liquidity, a one standard deviation shock in market liquidity is three times larger than a one standard deviation shock in industry liquidity. Hence, market liquidity is the most important source of commonality in liquidity as it has the overall highest economic significance.

Summing up the results of Table 4.8, credit rating bucket, maturity group, amount outstanding quintile, and industry liquidity are additional sources of commonality in liquidity while market liquidity seems to play the most important role for commonality in liquidity.

Overall, the results of Section 4.3 clearly document the existence of commonality in liquidity among US corporate bonds. Individual bonds' comovement with market liquidity is driven by bond, firm, and industry characteristics related to supply- and demand-side effects. In addition, this section reveals that commonality in liquidity may also arise through individual bonds' comovement with credit rating bucket, maturity group, amount outstanding quintile, or industry liquidity while market liquidity remains the most important source of liquidity comovement.

[55] Firms within the same three-digit SIC code range are defined as one industry.

Table 4.8: Alternative sources of commonality in liquidity

	Trades	Volume	Turnover	Depth	Amihud	Roll	IQR
Panel A: Market + Rating liquidity innovations							
Conc. market	0.7082 ***	0.6053 ***	0.6040 ***	0.5472 ***	0.5318 ***	0.7593 ***	1.0901 ***
Lag market	-0.0598	-0.0357	-0.0353	-0.0127	0.0639	0.0780 *	0.2354 **
Lead market	-0.0830 **	0.0011	0.0005	0.0117	0.0862 *	-0.0290	0.1209
Sum market	0.5654 ***	0.5707 ***	0.5692 ***	0.5463 ***	0.6820 ***	0.8083 ***	1.4464 ***
Conc. rating	0.2830 ***	0.2964 ***	0.2965 ***	0.2435 ***	0.1817 ***	0.1633 ***	0.2180 ***
Lag rating	0.0785 ***	0.0703 ***	0.0706 ***	0.0772 ***	-0.0042	-0.0003	0.0411
Lead rating	0.0987 ***	0.0213	0.0222	0.0243	0.0074	0.0586 **	0.1298 *
Sum rating	0.4603 ***	0.3880 ***	0.3893 ***	0.3451 ***	0.1849 ***	0.2216 ***	0.3889 ***
Adj. R^2	2.10	1.76	1.75	1.27	3.06	1.67	2.26
	Trades	Volume	Turnover	Depth	Amihud	Roll	IQR
Panel B: Market + Time to maturity liquidity innovations							
Conc. market	0.7033 ***	0.6311 ***	0.6318 ***	0.6212 ***	0.5909 ***	0.7534 ***	0.9513 ***
Lag market	0.0276	0.0136	0.0133	0.0830	0.0504	0.0506	0.2191 **
Lead market	-0.0291	-0.0015	-0.0044	-0.0241	-0.0155	0.0667	0.2663 ***
Sum market	0.7017 ***	0.6432 ***	0.6407 ***	0.6801 ***	0.6258 ***	0.8707 ***	1.4367 ***
Conc. maturity	0.3297 ***	0.3162 ***	0.3157 ***	0.2149 ***	0.1281 ***	0.1937 ***	0.3642 ***
Lag maturity	0.0324	0.0742 **	0.0759 **	0.0190	0.0208	0.0366	0.0786
Lead maturity	0.0769 **	0.0466	0.0481	0.0645	0.0714 *	0.0103	-0.0284
Sum maturity	0.4389 ***	0.4370 ***	0.4397 ***	0.2985 ***	0.2203 ***	0.2405 ***	0.4143 ***
Adj. R^2	2.01	1.89	1.88	1.19	2.99	1.80	2.16
Panel C: Market + Amount outstanding liquidity innovations							
Conc. market	0.7338 ***	0.7458 ***	0.7459 ***	0.6546 ***	0.4813 ***	0.5415 ***	0.7774 ***
Lag market	0.0427	0.1036 **	0.1038 **	0.1155 **	0.1188 **	0.0780 *	0.3080 ***
Lead market	0.0336	0.0669	0.0680 *	0.0634	0.1007 **	0.1284 ***	0.2138 **
Sum market	0.8101 ***	0.9163 ***	0.9177 ***	0.8335 ***	0.7009 ***	0.7480 ***	1.2992 ***
Conc. amount	0.1836 ***	0.1549 ***	0.1553 ***	0.1108 ***	0.1478 ***	0.2359 ***	0.4025 ***
Lag amount	0.0146	-0.0505 *	-0.0505 *	-0.0457	-0.0302	0.0491 *	0.0611
Lead amount	0.0309	-0.0263	-0.0274	-0.0221	0.0048	-0.0061	0.0870
Sum amount	0.2291 ***	0.0781	0.0774	0.0430	0.1224 **	0.2789 ***	0.5506 ***
Adj. R^2	2.04	1.76	1.75	1.29	2.98	1.68	2.43

(Continued)

Table 4.8: Alternative sources of commonality in liquidity

	Panel D: Market + Industry liquidity innovations						
Conc. market	0.8989 ***	0.7813 ***	0.7795 ***	0.7226 ***	0.6728 ***	0.9180 ***	1.3392 ***
Lag market	0.0343	0.0209	0.0220	0.0563	0.0806 *	0.0911 ***	0.1692 **
Lead market	-0.0069	-0.0165	-0.0155	0.0015	0.0655	0.0561	0.1816 ***
Sum market	0.9263 ***	0.7856 ***	0.7860 ***	0.7803 ***	0.8188 ***	1.0652 ***	1.6919 ***
Conc. industry	0.1304 ***	0.1623 ***	0.1629 ***	0.1152 ***	0.0088	0.0608 ***	0.0916 ***
Lag industry	0.0317 ***	0.0392 ***	0.0391 ***	0.0143	0.0094	0.0163	0.0400 *
Lead industry	0.0474 ***	0.0498 ***	0.0496 ***	0.0393 ***	0.0018	-0.0075	0.0446 **
Sum industry	0.2095 ***	0.2513 ***	0.2517 ***	0.1688 ***	0.0200	0.0696 ***	0.1762 ***
Adj. R^2	2.37	2.11	2.10	1.41	2.95	1.75	2.30

Notes: The table reports the results of time-series regressions that relate daily individual bond liquidity innovations to the respective market, credit rating bucket, time to maturity group, amount outstanding quintile, and industry liquidity innovations for all bonds in the sample. In each individual regression, the market liquidity innovations are the averages of the respective liquidity measure for all bonds excluding the dependent variable bond, the credit rating bucket liquidity innovations are the credit rating bucket averages of the respective liquidity measure excluding the dependent variable bond using five credit rating buckets (AAA, AA, A, BBB, below BBB-), the maturity group liquidity innovations are the maturity group averages of the respective liquidity measure excluding the dependent variable bond using three maturity groups (< 3 years, between 3 and 7 years, > 7 years), the amount outstanding quintile liquidity innovations are the amount outstanding quintile averages of the respective liquidity measure excluding the dependent variable bond, and the industry liquidity innovations are the three-digit SIC code industry averages of the respective liquidity measure excluding the dependent variable bond. Column 1 to 7 provide the results for the different liquidity measures. Trades is daily number of trades. Volume is the daily trading volume. Depth is the daily realized depth of each bond computed as the mean of daily buy and sell volume. Turnover is daily trading volume as a percentage of outstanding volume. Amihud is the Amihud measure. Roll is the roll measure. IQR is the inter quartile range. The liquidity measures (Amihud, Roll, inter quartile range) are computed as described in the Appendix.
Cross-sectional averages of concurrent (Conc.), lagging (Lag), and leading (Lead) time-series slope coefficients of market, credit rating bucket, maturity group, amount outstanding quintile, and industry liquidity innovations are reported. Sum market/rating/maturity/amount/industry is the average sum of the concurrent, lagging, and leading coefficients of market, credit rating bucket, maturity group, amount outstanding quintile, and industry liquidity innovations. Adj. R^2 is the cross-sectional average of adjusted R^2 statistics in percentage points. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.
Panel A shows the respective statistics where market and credit rating bucket liquidity innovations are used as explanatory variables. Panel B shows the respective statistics where market and maturity group liquidity innovations are used as explanatory variables. Panel C shows the respective statistics where market and amount outstanding quintile liquidity innovations are used as explanatory variables. Panel D shows the respective statistics where market and industry liquidity innovations are used as explanatory variables. The concurrent, lagging, and leading values of the market return, and the proportional daily change in dependent variable bond's squared return (a measure of change in return volatility) are additional regressors; coefficients not reported.

4.4. Commonality in liquidity over time

After documenting the existence and cross-sectional determinants of individual bonds' comovement with market liquidity, this section focuses on the time-series variation of market-wide commonality in liquidity. First, I describe the approach used to proxy for market-wide commonality in liquidity for US corporate bonds and show its evolution over time in Section 4.4.1. Second, I present more detailed evidence on the determinants of market-wide commonality in liquidity over time in Section 4.4.2.

4.4.1. Time-series evolution of commonality in liquidity

The findings of the previous section show a high cross-sectional variation in commonality in liquidity for corporate bonds. For stocks, Kamara et al. (2008), Hameed et al. (2010), and Rösch and Kaserer (2013) document that market-wide commonality in liquidity also varies heavily over time. They find market-wide commonality in liquidity to be higher in times of financial stress. Considering the results of sharp liquidity dry-ups for corporate bonds during the financial crisis in 2008 reported by Friewald et al. (2012) and Dick-Nielsen et al. (2012), I also expect market-wide commonality in liquidity of US corporate bonds to vary over time and to be higher in months with severe financial stress events.

To analyze time-series variation in market-wide commonality in liquidity, I run a monthly single factor regression that relates individual bond liquidity innovations to market liquidity innovations for each bond that is traded on at least 75% of a month's trading days

$$\varepsilon_{Liq,t} = \alpha + \beta_{Liq}^{Mkt} \cdot \varepsilon_{Liq,t}^{Mkt} + \varepsilon_t, \tag{4.9}$$

where $\varepsilon_{Liq,t}$ are the respective residuals from Equation (4.1) and $\varepsilon_{Liq,t}^{Mkt}$ are the respective market averages of $\varepsilon_{Liq,t}$ for all bonds excluding the dependent variable bond.[56,57] Following Hameed et al. (2010), Karolyi et al. (2012), and Rösch and Kaserer (2013), I compute the monthly average R^2 statistic of the bond-specific regressions from Equation (4.9) for each liquidity measure. A higher average R^2 statistic indicates a higher market-wide commonality in liquidity. Figure 4.1 shows how market-wide commonality in liquidity based on the different liquidity measures evolves over time.

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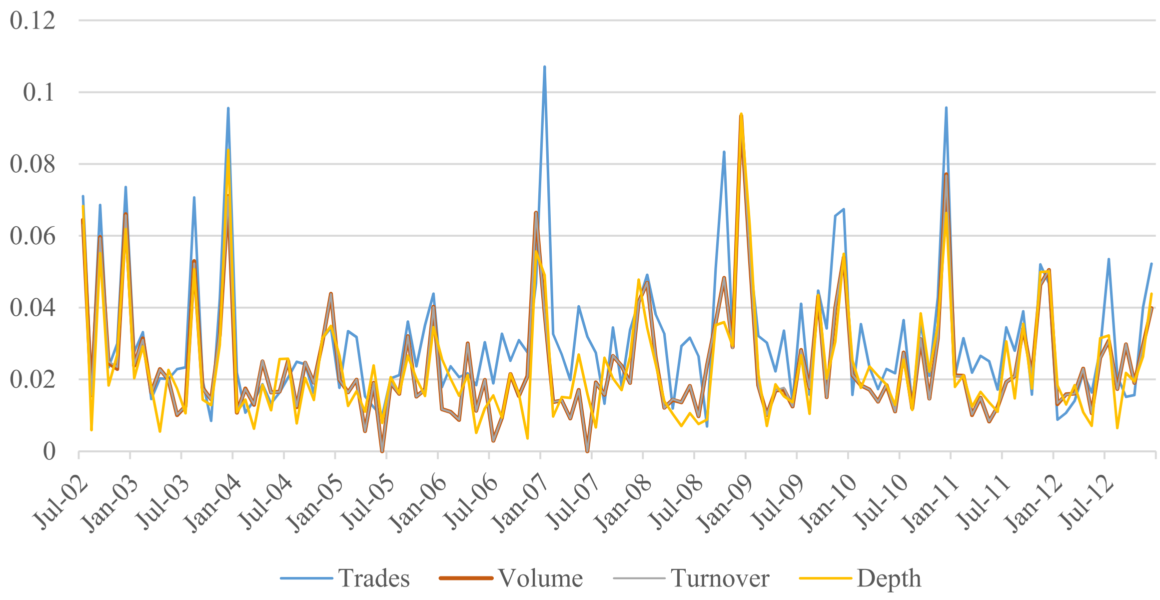
[56] The computation of residuals in Equation (4.1) is adjusted to the monthly frequency. Each month, I regress the natural logarithm of a bond's liquidity measures on the respective one trading day lagging natural logarithm of the bond's liquidity measures and day-of-the-week dummies.

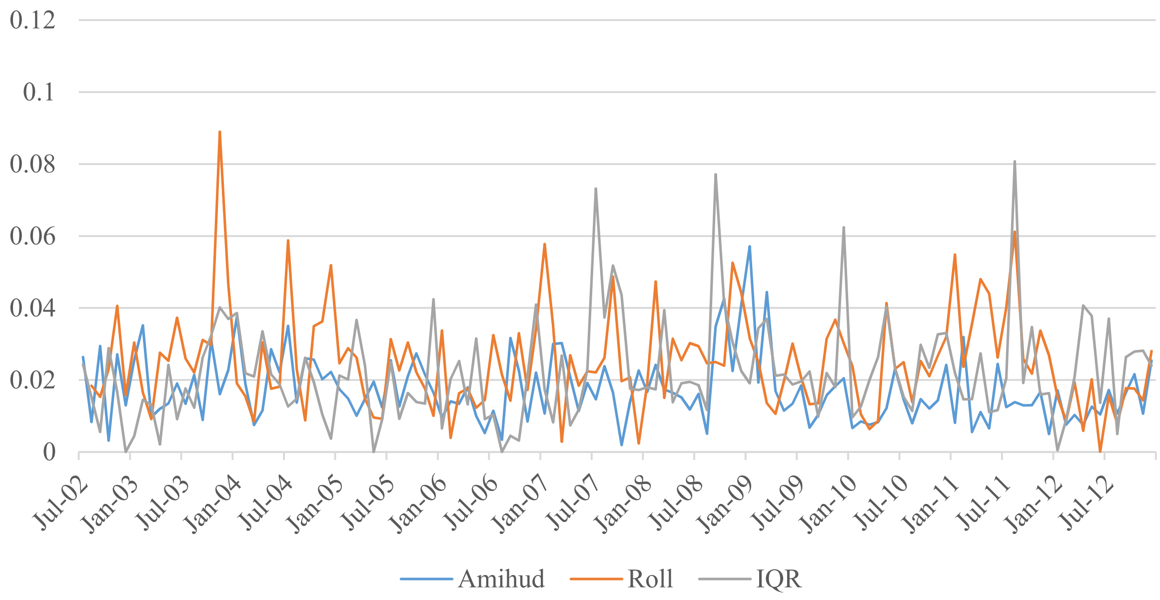
[57] In the robustness section I also use the approach of Karolyi et al. (2012) and add one trading day leading and lagging values of the respective market liquidity innovations to Equation (4.9).

Figure 4.1: Commonality in liquidity over time

Panel A: Trades, Volume, Turnover, and Depth commonality time series

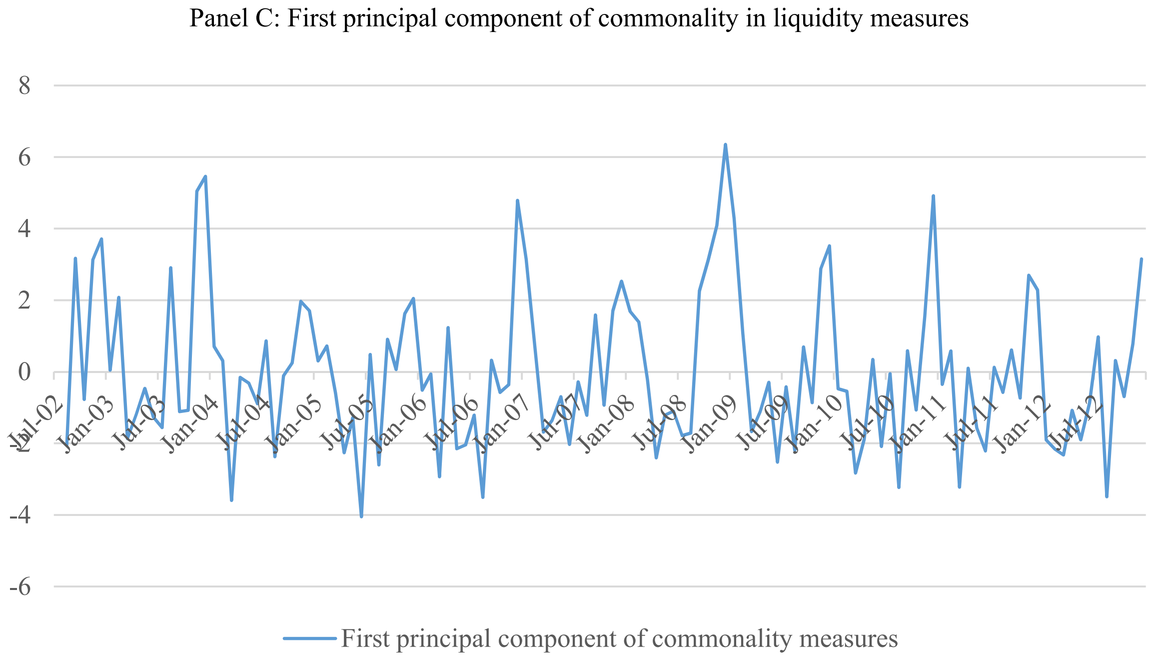


Panel B: Amihud, Roll, and IQR commonality time series



(Continued)

Figure 4.1 (Continued): Commonality in liquidity over time



Notes: The Figure shows commonality in liquidity over time for the period July 2002 to December 2012. Panels A and B show time-series plots of monthly cross-sectional averages of the R^2 statistics of single factor regressions that relate daily individual bond liquidity innovations to the respective market liquidity innovations for all bonds in the sample. In each individual regression, the market liquidity innovations are the averages of the respective liquidity measure for all bonds excluding the dependent variable bond. Trades is the daily number of trades. Volume is the daily trading volume. Depth is the daily realized depth of each bond computed as the mean of daily buy and sell volume. Turnover is daily trading volume as a percentage of outstanding volume. Amihud is the Amihud measure. Roll is the roll measure. IQR is the inter quartile range. The liquidity measures (Amihud, Roll, inter quartile range) are computed as described in the Appendix. Panel A shows the time-series plots based on the liquidity measures Trades, Volume, Turnover, and Depth. Panel B shows the time-series plots based on the liquidity measures Amihud, Roll, and IQR. Panel C shows the time-series plot of the first principal component of the logistic transformation of the monthly cross-sectional averages of the R^2 statistics of the liquidity measures.

Panel A of Figure 4.1 shows the time-series evolution of average R^2 statistics based on the Trades, Volume, Turnover, and Depth liquidity measure regressions. As expected, market-wide commonality in liquidity varies heavily over time and peaks often may be linked to months with severe financial stress events. The time series peak in late 2006 (early 2007) when the awareness of a US housing price bubble rose among market participants (e.g., announcement of Freddie Mac not to buy more of the most risky subprime mortgages and mortgage-related securities on February 27). Further peaks are around the acquisition of Bear Stearns by JPMorgan (March 16, 2008) and the September 2008 turmoil (federal takeover of Fannie Mae and Freddie Mac on September 7, the acquisition of Merrill Lynch by Bank of

America on September 14, and the Lehman default on September 15). Panel B of Figure 4.1 shows the time-series evolution of average R^2 statistics based on the Amihud, Roll, and IQR liquidity measure regressions. Although the time series seem to be more volatile, all time series show a similar pattern of peaks compared to Panel A of Figure 4.1. Finally, Panel C of Figure 4.1 summarizes the common information of R^2 statistics based on the seven liquidity measures. It describes the time-series evolution of the first principal component of the seven R^2 statistic time series. Again, this time series shows a similar pattern of peaks as those in Panel A of Figure 4.1.[58] Overall, Figure 4.1 shows that market-wide commonality in liquidity varies heavily over time and peaks in months with severe financial stress events.

4.4.2. Time-series determinants of commonality in liquidity

In this section, I extend the analysis of the R^2 statistic time series from the previous section and try to identify the determinants of time-series variation. Recent evidence by Rösch and Kaserer (2013) suggests funding liquidity to be an important determinant of market-wide commonality in liquidity for German stocks. Considering the over-the-counter (OTC) market structure of the US corporate bond market, dealers are important in providing liquidity and arranging trades (Bessembinder et al., 2016). Thus, I expect funding liquidity to be a major determinant of market-wide commonality in liquidity for corporate bonds. Commonality is expected to be high when funding liquidity is low. Given the theoretical implications of Brunnermeier and Pedersen (2009), I expect this relation to be especially pronounced in times of financial stress.

To test for the time-series determinants of market-wide commonality in liquidity, I run the following regression for monthly average R^2 statistics resulting from Equation (4.9) based on the different liquidity measures

$$\begin{aligned}\ln\left[\frac{R_t^2}{\left(1-R_t^2\right)}\right] &= \alpha + \beta_{\text{Business}} \cdot \text{ADS index}_t + \beta_{\text{Default}} \cdot \text{default spread} \\ &\quad + \beta_{\text{Mkt Liq}} \cdot \text{market liquidity}_t + \beta_{\text{Funding Liq}} \cdot \text{funding liquidity}_t + \varepsilon_t\end{aligned} \tag{4.10}$$

where $\ln\left[R_t^2/\left(1-R_t^2\right)\right]$ is the logistic transformation of the respective R^2 statistic (e.g., Morck et al., 2000; Hameed et al., 2010; Karolyi et al., 2012; Rösch and Kaserer, 2013), ADS index

[58] I compute the first principal component using the logistic transformation $\ln\left[R^2/\left(1-R^2\right)\right]$ of the R^2 statistics. Again, the logistic transformation is used to obtain an unbounded variable (e.g., Hameed et al., 2010; Karolyi et al., 2012).

is the Aruoba-Diebold-Scotti Business Conditions Index[59], default spread is the difference between Moody's Baa and Aaa yield, overall market liquidity is the first principal component of the monthly averages of the liquidity measures, and funding liquidity is the difference between the 90-day AA nonfinancial commercial paper interest rate and the three-month US Treasury bill rate as in Karolyi et al. (2012). Higher values of the ADS index indicate better economic conditions, higher values of the default spread indicate a more risky market environment and higher values of the market and funding liquidity proxies are associated with higher illiquidity. The ADS index controls for the overall state of the economy that might be related to market-wide commonality in liquidity since Rösch and Kaserer (2013) find commonality in liquidity to be higher during times of financial stress. I add the default spread to capture the overall corporate bond market conditions as market conditions are identified to drive market-wide commonality in liquidity (e.g., Hameed et al., 2010; Rösch and Kaserer, 2013). Finally, market liquidity and funding liquidity capture the implications of the self-reinforcing interplay of both measures proposed by Brunnermeier and Pedersen (2009). Overall, the proxies capture aggregate demand-side (e.g., correlated trading in times of financial stress) and supply-side effects (e.g., funding liquidity evaporating) potentially influencing market-wide commonality in liquidity.

As seen in Section 4.3 and documented by the existing literature (e.g., Edwards et al., 2007; Dick-Nielsen et al., 2012; Acharya et al., 2013), commonality in liquidity differs across credit rating buckets. For this reason, the influence of the above proxies on aggregate commonality in liquidity may also differ across credit rating buckets. Thus, I compute the first principal component of the logistic transformation of monthly average R^2 statistics of the seven liquidity measures for seven different subsets of the sample: all bonds in the sample, all investment grade (IG) bonds, AAA-rated bonds, AA-rated bonds, A-rated bonds, BBB-rated bonds, and high yield (HY) bonds. Then, I regress the respective first principal component on the same explanatory variables as in Equation (4.10). Table 4.9 reports the results for the time-series regressions based on Equation (4.10).

[59] The index is based on Aruoba et al. (2009). I obtained its values from the following website: https://www.philadelphiafed.org/research-and-data/real-time-center/business-conditions-index.

Table 4.9: Time-series analyses of commonality in liquidity

Panel A: Commonality in liquidity determinants by liquidity measure							
	Trades	Volume	Turnover	Depth	Amihud	Roll	IQR
ADS index	0.0473	0.0580 *	0.0582 *	0.0839 **	-0.0117	0.0030	0.0141
	(0.1686)	(0.0676)	(0.0662)	(0.0189)	(0.7047)	(0.9115)	(0.7450)
Default spread	0.1144 *	0.0977	0.0980	0.1370 *	-0.0096	-0.0602	0.0140
	(0.0931)	(0.1751)	(0.1716)	(0.0539)	(0.8418)	(0.3712)	(0.8306)
Market liquidity	0.0085	0.0184	0.0184	0.0124	0.0190 **	0.0186	0.0037
	(0.5020)	(0.1441)	(0.1441)	(0.3437)	(0.0450)	(0.1237)	(0.7399)
Funding liquidity	0.1550 **	0.1378 **	0.1378 **	0.1593 ***	0.1200 ***	0.1068 *	0.2146 ***
	(0.0270)	(0.0337)	(0.0332)	(0.0070)	(0.0058)	(0.0778)	(0.0001)
Constant	-2.5144 ***	-2.5745 ***	-2.5750 ***	-2.6205 ***	-2.5486 ***	-2.3706 ***	-2.5258 ***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
N	126	126	126	126	126	125	126
Adj. R^2	5.07	5.99	6.03	5.80	10.70	0.62	5.50
Panel B: Commonality in liquidity determinants by credit rating bucket							
	Full Sample	IG bonds	AAA bonds	AA bonds	A bonds	BBB bonds	HY bonds
ADS index	0.4778	0.4964	0.5857 ***	0.5261 **	0.4686	0.3577	0.5355 **
	(0.1423)	(0.1336)	(0.0039)	(0.0434)	(0.1391)	(0.2366)	(0.0293)
Default spread	0.9119	0.9978	0.7114	0.7108	1.1675 *	0.6237	0.4614
	(0.1803)	(0.1444)	(0.1188)	(0.2710)	(0.0886)	(0.2388)	(0.3168)
Market liquidity	0.1342	0.1065	-0.0162	0.0963	0.0477	0.1574	0.2211 *
	(0.2804)	(0.3729)	(0.8447)	(0.4342)	(0.6741)	(0.1197)	(0.0764)
Funding liquidity	1.8813 ***	1.8974 ***	0.4209	1.9142 ***	1.3680 ***	1.4680 ***	0.8526
	(0.0010)	(0.0010)	(0.6479)	(0.0015)	(0.0083)	(0.0089)	(0.1726)
Constant	-1.2763 *	-1.3743 **	-0.6925	-1.0297	-1.4740 **	-0.8965 *	-0.5010
	(0.0669)	(0.0471)	(0.1626)	(0.1204)	(0.0350)	(0.0865)	(0.3610)
N	125	125	125	125	125	125	125
Adj. R^2	7.29	7.31	-0.38	5.89	5.10	6.33	3.42

Notes: The table reports the results of regressions of commonality in liquidity on different market variables. In Panel A, commonality in liquidity is measured by monthly cross-sectional averages of the R^2 statistics of single factor regressions that relate daily individual bond liquidity innovations to the respective market liquidity innovations for all bonds in the sample. I use the logistic transformation of cross-sectional averages of the R^2 statistic as dependent variable, determined as described in the main text in Section 4.4.2. Column 1 to 7 of Panel A show the results for commonality in liquidity based on the different liquidity measures as dependent variable. Trades is daily number of trades. Volume is the daily trading volume. Depth is the daily realized depth of each bond computed as the mean of daily buy and sell volume. Turnover is daily trading volume as a percentage of outstanding volume. Amihud is the Amihud measure. Roll is the roll measure. IQR is the inter quartile range. The liquidity measures (Amihud, Roll, inter quartile range) are computed as described in the Appendix. In Panel B, commonality in liquidity is measured as the first principal component of the logistic transformation of cross-sectional averages of the R^2 statistics of the different liquidity measures from Panel A for different credit rating buckets. Column 1 shows the results for all bonds in the sample. Column 2 shows the results for all investment grade (IG) bonds, i.e. bonds having a rating between AAA and BBB-. Column 3 to 6 show the results for all AAA- to BBB-rated bonds. Column 7 shows the results for all high yield (HY) bonds, i.e. bonds having a rating below BBB-. The explanatory market variables are the same in all regressions and are explained in the main text in Section 4.4.2. P-values are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Significance is determined using Newey-West standard errors. Adjusted R^2 statistics are in percentage points.

Panel A of Table 4.9 shows the regression results of Equation (4.10) for the seven liquidity measures. ADS index is significant in three out of seven cases. Default spread is significant in two cases, and overall market liquidity is significant in one case. The strongest effect on market-wide commonality in liquidity has funding liquidity, being significant in all cases. This supports the theoretical prediction of Brunnermeier and Pedersen (2009).

Panel B of Table 4.9 presents the results of the detailed credit rating bucket analysis based on the first principal component of the commonality in liquidity measures and on Equation (4.10). The first column supports the finding from Panel A of Table 4.9, funding liquidity seems to be the most important determinant for the full sample. Digging deeper into the rating bucket cross-section, I find funding liquidity to be important for IG bonds, but not HY bonds. Thereby, funding liquidity does not determine commonality in liquidity of AAA-rated bonds. This may be due to investors' flight-to-quality behavior induced by a funding liquidity shock. Dick-Nielsen et al. (2012) find a flight-to-quality to AAA-rated bonds during the financial crisis 2008. This might counteract an overall flight-to-quality from corporate bonds to more safety assets, i.e. Treasury bonds, and lead to an insignificant effect for AAA-rated bonds.

The results of Table 4.9 document that funding liquidity is an important determinant for corporate bonds' market-wide commonality in liquidity. According to the theoretical model of Brunnermeier and Pedersen (2009), this relation should be especially pronounced in times of financial stress. To test the impact of the above determinants in different market phases, the sample is split into two periods: July 2002 to February 2008 and March 2008 to December 2012. The second period covers the period of ongoing financial stress beginning with the financial crisis in 2008 and leading to the European sovereign debt crisis starting in 2009. I consider March 2008 as the splitting month, since the acquisition of Bear Stearns by JPMorgan on March 16, 2008, first obviously reveals severe liquidity problems of financial firms. The sample split reduces the number of observations for the time-series analyses. To maintain sufficient degrees of freedom in the time-series regressions, I focus on the most important determinants from Table 4.9 as explanatory variables: ADS index, default spread, and funding liquidity. For brevity, I report only the results for the detailed credit rating bucket analysis based on the first principal component of R^2 statistics of liquidity measures in Table 4.10.

Panel A of Table 4.10 replicates the analysis from Panel B of Table 4.9. It documents that the results remain unchanged when I consider only the most important determinants from Table 4.9. Panel B of Table 4.10 presents the results for the sample period before March 2008.

Table 4.10: Financial stress and commonality in liquidity

	Full Sample	IG bonds	AAA bonds	AA bonds	A bonds	BBB bonds	HY bonds
Panel A: Full time series							
ADS index	0.4167	0.4479	0.5930 ***	0.4823 *	0.4469	0.2862	0.4349 *
	(0.1979)	(0.1705)	(0.0023)	(0.0591)	(0.1539)	(0.3381)	(0.0988)
Default spread	1.2024 *	1.2283 **	0.6763	0.9191	1.2707 **	0.9644 *	0.9400 **
	(0.0518)	(0.0491)	(0.1120)	(0.1232)	(0.0385)	(0.0509)	(0.0134)
Funding liquidity	1.7594 ***	1.8007 ***	0.4356	1.8267 ***	1.3247 **	1.3250 **	0.6518
	(0.0033)	(0.0028)	(0.6306)	(0.0038)	(0.0149)	(0.0263)	(0.3029)
Constant	-1.6213 ***	-1.6481 ***	-0.6509	-1.2771 **	-1.5966 ***	-1.3011 ***	-1.0694 **
	(0.0094)	(0.0083)	(0.1500)	(0.0291)	(0.0086)	(0.0099)	(0.0101)
N				125			
Adj. R^2	7.13	7.48	0.43	6.05	5.76	5.49	0.78
Panel B: Before March 2008							
ADS index	0.7391	0.8671	0.6703 *	0.8412 *	0.7666	0.5398	0.1208
	(0.2069)	(0.1367)	(0.0997)	(0.0824)	(0.1900)	(0.3140)	(0.8317)
Default spread	3.3003 **	3.3532 **	1.2174	3.2981 ***	3.0600 **	2.5654 **	2.2281
	(0.0203)	(0.0134)	(0.2362)	(0.0099)	(0.0184)	(0.0219)	(0.1510)
Funding liquidity	0.9237	0.9188	-0.6387	1.1020 *	0.4723	0.2296	1.0984 **
	(0.1480)	(0.1897)	(0.5483)	(0.0939)	(0.4462)	(0.6918)	(0.0499)
Constant	-3.1803 **	-3.2090 **	-0.9086	-3.1990 ***	-2.8567 **	-2.3769 **	-2.3046 *
	(0.0153)	(0.0117)	(0.3272)	(0.0076)	(0.0209)	(0.0114)	(0.0865)
N				67			
Adj. R^2	2.81	3.13	-1.32	5.27	1.51	0.57	2.05
Panel C: From March 2008							
ADS index	0.4944	0.4973	0.8227 **	0.5343 *	0.5060	0.3915	0.5576 **
	(0.1556)	(0.1643)	(0.0224)	(0.0748)	(0.1369)	(0.2884)	(0.0444)
Default spread	1.4311 **	1.4142 **	0.5400	1.0725 *	1.4051 **	1.1731 **	1.5368 ***
	(0.0234)	(0.0244)	(0.3606)	(0.0889)	(0.0222)	(0.0207)	(0.0019)
Funding liquidity	2.3556 **	2.4156 **	2.2051 ***	2.3347 **	1.9378 **	2.3301 ***	-0.1134
	(0.0192)	(0.0139)	(0.0011)	(0.0344)	(0.0270)	(0.0069)	(0.9144)
Constant	-2.2534 ***	-2.2404 ***	-0.7129	-1.7046 **	-2.1152 ***	-1.9451 ***	-1.8144 **
	(0.0018)	(0.0014)	(0.3355)	(0.0149)	(0.0018)	(0.0012)	(0.0125)
N				58			
Adj. R^2	15.66	16.40	7.84	11.91	12.37	15.73	4.24

Notes: The table reports the results of regressions of commonality in liquidity on different market variables for different sample periods. Commonality in liquidity is measured as the first principal component of the logistic transformation of cross-sectional averages of the R^2 statistics of single factor regressions that relate daily individual bond liquidity innovations to the respective market liquidity innovations for the different liquidity measures. The first principal component is computed for different credit rating buckets. Column 1 shows the results for all bonds in the sample. Column 2 shows the results for all investment grade (IG) bonds, i.e. bonds having a rating between AAA and BBB-. Column 3 to 6 show the results for all AAA- to BBB-rated bonds. Column 7 shows the results for all high yield (HY) bonds, i.e. bonds having a rating below BBB-. Panel A shows results for the full sample period, Panel B shows results for the period before March 2008, and Panel C shows results for the period from March 2008 until December 2012. The explanatory market variables are the same in all regressions and are explained in the main text in Section 4.4.2. P-values are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Significance is determined using Newey-West standard errors. Adjusted R^2 statistics are in percentage points.

Higher market-wide risk is related to higher commonality in liquidity, the default spread has a positive significant impact when considering the full sample, IG bonds, AA-rated bonds, A-rated bonds, and BBB-rated bonds. Funding liquidity has only a minor impact. This finding is consistent with demand-side explanations of correlated trading theories (e.g., Bernardo and Welch, 2004; Vayanos, 2004). Panel C of Table 4.10 documents the determinants of commonality in liquidity for the period after February 2008. In line with Brunnermeier and Pedersen (2009), funding liquidity is the most important determinant for this period.

Overall, this section shows that demand- and supply-side effects determine market-wide commonality in liquidity. Thereby, the time-series results provide evidence on supply-side effects being more important. Commonality In liquidity is high, when funding liquidity is evaporating. This relation is especially pronounced since the financial crisis in 2008.

4.5. Robustness

This section provides various robustness tests. In Section 4.5.1, I check for the robustness of the cross-sectional results by modifying the method described in Equation (4.1) and (4.2) or considering subsets of the bond sample. In Section 4.5.2, I test the robustness of the time-series results by varying funding liquidity and market liquidity proxies, and modifying the method described in Equation (4.9).

4.5.1. Cross-sectional robustness analyses

Table 4.11 provides results for the robustness of Table 4.2. First, I change the time-series regression in Equation (4.2) to not include the market return control variables and the dependent variable bond's squared return as in Karolyi et al. (2012) (Panel A of Table 4.11). Next, I reduce the sample to often traded bonds. I compute commonality in liquidity for bonds that are traded on at least 75% of their possible trading days (Panel B of Table 4.11). A further robustness test changes the way of the computation of liquidity innovations in Equation (4.1) . Instead of running yearly bond-specific regressions, I add yearly dummies to Equation (4.1) , run one regression for each bond, and then compute commonality in liquidity based on these innovations (Panel C of Table 4.11). Then, I use the previously computed innovations and run the regression in Equation (4.2) not yearly but once for the full sample period for each bond (Panel D of Table 4.11). Finally, I average each liquidity measure for all bonds of the same

Table 4.11: Cross-sectional robustness analyses of commonality in liquidity

	Trades	Volume	Turnover	Depth	Amihud	Roll	IQR
				Panel A: Karolyi et al. (2012) model			
Concurrent	1.0059 ***	0.9696 ***	0.9684 ***	0.8930 ***	0.7793 ***	0.9667 ***	1.3868 ***
% + significant	0.2101	0.1615	0.1611	0.1456	0.0785	0.1472	0.1372
Sum	1.1057 ***	1.0796 ***	1.0796 ***	1.0295 ***	0.9205 ***	1.1179 ***	1.9215 ***
Adj. R^2	1.40	0.98	0.98	0.89	0.66	1.28	1.57
				Panel B: Only bonds with high trading frequency			
Concurrent	1.4780 ***	1.3026 ***	1.3029 ***	1.1295 ***	0.9788 ***	1.3381 ***	1.2777 ***
% + significant	0.4464	0.3159	0.3153	0.2858	0.1318	0.2695	0.1926
Sum	1.6096 ***	1.5310 ***	1.5313 ***	1.3497 ***	1.1461 ***	1.3765 ***	2.0225 ***
Adj. R^2	3.41	2.43	2.41	2.14	2.10	1.64	2.09
				Panel C: Alternative liquidity innovations computation			
Concurrent	1.0835 ***	1.0028 ***	1.0025 ***	0.8968 ***	0.8223 ***	0.9553 ***	1.4129 ***
% + significant	0.2170	0.1612	0.1618	0.1452	0.0974	0.1481	0.1641
Sum	1.1792 ***	1.1173 ***	1.1175 ***	1.0421 ***	1.0824 ***	1.1109 ***	2.1391 ***
Adj. R^2	2.67	1.77	1.77	1.23	3.24	1.50	4.43
				Panel D: Full sample commonality in liquidity			
Concurrent	0.9680 ***	0.9117 ***	0.9095 ***	0.8263 ***	0.7727 ***	0.7817 ***	1.3300 ***
% + significant	0.3569	0.3161	0.3161	0.2754	0.1589	0.2449	0.3076
Sum	1.0236 ***	1.0770 ***	1.0780 ***	1.0485 ***	0.9303 ***	0.9590 ***	1.6629 ***
Adj. R^2	8.13	7.78	7.78	7.27	9.38	7.49	10.68
				Panel E: Firm Sample			
Concurrent	0.7813 ***	0.7691 ***	0.7676 ***	0.7353 ***	0.5640 ***	0.4063 ***	0.6320 ***
% + significant	0.2374	0.2305	0.2264	0.2060	0.1184	0.0787	0.1078
Sum	0.9455 ***	0.9455 ***	0.9413 ***	0.9259 ***	0.7304 ***	0.6409 ***	1.0899 ***
Adj. R^2	10.17	10.06	9.94	9.89	9.89	9.62	11.27

Notes: The table reports robustness results of time-series regressions that relate daily individual bond liquidity innovations to the respective market liquidity innovations. In each individual regression, the market liquidity innovations are the averages of the respective liquidity measure for all bonds excluding the dependent variable bond. Column 1 to 7 provide the results for the different liquidity measures. Trades is daily number of trades. Volume is the daily trading volume. Depth is the daily realized depth of each bond computed as the mean of daily buy and sell volume. Turnover is daily trading volume as a percentage of outstanding volume. Amihud is the Amihud measure. Roll is the roll measure. IQR is the inter quartile range. The liquidity measures (Amihud, Roll, inter quartile range) are computed as described in the Appendix 4.A.
Cross-sectional averages of the concurrent time-series slope coefficients of market liquidity innovations and the average sum of the concurrent, lagging, and leading coefficients of market liquidity innovations are reported. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. "% + significant" gives the percentage of positive concurrent slope coefficients with p-values smaller than 5%. Adj. R^2 is the cross-sectional average of adjusted R^2 statistics in percentage points.
Panel A shows the results of time-series regressions with concurrent, leading, and lagging market liquidity innovations being the only explanatory variable as in Karolyi et al. (2012). Panel B to E show the results of time-series regressions where concurrent, lagging, and leading values of market liquidity innovations; concurrent, lagging, and leading values of the market return, and the proportional daily change in dependent variable bond's squared return (a measure of change in return volatility) are regressors. Panel B shows results based on bonds that are traded on more than 75% of their possible trading days. Panel C shows results based on liquidity innovations computed for the full sample period. Panel D shows results where only one time-series regression is computed per bond. Panel E shows results where liquidity measures are aggregated per firm.

firm and compute firm-specific commonality in liquidity using the regression model from Equation (4.2) (Panel E of Table 4.11).

Panels A to E of Table 4.11 documents that commonality in liquidity exists irrespective of how it is measured or which sample subsets are considered. In Panel A of Table 4.11 the results indicate the existence of commonality in liquidity not being driven by the market return and individual bonds' squared returns. Concurrent coefficients and the respective sum of coefficients are positive and highly statistically significant. Panel B of Table 4.11 shows that commonality in liquidity is even stronger among bonds that are traded frequently. Coefficients are roughly 40% higher relative to Table 4.2. Commonality in liquidity also exists when modifying the way liquidity innovations are computed (Panel C of Table 4.11) and when Equation (4.2) is run for the full time series of each bond (Panel D of Table 4.11). The last panel, Panel E of Table 4.11, suggest that commonality in liquidity also exists on an aggregate firm level. Thus, my findings are robust with respect to the used method and bond sample.

4.5.2. Time-series robustness analyses

In Table 4.12, I provide robustness results of the time-series analyses in Panel B of Table 4.9. First, I use an alternative funding liquidity proxy, the TED spread (Panel A of Table 4.12). It is defined as the difference between the three-month USD Libor and the three-month US Treasury bill rate (Fontaine and Garcia, 2012). Again, a higher value indicates higher funding illiquidity. Second, I use an alternative proxy for market liquidity associated with investor sentiment. Ben-Rephael et al. (2012) and Da et al. (2015) find equity mutual fund outflows and bond mutual fund inflows to be related to bad investor sentiment consistent with investors' flight-to-quality. In line with the theoretical predictions of Vayanos (2004), inflows to bond funds should increase the liquidity of the overall bond market of which corporate bonds are a subgroup. Hence, I use net flows to equity, bond, and money market mutual funds as indirect market liquidity proxies (Panel B of Table 4.12).[60] Finally, I extend the regression model in Equation (4.9) to include leading and lagging market liquidity innovations as in Karolyi et al. (2012) in Panel C of Table 4.12.

Panel A of Table 4.12 shows that the time-series results are robust to the alternative funding liquidity proxy. As the US commercial paper spread in Panel B of Table 4.9, the

[60] I obtain the fund flows from the Investment Company Institute (ICI) (2015). According to the Investment Company Institute (ICI) (2015) the three used mutual fund categories cover 91% of US mutual fund assets.

Table 4.12: Time-series robustness analyses of commonality in liquidity

	Full Sample	IG bonds	AAA bonds	AA bonds	A bonds	BBB bonds	HY bonds
Panel A: Funding liquidity proxied by the TED spread							
ADS index	0.4566	0.4871	0.5930 ***	0.5281 *	0.4297	0.3832	0.4425 *
	(0.1837)	(0.1629)	(0.0058)	(0.0637)	(0.1916)	(0.2236)	(0.0941)
Default spread	0.7174	0.7952	0.6614	0.5005	1.0385	0.4499	0.4172
	(0.3494)	(0.2995)	(0.1841)	(0.4975)	(0.1686)	(0.4330)	(0.4104)
Market liquidity	0.1280	0.1017	-0.0162	0.0927	0.0404	0.1574	0.2085 *
	(0.3155)	(0.4082)	(0.8424)	(0.4674)	(0.7276)	(0.1224)	(0.0895)
Funding liquidity	0.9315 ***	0.9751 ***	0.2441	1.0171 ***	0.6080 **	0.8504 ***	0.1765
	(0.0074)	(0.0048)	(0.6092)	(0.0065)	(0.0450)	(0.0043)	(0.7159)
Constant	-1.0921	-1.1929	-0.6557	-0.8508	-1.3317 *	-0.7680	-0.3875
	(0.1494)	(0.1121)	(0.2167)	(0.2448)	(0.0722)	(0.1695)	(0.4930)
N				125			
Adj. R^2	5.36	5.52	-0.45	3.87	3.66	5.63	2.25
Panel B: Market liquidity proxied by net mutual fund flows							
ADS index	0.3528	0.4047	0.6314 ***	0.4320 *	0.4030	0.2339	0.2797
	(0.2670)	(0.1957)	(0.0009)	(0.0980)	(0.1617)	(0.4249)	(0.4007)
Default spread	0.4314	0.5658	0.8442	0.3686	0.5693	0.2937	0.0591
	(0.4803)	(0.3559)	(0.1372)	(0.6039)	(0.3058)	(0.5974)	(0.9305)
Equity flow	-2.0124 *	-1.8067 *	0.2590	-1.4029	-1.9131 **	-1.7457 *	-1.8061 *
	(0.0716)	(0.0984)	(0.7142)	(0.1984)	(0.0457)	(0.0990)	(0.0922)
Bond flow	-0.9155 ***	-0.9243 ***	-0.1567	-0.5875 *	-0.9521 ***	-0.7279 **	-0.2900
	(0.0074)	(0.0066)	(0.5417)	(0.0753)	(0.0033)	(0.0148)	(0.2783)
Money mkt. flow	-0.2706	-0.2216	0.0514	-0.1930	-0.2113	-0.1840	-0.4815 **
	(0.2782)	(0.3723)	(0.7598)	(0.3355)	(0.3599)	(0.4249)	(0.0185)
Funding liquidity	1.6255 **	1.5703 **	0.2436	1.7748 ***	1.0477 *	1.1431 *	1.3766 *
	(0.0150)	(0.0196)	(0.8013)	(0.0047)	(0.0939)	(0.0670)	(0.0802)
Constant	-0.2249	-0.3359	-0.6958	-0.3293	-0.2065	-0.0922	-0.1905
	(0.7646)	(0.6539)	(0.2986)	(0.7086)	(0.7577)	(0.8913)	(0.8159)
N				125			
Adj. R^2	12.81	13.14	-1.29	8.13	12.59	9.70	5.39
Panel C: Karolyi et al. (2012) model							
ADS index	0.3240	0.2498	0.3504 *	-0.1024	0.2989	0.3890	0.5931 *
	(0.3275)	(0.4510)	(0.0950)	(0.7190)	(0.3593)	(0.2302)	(0.0715)
Default spread	0.1810	0.1232	0.6217	-0.3651	0.1923	0.2826	0.1740
	(0.8023)	(0.8657)	(0.1393)	(0.6198)	(0.7788)	(0.6295)	(0.7862)
Market liquidity	0.2599 *	0.2420 *	0.1344	0.1877 *	0.2364 *	0.2056 *	0.3141 ***
	(0.0520)	(0.0647)	(0.1144)	(0.0976)	(0.0548)	(0.0639)	(0.0049)
Funding liquidity	2.0164 ***	1.9770 ***	-0.5118	1.1536 *	1.9564 ***	2.2447 ***	0.7955
	(0.0019)	(0.0030)	(0.5618)	(0.0884)	(0.0014)	(0.0000)	(0.2114)
Constant	-0.5030	-0.4571	-0.4751	0.1494	-0.5145	-0.6476	-0.1246
	(0.5150)	(0.5559)	(0.3204)	(0.8490)	(0.4808)	(0.2938)	(0.8555)
N				125			
Adj. R^2	6.66	6.45	2.19	2.87	6.76	9.73	5.24

Notes: The table reports the results of regressions of commonality in liquidity on different market variables for different sample periods. Commonality in liquidity is measured as the first principal component of the logistic transformation of cross-sectional averages of the R^2 statistics of single factor regressions that relate daily individual bond liquidity innovations to the respective market liquidity innovations for the different liquidity measures. The first principal component is computed for different credit rating buckets. Column 1 shows the results for all bonds in the sample. Column 2 shows the results for all investment grade (IG) bonds, i.e. bonds having a rating between AAA and BBB-. Column 3 to 6 show the results for all AAA- to BBB-rated bonds. Column 7 shows the results for all high yield (HY) bonds, i.e. bonds having a rating below BBB-.

Table 4.12 (Continued): Time-series robustness analyses of commonality in liquidity

Panel A shows results using the TED spread as alternative funding liquidity proxy, Panel B shows results using mutual fund flows as alternative market liquidity proxies, and Panel C shows results using the method of Karolyi et al. (2012) adding leading and lagging market liquidity innovations to Equation (4.9).
The further explanatory market variables are the same in all regressions and explained in the main text in Section 4.4.2.
P-values are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Significance is determined using Newey-West standard errors. Adjusted R^2 statistics are in percentage points.

TED spread is significant in five out of seven cases. Considering mutual fund flows in Panel B of Table 4.12, I find equity mutual fund outflows to be significantly related to higher commonality in liquidity in 5 out of 7 cases, but with low significance. This finding might indicate overall investors' flight-to-quality into Treasury bonds. In line with the intuition of bond mutual fund flows being a market liquidity proxy, bond mutual fund inflows significantly decrease commonality in liquidity. Finally, Panel C of Table 4.12 shows that the results in Panel B of Table 4.9 are robust to using an alternative approach to measure commonality in liquidity.

Overall, Section 4.5 provides support for the robustness of the cross-sectional and time-series results documented in Section 4.3 and Section 4.4.

4.6. Conclusion

This paper documents the existence and determinants of commonality in liquidity among US corporate bonds. Bonds' individual liquidity depends strongly on market liquidity. Individual bonds' dependence on market liquidity is determined by bond, firm, and industry characteristics related to supply- and demand-side effects. The analyses also shed light on further sources of commonality in liquidity. They identify a bond's credit rating bucket, maturity, amount outstanding, and industry liquidity to be additional sources of commonality in liquidity while market liquidity is the most important source of commonality in liquidity.

Time-series results document a high variation of market-wide commonality in liquidity over time. Peaks may be related to important events disrupting markets. Consistent with the literature, the analyses reveal that funding liquidity is the most important determinant.

Summing up, the results contribute to the literature by providing a detailed picture of commonality in liquidity among corporate bonds. The results are highly relevant as commonality in liquidity decisively determines investors' diversification benefits across corporate bonds and issuers financing costs.

4.A. Description of liquidity measures

In this appendix I describe the liquidity measures used in this paper in more detail. The liquidity measures are number of trades (Trades), trading volume (Volume), turnover (Turnover), realized depth (Depth), Amihud measure (Amihud), Roll measure (Roll), and the inter-quartile range (IQR).

Following Friewald et al. (2012), number of trades is the sum of trades for one bond on each trading day. Trade volume is the sum of trade sizes for one bond on each trading day. Higher values of both measures should indicate higher liquidity. As in Dick-Nielsen et al. (2012) I use turnover as a further liquidity measure. Turnover is a bond's daily trade volume relative to its outstanding volume. Again, a higher turnover should indicate higher liquidity. In line with the given intuition, Friewald et al. (2012) find corporate bond yield spreads to be lower for higher number of trades and higher trade volumes. Dick-Nielsen et al. (2012) show that yield spreads are lower for bonds with higher turnover. Hence, the empirical evidence suggests that these measures convey information on corporate bond liquidity.

Due to the OTC market structure of the US corporate bond market, it is not possible to observe a limit order book as for centralized markets such as the New York Stock Exchange. Thus, computing the quoted depth as in Chordia et al. (2000) is not possible for corporate bonds. However, I am able to separate each bond's trading volume in customer buys, customer sells, and dealer trades. Thus, I roughly approximate a bond's market depth by computing its realized depth. Similar to Chordia et al. (2000), I define the realized depth as the mean of a bond's daily buy and sell volume.[61] Higher values of realized depth indicate higher liquidity.

Although bid and ask quotes in OTC markets are not observable, Roll (1984), Han and Zhou (2007), and Pu (2009) developed measures to approximate the (effective) bid-ask spread. Roll (1984) proxies for the effective bid-ask spread by making use of the negative auto-covariance of an asset's consecutive returns. Similar to Dick-Nielsen et al. (2012) and Schestag et al. (2016), I compute daily values of this measure for the relative effective bid-ask spread as follows

$$Roll_t = 2\sqrt{-Cov\left(r_i, \mathrm{r}_{i-1}\right)}, \tag{4.11}$$

[61] To be in line with the quoted depth in Chordia et al. (2000), I implicitly assume that daily buys and daily sells of a bond are settled at the same price, respectively.

where $r_i = \frac{P_i - P_{i-1}}{P_{i-1}}$ is the return of the *i*-th trade. $Cov(r_i, \mathrm{r}_{i-1})$ is set to 0 if it is larger than 0. A daily Roll measure is computed using a 21-trading-day rolling window. Higher values of the Roll measure indicate lower liquidity as shown by Bao et al. (2011), Dick-Nielsen et al. (2012), and Friewald et al. (2012).

An alternative measure to approximate the relative bid-ask spread is the inter-quartile range (IQR). This measure was introduced by Han/Zhou (2007) and Pu (2009) and is defined as the ratio of the difference between the upper and lower quartile of a bond's trade prices on day t to its average trade price on day t:

$$IQR_t = \frac{P_t^{75th} - P_t^{25th}}{\bar{P}_t}. \tag{4.12}$$

The measure is computed for all trading days of a bond with at least three trades. A higher inter quartile range indicates lower liquidity (see, e.g., Han and Zhou, 2007 and Pu, 2009).

Finally, I approximate the daily price impact of trades by the modified Amihud (2002) measure used in Dick-Nielsen et al. (2012). This measure proxies the price impact of a trade by relating the return to the trading volume of a trade

$$Amihud_t = \frac{1}{N_t} \sum_{i=1}^{N_t} \frac{|r_i|}{V_i}, \tag{4.13}$$

where N_t is the number of returns on day t and V_i is the trading volume of the *i*-th trade. For bonds with a higher Amihud measure price movements are stronger given the same trading volume. Thus, bonds with a higher Amihud measure are less liquid. Friewald et al. (2012) and Dick-Nielsen et al. (2012) show empirical evidence for this intuition.

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