A new perspective on the corporate bond liquidity factor

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Abstract

This study documents properties of market-wide corporate bond liquidity and suggests that liquidity risk is an important determinant of returns. In market downturns, transaction costs rise for sellers and fall for buyers. The negative relation between buyer and seller liquidity motivates a new across-measure liquidity factor that incorporates an asymmetric liquidity component. Shocks to market-wide liquidity explain a large fraction of bond return variation in the time series. Primarily driven by the asymmetric component, the liquidity factor attracts a cross-sectional risk premium that is robust to controls for credit, equity, and interest rate factors as well as the illiquidity level.

JEL classification: G12; G14

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1. Introduction

The systematic threat to financial markets arising from a liquidity crisis in U.S. corporate bonds has attracted increasing interest from policymakers, investors, and academic researchers over recent years. In March 2020, corporate bond mutual funds saw outflows exceeding $250 billion and dealers could not fully absorb the selling pressure (Sharpe and Zhou (2020)). The pandemic-induced shock to market-wide liquidity had a magnitude of approximately six standard deviations according to my estimates. This led to the creation of new facilities to stabilize the market, funded by the Federal Reserve and backed with equity invested by the U.S. Treasury Department. While the topic has proven systematically relevant, IOSCO (2019) points out that corporate bond market liquidity under stressed conditions remains understudied.

The contribution of this study to the literature is twofold. First, the paper adds to our understanding of the (non-normal) time series distribution of corporate bond liquidity, its conditional nature, its high degree of persistence, and its significant predictive power for returns. While some studies (e.g., Schestag, Schuster, and Uhrig-Homburg (2016)) benchmark different liquidity proxies, this study is the first to combine the information content of various measures into a common facet of corporate bond liquidity. I find that a newly proposed across-measure liquidity risk factor, *LRF*, explains more variation in corporate bond market returns than any single liquidity measure previously documented in the literature. Second, the paper evaluates the asset pricing role of liquidity risk and finds that it is a dominant driver of returns in the time series and that the liquidity risk premium is statistically significant and economically meaningful in the cross-section of corporate bond returns.

The paper identifies an asymmetry between liquidity faced by buyers and sellers. The asymmetry is documented through a negative time series relation between buyer and seller liquidity as increasing transaction costs for customer sell orders are associated with decreasing transaction costs for customer buy orders and vice versa. In a market downturn, the conditional cost of selling more than doubles while the cost of buying falls by approximately 80%. This asymmetry is cyclical in nature as its magnitude crucially depends on financial market sentiment. The underlying mechanism is that in a bear market many investors want to sell, which makes it relatively difficult to liquidate corporate bonds but easy to buy them. Traditional bid-ask spread measures hardly capture the asymmetry in liquidity as they imply that costs for buyer and seller-initiated trades are equal. Hence, my proposed factor incorporates symmetric and asymmetric liquidity components. *LRF* is defined as the average of the normalized innovation in the Roll (1984) spread and the normalized difference in sell and buy order price impact lambdas. Like in Brennan, Chordia, Subrahmanyam, and Tong (2012), the lambdas are estimated via an OLS regression that allows for an asymmetry in the price reaction function between buyer and seller-initiated order flow.

The literature identifies two potential channels for the pricing of liquidity. First, illiquidity can be considered as a non-stochastic security characteristic that varies cross-sectionally between bonds. According to Amihud and Mendelson (1986), a less liquid asset with the same promised cash flows, will trade less frequently, realize lower prices, and exhibit a higher characteristics risk premium. Second, as empirically documented by Pastor and Stambaugh (2003), a liquidity risk premium may arise from an asset's return exposure to market-wide liquidity shocks due to the commonality in liquidity across individual securities. Acharya and Pedersen (2005) develop a liquidity-adjusted capital asset pricing model under time-varying liquidity conditions. In their framework, the required return of an asset depends on expected liquidity and covariances of its returns and liquidity with market returns and aggregate liquidity. While my study focusses on the latter channel of aggregate liquidity as a state variable in a factor pricing framework, I consider the liquidity characteristic as a control variable. The research questions for the asset pricing section of the paper are as follows:

- Does liquidity risk explain variation in the time series of excess returns and what is the magnitude of the liquidity risk factor compared to other common risk factors?
- What is the compensation (risk premium) for liquidity risk in the cross-section of corporate bond portfolios?

I find that *LRF* not only explains more time series return variation than any other liquidity factor, but also dominates the economic and statistical significance of other common risk factors. The quantification of a cross-sectional price for liquidity risk, although consistently economically meaningful, depends on the model specification. My benchmark factor model estimates the annual liquidity risk premium at 3.63%. This magnitude drops by almost 50%, but remains significant at the 5% level, when controlling for the liquidity characteristics premium.

While the literature on the liquidity characteristic premium has established that illiquid bonds earn higher yield spreads (e.g., Chen, Lesmond, and Wei (2007), Bao, Pan, and Wang (2011), Dick-Nielsen, Feldhütter, and Lando (2012)), the literature is inconclusive on whether time-varying corporate bond market liquidity risk is priced. Lin, Wang, and Wu (2011) apply the idea of liquidity betas to corporate bonds. Like Pastor and Stambaugh (2003), they construct an aggregate liquidity risk factor and show that this state variable is priced in the cross-section of corporate bond returns. The authors report a 4% annualized average return premium for bond portfolios with high vs. low sensitivities to aggregate liquidity. In a more recent paper, Bai, Bali, and Wen (2019) identify common risk factors in the cross-section of corporate bond returns. The authors construct liquidity betas based on return differentials between illiquid and liquid bonds using a rolling liquidity beta estimation window for each individual bond. They find that liquidity risk (alongside downside and credit risk) attracts an economically and statistically significant risk premium.

However, the existence of a corporate bond liquidity risk premium is not universally accepted. Bongaerts, De Jong, and Driessen (2017) conduct asset pricing tests and, in line with my approach, define the liquidity factor as return sensitivity to aggregate liquidity shocks. The authors find that exposure to corporate bond liquidity shocks carries an economically negligible and negative risk premium. While they acknowledge that corporate bond liquidity shocks alone explain more than a quarter of the time series variation in corporate bond returns, they conclude that this risk is not priced. Choi and Yongjun (2018) test the integration of equity and corporate bond markets. They find that the risk premium for the bond liquidity factor is a small negative number and conclude that bond market liquidity tends not to be priced.

In addition to the development of a new liquidity measure, my data set and empirical methods differ from and thereby aim to contribute to a resolution of the literature's conflicting interpretation of the corporate bond liquidity risk premium. First, most papers investigate only a small set of individual liquidity proxies, although each measure may just be a noisy estimate of a single underlying liquidity risk. My study tests the significance of a wide array of liquidity proxies and then constructs a superior systematic liquidity factor. Second, because my sample covers a longer period than previous papers, it captures more liquidity crises. Third, while my main asset pricing tests assume a constant liquidity beta and risk premium, the paper also exploits the time variation in liquidity risk exposures to quantify the risk premium over shorter horizons. Fourth, predominantly due to the finite life of bonds, my portfolio-based asset pricing tests contain less noise than studies that estimate exposures at the security level. The choice of asset pricing factors emphasizes robustness and simplicity as opposed to an overfitted model. Although only containing liquidity, credit, equity, and interest rate risk factors, my four-factor benchmark model explains almost two thirds of the time series return variation of corporate bond portfolios.

2. Institutional background, data description, and liquidity estimation

With a market value of $10.41 trillion in outstanding corporate bonds, which compares to a market capitalization of $32.80 trillion for stocks, the secondary market in corporate debt is an important component of the U.S. financial market.[1] The level of trading costs in this relatively opaque and decentralized market, as measured by bid-ask spreads, is a multiple of the trading costs in the equity market and economically meaningful compared to total returns (e.g., Bessembinder, Spatt, and Venkataraman (2020)). Corporate bond trading primarily takes place in dealer-driven markets with electronic customer-to-customer trading platforms only making up a small but growing fraction of overall volume (O'Hara and Zhou (2021)). Although dealers have committed less market making capacity over the last decade, they still play a crucial role even though for an increasing proportion of trading they merely match customer buys and sells without taking bonds into inventory (e.g., Bao, O'Hara, and Zhou (2018)).

This study uses transaction-level data of individual bonds from the TRACE Enhanced database from July 2002 to June 2020. TRACE contains data on price, volume, trade direction, security identifiers as well as trade date and time. I extract all trades in corporate bonds[2] and apply the cleaning procedure of Dick-Nielsen (2009, 2014), which takes care of cancellations,

[1] Outstanding U.S. corporate bond volume is sourced from SIFMA (https://www.sifma.org/resources/research/fixed-income-chart/) and equity market cap on all U.S. exchanges from Bloomberg. As of June 2020.
[2] My definition of corporate bonds is in line with the WRDS Corporate Bond Database manual and contains the following bond types: US Corporate Convertible (CCOV), US Corporate Debentures (CDEB), US Corporate Medium Term Note (CMTN), US Corporate Medium Term Note Zero (CMTZ), or US Corporate Paper (CP).

corrections, reversals, and double counting of trade records. Further, I restrict the sample towards more liquid bonds to reduce measurement error in liquidity proxies. A return premium due to illiquidity should primarily depend on transaction costs incurred by marginal price setters. Hence, the focus of my study is on institutional investors and I remove retail-sized trades below $100,000 in value (as in Dick-Nielsen et al. (2012)). While this filter excludes 71% of trades, the impact on traded volume is less than 1% in my sample. In addition, I require at least eight trades per bond each month and I remove primary market transactions. All filters are outlined in Appendix 1.

From a total of 28.04 million trades in 21,043 unique corporate bonds over 216 months, I estimate a set of eleven liquidity measures for each bond-month. I cast a wide net of liquidity proxies to increase robustness in the asset pricing tests of market-wide liquidity shocks. The choice of liquidity measures spans from popular symmetric liquidity proxies (e.g., Roll spread and Amihud's (2002) ILLIQ measure) to asymmetric liquidity proxies (e.g., difference between buy and sell side transaction costs and price impact lambdas). All liquidity measures are defined in Appendix 2. On average, each liquidity measure is estimated over approx. 3,000 bonds, each month. I trim bond-month liquidity measures at the 99% and 1% level to reduce the impact of outliers given bond-level liquidity estimates can be noisy. To estimate liquidity at the market level, I compute the mean of the bond-month liquidity measures each month. My proxy of aggregate liquidity is representative of a (weighted) average between investment grade (IG) and high yield (HY) markets, which make up 77.7% and 21.8% of my bond-month sample, respectively (the remainder of bonds are unrated).

Some of the roundtrip liquidity measures have similar magnitudes and the same unit. However, the ILLIQ measure as well as the price impact lambdas vary in magnitude and units from the other proxies. This can lead to difficulties when comparing or weighting a combination of the measures. Hence, after reporting summary statistics for the raw liquidity measures in section 3.1, I follow Korajczyka and Sadka (2008) and standardize all measures. I modify the measures to proxy liquidity (as opposed to illiquidity) by multiplying them with (-1). Hence, when estimating liquidity betas of assets to liquidity shocks, a positive beta implies an increasing asset value when liquidity improves and vice versa. Let L^{i*} be the $n\ x\ T$ matrix of observation of the *i*th liquidity measure (*i* = 1, 2, …,11). Further, define μ_{t-1}^{i} and σ_{t-1}^{i} as the time series mean and the time series standard deviation of the aggregate liquidity measure i, estimated with the full sample up until month $t-1$ with at least one year of observations. I use past observations as opposed to the full sample mean and standard deviation to avoid a potential look-ahead bias. Then, L^i is the $n\ x\ T$ matrix of observations of the ith standardized liquidity measure, defined as follows:

$$L_t^i = \frac{L_t^{i*} - \mu_{t-1}^i}{\sigma_{t-1}^i} \quad (1)$$

While TRACE Enhanced is the primary data source, I make use of other data providers: Returns of fixed income benchmarks and macro as well as financial variables are compiled from the Bloomberg terminal. Fama-French and equity liquidity factors are sourced from WRDS. Interest rates are sourced from FRED and bond returns and security characteristics are sourced from WRDS Bond Returns. Prime dealer corporate bond inventory data comes from the New York Fed and monthly asset flows into corporate bond mutual funds is sourced from Morningstar Direct. SIFMA provides a time series of IG and HY debt issuance volumes.

3. Analysis of the time series properties of corporate bond market liquidity

3.1 Summary statistics

Table 1 reports that the popular Roll measure estimates the average bid-ask spread at 61 bps. Its interquartile range is 41 bps to 71 bps in the time series. Roundtrip costs of 36 bps and 49 bps are implied by the regression-based half bid-ask spread and the one-way transaction cost measure, respectively.[3] The imputed roundtrip cost (IRC) measure, which computes the spread between the daily minimum and maximum price for transactions of a given bond with identical notional quantity, has the lowest value of 30 bps. The measure primarily picks up principal trades in which dealers pass on bonds from one customer to another without taking the bond on inventory. These trades have low risk for brokers and attract lower transaction costs (see Bao et al. (2018)).

An analysis of asymmetry in liquidity measures indicates that the sell side of transaction costs and price impact lambdas is statistically not different from the buy side at any

[3] The Roll spread is non-negative by construction and thus higher than the roundtrip costs implied by the regression-based bid-ask and transaction cost measures.

conventional level. Table 1 reports that aggregate sell costs demonstrate a 27% larger standard deviation than buy costs, which implies that the cost incurred for liquidating corporate bonds is more uncertain over time than the cost associated with buying bonds. In terms of magnitude, the buy and sell lambdas, correspond to a $110 and $90 price impact for a one million dollar buy and sell, respectively. The buy and sell lambda coefficient values are economically and statistically indistinguishable from zero, on average.[4] I will later demonstrate that the time series variation of the liquidity asymmetry contains valuable information. The minimum aggregate buy cost and buy lambda are strongly negative and therefore imply that, in tail events, buyers receive compensation for providing liquidity. The maximum aggregate buy cost and buy lambda are less than half of the magnitude of the corresponding maximum sell-side measures, on average. This shows that extreme illiquidity penalizes sellers more than buyers, which is line with a downside characteristic of market liquidity.

<Insert Table 1 here>

In addition to the first two moments of aggregate corporate bond liquidity levels, Table 1 reports the third and fourth moments to assess the normality of the distribution. With an average of 2.0 across all measures, most are skewed towards the illiquid side. This characteristic is more pronounced for asymmetric proxies. Importantly, the buy transaction cost and buy lambda have the lowest magnitude in skewness and the buy cost distribution is skewed towards the side of lower transaction costs. While the average kurtosis of 17.0 across all illiquidity measures indicates materially fatter tails than implied by a normal distribution, the asymmetric proxies are again the outliers. Driven by the fat tails of the sell-side cost and lambda, these measures have extremely fat tails. The levels of skewness and kurtosis provide evidence of the downside characteristic embedded in the asymmetry between seller and buyer liquidity relative to symmetric liquidity proxies.[5] Figures 1 and 2 graph a time series of symmetric and asymmetric liquidity measures, respectively.

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[4] Two reasons explain lambdas close to zero: First, the return between two trades is regressed on the signed trade volume and the trade direction change indicator. Hence, the lambdas provide an estimate for the slope of the price function with respect to volume, only after controlling for the bid-ask bounce. Second, under normal market conditions, large bond trades attract better pricing than small trades due to the lower marketability of odd lot trades.

[5] The magnitude of non-normality in the asymmetric liquidity proxies is scaled down during the normalization process (Equation 1) because these measures demonstrate a comparatively high standard deviation, which serves as the denominator for the z-score.

<Insert Figure 1 and 2 here>

Pastor and Stambaugh (2019) note that a difficulty in assessing market liquidity and estimating liquidity betas arises from the rarity of liquidity crises. Liquidity betas are difficult to estimate in calm periods in which no crises occur. I circumvent this concern by using a long time series that contains two extreme liquidity shocks (financial crisis and pandemic sell-off) and by reporting conditional results for positive and negative financial market sentiments. I define bull and bear regimes as the subsamples of months where the S&P 500 total return is in the lowest and highest quartile of its monthly observations, respectively. The conditional means analysis (Panel B and C of Table 1) provides two main insights: First, as expected, illiquidity measures across the board are higher in bear than bull market periods. This finding underscores the pro-cyclicality embedded in market liquidity. Second, the average rise in asymmetric illiquidity measures conditional on a market downturn is more pronounced than the rise across symmetric illiquidity proxies. In a bear market, the sell-side transaction costs are approximately eleven times higher than the buy costs. This represents a 108% increase in bear market sell costs vs. the sell costs measured over the full sample. The symmetric transaction cost measure experiences a comparatively modest increase of 21% in bear markets. Similarly, the sell lambda exceeds the buy lambda as the buy lambda turns negative conditional on the bear market subsample. In such turbulent periods, buyers appear to act as providers (not consumers) of liquidity and get compensated with a negative price impact. These findings provide strong empirical support for the consideration of an asymmetry in buyer and seller liquidity when measuring corporate bond liquidity. In line with my findings, Choi and Huh (2019) report that customers increasingly provide liquidity and that conventional liquidity measures treat trades in which customers provide liquidity as trades in which customers demand liquidity.

The final six months of the sample period cover the pandemic-related sell-off and subsequent recovery in risk assets. O'Hara and Zhou (2020) find that during the crisis in March 2020 there is heightened demand for liquidity and dealers shift from buying bonds to selling bonds, exacerbating market illiquidity. Because order flow tilts towards the customer-sell side, the authors note that obtaining information on both bids and asks is challenging during the sell-off. While noting the one-sidedness of the market, they nevertheless use a symmetric transaction cost measure, which essentially averages buyer and seller costs.

My study provides new insights by splitting the transaction cost measure in O'Hara and Zhou (2020) into a buy and sell side to investigate the corporate bond liquidity crisis in March 2020. Figure 3 shows that the average buy trade has a negative cost of -0.67% at the height of the crisis while sell costs climb to 2.18%. Hence, the liquidity asymmetry (sell costs net of buy costs) increases materially, which implies that the symmetric transaction costs reported in O'Hara and Zhou (2020) are largely driven by the sell side and therefore underestimate the true illiquidity faced by sellers. The same pattern prevails in October 2008 during the height of the financial crisis, where the average buy and sell trade incurs transaction costs of -3.57% and 5.27%, respectively. Although neglected by previous corporate bond studies, the asymmetry between buyer and seller transaction costs appears too large in magnitude to be ignored. The observation of a negative price impact of a buy order during a bear market is not unique to corporate bond markets: Kwan, Philip, and Shkilko (2021) report that the price impact of a stock order can be opposite its direction, depending on the prevailing order book imbalance.

<Insert Figure 3 here>

3.2. Autocorrelation in aggregate liquidity

According to Acharya and Pedersen (2005), only persistent shocks to liquidity can lead to a theoretically justifiable risk premium for illiquidity. The autocorrelation function of various liquidity measures is reported in Figure 4. It turns out that liquidity conditions in the corporate bond market are very persistent. The symmetric liquidity proxies exhibit an average autocorrelation coefficient of +0.89 to their one month lagged observation. From there, the level of autocorrelation falls almost monotonically but remains at +0.76 across symmetric measures for a three-month lag. The persistence in aggregate liquidity only becomes statistically insignificant for a horizon beyond one year. These levels of autocorrelation in aggregate corporate bond liquidity are in line with the stock market, where most liquidity factors exhibit significant autocorrelations (Korajczyka and Sadka, 2008).

The degree of persistence for asymmetric liquidity measures is materially lower. The one-month autocorrelation coefficient average is +0.46 and the persistence already becomes insignificant from the second month lag. This is unsurprising because the asymmetry computes seller liquidity relative to buyer liquidity. This difference is more dynamic than the highly autocorrelated level of transaction costs. The imbalance between buyer and seller-initiated order flow, conceptually related to asymmetric liquidity measures, is not persistent over time with the one- and two-months lag correlation coefficients close to zero. The aggregate order imbalance measure, which is averaged across bonds each month, demonstrates its highest level of persistence at three- and twelve-months lags, hinting at quarterly and annual seasonality effects of one-sided order flow. By comparison, IG and HY market excess returns demonstrate autocorrelation of 0.22 and 0.30 at the one-month lag, respectively. Although this correlation drops close to zero in the second month and then remains insignificant at longer lags, the short-term return persistence poses a challenge to the efficient market hypothesis.

<Insert Figure 4 here>

The degree of persistence in (symmetric) liquidity measures motivates the application of an autoregressive model, which decomposes the liquidity observations into anticipated changes and unanticipated shocks. I use lagged market-wide liquidity observations to construct an out-of-sample prediction for each measure. Following Korajczyka and Sadka (2008), I estimate shocks (liquidity innovations) through the residuals of an AR(2) model, using two months of lagged liquidity observations as regressors. The resulting time series of liquidity shocks is shown in Figure 5. The residuals of the AR(2) regressions show no significant autocorrelation at conventional levels and thereby qualify as a proxy for liquidity surprises.

<Insert Figure 5 here>

3.3 Commonality across measures of liquidity

The focus of this section is to investigate the commonality between various market liquidity proxies to assess whether an across-measure factor may provide a more accurate estimate of the true systematic liquidity shock. I begin with an analysis of pair-wise correlations between the eleven liquidity measures as well as other financial and microstructure variables. This is followed by a principal component analysis (PCA) to formally test the degree of common systematic factors in the liquidity measures.

Table 2 reports pairwise time series correlations of market liquidity measures for the full sample (upper half) and for the bear market sample (lower half). The average pairwise correlation coefficient between the normalized innovation element of symmetric liquidity measures is +0.87. During bear market episodes, the across-measure correlations increase to even higher levels, which suggests common underlying factors in corporate bond liquidity measures. The correlation coefficient between the normalized levels of the two asymmetric measures is similarly high at +0.85. The average correlation between levels of asymmetric liquidity and symmetric liquidity innovation is somewhat lower at +0.60. This indicates that symmetric and asymmetric proxies capture different aspects of liquidity but tend to deviate from their mean into the same direction.

<Insert Table 2 here>

The buy cost and buy lambda are both significantly negatively correlated with their sell-side counterparts. When sellers face low liquidity, buyers tend to benefit from high liquidity and vice versa. This aligns with the analysis of summary statistics (Table 1), which shows that buyers receive a compensation for liquidity provision at a time when market participants struggle to liquidate corporate bonds. This mechanism appears to be driven by the microstructure of debt markets, where customers, facilitated through dealers who prefer not to take bonds into inventory during times of stress, provide liquidity to each other. By contrast, in equity markets, where comparatively deep limit order books are the norm, Brennan et al. (2012) report the opposite relation: The time series variation of aggregate buy and sell lambdas is shown to have a positive correlation coefficient >0.99. In my corporate bond study, the sell-side measures positively correlate with the symmetric measures, which indicates that the conventional (symmetric) measures are predominantly driven by the sell-side. Hence, commonly used symmetric liquidity measures may underrepresent true transaction costs when the lower sell-liquidity is averaged with the higher buy-liquidity. Given the negative relation between buyer and seller liquidity strengthens in the subsample of bottom-quartile stock market performance, just when liquidity conditions become more important to market participants, it appears necessary for the corporate bond literature to move beyond exclusively using proxies of (symmetric) roundtrip transaction costs.

Table 2 reports that market liquidity tends to improve with positive stock returns (S&P 500) and stock market liquidity, as represented by the aggregate liquidity innovation factor of Pastor and Stambaugh. It deteriorates with increasing market volatility (VIX), and funding costs (LIBOR spread “Ted”). The magnitude of the correlation coefficients increases in the bear market sample, which implies a non-linear relation between bond liquidity and financial market sentiment. This is an undesirable property for investors as, conditional on market downturns, corporate bond market liquidity deteriorates more than a linear model would suggest. In line with the above findings on liquidity asymmetry, buyer liquidity, as measured by the buy transaction cost and buy lambda measures, is negatively correlated with stock returns in the time series. Hence, it tends to be more expensive to buy when financial market sentiment is positive and vice versa. This finding aligns with the relation between the buy lambda and the order imbalance variable. An increase in order imbalance towards more customer buys than sells is associated with a decrease in the standardized buy lambda measure, which indicates a higher buy price impact at a time where buyers are the consumers of liquidity.

In addition to a subsample analysis, the downside risk embedded in corporate bond market liquidity is well-illustrated by the difference in correlation coefficients to upside and downside stock returns. I define the upside (downside) equity beta as the value of the S&P 500 return in months of positive (negative) returns and zero otherwise. Across all measures, except for the two buyer liquidity proxies, the relation to the downside equity beta is stronger than to the upside. Unsurprisingly, the sell-side liquidity proxies have the strongest positive correlation to stock market returns within the negative subspace. The empirical downside characteristic observed in corporate bond liquidity provides theoretical support for its role as an asset pricing factor based on Bawa and Lindenberg's (1977) framework of the mean-lower partial moment.

Large and abrupt outflows from corporate bond funds are considered a systematic risk for financial markets (e.g., Sharpe and Zhou (2020)) and accordingly Table 2 documents a positive association between net flows and market liquidity. The liquidity-flow relation is stronger for asymmetric liquidity proxies, which, by way of construction, better capture whether buyers or sellers are liquidity takers.[6] I discover and document another dimension of corporate bond liquidity risk in Table 2. The relation between market liquidity shocks and the monthly change of the cross-sectional standard deviation of bond-month transaction cost measures is negative. In short, when market-wide liquidity deteriorates, the dispersion of the

[6] Appendix C provides additional information on the financial market and macro variables that drive market liquidity. A set of 10 variables explains 62% of the variation of liquidity shocks. For example, the spread between the yield in ten-year swaps and U.S. Treasury bonds, a proxy for an illiquidity premium of physical government bonds over the derivatives market, relates low liquidity in government bonds to low liquidity in corporate bonds.

liquidity conditions across individual bonds increases, possibly making it harder for investors to transact in specific bonds they hold or would like to acquire.

The results of the PCA indicate that the first principal component (PC1) explains 73% of the time series variation across the standardized symmetric liquidity innovations and the asymmetric liquidity levels. The first three principal components cumulatively explain 93% of the time series variation. Table 3 reports that the PC1 loadings are very similar across most liquidity proxies. The exception are buyer liquidity measures, which have the opposite sign on the PC1 loading. The PC2 loadings are consistent across most liquidity proxies but demonstrate more variation in magnitude. The PC2, which on a standalone basis explains 16% of the variation across measures, appears to be the differentiating factor between symmetric and asymmetric aspects of liquidity. Its loading is positive for symmetric proxies and negative for seller liquidity and asymmetric proxies.

<Insert Table 3 here>

In conclusion, I document a strong positive correlation across the liquidity shock measures. I find evidence that surprises to market liquidity comove with stock returns and financial market sentiment indicators. This suggests that aggregate liquidity risk may be a priced factor. The PCA results provide evidence that the variation across liquidity measures is to a large extent driven by common systematic components. The dimensionality reduction procedure of the PCA also documents the differences between buyer and seller liquidity proxies and emphasizes that the asymmetry is driven by differing exposures to underlying systematic shocks. Therefore, an across-measure liquidity factor, which captures both symmetric and asymmetric liquidity, should provide a more accurate estimate of true liquidity shocks than each individual proxy on a standalone basis. Hence, I define my liquidity risk factor, *LRF*, as

$$LRF_t = \frac{1}{2}\varepsilon_{Roll,t} + \frac{1}{2}\lambda_t^{S-B}, \tag{2}$$

where $\varepsilon_{Roll,t}$ is the innovation element of an AR(2) model of the market-wide Roll spread and λ_t^{S-B} is the level of lambda asymmetry estimated at the bond-level and aggregated at the market level. Both measures are normalized as shown in Equation (1). The Roll spread is recommended by Schestag et al. (2016) due to its ability to capture transaction costs. The lambda asymmetry is chosen because it measures the difference in seller and buyer price impact while controlling for the symmetric bid-ask spread element (see Appendix B.2.1).

3.4 The temporal relation between liquidity and credit returns

Having established a strong link between contemporaneous market returns and liquidity shocks, the natural question arises whether one can predict the other. For brevity and considering the high degree of commonality across most of the liquidity measures, I report results for two symmetric measures (Roll spread and transaction costs), two asymmetric measures (sell-buy asymmetry in transaction costs and lambdas), and *LRF*.

Table 4 shows a significant positive correlation between contemporaneous corporate bond market returns and liquidity. Improving liquidity is associated with positive excess returns. This relation is stronger in the IG (ICE BofA US Corporate Index) than HY (ICE BofA US High Yield Index) market and stronger for asymmetric compared to symmetric liquidity proxies. Further, aggregate liquidity demonstrates a positive relation to future returns. The correlation to one-month forward returns is significant at the 1% level for most measures, stronger in the HY market, and strongest for asymmetric liquidity measures as well as *LRF*. Hence, a positive shock to liquidity in a given month is associated with positive excess returns in the coming month. The inverse relation, i.e., returns predicting liquidity, is significant at the 5% level across most liquidity measures. However, because the cross-serial correlation coefficient has a smaller magnitude, the linear relation between returns and future liquidity appears modestly weaker than vice versa. This finding differs from the relation observed in the presumably more efficient (and liquid) stock market. Based on U.S. data from 1983 to 2000, Korajczyka and Sadka (2008), report that liquidity shocks appear uncorrelated with future returns but that liquidity shocks can be predicted by historical returns.

<Insert Table 4 here>

The analysis above is set up with a one-month horizon. Figure 6 expands the predictability horizon to up to 12 monthly leads and lags of IG market excess returns. It becomes apparent that the cross-serial correlation coefficient quickly drops towards zero beyond one month, which indicates that shocks to liquidity do not demonstrate significant predictive power for longer term returns.

4. Asset pricing with liquidity factors

4.1 The asset pricing model

The above findings about the time series properties of the systematic corporate bond liquidity factor motivate an analysis of its effect on asset prices. The asset pricing model follows a standard risk factor approach. The benchmark model explains the test assets' excess return over the risk-free rate with exposures to four factors. The main factor of interest is *LRF*, with credit, equity, and interest rate factors acting as controls.

Credit risk is a common factor in corporate bond returns (e.g., Bai et al. (2019)) and is therefore included in my asset pricing model. The positive correlation between credit risk and illiquidity risk creates an endogeneity concern (reverse causality). Hence, instead of extracting a yield spread above a risk-free benchmark, which likely already contains a compensation for liquidity risk, I measure credit spreads from a credit default swap index (CDX). This derivative is a basket of North American single IG issuer credit default swaps. CDX are standardized instruments with large trading volumes and smaller bid-ask spreads compared to the average corporate bond (Boyarchenko, Gupta, Steele, and Yen (2018)) and a suitable proxy for liquid credit spreads. Specifically, my credit risk factor is the monthly change in a 5-year IG CDX contract. The factor is linearly related to an investable strategy of holding and rolling over CDX.

Bongaerts et al. (2017) state that any reasonable corporate bond asset pricing model should have at least one market risk factor and I follow their approach to include an equity risk factor as measured by S&P 500 returns. Because fixed income securities should be sensitive to changes in the market yields, an interest rate risk factor, as measured by changes of the yield on U.S. Treasury securities at 7-year constant maturity, completes the list of betas. The 7-year maturity point is chosen because it lies between the median (5.6 years) and mean (8.7 years) time to maturity across the bond sample. All risk factors are normalized as shown in Equation (1) to allow for a comparison of magnitudes. For consistency, the rates and credit factors are multiplied by (-1), so that an increase in the risk factor corresponds to a positive corporate bond return impact. Fig. 7 plots the monthly time series of the four factors.

The security-level regression approach that is commonly used in the equity literature is arguably less suitable for bonds. Bonds have finite lives, whereas stocks are a perpetual claim on a firm's cash flow. This implies that individual bonds mechanically demonstrate time variation in betas while approaching maturity. In addition to the bond-specific economic rational, Pastor and Stambaugh (2019) provide support from an econometric perspective as they argue that portfolio betas to aggregate liquidity shocks contain less measurement error than beta estimates from single securities. Similarly, Lin et al. (2011) note a reduction of noise when empirically estimating factor exposures using portfolio as opposed to individual bonds. The construction of portfolio test assets in my analysis follows Bai et al. (2019), who double sort corporate bonds into quintiles based on the outstanding amount and time to maturity. This results in 25 portfolios with a reasonable variation in the liquidity dimension as issue size is a common proxy for liquidity (e.g., Bongaerts et al. (2017)). An advantage over previous studies is that I investigate liquidity risk over 18 years and thereby cover the pre- and post-Volcker rule era, which constitute differing market making environments. This is important as the existence (or lack of) a risk premium can hardly be proven with insufficient data.

The first step of the Fama-MacBeth (1973) asset pricing analysis is to investigate if the test assets have a statistically and economically significant loading on the risk factors. Hence, the equally weighted excess returns over the risk-free rate of bonds in portfolio *i* are regressed on the four risk factors and a constant. The total return of each corporate bond is sourced from WRDS Bond Returns. It is a combination of the monthly price change (using the last traded price within the last five trading days of the month) and the accrued coupon interest. The time series regressions with monthly (t) frequency are set up as follows:

$$Excess\ return_{i,t} = \alpha_i + \beta_{1,i} Liquidity\ proxy_t + \beta_{2,i} Credit\ risk\ proxy_t + \beta_{3,i} Equity\ risk\ proxy_t + \beta_{4,i} Rates\ risk\ proxy_t + \varepsilon_{i,t} \tag{3}$$

The second step investigates if the factor loadings earn a cross-sectional risk premium. Hence, in the second stage, the betas from the first stage are regressed on the portfolios' average excess returns over the full sample. The estimated coefficient loadings then represent lambdas (risk premia) for the systematic factor exposures.

$$Average\ excess\ return_i = \lambda_\alpha + \lambda_{\beta_1} Liquidity\ beta_i + \lambda_{\beta_2} Credit\ beta_i + \lambda_{\beta_3} Equity\ beta_i + \lambda_{\beta_4} Rates\ beta_i + \varepsilon_i \tag{4}$$

Assuming the model captures all relevant risk factors, the intercept term λ_α should be zero in theory but it is included in the regression specification to test its value empirically. The coefficients λ_{β_1}, λ_{β_2}, λ_{β_3}, and λ_{β_4} measure the market prices of liquidity, credit, equity, and interest rate factor risks, respectively. The error term ε_i is the pricing error of portfolio *i*. The key research question is whether the liquidity risk premium, λ_{β_1}, is significantly positive after controlling for liquid credit, equity, and rates risk exposures.

4.2 Variance decomposition of corporate bond market excess returns

Before formally testing the significance of liquidity risk factors for the time series and cross-section of corporate bond portfolio returns, this section investigates the impact of liquidity shocks on the overall risk in IG and HY market returns as proxied by the same benchmarks as in section 3.4. To assess the magnitude of liquidity, credit, and equity risk, I decompose the realized volatility (annualized standard deviation) of excess returns over maturity-matched treasuries into risk factors. Because the market returns are measured in excess of the return of default risk-free bonds with the same maturity (as opposed to cash), they should not contain a term premium and the interest rate factor is not required.

Table 5 reports the coefficients and t-stats (Newey-West corrected with two monthly lags) as well as the model R^2 of market excess return regressions. It stands out that just three (normalized) factors, namely liquidity, credit, and equity, can explain up to three quarters of the time series variation in corporate bond market excess returns. The model fits equally-well to IG and HY market benchmarks. In a horse race of liquidity measures, the chosen proxies all prove significant at the 1% level in the IG market, but some add more explanatory power than others. In the IG market, the incremental R^2 is up to 7% and 11% for asymmetric and symmetric liquidity proxies, respectively. A combination of the two, as represented by *LRF*, achieves the highest incremental R^2 and statistical significance of any liquidity measure. The dominance of *LRF* also holds in the non-IG market, where the factor has a higher economic and statistical significance than other liquidity proxies (Table 5 – Panel B). HY market returns are comparatively more sensitive to asymmetric liquidity proxies. While the innovation element of the symmetric Roll measure is not significant at the 5% level, the lambda asymmetry is significant at the 1% level. This implies that the riskier segment of the bond market is more sensitive to asymmetric liquidity risk than to a shock in roundtrip transaction costs.

<Insert Table 5 here>

In a comparison of coefficient values across the three risk factors in the IG market, the loadings on liquidity risk are larger than on credit and equity risk. Focusing on the *LRF* regression as the baseline (Table 5 – Panel A – column VII), this indicates a higher sensitivity of IG excess returns to a one standard deviation change in liquidity (89 bps) than to credit (40 bps) and equity (36 bps) ceteris paribus.

The risk factor exposures, which conceptually correspond to the percentage market value allocation in the classical portfolio variance setup, can be used as inputs to compute their marginal risk contributions to market excess returns. For the decomposition of total volatility, where the comparability of the coefficient magnitudes is irrelevant, I use the original risk factor values as opposed to the normalized time series for liquidity, credit, and equity risk. This preserves the distribution of the raw risk factor observations and thereby increases the model's explanatory power. This analysis identifies the marginal contribution to risk coming from each risk factor *i* and is computed from the covariance matrix of factor and market returns as well as the factor *i*'s weight w_i, and the market portfolio *j*'s volatility:

$$MCTR_i = \frac{\partial \sigma_j}{\partial w_i} = \frac{1}{\sigma_j} \sum_i^n w_i cov(r_i, r_j) \qquad (5)$$

Figure 8 shows that the volatility of IG and HY market excess returns over maturity-matched government bonds over the full sample period is 5.59% and 10.38%, respectively. The graph illustrates a decomposition of the total volatility into contributions from statistically significant risk factors (at the 1% level). The proxies for symmetric and asymmetric liquidity risk contribute 1.60% and 0.90% of volatility in the IG market, respectively. The asymmetric liquidity measure contributes 2.14% to HY market volatility, while the symmetric proxy is not significant at conventional levels. Hence, the combination of symmetric and asymmetric liquidity risks makes up 45% of the overall risk in IG and 21% of the overall risk in HY. The credit risk factor contributes 33% (35%) and equity risk contributes 13% (33%) of overall volatility in IG (HY). Only around 9% (IG) and 12% (HY) of the total volatility are not explained by the above factors, as the regressions underlying Figure 8 report a model R^2 of 82% for IG and 78% for HY.

<Insert Figure 8 here>

4.3 Do exposures to liquidity risk drive variation in the time series of returns?

If liquidity, credit, equity, and rates risk capture the variation in corporate bond excess returns across the issue size and maturity spectrum well, the regressions specified in Equation (3) should yield reasonably high $R^{2\prime}s$ and significant coefficient values for most test assets. The time series regressions are estimated across the 25 test portfolios with 204 monthly observations and Newey-West corrected standard errors (with two lags).

The benchmark model in Panel A captures 64% of the portfolios' time series return variation, on average. The distribution of $R^{2\prime}s$ is remarkably stable with only five of the 25 portfolios demonstrating a value below 60%. All these five portfolios are in the lowest maturity quintile where risk factors naturally approach zero as the bonds near maturity.

Panel B of Table 6 contains the average coefficient values for a simple three-factor model of only credit, equity, and rates risk. The average R^2 drops to 45%, which implies an average incremental R^2 of 19 percentage points for *LRF* relative to the three-factor model. The explanatory power and coefficient magnitude of *LRF* is higher across the test assets than the IG market benchmark. This is a function of the characteristics-sorting of bonds by issue size, which biases weight towards the smaller issue sizes that tend to demonstrate more liquidity risk exposure (Table 6 – Panel A). In contrast, the value-weighted benchmark biases weight towards the larger issue sizes that tend to demonstrate less liquidity risk exposure.[7] An additional difference between the test assets and the benchmark is that the former only consist of bonds that are traded during the last five business days of a month while the latter contains all bonds that meet the index criteria. This implies that a fraction of bonds in the benchmark may be valued with stale prices. The smoothing bias in reported benchmark returns induced by a delayed or partial adjustment to market prices often arises in illiquid asset classes (e.g., Geltner (1991)) and can lead to downward biased volatility and liquidity beta estimates.

[7] Because my test assets are formed by ranking the outstanding amount of corporate bonds, the size distribution within each portfolio is almost uniform. The time series regression results are largely unchanged when value-weighting (mean *LRF* exposure of 1.37) as opposed to equal-weighting returns (mean *LRF* exposure of 1.38).

<Insert Table 6 here>

While the strong explanatory power of the model is an assuring feature, the main interest lies in the statistical and economic significance of the coefficient values with a particular focus on *LRF*, the newly proposed liquidity risk factor. Indeed, *LRF* appears to be a significant driver of monthly corporate bond excess returns. The factor has an average t-statistic of 8.7. The t-statistics range from 4.2 to 15.7 and hence all test assets demonstrate liquidity sensitivity at the 1% level of significance. The average coefficient value implies +1.38% excess return impact for a one standard deviation improvement in aggregate liquidity. This is economically meaningful as it corresponds to 27% of the test assets' mean annual excess return.

The t-statistics for equity and interest rate risk largely prove significant as their averages across the 25 test portfolios indicate significance at the 5% and 1% level, respectively. However, the distribution of t-statistics is not as stable for equity and interest rate risk as it is for the liquidity risk factor. At the 5% level, 60% and 68% of the test assets load statistically significant on equity risk and rates risk, respectively. The rates factor falls short of the 10% significance level for all portfolios in the lowest maturity quintile, which is intuitive as short-dated bonds are less sensitive to shifts in the government bond yield curve. The credit risk factor is insignificant at conventional levels in this setting, but I will demonstrate its importance by varying the risk factor specification and set of test assets. The economic magnitude of the coefficients can be compared conveniently due to the normalization procedure embedded in the risk factors. An instantaneous one standard deviation move in liquidity, equity, and rates is associated with 138 bps, 26 bps, and 54 bps of corporate bond portfolio excess returns, respectively.

The results in Table 6 are related to Table 8 in Bai et al. (2019), who suggest that their risk factor selection of the excess bond market return, a downside risk factor, a credit risk factor, and a liquidity risk factor substantially outperforms other models considered in the literature. I extract their risk factors and estimate time series regressions with my test assets.[8] Over a period from July 2004 to December 2019, Panel C of Table 6 reports an average R^2 of 72% for their four-factor model. A difference to their setup is that my benchmark model does not include a

[8] A time series of bond factors can be obtained from Professor Turan G. Bali's website: https://sites.google.com/a/georgetown.edu/turan-bali/data-working-papers

corporate bond market factor. This aims to reduce multicollinearity concerns due to the same liquidity and credit premia being present in multiple independent variables. However, for comparability of my results with Bai et al. (2019) and due to its strong significance, I add a corporate bond market factor to my benchmark model (Table 6 - Panel D). This factor is computed each month as the average excess return over the risk-free rate of all bonds in the sample. Over the same period as in Panel C, my five-factor model records a modestly higher average R^2 of 81%. The average corporate bond market coefficient is close to 1, which is intuitive given the aggregation of all portfolios adds up to the market. The other factor loadings can be interpreted as relative risk exposure compared to the market risk proxy and it is unsurprising that their mean coefficients are close to zero. The inclusion of the market risk factor not only increases the explanatory power of the model but also reduces the average intercept materially. Panel C and D estimate the alpha term at less than one basis point per month, which indicates a strong empirical performance of both models.

4.4 Estimation of a liquidity risk premium in the cross-section

The previous section estimates liquidity betas for the test assets. In the second stage of a classical Fama-MacBeth (1973) asset pricing analysis, the focus now shifts to the question whether the risk factor exposures from the first stage can explain cross-sectional variation in portfolio excess returns. This is an important question because the mere statistical significance of risk factors identified through time series regressions neither proves that these factors earn a statistically significant risk premium, nor does it reliably quantify the magnitude of any such factor premium. Specifically, the main research question is whether investors earn a (positive) compensation for exposure to the liquidity risk factor after controlling for other risks.

The mean excess return over the risk-free rate for the 25 test portfolios, which averages 0.42% per month (approx. 5.2% p.a.), is the dependent variable in the regression specified in Equation (4). Regression I of Table 7, which uses the risk factor loadings of the benchmark model (obtained in Panel A of Table 6), estimates the cross-sectional *LRF* risk premium at 22 bps per month. With an average *LRF* exposure of 1.38, this results in an annual return contribution of 3.63% from liquidity risk. This corresponds to 71% of the average excess return. In addition to being economically meaningful, the liquidity risk premium is statistically significant at the 1% level. Another perspective on the economic significance is that a one standard deviation change in *LRF* exposure is associated with an annualized return impact of 1.55%. Looking at quintiles of high vs. low liquidity beta portfolios and multiplying the respective average liquidity beta with the price of liquidity risk, yields a return differential of 4.53% attributable to the varying liquidity risk exposures. This is of moderately higher magnitude than the decile-based estimate of Lin et al. (2011), who report a return spread of about 4% annually for bonds with high relative to low sensitivities to liquidity. The cross-sectional (normalized) equity risk premium is estimated at 16 bps per month, which corresponds to a return contribution of 0.52% p.a. under consideration of the average first stage factor loading. The equity risk premium is statistically significant at the 5% level.

The model R^2 of 88% is an assuring feature that the four factors in combination not only explain most of the return variation in the time series (Table 6 – Panel A) but that their loadings also explain the cross-sectional variation in portfolio returns. The overall model fit is good but not optimal as indicated by the intercept term, which is statistically significant at the 5% level. However, given the intercept of 7.6 bps per month corresponds to less than a fifth of the portfolios' average excess return, it is economically small. In summary, I find strong empirical evidence that liquidity risk exposure attracts a positive risk premium in the cross-section of corporate bond returns.

<Insert Table 7 here>

The magnitude of return contribution from credit and rates risk is economically not meaningful in regression I. In regression II, I proceed with the second stage of the three-factor model (Table 6 – Panel B) to analyze the risk premia for credit, equity, and rates in the absence of the liquidity risk factor. I find that each of the three risk premia are significant at the 10% level once liquidity risk is omitted in the cross-sectional regression. The annual return contribution, based on the product of average factor exposures and price of risk, are 1.87%, 1.61%, and 0.51% for credit, equity, and rates, respectively. However, due to *LRF*'s significance in regression I, even after controlling for credit, equity, and rates, and because the intercept is modestly higher and the model R^2 marginally lower in regression II, the preference should be not to omit liquidity risk.

The results in Panel A and B of Table 6 indicate interaction effects between the four risk factors. This is not surprising as Table 2 suggests that market liquidity is related to financial market sentiment. Although the risk factors in this analysis have been chosen with consideration for multicollinearity and endogeneity, a particular concern is the time-series correlation between *LRF* and the credit (0.67) and equity (0.61) risk factors. I circumvent the concern that *LRF* may primarily pick up credit and equity risk by analyzing the component that is linearly unrelated to other risk factors in the model. To proxy for the component of liquidity risk that is unrelated to its embedded credit and equity risk, I regress the time series of *LRF* on monthly CDX changes and S&P 500 returns.[9] I then extract the time series of the error term that sets the predicted value of *LRF* equal to its actual value and name it $LRF_{idiosyncratic}$. This factor, which is orthogonal to the other factors in the model, remains significant at the 1% level with similar magnitude and only modestly lower incremental explanatory power than *LRF* itself in the time series of portfolio returns (Table 6 – Panel E). In the second stage Fama-MacBeth (regression III of Table 7), the estimated cross-sectional liquidity risk premium for $LRF_{idiosyncratic}$ remains significant at the 1% level. Based on the average beta in the first stage, the return contribution from $LRF_{idiosyncratic}$ is 1.98% p.a., which is economically meaningful. The cross-sectional risk premium for credit and equity risk is positive and significant at the 5% level in this setup. This strengthens the evidence for a positive liquidity risk premium as it contains information beyond credit and equity risk premia and can coexist with other factors.

Because *LRF* contains a symmetric and asymmetric component, the natural question arises whether the identified risk premium is primarily driven by the former or the latter. The model in Panel F of Table 6 includes both the market-wide Roll spread innovation and the level of aggregate lambda asymmetry. With a statistical significance at the 1% level, the asymmetric proxy dominates the symmetric liquidity proxy in the time series as the Roll spread innovation is insignificant at conventional levels. Under consideration of the average betas from the first stage, the second stage (Table 7 – regression IV) implies an annual return contribution of 3.66% from the asymmetric and 0.54% from the symmetric liquidity proxy. This suggests that the liquidity risk premium is predominantly driven by the asymmetric liquidity component.

[9] The OLS regression has 204 observations, a R^2 of 50%, and credit and equity risk are both significant at the 1% level with heteroscedasticity and autocorrelation robust standard errors using two monthly lags.

Due to the integration of corporate debt and equity markets, and because systematic liquidity shocks could affect multiple asset classes, the corporate bond literature commonly controls for equity market liquidity (e.g., Bai et al. (2019) and Choi and Yongjun (2018)). Bongaerts et al. (2017) report that the innovation element in equity liquidity is priced in the cross-section of characteristics-sorted corporate bond portfolios. To check whether this result holds in the presence of my newly proposed liquidity risk proxy, I repeat the first and second stage Fama-MacBeth regressions with the four-factor model and the Pastor-Stambaugh factor for aggregate stock liquidity innovation. The mean coefficient values and t-statistics of the first stage are reported in Panel G of Table 6. The bond liquidity factor, *LRF*, remains significant at the 1% level and has a modestly higher magnitude than in the baseline model in Panel A. The negative coefficient on equity liquidity shocks implies that corporate bond returns tend to go down when stock market illiquidity goes up. However, because the time series coefficient falls short of the 10% level of significance based on mean and median t-statistics, the relation is statistically weak at best. The cross-sectional regression V of Table 7 shows a positive price of risk for the equity liquidity beta. This is counterintuitive as the equity liquidity betas are all negative, one would require a negative price of risk to obtain a positive equity liquidity risk premium. The annualized return impact from equity liquidity risk exposure is -0.62% and significant at the 10% level. The time series and cross-sectional properties of *LRF* remain almost unchanged and therefore robust to the inclusion of the equity liquidity factor.

Lastly, I test if conditional *LRF* loadings, estimated in the subsample of the lowest quartile of monthly equity returns, have explanatory power for returns. The time series analysis in Panel H of Table 6 indicates that the liquidity betas estimated in equity bear markets are quantitatively similar to the unconditional liquidity betas (Panel A) and remain significant at the 1% level. The economic and statistical significance of the liquidity risk premium, as estimated in regression VI of Table 7 with conditional betas and unconditional corporate bond portfolio excess returns, remains almost identical to the baseline result (regression I).

4.5 The separation of liquidity level and liquidity risk

The focus in the asset pricing section of this paper is to measure corporate bond portfolios' factor exposures to market-wide liquidity shocks and to tests if these exposures are priced cross-sectionally. So far, the *level* of illiquidity in the test assets is not considered. This is in line with Bai et al. (2019), who only control for security characteristics like illiquidity in the bond-level analysis but not in the portfolio asset pricing tests. In contrast, Bongaerts et al. (2017) control for a portfolio liquidity characteristic in the cross-section.

In Panel I of Table 6, I start by adding the level of the market-wide (average) Roll spread to the time series regression. Indeed, the aggregate level of transaction costs has a positive loading that is significant at the 1% level. This implies higher returns when the level of illiquidity is high. The liquidity, equity, credit, and rates factors remain of similar magnitude and significance compared to the baseline model in Panel A, but the intercept turns from positive to negative (significant at the 5% level). This is not surprising as the level of aggregate transaction cost is persistent over time (see Figure 4) and therefore absorbs some of the loading of the regression intercept. The model R^2 increases by almost 7%, which demonstrates a non-negligible incremental explanatory power from the level of aggregate transaction costs.

After finding evidence of significance in the time series, the question arises if the level of liquidity can explain the variation in test asset returns in the cross-section and if the liquidity characteristic may make the liquidity beta premium obsolete. The liquidity beta (0.90) and the liquidity characteristic (0.96) have a positive cross-sectional correlation with excess returns, which informally suggests that both may be priced. Equation (6) follow Bongaerts et al. (2017) and add each portfolios' average transaction cost, as measured by the Roll spread, as control variable.

$$Average\ excess\ return_i = \lambda_\alpha + \lambda_{\beta_1} Liquidity\ beta_i + \lambda_{\beta_2} Credit\ beta_i + \lambda_{\beta_3} Equity\ beta_i + \lambda_{\beta_4} Rates\ beta_i + \lambda_C Roll\ spread_i + \varepsilon_i \tag{6}$$

Regression VII in Table 7 reports the prices of risk for the factors and the liquidity level characteristic, λ_C. The liquidity characteristic attracts a positive premium that is significant at the 1% level. The coefficient of 0.43 and the average transaction cost level of 0.57% imply a liquidity level premium of 2.97% per year. The statistical and economic significance of the liquidity level effect leads to an approx. 50% reduction of the estimated liquidity risk premium from 3.63% in regression I to 1.83%. While smaller in magnitude, the liquidity risk premium remains economically meaningful and significant at the 5% level.

The finding of a coexistence of the liquidity characteristics and liquidity risk premium in the cross-section of corporate bond returns contrasts Bongaerts et al. (2017). The authors report that transaction costs are sufficient to explain cross-sectional return variation as they find a modestly negative and statistically insignificant risk premium of bond liquidity betas. I therefore repeat the above two-stage asset pricing test for their study period (2003 to 2013). Most likely due to the differences in the construction of the liquidity factor between the two studies, I estimate a positive, but smaller risk premium of 0.97% for *LRF*. Importantly, however, the t-statistic of *LRF*'s cross-sectional price of risk is only 0.87. Hence, from 2003 to 2013, I find support for Bongaerts et al. (2017), who report that the corporate bond liquidity risk premium is negligible from a statistical perspective. This suggests that the importance of the liquidity factor relative to the liquidity characteristic increases after 2013.

4.6 Time-varying liquidity risk and expected returns

Because the previous analysis treats the betas and the associated risk premia as constant over time, I assess the robustness of my findings with rolling as opposed to pooled regressions over the full sample period. It appears reasonable to assume some degree of time variation in the sensitivity of corporate bond markets (and portfolios) to liquidity shocks. Further, the price investors assign to taking this risk may change over time.

I follow Bai et al. (2019) and estimate the time-varying factor exposures each month for each test asset with a rolling 36-months window of observations. I use the first stage four-factor model in Equation (3) for the rolling regressions. If *LRF* and the other factors truly capture systematic variation in corporate bond returns, exposures of test assets to these factors should predict cross-sectional differences in expected returns. Hence, the future cumulative three and twelve-months portfolio excess returns are the dependent variables in the second stage.[10] The independent variables are the rolling factor exposures and the liquidity level. This procedure generates 56 quarterly or 14 annual non-overlapping cross-sections. Due to the overlap of the 36-months rolling betas in quarterly and annual cross-sections, I use a Newey-West correction of standard errors with twelve and three lags, respectively.

[10] I focus on quarterly and annual future returns because monthly portfolio returns are noisier, but the main findings are similar for monthly cross-sections.

The repeated cross-sections not only capture time variation in risk premia but also have the advantage that the betas exhibit less cross-sectional correlation than over the full sample. This is particularly useful for the separation of liquidity risk from the liquidity level. The cross-sectional correlation coefficient between the full sample liquidity betas and the level of average Roll spread for the 25 portfolios is 0.91. This indicates that a portfolio with high transaction costs also tends to have a high return sensitivity to market-wide liquidity shocks and hence it is difficult to disentangle the two effects. Based on the rolling variables, however, the correlation coefficient between *LRF* and the average Roll spread drops to 0.39, which implies that their time series variation is different. In short, as Bongaerts et al. (2017) note, the sample of cross-sections contains more information than a single full-sample cross-section.

<Insert Table 8 here>

The average intercept and slope coefficients of the cross-sectional Fama-MacBeth regressions are reported in Table 8. The previously reported finding of a liquidity risk premium over the full sample remains valid in a setting of rolling regressions and future returns. Regression II explains the three-months forward portfolio excess returns with the rolling four factors as well as the 36-months moving-average of the Roll spread. The cross-sectional price of liquidity risk is estimated at 55 bps and is significant at the 10% level. Multiplying the price of risk by an average LRF exposure of 1.89 based on the rolling time series regression, corresponds to an annual liquidity risk premium of 4.15%, which is modestly larger than estimated over the full sample. The annual cross-sections in regression IV, estimate the average liquidity risk premium at 3.14% and report significance at the 5% level.

The model R^2 in Table 8 is naturally lower than in Table 7 as the former predicts future returns while the latter is based on realization of factors and portfolio returns over the same period. Nevertheless, the explanatory power of the rolling risk factor loadings for future portfolio excess returns is relatively high at above 70%. Liquidity risk dominates other risk factors in explaining cross-sectional variation of future portfolio returns over short horizons. The equity and rates factors are insignificant at conventional levels and the credit risk factor just falls short of the 10% significance level. The annualized liquidity characteristics premium, although not significant at the 10% level, is estimated at 1.02% and 2.16% based on quarterly and yearly cross-sections, respectively.

In regression V, I test if quarterly changes (as opposed to the levels) of the rolling factor exposures explain the cross-sectional return variation of future returns. The results are consistent with regressions I to IV in a sense that changes in systematic liquidity risk exposure attract a liquidity risk premium. In addition, the quarterly change of the rolling Roll spread attracts a liquidity characteristics premium, which is significant at the 5% level. In summary, the analysis of time-varying factor exposures in corporate bond portfolios further strengthens the evidence gathered over the full sample from 2003 to 2020. The liquidity risk premium dominates other risk premia in terms of economic and statistical significance and can coexist with the liquidity characteristics premium.

5. Robustness checks and additional analysis

The robustness checks tackle a few computational variations in estimating aggregate liquidity before testing the main result of time series and cross-sectional significance of corporate bond liquidity risk. To gauge market liquidity levels, I aggregate bond-month liquidity measures each month by computing their mean. Another approach, more representative of the average (traded) bond and less influenced by potential outliers, is to aggregate bond-month liquidity observations by their median. Due to the skewness towards the illiquid side of the distribution in the cross-section of bond-month observations, median roundtrip costs are lower than their mean-equivalents (median 44 bps vs. mean 61 bps for the Roll spread). To check whether *LRF* has similar explanatory power when estimated with a time series of normalized median liquidity proxies, I repeat the regressions in Table 5 Panel A with LRF_{Median}. I find that the coefficient estimates and the overall fit of the model are very similar (Table 9 – Panel A – regression I) and conclude that *LRF* is not sensitive to the aggregation procedure of individual bond liquidity observations to proxy market liquidity.

For ease of coefficient comparability, the regressions in Table 5 are estimated with normalized risk factors. While this mathematical operation aligns the measurement scale of the regressors, it modifies the original distribution of the explanatory variables by making the variances more uniform. In regressions II and III of Table 9 - Panel A, I find that the model R^2 for the Roll spread innovation and the lambda asymmetry measures increases by 6% on average (compared to the baseline model in Panel A of Table 5), when using the non-normalized time series of explanatory variables. The t-statistics of the liquidity factors become even larger, thereby strengthening the evidence of significance of liquidity risk in the time series of corporate bond market returns.

It is well known that odd-lot trades with a volume from $100,000 to below $1,000,000 incur higher transaction costs than larger institutional trades (e.g., O'Hara and Zhou (2021)). Hence, there may be a concern that my results are affected by relatively illiquid odd-lot trades. When I filter out trades below $1,000,000 volume, I reduce the trade count by 68% compared to my full sample (Appendix A). While average transaction costs are materially lower without odd-lot trades (e.g., Roll spread of 34 bps vs. 61 bps for the full sample), there is no material impact on the liquidity risk coefficients in the time series regressions (Table 9 – Panel A – regression IV). I conclude that *LRF* is robust to the exclusion of odd-lot trades.

To test if the liquidity risk premium remains priced in the presence of the corporate bond market factor, I estimate the second stage regressions based on the first stage factor loadings in Panel C and D of Table 6. Using the factor loadings of my four-factor model and the bond market factor, regression I of Panel B of Table 9 reports that *LRF* remains significant at the 1% level with a quantitively similar risk premium as in the benchmark model. Regression II indicates that the liquidity risk factor of Bai et al. (2019) is not significant at conventional levels in the cross-section of my test assets' returns. As a final step, I re-estimate Bai et al. (2019)'s model but replace their liquidity risk factor with *LRF*. Regression III shows that *LRF*'s cross-sectional price of risk is significant at the 1% level with a magnitude of 9 bps per month, while controlling for Bai et al. (2019)'s market, credit, and downside factors. This suggests that the combination of symmetric and asymmetric liquidity components in *LRF* leads to a superior liquidity risk factor.

My choice and definition of the of credit, equity, and rates risk factors are based on considerations for multicollinearity, the setup of the characteristics-sorted test assets and conceptually follow the related literature (e.g., default and term betas in Lin et al. (2011)). However, as is typical in asset pricing studies, I check the robustness of the risk premium of my newly proposed liquidity factor with the five-factor model (stock market return, size factor, book-to-market factor, the stock momentum factor, and the risk-free rate) of Fama and French (1993). Following Bai et al. (2019), I also add a corporate bond market factor. For brevity, I focus on the cross-sectional results that are shown in regression IV of Panel B of Table 9. The estimated price for liquidity risk remains significant at the 1% level and is estimated at 19 bps per month, which is close to the 22 bps in the baseline regression I of Table 7. The higher model R^2 and smaller intercept than in the benchmark model are primarily driven by the bond market factor. The equity market proxy remains priced although some of its premium appears to be absorbed by the bond market factor.

The cross-sectional asset pricing analysis in Table 7 contains a relatively small number of test assets (n=25). While there is a sufficient level of cross-sectional dispersion in *LRF* betas (standard deviation of 0.59), there may be concerns about the lower standard deviation of credit, equity, and rates betas (0.16, 0.15, and 0.42). The lower independent variation of the credit and equity loadings is a result of the test assets being obtained from characteristics-sorting by issue size (which correlates with bond liquidity) and maturity as opposed to credit risk (Lewellen, Nagel, and Shanken (2010)). Hence, I conduct an additional portfolio sort that is directly related to credit risk and conceptually aligned with the method used by Bongaerts et al. (2017). Specifically, I triple-sort bonds each month into six credit rating buckets (AAA & AA, A, BBB, BB, B, and CCC & lower) and maturity quintiles. The third sorting dimension is the liquidity level, where a bond is assigned to be below or above the median Roll spread in each rating-maturity bucket. This results in 60 (6x5x2) test assets. The results of the first and second stage Fama-MacBeth asset pricing test are reported in Panel J of Table 6 and regression V of Panel B of Table 9, respectively. The standard deviation of the liquidity, credit, equity, and rates factor loadings increases to 0.74, 0.43, 0.81, and 0.58, respectively. This leads to economically more meaningful and statistically more significant risk premia for credit and interest rate risk exposures. My previously reported findings are robust as liquidity risk remains a significant driver of time series excess returns with an average t-statistic of 5.93 and 52 out of 60 portfolios demonstrating *LRF* significance at the 1% level. The price of liquidity risk remains statistically significant at the 10% level in the cross-section. While the annualized liquidity risk premium of 0.84% (based on an average first-stage *LRF* loading of 1.45) is lower than in the benchmark model, it remains economically meaningful.

6. Conclusion

Covering one of the longest time periods in the transactions-based corporate bond liquidity literature, this study contributes to our understanding of the time-varying nature of liquidity and documents its downside characteristic. The cost of illiquidity, particularly for sellers, is shown to depend crucially on financial market sentiment. The paper exposes a shortfall in relying exclusively on symmetric (roundtrip) liquidity proxies. It proposes a new microstructure liquidity measure with superior explanatory power that incorporates the asymmetry between the cost of selling and the cost of buying. The paper has implications for risk management and provides portfolio managers a measurable liquidity risk factor. My findings imply that a portfolio should be more averse to liquidity risk exposure if it is likely that corporate bonds need to be sold to raise cash just when markets are in a turbulent state. The study also indicates that there is merit for active investors to act as providers of liquidity when sell costs are high.

The paper investigates if aggregate liquidity shocks are a state variable that is priced in corporate bond returns. In the time series of corporate bond portfolio excess returns, shocks to aggregate liquidity make up a material fraction of the overall risk. The economic magnitude of exposure to liquidity risk trumps the exposure to credit, equity, and rates risks. In the cross-sectional analysis, I find that corporate bond portfolios earn an economically meaningful risk premium as compensation for exposure to the liquidity risk factor. The covariance of corporate bond returns and market-wide liquidity shocks is significantly priced as liquidity risk matters over and above the effects of other risk factors, as well as the level of liquidity. The study contributes to the existing literature by documenting that the liquidity risk premium is primarily driven by the asymmetric liquidity risk component. While the estimated magnitude of the risk premium depends on the study period, the inclusion of a liquidity characteristics control, the choice of test assets, and to a lesser extent the choice of risk factor controls, the results consistently show that liquidity risk is priced in the corporate bond market.

Appendix A. Data filters for corporate bond trades in TRACE Enhanced

Data cleaning procedure and transaction filters

	Remaining trades	Reduction in trade count
Start with all corporate bond trades from TRACE Enhanced	124,085,346	
Data cleaning: Remove cancellations, corrections, reversals, and double counting. See Dick-Nielsen (2009, 2014)	106,278,529	-14.35%
Remove trades where reported price zero or negative	106,278,431	0.00%
Remove trades where dollar volume < USD 100,000*	30,849,090	-70.97%
Remove "special" trades (spcl_trd_fl ='Y')	30,739,239	-0.36%
Remove trades where commission incorporated in price	30,695,283	-0.14%
Remove trades without a change in price	30,616,484	-0.26%
Remove trades with an absolute price change >25%	30,607,695	-0.03%
Remove trades that are in the primary market (at issuance)	29,264,122	-4.39%
Remove trades where the reported price is below ten cents on the dollar	29,218,937	-0.15%
Remove bond-month observations where less than eight trades remain after all previous filters	28,043,921	-4.02%
Robustness: Remove trades where dollar volume < USD 1,000,000 and less than eight trades remain per bond-month after all previous filters	8,899,791	-68.26%

** This filter removes <1% of traded volume but a large number of retail-sized trades*

Appendix B. Definitions of liquidity measures

B.1 Symmetric liquidity measures

B.1.1 Amihud's (2002) ILLIQ measure

ILLIQ, a price impact measure, averages the price change r_t in relation to the trade volume Q_t. The ILLIQ measure is scaled by 10^6 and then multiplied by 10,000 to represent basis points.

$$\text{ILLIQ}_i = \frac{1}{N_t}\sum_{t=1}^{N}\frac{|r_{i,t}|}{Q_{i,t}} = \frac{1}{N_t}\sum_{t=1}^{N}\frac{\left|\frac{P_{i,t}-P_{i,t-1}}{P_{i,t-1}}\right|}{Q_{i,t}}$$

B.1.2 Roll spread

Roll's (1984) measure is based on trade-by-trade data and calculated each bond-month by estimating the bid-ask spread from the autocorrelation in price changes of trade t in bouncing between the bid and ask side. If the autocorrelation is positive, I set the measure to zero. The measure is multiplied by 10,000 to represent basis points.

$$S_{Roll,i} = 2\sqrt{-cov(\Delta p\%_{i,t}, \Delta p\%_{i,t-1})}$$

B.1.3 Imputed Roundtrip Costs (IRC)

The IRC measure, commonly used in bond markets, relies on identifying the daily minimum and maximum price for transactions of a given bond that is traded with identical notional quantity. It provides an estimated bid-ask spread by scaling the difference between the highest and lowest price of these trades. The measure is multiplied by 10,000 to represent basis points.

$$IRC_i = \frac{1}{N_t}\sum_{t=1}^{N} \frac{P_{i,t,max} - P_{i,t,min}}{P_{i,t,max}}$$

B.1.4 Transaction costs

As in O'Hara and Zhou (2020), for each customer-dealer trade, transaction cost is calculated as follows:

$$Cost_i = \ln(\frac{Trade\ price_i}{Benchmark\ price_i})\ x\ Trade\ sign_i$$

where $Trade\ price_i$ refers to the transaction price for trade *i*, $Benchmark\ price_i$ is the transaction price of the prior trade in that bond in the interdealer market, and $Trade\ sign_i$ is +1 for customer-buys and -1 for customer-sells. The transaction cost is then scaled by 10,000 to have the unit of basis points and averaged across all trade observations in a bond-month. I note that this number can be negative when customers buy (sell) below (above) the interdealer price.

B.1.5 Bid-ask coefficient

This is a coefficient obtained from a bond-month regression. For each bond i, for each calendar month, $\Delta p\%_{i,t}$ is a sample of the percentage changes in transaction prices over the month, $q^B_{i,t}$ is the signed square root of traded volume of each customer buy order, and $q^S_{i,t}$ is the signed square root of traded volume of sell orders. I use the square root of order flow because Hasbrouck and Seppi (2001) find that price impact is concave in trade size. The variable of interest, $\boldsymbol{\gamma}$, corresponds to half of the zero-quantity bid-ask spread as it captures the bid-ask bounce and d_t is the direction of the buy ($d_t = 1$) or sell ($d_t = -1$) order. An interdealer trade is assigned $d_t = 0$. The measure is multiplied by 10,000 to represent basis points.

$$\Delta p\%_{i,t} = \lambda^B_i q^B_{i,t} + \lambda^S_i q^S_{i,t} + \boldsymbol{\gamma_i}(d_{i,t} - d_{i,t-1}) + \varepsilon_{i,t}$$

B.2 Asymmetric liquidity measures

B.2.1 Lambda asymmetry

A separate estimation of buy and sell side lambdas allows for an asymmetry in the price reaction function to buyer and seller-initiated order flow. The OLS set-up is described in B.1.5. The lambdas are scaled by 10^6.

$$\Delta p\%_{i,t} = \boldsymbol{\lambda^B_i} q^B_{i,t} + \boldsymbol{\lambda^S_i} q^S_{i,t} + \gamma_i(d_{i,t} - d_{i,t-1}) + \varepsilon_{i,t}$$

The lambda asymmetry is calculated, for each bond *i*, each month *t*, by subtracting average buy lambda from average sell lambda:

$$\lambda^{S-B}_{i,t} = \lambda^S_{i,t} - \lambda^B_{i,t}$$

B.2.2 Transaction cost asymmetry

Buy costs and sell costs are calculated like in B.1.4 with the subsample of buys and sells, respectively. The cost asymmetry is calculated, for each bond *i*, each month *t*, by subtracting average buy costs from average sell costs:

$$Cost\ asymmetry_{i,t} = Cost^S_{i,t} - Cost^B_{i,t}$$

Appendix C. Determinants of contemporaneous market liquidity shocks

This table presents time series OLS regression results of market liquidity shocks as the dependent variable. The choice of independent variables is informed by LASSO regressions. Specifically, the selected variables remain non-zero with a $L1$penalty parameter of 0.5 or higher. The libor_spread (TED spread) and swap_spread are sourced from Bloomberg. The swap spread subtracts the yield of the current 3 months T-Bill from the 3 months

USD LIBOR. Lg_fund_hy_ig is the natural logarithm of the monthly net asset flow into IG and HY U.S. corporate bond mutual funds (source: Morningstar). The global_carry_adv_change is the monthly change in yield spread advantage (over government bonds) of U.S. BBB corporate bonds over the average yield of European, UK, and Japanese BBB's. Ig_issuance is the natural logarithm of the monthly new issuance of IG corporate bonds (source: SIFMA). Cp_spread is the spread in basis points of short-dated commercial papers over the risk-free rate (source: Bloomberg). Hy_cdx_level is the level of the "on the run" 5-year CDX contract on a basket of U.S. HY issuers (source: PIMCO). Before April 2005, the change in hy_cdx_level is estimated with a two-factor model on SPX and VIX. Lqd_volume_vs_6m_avg is the dollar trade volume of LQD, the largest corporate bond ETF, divided by its rolling six months average trade volume. Trading_cost_stddev_change is the monthly change of the cross-sectional standard deviation of bond-month transaction cost measures. Ps_stocks_agg_liquidity_innov is the 'non-traded' liquidity innovation factor from Pastor and Stambaugh. All coefficients except for equity liquidity were scaled up by 100. All liquidity measures are defined in Appendix B and winsorized at the 99% / 1% level. Each liquidity measure is normalized every month by its mean and standard deviation calculated up to the prior month (with at least one year of observations). To liquidity proxy innovation, the table uses the residuals of a second order autocorrelation model for each liquidity measure. T-statistics are reported in italics below each coefficient estimate. One, two, and three stars indicate significance at the 10%, 5%, and 1% level, respectively. Standard errors are heteroscedasticity and autocorrelation robust using two monthly lags. The sample includes all corporate bond trades from TRACE Enhanced that are not removed in the filtering process (Appendix A) for the period July 2003 until December 2019 (198 months).

Market liquidity drivers (full sample)

	Roll spread innovation	Cost innovation	Lambda asymmetry	Cost asymmetry
const	0.224	0.377***	0.180	0.175
	1.64	*2.76*	*0.65*	*0.95*
lqd_volume_vs_6m_avg	-0.040	-0.071	-0.261*	-0.473**
	-0.23	*-0.40*	*-1.69*	*-2.51*
trading_cost_stddev_change	-2.931***	-2.064***	-1.843**	-0.815
	-4.97	*-4.89*	*-2.54*	*-1.39*
lg_fund_hy_ig	0.498***	0.528***	1.366***	1.276***
	2.80	*3.20*	*6.24*	*6.39*
libor_spread	-1.425*	-0.997**	-0.590	-0.535
	-1.77	*-2.15*	*-0.81*	*-0.58*
global_carry_adv_change	-0.0010***	-0.014***	-0.010***	-0.009***
	-3.02	*-6.37*	*-3.09*	*-3.04*
ig_issuance	0.224**	0.203*	-0.145	0.165
	2.22	*1.86*	*-1.11*	*1.49*
cp_spread	0.869	0.412	0.194	-0.141
	1.18	*0.83*	*0.27*	*-0.16*
hy_cdx_level	-0.034*	-0.064***	0.016	-0.009
	-1.80	*-3.24*	*0.37*	*-0.24*
ps_stocks_agg_liquidity_innov	4.600***	2.772**	-0.339	-0.418
	2.60	*2.04*	*-0.35*	*-0.60*
swap_spread	0.216	-0.094	-0.669***	-0.701***
	0.86	*-0.62*	*-3.01*	*-3.15*
Obs.	198	198	198	198
Adj. R-squ.	64.8%	64.8%	54.4%	64.2%

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Table 1

Descriptive statistics of liquidity measures

This table reports summary statistics for aggregate (mean) liquidity measures. Panel B (C) reports the conditional mean and standard deviation for the bear (bull) subsamples, which are defined as the S&P 500 total return being in the bottom (top) quartile of monthly observations. All liquidity measures are defined in Appendix B and winsorized at the 99% / 1% level. The sample includes all corporate bond trades from TRACE Enhanced that are not removed in the filtering process (Appendix A) for the period from September 2002 until June 2020 (214 months).

	ILLIQ	Roll	IRC	Half B/A coefficient	Cost	Buy cost	Sell cost	Cost asymmetry	Buy lambda	Sell lambda	Lambda asymmetry
Panel A: Summary statistics of market liquidity (full sample)											
Mean	143.53	60.62	30.15	17.98	24.69	23.58	25.98	2.88	0.11	0.09	-0.02
Std. Dev.	70.62	30.42	13.56	8.36	13.29	44.95	56.93	99.99	0.49	0.58	0.95
Min	72.79	29.23	14.06	7.78	12.83	-356.57	-75.17	-219.91	-2.35	-1.29	-2.69
$Q_{0.05}$	79.73	32.82	16.35	9.99	14.70	-27.30	-30.08	-106.31	-0.52	-0.65	-1.39
$Q_{0.25}$	99.42	40.89	21.02	12.90	16.99	5.44	-1.38	-41.24	-0.12	-0.22	-0.50
Median	125.13	51.52	26.49	15.76	20.53	22.86	17.10	-6.11	0.10	0.04	-0.09
$Q_{0.75}$	164.42	71.02	34.82	20.70	27.29	43.52	38.58	33.33	0.30	0.30	0.37
$Q_{0.95}$	273.00	127.24	63.37	31.67	44.79	84.64	88.43	115.10	0.89	0.80	1.28
Max	501.19	226.68	84.48	62.88	110.67	143.23	527.09	886.56	2.40	4.20	6.49
Skewness	2.45	2.16	1.62	2.42	3.31	-2.79	4.31	3.84	0.07	2.83	1.70
Kurtosis	10.35	8.79	5.41	10.87	16.77	26.85	33.41	32.54	8.72	19.31	13.97
Obs	214	214	214	214	214	214	214	214	214	214	214
Panel B: Conditional mean and standard deviation of market liquidity (bear stock market sample)											
Mean	171.78	73.07	34.39	21.14	29.95	4.86	54.13	49.87	-0.09	0.41	0.50
Std. Dev.	99.49	41.49	16.52	11.92	20.18	66.99	90.85	156.58	0.59	0.87	1.31
Panel C: Conditional mean and standard deviation of market liquidity (bull stock market sample)											
Mean	153.68	63.97	32.29	18.89	25.57	43.84	7.99	-35.41	0.36	-0.16	-0.52
Std. Dev.	66.58	29.52	15.11	7.69	11.36	38.03	37.76	72.65	0.54	0.46	0.81

Table 2

Commonality across liquidity measures

This table reports the time series correlation of aggregate (mean) liquidity measures. The lower half of the table (shaded grey) reports the correlation for the bear subsample, defined as the S&P 500 being in its lowest quartile of monthly total returns, whereas the upper half of the table is computed across the full sample. SPX refers to the S&P 500 return. SPX up (down) is the SPX return if positive (negative) and zero otherwise. Given sample size, SPX up and down correlations are only computed for the full sample. VIX and Ted refer to the level of the VIX index and the Ted spread (source: Bloomberg). P-S stock liqu. innov. is the 'non-traded' liquidity innovation factor from Pastor and Stambaugh. Order imbalance is the monthly customer buy volume over total volume averaged across all bonds. Change cost std. dev. is the monthly change of the cross-sectional standard deviation of bond-month transaction cost measures. Fund net flow is the natural logarithm of the monthly net asset flow into IG and HY U.S. corporate bond mutual funds (source: Morningstar). Inventory change is the monthly change in the natural logarithm of the prime dealer inventory in IG and HY corporate bonds (source: NY Fed). All liquidity measures are defined in Appendix B and winsorized at the 99% / 1% level. Each liquidity measure is normalized every month by its mean and standard deviation calculated up to the prior month (with at least one year of observations). To proxy innovation, the table uses the residuals of an AR(2) model for each liquidity measure. The sample includes all corporate bond trades from TRACE Enhanced that are not removed in the filtering process (Appendix A) for the period July 2003 until June 2020 (204 months). The correlation coefficients for P-S stock liqu. innov. exclude the last six months of the sample due to data availability. Statistical significance of 5% and 1% correspond to correlation coefficients of 0.14 (0.28) and 0.18 (0.36) for the full (bear) sample, respectively.

Time series correlations (upper half - full sample; lower half - equity bear market sample)

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1	ILLIQ innov.	1.00	0.94	0.88	0.86	0.89	-0.50	0.64	0.59	-0.28	0.68	0.56	0.48	0.25	0.54	-0.46	-0.56	0.45	0.09	-0.81	0.32	0.03
2	Roll spread innov.	0.97	1.00	0.91	0.88	0.88	-0.53	0.63	0.60	-0.35	0.69	0.61	0.48	0.25	0.54	-0.40	-0.53	0.44	0.12	-0.79	0.34	0.04
3	IRC innov.	0.91	0.95	1.00	0.84	0.81	-0.54	0.64	0.61	-0.36	0.64	0.58	0.46	0.23	0.52	-0.35	-0.51	0.45	0.09	-0.72	0.34	-0.01
4	B/A coefficient innov.	0.94	0.94	0.92	1.00	0.84	-0.50	0.59	0.56	-0.43	0.65	0.62	0.47	0.29	0.49	-0.33	-0.50	0.38	0.14	-0.72	0.33	0.00
5	Cost innov.	0.94	0.94	0.87	0.90	1.00	-0.58	0.70	0.66	-0.37	0.75	0.65	0.50	0.26	0.56	-0.44	-0.56	0.37	0.12	-0.76	0.33	0.06
6	Buy cost	-0.54	-0.58	-0.56	-0.54	-0.63	1.00	-0.90	-0.97	0.70	-0.82	-0.87	-0.47	-0.34	-0.43	0.18	0.48	-0.17	-0.06	0.51	-0.50	0.02
7	Sell cost	0.66	0.68	0.67	0.68	0.74	-0.95	1.00	0.98	-0.55	0.84	0.80	0.50	0.27	0.55	-0.48	-0.73	0.29	0.00	-0.51	0.42	0.04
8	Cost asymmetry	0.62	0.65	0.63	0.63	0.70	-0.98	0.99	1.00	-0.63	0.85	0.85	0.50	0.31	0.51	-0.36	-0.63	0.24	0.03	-0.53	0.46	0.02
9	Buy lambda	-0.20	-0.31	-0.36	-0.32	-0.31	0.75	-0.69	-0.72	1.00	-0.55	-0.86	-0.41	-0.43	-0.27	-0.09	0.22	-0.09	-0.16	0.39	-0.39	0.07
10	Sell lambda	0.81	0.84	0.77	0.80	0.88	-0.86	0.92	0.91	-0.54	1.00	0.90	0.56	0.33	0.59	-0.38	-0.55	0.22	0.13	-0.65	0.49	-0.01
11	Lambda asymmetry	0.64	0.71	0.68	0.69	0.74	-0.92	0.93	0.94	-0.81	0.92	1.00	0.56	0.43	0.50	-0.18	-0.45	0.17	0.16	-0.60	0.50	-0.04
12	SPX	0.57	0.57	0.56	0.58	0.67	-0.46	0.59	0.55	-0.20	0.64	0.52	1.00	0.82	0.85	-0.46	-0.36	0.21	0.17	-0.47	0.40	-0.06
13	SPX up													1.00	0.39	-0.03	-0.12	0.14	0.17	-0.26	0.39	-0.08
14	SPX down														1.00	-0.70	-0.47	0.21	0.12	-0.51	0.28	-0.02
15	VIX	-0.53	-0.46	-0.42	-0.53	-0.58	0.39	-0.58	-0.51	0.12	-0.55	-0.42	-0.83			1.00	0.56	-0.25	0.03	0.24	0.02	-0.08
16	Ted spread	-0.62	-0.63	-0.63	-0.72	-0.65	0.71	-0.85	-0.80	0.52	-0.76	-0.74	-0.60			0.63	1.00	-0.35	0.13	0.37	-0.13	-0.11
17	P-S stock liqu. innov.	0.56	0.54	0.60	0.56	0.45	-0.16	0.28	0.24	-0.24	0.34	0.30	0.34			-0.20	-0.35	1.00	0.02	-0.14	0.13	-0.02
18	Order imbalance	0.12	0.16	0.17	0.11	0.16	-0.07	0.04	0.06	-0.05	0.09	0.08	0.07			0.07	0.00	-0.07	1.00	-0.19	0.15	-0.29
19	Change cost std. dev.	-0.93	-0.89	-0.86	-0.84	-0.91	0.65	-0.72	-0.70	0.22	-0.82	-0.65	-0.60			0.52	0.60	-0.37	-0.14	1.00	-0.28	0.06
20	Funds net flow	0.26	0.32	0.30	0.25	0.24	-0.38	0.27	0.32	-0.28	0.42	0.41	0.01			0.25	-0.10	0.13	0.13	-0.28	1.00	-0.12
21	Inventory change	0.00	0.02	-0.05	0.01	0.04	0.06	0.01	-0.02	0.19	0.08	-0.02	0.13			-0.13	-0.07	-0.17	-0.15	0.06	-0.07	1.00

Table 3

Principal component analysis of liquidity measures

This table reports the loadings on each of the aggregate (mean) liquidity measures and the explanatory power of each component from a principal component analysis. All liquidity measures are defined in Appendix B and winsorized at the 99% / 1% level. Each liquidity measure is normalized every month by its mean and standard deviation calculated up to the prior month (with at least one year of observations). To proxy innovation, the table uses the residuals of a second order autocorrelation model for each liquidity measure. The sample includes all corporate bond trades from TRACE Enhanced that are not removed in the filtering process (Appendix A) for the period July 2003 until June 2020 (204 months).

Principal component (PC) loadings					
Liquidity Measure	PC1	PC2	PC3	PC4	PC5
ILLIQ innov.	-0.38	-0.37	-0.06	-0.09	0.26
Roll spread innov.	-0.36	-0.31	0.07	-0.14	0.37
IRC innov.	-0.25	-0.19	0.06	-0.41	0.26
B/A coefficient innov.	-0.34	-0.25	0.34	-0.05	-0.57
Cost innov.	-0.36	-0.22	-0.06	0.46	-0.42
Buy cost	0.24	-0.35	0.21	0.23	0.04
Sell cost	-0.28	0.24	-0.40	-0.24	-0.23
Cost asymmetry	-0.27	0.29	-0.32	-0.24	-0.15
Buy lambda	0.21	-0.46	-0.69	0.12	-0.03
Sell lambda	-0.29	0.18	-0.21	0.57	0.32
Lambda asymmetry	-0.28	0.33	0.21	0.29	0.21
Explained variance	72.5%	15.5%	5.1%	2.1%	1.5%
Cum. % explained	72.5%	88.1%	93.2%	95.2%	96.7%

Table 4

Lead-lag correlation between liquidity measures and returns

This table reports the time series correlation of aggregate (mean) liquidity measures. The liquidity measures in this analysis are contemporaneous, whereas the IG and HY market excess returns have been lagged or advanced by one month. The IG and HY market excess returns over maturity-matched treasuries are represented by the ICE BofA US Corporate Index (C0A0) and ICE BofA US High Yield Index (H0A0), respectively. All liquidity measures are defined in Appendix B and winsorized at the 99% / 1% level. Each liquidity measure is normalized every month by its mean and standard deviation calculated up to the prior month (with at least one year of observations). To proxy innovation, the table uses the residuals of a second order autocorrelation model for each liquidity measure. *LRF* is the average of the normalized Roll spread innovation and lambda asymmetry. The sample includes all corporate bond trades from TRACE Enhanced that are not removed in the filtering process (Appendix A) for the period July 2003 until May 2020 (203 months). Statistical significance of 5% and 1% correspond to correlation coefficients of 0.14 and 0.18, respectively.

Lead-lag correlations

	Roll spread innov.	Cost innov.	Lambda asym.	Cost asym.	LRF	IG excess return	HY excess return	Lead IG excess return	Lead HY excess return	Lag IG excess return	Lag HY excess return
Roll spread innov.	1.00	0.88	0.61	0.60	0.92	0.76	0.61	0.09	0.28	0.13	0.14
Cost innov.	0.88	1.00	0.65	0.66	0.87	0.77	0.63	0.09	0.25	0.18	0.17
Lambda asymmetry	0.61	0.65	1.00	0.85	0.87	0.71	0.68	0.31	0.44	0.16	0.11
Cost asymmetry	0.60	0.66	0.85	1.00	0.79	0.66	0.65	0.19	0.34	0.42	0.41
LRF	0.92	0.87	0.87	0.79	1.00	0.82	0.71	0.21	0.39	0.16	0.14
IG excess return	0.76	0.77	0.71	0.66	0.82	1.00	0.88	0.22	0.30	0.21	0.23
HY excess return	0.61	0.63	0.68	0.65	0.71	0.88	1.00	0.24	0.30	0.30	0.30
Lead IG excess return	0.09	0.09	0.31	0.19	0.21	0.22	0.24	1.00	0.88	-0.02	-0.04
Lead HY excess return	0.28	0.25	0.44	0.34	0.39	0.30	0.30	0.88	1.00	0.04	-0.03
Lag IG excess return	0.13	0.18	0.16	0.42	0.16	0.21	0.30	-0.02	0.04	1.00	0.88
Lag HY excess return	0.14	0.17	0.11	0.41	0.14	0.23	0.30	-0.04	-0.03	0.88	1.00

Table 5

Risk factor regressions for IG and HY market

This table reports time series regression results of IG (Panel A) and HY (Panel B) market excess returns over maturity-matched treasuries as the dependent variable. The IG and HY markets are represented by the ICE BofA US Corporate Index (C0A0) and ICE BofA US High Yield Index (H0A0), respectively. All liquidity measures are defined in Appendix B and winsorized at the 99% / 1% level. Each liquidity measure is normalized every month by its mean and standard deviation calculated up to the prior month (with at least one year of observations). To proxy innovation, the table uses the residuals of a second order autocorrelation model for each liquidity measure. The liquidity risk factor, *LRF*, is the average of the normalized Roll spread innovation and lambda asymmetry. Credit is the normalized change in the "on the run" 5-year CDX contract on a basket of IG issuers and Equity is the normalized S&P 500 return. T-statistics are reported in italics below each coefficient estimate. One, two, and three stars indicate significance at the 10%, 5%, and 1% level, respectively. Standard errors are heteroscedasticity and autocorrelation robust using two monthly lags. The sample includes all corporate bond trades from TRACE Enhanced that are not removed in the filtering process (Appendix A) for the period July 2003 until June 2020 (204 months).

Panel A: Risk factor regressions for IG credit excess returns

	I	II	III	IV	V	VI	VII
Constant	0.134*	0.065	0.119*	0.196***	0.195***	0.121	0.127**
	1.95	*0.90*	*1.88*	*3.15*	*3.06*	*1.54*	*2.20*
Roll spread innov.		0.585***				0.473***	
		4.89				*3.37*	
Cost innov.			0.618***				
			5.34				
Lambda asymmetry				0.599***		0.410***	
				3.97		*2.92*	
Cost asymmetry					0.458***		
					3.21		
LRF							0.892***
							7.57
Credit	0.768***	0.454**	0.449***	0.600***	0.609***	0.399**	0.403***
	4.00	*2.51*	*2.84*	*3.37*	*3.22*	*2.50*	*2.61*
Equity	0.648***	0.491***	0.472***	0.420***	0.525***	0.365***	0.358***
	3.88	*4.16*	*3.71*	*3.06*	*4.07*	*2.85*	*2.97*
Obs.	204	204	204	204	204	204	204
Adj. R-squ.	63.7%	73.1%	74.4%	70.4%	67.4%	75.8%	75.9%

Panel B: Risk factor regressions for HY credit excess returns

	I	II	III	IV	V	VI	VII
Constant	0.415***	0.373***	0.404***	0.492***	0.509***	0.465***	0.409***
	3.39	*2.92*	*3.35*	*4.21*	*4.59*	*3.47*	*3.60*
Roll spread innov.		0.356*				0.170	
		1.78				*0.65*	
Cost innov.			0.437**				
			2.55				
Lambda asymmetry				0.747***		0.679*	
				2.62		*1.94*	
Cost asymmetry					0.715**		
					2.43		
LRF							0.777***
							4.33
Credit	1.179***	0.988***	0.954***	0.969***	0.930***	0.897***	0.861***
	4.47	*3.11*	*3.39*	*4.01*	*3.40*	*3.16*	*3.22*
Equity	1.594***	1.498***	1.469***	1.309***	1.402***	1.289***	1.341***
	5.62	*5.75*	*6.03*	*5.76*	*7.41*	*5.76*	*5.76*
Obs.	204	204	204	204	204	204	204
Adj. R-squ.	69.5%	70.3%	70.9%	72.4%	72.1%	72.5%	72.0%

Table 6

Time series factor loadings of corporate bond portfolio returns

This table reports time series OLS regression results of corporate bond portfolio excess returns over the risk-free rate as the dependent variable. The first digit of the test asset numbers in Panel A refers to amount outstanding (5 = largest size quintile) and the second digit refers to the maturity quintile (5=longest maturity). The liquidity, credit, and equity risk factors are defined in Table 5. The rates factor is the normalized change in the yield on U.S. Treasury securities at 7-year constant maturity. Equity liquidity is proxied by the Pastor-Stambaugh factor for aggregate stock liquidity innovation. The Roll spread level is the time series of the aggregate (mean) Roll spread as defined in Appendix B. The idiosyncratic LRF component represents the error term in a regression of *LRF* on monthly CDX changes and S&P 500 returns. The symmetric and asymmetric liquidity components are the normalized Roll spread innovation and the normalized lambda asymmetry, respectively (defined in Appendix B). The conditional betas are estimated in the subsample of the S&P 500 being in its lowest quartile of monthly total returns. Standard errors are heteroscedasticity and autocorrelation robust using two monthly lags. The sample includes all corporate bond trades from TRACE Enhanced that are not removed in the filtering process (Appendix A) for the period July 2003 until June 2020 (204 months). The sample period in Panels C and D is July 2004 to December 2019 and the sample period in Panel G is July 2003 to December 2019 due to data availability.

Panel A: First stage Fama-MacBeth - Four-factor model

Test asset	Intercept	β^{LRF}	β^{Credit}	β^{Equity}	β^{Rates}	Obs	Adj. R-squ.
11	0.38	0.55	-0.09	0.39	-0.05	204	47.4%
12	0.52	1.01	0.29	0.39	0.03	204	73.1%
13	0.59	1.39	0.27	0.38	0.11	204	76.6%
14	0.60	1.71	0.51	0.34	0.32	204	75.8%
15	0.72	2.20	0.15	0.42	0.86	204	76.9%
21	0.24	0.48	0.13	0.04	0.11	204	48.8%
22	0.37	1.42	-0.21	0.20	0.18	204	70.3%
23	0.46	1.37	0.30	0.41	0.37	204	72.7%
24	0.56	1.75	0.17	0.41	0.59	204	77.6%
25	0.63	2.27	0.11	0.02	1.17	204	72.5%
31	0.26	0.68	-0.01	0.05	0.11	204	35.4%
32	0.34	1.28	-0.03	0.16	0.29	204	70.7%
33	0.50	1.46	0.10	0.32	0.51	204	75.2%
34	0.52	1.53	0.20	0.23	0.91	204	76.0%
35	0.61	2.31	-0.06	-0.03	1.35	204	65.6%
41	0.18	0.53	-0.03	0.12	0.13	204	37.7%
42	0.35	1.03	0.02	0.13	0.35	204	62.2%
43	0.42	1.30	0.04	0.35	0.51	204	72.2%
44	0.50	1.83	-0.08	0.21	0.85	204	70.5%
45	0.60	2.41	-0.23	0.15	1.32	204	63.1%
51	0.18	0.39	0.01	0.22	0.29	204	27.2%
52	0.26	0.93	-0.04	0.28	0.47	204	59.4%
53	0.38	1.02	-0.01	0.54	0.58	204	68.0%
54	0.48	1.61	-0.09	0.45	0.94	204	71.9%
55	0.60	2.06	-0.03	0.36	1.31	204	61.6%
Mean coefficient	0.45	1.38	0.05	0.26	0.54	204	64.3%
Mean t-stat	*5.36*	*8.66*	*0.21*	*2.29*	*3.66*		

Panel B: First stage Fama-MacBeth - Three-factor model

	Intercept	β^{LRF}	β^{Credit}	β^{Equity}	β^{Rates}	Obs	Adj. R-squ.
Mean coefficient	0.46	-	0.74	0.70	0.88	204	45.3%
Mean t-stat	*4.74*	-	*3.69*	*4.00*	*4.67*		

Panel C: First stage Fama-MacBeth - Four-factor model of Bai et al. (2019)

	Intercept	$\beta^{MKTbond}$	β^{DRF}	β^{CRF}	β^{LRF}	Obs	Adj. R-squ.
Mean coefficient	0.01	0.99	-0.03	0.17	0.09	186	72.4%
Mean t-stat	*0.10*	*11.36*	*-0.63*	*2.87*	*1.35*		

Panel D: First stage Fama-MacBeth - Benchmark four-factor model and market factor

	Intercept	$\beta^{Bond\ mkt\text{-}rf}$	β^{LRF}	β^{Credit}	β^{Equity}	β^{Rates}	Obs	Adj. R-squ.
Mean coefficient	0.00	1.00	0.00	0.01	0.00	0.00	186	81.4%
Mean t-stat	*-0.01*	*9.51*	*-0.18*	*-0.06*	*0.19*	*-0.46*		

Panel E: First stage Fama-MacBeth - Idiosyncratic LRF component

	Intercept	$\beta^{LRF\ idio.}$	β^{Credit}	β^{Equity}	β^{Rates}	Obs	Adj. R-squ.
Mean coefficient	0.56	1.25	0.61	0.67	0.55	204	61.0%
Mean t-stat	*6.41*	*7.13*	*3.68*	*5.73*	*3.63*		

Panel F: First stage Fama-MacBeth - Symmetric and asymmetric LRF components

	Intercept	$\beta^{LRF\ sym.}$	$\beta^{LRF\ asym.}$	β^{Credit}	β^{Equity}	β^{Rates}	Obs	Adj. R-squ.
Mean coefficient	0.60	0.17	1.60	-0.10	0.07	0.06	204	71.4%
Mean t-stat	*6.64*	*0.93*	*7.61*	*-0.83*	*0.92*	*0.06*		

Panel G: First stage Fama-MacBeth - Four-factor model and equity liquidity innovation

	Intercept	β^{LRF}	$\beta^{Equ.\ Liq.\ Inno.}$	β^{Credit}	β^{Equity}	β^{Rates}	Obs	Adj. R-squ.
Mean coefficient	0.49	1.48	-3.81	0.04	0.26	0.50	198	61.5%
Mean t-stat	*5.37*	*8.29*	*-1.62*	*0.17*	*2.32*	*3.62*		

Panel H: First stage Fama-MacBeth - Conditional (bear) factors

	Intercept	β^{LRF}	β^{Credit}	β^{Equity}	β^{Rates}	Obs	Adj. R-squ.
Mean coefficient	0.27	1.39	0.01	0.07	0.45	49	71.7%
Mean t-stat	*0.65*	*7.32*	*-0.26*	*0.21*	*2.19*		

Panel I: First stage Fama-MacBeth - Four-factor model and aggregate bond liquidity level

	Intercept	β^{LRF}	β^{Credit}	β^{Equity}	β^{Rates}	$\beta^{Roll\ (Market)}$	Obs	Adj. R-squ.
Mean coefficient	-0.51	1.61	-0.04	0.30	0.44	1.65	204	70.9%
Mean t-stat	*-2.30*	*9.23*	*-0.43*	*2.80*	*3.18*	*3.72*		

Panel J: First stage Fama-MacBeth - Four-factor model (alternative test assets)

	Intercept	β^{LRF}	β^{Credit}	β^{Equity}	β^{Rates}	Obs	Adj. R-squ.
Mean coefficient	0.52	1.45	0.22	0.59	0.31	204	55.1%
Mean t-stat	*4.47*	*5.93*	*0.07*	*1.52*	*2.70*		

Table 7

Pricing liquidity in the cross-section of corporate bond portfolio returns

This table reports cross-sectional OLS regression results of the mean excess portfolio return over the risk-free rate (dependent variable) on the risk factor loadings (independent variables). Factor loadings are calculated using time series regressions of portfolio excess returns on the risk factors (see Table 6). The liquidity, credit, equity, and rates as well as equity liquidity risk factors are defined in Table 5 and Table 6, respectively. Regression III uses the idiosyncratic LRF component, which represents the error term in a regression of LRF on monthly CDX spread changes and S&P 500 returns. The symmetric and asymmetric liquidity components are the normalized Roll spread innovation and the normalized lambda asymmetry, respectively (defined in Appendix B). The conditional betas are estimated in the subsample of the S&P 500 being in its lowest quartile of monthly total returns. The equal-weighted Roll spread at each month for all bonds in each portfolio is used in regression VII. T-statistics are reported in italics below each coefficient estimate. One, two, and three stars indicate significance at the 10%, 5%, and 1% level, respectively. The sample includes all corporate bond trades from TRACE Enhanced that are not removed in the filtering process (Appendix A) for the period July 2003 until June 2020 (204 months).

Second stage Fama-MacBeth: Cross-sectional regressions							
Regression	I	II	III	IV	V	VI	VII
	Four-factor model	Three-factor model	Idiosyncratic LRF	Sym. & asym. liquidity	Four-factors & Equ. Liqu.	Conditional (bear) betas	Characteristics premium
Intercept	0.076**	0.091***	0.077**	0.077**	0.108***	0.112***	-0.008
	2.41	*2.91*	*2.52*	*2.37*	*2.65*	*6.14*	*-0.25*
λ^{LRF}	0.219***				0.196***		0.094**
	6.73				*5.07*		*2.23*
$\lambda^{LRF\ idio.}$			0.132***				
			2.66				
$\lambda^{LRF\ sym.}$				0.256***			
				3.31			
$\lambda^{LRF\ asym.}$				0.191***			
				10.67			
$\lambda^{LRF\ bear}$						0.216***	
						6.14	
λ^{Credit}	0.138**	0.210***	0.139**	0.146*	0.313***	0.131***	0.045
	2.04	*4.17*	*2.30*	*1.89*	*2.82*	*3.76*	*0.77*
λ^{Equity}	0.164**	0.191***	0.167***	0.172**	0.171**	0.068	0.139**
	2.42	*2.84*	*2.58*	*2.20*	*2.29*	*1.56*	*2.44*
λ^{Rates}	-0.012	0.048*	-0.029	-0.001	0.030	-0.005	-0.018
	-0.25	*1.86*	*-0.60*	*-0.02*	*0.53*	*-0.12*	*-0.50*
$\lambda^{Equ.\ Liqu.\ Innov.}$					0.014*		
					1.79		
$\lambda^{Roll\ level}$							0.431***
							3.26
Obs.	25	25	25	25	25	25	25
Adj. R-squ.	88.2%	87.5%	88.8%	87.6%	82.4%	82.4%	92.7%

Table 8

Rolling risk factors and future corporate bond excess returns

This table reports the mean coefficients of cross-sectional OLS regression results of three-months and twelve-months forward cumulative portfolio excess returns over the risk-free rate (dependent variable) on rolling risk factor loadings (independent variables). The rolling factor loadings are calculated using 36-months rolling time series regressions of portfolio excess returns on the risk factors. The liquidity, credit, equity, and rates risk factors are defined in Table 5 and Table 6, respectively. The Roll level is the 36-months moving average of the Roll spread for each portfolio. The independent variables in regression V are the quarterly changes in the rolling risk factor levels. T-statistics are reported in italics below each coefficient estimate. One, two, and three stars indicate significance at the 10%, 5%, and 1% level, respectively. Standard errors are heteroscedasticity and autocorrelation robust using twelve lags for regressions I, II, and V and three lags for regressions III and IV. The number of observations relates to the number of non-overlapping cross-sections. The sample includes all corporate bond trades from TRACE Enhanced that are not removed in the filtering process (Appendix A) for the period July 2003 until June 2020 (204 months).

Rolling risk factor model: Fama-MacBeth cross-sectional regression estimates					
Regression	I	II	III	IV	V
Dependent variable	Three-months ahead excess return	Three-months ahead excess return	Twelve-months ahead excess return	Twelve-months ahead excess return	Three-months ahead excess return
Independent variables	Factor level	Factor level	Factor level	Factor level	QoQ factor change
Intercept	0.300***	0.092	1.559**	0.645	0.551
	2.60	*0.33*	*2.09*	*0.54*	*1.51*
λ^{LRF}	0.673**	0.549*	2.678***	1.658**	14.260*
	2.45	*1.80*	*2.82*	*2.42*	*1.84*
$\lambda^{Roll\ level}$		0.441		3.744	25.324**
		0.46		*1.52*	*2.26*
λ^{Credit}	-0.009	0.287	1.368	0.821	2.485
	-0.03	*1.33*	*1.52*	*1.14*	*0.67*
λ^{Equity}	-0.055	-0.023	0.756	0.580	8.731
	-0.16	*-0.08*	*0.71*	*0.58*	*1.02*
λ^{Rates}	0.015	0.131	-0.274	0.021	-0.006
	0.05	*0.42*	*-0.24*	*-0.52*	*0.00*
Obs.	56	56	14	14	55
Adj. R-squ.	76.4%	79.0%	70.6%	73.4%	58.4%

Table 9

Additional analysis

Panel A of this table reports time series regression results of IG market excess returns over maturity-matched treasuries (represented by the ICE BofA US Corporate Index (C0A0)) as the dependent variable. All liquidity measures are defined in Appendix B and winsorized at the 99% / 1% level. Except for regressions II and III in Panel A, each liquidity measure is normalized every month by its mean and standard deviation calculated up to the prior month (with at least one year of observations). To proxy innovation, the table uses the residuals of a second order autocorrelation model. The liquidity, credit, equity, and rates risk factors are defined in Table 5 and Table 6, respectively. Panel B reports cross-sectional OLS regression results of the mean portfolio excess return over the risk-free rate (dependent variable) on the risk factor loadings (independent variables). Factor loadings are calculated using the full sample time series regressions of excess returns on the risk factors. The risk factors in regressions I and II are obtained from Prof. Turan G. Bali's website. The risk factors in regression IV of Panel B include the equal-weighted excess return of all bonds in the sample as a proxy for the corporate bond market factor. The regression also includes the Fama-French stock market return, size factor, book-to-market factor, the stock momentum factor, and the risk-free rate. The 60 test assets in regression V of Panel B are corporate bond portfolios triple-sorted by credit rating, maturity, and liquidity level. T-statistics are reported in italics below each coefficient estimate. One, two, and three stars indicate significance at the 10%, 5%, and 1% level, respectively. Standard errors in Panel A are heteroscedasticity and autocorrelation robust using two monthly lags. The transaction sample used for the liquidity measure computation in regression IV of Panel A is reduced to transaction volumes greater or equal to $1,000,000. The sample includes all corporate bond trades from TRACE Enhanced that are not removed in the filtering process (Appendix A) for the period July 2003 until June 2020 (204 months). The sample period for regression I to III of Panel B is July 2004 to December 2019.

Panel A: IG return regressions with variation in method of risk factor computation

Regression	I	II	III	IV
	LRF_{Median}	Non-normalized factors	Non-normalized factors	No odd-lot trades
Constant	0.156**	-0.008	0.014	0.150**
	2.53	*-0.15*	*0.21*	*2.50*
Roll spread innov.		0.049***		
		6.94		
Lambda asymmetry			0.562***	
			4.57	
LRF	0.735***			0.972***
	5.52			*7.19*
Credit	0.548***	-0.061***	-0.071***	0.398**
	3.18	*-4.31*	*-4.61*	*2.40*
Equity	0.400***	0.093***	0.082***	0.363***
	3.38	*3.93*	*2.78*	*3.22*
Obs.	204	204	204	204
Adj. R-squ.	72.3%	79.8%	75.8%	74.5%

Panel B: Second stage Fama-MacBeth cross-sectional regressions

Regression	I		II	III		IV		V
Independent variables	Four factors & Bond mkt	Independent variables	Bai et al. (2019) factors	Bai et al. (2019) & LRF	Independent variables	Bond mkt & FF 5 factors	Independent variables	Four factors (alt. assets)
Intercept	0.081	Intercept	0.189***	0.160***	Intercept	0.043	Intercept	0.195***
	1.23		*4.16*	*3.93*		*0.76*		*5.20*
$\lambda^{\text{Bond mkt-rf}}$	0.349***	$\lambda^{\text{MKTbond (Bai et al.)}}$	0.162***	0.191***	λ^{LRF}	0.186***	λ^{LRF}	0.049*
	5.44		*4.63*	*7.35*		*6.28*		*1.73*
λ^{LRF}	0.192***	$\lambda^{\text{DRF (Bai et al.)}}$	1.148***	1.100***	$\lambda^{\text{Bond mkt-rf}}$	0.380***	λ^{Credit}	0.289***
	3.82		*7.48*	*4.95*		*6.72*		*4.88*
λ^{Credit}	0.216**	$\lambda^{\text{CRF (Bai et al.)}}$	0.610***	0.543**	λ^{Mktrf}	0.594**	λ^{Equity}	0.127***
	2.52		*6.06*	*2.52*		*2.48*		*2.89*
λ^{Equity}	0.155**	$\lambda^{\text{LRF (Bai et al.)}}$	0.126		λ^{Smb}	0.228	λ^{Rates}	0.215***
	2.04		*1.33*			*0.47*		*4.96*
λ^{Rates}	0.027	λ^{LRF}		0.089***	λ^{Hml}	0.670*		
	0.37			*2.71*		*1.89*		
					λ^{Rf}	-0.101**		
						-2.23		
					λ^{Umd}	-0.196		
						-0.37		
Obs.	25		25	25		25		60
Adj. R-squ.	82.5%		92.5%	92.0%		92.2%		67.5%

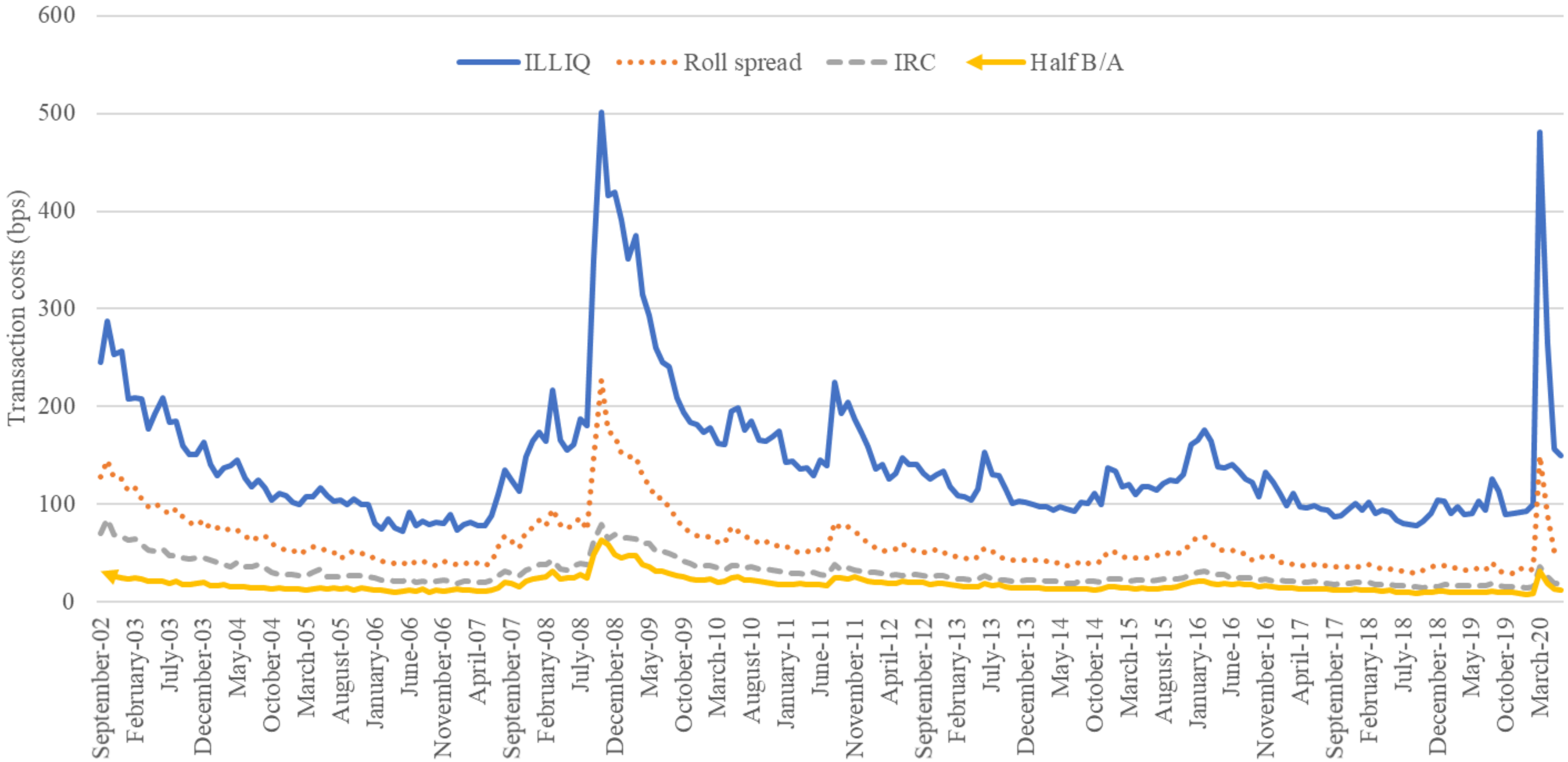

Figure 1. Symmetric liquidity measures

The figure shows aggregate (mean) symmetric liquidity measures. The vertical axis refers to transaction costs in basis points. All liquidity measures are defined in Appendix B and winsorized at the 99% / 1% level. The sample includes all corporate bond trades from TRACE Enhanced that are not removed in the filtering process (Appendix A) for the period September 2002 until June 2020 (214 months).

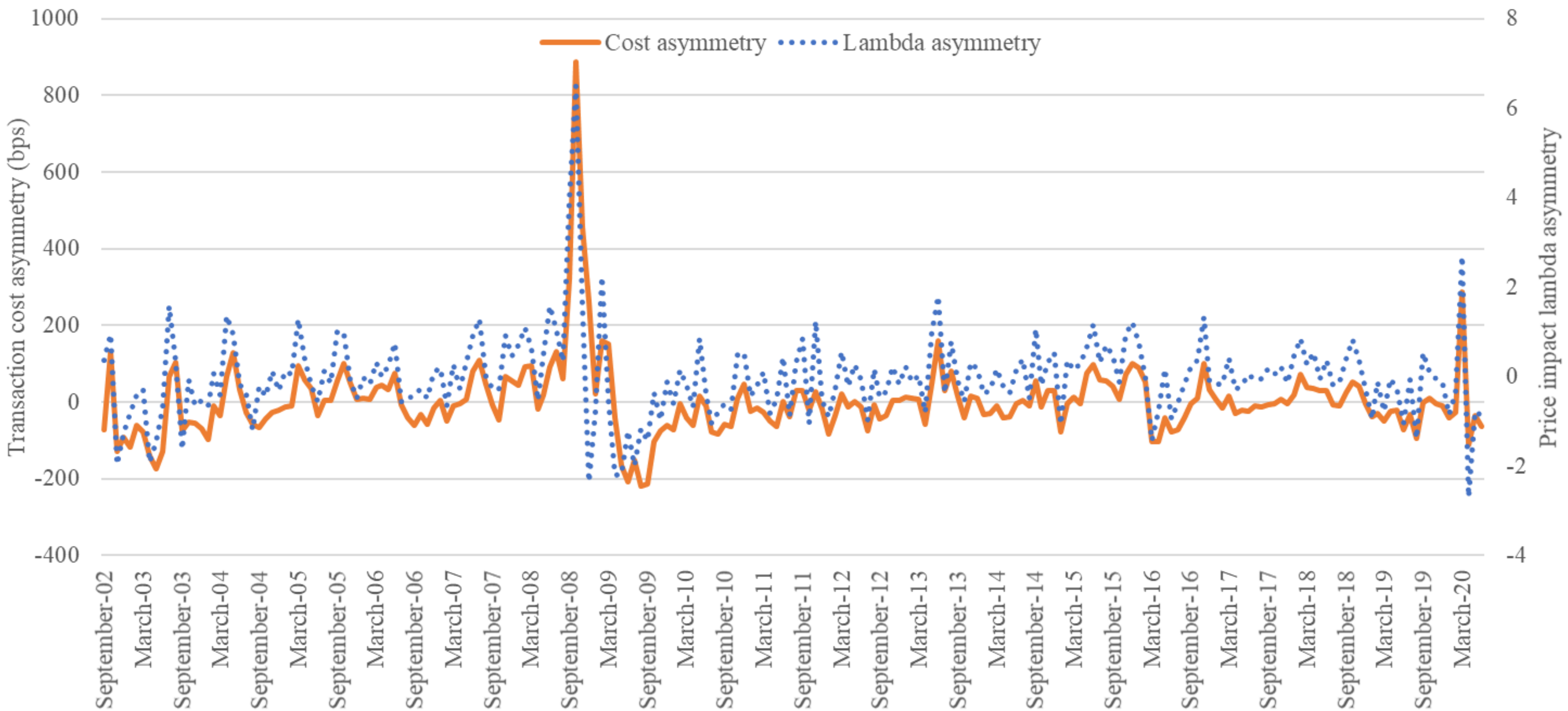

Figure 2. Asymmetric liquidity measures

The figure shows aggregate (mean) asymmetric liquidity measures. The left vertical axis refers to the difference between sell and buy costs in basis points. The right axis shows the difference in sell and buy lambda measures scaled by 10^6. All liquidity measures are defined in Appendix B and winsorized at the 99% / 1% level. The sample includes all corporate bond trades from TRACE Enhanced that are not removed in the filtering process (Appendix A) for the period from September 2002 until June 2020 (214 months).

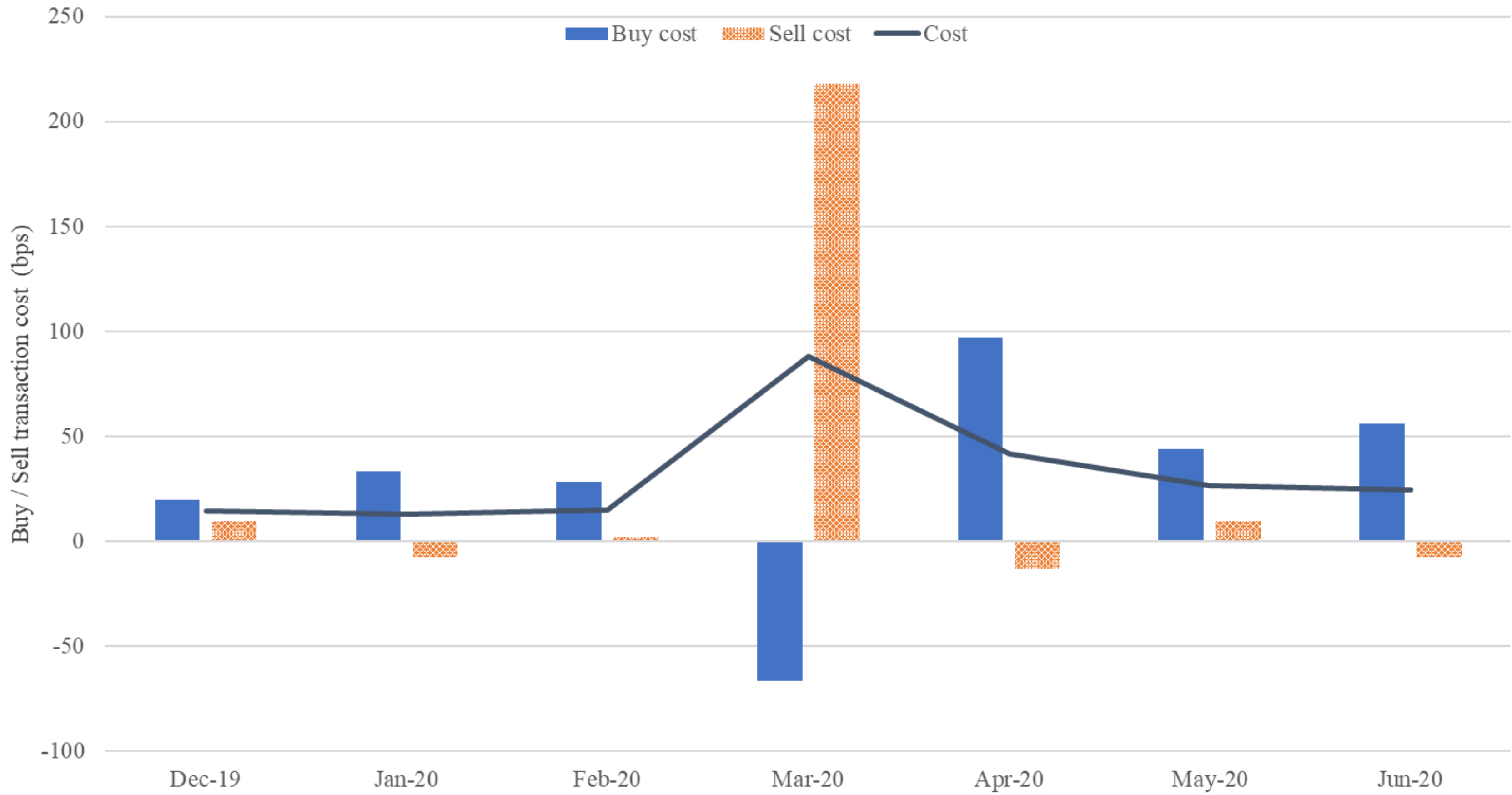

Figure 3. Buyer and seller transaction costs during the COVID liquidity shock

The bars in this chart shows the time series of the aggregate buy and sell costs over the period from December 2019 to June 2020. The line shows the aggregate transaction cost measure, which does not allow for asymmetric transaction costs between customer buys and sells. All liquidity measures are defined in Appendix B and winsorized at the 99% / 1% level. The sample includes all corporate bond trades from TRACE Enhanced that are not removed in the filtering process (Appendix A).

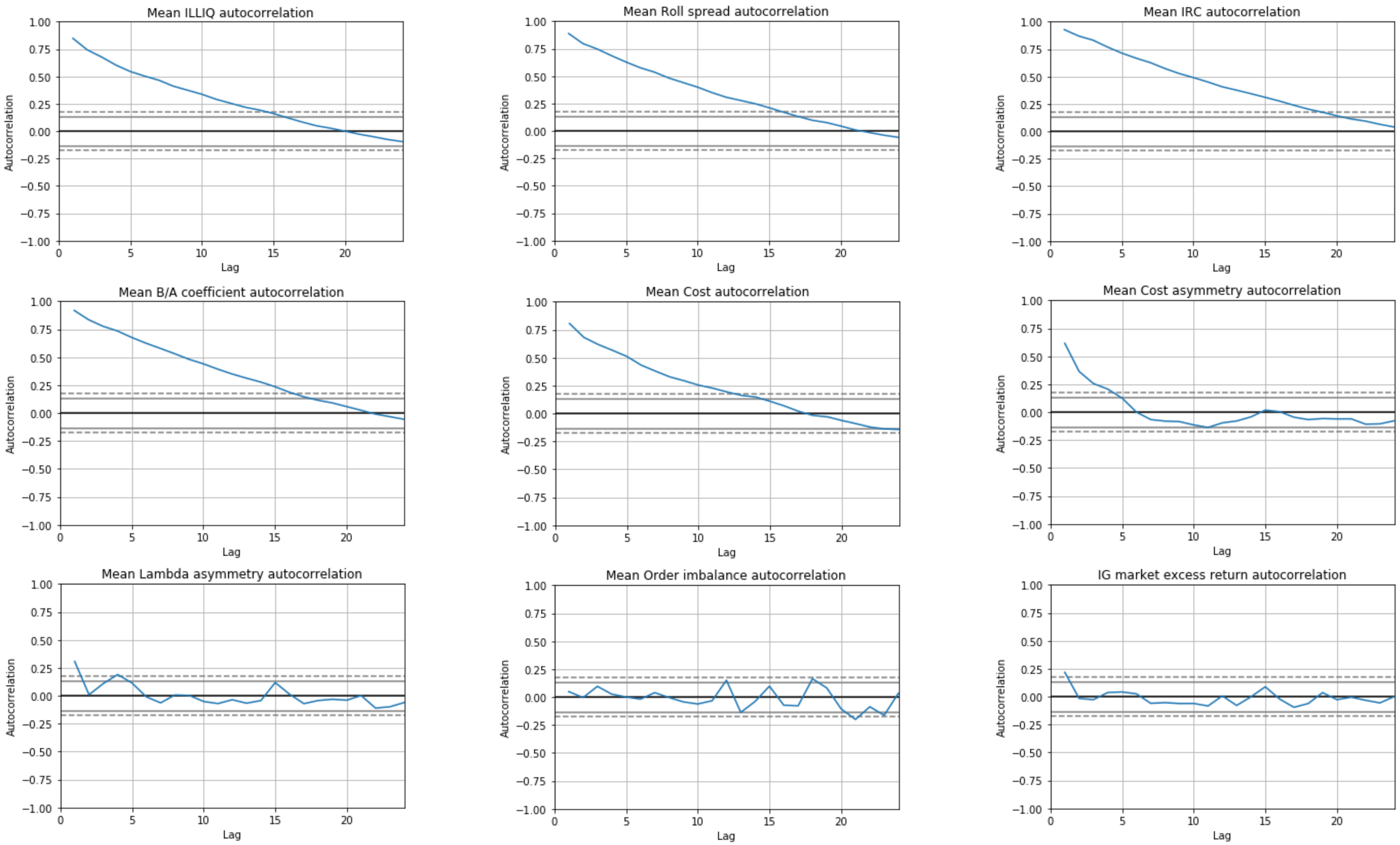

Figure 4. Autocorrelation in liquidity measures

This figure plots the autocorrelation of aggregate liquidity measures as a function of monthly lags. All liquidity measures are defined in Appendix B and winsorized at the 99% / 1% level. Each liquidity measure is normalized every month by its mean and standard deviation calculated up to the prior month (with at least one year of observations). Order imbalance is the monthly customer buy volume over total volume averaged across all bonds. The IG market excess return is proxied by the ICE BofA US Corporate Index (C0A0). The sample includes all corporate bond trades from TRACE Enhanced that are not removed in the filtering process (Appendix A) for the period September 2002 until June 2020 (214 months).

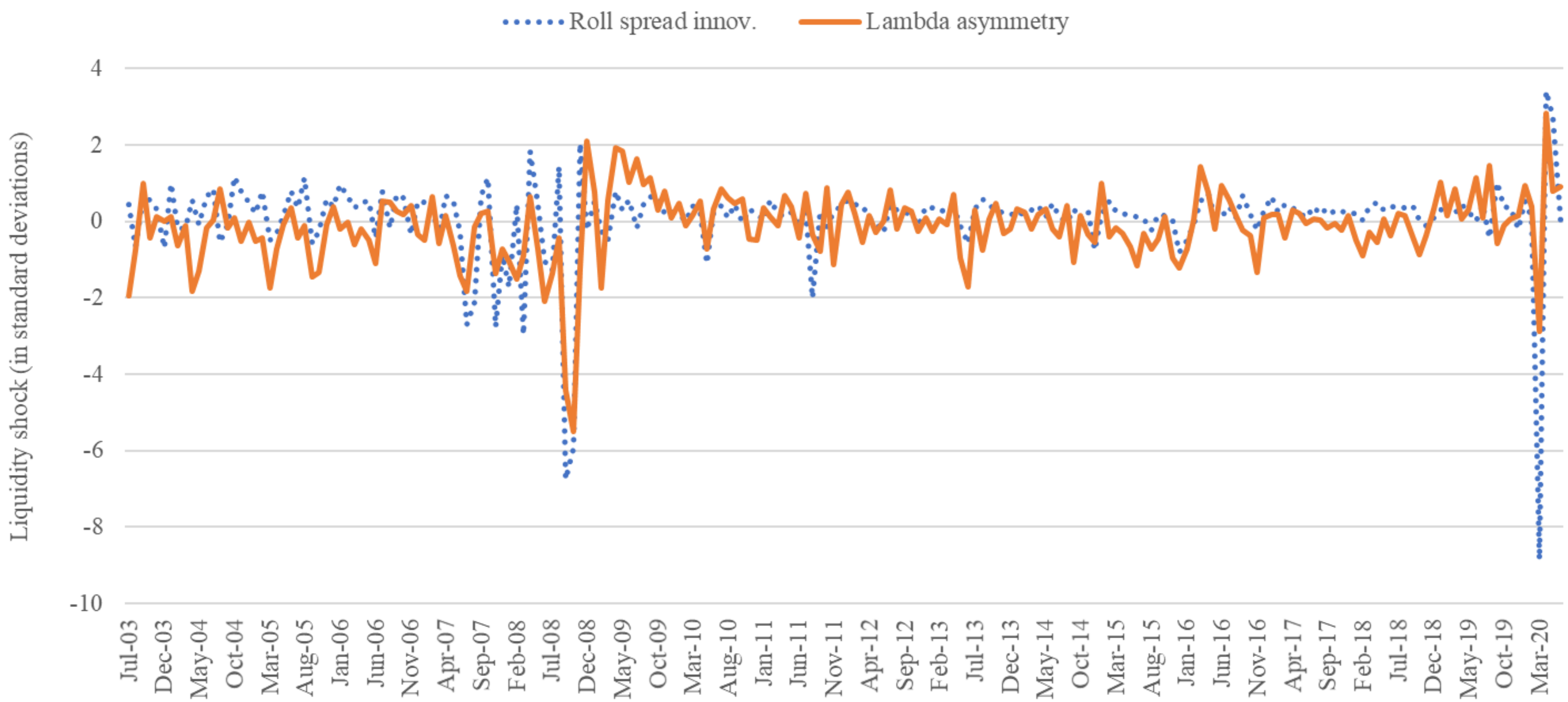

Figure 5. Time series of liquidity shocks

The figure shows the time series of shocks to aggregate liquidity. The shocks to symmetric liquidity (Roll spread) are estimated as the residuals of a second order autocorrelation model. The asymmetric liquidity shocks are the levels of the liquidity measure (lambda asymmetry). All liquidity measures are defined in Appendix B and winsorized at the 99% / 1% level. Each liquidity measure is normalized every month by its mean and standard deviation calculated up to the prior month (with at least one year of observations). The sample includes all corporate bond trades from TRACE Enhanced that are not removed in the filtering process (Appendix A) for the period July 2003 until June 2020 (204 months).

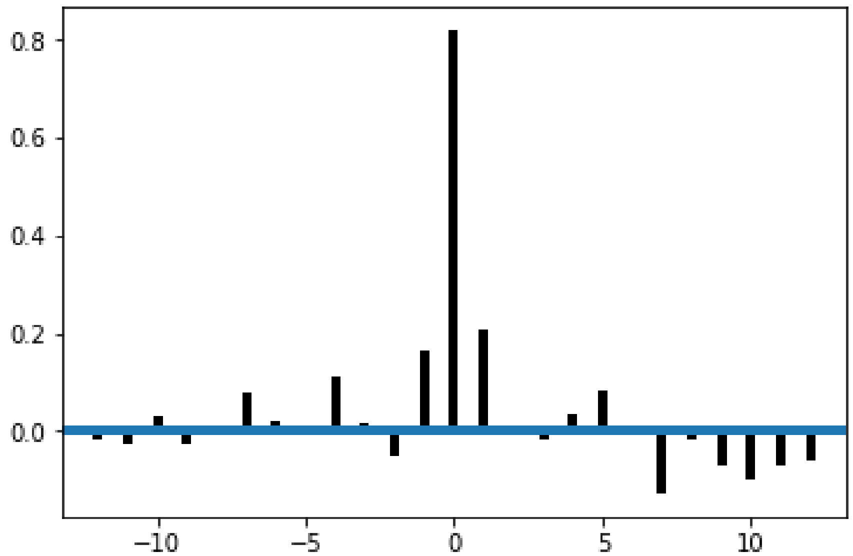

Figure 6. Lead-lag correlations of aggregate liquidity shocks and market returns

This figure plots the lead-lag correlation coefficient (vertical axis) between liquidity and IG market excess returns. The IG market excess return is represented by the ICE BofA US Corporate Index (C0A0) and lagged / advanced by up to 12 monthly observations. The liquidity shock is proxied by the liquidity risk factor, *LRF*, which is the average of the normalized Roll spread innovation and lambda asymmetry. All liquidity measures are defined in Appendix B and winsorized at the 99% / 1% level. The sample includes all corporate bond trades from TRACE Enhanced that are not removed in the filtering process (Appendix A) for the period July 2003 until June 2020 (204 months).

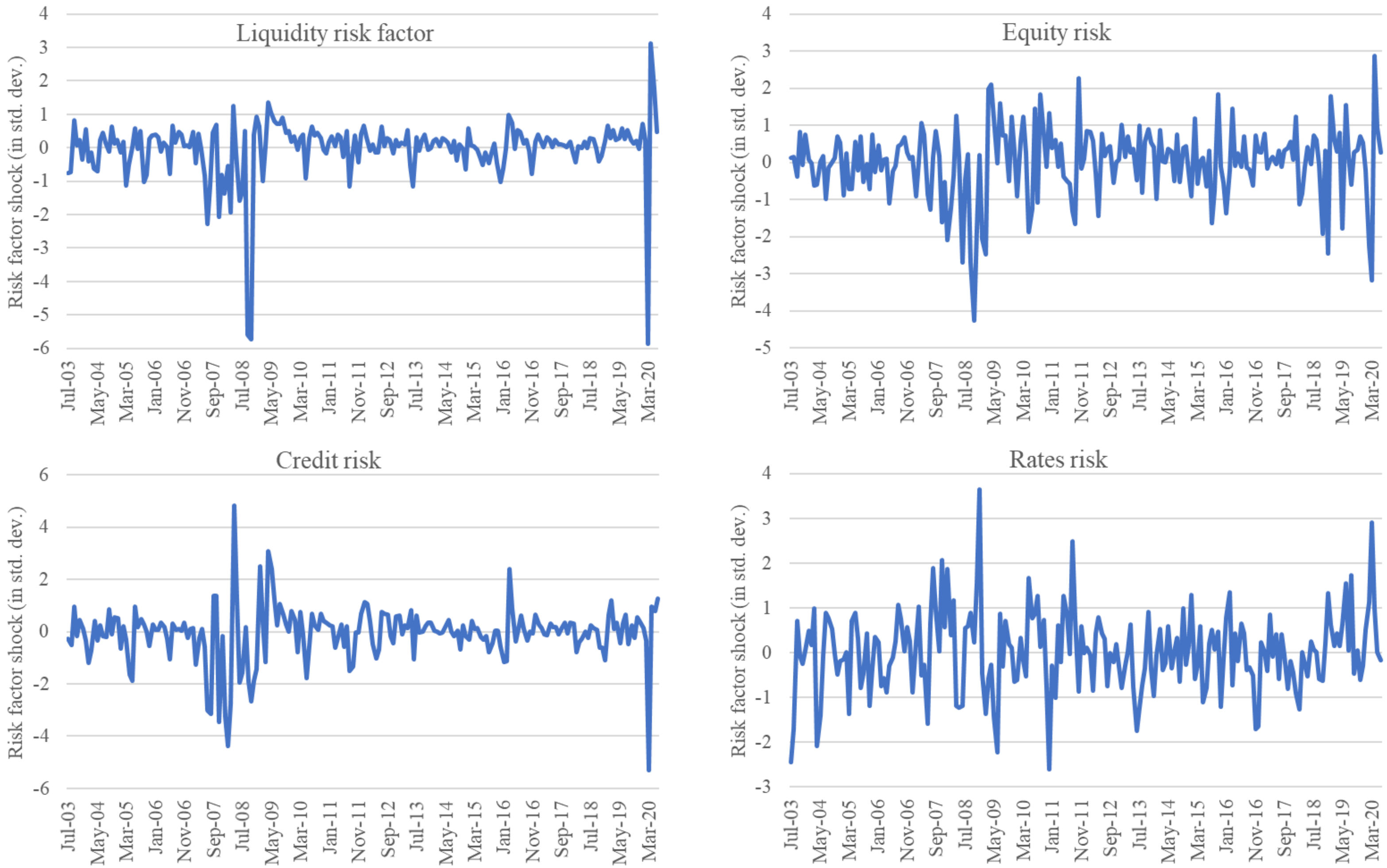

Figure 7. Risk factors

This figure plots the monthly time series of the three risk factors for liquidity, credit, and equity. Liquidity risk is proxied by the liquidity risk factor, *LRF*, which is the average of the normalized Roll spread innovation and lambda asymmetry. Credit risk is proxied by the normalized change in the "on the run" 5-year CDX contract on a basket of IG issuers and equity risk is proxied by the normalized S&P 500 return. Each risk factor is normalized every month by its mean and standard deviation calculated up to the prior month (with at least one year of observations). The sample period is July 2003 to June 2020.

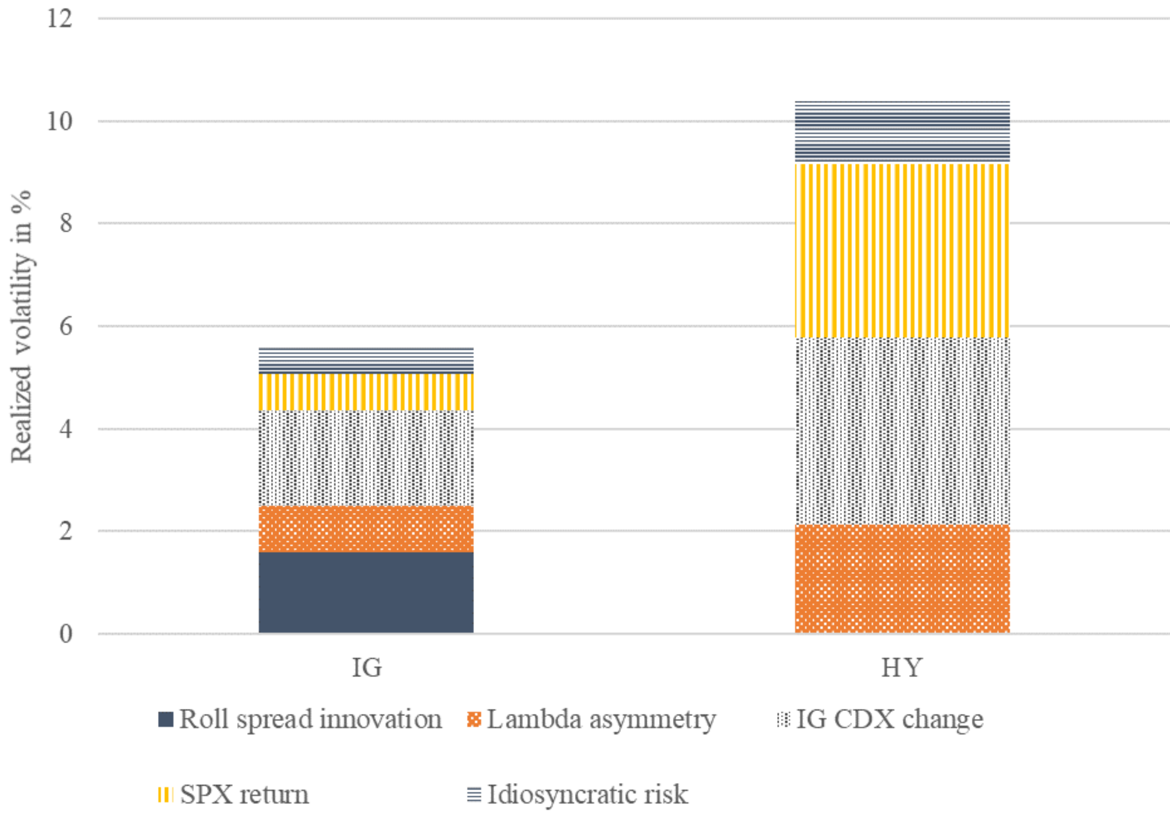

Figure 8. Decomposition of volatility into risk factor contributions

The figure shows the contribution to overall volatility from statistically significant risk factors (at the 1% level). The IG and HY markets are represented by the ICE BofA US Corporate Index (C0A0) and ICE BofA US High Yield Index (H0A0), respectively. The factor weight is estimated through OLS regressions. The liquidity measures (Roll spread innovation and lambda asymmetry) are defined in Appendix B and winsorized at the 99% / 1% level. Credit risk (IG CDX change) is represented by the change in the "on the run" 5-year investment grade CDX contract and equity risk (SPX) is represented by the S&P 500 return. The sample includes all corporate bond trades from TRACE Enhanced that are not removed in the filtering process (Appendix A) for the period July 2003 until June 2020 (204 months).