PIMCO

QUANTITATIVE RESEARCH

August 2018

Liquidity in Corporate Credit Markets

AUTHORS

Masoud Sharif
Executive Vice President
Quantitative Research Analyst

Angie Zheng
Vice President
Quantitative Research Analyst

Rama Nambimadom
Executive Vice President
Quantitative Research Analyst

Ravi Mattu
Managing Director
Global Head of Analytics

"Water, water everywhere, nor any drop to drink," lamented Coleridge's Ancient Mariner. His modern corporate bond portfolio manager counterpart may well add, "Billions and billions of corporate debt, and not a bond that trades." Well, matters are not quite that dire – about $30 billion of corporate debt trades on a daily basis. But illiquidity has always been a particularly important feature of corporate bonds. Structural shifts in the marketplace for corporate bonds following regulatory changes such as Dodd-Frank and Basel III have increased interest in measuring and understanding the impact of illiquidity. A number of papers in the academic literature and popular press have taken opposing views on the changes in levels of liquidity in corporate bond markets.[1]

Liquidity cost measures have been extensively studied, and several methods have been proposed. Two broad types of liquidity measures in the academic literature are: 1) the bid-ask spread and 2) the price impact of seeking liquidity, measured at either a high or a low frequency (i.e., trade level or daily[2]). A strand of the literature aggregates estimates of the liquidity cost for individual securities into a marketwide measure of illiquidity and gauges the covariation of returns with systematic illiquidity shocks.[3]

In this paper, we start by examining one important aspect of liquidity: the expected bid-ask cost of trading a corporate bond. In particular, we look at different approaches to quantifying this cost before settling on a functional form that uses certain bond characteristics to estimate the bid-ask cost. We find that the cost is determined by the age of the bond, the issue size, the maturity and the credit spread level. By estimating the bid-ask on bonds that don't trade, we use this relationship to characterize the liquidity cost for the entire universe of corporate bonds. However, we should note that bonds that do not trade may be less liquid than our model-based estimates, for reasons we have not established.

[1] https://www.bloomberg.com/view/articles/2017-12-03/bond-investors-are-worried-about-bond-market-liquidity
[2] See appendix for a comprehensive overview of the literature.
[3] See Pastor and Stambaugh (2003), Acharya and Pedersen (2005), Korajczyk and Sadka (2008), Lou and Sadka (2011), Lin et al. (2011) and Bongaerts et al. (2017).

Next, we look at the sensitivity of credit valuations to innovations in the level of liquidity and quantify this liquidity beta metric. We show the liquidity betas estimated at the issuer level are statistically significant once adjusted for term structure effects. Liquidity betas and bid-ask spreads also tend to be positively correlated, with the correlation rising in turbulent times.

We conclude by looking at the extent to which credit returns are explained by liquidity. In this exercise, we start with a relatively simple approach that suggests that, once it is adjusted for credit market beta, liquidity is not a factor in explaining credit returns. This result may be misleading, however, because credit spreads, which are used to identify beta to the credit market, are also correlated to liquidity. More-careful analysis that disentangles this correlation shows that liquidity does indeed play a significant role in explaining credit returns. Moreover, the liquidity cost factor has a positive risk premium - i.e., investors are paid to hold less liquid bonds.

The liquidity cost characteristics discussed in this paper can be used in many ways in portfolio construction. One important application is to provide managers with measures of the liquidity cost and risk embedded in the corporate bonds in their portfolios. Another application is to provide valuation signals in quantitative trading strategies.

2. LIQUIDITY COST ESTIMATION

One challenge of applying liquidity metrics used in equities to the corporate bond market is that in equities, market makers are required to post two-way markets and, hence, there is a reasonably reliable notion of a market price. In contrast, a sizable percentage of the corporate bond market does not trade regularly. Certain pricing providers estimate a daily mark for such securities, and one could mechanically implement equity-market-based liquidity metrics using these marks. However, these marks are, in effect, the pricing vendors' opinions. Although the opinions may be appropriate for many purposes, focusing on their changes may well mean that our results amount to reverse-engineering the pricing algorithms of the pricing vendors rather than statements of market behavior. For this reason, we focus on actual transactions as reported in the TRACE (trade reporting and compliance engine) database maintained by the Financial Industry Regulatory Authority (FINRA). From these transactions, we create a generic model based on bond characteristics that we can use for bonds without observed trades.

Mandatory TRACE reporting was introduced for all broker-dealers in 2002 and expanded in 2005 to improve the price transparency in over-the-counter market activity in corporate bonds.[4] The TRACE dataset covers all trades in the over-the-counter market for corporate bonds (as well as some other sectors, including municipal bonds) that are reported by broker-dealers. Trades are identified as either between dealers and customers or intradealer. Trade quantities are capped at $5 million and $2 million for the investment grade and high yield markets, respectively, in the standard data set, but in the enhanced data set, which is released after a six-month lag, the true trade quantities are disclosed. To maximize the data, we use the enhanced data set for bond characteristics analysis and the standard one to analyze liquidity cost, betas and cross-sectional returns.

Table 1 summarizes the average number and par value of the trades in the TRACE database, grouped by trade size, excluding dealer-to-dealer trades. While the majority (by count) of the trades in investment grade are below $5 million, the par value weight of the trades is distributed more evenly across trade sizes. The data in Table 1 are based on aggregated information from FINRA.

Table 1: TRACE dealer-to-customer transaction size breakdown, January 2013 to December 2017

Size ($)	Average daily trades	% of total trades	Average daily par value ($)	% of total par value
Investment grade				
<5mm	28,620	97%	7,434,368,626	44%
5mm-10mm	652	2%	3,916,974,936	23%
10mm+	350	1%	5,502,482,043	33%
Total	29,623	100%	16,853,825,604	100%
High yield				
<1mm	13,808	82%	1,688,926,255	15%
1mm-3mm	2,064	12%	3,194,729,656	29%
3mm-5mm	505	3%	1,739,382,059	16%
5mm+	545	3%	4,558,976,507	41%
Total	16,923	100%	11,182,014,477	100%

Source: FINRA

[4] Dick-Nielsen (2014) discusses the structure of the database and the cleaning methodology.

Using transaction-level data, there are several methods for estimating the liquidity cost measure categorized broadly as transaction cost (i.e., bid-ask) or price impact.[5] These measures tend to use trailing observations and can be based on high frequency (trade-level) or low frequency (daily-level) data. Though these measures can be different at the bond level, they tend to be highly correlated when aggregated at the sector level.

A number of aspects of liquidity have been explored in the literature. One set of metrics deals with the direct consequences of illiquidity – namely, transaction costs incurred in crossing the bid-ask spread and the impact cost of trading large quantities of bonds. Those are obviously of interest as metrics of portfolio liquidity and as inputs into developing trading strategies. But beyond these direct measures, we are interested in the effect of fluctuations in the level of liquidity on expected credit returns. In this section, we focus on the liquidity cost in a cross section of bonds and the relationship between liquidity cost and bond characteristics.

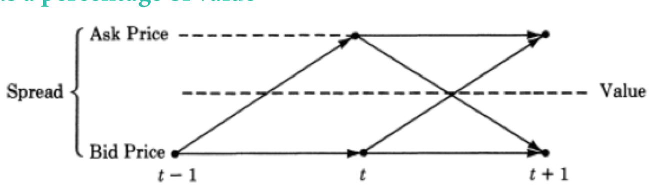
2.1 HOW DO WE ESTIMATE LIQUIDITY COST?

We define liquidity cost as

$$\textit{Liquidity Cost} = \frac{\textit{Ask Price} - \textit{Bid Price}}{1/2(\textit{Ask Price} + \textit{Bid Price})} \tag{1}$$

when transaction prices are observed (but not the bid and ask prices). We consider three types of estimators: the generic bid-ask spread and two more estimators that are based on market microstructure models – namely, the Roll measure and the Gibbs measure.

Figure 1: Liquidity cost: Spread between bid and ask prices as a percentage of value



BID-ASK SPREAD

As a proxy for bid-ask, one can estimate the average daily bid-ask at the bond level by using average customer buy and sell prices

$$\textit{Liquidity Cost}_{bidask_{i,t}} = \frac{\bar{P}_{Buy,i,t} - \bar{P}_{Sell,i,t}}{1/2(\bar{P}_{Buy,i,t} + \bar{P}_{Sell,i,t})} \tag{2}$$

where $\bar{P}_{Buy,i,t}$ is the average price of all customer buys for bond i on day t. To make the estimator more robust, we then estimate the bond-level bid-ask spread as the monthly rolling average of the daily estimate as defined in Equation (2). Obviously, this estimator relies on the assumption that customer buys (sells) happen at the ask (bid) price. This approach does not account for broad market moves that could affect the difference between buys and sells. There is evidence suggesting that since the financial crisis the bid-ask spread underestimates liquidity cost due to an increase in offsetting matched dealer-customer transactions within a short period of time.[6]

ROLL MEASURE

Roll (1984) exploited the fact that because a buy (sell) transaction can be followed with 50% probability by a sell (buy) transaction, we can proxy liquidity by the negative autocorrelation in returns. Formally, Roll's approach is based on modeling the dynamics of price as a latent fundamental value m_t and u_t public information innovation in period t:

$$m_t = m_{t-1} + u_t \tag{3}$$

and pricing dynamics is equal to

$$p_t = \log P_t = m_t + \frac{1}{2}\textit{Liquidity Cost} \times q_t \tag{4}$$

where q_t is the trade direction indicator (+1 for buy and -1 for sell). The effective bid-ask spread can then be inferred from the time series of prices:

$$\textit{Liquidity Cost}_{Roll_{i,t}} = 2\sqrt{\max\left(0, -cov(\Delta p_{i,t}, \Delta p_{i,t+1})\right)}\,. \tag{5}$$

Similar to the bid-ask spread, every trading day we estimate the Roll measure using intraday transaction prices and then take the trailing monthly rolling average of the daily measure.

The Roll measure makes two major assumptions: 1) the asset is traded in an informationally efficient market such that the bid-ask average (i.e., the "underlying value") follows a random walk and 2) the observed price changes are stationary. As with the bid-ask measure, part of the return could be the result of aggregate market movements.

[5] Price impact measures the impact on the price of a trade as a function of trade volume (or size). The most common impact cost measures are attributed to Amihud and Hasbrouck and used mostly in equities. The Amihud measure (Amihud (2002)) is defined as average trade by trade $(i=1,\ldots,N)$ return r_i per unit of quantity (Q_i) in a trailing period ending at t:

$$\textit{Amihud price Impact}(t) = 1/N\, \Sigma_{i=1}^{N} |r_i|/Q_i$$

Hasbrouck (2009) also proposed a lambda measure calibrated in $r_i = \lambda_t\, q_i\, \sqrt{Q_i} + u_i$, where q_i is the trade indicator.

[6] See Choi and Huh (2017).

GIBBS MEASURE

The Gibbs measure proposed by Hasbrouck (2009) generalizes the basic Roll model by taking into account this effect of market return r_t^m in the price of bond i and estimating an effective bid-ask spread:

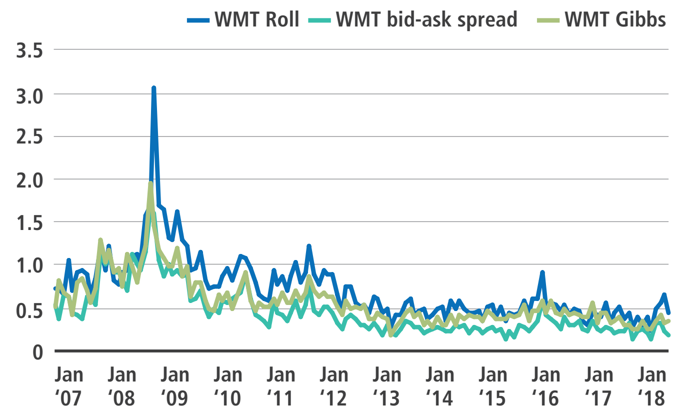
$$\Delta p_{i,t} = \frac{1}{2} LiquidityCost_{Gibbs_{i,t}} \Delta q_{i,t} + \beta_m r_t^m + u_{i,t}. \tag{6}$$

Equation (6) is based on Equation (4) and accounts for the market return term. By assuming that u_t follows i.i.d $N(0,\sigma_u^2)$, the Bayesian estimators, $LiquidityCost_{Gibbs_{i,t}}$, σ_u^2, the latent trade direction q_t,β_m and the latent fundamental value m_t (as defined in Equation (4)) are simulated using the Gibbs sampler and then estimated by the standard Bayesian regression. The Gibbs sampler is a Monte Carlo Markov chain algorithm that generates posterior samples by iteratively going through each variable to sample from its conditional distribution given the remaining variables.

Although the three liquidity measures are highly correlated, the Gibbs measure has a few advantages over the other two. In addition to adjusting for the move in overall market prices, the Gibbs measure relies only on the daily data. Figure 2 compares the three measures' averages for Walmart bonds. The Roll measure can be quite noisy because the covariance is estimated over the most recent (rolling-time-window) history, while the bid-ask measure tends to be the lowest. For Walmart, the correlation of monthly changes of liquidity cost is roughly 0.6, while the Roll measure shows the highest excess kurtosis, at 11.

For the remainder of this paper, we will use the Gibbs measure for liquidity cost, estimated using the last trade price (effectively, the closing price for the day, excluding retail trades – i.e., trade volume less than \$50,000). To keep the estimates statistically meaningful, the bond coverage is constrained by the trading frequency; only bonds that traded over at least 50% of the trailing 20 trading days are included. Furthermore, because we work with daily returns, bonds included on a given day are required to have traded that day and the prior day. These constraints restrict the estimation universe to about one-third of bonds in the investment grade and high yield benchmark universes. To estimate the liquidity cost for bonds that have not traded or do not satisfy the above criteria, we investigate the relationship between liquidity cost and various bond characteristics in Section 2.3.

Figure 2: Time series of liquidity measures for Walmart (WMT) bonds (as a percentage of value)



Source: PIMCO as of 28 February 2018

AVERAGES OF LIQUIDITY COST

In Table 2 we provide some evidence of the time-series variation of the liquidity cost average by quality and maturity for three dates: 1) the recent environment (April 2018) when volatility was relatively low, 2) the period after the energy price decline in 2016 and 3) during the financial crisis of 2008. As can be seen, liquidity cost increases with maturity and deteriorates with a decline in ratings. In terms of crisis events, liquidity cost almost doubled during the energy price decline; during the financial crisis, the cost went up more than five times.

2.2 LIQUIDITY COST AND BOND CHARACTERISTICS

In this section, we study the variation of liquidity cost in the cross section of bonds and its relationship to bond characteristics.[7] We start by showing the significance of age, issue size, trading volume and maturity for liquidity cost. We then consider a more comprehensive model to use for estimating generic liquidity cost, which can also be useful in estimating the liquidity cost for bonds that are not traded. This generic model has an explanatory power of variations in the cross section, with an R-squared of approximately 60%.

To explore the empirical relationship between liquidity cost and a bond's characteristics, we show in Figure 3 the scatter plots of liquidity cost versus age, maturity, issue size and trading volume over one trailing month.[8] We have shown these scatter plots by using the average liquidity cost for the various characteristics of various buckets of bonds. These all point to a higher liquidity cost for bonds with longer maturity and

[7] See Bao et al. (2011) and Konstantinovsky et al. (2016).
[8] In Figure 3, the monotonic relationship between age and liquidity cost is not as clear as other characteristics. Indeed, a piecewise linear function is a better way to model the relationship; this will be discussed in Section 2.3 with a broader sample of data and controlling for other factors.

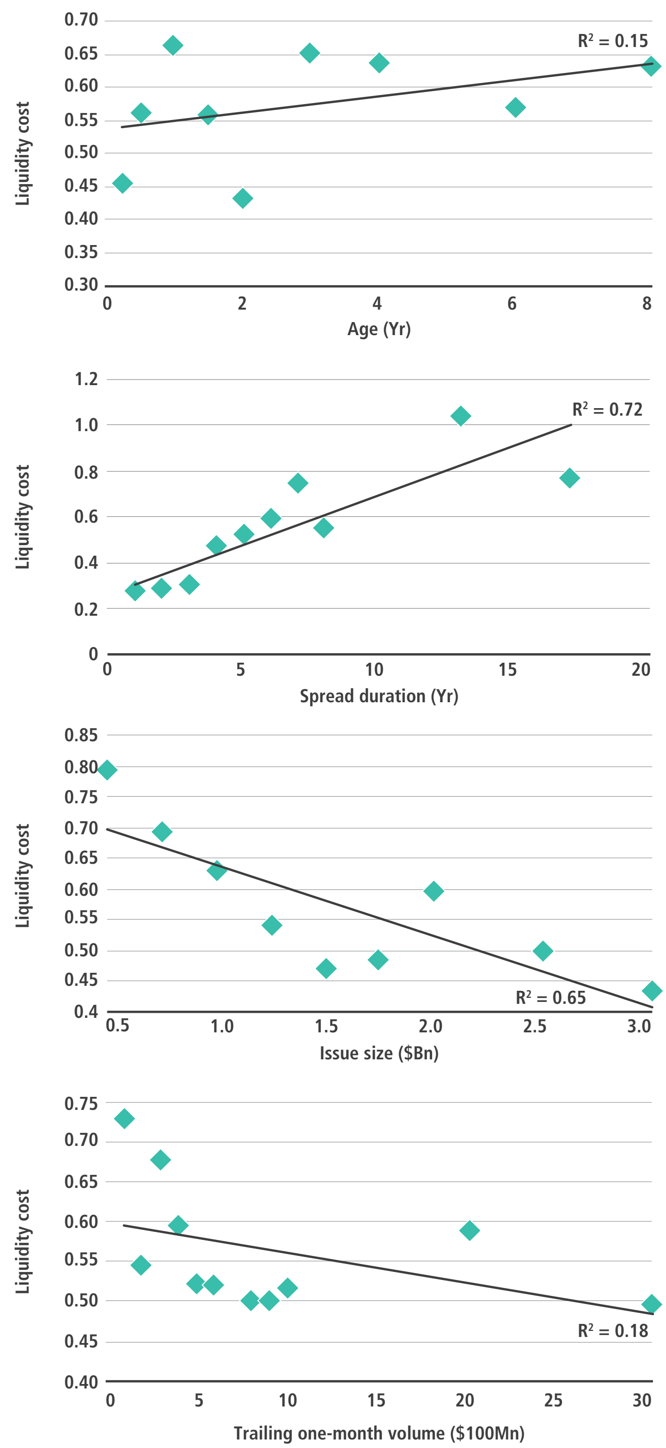
smaller size, and for older bonds. In fact, a more careful pooled cross sectional analysis of liquidity cost across bonds would show the statistical significance of all the aforementioned characteristics.

Table 2: Average liquidity cost: Normal versus stressed periods (as a percentage of value)

As of April 2018							
Maturity	0–3yr	3–5yr	5–7yr	7–10yr	10–20yr	20yr+	Average
AAA to AA-	0.16	0.31	0.38	0.35	0.32	0.47	0.28
A+ to A-	0.17	0.26	0.35	0.34	0.37	0.52	0.29
BBB+ to BBB-	0.23	0.33	0.46	0.42	0.55	0.62	0.42
BB+ to BB-	0.38	0.42	0.47	0.53	0.89	0.94	0.52
B+ and below	0.73	0.76	0.81	0.77	1.35	0.97	0.80
Average	0.25	0.38	0.49	0.44	0.58	0.61	0.42
Energy price decline (based on transactions during January 2016)							
Maturity	0–3yr	3–5yr	5–7yr	7–10yr	10–20yr	20yr+	Average
AAA to AA-	0.18	0.37	0.60	0.62	1.27	1.00	0.49
A+ to A-	0.22	0.46	0.64	0.72	1.02	1.25	0.61
BBB+ to BBB-	0.37	0.78	0.94	0.99	1.37	1.43	0.89
BB+ to BB-	0.90	1.18	1.25	1.26	1.53	2.50	1.27
B+ and below	1.32	1.39	1.53	1.23	1.41	1.75	1.42
Average	0.41	0.82	1.05	0.96	1.28	1.40	0.88
Global financial crisis (based on transactions during October 2008)							
Maturity	0–3yr	3–5yr	5–7yr	7–10yr	10–20yr	20yr+	Average
AAA to AA-	1.35	1.99	3.28	2.79	6.52	3.03	2.63
A+ to A-	2.14	2.75	4.75	3.82	4.47	3.64	3.49
BBB+ to BBB-	1.71	3.51	3.80	3.53	4.34	4.15	3.69
BB+ to BB-	2.70	2.77	2.73	2.98	3.58	7.05	3.25
B+ and below	2.46	4.05	3.95	4.83	2.86	6.15	4.23
Average	1.99	2.71	3.77	3.54	4.14	3.96	3.39

Source: PIMCO calculations based on TRACE database

Figure 3: Scatter plots of median liquidity cost (as a percentage of value) versus bond characteristics as of January 2016



Source: PIMCO

2.3 GENERIC MODEL OF LIQUIDITY COST

Guided by the foregoing analysis, we construct a model to proxy the liquidity cost for corporate bonds that do not trade or do not satisfy our computation criteria.[9] Our generic liquidity cost model is defined in Equation (7). The regression is pooled across all bonds for coefficients to all factors except option-adjusted spread (OAS). The R-squared of the regression is 59%, and all the factors are significant (the t-stat of each factor is reported in parentheses for each coefficient):

$$\begin{aligned} LiquidityCost_{i,t} &= \underset{[59.1]}{0.9263} + F(Age_{i,t}) + \underset{[43.1]}{0.072}\, Maturity_{i,t} + \underset{[2.2]}{0.0205} Floater_i \\ &\quad \underset{[63.3]}{-0.1345}\ \ln IssueSize(in\ \$B)_i + \beta_{rating(i,t)}\, OAS_{i,t}(\text{in }\%) + \varepsilon_{i,t}\,. \end{aligned} \tag{7}$$

The age function $F(Age_{i,t})$ is assumed to be piecewise linear, with knots at three months, one year and three years of aging to capture the different sensitivities to age (see Figure 4). It is worth noting that the maturity factor, fixed versus floater coupon indicator (an indicator variable that is 1 only for fixed coupon bonds) and the issue size factor all have the signs as expected; for instance, new and larger issues are cheaper to trade. Figure 5 shows estimated $\beta_{rating(i,t)}$ as a function of the issuer's rating[10] and illustrates that an increasing portion of spread is associated with liquidity as ratings improve.

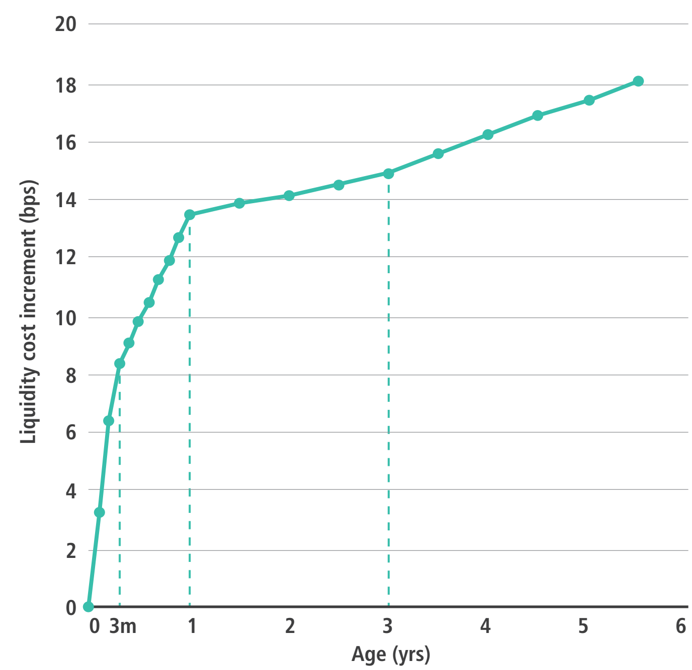
To study the robustness of the generic model, we estimated the model using a subset of the entire data. Using a five-year subsample of data from 2012 through 2016, we find no significant difference from the calibration over the entire period.

3. LIQUIDITY BETA TO SECTOR-WIDE LIQUIDITY SHOCKS

Liquidity cost measurement relies on the recent level of bond price fluctuations. Obviously, when liquidity shocks (i.e., a systemic increase in liquidity cost) occur, bonds experience both an increase in liquidity cost and spread widening. Though it is related to the sensitivity to these systematic liquidity shocks, liquidity cost does not directly measure this sensitivity.

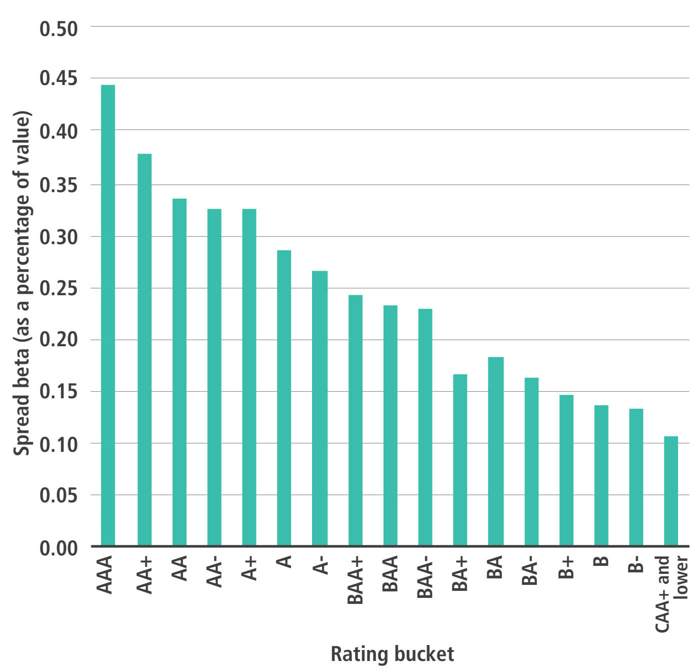
In this section, we study the effect of fluctuations in liquidity cost on credit returns. Specifically, we adjust changes in bond-level liquidity cost for serial correlation effects and then aggregate to obtain sector-level liquidity cost changes. We then look at the dependence of credit returns on these liquidity fluctuations to obtain liquidity betas.

Figure 4: Liquidity cost by age of bond (years)



Source: PIMCO as of 28 February 2018

Figure 5: Spread betas by rating bucket



Source: PIMCO as of 28 February 2018

[9] In Konstantinovsky et al. (2016), the nonquoted bonds' liquidity costs are estimated by leveraging the statistical relationship between a bond's liquidity cost and its characteristics, and adjusted upward because a bond without a quote over a month is expected to be less liquid than a bond with quoted prices and similar attributes.
[10] We use a combined rating, defined as the the lower of the ratings assigned by Standard & Poor's and Moody's Investor Services.

3.1 LIQUIDITY INNOVATION ESTIMATION

First, we estimate sector-level liquidity innovations. We estimate the innovations for four sectors – financials, consumers, energy/mining/materials and pipelines (EMMP), and industrials excluding EMMP – to account for the possibility of sector-specific shocks, such as experienced in financials during 2008 and more recently in the energy sector in early 2016.

The liquidity innovations $(\Delta L_{i,t})$ are estimated bottom-up by adjusting the serial correlation of liquidity changes $(\Delta \tilde{L}_{i,t})$ for every bond and then aggregating their changes at the sector level. The methodology is closely related to the liquidity literature on equities, such as Acharya and Pedersen (2005) and Pastor and Stambaugh (2003).

Bond-level liquidity innovations:[11]

$$\Delta\widetilde{L_{i,t}}: \quad \Delta L_{i,t} = \alpha_1 \Delta L_{i,t-1} + \alpha_2 \Delta L_{i,t-2} + \Delta\widetilde{L_{i,t}} \tag{8}$$

Sector-level average innovation:

$$\Delta\widetilde{L_{S,t}} = \frac{1}{S}\sum_{i\in S} \Delta\widetilde{L_{i,t}} \tag{9}$$

In our nomenclature, higher liquidity cost means lower liquidity, a positive number for liquidity innovations is an illiquidity shock, and a negative number implies an improvement in liquidity. As shown in Table 3, the long-term correlation of liquidity innovations and the percentage change of the credit default swap index for investment grade (CDX IG) spread is 30% to 40%, while the correlation to the CBOE Volatility Index (VIX) is slightly lower.

It is worth mentioning that the liquidity innovation process has a significant kurtosis even if we exclude the global financial crisis. In Figure 6, the biggest movements in the time series are in 2008, led by the financial sector. Subsequently, during the 2010 European sovereign debt crisis and the 2011 equity market sell-off, the liquidity shocks were consistent across all sectors. However, in the energy crisis of 2016, the liquidity shock was realized in the energy sector.

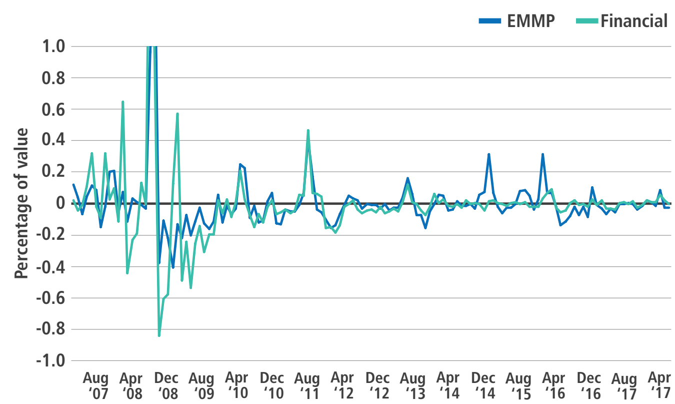
3.2 LIQUIDITY BETA ESTIMATION

Now that we have a time series of liquidity shocks, we estimate the liquidity beta to the sector liquidity shock using a time-series regression. Here we model liquidity beta of a bond as a function of the issuer and bond maturity for fixed coupon bonds.[12] The liquidity beta is estimated by pooling all the bonds (e.g., $i=1,\ldots,N$) by the same issuer (e.g., $Issuer_j$) and using the full history of monthly returns since 2007 and the following time-series regression for each issuer:

$$excess\ return_{i,t} = -(\theta_{i,5Y,t}\beta_{Issuer_j,5Y,t} + \theta_{i,10Y,t}\beta_{Issuer_j,10Y,t})\Delta\widetilde{L_t} + \epsilon_{i,t} \tag{10}$$

where excess return is defined as the bonds' return in excess of duration return. Here $\theta_{i,5Y,t}$ and $\theta_{i,10y,t}$ are interpolation variables [0,1] as a function of bond maturity and issuer j is the issuer of bond i, where the liquidity beta of a given bond is equal to $-(\theta_{i,5Y,t}\,\beta_{Issuer\,j,5Y,t} + \theta_{i,10Y,t}\,\beta_{Issuer\,j,10Y,t})$.

Figure 6: Market average liquidity innovation by sector



Source: PIMCO

Table 3: Summary statistics of liquidity innovation

2007 to 2017	CONSUMER	EMMP	FINANCIAL	INDUSTRIAL
Volatility	0.14	0.20	0.28	0.15
Kurtosis (excess)	63	38	38	44
Skewness	7	5	4	5
Corr to VIX	33%	40%	40%	36%
Corr to BarC A OAS	22%	23%	19%	23%
2010 to 2017	**CONSUMER**	**EMMP**	**FINANCIAL**	**INDUSTRIAL**
Volatility	0.04	0.10	0.07	0.05
Kurtosis (excess)	7	5	18	4
Skewness	1	2	3	1
Corr to VIX	25%	31%	27%	25%
Corr to BarC A OAS	32%	41%	39%	42%

Source: PIMCO

[11] The average α_1 is -0.51 and α_2 is -0.31 with average p-value 23% and 34%, respectively.
[12] We also use an indicator variable to account for floating-rate coupon bonds.

The model covers, on average, 60% of the issuers over time. The betas tend to be positive, implying a loss under a liquidity shock. Table 4 provides a snapshot of the summary statistics as of March 2018. For instance, a 4-standard-deviation move in liquidity innovation within the energy sector $(\Delta\tilde{L}_t = 0.8)$ for a bond with $\beta = 10$ (10 years or longer in maturity) implies an expected loss of 800 basis points due to the systematic liquidity shock. The front-end bonds have lower-magnitude beta, and the long-dated bonds have the highest; this means the front-end bonds bear less liquidity risk and suffer less in a crisis. However, the betas are higher than the ratio of spread duration or DTS.

It is worth noting that liquidity cost and liquidity beta measure different aspects of a bond's liquidity profile. The former measures the transaction cost at the bond level based on recent history, and the latter is the long-term sensitivity of price to market liquidity shocks at the issuer level. Usually, a bond with high liquidity beta tends to have a high cost, but this relationship varies over time. During a turbulent period, the correlation tends to be higher. To illustrate this variation, we compared the correlations for the EMMP sector in February 2016, after the oil price had declined, and in November 2017, when the market was calm. Figure 7 shows this correlation, which was 0.55 in the turbulent period and declined to 0.34 after the market recovery.

4. LIQUIDITY IN THE CROSS SECTION OF RETURNS

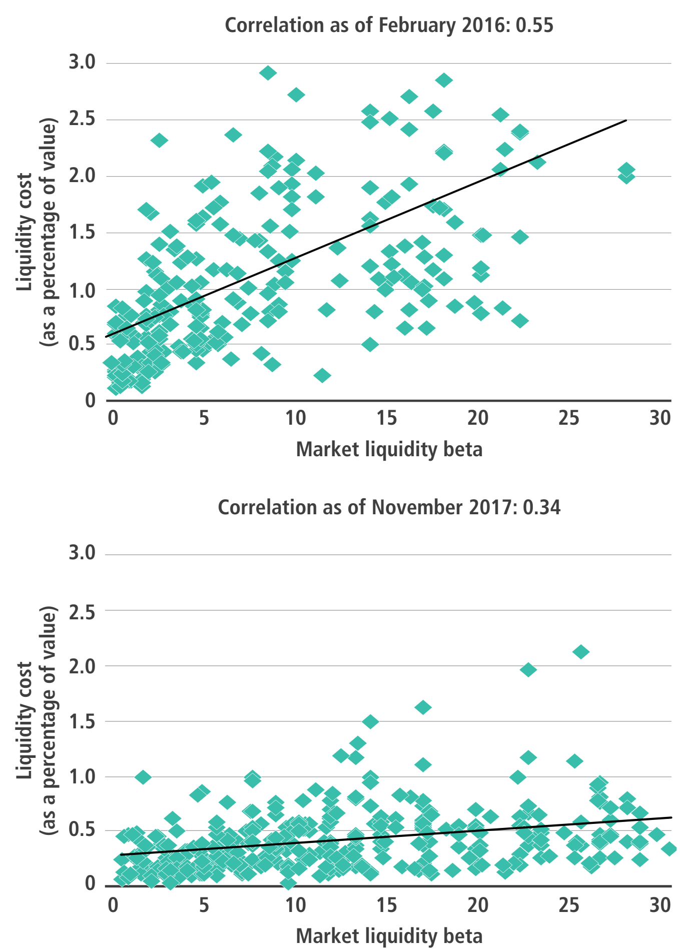
Building on our understanding of liquidity cost and liquidity beta, we study the significance of the liquidity factors in explaining the cross section of returns. In doing so, we want to ensure we take out the first-order effect of credit risk. It is empirically well understood that a lognormally specified spread factor has a significant explanatory power in the cross section of corporate bonds' excess returns.[14] This explanatory power can be further improved by accounting for the term structure volatility of the spread curve (Naik et al. (2016)). In this section, we use a baseline term structure spread-factor model to account for the first-order effect of credit risk and test the significance of an incremental liquidity factor in explaining credit returns. We study this at both the sector level and the issuer level.

In our analysis, we use the universe of bonds that traded in TRACE for that month. Also, the returns and prices are based on the last transaction in TRACE for the day, similar to what we use in liquidity cost estimation. Although this reduces the universe of bonds in the cross section, it avoids any matrix-pricing biases in our results.

Table 4: Summary statistics of the liquidity beta of investment grade bonds as of 31 March 2018

	Fixed <5yr			Fixed 5yr-10yr			Fixed >10yr		
Sector	Mean	Std Dev	Avg DTS[13]	Mean	Std Dev	Avg DTS	Mean	Std Dev	Avg DTS
Consumer	4	2	2	8	5	6	11	7	19
EMMP	5	3	2	10	7	7	17	8	21
Financial	4	4	2	9	6	6	15	8	18
Industrial	3	2	2	5	4	5	7	7	18

Figure 7: Correlations between beta and cost in the EMMP sector



[13] DTS refers to spread duration times the OAS of the bond.
[14] See Schönbucher (2000), Dor et al. (2007) and Naik et al. (2016).

4.1 SECTOR-LEVEL ANALYSIS

We consider the cross section of returns for the investment grade universe across our same four sectors: financials, consumers, EMMP and industrials excluding EMMP. To test the significance of the liquidity beta and liquidity cost measures, we estimate the following factor model:

$$excess\ return_{i,t} = \sum_{j=1}^{3} \theta_{i,j,t-1}\, DTS_{i,t-1} \times f_t^j + \overbrace{\beta_{i,t-1}^L \times f_t^L}^{liquidity\ beta\ return} + \overbrace{LC_{i,t-1} \times f_t^{LC}}^{bond\ liquidity\ cost\ return} + \varepsilon_{i,t} \quad (11)$$

where

- Excess return is defined as total return in excess of duration return.
- The factors f_t^j*'s for j=1,2,3,* capture the effective percentage of OAS changes for short maturity (three years), intermediate (seven years) and long end (10 years or more), respectively.
- $DTS_{i,t-1}$ is spread duration times OAS of the *i*'th bond at time *t*.
- $\beta^L_{i,t}$ is the liquidity beta defined in Section 3 measuring time-series covariation to liquidity shocks.
- $\theta_{i,m,t}$'s are interpolation variables [0,1] as a function of bond maturity.
- $LC_{i,t}$ is the liquidity cost based on the Gibbs measure, defined in Equation (6).

One important modeling choice in implementing the above analysis is the DTS metric. Using the standard DTS metric is problematic because credit spreads, and consequently DTS, are influenced by liquidity. Hence, attempting to neutralize credit beta by using the standard DTS metric will also distort our estimates of the influence of liquidity characteristics on excess return. In this paper, we look at a few alternatives. Specifically, we look at an orthogonalized factor that isolates the nonliquidity part of the DTS factor and a version that uses a credit spread based on a Merton-type capital structure model-based credit spread. As we shall see, the results produced by these approaches are consistent with liquidity being a significant factor in explaining excess returns.[15]

We compare the following models in Table 5, using the full sample of 2007 to 2018 and the post-crisis sample of 2010 to 2018 to study the robustness of results when the financial crisis is excluded. M0 is a baseline model specification with credit-term-structure DTS factors. M1 to M3 are variations with only liquidity factors. M4 models the credit and liquidity factors simultaneously. The primary model specifications are M5 and M6, adjusting DTS factors in two ways. In the top panel of Table 5, we show the R-squared and sample size. The middle panel presents the statistical significance (i.e., the average and median p-value of the factors). In the bottom panel, we show the liquidity factor correlations with CDX IG credit return.

Table 5: Summary of sector-level analysis

Sample: IG Index 2007-2018

	M0	M1	M2	M3	M4	M5	M6
R-squared	63%	51%	46%	56%	66%	65%	65%
Avg sample size	1,044						661[16]
Average p-value and median p-value[17]							
Liquidity beta		5% and 0%		10% and 0%	26% and 11%	12% and 0%	24% and 12%
Liquidity cost			4% and 0%	17% and 1%	30% and 20%	16% and 0%	31% and 20%
DTS	15% and 0%				19% and 2%		
Orthogonalized DTS						22% and 5%	
DD-based DTS							29% and 15%
Correlation to CDX IG OAS % change							
Liquidity beta		-35%		-34%	-19%	-32%	-19%
Liquidity cost			-33%	-27%	22%	-29%	-8%

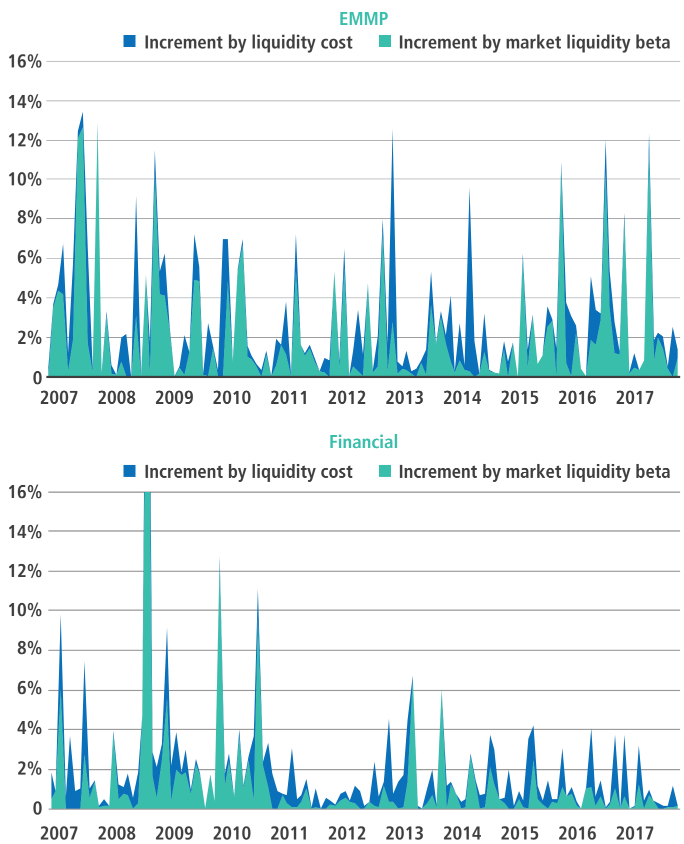
Sample: IG Index 2010-2018

	M0	M1	M2	M3	M4	M5	M6
R-squared	62%	46%	45%	52%	63%	62%	61%
Avg sample size	1,261						781
Average p-value and median p-value							
Liquidity beta		5% and 0%		10% and 0%	25% and 11%	11% and 0%	24% and 0%
Liquidity cost			4% and 0%	14% and 0%	28% and 17%	13% and 0%	29% and 19%
DTS	13% and 0%				15% and 0%		
Orthogonalized DTS						19% and 2%	
DD-based DTS							27% and 10%
Correlation to CDX IG OAS % change							
Liquidity beta		-75%		-75%	-40%	-75%	-59%
Liquidity cost			-75%	-67%	17%	-68%	-33%

Source: PIMCO

[15] Instead of using DTS factor exposures, one could estimate market exposures by estimating the beta of each bond to market controlled for rating, sector and maturity.
[16] We have only the nonfinancial sectors in the sample.
[17] Here we also show median p-value, as the liquidity factors tend to be less significant in quiet periods.

Figure 8: R-squared increments by liquidity factor



Source: PIMCO

(M0): Base model where we have only credit-term-structure DTS factors and no liquidity factors. As discussed above, the standard DTS factor is problematic in this context, but it is used here as a baseline. A DTS factor and its extension to term structure factors are, obviously, statistically significant and have an R-squared of 63%.

(M1/M2): Next, we test the significance of liquidity-only factor models, considering each separately. Given the strong relationship of liquidity to bond spread and maturity, it is not surprising that both liquidity cost and liquidity beta are significant (with an average p-value of 4%~5%). However, the R-squared of the regression is lower than that of the M0 model. Also, the factor returns from the M1 and M2 models are correlated around 60%.

(M3): The results from M1 and M2 would raise the question of whether liquidity beta and liquidity cost are jointly significant. We test that in the M3 setting, which shows a slight improvement in the R-squared compared with the one-factor liquidity models and average p-values around 10%~15% (with a median p-value less than 1%).

(M4): We now test whether liquidity factors can add any value to the M0 model. In this specification, we continue to use the standard DTS metric. It turns out that the incremental pooled R-squared is quite low, with average p-values around 25%~30%. Though the pooled R-squared shows minimal improvements, as shown in Figure 8, the time series of the R-squared indicates that during the crisis periods (for the financials and EMMP sectors), the liquidity beta factor has a significant incremental R-squared. The liquidity beta factor with significant fat tails has low volatility and low positive correlation to spread changes. We also found, however, that the liquidity cost factor tends to be more significant when there is no systematic liquidity shock.

The results so far indicate that liquidity factors are not jointly significant with DTS factors. However, given that the spread levels embed the liquidity premium, as shown in Section 2, this does not suggest that liquidity has no explanatory power in the cross section of returns.

In what follows, we attempt to disentangle the liquidity impact on returns from the credit risk component in two ways. In the first approach (M5), we orthogonalize the DTS from liquidity cost and liquidity beta cross-sectionally and use the "residual" DTS in the regression defined in Equation (11). In the second approach (M6), rather than use market spreads to compute DTS, we use the fair spread implied by PIMCO's proprietary Merton-type model, which employs market equity valuations and equity option implied volatility. This ensures we do not contaminate the adjustment for the first-order credit factor with liquidity-related effects.

(M5): Similar to M4, we use orthogonalized DTS (to liquidity cost and beta) instead of DTS in the regression. This is done by first regressing the DTS cross-sectionally each month on the two liquidity loadings and then taking the residuals to replace the DTS in the original cross-sectional regression, i.e.,

$$DTS_{i,t} = \lambda_{0,t} + \lambda_{1,t}\beta^{L}_{i,t} + \lambda_{2,t}L_{i,t} + e_{i,t} \quad \Rightarrow \quad \widetilde{DTS}_{i,t} = DTS_{i,t} - \hat{\lambda}_{1,t}\beta^{L}_{i,t} - \hat{\lambda}_{2,t}L_{i,t}. \tag{12}$$

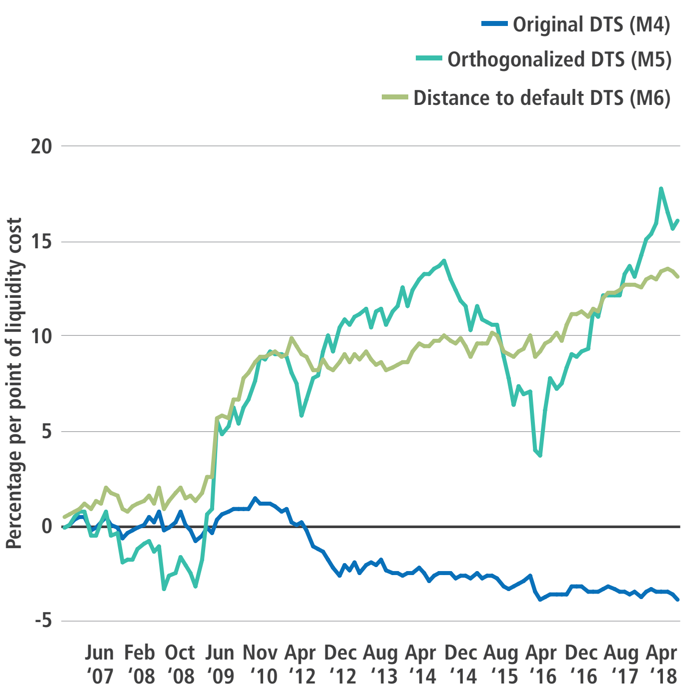
This regression has a pooled R-squared of 50%.

Using $\widetilde{DTS}_{i,t}$ in the cross-sectional regression (11), we get the results shown in Table 5. It is worth noting that the R-squared of the regression on the orthogonalized DTS only lowers the R-squared to 28% for the period of 2007-2018. Including the liquidity beta and liquidity cost factors would then increase the R-squared to 65%. The liquidity factors have become more significant, with average (median) p-values around 12% (0%), similar to M3.

(M6): Now we use the spread implied by distance to default in M4. This model, similar to M5, results in a similar pooled R-squared. The liquidity factors are less significant than in M5, which is not surprising given the forward-looking nature of the distance-to-default model. Having said that, the liquidity cost factors from M6 and M5 are highly correlated around 60%.

Figure 9 shows that the cumulative liquidity-cost-factor returns obtained from the M5 and M6 models are positive. This supports the use of liquidity characteristics as a source of bottom-up alpha in corporate credit. It is worth noting that the liquidity-cost-factor returns from the M4 model, which uses the standard DTS metric, are effectively small, highlighting the importance of disentangling liquidity return from DTS factors' return.

Figure 9: Cumulative returns of liquidity cost factors in M4, M5 and M6



Source: PIMCO as of 28 February 2018

4.2 ISSUER-LEVEL ANALYSIS

In this section, we take another approach to studying the significance of liquidity cost, without getting affected by the relationship among DTS, liquidity beta and liquidity cost. Instead of using excess return and adjusting for sector spread factors in the regression, we use the excess return adjusted for issuer-implied spread returns as the dependent variable in the regression. The issuer-implied spread returns are estimated from the excess return of all bonds of the same issuer and adjusted for the first principal component of the spread-term-structure changes. Compared with the previous section, this approach adjusts better for the idiosyncrasy of issuers and provides a sharper test of the relationship between liquidity cost and the richness or cheapness of bonds across the issuer's spread curve.

The cross-sectional regression considers pooling issuers with more than five bonds in the investment grade index. Using the TRACE database, we have 46 issuers and 538 bonds monthly, on average, in the cross section; the numbers have been in an upward trend since 2007.

To adjust for issuer-implied returns, we first estimate the average excess return per unit of DTS across the curve accounting for volatility term structure $\gamma_{i,t-1}$.[18] In particular, for month t and all the bonds $i=1,\dots N$ belonging to j'th issuer, we solve for issuer-implied $f_t^{issuer(j)}$ by accounting for $\gamma_{i,t-1}$ based on the maturity of i'th bond at time t:

$$excess\ return_{i,t}^{issuer(j)} = \gamma_{i,t-1}\ spread\ dur_{\ i,t-1} OAS_{i,t-1} \times f_t^{issuer(j)} + \varepsilon_{i,t}. \tag{13}$$

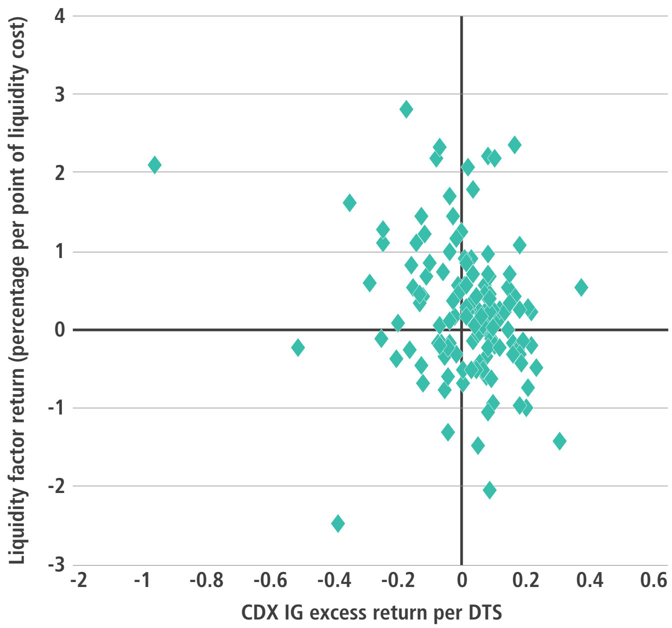
We then solve a monthly cross-sectional regression of the excess return of all bonds after adjusting for their corresponding issuer average return against the liquidity cost of the bond:

$$excess\ return_{i,t} - issuer\ implied\ spread\ return_{i,t} = LC_{i,t-1} \times f_{i,t} + \varepsilon_{i,t}. \tag{14}$$

The pooled R-squared of the regression in (14) is 11%, and the liquidity cost factor is indeed significant, with an average p-value of 12% (median of 0.5%). The Sharpe ratio of going long the factor (i.e., long bonds with higher costs and short lower-cost bonds of the same issuer, controlling for DTS) is 0.95 since 2007, with a correlation of -0.22 to CDX IG excess return per DTS (see Figure 10). The cumulative return associated with the liquidity provision is 31% since 2007 (see Figure 11).

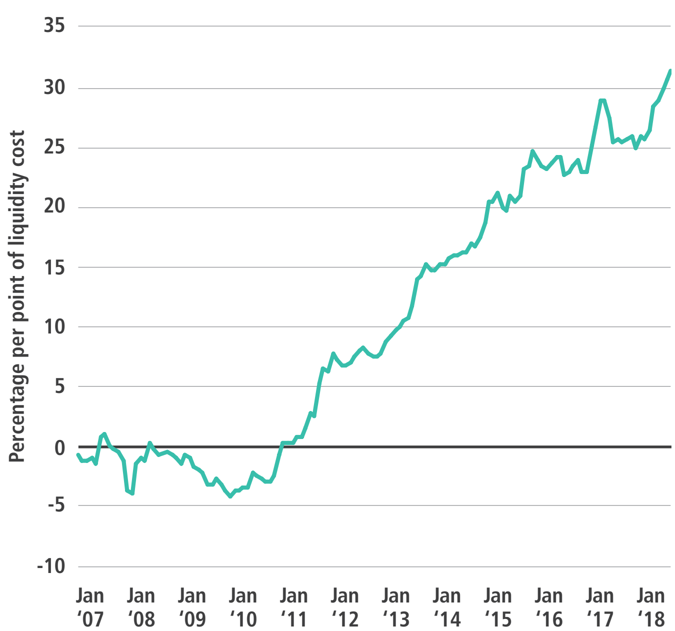
[18] In this study, we assume γ is 1.25 for a two-year bond and 0.75 for 10-year and longer bonds, consistent with the empirically estimated volatility term structure of spreads.

Figure 10: Scatter plot of liquidity factor return versus the CDX IG excess return index



Source: PIMCO

Figure 11: Cumulative return of liquidity factor return in Equation (14) for January 2007 to January 2018



Source: PIMCO

5. PORTFOLIO MANAGEMENT APPLICATIONS

At PIMCO, the security-level metrics discussed in the preceding sections are used in a number of ways in the portfolio management process. One important application is to provide portfolio managers with indications of the liquidity distribution of the corporate bonds in their portfolios. Figure 12 and Figure 13 show the security-level liquidity cost in PIMCO's position blotter and a historical chart of issuer/maturity bucket-level liquidity cost in our proprietary portfolio risk system. Another important application of these metrics is in testing quantitative trading strategies. In backtesting trading strategies in corporate bonds, persistent questions are whether the mispriced bonds are tradable and whether past periods when the valuation signals were particularly useful were also periods when liquidity was too poor to act on them. By incorporating these CUSIP-level, time-varying liquidity estimates, we are able to perform realistic backtests of trading strategies.

6. CONCLUSION

This paper looks at various empirical aspects of liquidity in corporate bonds. Specifically, we use return data from actual transactions reported in TRACE to estimate three different metrics of the bid-ask spread, with the Gibbs measure being the preferred metric. We find that during the energy crisis of early 2016, bid-ask prices were twice as high as current levels; they were more than five times higher than the current levels in the midst of the global financial crisis, a decade ago. Following this, we explore the relation between the bid-ask spread and bond characteristics, and estimate a generic model based on bond characteristics. We estimate a bond-level liquidity beta metric that measures the sensitivity of individual corporate bond valuations to variations in systemic measures of the level of liquidity. These liquidity betas are correlated (but not perfectly) with liquidity cost, with correlation rising in turbulent times.

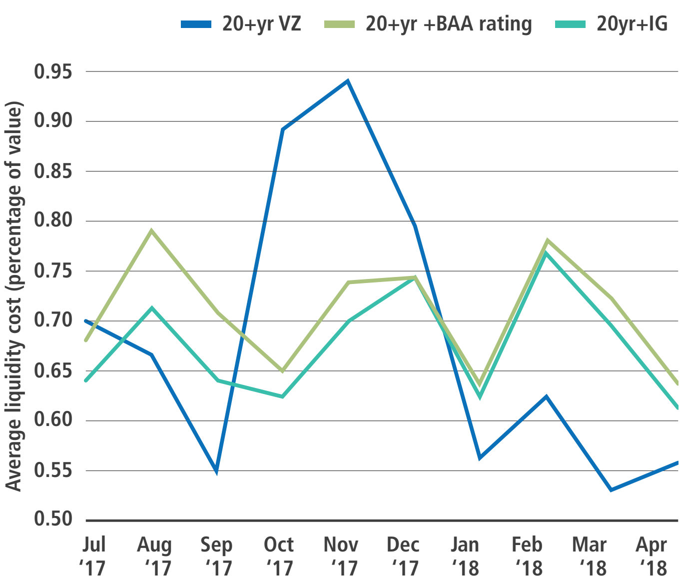
After estimating these security-level liquidity metrics, we explore the question of whether these metrics explain security-level credit returns after controlling for credit beta. The simplest way of correcting for credit beta using DTS (with adjustments for differences in spread volatility over the term structure) suggests that liquidity factors do not have a role in explaining credit returns. But this adjustment for credit beta is problematic, as credit spreads presumably compensate investors for liquidity

Figure 12: Security-level liquidity cost in PIMCO’s position blotter

SSM ID	ISIN	PIMCO Desc	Street Ticker	Coupon	Maturity Date	Quantity	PMV	MWS*	OAS*	Liquidity Cost (Generic)
[illegible]	[illegible]	[illegible]	[illegible]	4.3750	4/1/2022	6,623	0.01	4.10	82	0.4971
[illegible]	[illegible]	[illegible]	[illegible]	3.5000	10/1/2026	6,623	0.01	12.03	142	0.6197
[illegible]	[illegible]	[illegible]	[illegible]	3.5000	9/15/2022	8,279	0.01	6.70	125	0.5669
[illegible]	[illegible]	[illegible]	[illegible]	4.0000	11/15/2023	4,967	0.01	8.29	131	0.6403
[illegible]	[illegible]	[illegible]	[illegible]	2.8750	5/10/2023	4,967	0.00	7.00	87	0.5780
[illegible]	[illegible]	[illegible]	[illegible]	4.3750	5/10/2043	11,590	0.01	29.34	136	0.7386
[illegible]	[illegible]	[illegible]	[illegible]	7.4000	11/1/2046	6,595	0.01	37.84	251	1.2248
[illegible]	[illegible]	[illegible]	[illegible]	6.6250	10/1/2028	10,560	0.01	18.99	196	0.7958
[illegible]	[illegible]	[illegible]	[illegible]	7.4500	7/16/2031	29,696	0.04	25.46	235	0.7377
[illegible]	[illegible]	[illegible]	[illegible]	4.7500	1/15/2043	33,115	0.03	34.50	256	0.8203
[illegible]	[illegible]	[illegible]	[illegible]	4.3460	12/8/2026	24,836	0.02	13.64	159	0.4812
[illegible]	[illegible]	[illegible]	[illegible]	5.2910	12/8/2046	21,525	0.02	35.83	253	0.8607
[illegible]	[illegible]	[illegible]	[illegible]	8.1250	1/15/2020	20,697	0.02	1.53	51	0.2968
[illegible]	[illegible]	[illegible]	[illegible]	5.7500	2/1/2021	20,697	0.02	3.22	81	0.3508
[illegible]	[illegible]	[illegible]	[illegible]	5.8750	8/2/2021	33,115	0.04	4.08	92	0.3003
[illegible]	[illegible]	[illegible]	[illegible]	4.2500	9/20/2022	16,557	0.02	6.12	111	0.4378
[illegible]	[illegible]	[illegible]	[illegible]	4.3750	8/6/2023	16,557	0.02	7.70	123	0.4596
[illegible]	[illegible]	[illegible]	[illegible]	3.6640	9/8/2024	12,418	0.01	10.51	148	0.5974
[illegible]	[illegible]	[illegible]	[illegible]	2.5970	11/4/2019	20,697	0.02	1.16	39	0.2063
[illegible]	[illegible]	[illegible]	[illegible]	3.2190	1/9/2022	12,418	0.01	4.66	95	0.4003
[illegible]	[illegible]	[illegible]	[illegible]	2.4590	3/27/2020	9,934	0.01	1.98	62	0.3524
[illegible]	[illegible]	[illegible]	[illegible]	3.1570	8/4/2020	21,525	0.02	2.12	58	0.2354
[illegible]	[illegible]	[illegible]	[illegible]	4.1340	8/4/2025	23,180	0.02	12.10	156	0.4737
[illegible]	[illegible]	[illegible]	[illegible]	3.2000	1/15/2021	21,525	0.02	2.83	70	0.2799
[illegible]	[illegible]	[illegible]	[illegible]	4.3890	1/8/2026	19,869	0.02	13.05	162	0.5164
[illegible]	[illegible]	[illegible]	[illegible]	3.3360	3/18/2021	28,975	0.03	3.31	79	0.2445
[illegible]	[illegible]	[illegible]	[illegible]	2.0210	5/3/2019	20,697	0.02	0.64	25	0.1553
[illegible]	[illegible]	[illegible]	[illegible]	3.0960	5/4/2023	16,557	0.02	7.35	121	0.4275
[illegible]	[illegible]	[illegible]	[illegible]	1.8970	8/12/2019	11,590	0.01	1.11	44	0.3105
[illegible]	[illegible]	[illegible]	[illegible]	2.6810	1/9/2020	20,697	0.02	1.54	51	0.2129
[illegible]	[illegible]	[illegible]	[illegible]	3.8100	1/9/2024	12,418	0.01	9.06	138	0.5015
[illegible]	[illegible]	[illegible]	[illegible]	3.3390	3/28/2022	14,074	0.01	5.25	103	0.3962
[illegible]	[illegible]	[illegible]	[illegible]	2.4250	6/12/2020	10,762	0.01	1.77	49	0.3147
[illegible]	[illegible]	[illegible]	[illegible]	2.9790	8/3/2022	14,902	0.01	5.85	108	0.3783

Source: PIMCO

Figure 13: Historical time series of average liquidity cost in PIMCO's proprietary portfolio risk system



Source: PIMCO

cost as well as liquidity risk. In other words, the DTS measure already adjusts for the differentiated liquidity risk of bonds. To disentangle this correlation, we try a few different approaches, which reveal a dependence of credit returns on liquidity characteristics. Specifically, in the first approach we adjust for credit beta using a DTS metric that has been stripped of correlations with liquidity characteristics. In the second approach, instead of using actual bond-level credit spreads, we use a proprietary Merton-type model that is calibrated to the cross section of credit spreads to obtain a fair spread and use this to calculate our DTS metric. In a third approach, we consider issuers with more than five bonds and study the outperformance of individual bonds over the issuer-implied return. All approaches reveal that credit returns are indeed influenced by liquidity characteristics.

REFERENCES

Acharya, Viral V. and Lasse Heje Pedersen. 2005. "Asset Pricing with Liquidity Risk." *Journal of Financial Economics* 77, no. 2: 375-410.

Amihud, Yakov. 2002. "Illiquidity and Stock Returns: Cross-Section and Time-Series Effects." *Journal of Financial Markets* 5, no. 1: 31-56.

Bao, Jack, Jun Pan, and Jiang Wang. 2011. "The Illiquidity of Corporate Bonds." *Journal of Finance* 66, no. 3: 911-946.

Bongaerts, Dion, Frank de Jong, and Joost Driessen. 2017. "An Asset Pricing Approach to Liquidity Effects in Corporate Bond Markets." *Review of Financial Studies* 30, no. 4: 1229-1269.

Corwin, Shane A. and Paul H. Schultz. 2012. "A Simple Way to Estimate Bid-Ask Spreads from Daily High and Low Prices." *Journal of Finance* 67, no. 2: 719-760.

Dick-Nielsen, Jens. 2014. "How to Clean Enhanced TRACE Data." Working Paper.

Dick-Nielsen, Jens, Peter Feldh Feld, and David Lando. 2012. "Corporate Bond Liquidity Before and After the Onset of the Subprime Crisis." *Journal of Financial Economics* 103, no. 3: 471-492.

Feldh l of, Peter. 2010. "The Same Bond at Different Prices: Identifying Search Frictions and Selling Pressures." *Review of Financial Studies* 25, no. 4: 1155-1206.

Han, Song and Hao Zhou. 2007. "Nondefault Bond Spread and Market Trading Liquidity." FDIC Working Paper.

Hasbrouck, Joel. 2009. "Trading Costs and Returns for U.S. Equities: Estimating Effective Costs from Daily Data." *Journal of Finance* 64, no. 3: 1445-1477.

Roll, Richard. 1984. "A Simple Implicit Measure of the Effective Bid-Ask Spread in an Efficient Market." *Journal of Finance* 39, no. 4: 1127-1139.

Schestag, Raphael, Philipp Schuster, and Marliese Uhrig-Homburg. 2016. "Measuring Liquidity in Bond Markets." *Review of Financial Studies* 29, no. 5: 1170-1219.

Korajczyk, Robert A. and Ronnie Sadka. 2008. "Pricing the Commonality Across Alternative Measures of Liquidity." *Journal of Financial Economics* 87: 45-72.

Pastor, Lubos and Robert F. Stambaugh. 2003. "Liquidity Risk and Expected Stock Returns." *Journal of Political Economy* 111, no. 3: 642-685.

Lou, Xiaoxia and Ronnie Sadka. 2011. "Liquidity Level or Liquidity Risk? Evidence from the Financial Crisis." *Financial Analysts Journal* 67, no. 3: 51-62.

Brogaard, Jonathan, Terrence Hendershott, Stefan Hunt, and Carla Ysusi. 2014. "High-Frequency Trading and the Execution Costs of Institutional Investors." *Financial Review* 49, no 2: 345-369.

Di Maggio, Marco, Amir Kermani, and Zhaogang Song. 2017. "The Value of Trading Relations in Turbulent Times." *Journal of Financial Economics* 124, no. 2: 266-284.

Bessembinder, Hendrik, William Maxwell, and Kumar Venkataraman. 2006. "Market Transparency, Liquidity Externalities, and Institutional Trading Costs in Corporate Bonds." *Journal of Financial Economics*, 82: 251-288.

Dick-Nielsen, Jens. 2009. "Liquidity Biases in TRACE." *Journal of Fixed Income* 19: 43-55.

Edwards, Amy K., Lawrence E. Harris, and Michael S. Piwowar. 2007. "Corporate Bond Market Transaction Costs and Transparency." *Journal of Finance* 62: 1421-1451.

Lin, Hai, Junbo Wang, and Chunchi Wu. 2011. "Liquidity Risk and Expected Corporate Bond Returns." *Journal of Financial Economics 99*: 628-650.

Dor, Arik Ben, Lev Dynkin, Jay Hyman, and Patrick Houweling. 2007. "DTSSM (Duration Times Spread)." *Journal of Portfolio Management* 33, no. 2: 77.

Schönbucher, Philipp. 2000. "A Libor Market Model with Default Risk." Working Paper.

Ruslan Y. Goyenko, Ruslan Y., Craig W. Holden, and Charles A. Trzcinka. 2009. "Do Liquidity Measures Measure Liquidity?" *Journal of Financial Economics* 92, no. 2: 153-181.

Chordia, Tarun, Richard Roll, and Avanidhar Subrahmanyam. 2000. "Commonality in Liquidity." *Journal of Financial Economics* 56: 3-28.

Naik, Vasant, Mukundan Devarajan, Andrew Nowobilski, Sebastien Page, and Niels Pedersen. 2016. "Factor Investing and Asset Allocation: A Business Cycle Perspective." Research Foundation Publications 2016.4: 1-172.

Choi, Jaewon and Yesol Huh. 2017. "Customer Liquidity Provision: Implications for Corporate Bond Transaction Costs." Working Paper.

Konstantinovsky, Vadim, Kwok Yuen Ng, and Bruce D. Phelps. 2016. "Measuring Bond-Level Liquidity." *Journal of Portfolio Management* 42, no. 4: 116.

Schultz. 2001, Paul H. "Corporate Bond Trading Costs: A Peek Behind the Curtain." *Journal of Finance* 56, no. 2: 677–698.

Jankowitsch, Rainer, Amrut Nashikkar, and Marti G. Subrahmanyam. 2011. "Price Dispersion in OTC Markets: A New Measure of Liquidity." *Journal of Banking & Finance* 35, no. 2: 343-357.

Lesmond,eDavid A., Joseph P. Ogden, and ww.sciencedTrzcinka. 1999. "A New Estimate of Transaction Costs." *Review of Financial Studies* 12, no. 5: 1113-41.

Fong, Kingsley Y. L., Craig W. Holden, and Charles A. Trzcinka. 2017. "What Are the Best Liquidity Proxies for Global Research?" *Review of Finance* 21, no. 4: 1355-1401.

Hong, Gwangheon, and Arthur Warga. "An empirical study of bond market transactions." *Financial Analysts Journal* 56.2 (2000): 32-46.

Chakravarty, Sugato, and Asani Sarkar. "Trading costs in three US bond markets." *The Journal of Fixed Income* 13.1 (2003): 39-48

APPENDIX – OVERVIEW OF LIQUIDITY COST MEASURE

Type	Frequency	Measure	Definition	Reference
Transaction cost	**Low frequency (daily level)**	**Roll**	$2\sqrt{-\min\,(0, Cov(r_t, r_{t-1}))}$ where r_t is the return of day t.	Roll (1984)
		Gibbs(c)	$r_t = c\Delta D_t + \beta^m r_t^m + \epsilon_t$ where c is the Roll measure; D_t is the sell-side indicator, which both c and β^m estimated using Gibbs sampling; and r_t^m is the market (Bloomberg Barclays US Credit Index) daily return.	Hasbrouck (2009)
		High-low spread	$\frac{2(e^\alpha-1)}{1+e^\alpha}$ where $\alpha = \frac{\sqrt{2\beta}-\sqrt{\beta}}{3-2\sqrt{2}} - \sqrt{\frac{\gamma}{3-2\sqrt{2}}}$, $\beta = \sum_{j=0}^{1}\left(\log\left(\frac{H_{t+j}}{L_{t+j}}\right)\right)^2$ and $\gamma = \left(\log\left(\frac{H_{t,t+1}}{L_{t,t+1}}\right)\right)^2$. $H_t(L_t)$ is the highest (lowest) price on day t and $H_{t,t+1}(L_{t,t+1})$ is the highest (lowest) price on two consecutive days t and $t+1$. This measure approximates bid-ask spreads based on the argument that daily high prices are likely to result from buy orders and low prices correspond to sell orders.	Corwin and Schultz (2012)
		Effective tick	$\sum_{j=1}^{J}\frac{\widehat{\gamma_j} s_j}{\bar{P}}$ where s_j is the effective spread and, $\bar{P}$ is the average trade price in the observation period, the constrained probability γ_j is defined as $\gamma_j = \begin{cases} \min\,[\max\{U_j, 0\}, 1] & if\ j = 1 \\ \min\,[\max\{U_j, 0\}, 1 - \sum_{k=1}^{j-1}\hat{\gamma}_k] & if\ j = 2,3,\dots,J \end{cases}$ with $U_j = \begin{cases} 2F_1 & if\ j = 1 \\ 2F_j - F_{j-1} & if\ j = 2,3,\dots,J-1 \\ F_j - F_{j-1} & j = J \end{cases}$ and $F_j = \frac{N_j}{\sum_{j=1}^{J} N_j}\ for\ j = 1,2,\dots,J$. F_j and N_j give the empirical probability and number of prices of the jth spread for trade days, respectively.	Goyenko, Holden and Trzcinka (2009)
		Zeros	$\frac{\#\text{ of zero return days}}{T}$	Lesmond, Ogden and Trzcinka (1999)
		FHT	$2\sigma\Phi^{-1}\left(\frac{1+P_{zeros}}{2}\right)$ where σ is the volatility of a bond's return and Φ^{-1} is the inverse of the cumulative standard normal distribution.	Fong, Holden and Trzcinka (2017)
		Quoted spread	$\frac{A_t - B_t}{\frac{1}{2}(A_t + B_t)}$	Schestag, Schuster and Uhrig-Homburg (2016)
	High frequency (trade level)	**Bid-ask spread**	$\frac{\overline{P_t^{buy}} - \overline{P_t^{sell}}}{0.5(\overline{P_t^{buy}} + \overline{P_t^{sell}})}$ where $\overline{P_t^{buy/sell}}$ is the average price of all customer buy/sell trades on day t. The monthly measure is the mean of the daily measures.	Hong and Warga (2000); Chakravarty and Sarkar (2003)
		Imputed round-trip Cost (IRC)	$\frac{2\lvert P^{buy} - P^{sell}\rvert}{\bar{P}}$ where P^{buy} and P^{sell} are the paired trade happening in opposite directions, same volumes within a 15-minute time window and $\bar{P}$ is the average price of the paired trade. The monthly measure is the average of the daily measures over a month.	Feldhütter (2010)
		Roll	$2\sqrt{-\min\,(0, Cov(r_i, r_{i-1}))}$ where $r_i = \frac{P_i - P_{i-1}}{P_{i-1}}$ is the return of the ith trade.	Dick-Nielsen, Feldhütter and Lando (2012); Roll (1984)
		Interquartile range (IQR)	$(P_t^{75th} - P_t^{25th})/\bar{P}_t$ where P_t^{75th} and P_t^{25th} are the 75th and 25th percentiles of intraday prices on day t. The monthly measure is the mean of the daily measures.	Han and Zhou (2007)
		Schultz(α_1)	$\Delta_i = \alpha_0 + \alpha_1 D_i + \epsilon_i$ where Δ_i is the difference between the trade price and the asset's bid quote and D_i is the trade direction.	Schultz (2001)
		EHP(c)	$r_i^{Obs} - r_i^{Composite} = c(D_i - D_{i-1}) + \eta_i$ where D_i is the buyer indicator and η_i is the error term with mean zero and variance as the sum of error variances from the measurement of unobserved true value returns, transaction cost and interdealer price concessions.	Edwards, Harris and Piwowar (2007)
Price impact	**Low frequency (daily level)**	**Amihud**	$\frac{1}{N}\sum_{t=1}^{N}\frac{\lvert r_t\rvert}{Q_t}$ where N is the number of trade days in a given month.	Amihud (2002)
		Pastor and Stambaugh($-\gamma$)	$r_{t+1}^e = \theta + \phi r_t + \gamma \cdot \text{sign}(r_t^e)Q_t + \epsilon_t$ where r_t^e is the asset's excess return over a market index, r_t is the asset's return and Q_t is the traded dollar volume on day t.	Pastor and Stambaugh (2003)
	High frequency (trade level)	**Amihud**	$\frac{1}{N}\sum_{i=1}^{N}\frac{\lvert r_i\rvert}{Q_i}$ where N is the number of trade-by-trade return r_i in a month and Q_i is the volume.	Dick-Nielsen, Feldhütter and Lando (2012); Amihud (2002)
		Lambda (λ)	$r_i = \lambda D_i\sqrt{Q_i} + \epsilon_i$ where D_i is the sell-side indicator and the monthly measure λ is estimated in a month, excluding overnight returns.	Hasbrouck (2009)
Others	**Low frequency (daily level)**	**Quote dispersion**	$2\sqrt{\frac{1}{2N}\sum_{i=1}^{N}\left(\left(\frac{B_i - m}{m}\right)^2 + \left(\frac{A_i - m}{m}\right)^2\right)}$	Schestag, Schuster and Uhrig-Homburg (2016)
	High frequency (trade level)	**Price dispersion**	$2\sqrt{\frac{1}{\sum_{i=1}^{N} Q_i}\sum_{i=1}^{N}\left(\frac{P_i - m}{m}\right)^2 Q_i}$. The measure gives the daily dispersion of all N intraday trade prices P_i from the market price m. The volume Q_i is used as a weighting factor.	Jankowitsch, Nashikkar and Subrahmanyam (2011)

PIMCO

This paper contains **hypothetical analysis**. Results shown may not be attained and should not be construed as the only possibilities that exist. The analysis reflected in this information is based upon data at time of analysis. Forecasts, estimates, and certain information contained herein are based upon proprietary research and should not be considered as investment advice or a recommendation of any particular security, strategy or investment product.

Hypothetical and simulated examples have many inherent limitations and are generally prepared with the benefit of hindsight. There are frequently sharp differences between simulated results and the actual results. There are numerous factors related to the markets in general or the implementation of any specific investment strategy, which cannot be fully accounted for in the preparation of simulated results and all of which can adversely affect actual results. No guarantee is being made that the stated results will be achieved.

All investments contain risk and may lose value. Investing in the **bond** market is subject to risks, including market, interest rate, issuer, credit, inflation risk, and liquidity risk. The value of most bonds and bond strategies are impacted by changes in interest rates. Bonds and bond strategies with longer durations tend to be more sensitive and volatile than those with shorter durations; bond prices generally fall as interest rates rise, and the current low interest rate environment increases this risk. Current reductions in bond counterparty capacity may contribute to decreased market liquidity and increased price volatility. Bond investments may be worth more or less than the original cost when redeemed. **Corporate debt securities** are subject to the risk of the issuer's inability to meet principal and interest payments on the obligation and may also be subject to price volatility due to factors such as interest rate sensitivity, market perception of the creditworthiness of the issuer and general market liquidity. **Derivatives** may involve certain costs and risks, such as liquidity, interest rate, market, credit, management and the risk that a position could not be closed when most advantageous. Investing in derivatives could lose more than the amount invested.

The **credit quality** of a particular security or group of securities does not ensure the stability or safety of the overall portfolio. **Management risk** is the risk that the investment techniques and risk analyses applied by an active manager will not produce the desired results, and that certain policies or developments may affect the investment techniques available to the active manager in connection with managing the strategy. References to specific securities are not intended and should not be interpreted as recommendations to purchase, sell or hold these securities. PIMCO products and strategies may or may not include the securities referenced and, if such securities are included, no representation is being made that the securities will continue to be included.

This material has been distributed for informational purposes only. This material contains the current opinions of the managers and such opinions are subject to change without notice. Statements concerning financial market trends are based on current market conditions, which will fluctuate. Forecasts, estimates and certain information contained herein are based upon proprietary research and should not be considered as investment advice or a recommendation of any particular security, strategy or investment product. Information contained herein has been obtained from sources believed to be reliable, but not guaranteed.

Newport Beach Headquarters
650 Newport Center Drive
Newport Beach, CA 92660
+1 949.720.6000

Hong Kong

London

Milan

Munich

New York

Rio de Janeiro

Singapore

Sydney

Tokyo

Toronto

Zurich

pimco.com
blog.pimco.com

CMR2018-0726-346498

60037