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Dynamic effects of idiosyncratic volatility and liquidity on corporate bond spreads



Madhu Kalimipalli*, Subhankar Nayak¹, M. Fabricio Perez²

School of Business & Economics, Wilfrid Laurier University, Waterloo, Canada N2L 3C5

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ABSTRACT

We study the dynamic impact of idiosyncratic volatility and bond liquidity on corporate bond spreads *over time* and empirically disentangle both effects. Using an extensive data set, we find that *both* idiosyncratic volatility and liquidity are critical mainly for the distress portfolios, i.e., low-rated and short-term bonds; for others only volatility matters. The effects of volatility and liquidity shocks on bond spreads were both exacerbated during the recent financial crisis. Liquidity shocks are quickly absorbed into bonds prices; however, volatility shocks are more persistent and have a long-term effect. Our results overall suggest significant differences between how volatility and liquidity dynamically impact bond spreads.

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1. Introduction

Does idiosyncratic risk contain information about liquidity in explaining the time-series of corporate bond prices? We examine this question by studying the relative importance of idiosyncratic volatility and liquidity for corporate bond yield spreads *over time* and empirically disentangling both effects.

Idiosyncratic equity volatility (idiosyncratic volatility, hereafter) can be defined as the residual firm volatility after controlling for systematic market risk factors. Theoretically, an increase in idiosyncratic volatility, following a lower stock price, leads to lower "distance-to-default" or higher default intensity of a firm and hence higher ex-ante bond spreads (Merton, 1974³; Das and Sundaram, 2007). This theoretical result is empirically confirmed by Campbell and Taksler (2003), who find that idiosyncratic volatility is a significant driver of bond spreads, after controlling for several bond characteristics.

Motivated by the fact that the secondary market for corporate debt remains highly illiquid (e.g., Henderson et al., 2006; Edwards et al., 2007), several studies find that incorporating non-default

sources of risk such as illiquidity can help address pricing biases in the structural models and explain the "credit puzzle" (e.g., Huang and Huang, 2003; Driessen, 2005; and Covitz and Downing, 2007). Further, Kalimipalli and Nayak (2012) document the importance of controlling for both idiosyncratic volatility and liquidity, and disentangle their relative effects using cross-sectional bond spreads.

In this paper, we explore the differential effects of idiosyncratic volatility and liquidity on bond spread changes over time and study their dynamic relationships. While most previous papers exclusively focus on *either* volatility or liquidity variables, we emphasize the *joint impact* of both variables in the dynamics of bond pricing. In addition, we employ a "ground-up" approach, for which we utilize an extensive sample of individual bond trades to construct aggregate bond portfolios and corresponding equity indices of interest. Specifically, our sample includes over 200,000 secondary trades of option-free corporate bonds issued by 836 firms over the 17-year period, 1994 through 2010. Our work therefore provides a comprehensive study of the volatility and liquidity effects on bond spreads, employing an extensive panel data of corporate bonds and exhaustive list of volatility and liquidity variables.⁵

^{*} Corresponding author. Tel.: +1 519 884 0710x2187.

E-mail addresses: mkalimipalli@wlu.ca (M. Kalimipalli), snayak@wlu.ca (S. Nayak), mperez@wlu.ca (M.F. Perez).

¹ Tel.: +1 519 884 0710x2206.

² Tel.: +1 519 884 0710x2532.

³ Following Campbell and Taksler (2003), we use idiosyncratic stock volatility as a proxy for total firm or asset volatility.

⁴ Lack of liquidity leads to increased hedging risk and thereby higher liquidity risk premiums, causing bond spreads to go up (Lo et al., 2004).

 $^{^5}$ For example, Longstaff et al. (2005) employ bond data for 68 U.S. firms from 03/2001 to 10/2002; Driessen (2005) considers 104 U.S. firms for 02/1991 to 02/2000 and Chen et al. (2007) use 4,000 U.S. corporate bonds during 1995-2003.

Our paper extends Kalimipalli and Nayak (2012) by studying how the relationships among bond spread, idiosyncratic volatility and liquidity evolve over time. We condition such dynamic effects on the underlying regimes that are identified using a regime-switching approach. We analyze the short- and long-term effects of credit, liquidity and idiosyncratic volatility shocks on corporate bond markets using impulse reaction functions and further study information shares of volatility and liquidity variables using the variance-decompositions of spreads. We also extend the Kalimipalli and Nayak (2012) sample period until 2010 and analyze the implications of the recent financial crisis.⁶

Overall, six key findings emerge from our study that are robust to a variety of tests. *First*, both idiosyncratic volatility and liquidity effects jointly and significantly matter only for the distress portfolios, i.e., low-rated and short-term bonds; for other portfolios, only volatility matters. The effect of 1σ volatility (bond illiquidity) shock on monthly aggregate bond spreads is 16 basis points, or bps, (3 bps), which increases to 23 bps (6 bps) for low-rated bonds. In general, the volatility has a first order-impact on bond spreads compared to bond illiquidity; however, the liquidity effect significantly matters while pricing distressed bonds. Principal component tests show that the idiosyncratic volatility and illiquidity variables mainly capture idiosyncratic or portfolio-specific information and not the systematic variation that can address the Collin-Dufresne et al. (2001) puzzle.

Second, there is a differential impact of volatility and liquidity on bond spreads, conditional on the underlying economic regime. Both volatility and illiquidity effects are pronounced mainly in the high mean–variance regimes; thus, investors may be pricing default and liquidity risks differentially conditioned on the latent regime. Third, Granger-causality tests show that lagged volatility and illiquidity forecast bond spreads for distress portfolios. Past changes in spreads or volatility, however, do not Granger-cause bond illiquidity.

Fourth, impulse response analysis shows that there is a differential impact between how volatility and liquidity shocks influence bond spreads. While the liquidity shocks are quickly absorbed into bonds prices, volatility shocks are more persistent and have an unequivocal long-term effect. Fifth, variance decomposition tests show that liquidity can explain a significant residual variance for the short-term portfolios, and that effect is concentrated in the high-spread, high-volatility, or high-illiquidity regime. Volatility, however, has the dominant explanatory power for all the portfolios in both regimes and under different orderings. Finally, the financial crisis of 2008–2010 significantly amplifies the impact of 1σ shocks in volatility and liquidity on bond spreads. Including the crisis period, a 1σ volatility (illiquidity) shock results in a 30 bps (19 bps) increase on monthly aggregate bond spreads and 54 bps (26 bps) for low-rated bonds. While both volatility and liquidity shocks now have a larger and more persistent effect on bond prices, the former effects clearly dominate in the long run.

Collectively, our results imply that idiosyncratic volatility does not eliminate a liquidity effect in explaining bond prices for distress portfolios, in contrast to the equity market findings (Spiegel and Wang, 2005). While volatility has a significant effect on bond spreads, liquidity has a non-trivial effect, especially for distress portfolios and during distress regimes. Our results, therefore, suggest that volatility and liquidity effects together are important for bond pricing and can have differential short- and long-run impacts

on bond spreads conditioned on the underlying portfolios and economic regimes.

The paper proceeds as follows. Section 2 discusses the background literature. Section 3 describes the data, alternative variables, and construction of bond portfolios. Section 4 presents time-series portfolio regressions. Section 5 reports the dynamic relationships among the key variables of interest. Section 6 conducts variance decomposition tests, and, finally, Section 7 concludes.

2. Background and related literature

Our paper is related to the previous literature that examines the role of either equity volatility or bond liquidity in corporate bond spreads. Equity volatility studies include Campbell and Taksler (2003) and Cremers et al. (2008a,b), who, respectively, document the significant role of historical and option implied equity volatility in determining corporate bond spreads. Alexander and Kaeck (2008) and Zhang et al. (2009) further explore the role of stock volatility for credit default swap spreads. Studies on corporate bond liquidity include Chen et al. (2007) and Houweling et al. (2005), who examine the impact of liquidity proxies on bond spreads, and Mahanti et al. (2008), who develop an aggregate bond liquidity measure based on the custodian bank's turnover.^{7,8}

Our work is also related to recent literature on disentangling yield spreads into credit and liquidity risks (e.g., Longstaff et al., 2005; Driessen, 2005; Covitz and Downing, 2007; Beber et al., 2009; and Schwartz, 2010)⁹ and measuring the relative information content of volatility and liquidity risks in equity returns (e.g., Bali et al., 2005; Boehme et al., 2006; and Spiegel and Wang, 2005).

Our work has bearings on the previous corporate bond spread studies (e.g., Collin-Dufresne et al., 2001; Avramov et al., 2007; Van Landschoot, 2008; Güntay and Hackbarth, 2010; Chen et al., 2011).¹⁰

Finally, our paper is broadly related to the literature on information linkages between stock and corporate bond markets:

- (i) As bonds and stocks are joint claims on the underlying firm's assets, firm-specific information shocks affect the joint dynamics of returns, volatility and liquidity. Previous literature has examined the relative informational efficiency of stock and bond markets (Kwan, 1996; Hotchkiss and Ronnen, 2002; Downing et al., 2009) and associated momentum spillovers (Gebhardt et al., 2005b). Corporate news events such as mergers, takeovers, new debt issues and/or stock repurchases involving wealth transfer to equity holders can further induce linkages between bonds and underlying stocks (Alexander et al., 2000a; Maxwell and Stephens, 2003).
- (ii) According to the microstructure theory, an increase in volatility of underlying security returns implies higher bid-ask spreads because of higher inventory rebalancing costs,

⁶ Moreover we use idiosyncratic volatility in our tests, unlike Chen et al. (2007), who use total stock volatility (that aggregates both idiosyncratic and systematic components), which may have an ambiguous effect on bond spreads. As Campbell et al. (2001) demonstrate, idiosyncratic and systematic stock volatilities demonstrate very different long-term time-series properties.

 $^{^7}$ Other bond liquidity studies include Alexander et al. (2000b), Hong and Warga (2000), Buraschia and Menini (2002), Kalimipalli and Warga (2002), Longstaff et al. (2005), Bessembinder et al. (2006), Edwards et al. (2007), Bao and Pan (2008), Jankowitsch et al. (2011), Das and Hanouna (2009) and Kalimipalli and Nayak (2012).

⁸ Extant literature has mainly examined the information linkages between equity and Treasury bond markets. They include Fleming et al. (1998), Chordia et al. (2005), Bansal et al. (2009), Connolly et al. (2005, 2007), Underwood (2009) and Goyenko and Ukhov (2009).

⁹ Extant work also examines liquidity and credit risk decomposition in the interest rate swap and CDS markets (e.g., Liu et al., 2006; Tang and Yan, 2010; Das and Hanouna, 2009; Ericsson et al., 2009).

¹⁰ Other corporate bond pricing studies include Gebhardt et al. (2005a), Gilchrist et al. (2009), and Krishnan et al. (2010).

and/or greater adverse selection risks, due to the increased possibility of trading with informed traders, for risk-averse dealers. This in turn leads to lower liquidity due to higher transaction costs and higher volatility because of higher bid-ask bounce (McInish and Wood, 1992; O'Hara, 2003). If unexpected firm-specific news shocks impact both stocks and bonds, then corresponding volatility and liquidity variables are likely to be strongly correlated.

- (iii) When there is a high divergence of opinion about the true value of a financial asset, the speculative component of volume tends to be high, and liquidity tends to be low since large movements in security prices are needed to absorb changes in trading volume (Harris and Raviv, 1993; Kandel and Pearson, 1995; Bamber et al., 1999). Therefore, during firm-specific news or shock events, when there exists a large disagreement about the intrinsic value of a firm, idiosyncratic volatility goes up and liquidity drops, affecting the required rates of returns for both stocks and bonds.
- (iv) Events that lead to high idiosyncratic volatility and hence credit risk, for a given firm, also typically lead to high liquidity risk (Ericsson and Renault, 2006). When idiosyncratic volatility goes up, impending credit concerns, and resulting flights to quality and liquidity, can drive up credit and liquidity spreads.
- (v) Active capital structure arbitrage strategies implemented by hedge funds can reinforce the news spillovers between equity and debt markets and imply long-term co-movements of underlying stocks and bonds (Duarte et al., 2005; Yu, 2006).
- (vi) Joint liquidity and volatility shocks can endogenously result from margin spirals arising from funding problems for financial firms (Brunnermeier and Pedersen, 2009; Brunnermeier, 2009).

We differ from the previous studies by focusing on the relative contribution of volatility and liquidity on the bond spread dynamics. We next describe in detail the construction of relevant stock and bond variables and corresponding portfolios and their timeseries properties.

3. Data, variables, descriptive statistics and time-series properties

3.1. Corporate bond trades

We use a sample of corporate bonds that covers a 17-year period from 1994 through 2010 and comes from two complementary sources: the Mergent Fixed Investment Securities Database (FISD) issuance data and the National Association of Insurance Commissioners (NAIC) pricing database. ¹¹ Our final sample consists of 204,270 buy and sell bond trades by insurance companies for 3119 straight bonds issued by 836 publicly listed companies spanning 204 months over the 17-year period from 1994 through 2010 (the sample selection procedure is detailed in Appendix A).

Table 1 reports the number of bond trades and average yield spreads for different sub-samples based on industry, rating, maturity and time period criteria. Panel A shows that the majority of the total 204,270 bond transactions correspond to Industrial, short-term maturity (1–7 years), and A-rated bonds. On average, Industrial firms have the highest cost of borrowing, closely followed by Utilities; Financials have the lowest spreads. The high-tech bub-

ble period (1994-1999) was followed by economic recession (2000–2004) in the United States, which then witnessed a significant decline in bond trades and about a threefold rise in average spreads (from 0.55% to 1.63%). The subsequent bull-phase of the economy (2005-2007) was characterized by a considerable drop in spreads (from 1.63% to 0.92%). This was is followed by the financial-crisis sub-sample (2008-2010), when bond trades fell significantly (over 40%) and average spreads went up fivefold compared to the pre-crisis period. Panel B indicates that the term-structure of yield spreads is upward sloping during the boom periods (1994-1999 and 2005-2007), but becomes U-shaped (2000-2004) or downward sloping (2008-2010) during the financial crisis as markets perceived high short-term default risks in the corporates. Trades in Industrial and Utility bonds are mostly in A or BBB rated issues, while trades for the Financial sector are largely in A rated issues. Financial firms experience the greatest increase in spreads during the 2008–2010 crisis for all rating categories. implying heightened credit risk for all financial issuers. Overall, the financial crisis impacted borrowing costs for all rating categories, including the AA rated issuers.

3.2. Volatility and liquidity proxies

Based on the current literature, we employ four different volatility and liquidity measures. Table 2 defines the volatility and liquidity variables used in our study.

3.2.1. Volatility measures

The four equity volatility measures include daily and monthly idiosyncratic volatility measures based on Fama–French 3- and 4-factor models. Specifically, we compute the idiosyncratic volatility, *IV*, of any stock *i* as the variance of the residuals in the 3-factor or 4-factor Fama and French (1993) models applied to a 125-day or 6-month period returns preceding a bond trade:

$$IV_i = \text{variance}_{125-\text{day}}(\varepsilon_{i,t}) \quad or \quad \text{variance}_{6-\text{month}}(\varepsilon_{i,t})$$
 (1)

where $\forall i$ and i, $\varepsilon_{i,t}$ is obtained as residuals from either of the following models:

3-factor model:
$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{i,MKT}(r_{MKT,t} - r_{f,t}) + \beta_{i,SMB}(SMB_t) + \beta_{i,HML}(HML_t) + \varepsilon_{i,t}$$

4-factor model: $r_{i,t} - r_{f,t} = \alpha_i + \beta_{i,MKT}(r_{MKT,t} - r_{f,t}) + \beta_{i,SMB}(SMB_t) + \beta_{i,HML}(HML_t) + \beta_{i,MOM}(MOM_t) + \varepsilon_{i,t}$

where t is the date of a bond trade, $r_{i,t}$ is the return of stock i on date t, $r_{MKT,t}$ and $r_{f,t}$ are the market (CRSP value-weighted index) and risk-free (30-day Treasury Bill) returns on date t, SMB_t , HML_t and MOM_t are the returns on small minus big capitalization factor, high minus low book-to-market equity value factor and momentum factor, respectively, on date t, ε is the regression residual and variance denotes the 125-day or 6-month variance. Daily (monthly) return volatility variables are annualized by scaling with 252 (12). All volatility variables are winsorized at the 1% level. Though the results below are based on 3-factor daily idiosyncratic volatility, qualitatively similar results were found using any of the other volatility measures.

3.2.2. Liquidity measures

Bonds do not trade frequently, and hence returns on a daily basis may not be available during a given monthly time window. For example, in our NAIC bond sample, which consists of bond trades of insurance companies, the median number of transactions for a bond is 18 per year (i.e., one trade every 20 calendar days or, equivalently, once every 14 trading days). With such sparse trading and large gaps between successive trades in the NAIC database, high

¹¹ Previous studies that have used the NAIC database include Schultz (2001), Hong and Warga (2000), Campbell and Taksler (2003), Bessembinder et al. (2006) and Kalimipalli and Nayak (2012).

Table 1 Summary statistics of bonds underlying bond portfolios (1994–2010).

| | By | industry | | | | Ву і | ating | | | | | | Total |
|--------------------------------------|-------------|-------------|--------------|---------------|---------------|---------------|----------------|-----------------|------------|--------|-------|------------|--------|
| | FI | N | IND | | UTL | AA | | Α | | BBB | ≼BB | | |
| Panel A: Number | of bond tra | des and bor | nd spreads b | y industry, r | ating and ma | turity catego | ories, for dij | fferent sub-sa | mple perio | ods | | | |
| By maturity | | | - | | _ | | | - | | | | | |
| Long-term | 54 | 151 | 23,92 | 0 | 1832 | 311 | 3 | 14,914 | | 10,440 | 273 | õ | 31,203 |
| >15 years | 1. | 19 | 1.53 | | 1.51 | 0.68 | 3 | 0.89 | | 1.64 | 4.83 | | 1.47 |
| Medium-term | 24 | 1,035 | 31,11 | 9 | 5395 | 734 | 1 | 31,177 | | 16,727 | 530 | 4 | 60,549 |
| 7-15 years | 0.0 | | 1.06 | | 0.76 | 0.29 |) | 0.53 | | 0.97 | 3.51 | | 0.88 |
| Short-term | | 5,934 | 54,36 | 7 | 11,217 | 12,5 | | 57,866 | | 31,527 | 10,5 | | 112,51 |
| 1–7 years | 0.3 | | 1.49 | | 1.47 | 0.34 | | 0.55 | | 1.26 | 5.91 | | 1.23 |
| By time period | | | | | | | | | | | | | |
| 1994–1999 | 36 | 5,827 | 54,14 | 3 | 10,774 | 12,6 | 696 | 51,416 | | 31,290 | 6342 | 2 | 101,74 |
| | 0.4 | 47 | 0.62 | | 0.46 | 0.20 |) | 0.37 | | 0.70 | 1.99 | | 0.55 |
| 2000-2004 | 30 | ,315 | 43,22 | 7 | 6413 | 781 | 3 | 41,384 | | 22,064 | 8694 | 4 | 79,95 |
| | 0.3 | | 2.05 | | 2.54 | 0.43 | | 0.73 | | 1.84 | 6.49 | | 1.63 |
| 2005-2007 | | 817 | 7512 | | 840 | 153 | | 7178 | | 3361 | 2092 | | 14,169 |
| | 0.4 | | 1.28 | | 1.20 | 0.32 | | 0.36 | | 0.91 | 3.30 | | 0.92 |
| 2008-2010 | | 161 | 4524 | | 417 | 943 | | 3979 | | 1979 | 150 | | 8402 |
| 2000 2010 | 5. | | 4.11 | | 2.84 | 2.20 | | 2.54 | | 3.85 | 12.2 | | 4.55 |
| Total . | | 5,420 | 109,4 | 06 | 18,444 | 22,9 | | 103,957 | | 58,694 | 18,6 | | 204,2 |
| | 0.8 | | 1.38 | | 1.27 | 0.37 | | 0.59 | | 1.24 | 5.07 | | 1.16 |
| | 4.4 | | | | | | DDD | | | < DD | | | T-4-1 |
| | AA | | | <u>A</u> | | | BBB | | | ≪BB | | | Total |
| | FIN | IND | UTL | FIN | IND | UTL | FIN | IND | UTL | FIN | IND | UTL | |
| Panel B: Number (Sub-sample: 199 | | des and bor | nd spreads b | y rating, ind | ustry, and ma | turity sub-g | roups for d | ifferent sub-so | ample per | iods | | | |
| ong-term | 611 | 832 | 159 | 1395 | 4795 | 164 | 372 | 3360 | 456 | _ | 665 | 53 | 12,86 |
| 15 years | 0.69 | 0.49 | 0.53 | 0.80 | 0.67 | 0.64 | 1.20 | 1.10 | 1.01 | | 2.22 | 1.06 | 0.89 |
| Medium-term | 2072 | 2641 | 779 | 10,284 | 7814 | 1344 | 2373 | 7513 | 1481 | 179 | 1859 | 521 | 38,86 |
| 7–15 years | 0.32 | 0.08 | 0.11 | 0.41 | 0.29 | 0.23 | 0.63 | 0.67 | 0.53 | 2.73 | 1.92 | 1.50 | 0.51 |
| Short-term | 1954 | 2763 | 885 | 13,953 | 9614 | 2053 | 3455 | 9907 | 2373 | 179 | 2380 | 506 | 50,02 |
| 1–7 years | 0.25 | 0.04 | 0.12 | 0.35 | 0.25 | 0.21 | 0.61 | 0.67 | 0.47 | 5.72 | 1.95 | 1.16 | 0.49 |
| Fotal | 4637 | 6236 | 1823 | 25,632 | 22,223 | 3561 | 6200 | 20,780 | 4310 | 358 | 4904 | 1080 | 101,74 |
| iotai | 0.34 | 0.12 | 0.15 | 0.40 | 0.36 | 0.24 | 0.65 | 0.74 | 0.55 | 4.22 | 1.97 | 1.32 | 0.55 |
| Sub-sample: 200 | 0-2004 | | | | | | | | | | | | |
| Long-term | 389 | 671 | 46 | 1529 | 4783 | 155 | 285 | 4134 | 429 | 14 | 907 | 150 | 13,49 |
| >15 years | 0.82 | 0.45 | 0.66 | 0.89 | 0.95 | 0.65 | 2.18 | 1.91 | 1.83 | 12.47 | 5.77 | 4.01 | 1.63 |
| Medium-term | 778 | 556 | 39 | 5270 | 3177 | 511 | 601 | 3054 | 376 | 70 | 1540 | 205 | 16,17 |
| 7–15 years | 0.63 | 0.19 | 0.33 | 0.74 | 0.70 | 0.56 | 1.43 | 1.51 | 1.62 | 3.33 | 4.68 | 5.09 | 1.33 |
| Short-term | 3153 | 1984 | 197 | 16,207 | 8061 | 1691 | 1598 | 9855 | 1732 | 421 | 4505 | 882 | 50,286 |
| 1–7 years | 0.51 | 0.17 | 0.87 | 0.68 | 0.69 | 0.63 | 1.60 | 1.87 | 2.42 | 5.87 | 7.12 | 8.37 | 1.73 |
| _ | | | | | | | | | | | | | |
| Total | 4320 | 3211 | 282 | 23,006 | 16,021 | 2357 | 2484 | 17,043 | 2537 | 505 | 6952 | 1237 | 79,95 |
| | 0.56 | 0.23 | 0.76 | 0.71 | 0.77 | 0.62 | 1.63 | 1.82 | 2.20 | 5.70 | 6.41 | 7.29 | 1.63 |
| Sub-sample: 200 | | 127 | 4 | 202 | 002 | 20 | 51 | 770 | 2.4 | 22 | 560 | 5 4 | 202: |
| Long-term | 58 | 137 | 4 | 302 | 892 | 28 | 51 | 779 | 34 | 22 | 563 | 54 | 2924 |
| >15 years | 0.83 | 0.50 | 0.56 | 0.69 | 0.68 | 0.66 | 1.94 | 1.62 | 1.48 | 2.87 | 4.01 | 2.18 | 1.64 |
| Medium-term | 252 | 36 | - | 1265 | 421 | 53 | 99 | 631 | 32 | 52 | 501 | 1 | 3343 |
| 7–15 years | 0.67 | 0.19 | | 0.45 | 0.49 | 0.44 | 0.62 | 1.11 | 0.46 | 1.86 | 3.08 | 1.27 | 1.01 |
| Short-term | 734 | 317 | - | 2630 | 1315 | 272 | 328 | 1126 | 281 | 24 | 794 | 81 | 7902 |
| 1–7 years | 0.25 | 0.01 | | 0.26 | 0.18 | 0.14 | 0.49 | 0.53 | 0.34 | 1.66 | 2.70 | 7.96 | 0.61 |
| Γotal | 1044 | 490 | 4 | 4197 | 2628 | 353 | 478 | 2536 | 347 | 98 | 1858 | 136 | 14,169 |
| | 0.39 | 0.16 | 0.56 | 0.35 | 0.40 | 0.22 | 0.67 | 1.01 | 0.47 | 2.04 | 3.20 | 5.61 | 0.92 |
| Sub-sample: 200 | | 40- | | | =0.5 | | | | | 4.5 | | | |
| ong-term | 75 | 129 | 2 | 234 | 593 | 44 | 74 | 441 | 25 | 40 | 239 | 29 | 1925 |
| 15 years | 2.68 | 1.85 | 2.30 | 3.16 | 2.11 | 1.92 | 4.92 | 3.09 | 3.81 | 8.03 | 11.49 | 5.77 | 3.94 |
| Medium-term | 147 | 41 | - | 442 | 577 | 19 | 103 | 434 | 30 | 48 | 324 | 4 | 2169 |
| 7–15 years | 2.36 | 1.70 | | 3.57 | 1.72 | 2.06 | 5.94 | 2.92 | 2.97 | 11.61 | 9.48 | 4.53 | 3.98 |
| Short-term | 394 | 155 | - | 1361 | 535 | 174 | 256 | 567 | 49 | 287 | 489 | 41 | 4308 |
| | 2.71 | 0.92 | | 3.25 | 1.32 | 1.59 | 8.04 | 2.87 | 2.84 | 21.54 | 10.44 | 6.54 | 5.11 |
| 1–7 years | | | | | | | | | | | | | |
| 1–7 years Fotal | 616 | 325 | 2 | 2037 | 1705 | 237 | 433 | 1442 | 104 | 375 | 1052 | 74 | 8402 |

Panel A reports the number of observations of bond trades and average% yield spreads (first and second rows, respectively) for different sub-samples of bonds based on industry, rating and maturity categories for different time-periods. FIN, IND and UTL refer to Financial, Industrial, and Utility firms. Rating \leq BB indicates bonds with BB or lower ratings. Panel B further reports the same metrics for different rating-industry subsamples for each maturity and time period. Missing observations in Panel B refer to zero bond trades for a given sub-category.

Table 2 Variable definitions.

Portfolios: Overall, we consider 8 equally weighted portfolios: 2 industries (Industrials and non-Industrials) × 2 ratings (high and low) × 2 maturity (short- and long-term) categories. Low (high-) -ratings refer to bonds rated BBB and below (AA or A). Short- (long-) term bonds refer to maturities ≤7 years (>7) years. For each portfolio, we obtain equally weighted indices of bond spreads, equity volatility and bond/equity liquidity

Bond spread (Data Sources: DATASTREAM, NAIC) Yield spread is obtained as the bond yield minus equal maturity swap yield, linearly interpolated from daily swap rates Equity Volatility measures (Data Sources: CRSP, Wharton Research Data Services or WRDS)

- (1) Id. Volatility (3-factor, daily or monthly): Idiosyncratic volatility computed as the variance of residuals from the application of the Fama–French 3-factor model on 125 days (or 6 months) of daily (or monthly) stock returns prior to the transaction date
- (2) Id. Volatility (4-factor, daily or monthly): Idiosyncratic volatility computed as the variance of residuals from the application of the Fama-French 4-factor model on 125 days (or 6 months) of daily (or monthly) stock returns prior to the transaction date

Bond Liquidity measures (Data Sources: FISD, NAIC)

Trade variables

- (1) Trade size (in 000's of dollars): based on NAIC variable "actual_cost" if it is a buy trade, and NAIC variable "consideration" if it is a sell trade. Higher trade size is associated with lower transaction costs and hence higher liquidity (Edwards et al., 2007)
- (2) Annual trading frequency: number of transactions in one year prior to the transaction date. The higher the trading frequency, the more actively the bond is traded, and hence liquidity is higher (Edwards et al., 2007)

Price Impact variables

- (3) Bond liquidity index 1: bond price impact variable calculated based on the transaction prices of all trades in one year prior to the transaction date as: $10^8 \times (\sigma_{prices})/10^8$ total volume, where σ_{prices} is the standard deviation of transaction prices of all trades and total volume is the dollar volume of all trades in the one-year window prior to the transaction date. Higher price impact values imply lower liquidity (Gady et al., 2007)
- (4) Bond liquidity index 2: bond price impact variable calculated based on the transaction prices of all trades in the one-year window prior to the transaction date as: $10^8 \times \left(\frac{\text{maximum price-minimum price}}{\text{average price}}\right)/\text{total volume, where the maximum, minimum and average prices, respectively, denote the highest, lowest and mean prices based on all the observed trades over the last year, and total volume is defined as in variable 3 above. Higher price impact values imply lower liquidity (Edwards et al., 2007)$

We next employ a principal component procedure (Bai and Ng, 2002) to combine the four bond liquidity series for each portfolio. The first principal component obtained from the procedure is referred to as the bond illiquidity in the subsequent exhibits Equity Liquidity (Data Sources: CRSP)

Inverse of Amihud (2002) equity impact measure computed over a 125-day window as inverse of $\sum_{k=1}^{125} 10^8 \times (|\text{returns}_{t-k}|/\$\text{trading volume}_{t-k})/125$ (excluding days of zero trading volume). It measures the inverse of the cumulative price impact of order flow. Lower price impact values imply higher illiquidity Aggregate market factors (Data Sources: 1.2.3.6:DATASTREAM: 4:NAIC: 5.7.8:WRDS)

(1) Term-structure factor (Slope): 10-year swap rate minus 2-year swap rate; (2) Default factor (Def_spd): Moody's BAA yield minus 10-year swap rate; (3) Aggregate liquidity factor (TED): 30-day LIBOR minus 3- month T-Bill rate; (4) Aggregate bond illiquidity factor (Agg Illiq): equally-weighted average of aggregate bond portfolio liquidity index 1 values each month; (5) Risk-free rate: 1-month T-Bill rate; (6) Equity market volatility factor: VIX index; (7) Aggregate idiosyncratic volatility factor (Agg Vol): equally-weighted average of idiosyncratic volatilities of all equities underlying the overall bond portfolio each month; and (8) Equity market factors: Small minus big (SMB) size, high minus low book-to-market (HML) value and momentum factors

The table defines different variables and portfolios used in the paper.

frequency bond returns are hard to calculate.¹² Based on the available data from NAIC and FISD databases, we employ four different time varying bond liquidity variables. These consist of two tradebased variables (trade size and annual trading frequency), and two bond price impact variables.

Trade size is computed as the actual dollar cost incurred for buy trades and amount received for sell trades; the dollar amounts exclude accrued interest (and hence reflect clean prices) but include commissions and fees. Trading frequency is the number of transactions in the year prior to a specific bond trade.

The two bond price impact variables measure the price impact of order flow on current returns and are computed as the impact of total trading volume on the standard deviation as well as range of bond prices, where trading volume is obtained as the total dollar value of trades in the year prior to a bond transaction. Due to such low liquidity of corporate bonds, we employ a modified version of the Amihud (2002) measure. We measure illiquidity as the impact of trading volume on price volatility over the one-year time window (Downing et al., 2005; Gady et al., 2007; Maalaoui et al., 2009). Volatility is measured using two alternative definitions, i.e., as the standard deviation and range of bond prices in the given year. Accordingly, we measure price impact as (σ_{prices}) /total volume (referred to as Liquidity Index 1), where σ_{prices} is the standard deviation of transaction prices of all trades and total volume is the dollar volume of all trades in the one-year window prior to the transaction date. Alternatively, we employ a range based measure defined (maximum price-minimum price average price)/total volume (referred to as Liquidity

Index 2), where the maximum, minimum and average prices, respectively, denote the highest, lowest and mean prices over the one-year window of all observed trades. Both measures determine the impact of the trading volume on price volatility. Larger values suggest that prices move by a large magnitude in response to a given trading volume and, hence, denote higher illiquidity in the underlying bond market. We find that Liquidity Index variables 1 and 2 in our data are strongly correlated with a correlation coefficient of 0.96.

All the four liquidity variables are winsorized at the 1% level. Previous literature documents the relationship between different liquidity proxies with bond liquidity and yield spreads. Higher bond liquidity (and hence lower bond spread) is associated with larger trade size, higher trading frequency and smaller bond price impact variables.

3.3. Constructing bond portfolios

In order to explain the effect of volatility and liquidity on individual bond spreads, we require individual bond pricing data at a regular (high) frequency. NAIC trading data is, however, not amenable to such an exercise because the underlying bonds are illiquid and do not trade frequently. Because of the sparse trading and large gaps between successive trades in the NAIC database, spread changes for individual bonds at a regular frequency cannot be obtained. As a result, it is infeasible to measure the spread changes on a bond-by-bond basis and conduct regressions using individual bond spreads.

We, therefore, pursue an alternative portfolio-based approach, where we employ equally weighted rating and maturity specific bond portfolios to study the impact of bond liquidity and equity volatility on portfolio bond spreads.

¹² The NAIC database has no quote data. One can alternatively employ Roll's (1984) effective bid-ask measure based on prices of successive bond trades (e.g., Han and Zhu, 2008); however, infrequent and irregularly spaced trades in the NAIC database preclude us from using Roll's measure.

Table 3 Summary statistics of bond portfolios.

| | 1994-20 | 007 | | | | | | 2008-2 | 010 | | | | | |
|--|--|--|--|------------------------------|--|---------------------------------------|-----------------------------|--|------------------|--|-------------------|--|---|----------------------|
| | Mean | Med. | Max. | Min. | Std. dev. | Skew. | Kurt. | . Mean | Med. | Max. | Min. | Std. dev | . Skew. | Kurt. |
| Panel A: Summary | statistics | | | | | | | | | | | | | |
| Spreads (%) | 1 220 | 1.001 | 2 1 42 | 0.202 | 0.741 | 0.004 | 2.00 | 0 4160 | 2 244 | 10.624 | 1 705 | 2 220 | 1 221 | 2.61 |
| Aggregate portfoli | | 1.061 | 3.142 | 0.302 | 0.741 | 0.804 | 2.680 | | 3.311 | 10.624 | 1.705 | 2.329 | 1.321 | 3.61 |
| High-rated portfol | | 0.358 | 1.201 | 0.071 | 0.231 | 1.127 | 3.580 | | 1.376 | 3.362 | 0.824 | 0.699 | 0.847 | 2.42 |
| Low-rated portfoli | | 1.597 | 5.420 | 0.488 | 1.162 | 0.938 | 3.022 | | 5.028 | 19.404 | 2.558 | 4.076 | 1.566 | 4.58 |
| Short-term portfol Long-term portfoli | | 0.829 1.193 | 3.773 3.207 | 0.074 0.346 | 0.937 0.626 | 1.105 0.556 | 3.087 2.670 | | 3.687 3.053 | 9.889 11.958 | 1.137 1.881 | 2.529 2.416 | 0.826 1.625 | 2.58 4.95 |
| Idiosyncratic volat | | | | | | | | | | | | | | |
| Aggregate portfoli | | 0.069 | 0.263 | 0.032 | 0.061 | 1.098 | 2.967 | 7 0.135 | 0.095 | 0.472 | 0.033 | 0.113 | 1.603 | 4.59 |
| High-rated portfol | | 0.056 | 0.215 | 0.023 | 0.046 | 1.443 | 4.378 | | 0.051 | 0.162 | 0.024 | 0.041 | 0.921 | 2.53 |
| Low-rated portfoli | | 0.030 | 0.353 | 0.023 | 0.040 | 1.069 | 2.904 | | 0.131 | 0.780 | 0.024 | 0.190 | 1.567 | 4.52 |
| Short-term portfol | | 0.069 | 0.333 | 0.033 | 0.066 | 1.101 | 3.07 | | 0.131 | 0.730 | 0.026 | 0.130 | 1.363 | 4.08 |
| Long-term portfoli | | 0.066 | 0.246 | 0.032 | 0.055 | 1.124 | 3.014 | | 0.038 | 0.339 | 0.020 | 0.123 | 1.890 | 5.97 |
| Bond illiquidity (× | | | | | | | | | | | | | | |
| Aggregate portfoli | , | -2.194 | 13.002 | -11.114 | 4.299 | 0.437 | 3.110 | 0 9.812 | 7.726 | 30.239 | -6.665 | 8.792 | 0.503 | 2.71 |
| High-rated portfol | | -2.845 | 28.757 | -10.652 | 6.134 | 1.827 | 7.422 | | 5.471 | 29.478 | -4.767 | 7.679 | 1.211 | 4.78 |
| Low-rated portfoli | | -1.881 | 18.965 | -15.752 | 4.747 | 0.342 | 4.190 | | 9.284 | 32.505 | -7.723 | 8.981 | 0.478 | 3.52 |
| Short-term portfol | | -0.809 | 14.895 | -12.943 | 5.009 | 0.227 | 3.19 | | 1.341 | 53.312 | -7.723 -7.608 | 11.98 | 2.329 | 9.15 |
| Long-term portfoli | | -0.303 -2.248 | 20.379 | -12.345 -13.256 | 4.585 | 0.793 | 5.272 | | 9.451 | 34.227 | -7.008 -16.494 | 9.385 | 0.016 | 3.80 |
| | 1994–200 Spread-Id | | Spread-Ill | iguidity p- | val Illiquid | itv-Idio. | p-val | 2008–201 Spread-Idi | | Spread-I | Iliquidity | <i>p</i> -val Illi | auiditv-Idio |). <i>p</i> -v |
| Danal P. Correlation | Spread-Id Vol. | io. p-val | Spread-Ill | iquidity p- | val Illiquid Vol. | ity-Idio. | p-val | - | | Spread-I | lliquidity | p-val Illi Vo | quidity-Idio l. | o. p-va |
| Panel B: Correlation | Spread-Id Vol. ns among level | io. p-val | | iquidity p- | Vol. | | p-val | Spread-Idi Vol. | | | lliquidity | Vo | ĺ. |). p-va |
| Aggregate portfoli | Spread-Id Vol. as among level 0 0.523 | io. p-val | 0.256 | _* | Vol. | · · · · · · · · · · · · · · · · · · · | _*** | Spread-Idi Vol. | o. <i>p</i> -val | 0.462 | lliquidity | -*** 0.4 | 13 | |
| Aggregate portfolion High-rated portfol | Spread-Id Vol. as among level to 0.523 to 0.300 | s -*** | 0.256 -0.274 | _** | Vol0.219 -0.313 | · · · · · · · · · · · · · · · · · · · | <i>p</i> -val | Spread-Idi Vol. 0.932 0.791 | o. <i>p</i> -val | 0.462 0.013 | lliquidity | -*** 0.4 | 13 ,204 | |
| Aggregate portfolion High-rated portfol Low-rated portfoli | Spread-Id Vol. as among level o 0.523 io 0.300 o 0.621 | s -*** | 0.256 -0.274 0.473 | _*: -*: -*: | Vol. -0.219 -0.313 |) | _*** | Spread-Idi Vol. 0.932 0.791 0.935 | o. <i>p</i> -val | 0.462 0.013 0.604 | lliquidity | -*** 0.4 -0.5 | 13 .204 88 | _*** |
| Aggregate portfoli High-rated portfol Low-rated portfoli Short-term portfol | Spread-Id Vol. as among level to 0.523 to 0.300 to 0.621 tio 0.643 | s -*** -*** | 0.256 -0.274 0.473 0.294 | -*- -*- -*- -*- | Vol. -0.219 -0.313 0.014 -0.089 | | _*** | Spread-Idi Vol. 0.932 0.791 0.935 0.848 | o. <i>p</i> -val | 0.462 0.013 0.604 0.549 | Illiquidity | -*** 0.4 -0.5 -*** 0.5 | 13 .204 88 55 | _*** |
| Aggregate portfoli High-rated portfol Low-rated portfoli Short-term portfol | Spread-Id Vol. as among level to 0.523 to 0.300 to 0.621 tio 0.643 | s -*** | 0.256 -0.274 0.473 | _*: -*: -*: | Vol. -0.219 -0.313 -0.014 -0.089 | | _*** | Spread-Idi Vol. 0.932 0.791 0.935 | o. <i>p</i> -val | 0.462 0.013 0.604 | Illiquidity | -*** 0.4 -0.5 | 13 .204 88 55 | _*** |
| Aggregate portfoli High-rated portfol Low-rated portfoli Short-term portfol Long-term portfoli | Spread-Id Vol. as among level to 0.523 to 0.300 to 0.621 tio 0.643 | s -*** -*** | 0.256 -0.274 0.473 0.294 | -*- -*- -*- -*- | Vol. -0.219 -0.313 0.014 -0.089 | | _*** | Spread-Idi Vol. 0.932 0.791 0.935 0.848 | o. <i>p</i> -val | 0.462 0.013 0.604 0.549 | lliquidity | -*** 0.4 -0.5 -*** 0.5 | 13 .204 88 55 | _*** |
| Aggregate portfoli High-rated portfol Low-rated portfoli Short-term portfol Long-term portfoli | Spread-Id Vol. as among level 0 0.523 io 0.300 0 0.621 io 0.643 0 0.290 ASpread- | s | 0.256 -0.274 0.473 0.294 0.424 | -* | Vol0.219 -0.313 -0.014 -0.089 -0.240 ΔIlliquidity |)) | -*** -*** _*** | Spread-Idi Vol. 0.932 0.791 0.935 0.848 0.927 2008–2010 ΔSpread- | o. p-val | 0.462 0.013 0.604 0.549 0.493 | d- | Vo -** 0.4 -0.5 -** 0.5 -** 0.5 -** 0.5 | 13 .204 88 55 14 quidity- | _*** _*** _*** |
| Aggregate portfoli High-rated portfol Low-rated portfoli Short-term portfol Long-term portfoli | Spread-Id Vol. as among level o 0.523 io 0.300 o 0.621 io 0.643 o 0.290 1994–2007 \(\text{\text{Spread-}} \) | p- val | 0.256 -0.274 0.473 0.294 0.424 | _** | Vol. -0.219 -0.313 -0.014 -0.089 -0.240 |)) | -*** -*** _*** | Spread-Idi Vol. 0.932 0.791 0.935 0.848 0.927 | o. p-val | 0.462 0.013 0.604 0.549 0.493 | d- | Vo -** 0.4 -0.5 -** 0.5 -** 0.5 -** 0.2 -** 0.5 | 13 .204 88 55 14 | _*** |
| Aggregate portfoli High-rated portfol Low-rated portfoli Short-term portfoli Long-term portfoli | Spread-Id Vol. as among level 0 | p- val | 0.256 -0.274 0.473 0.294 0.424 ΔSpread- ΔIlliquidity | -* | Vol. -0.219 -0.313 -0.014 -0.089 -0.240 ΔIlliquidity ΔIdio. Vol. |)) | -*** -*** -*** p- 42 val 4 | Spread-Idi Vol. 0.932 0.791 0.935 0.848 0.927 2008–2010 ΔSpread- ΔIdio. Vol. | o. p-val | 0.462 0.013 0.604 0.549 0.493 | d- | Vo -** 0.4 -0.5 -** 0.5 -** 0.5 -** 0.2 -** 0.5 | 13 .204 88 55 14 quidity- o. Vol. | _*** _*** _*** |
| Aggregate portfoli High-rated portfol Low-rated portfoli Short-term portfoli Long-term portfoli | Spread-Id Vol. as among level o 0.523 io 0.300 o 0.621 io 0.643 o 0.290 1994–2007 \(\text{\text{Spread-}} \) | p- val | 0.256 -0.274 0.473 0.294 0.424 | -* | Vol0.219 -0.313 -0.014 -0.089 -0.240 ΔIlliquidity |)) | -*** -*** -*** p- 42 val 4 | Spread-Idi Vol. 0.932 0.791 0.935 0.848 0.927 2008–2010 ΔSpread- | o. p-val | 0.462 0.013 0.604 0.549 0.493 | d- | Vo -** 0.4 -0.5 -** 0.5 -** 0.5 -** 0.5 | 13 .204 88 55 14 quidity- o. Vol. | _*** _*** _*** |
| Aggregate portfoli High-rated portfoli Low-rated portfoli Short-term portfoli Long-term portfoli Panel C: Correlation Aggregate portfolio | Spread-Id Vol. as among level o 0.523 io 0.300 o 0.621 io 0.643 o 0.290 1994–2007 ASpread-Aldio. Vol. as among chan 0.567 | p- val gges | 0.256 -0.274 0.473 0.294 0.424 \[\Delta \text{Spread-} \] \[\Delta \text{Spread-} \] \[\Delta \text{Spread-} \] | | Vol. -0.219 -0.313 0.014 -0.089 -0.240 ΔIlliquidity ΔIdio. Vol. |)) | -*** 2 2 2 2 val 2 | Spread-Idi Vol. 0.932 0.791 0.935 0.848 0.927 2008–2010 ΔSpread-Δldio. Vol. 0.593 | o. p-val | 0.462 0.013 0.604 0.549 0.493 ΔSpread ΔIlliqui | d- | Vo -*** 0.4 -*** 0.5 -*** 0.2 -*** 0.5 p- ΔIIII val ΔIdi -*** 0.26 | 13 .204 88 55 14 quidity- o. Vol. | _*** _*** _*** |
| Aggregate portfoli High-rated portfoli Low-rated portfoli Short-term portfoli Long-term portfoli | Spread-Id Vol. as among level 0 | p- val gges | 0.256 -0.274 0.473 0.294 0.424 ΔSpread- ΔIlliquidity | -* | Vol. -0.219 -0.313 -0.014 -0.089 -0.240 ΔIlliquidity ΔIdio. Vol. |)) | -*** 2 2 2 2 val 2 | Spread-Idi Vol. 0.932 0.791 0.935 0.848 0.927 2008–2010 ΔSpread- ΔIdio. Vol. | o. p-val | 0.462 0.013 0.604 0.549 0.493 | d- | Vo -** 0.4 -0.5 -** 0.5 -** 0.5 -** 0.2 -** 0.5 | 13 .204 88 55 14 quidity- o. Vol. | _*** _*** _*** |
| Aggregate portfoli High-rated portfoli Low-rated portfoli Short-term portfoli Long-term portfoli Panel C: Correlation Aggregate portfolio High-rated portfolio | Spread-Id Vol. as among level b | p- 4 2 ges (| 0.256 -0.274 0.473 0.294 0.424 \[\Delta \text{Spread-} \] \[\Delta \text{Spread-} \ | -*** -*** -*** -*** | Vol. -0.219 -0.313 0.014 -0.089 -0.240 ΔIlliquidity ΔIdio. Vol. 0.371 |)) | 2 p- 2 val 2 | Spread-Idi Vol. 0.932 0.791 0.935 0.848 0.927 2008–2010 ΔSpread-Δidio. Vol. 0.593 | o. p-val | 0.462 0.013 0.604 0.549 0.493 ΔSpread ΔIlliqui 0.506 | d- | Vo - 0.4 - 0.5 - 0.5 - 0.5 - 0.2 - 0.5 - 0.2 - 0.5 | 13 .204 88 55 14 quidity- o. Vol. | _*** _*** _*** |
| Aggregate portfoli High-rated portfoli Low-rated portfoli Short-term portfoli Long-term portfoli | Spread-Id Vol. as among level o 0.523 io 0.300 o 0.621 io 0.643 o 0.290 1994–2007 ASpread-Aldio. Vol. as among chan 0.567 | p- 4 2 ges (| 0.256 -0.274 0.473 0.294 0.424 \[\Delta \text{Spread-} \] \[\Delta \text{Spread-} \] \[\Delta \text{Spread-} \] | | Vol. -0.219 -0.313 0.014 -0.089 -0.240 ΔIlliquidity ΔIdio. Vol. |)) | 2 p- 2 val 2 | Spread-Idi Vol. 0.932 0.791 0.935 0.848 0.927 2008–2010 ΔSpread-Δldio. Vol. 0.593 | o. p-val | 0.462 0.013 0.604 0.549 0.493 ΔSpread ΔIlliqui | d- | Vo -*** 0.4 -*** 0.5 -*** 0.2 -*** 0.5 p- ΔIIII val ΔIdi -*** 0.26 | 13 .204 88 55 14 quidity- o. Vol. | _*** _*** _*** |
| Aggregate portfoli High-rated portfoli Low-rated portfoli Short-term portfoli Long-term portfoli Panel C: Correlation Aggregate portfolio High-rated portfolio | Spread-Id Vol. as among level b | p- 4 2 ges (| 0.256 -0.274 0.473 0.294 0.424 \[\Delta \text{Spread-} \] \[\Delta \text{Spread-} \ | -*** -*** -*** -*** | Vol. -0.219 -0.313 0.014 -0.089 -0.240 ΔIlliquidity ΔIdio. Vol. 0.371 |)) | 2 p- 2 val 2 | Spread-Idi Vol. 0.932 0.791 0.935 0.848 0.927 2008–2010 ΔSpread-Δidio. Vol. 0.593 | o. p-val | 0.462 0.013 0.604 0.549 0.493 ΔSpread ΔIlliqui 0.506 | d- | Vo -*** 0.4 -0.5 -*** 0.5 -*** 0.5 p- ΔIIIi val ΔIdi -*** 0.26 -0.0 | 13 .204 88 55 14 quidity- o. Vol. | -*** -*** p- |
| Aggregate portfoli High-rated portfoli Low-rated portfoli Short-term portfoli Long-term portfoli Panel C: Correlation Aggregate portfolio High-rated portfolio Low-rated portfolio | Spread-Id Vol. as among level b | p- 4 2 ges (| 0.256 -0.274 0.473 0.294 0.424 \[\Delta \text{Spread-} \] \[\Delta \text{Spread-} \ | -*** -*** -*** -*** | Vol. -0.219 -0.313 0.014 -0.089 -0.240 ΔIlliquidity ΔIdio. Vol. 0.371 |)) | 2 p- 2 val 2 | Spread-Idi Vol. 0.932 0.791 0.935 0.848 0.927 2008–2010 ΔSpread-Δidio. Vol. 0.593 | o. p-val | 0.462 0.013 0.604 0.549 0.493 ΔSpread ΔIlliqui 0.506 | d- | Vo - 0.4 - 0.5 - 0.5 - 0.5 - 0.2 - 0.5 - 0.2 - 0.5 | 13 .204 88 55 14 quidity- o. Vol. | -*** -*** p- |
| Aggregate portfoli High-rated portfoli Low-rated portfoli Short-term portfoli Long-term portfoli Panel C: Correlation Aggregate portfolio High-rated portfolio Low-rated portfolio | Spread-Id Vol. as among level o | p- 4 2 ges (| 0.256 -0.274 0.473 0.294 0.424 ΔSpread- ΔIlliquidity 0.390 0.146 0.282 | p- val | Vol. -0.219 -0.313 0.014 -0.089 -0.240 ΔIlliquidity ΔIdio. Vol. 0.371 0.073 |)) | 2 p- 2 val 2 | Spread-Idiv Vol. 0.932 0.791 0.935 0.848 0.927 2008–2010 ΔSpread-ΔIdio. Vol. 0.593 0.236 0.630 | o. p-val | 0.462 0.013 0.604 0.549 0.493 ASpread Allliqui 0.506 0.191 | d- dity | Vo -*** 0.4 -*** 0.5 -*** 0.2 -*** 0.26 -*** 0.38 -*** 0.21 | 13 .204 88 55 14 quidity- o. Vol. | _*** _*** _*** |
| Aggregate portfoli High-rated portfoli Low-rated portfoli Short-term portfoli Long-term portfoli Panel C: Correlation Aggregate portfolio High-rated portfolio Low-rated portfolio Short-term portfolio | Spread-Id Vol. as among level o | p- val p- | 0.256 -0.274 0.473 0.294 0.424 ΔSpread- ΔIlliquidity 0.390 0.146 0.282 | -*** -*** -*** -*** | Vol. -0.219 -0.313 0.014 -0.089 -0.240 ΔIlliquidity ΔIdio. Vol. 0.371 0.073 |)) | (c | Spread-Idiv Vol. 0.932 0.791 0.935 0.848 0.927 2008–2010 ΔSpread-ΔIdio. Vol. 0.593 0.236 0.630 | o. p-val | 0.462 0.013 0.604 0.549 0.493 ASpread Allliqui 0.506 0.191 | d- dity | P- AIIII val AIdi 0.26 0.38 | 13 .204 88 55 14 quidity- o. Vol. | -*** -*** p- |

Panel A presents the summary statistics (i.e., mean, median, maximum, minimum, standard deviation, skewness and kurtosis) for portfolio credit spreads, idiosyncratic equity volatility and bond illiquidity, as defined in Table 2. We consider the overall value-weighted Industrial portfolio, and different sub-sample portfolios of Industrial bonds based on ratings and maturity, both for the pre-crisis period (1994-2007) and crisis-period (2008-2010). Low-rated (high-rated) portfolio consists of bonds rated BBB and below (above BBB, i.e., AA or A). Short- (long-) term portfolios have bonds with maturities 7 years or below (greater than 7 years). Panel B reports correlations among the key variables, along with respective p-values, for different portfolios. Finally, Panel C reports correlations (and respective p-values) for first differenced variables.

Specifically, we consider eight weekly and monthly bond portfolios, by classifying all individual bond observations each week or month into two industries (Industrials and non-Industrials), two ratings (high and low) and two maturity (high and low) categories. A low-rated portfolio consists of bonds rated BBB and below, while high-rated bonds bear ratings above BBB, i.e., AA or A. Short-term portfolios have bonds with maturities 7 years or below, while long-term portfolios correspond to bonds with maturities greater than 7 years. For each of the eight bond portfolios, we obtain time-series indices of bond spreads and liquidity variables as the equally weighted average of corresponding variables for component individual bonds. For each bond portfolio, we also obtain corresponding equally weighted equity indices of returns and idiosyncratic volatility of the underlying stocks. 13

3.4. Constructing the bond liquidity factor

Using the four portfolio liquidity indices (i.e., trade size, annual trading frequency and the two bond price impact variables), we implement a principal component procedure and extract the first principal component that captures the illiquidity of the bonds

Significance at 1% level.

^{**} Significance at 5% level.

Significance at 10% level.

¹³ Though we construct both weekly and monthly indices, we tabulate only monthly results in Sections 3-6.

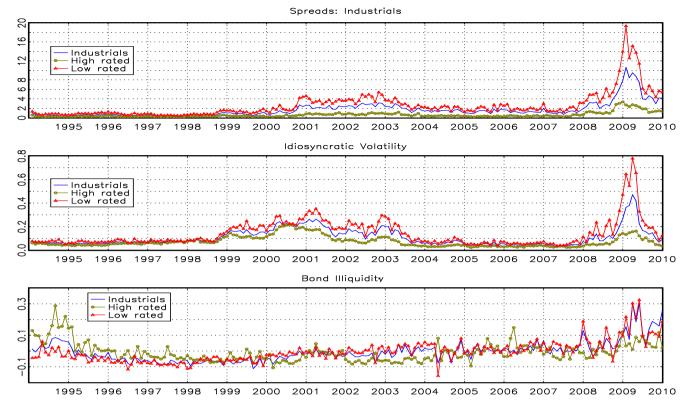


Fig. 1. Monthly Industrial portfolio indices based on ratings (1994–2010). The figure plots the monthly bond spreads, underlying idiosyncratic stock volatility and bond illiquidity for overall, low- and high-rated Industrial bond portfolios for the sample period 1994–2010. All the variables are defined in Table 2 of the paper. Low- (high-) rated portfolio, represented as triangles (circles), consists of bonds rated BBB and below (above BBB, i.e., AA and A).

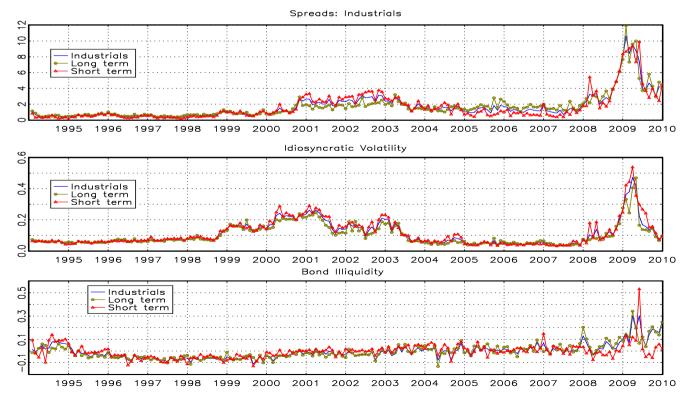


Fig. 2. Monthly Industrial portfolio indices based on maturity (1994–2010). The figure plots the monthly bond spreads, underlying idiosyncratic stock volatility and bond illiquidity for overall, short- and long-term Industrial bond portfolios for the sample period 1994–2010. All the variables are defined in Table 2 of the paper. Short- (long-) term portfolio, represented as triangles (circles), consists of bonds with maturities 7 years or below (greater than 7 years).

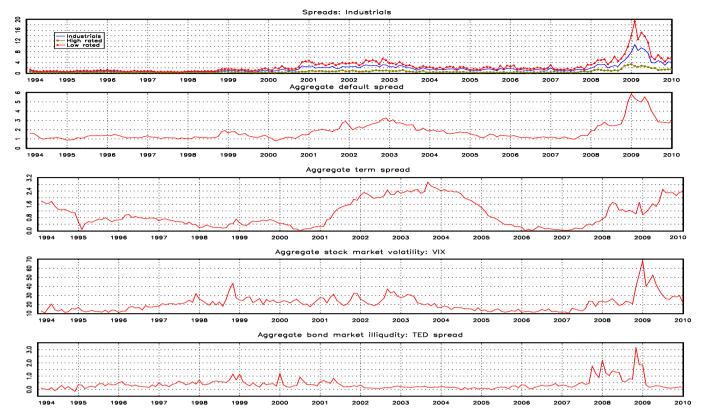


Fig. 3. Monthly Industrial bond spreads, and aggregate bond and stock market variables (1994–2010). The figure plots the monthly bond spreads for overall, low- and high-rated Industrial portfolios along with the aggregate market variables: default and term spreads, stock market volatility (VIX) and bond illiquidity variables for the sample period 1994–2010. All the variables are defined in Table 2 of the paper. Low- (high-) rated portfolios, represented as triangles and circles, respectively, consist of bonds rated BBB and below (above BBB, i.e., AA and A).

Table 4 Augmented Dickey Fuller (ADF) tests for unit roots (1994–2010).

| | 1994-20 | 07 | | | | | | | |
|----------------------|-----------|----------|-------|-----------|-----------------|-------|-----------|----------|-------|
| | Credit Sp | oreads | | Idiosynci | atic Volatility | | Bond Illi | quidity | |
| | Lags | No trend | Trend | Lags | No trend | Trend | Lags | No trend | Trenc |
| Aggregate portfolio | 2 | 0.39 | 0.57 | 0 | 0.32 | 0.63 | 1 | 0.79 | 0.01 |
| High-rated portfolio | 2 | 0.23 | 0.40 | 0 | 0.63 | 0.84 | 0 | 0.17 | 0.00 |
| Low-rated portfolio | 2 | 0.36 | 0.52 | 1 | 0.39 | 0.71 | 1 | 0.81 | 0.04 |
| Short-term portfolio | 2 | 0.33 | 0.62 | 3 | 0.30 | 0.60 | 1 | 0.37 | 0.00 |
| Long-term portfolio | 2 | 0.28 | 0.01 | 1 | 0.48 | 0.77 | 0 | 0.03 | 0.00 |
| | 1994-20 | 10 | | | | | | | |
| Aggregate portfolio | 1 | 0.23 | 0.26 | 7 | 0.05 | 0.16 | 1 | 0.02 | 0.00 |
| High-rated portfolio | 0 | 0.07 | 0.05 | 2 | 0.19 | 0.29 | 4 | 0.90 | 0.00 |
| Low-rated portfolio | 0 | 0.04 | 0.03 | 0 | 0.03 | 0.11 | 4 | 0.26 | 0.00 |
| Short-term portfolio | 1 | 0.08 | 0.10 | 5 | 0.03 | 0.13 | 5 | 0.03 | 0.00 |
| Long-term portfolio | 1 | 0.07 | 0.03 | 4 | 0.01 | 0.03 | 0 | 0.29 | 0.00 |

This table reports *p*-values for the null hypothesis that the monthly data series follows a unit root process using the ADF test. We consider equally weighted indices of credit spreads, bond illiquidity and idiosyncratic volatility for different industrial bond portfolios (as defined in Table 2) for both the pre-crisis period (1994–2007) and the full sample period (2008–2010). Lags are selected using the BIC. Results are reported using deterministic trends and without trends. Low-rated (high-rated) portfolio consists of bonds rated BBB and below (above BBB, i.e., AA or A). Short- (long-) term portfolios have bonds with maturities 7 years or below (greater than 7 years).

across time. Specifically, we implement the following steps based on Bai and Ng (2002) and Stock and Watson (2002)¹⁴: (1) check if each liquidity index is stationary. If not, difference the series to ensure stationarity; (2) standardize each series by demeaning the ser-

ies and dividing by the standard deviation; (3) extract the first principal component of the four standardized liquidity series and (4) obtain the cumulative additive series of the first principal component. This cumulative series is referred to as bond illiquidity factor hereafter.

3.5. Time-series properties of spreads, bond illiquidity, and idiosyncratic equity volatility for portfolios

Table 3 provides the summary statistics for different monthly industrial portfolios separately for pre-crisis (1994–2007) and

¹⁴ This procedure is commonly employed in time-series analysis to analyze dynamic interactions with vector autoregression models (VAR) (e.g., Bernanke et al., 2005). Traditional VAR models often used in the literature present estimation problems when the number of variables included in the VAR system is large. The main motivation of the factor augmented VAR models is to reduce the dimensionality (or number or variables used) in the VAR system without losing any available information.

Table 5Monthly Collin-Dufresne et al. (2001) time-series regression tests for volatility and liquidity (1994–2007).

| | Constant | Equity_ret _t | Δr_t | $(\Delta r_t)^2$ | $\Delta Slope_t$ | ΔVIX_t | Mkt_ret _t | ΔVol_t | $\Delta Illiq_t$ | ΔCS_{t-1} | ΔVol_{t-1} | $\Delta Illiq_{t-1}$ | ΔAgg Vol_t | ΔAgg Illi q_t | Adj R ² | NOBS |
|------------------|-----------------------|---|------------------------|--------------------------|-------------------------|-----------------------|-----------------------|-----------------------|-----------------------|--------------------------|--------------------|----------------------|-------------------------|-------------------------|--------------------|------|
| | | riable: \DSprea gate Industrial | | | | | | | | | | | | | | |
| Α | 0.017 0.366 | -0.010 0.136 | -0.032 0.956 | -7.073 0.269 | 0.057 0.781 | 0.016 0.011 | 0.019 0.012 | | | | | | | | 0.018 | 167 |
| В | 0.032 | -0.010 | -0.241 | -11.517 | 0.058 | 0.008 | 0.008 | 10.252 | | | | | | | 0.324 | 167 |
| С | 0.149 0.019 | 0.108 - 0.011 | 0.615 -0.536 | 0.018 -8.661 | 0.684 -0.019 | 0.103 0.012 | 0.282 0.017 | 0.000 | 1.888 | | | | | | 0.137 | 167 |
| D | 0.300 0.032 | 0.091 - 0.011 | 0.373 -0.526 | 0.201 - 12.011 | 0.910 0.012 | 0.050 0.006 | 0.010 0.008 | 9.157 | 0.000 1.152 | | | | | | 0.363 | 167 |
| | 0.139 | 0.085 | 0.293 | 0.023 | 0.928 | 0.188 | 0.269 | 0.000 | 0.007 | | | | | | | |
| E | 0.031 0.182 | -0.006 0.366 | -0.682 0.158 | - 12.448 0.025 | -0.020 0.882 | 0.006 0.234 | 0.005 0.555 | 8.681 0.000 | 1.114 0.005 | - 0.168 0.016 | | | | | 0.385 | 166 |
| F | 0.029 | -0.005 | -0.733 | -12.463 | -0.034 | 0.005 | 0.004 | 8.489 | 1.047 | -0.110 | -1.697 | -0.175 | | | 0.384 | 166 |
| Ĵ | 0.163 0.026 | 0.488 0.000 | 0.112 -0.509 | 0.019 - 12.580 | 0.794 0.011 | 0.257 0.007 | 0.603 0.003 | 0.000 | 0.010 | 0.228 - 0.202 | 0.364 | 0.520 | 9.776 | 0.842 | 0.287 | 166 |
| _ | 0.282 | 0.972 | 0.346 | 0.034 | 0.936 | 0.185 | 0.678 | | | 0.002 | | | 0.000 | 0.018 | 0.207 | 100 |
| H | 0.030 0.187 | -0.006 <i>0.423</i> | -0.654 0.174 | - 12.589 0.019 | 0.008 0.951 | 0.005 0.221 | 0.004 0.559 | 7.450 0.005 | 1.626 0.003 | - 0.166 0.019 | | | 1.519 <i>0.575</i> | -0.606 0.219 | 0.382 | 166 |
| | | iable: ΔSprea | | | | | | | | | | | | | | |
| Pan A | el B: High-r 0.000 | ated Industria 0.000 | il Portfolio -0.209 | 0.328 | 0.047 | 0.004 | 0.001 | | | | | | | | -0.018 | 167 |
| | 0.965 | 0.964 | 0.607 | 0.932 | 0.607 | 0.211 | 0.820 | 0.000 | | | | | | | | 4.65 |
| В | 0.003 0.706 | -0.001 0.909 | -0.314 0.438 | -1.017 0.783 | 0.043 0.615 | 0.004 0.197 | 0.001 0.878 | 2.799 0.014 | | | | | | | 0.014 | 167 |
| С | 0.002 | -0.001 | -0.336 | -0.521 | 0.041 | 0.004 | 0.001 | | 0.449 | | | | | | -0.001 | 167 |
| D | 0.825 0.005 | 0.926 -0.001 | 0.397 -0.413 | 0.889 -1.630 | 0.643 0.039 | 0.228 0.004 | 0.799 0.001 | 2.567 | 0.029 0.383 | | | | | | 0.024 | 167 |
| E | 0.567 0.003 | 0.882 0.002 | 0.297 -0.424 | 0.652 -1.075 | 0.647 0.048 | 0.213 0.003 | 0.856 -0.001 | 0.024 2.237 | 0.057 0.293 | -0.303 | | | | | 0.105 | 166 |
| | 0.760 | 0.721 | 0.222 | 0.775 | 0.571 | 0.279 | 0.870 | 0.041 | 0.100 | 0.000 | | | | | | |
| 7 | 0.003 0.761 | 0.002 0.773 | -0.454 0.207 | -1.013 <i>0.790</i> | 0.043 0.615 | 0.004 0.257 | 0.000 0.939 | 2.346 0.039 | 0.305 0.128 | - 0.292 0.000 | -1.017 0.326 | 0.067 0.759 | | | 0.099 | 166 |
| Ĵ | 0.002 | 0.003 | -0.278 | -0.585 | 0.071 | 0.002 | -0.003 | 0.035 | 0.120 | -0.293 | 0.520 | 000 | 2.855 | 0.007 | 0.149 | 166 |
| I | 0.822 0.003 | 0.637 0.002 | 0.405 -0.330 | 0.873 -0.992 | 0.339 0.078 | 0.513 0.002 | 0.591 -0.002 | -0.566 | 0.364 | 0.000 - 0.290 | | | 0.001 3.099 | 0.951 -0.104 | 0.151 | 166 |
| | 0.721 | 0.691 | 0.336 | 0.776 | 0.290 | 0.518 | 0.639 | 0.669 | 0.058 | 0.000 | | | 0.003 | 0.403 | | |
| Pan A | el C: Low-ro 0.035 | ated Industria – 0.030 | l Portfolio 0.446 | -8.073 | 0.023 | 0.030 | 0.034 | | | | | | | | 0.054 | 167 |
| | 0.244 | 0.000 | 0.584 | 0.261 | 0.935 | 0.003 | 0.016 | | | | | | | | | |
| 3 | 0.049 0.107 | - 0.028 0.004 | 0.448 0.548 | - 12.727 0.035 | 0.076 0.720 | 0.017 0.097 | 0.019 0.175 | 9.257 0.000 | | | | | | | 0.271 | 167 |
| С | 0.031 | - 0.031 | 0.172 | -8.576 | -0.059 | 0.025 | 0.032 | | 2.434 | | | | | | 0.131 | 167 |
|) | 0.272 0.045 | 0.000 - 0.029 | 0.834 0.295 | 0.282 - 12.532 | 0.799 0.025 | 0.015 0.015 | 0.012 0.020 | 8.312 | 0.006 1.357 | | | | | | 0.290 | 167 |
| | 0.130 | 0.003 | 0.700 | 0.052 | 0.905 | 0.138 | 0.155 | 0.000 | 0.099 | 0.040 | | | | | 0.000 | 100 |
| | 0.048 0.167 | - 0.023 0.017 | 0.010 0.989 | - 14.436 0.069 | 0.025 0.900 | 0.016 0.098 | 0.017 0.251 | 7.819 0.000 | 1.448 0.035 | - 0.219 0.032 | | | | | 0.333 | 166 |
| F | 0.049 | - 0.023 | 0.045 | - 14.474 | 0.022 | 0.016 | | 7.931 | 1.358 | - 0.221 | 0.475 | -0.238 | | | 0.325 | 166 |
| j | 0.168 0.053 | 0.010 - 0.018 | 0.949 -0.347 | 0.067 - 17.340 | 0.910 0.004 | 0.090 0.020 | 0.220 0.014 | 0.000 | 0.038 | 0.085 - 0.255 | 0.819 | 0.721 | 14.085 | 1.453 | 0.280 | |
| T | 0.172 | 0.070 | 0.654 | 0.027 | 0.983 | 0.017 | 0.267 | 5 0 4 B | 1 224 | 0.004 | | | 0.000 | 0.010 | 0.221 | 100 |
| ŀ | 0.050 0.163 | - 0.021 0.039 | -0.089 <i>0.900</i> | - 15.694 0.044 | 0.026 0.896 | 0.016 0.087 | 0.014 0.301 | 5.948 0.021 | 1.324 0.175 | − 0.227 0.027 | | | 4.765 0.254 | 0.237 0.774 | 0.331 | 166 |
| | | riable: <i>ASprea</i> term Industria | | | | | | | | | | | | | | |
| - <i>un</i> 4 | 0.012 | -0.006 | -0.911 | -6.018 | -0.045 | 0.020 | 0.017 | | | | | | | | 0.008 | 167 |
| 3 | 0.658 0.028 | 0.471 -0.006 | 0.223 -0.856 | 0.591 -10.757 | 0.869 | 0.012 | 0.152 | 10.694 | | | | | | | 0.211 | 167 |
| 3 | 0.028 | -0.006 0.438 | -0.856 0.135 | -10.757 0.128 | 0.032 0.869 | 0.010 0.139 | 0.005 0.625 | 0.000 | | | | | | | 0.311 | 167 |
| 2 | 0.011 | -0.008 | -0.828 | -3.360 0.764 | -0.135 <i>0.508</i> | 0.017 | 0.016 | | 3.070 | | | | | | 0.233 | 167 |
|) | 0.671 0.024 | 0.403 -0.007 | 0.271 -0.806 | -7.964 | -0.047 | 0.027 0.009 | 0.195 0.006 | 8.732 | 0.000 2.222 | | | | | | 0.418 | 167 |
| Е | 0.321 0.024 | 0.378 -0.001 | 0.166 -0.887 | 0.297 -10.113 | 0.780 -0.025 | 0.184 0.008 | 0.569 0.002 | 0.000 8.435 | 0.003 2.030 | -0.157 | | | | | 0.432 | 166 |
| د | 0.024 | -0.001 0.900 | -0.887 0.103 | -10.113 0.184 | -0.025 0.875 | 0.008 | 0.002 | 8.435 0.000 | 0.006 | - 0.15 7 0.005 | | | | | 0.432 | 100 |
| F | 0.025 0.369 | 0.002 0.845 | -0.856 <i>0.106</i> | -9.769 <i>0.217</i> | -0.017 <i>0</i> .915 | 0.008 0.214 | 0.002 0.858 | 8.573 0.000 | 2.097 0.005 | −0.193 0.027 | 0.601 0.766 | 0.295 0.454 | | | 0.427 | 166 |
| G | 0.025 | 0.008 | -1.457 | -14.972 | -0.054 | 0.010 | -0.002 | 0.000 | 0.003 | -0.274 | 0.700 | 0.434 | 10.274 | 1.257 | 0.227 | 166 |
| Н | 0.426 0.024 | 0.402 -0.002 | 0.029 -0.857 | 0.156 -9.610 | 0.770 -0.025 | 0.138 0.008 | 0.875 0.004 | 9.235 | 2.054 | 0.000 - 0.153 | | | 0.000 -1.737 | 0.029 -0.041 | 0.426 | 166 |
| . 1 | 0.353 | 0.820 | -0.837 0.103 | -9.010 0.188 | 0.876 | 0.008 | 0.762 | 0.000 | 0.012 | - 0.133 0.011 | | | 0.565 | 0.928 | 0.720 | 100 |

(continued on next page)

Table 5 (continued)

| | Constant | Equity_ret _t | Δr_t | $(\Delta r_t)^2$ | $\Delta Slope_t$ | ΔVIX_t | Mkt_ret _t | ΔVol_t | $\Delta Illiq_t$ | ΔCS_{t-1} | ΔVol_{t-1} | $\Delta Illiq_{t-1}$ | ΔAgg Vol_t | ΔA gg $Illiq_t$ | Adj R ² | NOBS |
|------|--------------|-------------------------|--------------|------------------|------------------|----------------|----------------------|----------------|------------------|-------------------|--------------------|----------------------|----------------------|-------------------------|--------------------|------|
| Pane | el E: Long-t | erm Industria | l Portfolio | | | | | | | | | | | | | |
| A | 0.024 | -0.014 | 1.063 | -8.286 | 0.133 | 0.011 | 0.018 | | | | | | | | 0.010 | 167 |
| | 0.120 | 0.119 | 0.171 | 0.218 | 0.463 | 0.118 | 0.032 | | | | | | | | | |
| В | 0.038 | -0.013 | 0.597 | -13.495 | 0.059 | 0.006 | 0.007 | 10.478 | | | | | | | 0.317 | 167 |
| | 0.066 | 0.133 | 0.346 | 0.022 | 0.686 | 0.313 | 0.399 | 0.000 | | | | | | | | |
| С | 0.024 | -0.014 | 0.748 | -9.433 | 0.097 | 0.008 | 0.016 | | 0.796 | | | | | | 0.024 | 167 |
| | 0.088 | 0.105 | 0.342 | 0.156 | 0.588 | 0.232 | 0.032 | | 0.165 | | | | | | | |
| D | 0.038 | -0.013 | 0.484 | -13.852 | 0.047 | 0.006 | 0.006 | 10.313 | 0.305 | | | | | | 0.316 | 167 |
| | 0.063 | 0.133 | 0.450 | 0.019 | 0.747 | 0.390 | 0.409 | 0.000 | 0.535 | | | | | | | |
| Е | 0.033 | -0.012 | 0.061 | -10.720 | -0.086 | 0.005 | 0.008 | 8.791 | 0.398 | -0.334 | | | | | 0.417 | 166 |
| | 0.158 | 0.131 | 0.912 | 0.028 | 0.572 | 0.439 | 0.309 | 0.000 | 0.219 | 0.000 | | | | | | |
| F | 0.032 | -0.012 | 0.069 | -10.511 | -0.081 | 0.005 | 0.007 | 8.505 | 0.498 | -0.319 | -0.821 | 0.207 | | | 0.412 | 166 |
| | 0.156 | 0.130 | 0.901 | 0.032 | 0.589 | 0.488 | 0.312 | 0.000 | 0.216 | 0.000 | 0.660 | 0.548 | | | | |
| G | 0.028 | -0.010 | 0.435 | -8.800 | 0.002 | 0.004 | 0.009 | | | -0.398 | | | 8.312 | 0.196 | 0.283 | 166 |
| | 0.279 | 0.262 | 0.494 | 0.048 | 0.989 | 0.529 | 0.279 | | | 0.000 | | | 0.000 | 0.650 | | |
| Н | 0.033 | -0.012 | 0.075 | -10.920 | -0.068 | 0.005 | 0.007 | 8.324 | 0.554 | -0.337 | | | 1.008 | -0.266 | 0.411 | 166 |
| | 0.159 | 0.147 | 0.891 | 0.019 | 0.654 | 0.479 | 0.366 | 0.001 | 0.269 | 0.000 | | | 0.657 | 0.667 | | |

In this table, we implement Collin-Dufresne et al. (2001; page 2185, eq 2) type regressions and test for the incremental significance of idiosyncratic volatility and bond illiquidity for different monthly portfolios from 1994 to 2007. We employ Regressions (2.1) to (2.5) in the paper, and regress portfolio bond spreads (CS) on several time-series variables: $Equity_ret$ (the equally weighted stock returns corresponding to the bond portfolio); r (the risk free rate); Slope (the slope of the term structure); Mkt_ret (the CRSP value weighted equity index return); Vol (the equally weighted equity volatility corresponding to the underlying bond portfolio); Illiq (the equally weighted bond illiquidity factor); RegVol (the equally weighted equity volatility underlying the overall bond portfolio); and RegVol (the equally weighted equity volatility underlying the overall bond portfolio). For each regression, we report heteroscedasticity-autocorrelation consistent p-values based on the Newey-West procedures (1987) (in italics), adjusted R^2 values (adj R^2) and respective number of observations (NOBS). Significant variables (at 10% significance level or below) in each regression are highlighted in bold. Low-rated (high-rated) portfolio consists of bonds rated BBB and below (above BBB, i.e., AA or A). Short- (long-) term portfolio has bonds with maturities 7 years or below (greater than 7 years).

crisis (2008–2010) periods. From panel A, we observe that during the pre-crisis period low-rated bond portfolios have the highest (mean and median levels of) spreads and equity volatility. Spreads and equity volatility for low-rated bonds are also very volatile during 1994–2007 (as indicated by large range and standard deviation values). Similarly, short-term and low-rated bonds have the highest illiquidity levels compared to others. All three variables, i.e., spreads, volatility and bond illiquidity, evidence substantial increases in the post-crisis period, especially for low-rated bonds. While equity volatility experiences high kurtosis (and hence potential high outliers), bond spreads and illiquidity for all portfolios become more volatile during 2008–2010.

Panels B and C further show that strong correlations exist during 1994–2007 between spreads/volatility and spreads/illiquidity variables for aggregate portfolios and mainly for low-rated and short-term portfolios. Short-term bond spreads are also significantly correlated to underlying illiquidity. Such correlations, however, significantly increase in the recent financial crisis period. The financial crisis of 2008–2010 witnessed high correlations between spread levels and underlying equity volatility for all portfolios. Further, the illiquidity impact on bond spreads was most perceptible for low-rated and short-term portfolios.

Fig. 1 plots the monthly time-series of bond spreads, idiosyncratic volatility and bond market illiquidity for the aggregate and the rating based bond portfolios. The bond spreads went up steeply following the high-tech bubble crash (i.e., during 2000-2004), and during the recent financial crisis (2008-2010), and such an increase is more evident in the low-rated bond portfolio. Fig. 1 also reveals that bond illiquidity and idiosyncratic volatility are both significantly higher for low-rated bonds, and trended up following the tech bubble crash, and more recently since 2008. Bond illiquidity seems to have become more volatile since the onset of the financial crisis. Fig. 2 indicates that short-term bonds had higher spread, volatility and illiquidity levels relative to the long term bonds during the post-bubble crash and financial crisis periods. Fig. 3 presents aggregate bond and stock market variables along with the bond portfolio spreads. We observe that aggregate default spread experienced a spike during the 2000–2004 period, whereas the VIX levels went up as early as mid-1998 and reverted to normal levels by the end of 2003. The term-spread went up in 2001 and remained high until 2006 in response to the Fed's low short-term rate strategy. Aggregate bond market illiquidity (as measured by the TED spread) remained high during 1999–2001 period. All the four aggregate variables were also impacted during the financial crisis. While the TED spreads seem to have subsided, the aggregate default spreads still seem to be high.

Next, we analyze the stationary properties of our series. We conduct Augmented Dickey Fuller (ADF) tests and evaluate the null of unit root (or deterministic trend) process against the alternative of a stationary process. The number of lags is selected using the Bayesian Information Criterion (BIC).

Table 4 presents the ADF test results for monthly portfolios, separately for pre-crisis (Panel A) and full-sample (Panel B), respectively, for the 1994-2004 and 1994-2010 periods. This is done to better control for the endogenous impact of the financial crisis. Overall, there is strong evidence for non-stationarity in credit spreads pre-crisis, where *p*-values for the ADF test are larger than 0.20 in all cases. When we include the crisis period 2008-2010, stationarity is still rejected at the 5% significance level, for most portfolios. These results imply that credit spread is a close to non-stationary process. For the illiquidity factor, we find the evidence of non-stationarity for all monthly portfolios for all periods; however, the series becomes stationary when we include a deterministic trend, implying that it follows a deterministic trend model. For volatility, there is a clear case for unit-root in the pre-crisis period. Inclusion of the 2008–2010 sample leads to lower *p*-values; however, stationarity is still rejected at the 1% significance level; thus, volatility is a close to non-stationary process. 15

In conclusion, we find evidence that credit spread and volatility are close to non-stationary processes, and bond illiquidity follows a deterministic trend model. However, once we take the first differences, all the three series (i.e., spreads, illiquidity and volatility) become stationary. The time-series regressions presented in the next

¹⁵ Similar findings are found in the weekly data.

Table 6Monthly time-series regression tests for volatility and liquidity with additional control variables (1994–2007).

| Constant | Equity_ret _t | Δr_t | $(\Delta r_t)^2$ | $\Delta Slope_t$ | ΔVIX_t | Mkt_ret _t | TED_t | $(\Delta r_t)^3$ | SMB_t | HML_t | r_{t-1} | VIX_{t-1} | Def_spd_{t-1} | Mkt_ret_{t-1} | ΔVol_t | $\Delta Illiq_t$ | ΔAgg Vol_t | ΔAgg Illi q_t | Adj R^2 | NOB |
|----------------------------------|-------------------------|--------------------|------------------|------------------|----------------|-----------------------|----------------------|------------------|-----------------|-----------------|----------------|----------------|------------------|-------------------------|---------------------|--------------------|-------------------------|-------------------------|-----------|-----|
| Dependent vai Panel A: Aggres | - | - | | | | | | | | | | | | | | | | | | |
| A 0.258 | -0.005 | -0.509 | -8.298 | 0.083 | 0.008 | 0.012 | -0.007 | 33.690 | -0.003 | -0.001 | -0.315 | 0.010 | -0.209 | -0.015 | | | | | 0.052 | 167 |
| 0.040 | 0.528 | 0.650 | 0.328 | 0.659 | 0.238 | 0.133 | 0.935 | 0.749 | 0.705 | 0.919 | 0.198 | 0.008 | 0.002 | 0.017 | | | | | | |
| 3 0.222 | -0.011 | -0.864 | -7.396 | 0.089 | 0.003 | 0.008 | -0.043 | 67.733 | 0.005 | 0.005 | -0.204 | 0.005 | -0.139 | -0.011 | 9.778 | | | | 0.321 | 16 |
| 0.120 | 0.186 | 0.383 | 0.346 | 0.517 | 0.604 | 0.294 | 0.336 | 0.474 | 0.444 | 0.523 | 0.371 | 0.081 | 0.049 | 0.067 | 0.000 | | | | | |
| 0.193 | -0.006 | -1.002 | -8.751 | -0.011 | 0.003 | 0.009 | -0.123 | 14.690 | -0.006 | -0.007 | -0.105 | 0.010 | -0.184 | -0.014 | | 1.995 | | | 0.181 | 16 |
| 0.158 | 0.406 | 0.346 | 0.330 | 0.938 | 0.655 | 0.169 | 0.094 | 0.886 | 0.308 | 0.345 | 0.683 | 0.003 | 0.007 | 0.008 | | 0.000 | | | | |
| D 0.185 | -0.011 | -1.132 | -7.804 | 0.028 | 0.001 | 0.007 | -0.113 | 51.130 | 0.001 | 0.000 | -0.084 | 0.006 | -0.133 | -0.011 | 8.496 | 1.274 | | | 0.368 | 16 |
| 0.200 | 0.160 | 0.236 | 0.336 | 0.817 | 0.904 | 0.328 | 0.009 | 0.588 | 0.808 | 0.987 | 0.721 | 0.040 | 0.059 | 0.043 | 0.000 | 0.006 | | | | |
| E 0.175 | -0.013 | -1.052 | -9.944 | 0.053 | 0.001 | 0.009 | -0.129 | 32.397 | 0.001 | 0.000 | -0.033 | 0.005 | -0.125 | -0.010 | 7.743 | 1.541 | 0.266 | 0.546 | 0.375 | 16 |
| 0.213 | 0.105 | 0.252 | 0.211 | 0.647 | 0.885 | 0.226 | 0.000 | 0.726 | 0.885 | 0.948 | 0.889 | 0.067 | 0.069 | 0.078 | 0.002 | 0.001 | 0.925 | 0.076 | | |
| Dependent vai Panel B: High-i | - | | | | | | | | | | | | | | | | | | | |
| A 0.094 | 0.002 | -0.311 | -0.876 | 0.057 | -0.002 | -0.002 | 0.046 | 4.268 | -0.006 | -0.004 | -0.133 | 0.002 | -0.063 | -0.009 | | | | | 0.050 | 16 |
| 0.100 | 0.743 | 0.533 | 0.860 | 0.557 | 0.525 | 0.694 | 0.231 | 0.930 | 0.117 | 0.252 | 0.121 | 0.238 | 0.027 | 0.009 | | | | | | |
| B 0.085 | 0.001 | -0.379 | -1.492 | 0.049 | -0.003 | -0.002 | 0.043 | 5.168 | -0.004 | -0.002 | -0.109 | 0.001 | -0.054 | -0.009 | 1.949 | | | | 0.061 | 10 |
| 0.129 | 0.836 | 0.448 | 0.772 | 0.601 | 0.457 | 0.743 | 0.273 | 0.917 | 0.228 | 0.394 | 0.196 | 0.410 | 0.054 | 0.007 | 0.060 | | | | | |
| 0.089 | 0.001 | -0.457 | -1.890 | 0.049 | -0.003 | -0.002 | 0.047 | 5.511 | -0.006 | -0.003 | -0.108 | 0.001 | -0.058 | -0.009 | | 0.514 | | | 0.075 | 1 |
| 0.116 | 0.784 | 0.342 | 0.693 | 0.600 | 0.405 | 0.747 | 0.206 | 0.908 | 0.100 | 0.341 | 0.172 | 0.366 | 0.049 | 0.005 | | 0.007 | | | | |
| 0.081 | 0.001 | -0.503 | -2.330 | 0.042 | -0.003 | -0.001 | 0.044 | 6.173 | -0.005 | -0.002 | -0.091 | 0.001 | -0.050 | -0.009 | 1.649 | 0.473 | | | 0.081 | 1 |
| 0.141 | 0.864 | 0.298 | 0.638 | 0.637 | 0.364 | 0.787 | 0.243 | 0.899 | 0.176 | 0.476 | 0.251 | 0.521 | 0.078 | 0.004 | 0.107 | 0.011 | | | | |
| 0.084 | 0.000 | -0.483 | -2.532 | 0.075 | -0.003 | -0.001 | 0.044 | 9.331 | -0.004 | -0.001 | -0.085 | 0.000 | -0.043 | -0.008 | -0.022 | 0.537 | 2.113 | 0.199 | 0.115 | 1 |
| 0.135 | 0.967 | 0.313 | 0.586 | 0.375 | 0.375 | 0.821 | 0.276 | 0.850 | 0.245 | 0.843 | 0.299 | 0.851 | 0.143 | 0.014 | 0.987 | 0.007 | 0.044 | 0.109 | | |
| Panel C: Low-r | | | 12.051 | 0.056 | 0.010 | 0.025 | 0.100 | 20.042 | 0.005 | 0.000 | 0.100 | 0.000 | 0.105 | 0.021 | | | | | 0.050 | 1. |
| A 0.238 | - 0.028 | 0.277 | -12.051 | 0.056 | 0.018 | 0.035 | - 0.102 | -20.043 | -0.005 | 0.008 | -0.100 | 0.009 | -0.195 | -0.021 | | | | | 0.058 | 16 |
| 0.282 B 0.235 | 0.001 | 0.862 | 0.151 | 0.829 | 0.201 | 0.003 | 0.002 | 0.891 | 0.688 | 0.637 | 0.805 | 0.110 | 0.100 | 0.132 | 0.000 | | | | 0.250 | 1, |
| B 0.235 0.291 | -0.032 | -0.257 | -7.083 | 0.135 | 0.012 | 0.026 | - 0.174 0.000 | 73.036 | 0.005 | 0.012 0.390 | -0.068 | 0.006 | -0.154 | -0.012 | 8.982 | | | | 0.258 | 16 |
| | 0.003 | 0.859 | 0.371 | 0.521 | 0.421 | 0.049 | | 0.583 | 0.682 | | 0.853 | 0.261 | 0.174 | 0.383 | 0.000 | 2742 | | | 0.140 | 1/ |
| 0.122 | - 0.030 | 0.216 | -11.767 | -0.048 | 0.014 | 0.032 | - 0.328 | -80.057 | -0.010 | -0.004 | 0.213 | 0.011 | -0.164 | -0.015 | | 2.742 | | | 0.148 | 16 |
| 0.614 | 0.000 | 0.878 | 0.175 | 0.821 | 0.322 | 0.002 | 0.000 | 0.559 | 0.351 | 0.828 | 0.637 | 0.038 | 0.162 | 0.237 | 7 020 | 0.002 | | | 0.205 | 1, |
| D 0.166 | -0.032 | -0.225 | -7.548 | 0.062 | 0.010 | 0.026 | -0.301 | 24.838 | 0.000 | 0.005 | 0.117 | 0.008 | -0.140 | -0.010 | 7.830 | 1.656 | | | 0.285 | 16 |
| 0.470 E 0.160 | 0.002 | 0.870 | 0.330 | 0.761 | 0.487 | 0.041 | 0.000 | 0.849 | 0.993 | 0.748 | 0.765 | 0.149 | 0.206 | 0.453 | 0.000 | 0.034 | 2.505 | 0.100 | 0.270 | 1. |
| E 0.160 0.478 | − 0.032 0.004 | -0.277 0.841 | -7.363 0.365 | 0.066 0.756 | 0.010 0.476 | 0.026 0.045 | - 0.291 0.000 | 34.170 0.784 | 0.002 0.822 | 0.008 0.510 | 0.124 0.749 | 0.007 0.219 | -0.128 0.223 | -0.010 0.429 | 6.601 0.005 | 1.588 0.064 | 3.585 0.429 | -0.192 0.750 | 0.279 | 10 |
| | | | 0.303 | 0.730 | 0.476 | 0.045 | 0.000 | 0.764 | 0.822 | 0.510 | 0.749 | 0.219 | 0.223 | 0.429 | 0.003 | 0.004 | 0.429 | 0.750 | | |
| Dependent vai | - | - | | | | | | | | | | | | | | | | | | |
| Panel D: Short- | | | | 0.022 | 0.015 | 0.000 | 0.125 | 100 404 | 0.007 | 0.001 | 0.200 | 0.007 | 0.107 | 0.013 | | | | | 0.017 | 1. |
| A 0.234 | 0.000 | - 2.294 | -1.076 | -0.022 | 0.015 | 0.008 | 0.125 | 190.404 | -0.007 | -0.001 | -0.360 | 0.007 | - 0.187 | -0.012 | | | | | 0.017 | 16 |
| 0.232 | 0.995 | 0.087 | 0.913 | 0.931 | 0.178 | 0.455 | 0.008 | 0.131 | 0.505 | 0.907 | 0.305 | 0.168 | 0.055 | 0.249 | 10.054 | | | | 0.207 | 4. |
| B 0.168 | -0.006 | -1.958 | -2.966 | 0.046 | 0.005 | 0.005 | 0.030 | 155.228 | 0.002 | 0.006 | -0.163 | 0.003 | -0.101 | -0.011 | 10.354 | | | | 0.297 | 16 |
| 0.414 | 0.570 | 0.115 | 0.733 | 0.809 | 0.616 | 0.624 | 0.402 | 0.166 | 0.864 | 0.569 | 0.620 | 0.541 | 0.300 | 0.199 | 0.000 | 2.076 | | | 0.250 | 4. |
| C 0.140 | -0.001 | -2.180 | 3.547 | -0.148 | 0.008 | 0.006 | 0.052 | 182.312 | -0.010 | -0.004 | -0.150 | 0.005 | -0.132 | -0.015 | | 3.070 | | | 0.250 | 16 |
| 0.479 | 0.898 | 0.067 | 0.752 | 0.405 | 0.360 | 0.541 | 0.529 | 0.148 | 0.326 | 0.722 | 0.670 | 0.247 | 0.152 | 0.103 | 0.004 | 0.000 | | | 0.44 * | |
| D 0.111 | -0.006 | -1.940 | 0.851 | -0.061 | 0.002 | 0.005 | -0.006 | 156.214 | -0.002 | 0.003 | -0.046 | 0.002 | -0.077 | -0.013 | 8.291 | 2.284 | | | 0.414 | 16 |
| 0.575 | 0.575 | 0.088 | 0.931 | 0.693 | 0.838 | 0.659 | 0.920 | 0.173 | 0.844 | 0.806 | 0.888 | 0.560 | 0.400 | 0.085 | 0.000 | 0.003 | 4.000 | 0.754 | 0.400 | |
| E 0.099 0.620 | -0.009 0.380 | -1.590 0.146 | -2.107 0.817 | -0.037 0.808 | 0.001 0.874 | 0.008 0.486 | -0.022 0.681 | 110.179 0.304 | -0.005 0.616 | -0.001 0.955 | 0.009 0.979 | 0.002 0.535 | -0.075 0.423 | - 0.014 0.088 | 10.082 0.000 | 2.489 0.001 | -4.686 0.110 | 0.751 0.043 | 0.430 | 16 |
| 0.020 Panel E: Long-t | | | 0.017 | 0.000 | 0.074 | 0.00 | 0.001 | 0.504 | 0.010 | 0.555 | 0.513 | 0.333 | 0.723 | 5.000 | 0.000 | 0.001 | 0.110 | 0.043 | | |
| 4 0.265 | -0.014 | 1.588 | -15.389 | 0.176 | 0.003 | 0.017 | -0.193 | -141.063 | 0.002 | -0.002 | -0.237 | 0.013 | -0.222 | -0.015 | | | | | 0.026 | 16 |
| 0.027 | 0.182 | 0.254 | 0.167 | 0.176 | 0.697 | 0.017 | 0.217 | 0.279 | 0.846 | 0.851 | 0.353 | 0.015 | 0.000 | 0.008 | | | | | 0.020 | 10 |
| B 0.247 | -0.016 | 0.234 | -11.693 | 0.108 | 0.003 | 0.009 | - 0.169 | -23.384 | 0.006 | 0.001 | -0.189 | 0.003 | - 0.158 | - 0.009 | 10.073 | | | | 0.308 | 16 |
| D U.241 | -0.010 | J. 11 / | -11.033 | 0.100 | 0.005 | 0.003 | -0.109 | -23,304 | 0.000 | 0.001 | -0.103 | 0.000 | -0.130 | -0.003 | 10.073 | | | | 0.508 | 10 |

1

| | NOBS | | 167 | | 167 | | 167 | |
|--------------------------------------|------------------------------|-------|----------|-------|---------|-------|---------|-------|
| | $\mathop{\rm Adj}_{R^2}$ | | 0.052 | | 0.311 | | 0.307 | |
| | ΔAgg Illi q_t | | | | | | 0.377 | 0.272 |
| | $\Delta Agg \ Vol_t$ | | | | | | 0.762 | 0.754 |
| | $\Delta IIliq_t$ | | 1.024 | 0.112 | 0.485 | 0.383 | 0.598 | 0.314 |
| | ΔVol_t | 0.000 | | | 9.784 | 0.000 | 9.065 | 0.000 |
| | $\mathit{Mkt_ret}_{t-1}$ | 860.0 | -0.014 | 0.013 | -0.009 | 0.110 | -0.008 | 0.148 |
| | Def_spd _{t-1} | 0.012 | -0.217 | 0.001 | -0.157 | 0.013 | -0.152 | 0.016 |
| | VIX_{t-1} | 0.033 | 0.014 | 0.002 | 0.008 | 0.025 | 0.008 | 0.030 |
| | r_{t-1} | 0.368 | -0.124 | 0.631 | -0.137 | 0.537 | -0.104 | 0.631 |
| | HML_t | 0.849 | -0.006 | 0.515 | -0.001 | 0.926 | 0.000 | 0.965 |
| | SMB_t | 0.395 | 0.000 | 0.960 | 0.005 | 0.506 | 0.005 | 0.510 |
| | $(\Delta r_t)^3$ | 0.825 | -142.486 | 0.258 | -27.430 | 0.794 | -42.917 | 0.680 |
| | TED_t | 0.059 | -0.279 | 0.031 | -0.211 | 0.024 | -0.225 | 0.013 |
| | Mkt_ret _t | 0.386 | 0.015 | 0.165 | 0.008 | 0.402 | 0.010 | 0.351 |
| | $\Delta V I X_t$ | 0.717 | 0.000 | 0.955 | 0.002 | 0.834 | 0.002 | 0.842 |
| | $\Delta Slope_t$ | 0.495 | 0.128 | 0.497 | 0.087 | 0.575 | 0.115 | 0.481 |
| | $(\Delta r_t)^2$ | 0.228 | -15.150 | 0.168 | -11.686 | 0.224 | -13.309 | 0.167 |
| | Δr_t | 829.0 | 1.118 | 0.413 | 0.257 | 0.805 | 0.346 | 0.737 |
| d) | Equity_ret $_t$ Δr_t | 0.103 | -0.014 | 0.133 | -0.016 | 0.091 | -0.017 | 0.074 |
| l able 6 (<i>continued</i>) | Constant | 0.043 | 0.237 | 0.056 | 0.235 | 0.062 | 3 0.231 | 0.062 |
| Iab | | | J | | I | | E | |

Newey-West procedures (1987) (in italics), adjusted R² values refers to the bond illiquidity factor); Vol (the equally weighted equity volatility corresponding to the underlying bond portfolio); Agg Vol (the equally weighted equity volatility underlying the overall bond portfolio); and Agg Illiq portfolio consists of bonds rated BBB and below (3)) type regressions and test for the incremental significance of idiosyncratic volatility and bond illiquidity for different monthly portfolios from 1994 to 2007. We employ Regression (3) in the paper and regress portfolio bond spreads (CS) on several additional time-series variables (compared to Table 5): Equity _ret (the equally weighted stock returns corresponding to the bond portfolio); the equally weighted bond illiquidity of the overall bond portfolio). For each regression, we report heteroscedasticity-autocorrelation consistent p-values based on the Newey-West adj R²) and respective number of observations (NOBS). Significant variables (at 10% significance level or below) in each regression are highlighted in bold. Low-rated (high-rated) above BBB, i.e., AA or A). Short- (long-) term portfolio has bonds with maturities 7 years or below (greater than 7 years) n this table, we implement Collin-Dufresne et al. (2001; p. 2197, Eq.

sections, therefore, use first differenced variables to prevent possible spurious results. We further examine the nature of the non-stationarity of the series by analyzing changes in regime and possible cointegration relations.

4. Time series regressions

In this section we examine the dynamic impact of volatility and liquidity on bond spreads. We employ the regression framework of Collin-Dufresne et al. (2001) and study the incremental information content of these variables.

4.1. Collin-Dufresne et al. (2001) regression tests

Collin-Dufresne et al. (2001) employ monthly *individual* corporate bond spreads in their study. Given the limitations of the NAIC trading data, we conduct portfolio based regressions. We employ variants of the following portfolio regressions of bond spread changes:

$$\Delta CS_{t} = \beta_{0} + \beta_{1} Equity_ret_{t} + \beta_{2} \Delta r_{t} + \beta_{3} (\Delta r_{t})^{2} + \beta_{4} \Delta Slope_{t}$$

$$+ \beta_{5} \Delta VIX_{t} + \beta_{6} Mkt_ret_{t} + \varepsilon_{t}$$
(2.1)

$$\Delta CS_{t} = \beta_{0} + \beta_{1} Equity_ret_{t} + \beta_{2} \Delta r_{t} + \beta_{3} (\Delta r_{t})^{2} + \beta_{4} \Delta Slope_{t}$$

$$+ \beta_{5} \Delta VIX_{t} + \beta_{6} Mkt_ret_{t} + \beta_{7} \Delta Vol_{t} + \beta_{8} \Delta Illiq_{t} + \varepsilon_{t}$$
(2.2)

$$\Delta CS_{t} = \beta_{0} + \beta_{1} Equity_ret_{t} + \beta_{2} \Delta r_{t} + \beta_{3} (\Delta r_{t})^{2} + \beta_{4} \Delta Slope_{t}$$

$$+ \beta_{5} \Delta VIX_{t} + \beta_{6} Mkt_ret_{t} + \beta_{7} \Delta Vol_{t} + \beta_{8} \Delta Illiq_{t}$$

$$+ \beta_{9} \Delta CS_{t-1} + \varepsilon_{t}$$
(2.3)

$$\Delta CS_{t} = \beta_{0} + \beta_{1} Equity_ret_{t} + \beta_{2} \Delta r_{t} + \beta_{3} (\Delta r_{t})^{2} + \beta_{4} \Delta Slope_{t}$$

$$+ \beta_{5} \Delta VIX_{t} + \beta_{6} Mkt_ret_{t} + \beta_{7} \Delta Vol_{t} + \beta_{8} \Delta Illiq_{t}$$

$$+ \beta_{9} \Delta CS_{t-1} + \beta_{10} \Delta Vol_{t-1} + \beta_{11} \Delta Illiq_{t-1} + \varepsilon_{t}$$

$$(2.4)$$

$$\Delta CS_{t} = \beta_{0} + \beta_{1} Equity_ret_{t} + \beta_{2} \Delta r_{t} + \beta_{3} (\Delta r_{t})^{2} + \beta_{4} \Delta Slope_{t}$$

$$+ \beta_{5} \Delta VIX_{t} + \beta_{6} Mkt_ret_{t} + \beta_{7} \Delta Vol_{t} + \beta_{8} \Delta Illiq_{t}$$

$$+ \beta_{9} \Delta CS_{t-1} + \beta_{10} \Delta AggVol_{t} + \beta_{11} \Delta AggIlliq_{t} + \varepsilon_{t}$$

$$(2.5)$$

where Δ represents the differenced series: t denotes the time index: CS refers to average credit or bond spreads for each portfolio; Equity_ret indicates the average stock returns corresponding to the bond portfolio; r is to the risk free rate, measured as the 1-month T-bill rate; Slope denotes the slope of the term structure (defined as 10year swap rate minus 2-year swap rate); Mkt_ret refers to the CRSP value weighted equity index return; Illiq represents the average bond illiquidity of the underlying bond portfolio and refers to the bond illiquidity factor obtained in Section 3.4; and Vol refers to the average equity volatility of the corresponding bond portfolio. Regression (2.1) is similar to the equation 2 used in Collin-Dufresne et al. (2001, p. 2185). 16 Regression (2.1) includes equity returns (as a proxy for the firm's health), risk-free rate and its squared term (for possible non-linear effects), term-spread, aggregate stock market volatility and equity index returns. Regression (2.2) augments Regression (2.1) with underlying idiosyncratic volatility and bond illiquidity. Regression (2.3) includes the lagged credit spread variable to account for possible auto-correlations in the dependent variable. Regression 2.4 (2.5) further augments Regression 3 with lagged volatility and illiquidity (aggregate volatility and illiquidity¹⁷) variables.

 $^{^{\,16}\,}$ We are, however, missing the jump variable obtained as the slope of the implied volatility as we do not have the underlying option data.

 $^{^{17}}$ Aggregate liquidity and volatility are based on the aggregate bond portfolio and corresponding equity portfolio, respectively.

Table 7Monthly Collin-Dufresne et al. (2001) time-series regression tests for volatility and liquidity for the extended sample (1994–2010).

| | Aggregate | e Industria | l Portfolio | High-rate | d Industri | al Portfolio | Low-rate | d Industria | al Portfolio | Short-teri | m Industri | al Portfolio | Long-terr | n Industria | l Portfolio |
|-----|--------------------|----------------|--------------------|--------------------|----------------|--------------------|--------------------|----------------|--------------------|--------------------|----------------|--------------------|--------------------|----------------|--------------------|
| | ΔVol_{t-1} | ΔLiq_t | Adj R ² | ΔVol_{t-1} | ΔLiq_t | Adj R ² | ΔVol_{t-1} | ΔLiq_t | Adj R ² | ΔVol_{t-1} | ΔLiq_t | Adj R ² | ΔVol_{t-1} | ΔLiq_t | Adj R ² |
| Pai | nel A: Table | 5 regressi | ons | | | | | | | | | | | | |
| В | 12.966 | _ | 0.326 | 2.813 | | 0.233 | 13.211 | | 0.349 | 15.428 | | 0.301 | 16.123 | | 0.439 |
| | 0.000 | | | 0.117 | | | 0.000 | | | 0.000 | | | 0.000 | | |
| C | | 6.514 | 0.229 | | 0.545 | 0.225 | | 8.308 | 0.189 | | 8.091 | 0.415 | | 3.938 | 0.046 |
| | | 0.000 | | | 0.078 | | | 0.003 | | | 0.000 | | | 0.049 | |
| D | 10.700 | 4.585 | 0.421 | 2.815 | 0.545 | 0.241 | 11.314 | 5.037 | 0.401 | 11.477 | 6.747 | 0.570 | 15.834 | 0.600 | 0.437 |
| | 0.000 | 0.000 | | 0.107 | 0.075 | | 0.000 | 0.020 | | 0.000 | 0.000 | | 0.000 | 0.516 | |
| E | 10.980 | 4.315 | 0.439 | 2.871 | 0.503 | 0.247 | 11.294 | 4.976 | 0.420 | 11.089 | 5.881 | 0.620 | 14.843 | 0.627 | 0.475 |
| | 0.000 | 0.005 | | 0.106 | 0.092 | | 0.000 | 0.024 | | 0.000 | 0.000 | | 0.000 | 0.501 | |
| F | 10.760 | 3.519 | 0.455 | 2.856 | 0.450 | 0.241 | 11.435 | 4.616 | 0.446 | 11.502 | 6.422 | 0.626 | 16.308 | 0.516 | 0.542 |
| | 0.000 | 0.003 | | 0.107 | 0.209 | | 0.000 | 0.015 | | 0.000 | 0.000 | | 0.000 | 0.573 | |
| Η | 11.552 | 2.612 | 0.457 | 1.605 | 0.804 | 0.284 | 11.899 | 1.172 | 0.453 | 10.865 | 5.950 | 0.619 | 16.323 | -2.739 | 0.562 |
| | 0.000 | 0.195 | | 0.335 | 0.009 | | 0.000 | 0.690 | | 0.000 | 0.000 | | 0.000 | 0.058 | |
| Pai | nel B: Table | 6 regression | ons | | | | | | | | | | | | |
| В | 11.719 | | 0.326 | 1.409 | | 0.286 | 12.303 | | 0.345 | 15.745 | | 0.293 | 15.552 | | 0.427 |
| | 0.000 | | | 0.350 | | | 0.000 | | | 0.000 | | | 0.000 | | |
| C | | 6.361 | 0.318 | | 0.533 | 0.294 | | 7.702 | 0.245 | | 7.969 | 0.424 | | 3.919 | 0.100 |
| | | 0.000 | | | 0.063 | | | 0.001 | | | 0.000 | | | 0.025 | |
| D | 8.945 | 4.776 | 0.430 | 1.426 | 0.536 | 0.295 | 10.311 | 5.022 | 0.398 | 11.638 | 6.731 | 0.564 | 15.130 | 0.806 | 0.427 |
| | 0.000 | 0.000 | | 0.330 | 0.060 | | 0.001 | 0.015 | | 0.000 | 0.000 | | 0.000 | 0.380 | |
| E | 9.310 | 4.622 | 0.429 | 0.651 | 0.598 | 0.314 | 10.606 | 4.682 | 0.398 | 11.117 | 7.017 | 0.594 | 16.293 | -0.069 | 0.466 |
| | 0.000 | 0.000 | | 0.629 | 0.052 | | 0.001 | 0.042 | | 0.000 | 0.000 | | 0.000 | 0.933 | |

In this table, we implement Table 5 and 6 regressions for the full data sample and test for the incremental significance of idiosyncratic volatility and bond illiquidity for different monthly portfolios. For brevity, we report regression coefficients and corresponding Newey-West *p*-values only for idiosyncratic volatility and bond illiquidity variables, along with adjusted R^2 values. Accordingly, Panel A reports Table 5 regressions (B, C, D, E, F and H), and Panel B reports Table 6 regressions (B, C, D and E), where NOBS for each regression is 203. Significant variables (at 10% significance level or below) in each regression are highlighted in bold. Low-rated (high-rated) portfolio consists of bonds rated BBB and below (above BBB, i.e., AA or A). Short- (long-) term portfolio has bonds with maturities 7 years or below (greater than 7 years).

We first implement regressions for the pre-financial crisis period (1994–2007) in order to minimize the potential impact of crisis-driven volatility on our results. We later study the effects of the crisis using the complete sample in Section 4.3.

Table 5 reports results for alternative regression models separately for different monthly bond portfolios for the 1994-2007 period. Overall, we present eight regressions (labeled A to H) for each portfolio. We also report heteroscedasticity-autocorrelation consistent p-values based on the Newey and West (1987) procedure (with lag length set to 2). We observe that Regression A variables have the lowest explanatory power across different portfolios, verifying the findings in Collin-Dufresne et al. (2001) that a large part of the variation in credit spreads is not captured by such variables. Out of all the Regression A variables, only four variables (i.e., underlying stock returns, nonlinear changes in riskfree rate, aggregate stock market returns and VIX) have significant impact on bond spreads, especially for the low-rated bond portfolio. We, however, notice that idiosyncratic volatility has a significant contribution to the explanatory power of credit spreads for all bond portfolios, and the effect is strongly evident for low-rated, short- and long-term portfolios, where the adjusted R² values increase between 22% and 30% based on Regressions A and B. Bond illiquidity further increases the explanatory power of the regressions; the illiquidity effect is strongly present for lowrated and short-term bond portfolios. Adding the illiquidity factor increases the adjusted R^2 values between 12% and 22% based on Regressions A and C and between 2% and 11%, comparing Regressions B and D.

Further, comparing Regressions D and A in each panel we notice that volatility and illiquidity together have the highest incremental effect for short-term bonds, followed by low-rated bonds, where the adjusted R^2 values go up by 40% and 24%, respectively. For long-term bonds, volatility effect is highly significant and adds 30% to regression D. Regressions E–G indicate that idiosyncratic volatility and illiquidity variables still remain significant even after adding several control variables. The lagged bond spreads have

significant information content (particularly for high-rated and long-term bond portfolios), indicating the persistence in time-series behavior of bond spreads. Lagged volatility and illiquidity variables are not significant for any portfolio, implying that the impact of volatility and liquidity on bond spreads is mostly contemporaneous.

Our results are robust to the inclusion of aggregate volatility and liquidity variables for all the portfolios except the high-rated bonds, where the systematic volatility swamps the individual volatility effect. Moreover, Regression E has the highest adjusted R^2 values overall and for low-rated, short- and long-term portfolios, indicating that once conditioned for contemporaneous volatility and illiquidity, respective aggregate portfolio effects are insignificant. Overall, we find that both idiosyncratic volatility and illiquidity effects together have the highest impact for low-rated and short-term portfolios (Regression D), while for others volatility remains the key driver.

We implement several robustness checks to test the validity of our results. First we include portfolio stock liquidity based on Amihud's measure (as defined in Table 2) as an additional control variable and find the variable to be not significant. Second, we also implement the regressions using weekly data and find qualitatively similar results. For weekly trades, the illiquidity effect is even stronger for low-rated and long-term bonds. Lagged volatility also matters in explaining the weekly bond spreads. Finally, we test if the regression estimates on Table 5 are robust to the inclusion of industry production growth proxies and interaction effects between (a) leverage and VIX and (b) bond illiquidity and VIX. All results in Table 5 are robust to the inclusion of these control variables. ¹⁸

¹⁸ Our untabulated results show that industrial production growth has no significant effect in the regressions. We also find no economically significant evidence that leverage impacts bond spreads differently during high- versus low-aversion periods. Finally there is no evidence to support that liquidity impact is pronounced during high uncertain periods, once we control for idiosyncratic volatility. We thank the anonymous referee for suggesting these tests.

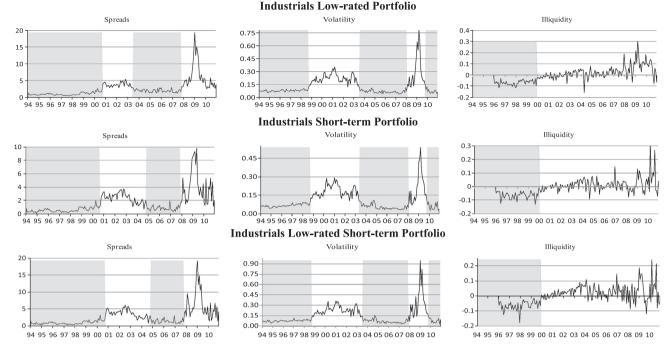


Fig. 4. Underlying regimes in monthly Industrial bond spreads idiosyncratic volatility and bond liquidity (1994–2010). The figure plots the Markov switching regimes based on the two-state Hamilton (1989) model for different monthly Industrial portfolios for bond spread, idiosyncratic volatility and bond illiquidity variables for the period 1994–2010

We next examine the economic significance of volatility and liquidity by conducting shock analysis based on Regression E (i.e., measuring the individual effect of one sigma (1σ) shock of volatility and liquidity on monthly bond spreads for different portfolios). 15 The 1σ volatility shock is obtained as the product of Δ volatility coefficient (in Regression E) and sample standard deviation of Δ volatility variable, and similarly for liquidity. We find that the effect of 1σ shock of volatility for aggregate portfolio is 16 bps and ranges from 18 bps for short- and long-term bonds to as high as 23 bps for lowrated bonds. On the other hand, 1σ liquidity shock implies an increase of bond spreads by 3 bps for aggregate portfolio and 6 bps and 8 bps, respectively, for low-rated and short-term portfolios. Both liquidity and volatility shocks, however, have negligible impact on bond spreads (1 and 2 bps, respectively) for high-rated bonds. Overall we find that volatility has a first-order impact relative to liquidity on bond spreads, especially for low-rated bonds, and the bond illiquidity significantly matters for pricing low-rated and short-term bonds.

Do volatility and liquidity explain the Collin-Dufresne et al. (2001) puzzle? To answer this question, we consider all the eight (issuer \times rating \times maturity) non-overlapping bond portfolios and examine the first principal component of the regression residuals from Regression E (results untabulated). We do not find any significant attrition in the first principal component value even after accounting for volatility and illiquidity variables, and hence the puzzle remains at large. Our results therefore imply that though idiosyncratic volatility and bond illiquidity effects are significant in explaining bond spreads, they perhaps account only for idiosyncratic or portfolio specific information and do not capture the systematic factor that affects all the bond portfolios.

4.2. Expanded Collin-Dufresne et al. (2001) regression tests

We also investigate the following expanded version of the Regressions (2.1) and (2.2) similar to Collin-Dufresne et al. (2001, p. 2197):

$$\Delta CS_{t} = \beta_{0} + \beta_{1} Equity.ret_{t} + \beta_{2} \Delta r_{t} + \beta_{3} (\Delta r_{t})^{2} + \beta_{4} \Delta Slope_{t}$$

$$+ \beta_{5} \Delta VIX_{t} + \beta_{6} Mkt.ret_{t} + \beta_{7} TED_{t} + \beta_{8} (\Delta r_{t})^{3} + \beta_{9} SMB_{t}$$

$$+ \beta_{10} HML_{t} + \beta_{11} r_{t-1} + \beta_{12} VIX_{t-1} + \beta_{13} Def.spd_{t-1}$$

$$+ \beta_{14} Mkt.ret_{t-1} + \beta_{15} \Delta Vol_{t} + \beta_{16} \Delta Illiq_{t} + \varepsilon_{t}$$
(3)

The additional variables included are as follows: TED is the aggregate liquidity spread and is measured as the 30-day LIBOR minus 3-month T-Bill rate; SMB and HML are Fama-French equity market factors; Def_spd is the aggregate default spread and is measured as Moody's BAA yield minus 10-year swap rate. We also include the lagged interest rate (r_{t-1}) , market returns (Mkt_ret_{t-1}) and VIX (VIX_{t-1}) and the non-linear interest rate effects $(\Delta r_t)^2$ and $(\Delta r_t)^3$. As in the previous section, we first focus on the 1994–2007 subsample.

Results in Table 6 imply that idiosyncratic volatility continues to have a significant explanatory power for credit spreads for all bond portfolios, adding 20-28% to the adjusted R^2 values for low-rated, short- and long-term bonds (comparing Regressions A and B). The illiquidity effect is strongly present for low-rated and short-term bond portfolios and increases the explanatory power by similar magnitudes as in Table 5. Regression D and E results further show that both idiosyncratic volatility and illiquidity effects significantly matter, once again, only for low-rated and short-term portfolios, while for others only volatility matters. Moreover, comparing Tables 5 and 6 results, we find that the highest adjusted R^2 values are still obtained using Regression E in Table 5.

4.3. Effects of the financial crisis (2008–2010)

Here we reevaluate Tables 5 and 6 regressions by extending the sample to include the recent crisis period. Table 7 reports the incremental significance of idiosyncratic volatility and bond illi-

¹⁹ Untabulated results and are available upon request.

²⁰ We are, however, missing data on the firm-specific leverage used by Collin-Dufresne et al. (2001). We use TED spread in lieu of the aggregate liquidity proxies used by Collin-Dufresne et al. (2001).

Table 8Monthly time-series regression tests with regime breaks for volatility and liquidity (1994–2010).

| Constant | Equity_ret _t | Δr_t | $(\Delta r_t)^2$ | $\Delta Slope_t$ | ΔVIX_t | Mkt_ret _t | $\Delta Vol_t 	imes 	ext{Low-}$ $	ext{Vol_reg}$ | $\Delta Vol_t 	imes 	ext{High-} \ 	ext{Vol_reg}$ | $\Delta Liq_t 	imes 	ext{Low-} \ 	ext{Illiq_reg}$ | $\Delta Liq_t 	imes 	ext{High-} $ $Illiq_reg$ | ΔCS_{t-1} | Adj R ² | NOBS |
|-------------------------------|------------------------------------|---------------------------------------|------------------------------|----------------------|--------------------|----------------------|--|---|---|--|-------------------------|-----------------------|------|
| | t variable: ⊿Sp Industrial Po | | | | | | | | | | | | |
| 0.014 0.660 | 0.001 0.911 | - 1.631 0.032 | 0.627 0.951 | -0.425 0.159 | 0.003 0.822 | -0.014 0.351 | 9.037 0.000 | 11.166 0.000 | 0.756 0.433 | 4.800 0.003 | − 0.142 0.046 | 0.443 | 202 |
| High-rate 0.001 0.958 | d Industrial Po -0.002 0.804 | ortfolio - 0.978 0.027 | 1.968 0.682 | -0.155 0.069 | 0.021 0 | 0 0.948 | 1.617 0.427 | 3.820 0.038 | 0.433 0.169 | 0.462 0.269 | -0.094 0.106 | 0.252 | 202 |
| Low-rated 0.014 0.774 | Industrial Po 0.003 0.862 | ortfolio -1.540 0.187 | 9.616 0.581 | - 0.804 0.091 | 0.001 0.977 | -0.028 0.309 | 10.773 0.000 | 11.132 0.002 | -0.181 0.890 | 5.684 0.015 | - 0.145 0.036 | 0.423 | 202 |
| Short-rate 0.018 0.548 | ed Industrial F -0.004 0.827 | ortfolio -0.818 0.281 | -6.358 0.426 | -0.203 0.427 | 0.032 0.043 | -0.002 0.909 | 5.823 0.002 | 11.972 0.000 | - 0.817 0.058 | 6.865 0.000 | - 0.214 0.017 | 0.659 | 202 |
| Long-rate 0.027 0.388 | d Industrial Pe -0.007 0.500 | ortfolio -1.267 0.245 | 0.017 0.999 | -0.361 0.249 | -0.013 0.644 | -0.012 0.359 | 14.698 0.000 | 14.979 0.000 | 1.513 0.306 | 0.491 0.628 | - 0.211 0.010 | 0.470 | 202 |
| High-rated -0.004 0.823 | d Short-term -0.004 0.646 | Industrial - 1.344 0.011 | Portfolio 4.368 0.468 | -0.024 0.868 | 0.027 0.016 | -0.001 0.874 | 0.630 0.831 | 2.172 0.565 | 0.646 0.148 | -0.607 0.498 | - 0.304 0.014 | 0.206 | 202 |
| High-rate 0.001 0.940 | d Long-term I -0.009 0.190 | ndustrial -0.557 0.165 | Portfolio 4.829 0.310 | - 0.159 0.078 | 0.017 0.000 | 0.004 0.474 | 1.067 0.495 | 2.708 0.178 | 0.170 0.780 | 0.422 0.131 | - 0.160 0.005 | 0.234 | 202 |
| Low-rated -0.018 0.731 | Short-term I 0.008 0.803 | ndustrial 1 0.755 0.494 | Portfolio 7.673 0.590 | -0.391 0.505 | 0.052 0.014 | -0.020 0.570 | 1.057 0.716 | 9.920 0.000 | 0.362 0.750 | 9.399 0.000 | - 0.166 0.029 | 0.537 | 202 |
| Low-rated -0.010 0.843 | Long-term Ir 0.005 0.738 | ndustrial F —1.882 0.247 | Portfolio 16.140 0.483 | - 1.169 0.045 | -0.022 0.615 | - 0.045 0.045 | 5.701 0.143 | 11.471 0.000 | 1.192 0.537 | 2.768 0.124 | -0.136 0.179 | 0.413 | 202 |

In this table we report the monthly portfolio regression results with volatility and illiquidity regimes for different bond portfolios. We implement Regression (4) in the paper, or equivalently Regression E, Table 5, augmented with regime-specific dummies; i.e., we regress portfolio bond spreads (CS) on volatility and illiquidity, and corresponding low- and high-regime dummy variables (denoted respectively as Low- and High-Vol_reg and Low- and High-Illiq_reg). Regimes for each variable are identified using the Hamilton (1989) regime-switching model as depicted in Fig. 4. For each regression, we report heteroscedasticity-autocorrelation consistent p-values based on the Newey-West procedures (1987) (in italics), adjusted R^2 values (adj R^2) and respective number of observations (NOBS). We highlight significant variables (at 10% significance level or below) in each regression in bold; in addition for each portfolio, we also highlight the regime that has a larger volatility or illiquidity coefficient. Low-rated (high-rated) portfolio consists of bonds rated BBB and below (above BBB, i.e., AA or A). Short- (long-) term portfolio has bonds with maturities 7 years or below (greater than 7 years).

Table 9Granger casualty tests for monthly bond spreads, volatility and liquidity (1994–2010).

| Dependen | ıt variable: ∆Sp | $read_t$ | | Dependent v | ariable: ΔVol_t | | | Dependent v | ariable: $\Delta Illiq_t$ | | |
|------------------|-------------------|-------------|-----------------|-------------------|-------------------------|----|-----------------|-------------------|---------------------------|----|-----------------|
| | Chi-sq | df | <i>p</i> -value | | Chi-sq | df | <i>p</i> -value | | Chi-sq | df | <i>p</i> -value |
| VAR Grang | ger Causality/Blo | ck Exogene | ity Wald Tests | | | | | | | | |
| Low-rated | l Industrial Port | folio | | | | | | | | | |
| ΔVol_t | 6.638 | 3 | 0.084 | $\Delta Spread_t$ | 35.931 | 3 | 0.000 | $\Delta Spread_t$ | 3.7361 | 3 | 0.291 |
| $\Delta Illiq_t$ | 8.716 | 3 | 0.033 | $\Delta Illiq_t$ | 6.564 | 3 | 0.087 | ΔVol_t | 3.1398 | 3 | 0.371 |
| All | 16.234 | 6 | 0.013 | All | 40.850 | 6 | 0.00 | All | 10.62 | 6 | 0.101 |
| Short-tern | n Industrial Por | tfolio | | | | | | | | | |
| ΔVol_t | 5.966 | 3 | 0.093 | $\Delta Spread_t$ | 17.990 | 3 | 0.000 | $\Delta Spread_t$ | 4.0158 | 3 | 0.260 |
| $\Delta Illiq_t$ | 7.839 | 3 | 0.050 | $\Delta Illiq_t$ | 5.746 | 3 | 0.125 | ΔVol_t | 1.7957 | 3 | 0.616 |
| All | 15.001 | 6 | 0.020 | All | 21.154 | 6 | 0.002 | All | 7.5824 | 6 | 0.270 |
| Low-rated | l Short-term Ind | dustrial Po | rtfolio | | | | | | | | |
| ΔVol_t | 19.207 | 3 | 0.000 | $\Delta Spread_t$ | 37.503 | 3 | 0.000 | $\Delta Spread_t$ | 7.5662 | 3 | 0.056 |
| $\Delta Illiq_t$ | 29.632 | 3 | 0.000 | $\Delta Illiq_t$ | 16.950 | 3 | 0.001 | ΔVol_t | 1.1219 | 3 | 0.772 |
| All | 48.572 | 6 | 0.000 | All | 49.658 | 6 | 0.000 | All | 16.282 | 6 | 0.012 |

In this table, we conduct Granger casualty tests to study the mutual lead-lag impact of bond spread, volatility and illiquidity variables. We report Chi-square tests and corresponding degrees of freedom (*df*) and *p*-values for the *null* of no-significance for each variable individually and jointly. The *df* accounting for the maximum number of lags for each variable is chosen based on the BIC selection criterion. We present three tables for each of the following monthly Industrial portfolios: Low-rated, Short-term and Low-rated/short-term. The first, second and third tables horizontally for each portfolio conduct Granger casualty tests respectively using changes in spreads, volatility and illiquidity as the dependent variables. In each panel, we highlight whenever a given variable (or a set of variables) is significant.

quidity for different portfolios. While all the previous results hold, we find that the coefficients of volatility and liquidity increase substantially, implying the amplification of such effects on account of the crisis. Once the crisis period is included, based on regression E

from Panel A, we find that the effect of 1σ volatility shock on spreads increases from 16 bps to 30 bps for aggregate portfolio, and from 6 to 54 (8 to 40) bps for low-rated (short-term) bonds. Similarly 1σ liquidity shock engenders 19, 26 and 44 bps impact

Table 10Generalized impulse response functions for monthly credit spread changes.

| Period | Industrials Lo | ow-rated | | Industrials Sh | ort-term | | Industrials Lov | v-rated Short-tern | n |
|--------------|-----------------------|-----------------------|------------------------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|------------------|
| | $\Delta Spread_t$ | ΔVol_t | $\Delta Illiq_t$ | $\Delta Spread_t$ | ΔVol_t | $\Delta Illiq_t$ | $\Delta Spread_t$ | ΔVol_t | $\Delta Illiq_t$ |
| Panel A: Acc | cumulated Impulse | Response Function | ons for ⊿Bond Spr | reads (1994–2007) | | | | | |
| 1 | 0.490 | 0.230 | 0.110 | 0.390 | 0.200 | 0.170 | 0.660 | 0.320 | 0.220 |
| | 0.000 | 0.000 | 0.002 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 2 | 0.300 | 0.040 | -0.050 | 0.260 | 0.090 | 0.020 | 0.460 | 0.130 | -0.080 |
| | 0.000 | 0.340 | 0.317 | 0.000 | 0.021 | 0.677 | 0.000 | 0.060 | 0.269 |
| 3 | 0.230 | 0.020 | 0.060 | 0.220 | 0.000 | 0.000 | 0.380 | 0.030 | -0.050 |
| | 0.000 | 0.654 | 0.249 | 0.000 | 0.996 | 0.977 | 0.000 | 0.665 | 0.539 |
| 4 | 0.260 | 0.090 | -0.040 | 0.230 | 0.100 | 0.020 | 0.380 | 0.170 | -0.050 |
| | 0.000 | 0.085 | 0.407 | 0.000 | 0.034 | 0.616 | 0.000 | 0.045 | 0.481 |
| 5 | 0.260 | 0.070 | 0.010 | 0.240 | 0.060 | 0.080 | 0.390 | 0.130 | 0.050 |
| | 0.000 | 0.099 | 0.649 | 0.000 | 0.240 | 0.005 | 0.000 | 0.098 | 0.363 |
| 6 | 0.270 | 0.070 | -0.020 | 0.210 | 0.030 | 0.030 | 0.390 | 0.100 | -0.040 |
| | 0.000 | 0.096 | 0.550 | 0.000 | 0.518 | 0.252 | 0.000 | 0.208 | 0.485 |
| 7 | 0.270 | 0.070 | -0.030 | 0.240 | 0.080 | 0.030 | 0.410 | 0.150 | 0.010 |
| | 0.000 | 0.099 | 0.499 | 0.000 | 0.092 | 0.296 | 0.000 | 0.052 | 0.866 |
| 8 | 0.260 | 0.070 | -0.020 | 0.230 | 0.060 | 0.040 | 0.390 | 0.120 | -0.020 |
| _ | 0.000 | 0.095 | 0.519 | 0.000 | 0.181 | 0.246 | 0.000 | 0.099 | 0.668 |
| 9 | 0.260 | 0.070 | -0.020 | 0.230 | 0.050 | 0.040 | 0.390 | 0.110 | -0.010 |
| | 0.000 | 0.095 | 0.616 | 0.000 | 0.312 | 0.105 | 0.000 | 0.091 | 0.845 |
| 10 | 0.270 | 0.070 | -0.020 | 0.230 | 0.070 | 0.040 | 0.400 | 0.140 | -0.010 |
| 10 | 0.000 | 0.097 | 0.579 | 0.000 | 0.098 | 0.150 | 0.000 | 0.075 | 0.897 |
| Panel R. Ac | cumulated Impulse | Resnonse Functio | ons for ARond Snr | eads (1994_2010) | | | | | |
| 1 | 1.135 | 0.766 | 0.452 | 0.934 | 0.535 | 0.431 | 1.414 | 0.881 | 0.537 |
| • | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 2 | 1.028 | 0.778 | 0.281 | 0.549 | 0.258 | 0.114 | 1.211 | 0.673 | 0.093 |
| - | 0.000 | 0.000 | 0.015 | 0.000 | 0.002 | 0.164 | 0.000 | 0.000 | 0.553 |
| 3 | 1.062 | 0.811 | 0.424 | 0.707 | 0.509 | 0.180 | 1.183 | 0.837 | 0.422 |
| , | 0.000 | 0.000 | 0.002 | 0.000 | 0.000 | 0.057 | 0.000 | 0.000 | 0.009 |
| 4 | 1.116 | 0.723 | 0.200 | 0.774 | 0.460 | 0.169 | 1.108 | 0.474 | 0.064 |
| • | 0.000 | 0.000 | 0.235 | 0.000 | 0.000 | 0.108 | 0.000 | 0.011 | 0.731 |
| 5 | 1.139 | 0.776 | 0.220 | 0.761 | 0.481 | 0.274 | 1.100 | 0.621 | 0.270 |
| 3 | 0.000 | 0.000 | 0.068 | 0.000 | 0.000 | 0.001 | 0.000 | 0.000 | 0.102 |
| 6 | 1.115 | 0.794 | 0.249 | 0.789 | 0.505 | 0.246 | 1.062 | 0.604 | 0.240 |
| · · | 0.000 | 0.000 | 0.051 | 0.000 | 0.000 | 0.009 | 0.000 | 0.000 | 0.122 |
| 7 | 1.053 | 0.727 | 0.250 | 0.763 | 0.474 | 0.226 | 0.978 | 0.504 | 0.112 |
| , | 0.000 | 0.000 | 0.056 | 0.000 | 0.000 | 0.014 | 0.000 | 0.003 | 0.112 |
| 8 | 1.084 | 0.738 | 0.050 0.252 | 0.791 | 0.507 | 0.014 0.240 | 1.106 | 0.629 | 0.442 |
| U | 0.000 | 0.000 | 0.053 | 0.000 | 0.000 | 0.008 | 0.000 | 0.000 | 0.075 |
| 9 | 1.090 | 0.754 | 0.033 0.240 | 0.780 | 0.491 | 0.008 0.180 | 1.049 | 0.567 | 0.175 |
| J | 0.000 | 0.754 | | 0.780 | 0.491 | 0.180 0.045 | 0.000 | 0.000 | 0.175 |
| 10 | 0.000 1.078 | 0.000 0.756 | 0.053 0.220 | 0.000 0.784 | 0.000 0.499 | 0.045 0.171 | 0.000 1.049 | 0.000 0.591 | 0.220 0.220 |
| 10 | | | | | | | | | |
| | 0.000 | 0.000 | 0.077 | 0.000 | 0.000 | 0.060 | 0.000 | 0.000 | 0.103 |

In this table we report accumulated responses of Δ Bond Spreads to a generalized one sigma (or 1σ) innovation in each of three variables: Δ Bond Spread, Δ Idiosyncratic Volatility and Δ Bond Illiquidity. We present the accumulated impulse responses up to 10 periods ahead and the corresponding p-values (in italics) for Low-rated, Short-term and Low-rated/short-term Industrial portfolios, based on the monthly VAR model (5). Panel A reports the results for the pre-crisis or 1994–2007 period and Panel B for the 1994–2010 period. Significant responses (at 10% significance level or below) in each regression are highlighted in bold. Low-rated portfolio consists of bonds rated BBB and below. Short-term portfolio has bonds with maturities 7 years or below.

on aggregate, low-rated, short-term portfolio spreads respectively, implying over three-, four- or fivefold increases compared to precrisis period. Similar results follow from panel B.²¹

4.4. Additional regressions with regime breaks

We next examine the robustness of the Collin-Dufresne et al. (2001) type regressions in Section 4.1 by incorporating any possible structural breaks in the variables of interest. Specifically, our objective is to test if changes in bond illiquidity and idiosyncratic volatility across low or high regimes differentially impact credit spread changes.²²

We first apply Hamilton's (1989) two-state Markov regimeswitching model to the monthly portfolios of spreads, volatility and liquidity and identify the underlying regimes. Fig. 4 plots the monthly time series of the key variables, along with the low- (i.e., the low-mean-low-variance) and high- (i.e., the high-mean-high-variance) regimes.²³ For credit spreads, the high-regime prevails during mid-2000 to mid-2003 (or end of 2004 depending upon the portfolio) and also during the recent financial crisis period of 2008–2010. For idiosyncratic volatility we identify a clear regime break towards the end of 1998 (coinciding with the Russian debt crisis); we also observe a high-regime for volatility from 10/1998 to 06/2003 and again during the recent crisis. Switches in bond spreads seem to parallel low- and high-regimes in equity volatility.²⁴ Moreover, switches in idiosyncratic volatility seem to lead bond-spread movements over time. For example, volatility first shifts to a high-regime in late-98, followed by a similar switch in bond spreads later during mid-2000. Again volatility reverts to a

²¹ Results untabulated, and are available upon request.

²² Several previous papers explore the role of regimes in the dynamic behavior of corporate spreads, like Pedrosa and Roll (1998); Davies (2008), Avramov et al. (2007), Maalaoui et al. (2009); and Acharya et al. (2012).

²³ In untabulated results, we find clear evidence of two regimes for all the analyzed variables. Differences in mean and variances for all regimes are different than zero, and results are consistent across weekly and monthly portfolios.

²⁴ In untabulated results, we also test for structural breaks using the CUSUM test (Brown et al., 1975) and find that the dates for the structural breaks obtained at the 1% significance level are almost identical to those from the Markov switching model.

Panel A: 1994-2007 sub-sample

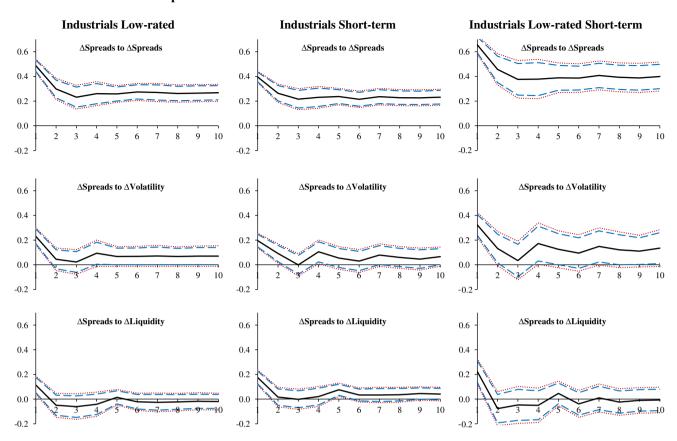


Fig. 5. Generalized impulse response functions for monthly credit spread changes. We plot the accumulated responses of Δ Bond Spreads to a generalized one sigma (or 1σ) innovation (solid line) in each of the three variables, Δ Bond Spread, Δ Idiosyncratic Volatility and Δ Bond Illiquidity, using the monthly VAR model (5) for both the 1994–2007 (Panel A) and 1994–2010 (Panel B) periods. We also plot the response confidence bands for 90% (dotted) and 95% (dashed) confidence levels. We present three plots for each of the Low-rated, Short-term and Low-rated/short-term Industrial portfolios. The *first* plot under each portfolio refers to the accumulated response of Δ Bond Spread to 1σ shock in Bond Spread. The *second* plot refers to the accumulated response of Δ Bond Spreads to 1σ shock in Idiosyncratic Volatility. The *third* plot refers to the accumulated response of Δ Bond Spread to 1σ shock in Bond Spread to 1

low regime in the middle of 2003, subsequently followed by bond spreads; during late 2009, while volatility reverts to a low regime, bond spreads continue to be in high regime. For the bond illiquidity measure, the regime switch to a permanent high regime happens at the beginning of 2000, and no reversion to low-regime is evident until end of the sample.²⁵

Finally, we conduct regime-break regressions for various sub-portfolios, where regimes for volatility and liquidity are pre-identified using Hamilton's model. We employ Regression (2.3) augmented with regime-specific dummies separately for volatility and liquidity variables as shown below:

$$\begin{split} \Delta CS_t &= \beta_0 + \beta_1 Equity_ret_t + \beta_2 \Delta r_t + \beta_3 (\Delta r_t)^2 + \beta_4 \Delta Slope_t \\ &+ \beta_5 \Delta VIX_t + \beta_6 Mkt_ret_t + \beta_7 (\Delta Vol_t \times LowVol_reg) \\ &+ \beta_8 (\Delta Vol_t \times HighVol_reg) + \beta_9 (\Delta Illiq_t \times LowIlliq_reg) \\ &+ \beta_{10} (\Delta Illiq_t \times HighIlliq_reg) + \beta_{11} \Delta CS_{t-1} + \varepsilon_t \end{split} \tag{4}$$

where Low/High Vol_reg and Low/High Illiq_reg refer to dummy variables for low- or high- volatility and illiquidity regimes, respec-

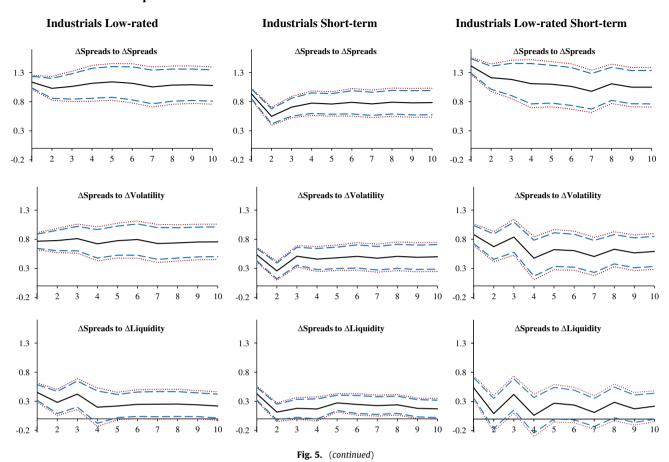
tively. Regression 4 captures the differential effect of low and high regimes on bond spreads.

Table 8 results imply that volatility overall has a pronounced impact mainly in high-regimes for most of the portfolios. While volatility effects are significant in both volatility regimes for lowrated and short rated portfolios, the high-regime coefficient seems to be higher. Similarly, the illiquidity effect seems to arise primarily from high- illiquidity regimes, mainly for bonds in the lowrated/short-term and low-rated/long-term portfolios. We also examine the economic significance based on shock analysis (results not tabulated). We observe that the effect of 1σ shock of volatility on monthly aggregate, low-rated and short-term portfolio spreads amounts to 15, 28 and 11 bps, respectively, in the lowvolatility regime. Corresponding magnitudes are 30, 52 and 43 bps respectively in the high-volatility regime. Similar statistics for 1σ liquidity shock stack up to 1, .3 and 2 bps (20, 29 and 50 bps) in the low- (high-) liquidity regime. The adjusted R^2 values overall improve in Table 8 versus Table 5 (Regression E), implying that conditioning on latent regimes can significantly improve bond

In summary, while idiosyncratic volatility and liquidity effects jointly and significantly matter for low-rated and short-term portfolios (based on Tables 5 and 6), there can be a differential impact of such variables on bond spreads, conditional on the underlying regime (Table 8). Having investigated the time-series spread

We also model liquidity using a Markov- switching model with three regimes. The financial crisis periods are here identified as a third regime with higher mean and variance. However, the use of this more complicated model does not bring any additional insights to our reported regression results.

Panel B: 1994-2010 sample



regressions, we next ask what are the dynamic relationships among spreads, volatility and liquidity and how the three variables impact each other over time. We therefore investigate the lead-lag relationships among the key variables.

5. Dynamic interactions among spreads, idiosyncratic volatility, and liquidity

In order to analyze the dynamic relations among spreads, volatility and illiquidity, we consider a vector-autoregressive (VAR) model in changes as follows:

$$\begin{split} \Delta CS_t &= \alpha_1 + \sum_{i=1}^p \beta_{1,i} \Delta CS_{t-1} + \sum_{i=1}^p \delta_{1,i} \Delta Illiq_{t-1} + \sum_{i=1}^p \gamma_{1,i} \Delta Vol_{t-1} + \varepsilon_{1t} \\ \Delta Illiq_t &= \alpha_2 + \sum_{i=1}^p \beta_{2,i} \Delta CS_{t-1} + \sum_{i=1}^p \delta_{2,i} \Delta Illiq_{t-1} + \sum_{i=1}^p \gamma_{2,i} \Delta Vol_{t-1} + \varepsilon_{2t} \\ \Delta Vol_t &= \alpha_3 + \sum_{i=1}^p \beta_{3,i} \Delta CS_{t-1} + \sum_{i=1}^p \delta_{3,i} \Delta Illiq_{t-1} + \sum_{i=1}^p \gamma_{3,i} \Delta Vol_{t-1} + \varepsilon_{3t} \end{split}$$

Given the non-stationary or near non-stationary properties of our series, we tested for cointegration and find no statistical evidence of any cointegration relations between our series.²⁶ As a result,

we do not include any error correction term in our estimation. We set the number of lags used as three, based on the BIC and AIC selection criterion. All our VAR specifications are stationary models, as we test whether all inverse roots of the characteristic polynomial lie inside the unit circle.

5.1. Granger causality tests

We use the estimated parameters from the VAR model (5) to analyze how changes in the lagged variables predict changes in their future values. Essentially, we want to explore how bond spread changes can be predicted using past values of liquidity, of volatility or both. Similarly, we study the predictability of volatility and liquidity based on past values of the other variables in the VAR. We implement the Granger causality tests for these hypotheses and summarize the results in Table 9.

We find strong evidence for volatility and illiquidity individually Granger-causing bond spreads for all distress portfolios. Further, the joint test indicates that volatility and illiquidity together Granger-cause spreads for all the three portfolios, implying that bond prices slowly process information from other variables. The chi-squared test values and their corresponding *p*-values also suggest that the effect of volatility is more persistent than that of liquidity.

We observe that bond spreads Granger-cause volatility and illiquidity changes for all the portfolios, confirming the feedback effects for distressed bonds. Finally, the Granger-casualty results imply that illiquidity generally cannot be forecasted using past values of spreads and volatility. It is, however, possible that past

²⁶ The number of lags is selected using the BIC and AIC selection criteria. All our VAR specifications are stationary models, as we test whether all inverse roots of the characteristic polynomial lie inside the unit circle.

1994-2010

Table 11 Cholesky variance decomposition of volatility and liquidity effects on bond spreads (1994–2010).

| Ordering 1 | | Ordering 2 | | Ordering 1 | | Ordering 2 | |
|---|-----------------------|---------------------------|---------------------------|------------------------|-----------------------------|----------------|------------------|
| ΔVol_t | $\Delta Illiq_t$ | ΔVol_t | $\Delta Illiq_t$ | ΔVol_t | $\Delta Illiq_t$ | ΔVol_t | $\Delta Illiq_t$ |
| Panel A: Information | n shares for volatili | ty and illiquidity for th | ne pre-crisis and overall | periods | | | |
| Aggregate Industria 0.187 | 0.113 | 0.265 | 0.035 | 0.199 | ustrial Portfolio 0.200 | 0.316 | 0.083 |
| High-rated Industr 0.024 | 0.014 | 0.029 | 0.009 | 0.025 | dustrial Portfolio 0.013 | 0.026 | 0.012 |
| ow-rated Industri 0.144 | 0.093 | 0.208 | 0.029 | 0.204 | lustrial Portfolio 0.171 | 0.320 | 0.055 |
| Short-term Industr 0.165 | 0.189 | 0.269 | 0.086 | 0.167 | dustrial Portfolio 0.317 | 0.284 | 0.200 |
| .ong-term Industri).224 | al Portfolio 0.025 | 0.246 | 0.004 | Long-term Inc 0.325 | dustrial Portfolio 0.055 | 0.377 | 0.002 |
| Panel B: Information Credit spread regin | • | ty and illiquidity for h | igh and low regimes (19 | 994–2010) | | | |
| ow regime | | | | High regime | | | |
| Ordering 1 | | Ordering 2 | | Ordering 1 | | Ordering 2 | |
| ΔVol_t | $\Delta Illiq_t$ | ΔVol_t | $\Delta Illiq_t$ | ΔVol_t | $\Delta Illiq_t$ | ΔVol_t | $\Delta Illiq_t$ |
| Aggregate Industria 0.062 High-rated Industr | 0.061 | 0.085 | 0.038 | 0.203 | 0.230 | 0.340 | 0.093 |
| 0.036 .ow-rated Industri | 0.046 | 0.047 | 0.035 | 0.022 | 0.005 | 0.021 | 0.005 |
| 0.029 Short-term Industr | 0.051 | 0.040 | 0.040 | 0.210 | 0.195 | 0.347 | 0.058 |
|).038 .ong-term Industri | 0.072 | 0.065 | 0.045 | 0.169 | 0.363 | 0.300 | 0.232 |
| 0.126 Volatiltiy based reg | 0.015 | 0.122 | 0.019 | 0.343 | 0.065 | 0.408 | 0 |
| Low regime | giiies | | | High regime | | | |
| | -1 D. Af-II. | | | nigii regiiile | | | |
| Aggregate Industria).235 High-rated Industr | 0.145 | 0.347 | 0.033 | 0.188 | 0.225 | 0.313 | 0.100 |
| 0.049 Dow-rated Industri | 0.028 | 0.052 | 0.025 | 0.020 | 0.008 | 0.020 | 0.007 |
| 0.200 Short-term Industr | 0.085 | 0.266 | 0.019 | 0.183 | 0.215 | 0.326 | 0.073 |
|).176 .ong-term Industri | 0.145 | 0.256 | 0.064 | 0.160 | 0.362 | 0.287 | 0.235 |
|).322 | 0.015 | 0.334 | 0.003 | 0.309 | 0.075 | 0.382 | 0.002 |
| lliquidity based re | gimes | | | | | | |
| ow regime | | | | High regime | | | |
| Aggregate Industria 2.081 Light rated Industr | 0.004 | 0.084 | 0.001 | 0.199 | 0.230 | 0.333 | 0.096 |
| ligh-rated Industr 1.035 .ow-rated Industri | 0.022 | 0.043 | 0.013 | 0.024 | 0.011 | 0.023 | 0.012 |
| 0.032 Short-term Industr | 0.001 | 0.033 | 0 | 0.206 | 0.196 | 0.340 | 0.062 |
| 0.095 .ong-term Industri | 0 | 0.089 | 0.006 | 0.164 | 0.364 | 0.293 | 0.236 |
|).129 | 0.001 | 0.129 | 0 | 0.335 | 0.066 | 0.399 | 0.001 |

In this table, we conduct Cholesky variance decomposition to study the impact of volatility and illiquidity variables on the variance of the residual bond spreads. We consider two different orderings of the volatility and illiquidity variables.

For Ordering 1, we employ the following residual regression to obtain the variance shares:
$$\text{Res}_t = \alpha_0 + \alpha_1 e_{1,t} + \alpha_2 \Delta I l l i q_t + \eta_t$$
, where $\text{Res}_t = \Delta C S_t - \left(\widehat{\beta}_0 + \widehat{\beta}_1 E q u t t y r e t_t + \widehat{\beta}_2 \Delta r_t + \widehat{\beta}_3 (\Delta r_t)^2 + \widehat{\beta}_4 \Delta S l o p e_t + \widehat{\beta}_5 \Delta V I X_t + \widehat{\beta}_6 M k t r e t_t\right)$ and $e_{1,t} = \Delta V o l_t - (\widehat{\gamma}_0 + \widehat{\gamma}_1 \Delta I l l i q_t)$

The variance share explained by volatility is obtained as: $var(\alpha_1e_{1,t})/var(Res_t)$, and the variance share explained by illiquidity as: $var(\alpha_2\Delta Illiq_t)/var(Res_t)$. Next for Ordering 2, we reorder the volatility and illiquidity variables and define the residual equation as $Res_t = \alpha_0 + \alpha_1\Delta Vol + \alpha_{2t}e_{2t} + \eta_t$ where Res_t is obtained as before and $e_{2,t} = \Delta Illiq_t - (\hat{\gamma}_0 + \hat{\gamma}_1\Delta Vol_t)$. We obtain the variance shares for the pre-crisis and overall periods (Panel A) and separately for the low- and high-credit spread, volatility and illiquidity regimes (Panel B). The low- and high-regimes are identified using the two-state Hamilton (1989) model as in Fig. 4 and explained under Table 8. For each ordering, we highlight whichever variable has a higher variance share.

information in volatility and spreads is quickly incorporated into market liquidity, and hence their effects are not observable at a monthly frequency. Granger causality tests overall provide insights on differential lead-lag interactions among the key variables. The next step is to analyze how unexpected shocks to the variables influence their future values.

5.2. Impulse response analysis

We analyze the short- and long-run impact of unexpected liquidity and volatility shocks on credit spreads by employing the vector-autoregressive (VAR) model (5) described earlier. We estimate the generalized impulse response functions and quantify the effects of current unforecastable liquidity and volatility shocks on credit spreads. We follow Koop et al. (1996) and estimate the generalized impulse responses that are robust to variable reorderings in the VAR. Monthly results for the accumulated generalized impulse response functions for three different portfolios are presented in Table 10 and Fig. 5. Since the recent financial crisis may be interpreted as a large unanticipated volatility and liquidity shock, impulse responses may behave very differently between crisis and non-crisis periods. Accordingly, we first document a precrisis sample (1994–2007), where our results may be interpreted as effects of "normal" shocks to volatility and liquidity; we next present impulse response functions including the crisis period (1994-2010), and analyze the main differences.

In Table 10, we report the accumulated impulse responses and the associated p-values for sample periods with and without the recent financial crisis. Panel A, spanning the 1994-2007 period, shows that shocks to bond spreads are highly persistent over time. Current period shock to spread has a strong effect (ranging between 39 and 66 bps) on the next month's spread, and a long-term impact of 23-40 bps after 10 months on future spreads. All multiperiod responses to a bond spread shock are significant at 10% level. The effect of volatility shock on bond spreads ranges from 20 to 32 bps after one month and 7 to 14 bps after ten months, and the shock effects are significant at both horizons. Relatively, the impact of liquidity shock on spreads is weak; the short-term effect is 11-22 bps of higher spreads after one month, while the cumulative long-term effect is small and not significantly different from zero. Unlike the volatility shocks, the effect of liquidity shocks on bond spreads is generally not significant after the first month.

Once we extend the sample to include the financial crisis period (i.e., 2008–2010, Panel B), magnitudes of the shock impact for all three variables (i.e., spreads, volatility and liquidity) significantly increase across portfolios. Credit spread and volatility shocks are still persistent and larger in magnitude compared to liquidity shocks as before. Liquidity shocks now become more persistent and have a larger impact for low-rated and short-term portfolios. However, as in the non-crisis subsample, the effect of liquidity shocks on bond spreads is not consistently significant after the first month, and there is little evidence of a long-term effect at the 5% significance level.²⁷

Similar results can be observed in Fig. 5, where we plot the accumulated impulse response functions and their corresponding 5% and 10% confidence bounds for sample periods with (Panel A) and without (Panel B) the recent financial crisis.

Overall, our findings imply that the effects of volatility shocks are more persistent and significant in magnitude; liquidity shocks in general are less persistent and seem to be processed into bond prices under a month. Large liquidity and volatility shocks, as evidenced during the recent financial crisis, increase the magnitude and persistency of the responses. Volatility shocks, however, are still more persistent and have a significant long-run effect on spreads compared to liquidity shocks, whose affects are mainly short-lived.

6. Cholesky variance decomposition tests

Finally, we explore to what extent the volatility and liquidity variables can each explain the error variance of bond spreads. The variance decomposition will enable us to tease out the relative contribution of volatility and liquidity in explaining the residual bond spreads. We follow a two step procedure: *first*, we use the Regression model (2.3) to estimate bond spread residuals; *second*, we determine the contribution of volatility and liquidity variables to the variance of the bond residuals, under two different orderings. We therefore parse the total variance of residual bond spreads into information shares individually explained by each of the regressors (i.e., volatility and liquidity) using the expressions under Table 11. We obtain the variance shares for the pre-crisis and overall periods and separately for the low- and high- bond spread, volatility and liquidity regimes.

The information shares for volatility and liquidity all increase in magnitude once we include the financial crisis (Panel A). We observe that illiquidity can explain a significant residual variance for short-term portfolios under the first ordering for the overall period (Panel A), and that effect mainly is seen in the high-spread, high-volatility or high-illiquidity regime (Panel B). Illiquidity is also important for the high-rated and high-rated long-term portfolio bonds in the low-regimes (not tabulated). In all other cases, volatility has the dominant explanatory power in both regimes and under different orderings.

7. Summary and conclusions

In this paper we study the dynamic effects of idiosyncratic volatility and liquidity on bond spreads over time. We analyze how such dynamic effects are impacted by underlying portfolio characteristics and market regimes. Our study is unique in that we follow a "ground-up" approach, where we employ an extensive sample of individual bond trades to build aggregate bond portfolios and corresponding equity indices of interest.

We observe and document many critical differences between how volatility and liquidity impact bond spread over time and across regimes. Our results imply that idiosyncratic volatility and liquidity effects can significantly matter for the distress portfolios (i.e., low-rated and short-term bonds), while for others volatility overwhelms liquidity. Volatility, overall, has a first order-impact compared to bond illiquidity. Illiquidity shocks are quickly processed into bonds prices, whereas volatility and credit (bond spread) shocks are more persistent and have long-term effects. Both volatility and bond illiquidity shocks are intensified during crisis regimes and tend to have larger and more persistent effect on bond spreads.

Our results can be useful to wide interest groups. Practitioners may incorporate our findings into improved pricing models based on differential impact of volatility and liquidity. Investors can build better asset allocation and trading strategies.²⁸ Debt issuers can effectively manage their credit versus liquidity components of their funding costs by better timing their debt issuance.

Determining the relative magnitudes and dynamic effects of credit versus liquidity components is also vital for policy makers. If illiquidity is the main driver behind high yields, measures to improve bond market liquidity are more appropriate. Liquidity shocks in turbulent regimes can be virulent, as this study shows, and hence quick effort to contain the funding risk mainly for low-rated and short-term issuers is imperative. This is partly because both

²⁷ In further untabulated results, we find that effects of contemporaneous shocks to the variables vary depending on the underlying bond ratings and maturities. The shock effects are stronger for low-rated versus high-rated bonds. While the volatility shocks have a similar effect on short- and long-term bonds, liquidity shocks matter only for the short-term bonds Impulse response analysis conducted using weekly data, which further confirms the monthly results.

²⁸ For example, long-horizon investors may find spreads from high-yield debt attractive, if such spreads are attributable to low liquidity rather than high default risk

low-rated and short-term issuers will experience a sudden increase in yield spreads as markets experience marked flights to quality and liquidity. Moreover deterioration in debt market liquidity, particularly for financial firms, can engender severe funding difficulties and further exacerbate their credit risk by intensifying their implicit rollover risk (He and Xiong, 2012). Early detection of liquidity-driven distress regimes can therefore help regulators formulate better policy responses for financial bailouts and avoid costly liquidity-credit risk spirals.

On the other hand, if bond spread changes are mainly impacted by default risks, policy actions aimed at improving the solvency of the underlying banks and issuers become critical. Unlike liquidity shocks, crisis induced volatility shocks are strong and persistent as solvency of balance sheets, mainly consisting of low-rated, short-and long-term debt, is adversely impacted. Therefore, identifying the differential characteristics of liquidity vs. volatility shocks as documented in this study can enable better, more timely policy decisions.

Such a differential policy treatment was, for example, illustrated in the recent financial crisis (for e.g., Sarkar, 2009). In particular, the Federal Reserve's primary response from 12/2007 to 03/2008 emphasized the provision of liquidity to solvent institutions as illiquidity rather than credit risk seemed to be the main problem. In contrast, policy initiatives starting in 09/2008 reflected the Federal Reserve's views of the increasing importance of counterparty credit risk. Finally, our findings with respect to the persistence and long-term effects of credit, liquidity and volatility shocks may also have direct policy implications. For example, policy measures intended to improve credit and solvency conditions and reduce volatility need to be long-term based, while those aimed at improving liquidity need to focus on alleviating short-term funding squeezes.

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Appendix A. Bond sample selection

From the NAIC database, we first extract transaction information on U.S. corporate bond trades between 1994 and 2010. The NAIC bond trades are then merged with various bond attributes from FISD. Based on the 6-digit CUSIP numbers, the corporate bonds are further matched to the stock price data in the CRSP database. Bond ratings on the transaction date of each bond trade are extracted from ratings tables in FISD. For bond ratings, we use Standard & Poor's (S&P) rating value if it exists; otherwise, we use Moody's rating data. On the transaction dates of bond trades, we compute yield-to-maturity and Macaulay duration based on reported buy or sell prices and other related variables. We obtain yield spreads for each bond transaction using matching maturity swap rates as benchmark (Houweling et al., 2005). Daily swap rates for 15 different maturities (ranging between 1 and 30 years) are obtained from DATASTREAM. Each bond trade is matched to a corresponding swap rate based on linear interpolation of the two closest neighboring maturity swap yields. Since the tax treatment of swaps is similar to that of corporate bonds, the bond spreads with the swap benchmark have little tax component in them (see Longstaff et al., 2005).

Several screening criteria are employed. From the NAIC database, we exclude bond trades characterized by any of the following: (a) existing erroneous trade dates and incorrect third-party vendor names; (b) underlying maturity less than one year on transaction date; (c) missing or extreme transaction prices (transaction price is below \$100 or above \$10,000, where \$1000 is the par value); (d) variables needed to compute yield-to-maturity missing or are erroneous; (e) inability to compute yield-to-maturity due to non-convergence of pricing formula, or a computed yield greater than 100% or less than 1%; or (f) variables needed to compute Macaulay duration missing or inability to compute Macaulay duration

The following bond issues are further excluded: bonds with callable, redeemable, putable, exchangeable, convertible, sinking fund, enhancement or asset-backed features; perpetual and variable rate bonds: medium-term notes: Yankee. Canadian and foreign currency issues: Rule 144a issues: TIPS, Treasuries, Munis. Treasury coupon- and principal-strips; and agency-type bonds. We also drop bond issues that are unrated or have either missing or extreme bond ratings (below C grade or belonging to AAA or Aaa ratings²⁹). Finally, we drop all bond trade observations that (a) do not have any matching stock in the CRSP database or (b) have insufficient stock returns data in the six months prior to the bond transaction date (and hence equity volatilities cannot be computed). All computed bond measures (yield-to-maturity, yield spread and duration) are winsorized at the 1% level. The final matched dataset consists of issuance- and transaction-related information on fixedrate, U.S. dollar-denominated, domestic, straight corporate bond trades by all insurance companies for publicly traded equity firms.

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