Illiquidity linkages between individual stocks and corporate bonds

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Abstract

This paper evaluates the cross comovements of illiquidity between stocks and corporate bonds issued by the same firm employing individual corporate bonds information from TRACE from July 2002 to December 2014. We analyze these relations in both a time series and a cross-sectional framework, employing different statistical approaches. Our results consistently confirm a positive linkage between the liquidity of the two assets, except for bonds in the AAA rating category. Therefore, flight to liquidity seems to arise only for very low-risk corporate bonds. Additionally, we find that the stock–bond liquidity relation strengthens with firm risk.

Keywords: individual illiquidity, stocks, corporate bonds, firm risk, panel estimation

JEL classification: G12; G14

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1. Introduction

Firms use a combination of equity and debt to finance their assets. Therefore, credit risk (or cash flow risk) affects both stock and corporate bond returns. This argument supports structural models for pricing risky corporate debt, starting with Merton's (1974). In a separate issue, liquidity is an important characteristic of financial assets. The level of liquidity determines expected returns, since illiquid assets involve higher transaction costs and investors will require paying less for them. Amihud and Mendelson (1986) and Chen et al. (2007) give examples that show an illiquidity premium in returns or yields for the stock and corporate bond markets, respectively.

Given the relevance of liquidity to asset pricing, on the one hand, and the relation between the returns on bonds and stocks with a common issuer, on the other, our hypothesis is that investors' willingness to trade assets from the same firm diminishes as the firm's risk increases. Therefore, we expect a positive relation between the liquidity of the two assets. Moreover, indirect empirical evidence suggests this to be the case. Chordia et al. (2017) find that stock illiquidity is a significant positive predictor of the same firm's bond returns, and Acharya et al. (2013) evaluate the exposure of returns on corporate bonds and find a reaction to shocks in liquidity in the same direction in both the Treasury and equity markets.

Previous literature on the relation between the liquidity for different classes of assets is exclusively focused on an aggregate level and reveals a positive time series association in the liquidity between equity and both the Treasury and corporate bond markets.[1] Papers on the case of corporate bonds are scarce, with the exception of those of Jacoby et al. (2009) and Liew et al. (2022), who show commonality in liquidity and positive connectedness, respectively. A direct analysis about comovements in liquidity at the individual level is lacking, this being the main contribution of our paper. Additionally, the use of individual information ensures that cross-sectional dispersion in risk is

[1] In the case of Treasury bonds, Chordia et al. (2005) and Goyenko and Ukhov (2009) find a positive correlation and bidirectional Granger causality. They conclude that the common driver is related to the role of monetary policy.

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adequately captured, allowing us to identify which types of bonds or firms are more likely to show a strong bond–stock liquidity relation, which is especially relevant for investment purposes.[2]

We work with a sample of 4,318 U.S. bonds issued by 1,001 different firms from July 2002 to December 2014. We compute the illiquidity measure for each bond and the corresponding stock following Nieto's (2018) proposal, an extension of Corwin and Schultz's (2012) transaction costs proxy.

We consider three complementary statistical strategies: time series regressions, Fama–MacBeth (1973) two-pass cross-sectional regressions, and panel data methods that account for error cross-sectional dependence. In all cases, we control for individual asset characteristics and different cycle indicators. Our results consistently confirm a positive linkage between the liquidity of corporate bonds and the liquidity of stocks issued by the same firm. This linkage appears to strengthen as bond volatility and maturity increase or as the bond rating category worsens. In addition, we find stronger stock–bond liquidity relations for firms in the consumption goods and high-tech industries. Our results also reveal the important connection between liquidity and risk in the corporate bond market. We find a positive and significant cross-sectional relation between bond illiquidity and its market beta, default beta, maturity, and rating. This reinforces the conclusion that accounting for illiquidity is crucial to price corporate bonds.

The remainder of the paper proceeds as follows. Section 2 describes our data. Section 3 shows the results of different statistical strategies when analyzing the relation between bond and stock illiquidity. Finally, Section 4 summarizes our main conclusions.

2. Data

We use intraday U.S. corporate bond transaction data from the Trade Reporting and Compliance Engine database from July 2002 to December 2014. The corresponding bond characteristics are from the Mergent Fixed Income Securities Database. We select non-perpetual bonds with fixed coupons with at least one year of active trading and that are traded on at least 75% of trading days. Our final sample

[2] Bai et al. (2019) confirm the importance of individual information in properly capturing risk and liquidity for corporate bonds.

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consists of 4,318 bonds from 1,001 issuers, with daily stock prices obtained from the Datastream database.

Our measure of illiquidity is based on Corwin and Schultz's (2012) transaction costs proxy. This measure has the advantage of being computed with low-frequency data (daily), and it is shown to be an accurate proxy not only for stocks, but also for corporate bonds (Schestag et al., 2016). Specifically, we use the generalization proposed by Nieto (2018) that improves the implementation for assets that do not trade continuously. The illiquidity is computed daily for each bond and stock in our sample. The monthly measures are then the average of the daily measures within the month.[3]

To control for other possible explanations of cross-sectional changes in illiquidity, we compute and include in the regressions different bond characteristics, namely, the return, volatility, maturity, rating, dollar trading volume, and betas regarding the three most common systematic risk factors in the corporate bond market (i.e., market, term, and default indexes). Additionally, we use the industry of the bond issuer and the dollar offering amount of the issuance.[4]

Since aggregate liquidity decreases dramatically during crises (Naes et al., 2011), we control for time series variation with a set of business cycle indicators, that is, the return and volatility for both the equity and corporate bond markets, the risk-neutral volatility and skewness of the stock market (i.e., *VIX* and *SKEW*, respectively), the term and default spreads, a proxy for funding liquidity (i.e., the spread between the three-month London Interbank Offered Rate based on U.S. dollars and the three-month Treasury bill), the growth rate of the industrial production index, and indicators of the monetary policy stance (i.e., the effective federal funds rate and the U.S. shadow rate).[5]

Given that our sample of individual bonds is not homogeneous in either the time dimension or cross-sectionally, we construct portfolios to be used as our final set of testing assets. At the end of each month, we sort the bonds in the basis of their different characteristics and group them into several

[3] The entire analysis in the next section has been also conducted using Corwin and Schultz's (2012) original proxy; the main results (available upon request) hold.

[4] We compute similar characteristics for each bond-corresponding stock. However, these variables are usually nonsignificant in the regression analysis; so we do not include their description or corresponding regression results.

[5] More details about the sample selection, illiquidity measure, and description and data sources of all the variables can be found in Section A of the Appendix.

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portfolios. After careful analysis of the dispersion in liquidity of the resulting portfolios, we select 29 portfolios based on the bonds' return (five), volatility (five), industry (five), maturity (seven), and rating (seven).[6]

3. Empirical analysis of the relation between corporate bond and stock illiquidity

3.1. Time series approach

We run single ordinary least squares (OLS) regressions of bond illiquidity (*SB*) on stock illiquidity (*SS*) for each of the 29 constructed portfolios. The direction of the relation is justified by the results of Toda and Yamamoto's (1995) modified Granger causality test: the null that *SS* (*SB*) does not cause *SB* (*SS*) cannot be rejected in 21% (50%) of the portfolios.[7]

As shown in Table 1, we find a positive and clearly significant slope and considerably large *R*-squared values for all the portfolios in the five sorts. The unique exception is the AAA portfolio. Since bonds in the best rating class are virtually risk free and given the association between liquidity and risk, this result is expected and consistent with flight to liquidity: when liquidity in the stock market is low, these bonds are an alternative for investors seeking liquid assets.

Comparing the slopes across portfolios within each sort, we find that the stock–bond illiquidity relation is monotonically stronger as bond volatility increases or when bonds have longer maturities. In addition, the slopes are the greatest for the worst rating portfolio, larger bond returns, and for bonds in the first industry portfolio (consumption goods firms).

Next, we reevaluate this time series relation, controlling for economic conditions, by a multiple regression that includes different combinations of cycle indicators as explanatory variables. The results (not tabulated here to save space, but available upon request) confirm the strong bond–stock liquidity relation. Other findings, although not consistent across all portfolios, are as follows. Bond liquidity

[6] Another reason for using portfolios instead of individual bonds as testing assets is to have a time dimension sufficiently long so that panel data models that account for possible cross-sectional dependence in errors can be estimated for each cross-sectional unit. This would not be the case for individual bonds with short expirations.

[7] In our panel data analysis, Dumitrescu and Hurlin's (2012) test consistently shows that the null that *SS* does not cause *SB* can be rejected, whereas the opposite is not the case.

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decreases when volatility is high in both the bond and stock markets. This result is consistent with spillover effects between volatility and illiquidity across markets (Chordia et al., 2005; Goyenko and Ukhov, 2009). In line with the results of Chordia et al. (2005) and Goyenko and Ukhov (2009), restrictive monetary policies produce a generalized decrease in individual bond liquidity.

3.2. Cross-sectional analysis

We employ the Fama–MacBeth (1973) methodology to evaluate the cross-sectional relation between *SB* and *SS*, controlling for asset characteristics. The results in Table 2 involve those combinations of controls that are consistently significant and produce the highest *R*-squared coefficients.[8]

Note that the stock–bond liquidity relation is again confirmed, regardless of the control variables included. Additionally, we find that bonds are less liquid the higher their risk: the larger the market or the default betas, the worse the rating class, and the longer the maturity.[9] Bonds from larger issues have higher liquidity, on average, and illiquidity and trading volume are inversely related, as expected.

3.3. Panel data approach

In this section, we analyze whether *SS* has a long-run effect on *SB*, controlling for bond characteristics and state variables, simultaneously. For this, we use the cross-sectionally augmented autoregressive distributed lag (CS-ARDL) approach proposed by Chudik et al. (2013) and Chudik and Pesaran (2015) to address the cross-sectional dependence in errors.[10] The CS-ARDL methodology can be used regardless of whether the variables in the model are I(1) or I(0), and it does not require the regressors to be exogenous. However, the estimates can be quite sensitive to the lag orders chosen. We therefore also apply a cross-sectionally augmented distributed lag (CS-DL) approach proposed by Chudik et al. (2013, 2016) that requires only the selection of a truncation lag order; in addition, this method is

[8] The results with other control combinations, including stock characteristics, are available upon request.
[9] Apart from term risk, the positive association between maturity and illiquidity is also explained by long-term bond investors' potential preference for cash flow from coupon payments and less frequent trading (Edwards et al., 2007).
[10] We initially estimated a panel autoregressive distributed lag model, and the Pesaran's (2015) test showed error cross-sectional dependence.

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robust to serial correlation in errors and possible breaks. A disadvantage, however, is this methodology would not be valid in the case of reverse causality.[11]

Panel A of Table 3 shows the mean group estimates from the CS-ARDL model for different combinations of control variables with three lags for the dependent variable and the regressors. The last column, which reports Pesaran's (2015) test results, indicates that the null hypothesis of no cross-sectional dependence in the errors cannot be rejected in any of the models. None of the control variables are consistently significant across the models. However, except for the third model, we find a positive and clearly significant long-run coefficient for stock illiquidity with a magnitude similar to those obtained in the cross-sectional regressions in Table 2.

Panel B of Table 3 shows the mean group estimates from the CS-DL methodology with a lag order of three.[12] Once again, stock illiquidity has a positive and significant long-run effect on corporate bond illiquidity in all the models. Additionally, the higher the systematic default risk, the greater the illiquidity of the bonds. Moreover, there is evidence that bonds with longer maturities and worse rating classifications tend to have higher illiquidity, as expected.

4. Conclusions and implications

Focusing on the liquidity of individual portfolios, instead of considering marketwide liquidity measures as previous papers do, our results show i) a clearly positive and consistent relation between the liquidity of corporate bonds and stocks issued by the same firm and ii) the importance of risk in understanding the flight to liquidity phenomenon. Shocks that increase company risk or worsen overall economic conditions will have a negative impact on the liquidity of firms' financial assets, reducing their market value. Our findings have relevant implications for firms' capital structure decisions. More precisely, two arguments support the connection between the liquidity of a firm's securities and its leverage: the cost of capital (the higher the asset liquidity, the lower the return required by investors)

[11] A more detailed description of these methods and their implementation is presented in Section B of the Appendix.

[12] As a robustness check, we also use lag orders of two, four, and five for both the CS-ARDL and CS-DL models. The results, available upon request, are quite similar. Generally, error cross-sectional dependence is better controlled for in the CS-DL specifications when considering $p = 4$ or $p = 5$. The estimates in Section 3.3 were obtained using Stata's xtdcce221 command, developed by Ditzen (2021).

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and/or the availability of funding (the lower the trading costs, the greater investors' incentives to participate in financial markets).

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Table 1. Time series relation between corporate bond and stock illiquidity

Sort	B1	B2	B3	B4	B5
Return	0.674	0.598	0.593	0.585	0.726
	(13.67)	(15.45)	(12.26)	(8.80)	(14.97)
	0.648	0.691	0.698	0.544	0.588
Volatility	0.414	0.587	0.614	0.614	0.680
	(5.49)	(12.82)	(13.29)	(16.82)	(13.99)
	0.559	0.713	0.728	0.738	0.684
Industry	0.821	0.521	0.803	0.648	0.506
	(11.34)	(9.61)	(9.80)	(8.71)	(13.62)
	0.722	0.747	0.838	0.579	0.705

Maturity	≤1	(1–3]	(3–5]	(5–7]	(7–10]	(10–20]	>20
	0.364	0.564	0.570	0.615	0.645	0.755	0.770
	(9.65)	(15.61)	(13.57)	(10.03)	(11.38)	(7.92)	(8.56)
	0.629	0.783	0.769	0.569	0.694	0.547	0.639
Rating	**AAA**	**AA**	**A**	**BBB**	**BB**	**B**	**C bel.**
	0.019	0.582	0.706	0.738	0.494	0.548	0.763
	(0.20)	(13.85)	(18.20)	(5.16)	(2.16)	(4.99)	(3.82)
	0.002	0.766	0.833	0.438	0.133	0.375	0.555

This table shows the results from the following time series OLS regression of bond illiquidity (*SB*) on stock illiquidity (*SS*) for each portfolio *j*:

$$SB_t^j = \alpha^j + \beta^j SS_t^j + u_t^j.$$

We estimate the illiquidity measure for each bond in our sample and for each corresponding stock issuer by using the transaction costs measure proposed by Corwin and Schultz (2012) and extended by Nieto (2018) to account for infrequent trading. At the end of each month, the bonds are sorted by the different characteristics shown in the first column and grouped into portfolios. For the sorts based on return and volatility, we use quintiles. The industry sort follows the distribution of the five industry portfolios provided in the data library of Kenneth French, namely, consumer goods, manufacturing, high tech, health, and other. The bonds are grouped into seven portfolios on the basis of maturity and rating. The illiquidity measure for each portfolio is the average of the illiquidity estimates for the individual bonds and stocks within the portfolio. For each portfolio, we display the slope estimate, the heteroscedasticity- and autocorrelation-adjusted *t*-statistics according to Newey and West (1987), in parentheses, and the *R*-squared statistic. The sample period is from July 2002 to December 2014.

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Table 2. Cross-sectional relation between corporate bond and stock illiquidity

Intercept	*SS*	β^{RB}	β^{TERM}	β^{DEF}	*Rat*	*Mat*	*Size*	*Volume*	R^2
0.125	0.327	0.561	-0.125	0.236					0.937
(3.01)	(7.14)	(6.13)	(-0.88)	(2.18)					
0.505	0.361	0.632	-0.177	0.159			-0.405		0.962
(12.54)	(10.16)	(8.19)	(-1.58)	(1.94)			(-18.12)		
0.519	0.370	0.655	-0.189	0.144			-0.393	-0.832	0.967
(12.36)	(10.13)	(8.39)	(-1.67)	(1.75)			(-12.92)	(-2.85)	
0.014	0.202	0.126			0.034	0.035			0.919
(0.44)	(6.15)	(1.70)			(14.05)	(15.46)			
0.411	0.322	0.230			0.013	0.031	-0.335	-0.858	0.956
(9.17)	(8.79)	(3.38)			(4.62)	(14.30)	(-9.14)	(-1.93)	
0.158	0.171	0.120	-0.065	0.194	0.014	0.025			0.958
(4.93)	(4.69)	(1.74)	(-0.65)	(2.70)	(3.80)	(13.62)			

This table shows the results from the following cross-sectional regression of bond illiquidity (*SB*) on stock illiquidity (*SS*) and different combinations of bond characteristics, namely, the market beta (β^{RB}), term beta (β^{TERM}), default beta (β^{DEF}), rating (*Rat*), maturity (*Mat*), offering amount at issuance (*Size*), and dollar trading volume (*Volume*):

$$SB_j = \lambda_0 + \lambda_1 SS_j + \lambda_2 \beta_j^{RB} + \lambda_3 \beta_j^{TERM} + \lambda_4 \beta_j^{DEF} + \lambda_5 Rat_j + \lambda_6 Mat_j + \lambda_7 Size_j + \lambda_8 Volume_j + \varepsilon_j.$$

The estimation follows the two-pass Fama–MacBeth (1973) approach and the betas are estimated monthly, using daily returns on the previous six-month rolling window. The test assets are 29 portfolios constructed monthly, sorting individual bonds by the following bond characteristics: the return (five), volatility (five), rating (seven), maturity (seven), and industry (five). We estimate the illiquidity measure for each bond in our sample and for each corresponding stock issuer by using the transaction costs measure proposed by Corwin and Schultz (2012) and extended by Nieto (2018) to account for infrequent trading. The illiquidity measures and the other portfolio characteristics are computed as the average of the individual variables within the portfolio. The *t*-statistics are in parentheses, and the last column reports the *R*-squared statistic. The sample period is from December 2002 to December 2014.

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Table 3. Long-run coefficients for the stock–bond illiquidity relation from a panel data approach

Panel A: CS-ARDL (mean group estimates)

SS	β^{RB}	β^{TERM}	β^{DEF}	Rat	Mat	Size	$Volume$	RMB	VMB	RMS	VIX	$SKEW$	$SHADOW$	FED	CD test
0.426	0.248	0.053	0.006			0.012	4.517	0.799		-0.234	-0.194	-0.905		0.199	-1.43
(3.79)	(1.71)	(1.27)	(0.19)			(0.05)	(3.82)	(1.02)		(-0.72)	(-0.69)	(-0.45)		(0.18)	[0.15]
0.283	0.104	0.038	-0.009			-0.027	5.288	0.461	-3.001	-0.033		-2.922	0.256		-0.80
(2.78)	(0.61)	(1.11)	(-0.25)			(-0.15)	(4.14)	(0.39)	(-1.10)	(-0.08)		(-0.77)	(0.48)		[0.42]
0.187	0.115	0.013	0.033					-1.429	1.278	-0.328		1.674	0.095		-1.26
(1.35)	(0.75)	(0.37)	(1.44)					(-1.08)	(0.43)	(-0.37)		(0.42)	(0.17)		[0.21]
0.243	0.108	0.008	0.026					-0.341		0.032	0.021	0.601		-0.038	-1.35
(2.95)	(0.76)	(0.22)	(1.01)					(-0.36)		(0.04)	(0.09)	(0.21)		(-0.07)	[0.18]
0.229	-0.030			0.058	0.051	-0.051	3.956	-0.035	-1.394	0.045		-0.620	2.655		-1.68
(2.79)	(-0.23)			(0.73)	(1.13)	(-0.30)	(2.13)	(-0.04)	(-0.29)	(0.16)		(-0.18)	(1.43)		[0.09]
0.343	0.150			0.026	0.115	0.175	2.242	-0.895		-0.075	-0.535	0.568		2.533	-1.51
(3.39)	(0.81)			(0.36)	(1.87)	(0.68)	(1.20)	(-1.13)		(-0.14)	(-1.44)	(0.32)		(1.61)	[0.13]
0.216			0.020	-0.115	0.069			-1.728	-3.387	-0.260		3.340	0.154		-0.11
(3.60)			(0.74)	(-1.06)	(2.52)			(-1.36)	(-0.70)	(-0.49)		(2.10)	(0.22)		[0.92]
0.151			0.027	-0.145	0.092			-1.192		-0.008	-0.000	3.170		-0.261	0.71
(2.43)			(1.22)	(-1.10)	(2.54)			(-1.30)		(-0.02)	(-0.00)	(1.03)		(-0.41)	[0.48]

Panel B: CS-DL (mean group estimates)

SS	β^{RB}	β^{TERM}	β^{DEF}	Rat	Mat	Size	$Volume$	RMB	VMB	RMS	VIX	$SKEW$	$SHADOW$	FED	CD test
0.347	0.109	0.019	0.069			-0.199	4.130	0.775		-0.293	-0.090	-0.386		0.293	2.29
(4.45)	(1.00)	(0.90)	(4.12)			(-1.62)	(4.85)	(1.30)		(-1.18)	(-0.48)	(-0.33)		(0.36)	[0.02]
0.274	0.059	0.008	0.073			-0.221	4.337	0.849	-0.777	-0.074		0.573	0.185		3.78
(3.43)	(0.55)	(0.37)	(3.93)			(-2.36)	(4.87)	(0.89)	(-0.44)	(-0.33)		(0.55)	(0.46)		[0.00]
0.257	0.017	0.010	0.076					0.495	2.718	-0.001		1.342	-0.124		1.71
(4.95)	(0.15)	(0.38)	(3.68)					(0.82)	(1.81)	(-0.00)		(1.00)	(-0.39)		[0.09]
0.227	0.061	0.010	0.077					0.677		0.018	0.075	-0.267		-0.283	1.31
(4.32)	(0.68)	(0.40)	(3.68)					(1.32)		(0.05)	(0.62)	(-0.17)		(-0.67)	[0.19]
0.192	-0.053			0.094	0.025	-0.174	3.468	0.094	0.770	-0.174		0.860	0.559		1.43
(3.22)	(-0.54)			(2.37)	(0.74)	(-1.50)	(3.14)	(0.15)	(0.32)	(-0.70)		(0.64)	(1.41)		[0.15]
0.197	-0.015			0.045	0.036	-0.180	3.329	-0.057		-0.138	-0.117	0.349		0.164	2.49
(3.78)	(-0.18)			(1.36)	(1.26)	(-1.61)	(3.17)	(-0.12)		(-0.55)	(-0.93)	(0.26)		(0.29)	[0.01]
0.180			0.050	0.032	0.044			-0.455	0.769	-0.197		1.569	-0.292		3.14
(3.19)			(2.97)	(1.54)	(2.66)			(-0.72)	(0.47)	(-0.89)		(1.44)	(-1.14)		[0.00]
0.164			0.056	0.019	0.063			-0.097		-0.127	-0.079	0.239		-0.521	3.43
(2.72)			(3.16)	(0.74)	(3.04)			(-0.19)		(-0.56)	(-0.80)	(0.23)		(-1.53)	[0.00]

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This table displays the panel estimation results of bond illiquidity (*SB*) on stock illiquidity (*SS*) and different combinations of bond characteristics and state variables. The bond characteristics are the market beta (β^{RB}), term beta (β^{TERM}), default beta (β^{DEF}), rating (*Rat*), maturity (*Mat*), offering amount at issuance (*Size*), and dollar trading volume (*Volume*). The three betas are estimated monthly using daily returns on the previous six-month rolling window. The state variables are the return on the equity market (*RMS*), the return on the corporate bond market (*RMB*), the volatility of the corporate bond index (*VMB*), the risk-neutral equity volatility and skewness (*VIX* and *SKEW*, respectively), the effective federal funds rate (*FED*), and the shadow rate (*SHADOW*). The sample period is from December 2002 to December 2014, and the cross-sectional dimension is a set of 28 portfolios constructed monthly by sorting individual bonds on the following bond characteristics: the return (five), volatility (five), rating (six), maturity (seven), and industry (five). We estimate the illiquidity measure for each bond in our sample and for each corresponding issuer stock by using the transaction costs measure proposed by Corwin and Schultz (2012) and extended by Nieto (2018) to account for infrequent trading. The illiquidity measures and other portfolio characteristics are computed as the average of the individual variables within the portfolio. The *t*-statistics are in parentheses. The last column reports the cross-sectional dependence (CD) test (Pesaran, 2015) for the null of weak cross-sectional dependence in errors, with the corresponding *p*-values in square brackets. Panel A shows the mean group estimators of the long-run coefficients in the CS-ARDL model (Chudik et al., 2013; Chudik and Pesaran, 2015)

$$y_{j,t} = \mu_j + \sum_{l=1}^{p_y} \delta_{j,l} y_{j,t-l} + \sum_{l=0}^{p_x} \varphi'_{j,l} x_{j,t-l} + \sum_{l=0}^{p_T} \gamma'_{j,l} \bar{Z}_{t-l} + e_{j,t},$$

where $\bar{Z}_t = (\bar{y}_t, \bar{x}_t)'$, $\bar{y}_t$ and $\bar{x}_t$ are the cross-sectional averages of the dependent variable and the regressors, respectively, p_T indicate the number of lags of these cross-sectional averages, $p_y = p_x = 3$, and, following Chudik et al. (2013), $p_T = \left[T^{\frac{1}{3}}\right] = 5$. Panel B reports the mean group estimators of the long-run coefficients in the CS-DL model (Chudik et al., 2013, 2016)

$$y_{j,t} = \mu_j + \varphi'_{j,l} x_{j,t} + \sum_{l=0}^{p-1} \theta'_{j,l} \Delta x_{j,t-l} + \gamma_{yj}\, \bar{y}_t + \sum_{l=0}^{p_T} \gamma'_{xj,l} \bar{x}_{t-l} + e_{j,t},$$

with $p = 3$, and $p_T = \left[T^{\frac{1}{3}}\right] = 5$.

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Appendix A: Data description and the illiquidity measure

A.1 Bond sample selection

The initial sample consists of intraday U.S. corporate bond transaction data from the Trade Reporting and Compliance Engine (TRACE) database and the corresponding bond characteristics from the Fixed Income Securities Database (FISD), all provided by Mergent, from July 2002 to December 2014. We apply the filters described by Dick-Nielsen (2009, 2014) to remove duplicates, corrections, and reversals, and a median filter with five standard deviations computed with a previous window of 90 natural days is used to eliminate extreme outliers and erroneous reports.[13] We select non-perpetual bonds with fixed coupons with FISD information. Any information on trades on holidays or days outside of the bond's life, defined by the offering and maturity dates available from FISD, is removed. Additionally, bonds in default are included only up to three months before the default date and after the reinstated date, if any. This approach provides a final sample of 89,654 bonds from 5,457 issuers. Panel A of Table A1 provides the mean, median, and standard deviation of some of the characteristics of this complete and clean database.

Given that this research focuses on liquidity, we impose the following liquidity requirements for a bond to be included in our analysis. Bonds must show at least one year of active trading and must be traded on at least 75% of the trading days. The application of these requirements generates a sample of 4,647 bonds. Finally, we dispense with the bonds of issuers for which stock information could not be matched. The final sample consists of 4,318 bonds from 1,001 issuers. Panel B of Table A1 presents the descriptive statistics of these selected bonds. These bonds are mostly issued by industrial firms and show considerably greater size (offering amount), higher average coupons, longer maturities, and worse rating classifications than the total population (Panel A). Of course, they are much more liquid in terms of trading activity.

To merge data on issuers in TRACE with the firm information from Datastream, we use the stock ticker, the issuer CUSIP number, and the issuer and parent names in TRACE. The matching process over time takes into account firm mergers, acquisitions, and changes in company names.

[13] After robustness checks, we find that this filter cleans better than alternative ones that use the mean instead of the median, different numbers of standard deviations, different window lengths, or the filter proposed by Rossi (2014).

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Table A1. Descriptive statistics of the corporate bond sample selection

Panel A: All TRACE data after filters for duplicates, cancelations, corrections, reversals, and outliers. Only market days and dates during the bond's life and until three months up to default are included.

No. Bonds: 89,654

No. Issuers: 5,457

Industry distribution:

Industrial	*Financial*	*Utilities*	*Government*	*Miscellaneous*
16.46%	56.09%	3.36%	23.95%	0.15%

	Mean	*Median*	*St. Dev.*
Time to maturity at issuance	9.769	5.247	14.964
Offering amount (millions of USD)	178.074	20	446.565
Coupon	3.643	3.54	2.972
Treasury spread at issuance	162.949	125	126.494
Rating (average in the bond's life)	5.397	5	4.220
Days with trades (%)	40.215	17.518	47.292
Average number of trades per day	4.113	2.560	11.555

Panel B: Selected bonds with the liquidity requirements of one year between the first and last transaction dates and trades on at least 75% of trading days.

No. Bonds: 4,318

No. Issuers: 1,001

Industry distribution:

Industrial	*Financial*	*Utilities*	*Government*	*Miscellaneous*
54.79%	39.28%	2.85%	2.66%	0.42%

	Mean	*Median*	*St. Dev.*
Time to maturity at issuance	10.303	9.462	8.357
Offering amount (millions of USD)	1,087.285	850.000	934.378
Coupon	5.050	5.200	2.195
Treasury spread at issuance	175.330	135.000	133.295
Rating (average in the bond's life)	6.805	6.000	3.590
Days with trades (%)	89.595	9G0.358	7.639
Average number of trades per day	10.862	7.643	9.977

This table reports the descriptive statistics of bond characteristics for the overall TRACE data set (Panel A) and the selected sample (Panel B). The sample period is from July 1, 2002, to December 31, 2014. The Treasury spread is the difference between the bond yield and the yield on Treasury securities with the same maturity. The Treasury yields for all possible maturities are obtained by interpolation. Days with trades refer to the percentage of days with at least one trade in the bond's trading life span.

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A.2 Illiquidity measure

The proxy for transaction costs proposed by Corwin and Schultz (2012) has the advantage of being easy to compute and only employing high (H) and low (L) daily prices. The main idea of the model from which the measure is derived is that the high–low price ratio incorporates two components: the price volatility and the bid–ask spread. The volatility is proportional to the data frequency, whereas the spread is not. Therefore, working simultaneously with two frequencies (one and two days) allows us to identify (and estimate) these two components.

However, the empirical application of this estimator has the problem of requiring the assets to trade continuously on all days and at least twice a day (so that different high and low prices are available). This is not the case for some assets. The authors therefore adopt the following practical solution. For those days when an asset shows only one trade, they propose an adjustment that allows the generation of different high and low prices, and, for cases of no trades during a day, the high and low prices are assumed to be the same as those observed in the most recent prior trading day. The problem is that this assumption imposes zero volatility and overestimates the spread for days without trades.

The adjustment proposed by Nieto (2018) avoids this problem by generalizing the model to the case in which two trades can occur with a gap of n days between them. The resulting spread (S) estimator is

$$ln\left[(2+\hat{S}_t^*)/(2-\hat{S}_t^*)\right] = \frac{\sqrt{n\beta^*}-\sqrt{\beta^*}}{n+1-2\sqrt{n}} - \sqrt{\frac{\gamma^*}{n+1-2\sqrt{n}}},$$

with $\beta^* = \left[ln\left(\frac{H_{t-n-1}}{L_{t-n-1}}\right)\right]^2 + \left[ln\left(\frac{H_t}{L_t}\right)\right]^2$ and $\gamma^* = \left[ln\left(\frac{H_{t-n-1,t}}{L_{t-n-1,t}}\right)\right]^2$.

We employ this adjusted spread estimator to compute daily the illiquidity measure for each bond and its corresponding stock in our sample.[14] Table A2 displays the descriptive statistics of these measures for the sets of bonds and stocks separately. Each day we compute the cross-sectional mean and median of the spreads for all the bonds and stocks. The descriptive statistics refer to these two aggregate time series. We report the mean, standard deviation, minimum,

[14] We discard negative daily spread estimates. Nieto (2018) shows that the adjusted estimator performs better in both a time series and cross-sectional framework when negative spreads are removed instead of being set to zero.

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maximum, and three quartiles of their distributions. As expected, the estimated transaction costs are larger for stocks than for bonds. The average spread for all bonds (stocks) and over time is 0.79% (1.39%). Also as expected is the result that the average spread shows higher time series volatility for the stock market than for the bond market. However, although the range between the minimum and maximum is much greater for stocks, the amplitude of the interquartile range is similar for the two asset classes.

Table A2. Descriptive statistics of illiquidity measures

	Mean	*St. Dev.*	*Min*	*Max*	*Q0.25*	*Q0.5*	*Q0.75*
Bonds							
Mean	0.7926	0.5686	0.0125	4.2473	0.3782	0.6448	1.0521
Median	0.5275	0.5140	0.0000	4.0651	0.1788	0.3421	0.6882
Stocks							
Mean	1.3930	1.6000	0.2239	28.6219	0.8910	1.1436	1.4315
Median	1.0157	0.8319	0.1590	16.4920	0.7066	0.8615	1.1250

This table reports the descriptive statistics of the illiquidity measure for individual bonds and stocks issued by the same firm. The illiquidity measure is the transaction costs estimator proposed by Corwin and Schultz (2012) and extended by Nieto (2018) to account for infrequent trading. We compute the cross-sectional mean and median across bonds, on the one hand, and across stocks, on the other hand. The table shows the descriptive statistics for these series, and *Q0.25*, *Q0.*5, and *Q0.75* refer to the first three quartiles of the distribution.

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A.3 Bond characteristics and portfolio construction

The variables in Table A3 are computed for each bond at the end of each month in our sample. In addition, the returns are computed daily.

Table A3. Bond characteristics description

VARIABLE	DESCRIPTION
Return	Computed using the trading volume–weighted average of intraday prices and including the accrued interest and the coupon.[15]
Volatility	Standard deviation of daily returns within the last three months.
Dollar trading volume	Computed by accumulating all the trades within the month.
Dollar offering amount	Offering amount at issuance.
Maturity	Number of days until the bond maturity date.
Rating	Calculated from the historical rating information available from FISD. The historical rating values range from 1 for the AAA category to 28 for defaulted bonds.
Market, term, and default betas	Bond betas are computed monthly using daily bond returns in the window of the last six months, with a minimum of 50 observations required. We use the bond market index and the term and default spreads described in the cycle indicators subsection.
Industry	We use the SIC code to identify the industry of the bond issuer.

With the above information, we construct our portfolios as follows. At the end of each month in our sample, we sort individual bonds according to their characteristics and distribute them into portfolios. For the sorts based on the bond return, volatility, size, volume, and betas, we employ the 20th, 40th, 60th, and 80th percentiles to split the bonds, constructing five portfolios for each bond. We form seven portfolios based on maturity with breakpoints of one, three, five, seven, 10, and 20 years. The distribution of bonds by rating also produces seven different portfolios, following the standard classification AAA, AA, A, BBB, BB, B, and C or below. The correspondence between the historical rating values and the seven rating categories is as follows: ≤1, [2, 5), [5, 8), [8. 11), [11, 14), [14, 17), and ≥17. We also obtain five portfolios by sorting our bonds by industry, following the distribution for the five industry portfolios provided in the data library of Kenneth French (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).

[15] The weighted price would reflect more accurately the underlying price than the last price in the case of large execution costs affecting the last specific trade (Bessembinder et al., 2009).

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A.4 Cycle indicators

We consider the variables in Table A4 as cycle indicators or predictors at a monthly frequency.

Table A4. Cycle indicators description

VARIABLE	DESCRIPTION	DATA SOURCE
Bond market return	FRED's ICE BofA US Corporate Total Return.	Federal Reserve Bank of St. Louis' Federal Reserve Economic Data (FRED) database (https://fred.stlouisfed.org)
Stock market return	Value-weighted return of all CRSP firms incorporated in the United States and listed on the NYSE, AMEX, or NASDAQ that have a CRSP share code of 10 or 11.	Kenneth French's data library (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html)
Bond and stock market volatility	Standard deviation of daily bond or stock market returns, respectively.	
Risk-neutral volatility (VIX)	Estimated from options prices on the Standard & Poor's (S&P) 500 index with 1 month to expiration. Out-of-the-money put options are especially relevant, since options are weighted by the inverse of the squared strikes over a wide range of exercise prices.	Chicago Board Options Exchange (www.cboe.com)
Risk-neutral skewness (SKEW)	Estimated from options prices on the S&P's 500 index with 1 month to expiration. The *SKEW* index is a function of the relative demand of puts out-of-the-money with respect to at-the-money options, and it captures the perception of tail risk in the market: the higher *SKEW* is, the greater the probability of a big drop in the stock market. In both cases, we use the data from the last day of each month.	Chicago Board Options Exchange (www.cboe.com)
Term spread	Difference between the yield on the 10-year government bond and the 3-month Treasury bill rate.	FRED Database (https://fred.stlouisfed.org)
Default spread	Difference between Moody's yield on Baa corporate bonds and the 10-year government bond yield.	FRED Database (https://fred.stlouisfed.org)
Funding liquidity	Difference between the 3-month LIBOR based on U.S. dollars and the 3-month Treasury bill.	FRED Database (https://fred.stlouisfed.org)
Effective FED funds rate	Volume-weighted average of the borrowing and lending rates across banks using federal funds.	FRED Database (https://fred.stlouisfed.org)
Shadow rate	Estimated by Krippner (2015) and interpreted as an "unobservable policy rate" that captures the effects of the unconventional monetary measures implemented by the Federal Reserve. As a result, it is allowed to be negative and reflects the true stance of monetary policy better than the federal funds rate when this is restricted by the zero lower bound.	Reserve Bank of New Zealand (rbnz.govt.nz)
Economic growth	Growth rate of the industrial production index.	FRED Database (https://fred.stlouisfed.org)

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Appendix B: Panel data methodologies

The autoregressive distributed lag (ARDL) methodology has the advantage that it can be used regardless of whether the variables involved in the model are I(1) or I(0). In addition, it does not require the regressors to be exogenous (Chudik et al., 2016). This could be especially relevant in our case, since, if we do not want to rule out the possibility that corporate bond illiquidity could affect some regressors, we need to address this possible reverse causation.

An ARDL (p_y, p_x) model can be written as

$$y_{j,t} = \mu_j + \sum_{l=1}^{p_y} \delta_{j,l} y_{j,t-l} + \sum_{l=0}^{p_x} \varphi'_{j,l} x_{j,t-l} + e_{j,t},$$

where $y_{j,t}$ is the dependent variable (in our case, the bond illiquidity of portfolio *j* in month *t*), $x_{j,t}$ is a vector of the explanatory variables, and p_y and p_x are their lag orders, respectively. The long-run coefficients of the explanatory variables can be obtained as:

$$\widehat{\vartheta_J} = \frac{\sum_{l=0}^{p_x} \widehat{\varphi_{J,l}}}{1-\sum_{l=1}^{p_y} \widehat{\delta_{J,l}}}.$$

To allow these slope coefficients to vary across portfolios, we use the mean group estimator. Note, however, that for mean group estimators to be consistent, the errors $e_{j,t}$ must be cross-sectionally independent (Pesaran and Smith, 1995). This is a very strong requirement for many financial and macroeconomic series. In our case, if there were unobserved common factors, such as an aggregate demand or supply shock (Chudik and Pesaran, 2015a), that affected both the bond illiquidity and the regressors (e.g., stock illiquidity) of the different portfolios at the same time, this requirement would not be fulfilled. In addition, if these factors were correlated to the regressors, the estimators would be biased.

When we initially estimated the panel ARDL models, we found that, according to the cross-sectional dependence test developed by Pesaran (2015), the null hypothesis that errors are cross-sectionally independent (or, strictly speaking, the null of weak cross-sectional dependence) was strongly rejected in all ARDL specifications considered. To address this problem, we decided to use factor-augmented regressions in which the proxies for unobserved common factors are included as additional regressors.

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The cross-sectionally augmented ARDL (CS-ARDL), proposed by Chudik et al. (2013) and Chudik and Pesaran (2015b), consists of augmenting the ARDL model with cross-sectional averages of the dependent variable, the regressors, and their lags.[16] The CS-ARDL estimator is based on the regression

$$y_{j,t} = \mu_j + \sum_{l=1}^{p_y} \delta_{j,l} y_{j,t-l} + \sum_{l=0}^{p_x} \varphi'_{j,l} x_{j,t-l} + \sum_{l=0}^{p_T} \gamma'_{j,l} \bar{Z}_{t-l} + e_{j,t},$$

where $\bar{Z}_t = (\bar{y}_t, \bar{x}_t)'$ and p_T indicates the number of lags of these cross-sectional averages. The sample period covers from December 2002 to December 2014 (i.e., $t = 1, \dots, T$, with $T = 145$) and the cross-sectional dimension is $N = 28$ portfolios (i.e., $j = 1, \dots, 28$). Since the portfolio comprising the lowest-rated bonds (category 7) had many missing values, we merged categories 6 and 7; so, we have 28 portfolios instead of the 29 used in Sections 3.1 and 3.2. We report the results for $p_y = p_x = 3$.[17] We use the same lag order for all the variables and portfolios, because this helps reduce the undesired effects of data mining that would emerge if information criteria were used to select each of the lag orders (Chudik et al., 2013). In addition, we find that the use of three lags is enough to capture the persistence in the illiquidity measures. Following Chudik et al. (2013), $p_T = \left[T^{\frac{1}{3}}\right] = 5$.

A drawback of both the ARDL and CS-ARDL approaches is that the estimates can be quite sensitive to the chosen lag order. The cross-sectionally augmented distributed lag (CS-DL) methodology proposed by Chudik et al. (2013, 2016) overcomes this drawback by requiring only the selection of a truncation lag order p. The CS-DL estimator is based on

$$y_{j,t} = \mu_j + \varphi'_{j,l} x_{j,t} + \sum_{l=0}^{p-1} \theta'_{j,l} \Delta x_{j,t-l} + \gamma_{yj}\, \bar{y}_t + \sum_{l=0}^{p_T} \gamma'_{xj,l} \bar{x}_{t-l} + e_{j,t},$$

where $\bar{y}_t$ and $\overline{x_t}$ are the cross-sectional averages of the dependent variable and the regressors, respectively.[18] As in the CS-ARDL model, by using these averages, this method accounts for error cross-sectional dependence. In addition, it is robust to serial correlation in errors and possible

[16] Another popular approach to overcome the cross-sectional dependence is the use of principal components to proxy for common factors (e.g., Greenaway-McGrevy et al., 2012). Evidence shown by Chudik et al. (2011) seems to indicate that estimators based on cross-sectional averages perform best.

[17] We also use $p_y = p_x = 2$,4, and 5 , and the results, available upon request, are quite similar.

[18] Note that the cross-sectional averages of the variables common to all the portfolios (e.g., *FED*) have not been included in either the CS-ARDL or CS-DL estimations, because, otherwise, they would obviously exhibit collinearity with these observed common factors.

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breaks (Chudik et al., 2013). In contrast, the CS-DL approach, unlike the CS-ARDL approach, is not valid in the case of reverse causality. The estimated long-run coefficients would not be consistent if, for instance, the lagged value of bond illiquidity affected stock illiquidity. In short, the CS-DL estimator addresses certain econometric issues not addressed by the CS-ARDL estimator, and vice versa. For practical application purposes, Chudik et al. (2013) recommend using both methods to check the robustness of the results. We report the mean group estimates from the CS-DL model for p=3 and $p_T = \left[T^{\frac{1}{3}}\right] = 5.$ When using p = 2, 4, and 5 the main results remain the same.

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