An asset pricing approach to liquidity effects in corporate bond markets[*]

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Abstract

We use an asset pricing approach to compare the effects of expected liquidity and liquidity risk on US corporate bond prices, and to assess whether liquidity effects can explain the credit spread puzzle. Liquidity measures are constructed for bond portfolios using a Bayesian approach to estimate Roll's effective cost measure. We find strong evidence that expected liquidity affects expected bond returns. In contrast, using various measures for liquidity risk we find no evidence for a liquidity risk premium. We develop a simple theoretical model to explain this result. Finally, we find that expected liquidity explains a substantial part of the credit spread puzzle.

Keywords: Liquidity premium, liquidity risk, corporate bonds, credit spread puzzle
JEL: C51, G12, G13

1 Introduction

Illiquidity plays a major role in corporate bond markets. While some corporate bonds are traded on a daily basis, many other bonds trade less frequently. The corporate bond market is therefore very well suited to study the price effects of liquidity. Several studies have recently examined whether illiquidity affects corporate bond prices. Most of these studies regress a panel of credit spreads on liquidity measures, thus using liquidity as a bond characteristic. A few recent articles analyze whether there is a premium associated with exposure to systematic liquidity risk.[1]

The first contribution of this paper is that we integrate these two approaches. We perform a detailed comparison of the effects of liquidity as a bond characteristic (liquidity level) and various forms of liquidity risk. We do this using a formal asset pricing approach, based on recent models of Acharya and Pedersen (2005) and Bongaerts, de Jong and Driessen (2011). Given that the liquidity level and liquidity risk exposures are typically strongly correlated, neglecting either the liquidity level or liquidity risk may lead to misleading conclusions on the effects of these different liquidity measures (Acharya and Pedersen (2005) illustrate this for the equity market). Determining which liquidity channel is most important is relevant for several reasons. First, most theoretical models that generate price effects of liquidity focus on the liquidity level, and not on liquidity risk (see, for example, Vayanos (2004) and Vayanos and Wang (2009)). Second, the extent to which optimal financial portfolios are affected by illiquidity also depends on whether liquidity risk or the liquidity level is priced. Finally, disentangling these liquidity effects is important for the valuation of illiquid assets (Longstaff (2010)). Our results show that the liquidity level has a strong and robust effect on bond prices, while the effect of systematic liquidity risk is mostly insignificant and always economically

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[1]In section 2 we discuss this literature in detail.

negligible. We argue that the absence of priced liquidity risk may be due to investors preferring to trade and rebalance their portfolio using liquid assets such as equities, thus trying to avoid trading in illiquid corporate bonds. We provide empirical evidence that supports this claim.

Our second contribution is to show that our liquidity-based asset pricing model sheds light on the "credit spread puzzle". This puzzle states that credit spreads on corporate bonds are much higher than what can be justified by expected losses and exposure to market risk factors (see Elton, Gruber, Agrawal and Mann (2001) and Huang and Huang (2003)). We show that liquidity effects play an important role in explaining this credit spread puzzle. Especially for high-rated bonds, a considerable part of the expected return can be explained by the illiquid nature of these bonds.

A final contribution of this paper concerns the measurement of liquidity. Measuring liquidity in illiquid markets is obviously challenging. For our application, we have data at the transaction level but do not know who initiated the trade. We do not have price quotes hence we cannot use the Lee and Ready (1991) method to assess the trade directions. In this context, Hasbrouck (2009) proposes a Bayesian approach to estimate the Roll (1984) measure of effective transaction costs. We extend his approach to a portfolio setting and adapt it to fit the bond market. Using the Gibbs sampler, this approach provides us with time series of returns and liquidity estimates at the portfolio level.

Our analysis uses data from TRACE (Trade Reporting and Compliance Engine), for a 2005 to 2008 sample period. Since 2005 essentially all US corporate bond transactions have been recorded in TRACE. Our sample period includes the 2007-2008 crisis period, which creates substantial variation that is useful to identify liquidity effects.

A critical issue in any asset pricing test is the measurement of expected returns. This

is particularly true for corporate bonds. Average returns on corporate bonds critically depend on the number of defaults over the sample period, and given the rare occurrence of default events this implies that average returns are noisy estimates of expected returns. In addition, transaction data for corporate bonds are only available for short sample periods. Therefore, we follow Campello, Chen and Zhang (2008) and de Jong and Driessen (2006) and construct forward-looking estimates of expected returns. We do this by correcting the credit spread, which captures the return of holding corporate bonds to maturity in excess over the government bond return, for the expected default losses. This expected loss is calculated using default probabilities from KMV-Moody's and assumptions on the loss rate in case of default.

Our empirical approach is as follows. We construct various double-sorted portfolios, sorting first on credit quality (credit rating, estimated default probabilities) and then on liquidity proxies (trading volume, bond age, amount issued, liquidity betas). In a first step, we estimate exposures of these portfolio returns to equity market risk, corporate bond market risk and systematic liquidity risk. Liquidity risk is captured by innovations in the aggregate Roll measure for the corporate bond market. In a second step, we regress the forward-looking expected returns on the portfolio liquidity level, market betas and various liquidity betas. This is in accordance with the liquidity CAPM of Acharya and Pedersen (2005) and the model for asset pricing with liquidity of Bongaerts, de Jong and Driessen (2011).

The first-step results show that corporate bonds have significant exposures to equity market returns, volatility risk, corporate bond market returns, and systematic liquidity risk. Equity market returns, volatility risk and liquidity risk together explain more than 60% of the variation in corporate bond returns.

The second-step cross-sectional regressions generate three key findings. First, we

find a positive and significant price of equity market risk (around 4% per year) and large negative volatility risk premium. Second, the liquidity level (expected liquidity) substantially affects expected returns, leading to higher expected returns for portfolios with lower expected liquidity. This estimate is both economically and statistically large. Third, we find no evidence that liquidity risk carries a risk premium. The premia related to the various liquidity risk measures (as prescribed by the Acharya and Pedersen (2005) model) have a negligible effect on expected returns. We validate these results using a Fama-MacBeth approach where we incorporate time-variation in expected returns, betas and liquidity levels. We also construct portfolios that are directly sorted on liquidity betas and find that even in the cross-section of these portfolios liquidity risk is not priced.

In sum, we show that an asset pricing model with expected liquidity, and equity and volatility risk premia provides a very good fit of expected bond returns, with a cross-sectional R^2 of about 70%. Across all portfolios, the expected excess bond return equals about 1.9% per year, of which about 1% is due to expected liquidity, 0.6% due to equity risk, and 0.3% due to volatility risk. This model fits both expected returns on high-rated and low-rated bonds very well, and thus goes a long way in explaining the credit spread puzzle. Including expected liquidity is particularly important for explaining the high returns on high-rated bonds.

Why is liquidity risk not priced in corporate bond markets, while there is substantial evidence for a liquidity risk premium in equity markets (Acharya and Pedersen (2005), Pastor and Stambaugh (2003))? We argue that this can be explained as follows. When investors want to or need to trade, they naturally prefer to trade more liquid assets and try to avoid trading less liquid assets.[2] Trading needs are often higher in bad times, since in these times investors need to reduce risk or have funding liquidity shocks that

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[2]Indeed, several articles study optimal rebalancing of assets in case of transaction costs, and derive no-trading ranges that are higher when transaction costs are higher (see Constantinides (1986) for a seminal contribution).

require a reduction of asset holdings. Hence, for relatively liquid assets such as equities, liquidity risk is very relevant as it captures the extent to which liquidity costs increase in bad times. For illiquid assets such as corporate bonds, liquidity risk is much less relevant as in most cases investors will try to avoid trading illiquid assets in bad times. We develop a simple asset pricing model to support this intuition. To provide empirical evidence for this hypothesis, we analyze turnover patterns in the equity and corporate bond market. First of all, we find that average turnover in the corporate bond market is much lower than turnover in the equity market. In addition, we find that corporate bond turnover goes down in bad times (when prices decline and liquidity costs go up). In contrast, for equity markets turnover actually increases in bad times, in line with the notion that in bad times, investors need to trade more and choose to use the most liquid assets to do so.

The remainder of this paper is organized as follows. In section 2 we discuss the related literature. Section 3 introduces the asset pricing models that we estimate. Section 4 describes the data and the Bayesian approach to estimate Roll's model. Section 5 contains the empirical results. Section 6 concludes.

2 Literature

Our paper is related to two streams in the literature on corporate bonds and liquidity. The first stream, by far the largest, uses liquidity as a bond characteristic, and analyzes, typically in a panel setting, the relation between the credit spread on a corporate bond and its liquidity. This stream includes Houweling, Mentink and Vorst (2003), Covitz and Downing (2006), Nashikkar and Subrahmanyam (2006), Chen, Lesmond and Wei (2007), Bao, Pan and Wang (2010), and Friewald, Jankowitsch and Subrahmanyam (2010). Our paper differs from this stream in two important ways. First, instead of analyzing credit

spreads in a panel setting, we estimate a formal asset pricing model, where we explain (in two steps) the time-series of returns and the cross-section of expected returns. Second, we include both liquidity level (a bond characteristic) and several liquidity risk exposures in the asset pricing model.

The second, smaller, stream in this literature analyzes the effect of liquidity risk on corporate bonds. De Jong and Driessen (2006) show that equity market liquidity risk is priced in a cross-section of corporate bond portfolios, while Acharya, Amihud and Bharath (2010) show that corporate bonds are exposed to liquidity shocks in equity and treasury markets. Both articles do not investigate corporate bond liquidity risk. Downing, Underwood, and Xing (2005) use corporate bond transaction data to construct price impact measures, and show that a portfolio that mimics illiquidity is priced in the cross-section of bond returns. Dick-Nielsen, Feldhütter and Lando (2009) mainly focus on liquidity levels to explain credit spread levels, but do find some effect of liquidity betas on credit spread levels as well. Lin, Wang and Wu (2010) construct various corporate bond liquidity risk measures, and show these are priced in a cross-section of corporate bond returns. We contribute to this literature by (i) studying the pricing of expected liquidity versus the various liquidity risk covariances in a formal asset pricing framework, (ii) analyzing in detail why liquidity risk is not priced, (ii) using forward-looking measures of expected returns, (iii) analyzing how the crisis has affected liquidity pricing, and (iv) by constructing portfolio-level liquidity measures using a Bayesian approach to estimate Roll's model. We show that corporate bond liquidity risk is not priced and that all liquidity effects on prices are due to the expected liquidity component.

Our paper is also related to the broader literature investigating liquidity effects in other markets, such as equity markets, government bond markets, hedge fund markets and private equity markets. This literature is too large to cite in a complete way. Amihud, Mendelson and Pedersen (2005) provide a thorough survey of this literature.

Recent work of Lou and Sadka (2010) compares the role of liquidity level and liquidity risk in the equity market during the recent financial crisis, and finds that stocks with high liquidity risk underperformed during the crisis relative to stocks with low liquidity risk, while there is less effect of liquidity level on returns during the crisis.

Finally, our liquidity-based asset pricing model helps to explain the "credit spread puzzle". In addition to the seminal work of Elton et al. (2001) and Huang and Huang (2003), previous work on this puzzle includes Cremers, Driessen and Maenhout (2005), David (2008) and Chen, Collin-Dufresne and Goldstein (2009). None of these articles incorporates liquidity effects.

3 Pricing models

In this paper, we follow two approaches to formalize the impact of liquidity on corporate bond prices. The simplest is a risk factor approach, following Pastor and Stambaugh (2003) who use this approach to study liquidity risk effects in equity markets. Here we regress weekly corporate bond excess returns r_{it} on a set of risk factor innovations (not necessarily returns)

$$r_{it} = \beta_{0i} + \beta_i' F_t + \epsilon_{it}. \tag{1}$$

The expected excess returns (constructed from credit spreads corrected for expected default losses, see section 4.4) are then regressed on the betas and the expected transaction costs

$$\widehat{E}(r_{it}) = \lambda' \beta_i + \zeta E(c_{it}) + \alpha_i, \tag{2}$$

where c_{it} denotes the transaction costs (relative to the asset price) and α_i denotes the error term of the cross-sectional regression, which can be interpreted as the pricing error of asset i. The theory predicts that the intercept in this regression is zero since we

focus on excess returns. The coefficients λ measure the market prices of factor risk, and ζ measures the impact of transaction costs and can be interpreted as the turnover rate of the asset (Amihud and Mendelson, 1986). The risk factors we include are the equity market return and the innovations in corporate bond market liquidity, while in robustness checks we also incorporate changes in the VIX index, risk-free rates, and equity market liquidity.

The second approach we take from Acharya and Pedersen (AP, 2005) which postulates

$$E(r_{it}) = \zeta E(c_{it}) + \phi \frac{Cov(r_{it} - c_{it}, r_{mt} - c_{mt})}{Var(r_{mt} - c_{mt})}, \tag{3}$$

where $r_{mt} - c_{mt}$ is the average (value weighted) net return on the corporate bond market.

One possible approach would be to use this AP model for the corporate bond market, in isolation from other markets. This is not very realistic as corporate bond returns are known to be strongly correlated with equity returns and also with volatility changes. Bongaerts, de Jong and Driessen (BDD, 2011) build a formal model of liquidity and liquidity risk pricing in markets with hedging pressure and (potentially) short selling, where asset returns can be partly hedged by other (so-called benchmark) assets. The equilibrium pricing equation is similar to the AP model, but the returns and costs are orthogonalized for their covariance with a set of benchmark assets. Formally, in case of a single benchmark asset we have

$$E(\widehat{r}_{it}) = \zeta E(\widehat{c}_{it}) + \phi \frac{Cov(\widehat{r}_{it} - \widehat{c}_{it}, \widehat{r}_{mt} - \widehat{c}_{mt})}{Var(\widehat{r}_{mt} - \widehat{c}_{mt})}, \tag{4}$$

with

$$\widehat{r}_{it} = r_{it} - \beta_i^r r_{b,t}, \qquad \beta_i^r = \frac{Cov(r_{it}, r_{b,t})}{Var(r_{b,t})},$$

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and

$$\widehat{c}_{it} = c_{it} - E_{t-1}(c_{it}) - \beta_i^c r_{b,t}, \qquad \beta_i^c = \frac{Cov(c_{it} - E_{t-1}(c_{it}), r_{b,t})}{Var(r_{b,t})},$$

and with r_{bt} the return on the benchmark asset.[3] Similar to AP, we incorporate that transaction costs are persistent over time by focusing on innovations $c_{it} - E_{t-1}(c_{it})$. The 'market' return and cost factors $\widehat{r}_m$ and $\widehat{c}_m$ are value weighted averages of the individual returns and costs.[4] Empirically, we allow for two benchmark assets, the equity market index and the VIX index.

The empirical model proceeds in two steps. In the first step, corporate bond excess returns and corporate bond transaction cost innovations are regressed on a set of benchmark assets. This produces estimates of the exposure coefficients β_i^r and β_i^c. We also calculate the elements of the last term in equation (4)

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\begin{aligned}
\beta_i^{rr} &= \frac{Cov(\widehat{r}_{it}, \widehat{r}_{mt})}{Var(\widehat{r}_{mt} - \widehat{c}_{mt})} \\
\beta_i^{rc} &= \frac{Cov(\widehat{r}_{it}, \widehat{c}_{mt})}{Var(\widehat{r}_{mt} - \widehat{c}_{mt})} \\
\beta_i^{cr} &= \frac{Cov(\widehat{c}_{it}, \widehat{r}_{mt})}{Var(\widehat{r}_{mt} - \widehat{c}_{mt})} \\
\beta_i^{cc} &= \frac{Cov(\widehat{c}_{it}, \widehat{c}_{mt})}{Var(\widehat{r}_{mt} - \widehat{c}_{mt})}.
\end{aligned}
\tag{5}
$$

The expected returns then follow from

$$E(r_{it}) - E(r_{bt})\beta_i^r = \zeta(E(c_{it}) - E(r_{bt})\beta_i^c) + \phi(\beta_i^{rr} - \beta_i^{rc} - \beta_i^{cr} + \beta_i^{cc}). \tag{6}$$

In practice, we do not know the expected return on the benchmark assets $E(r_{bt})$ and

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[3]This model is simpler than the original BDD model: it assumes there are no non-traded risk factors that correlate with corporate bond returns.

[4]Another possible approach would be to apply the Acharya-Pedersen model to both the entire equity market and the corporate bond market. This would assume perfect integration of the two markets, and require a liquidity factor that combines equity and corporate bond market liquidity.

treat it as a parameter (λ) to be estimated. This model is linear in all parameters except ζ. However, if we take a preliminary estimate $\zeta = \zeta_0$ to construct $\beta_i = \beta_i^r - \zeta_0 \beta_i^c$, the model is linear and can be estimated by OLS. In the empirical work, we set $\zeta_0 = 1.189$ (implying a turnover rate of about 10 months), which is the estimate from Table 2, specification (5).[5] Following AP, we also allow each component of the last covariance term to impact the expected return. The final model thus is

$$\widehat{E}(r_{it}) = \lambda(\beta_i^r - \zeta_0 \beta_i^c) + \zeta E(c_{it}) + \phi_1 \beta_i^{rr} + \phi_2 \beta_i^{rc} + \phi_3 \beta_i^{cr} + \phi_4 \beta_i^{cc} + \alpha_i. \qquad (7)$$

The residuals α_i can again be interpreted as pricing errors.

Note that the first approach, the risk-factor approach, can be used to study the credit spread puzzle, as long as we do not use the corporate bond market return as risk factor (to avoid that the puzzle is present on both the left-hand side and right-hand side of the equation). We then explain the expected corporate bond returns from equity market risk exposure and liquidity effects. The second approach has the corporate bond market return on the right-hand-side (through β_i^{rr} in equation (7)), and can therefore not be used to study the credit spread puzzle. The second approach is suited however to study the various sources of liquidity risk in detail.

4   Measuring bond returns and liquidity

For our analysis we use individual bond transaction data from the TRACE database.[6] From July 2002 onwards the NASD discloses all corporate bond trades that all its affiliated traders are required to report. Initially only trades in a limited number of bonds were disclosed, but gradually disclosure expanded to reach full disclosure from

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[5]In a next draft we plan to do full GMM estimation.
[6]A good description of the TRACE data can be found in Lin, Wang and Wu (2010).

October 2004 on. We thus download all trade data from TRACE from October 2004 up to end of December 2008 so that we have a sample with homogeneous coverage.

4.1 Data filters and portfolio selection

We apply several filters to our dataset to remove bonds with special features that we do not want to consider and to remove erroneous entries. Our filters are very similar to those employed in Bongaerts, Cremers and Goetzmann (2010). We remove all trades that include commission, that have a settlement period of more than 5 days, and all trades that are canceled or reversed. Trade volumes are truncated by the system and we replace truncated trade volumes by their respective truncation barrier ($5 million for Investment Grade and $1 million for High Yield). We remove all trades for which we have a negative reported yield, since these will be mainly driven by implicit option premia in the yield. We use Bloomberg to match the trades to bond characteristics and S&P ratings using CUSIPs. We discard all bonds with convertibility options, that are putable, that have a non-fixed coupon, that are subordinated, secured or guaranteed. We keep callable bonds because they comprise a large part of the sample. Moreover, we discard all zero-coupon bonds. We also remove trades with a settlement date later than or equal to the maturity date. Furthermore, we found several duplicate records, resulting from both parties involved in a trade reporting to the system. We filter out these trades by consecutively sorting on bond, date and volume and removing identical consecutive records. Moreover some of the yield changes are unrealistically high. Therefore, we remove trades with yield *changes* of more than 1000 basis points (about 0.15% of our trades). Finally, we focus on institutional trades since the corporate bond market is dominated by institutional traders.[7] To this end, we exclude all trades with a volume

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[7]Based on Federal Reserve Flow of Funds accounts, Campbell and Taksler (2003) report that only 15% of all US corporate bonds are held by households with another 15% to 20% held by foreign residents,

lower than $10,000. As Ford and GM together were responsible for more than 10% of all corporate bond trading, we excluded these issuers to avoid portfolios to be completely driven by individual companies. In total, we end up with approximately 4.4 million bond trades. For each bond we calculate a yield and a credit spread by comparing the bond yield with a duration-based weighted average of the yield on two treasuries with bracketing duration.

As is usual in the asset pricing literature, we fit the model to different test portfolios rather than to individual assets. To this end, we form portfolios which are sorted first on credit quality and thereafter on liquidity. To increase the number of test assets, we sort in each dimension using different variables. To conduct the credit quality sort, we use the S&P credit rating at the end of the previous quarter (AAA, AA, A, BBB, BB, B, CCC) or the cumulative default probability over the life of the bond estimated by Moody's-KMV EDFs (quintile portfolios). For the liquidity dimension, we sort by amount issued, bond age and number of trades in the previous quarter. Amount issued and age have been shown to be good proxies for liquidity by Houweling, Mentink and Vorst (2005), while typically the number of trades will be higher for more liquid securities. In the liquidity dimension, we categorize a bond as either liquid or illiquid. The cutoff point for amount issued and age is the median, whereas for the trade count it is the 70% percentile. This proportion is required to ensure that there are enough trades in the low activity portfolio. The AAA and CCC rated portfolios contain too few observations to conduct a double sort, but are included as rating portfolios. This yields 62 portfolios consisting of in total over 4 million trades in almost 15,000 different bonds. These portfolios form the basis of our tests.

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while the rest is held by institutions.

4.2 The Roll model for bond returns

Estimating returns and transaction costs from the TRACE data is not trivial. The data contain a record of transaction prices and trade volume, but no quote or bid-ask spread information. The data also do not indicate whether the transaction was a buy or a sell. The data are also irregularly spaced: some bonds trade several times a day, but many bonds trade very infrequently. To deal with these issues, we use the basic Roll (1984) model suggested by Hasbrouck (2009) as the basis of our analysis, and adapt it to a setting where we form portfolios of bonds. We start with modeling the credit spread of bond i at time t, denoted CS_{it} as

$$CS_{it} = m_{it} + c_{it}q_{it}, \tag{8}$$

where m_{it} is the efficient credit spread level and q_{it} is an i.i.d. trade indicator that can take values $+1$ and -1 with equal probability. The coefficient c_{it} is the effective bid-ask half-spread in yield terms (effective transaction costs). We focus on credit spreads rather than prices to take out most of the effects of interest-rate risk and implicit weighting induced by maturity differences.

Following Hasbrouck (2009), we write this model in first difference form

$$CS_{it} - CS_{i,t-1} = \Delta m_{it} + c_{it}q_{it} - c_{i,t-1}q_{i,t-1}, \tag{9}$$

where Δm_{it} is the innovation in the efficient credit spread. We model the change in this efficient credit spread as the sum of an element common to the portfolio to which bond i is allocated, and an idiosyncratic component

$$\Delta m_{it} = z_{it}\Delta M_t + u_{it}v_t, \tag{10}$$

where $\Delta M_t \sim N(0, \sigma_M^2)$ represents the portfolio-level spread change, $u_{it} \sim N(0, \sigma_u^2)$ the idiosyncratic shock with v_t an observable scale factor that captures heteroskedasticity. This is important as the volatility of idiosyncratic shocks may change over time. Empirically we use the level of the VIX index for v_t. We let the loading on the common factor ΔM be dependent on the bond duration with

$$z_{i,t_{ik}} = 1 + \gamma(Duration_{ik} - \overline{Duration}), \tag{11}$$

where γ is estimated in a first step, $Duration_{ik}$ is the duration of bond i at trade k, and $\overline{Duration}$ is the average duration of all bonds in the portfolio.[8] This factor z_{ik} captures patterns in the term structure of volatilities: for example, if long-term credit spreads are less volatile than short-term credit spreads, one would expect a negative γ. The latent components ΔM and u are independent. Furthermore, we assume that the transaction costs are the same for all bonds in the same portfolio

$$c_{it} = c_t. \tag{12}$$

In our analysis, we use hourly time intervals, but not every bond trades each hour and we therefore use a repeat sales methodology (see, for example, Case and Shiller (1987)). Let t_{ik} denote the time of the k'th trade in bond i. Taking differences with respect to the previous trade of bond i, these assumptions lead to the complete model for all data in the same portfolio

$$CS_{i,t_{ik}} - CS_{i,t_{i,k-1}} = \sum_{s=t_{i,k-1}+1}^{t_{ik}} z_{is}\Delta M_s + c_{t_{ik}}q_{i,t_{ik}} - c_{t_{i,k-1}}q_{i,t_{i,k-1}} + e_{it}, \tag{13}$$

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[8]Specifically, γ is estimated by using a repeat-sales methodology to estimate a restricted version of equation (13) with the transaction costs c set to zero.

where $e_{it} = \sum_{s=t_{i,k-1}+1}^{t_{ik}} u_{is}v_s$. We estimate the components of equation (13) using a Bayesian approach and the Gibbs sampler. For each portfolio, this approach gives us posterior distributions for the time-series of the common credit-spread factor ΔM, the transaction costs c, and the posterior probabilities of the trade indicators q. Appendix A details this estimation method (based on the work of Hasbrouck, 2009) in full detail.

In the actual estimation, we assume the transaction costs to be constant within every week, and estimate credit spread changes ΔM for every hour. We transform these credit spread changes to returns r by multiplying these changes with (minus) the duration of the bond portfolio. This gives (to first order) the return on the corporate bond portfolio in excess of the government bond return. Similarly, the transaction costs in terms of yields are transformed to price-based transaction costs by multiplying the costs c by the bond duration (see Bongaerts, de Jong and Driessen (2011) for a derivation of the relation between yield-based and price-based transaction costs).

These returns are then aggregated to weekly returns, so finally the Roll model produces a time series of weekly portfolio excess returns and transaction costs. In the equations above we suppressed the subscript of each portfolio j. In the remainder of the paper, the subscript j refers to portfolio j.

4.3 Validation of the liquidity estimates

As of November 2008, the TRACE data do contain the trade indicators q_{it}: for each transaction it is recorded whether this was buyer-initiated or seller-initiated. This allows us to do a strong check on the estimation of the Roll model describe above. We thus estimate the transaction costs in equation (13) in two ways. First, we use the Gibbs sampler, where we do not use information on the trade indicators ("indirect" approach). Second, we use the observed trade indicators in which case (13) can directly be estimated

using a repeat-sales regression approach ("direct" approach).

We perform this analysis on the portfolios where we first sorts on rating or EDF, and then on amount issued. We calculate the correlation between the weekly series of transaction costs, estimated using either the direct or indirect approach, using data until end of 2009. We find that the average of these time-series correlations equals 78%, and the correlations range between 63% and 97% across portfolios (except one portfolio which has correlation of -4.5%, this portfolio has relatively few bond issues). Also, the average level of the direct and indirect transaction costs is very similar: 1.35% (direct) versus 1.32% (indirect) on average. This shows that, even though we do not observe the trade indicators in 2005 to 2008, it is possible to reliably estimate transaction costs on corporate bonds using the Gibbs sampling method.[9]

4.4 Time series model for liquidity

The betas in the asset pricing model are defined as the ratio of conditional covariances and variances, that is, the (co)variances of the shocks (innovations) in returns and costs. We assume that returns have no serial correlation and we take the residuals of an autoregressive model as the liquidity innovations

$$c_{j,t} = b_{0j} + b_{1j}c_{j,t-1} + \varepsilon_{j,t}, \tag{14}$$

where $c_{j,t}$ denotes the portfolio-level transaction costs. The coefficient on the lagged transaction cost b_1 equals 0.837 (averaged across portfolios). We also estimate the market-wide transaction costs (averaging costs across portfolios). The innovations in these market-wide costs is what we use as liquidity risk factor in our asset pricing model.

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[9]We do not use 2009 data for our asset pricing tests since we do not have EDF data for this period.

As a robustness check, we also analyze the effects of exposure to equity market liquidity. Following Acharya and Pedersen (2005), we construct this measure by taking AR(1)-innovations to the value-weighted mean of Amihud's (2002) ILLIQ measure across all stocks in CRSP.

Innovations in the risk-free rate and volatility index VIX are also constructed using AR(1) models.

4.5 Expected return estimates

To calculate the expected excess return $\widehat{E}(r_j)$ on a corporate bond portfolio j, we take the observed credit spread and correct it for expected default losses. This procedure follows de Jong and Driessen (2006), Campello, Chen and Zhang (2008), and Bongaerts, de Jong and Driessen (2011), who show that it yields much more accurate estimates of expected returns than simple averaging of historical excess returns.

The method works as follows. Consider bond i. Denote the cumulative default probability over the entire maturity of the bond π_{it}, the loss given default L (assumed to be 60%), the yield on the bond y_{it} and the corresponding government bond yield y_{gt}. We approximate the coupon-paying bond by a zero-coupon bond with maturity equal to the duration of the coupon-paying bond, T_{it}. Assuming that default losses are incurred at maturity, the expected return of holding the bond to maturity equals $(1 + y_{it})^{T_{it}}(1 - L \cdot \pi_{it})$. We then annualize this number and subtract the annualized expected return on the corresponding government bond to obtain our expected excess return estimate

$$E_t(r_i) = (1 + y_{it})(1 - L \cdot \pi_{it})^{1/T_{it}} - (1 + y_{gt}). \tag{15}$$

Note that this gives an estimate for the expected return at each point in time t.

Default probability estimates π_{it}, needed to construct these expected excess returns, are obtained from *Moody's-KMV EDF Database.* We have data on the average 1-year and 5-year annualized expected default frequency *EDFs,* which capture the conditional default rate in the first and fifth year, respectively. We construct the conditional expected default frequency for every bond trade as the duration weighted average of the one-year and five-year EDFs. For durations longer than 5 years, we assume that the conditional default rate is flat beyond 5 years. From these bond-specific EDFs we obtain the expected cumulative default probabilities over the entire maturity of the bond (π_{it}).

We prefer using *Moody's-KMV EDFs* over rating-based historical default frequencies because, especially in the last two years of the sample (2007 and 2008), we observe a strong increase in the *EDFs*; it is not obvious how to adjust for these new market circumstances when using rating-based historical default frequencies. The expected excess portfolio return is then constructed each week by averaging the expected excess returns over all trades in the portfolio in that week that have an EDF available. The unconditional expected return for a portfolio is given by the time-series average across weeks.

5 Empirical results

5.1 Expected returns, transaction costs and betas

Table 1 presents averages of expected returns, costs, betas and associated t-stats across portfolios and over the full 2005 to 2008 sample period. The first key result in Table 1 is that the estimated transaction costs are substantial, on average about 0.8% across portfolios and over time. These numbers are very similar to those of Bao, Pan and Wang (2010) who use a different method to estimate Roll's model for corporate bonds. They

report a median bid-ask spread of 1.50%, implying transaction costs of 0.75%, close to our estimates. As noted by Bao, Pan and Wang (2010), these estimated costs are higher than quoted bid-ask spreads as found in Bloomberg, and they argue that the Roll model thus captures liquidity effects that go beyond the quoted bid-ask spread. The second result in Table 1 is that we find large positive expected returns (in excess of government bonds), around 1.9% per year on average, in line with earlier evidence on the credit spread puzzle. The Newey-West corrected t-statistics on the expected return estimates are high (average t-stat of 4.8), which shows the usefulness of estimating expected returns from credit spread levels.

The time series of market-wide average expected returns and transaction costs is shown in Figure 1. Clearly, the two series are strongly correlated and peak during events in the credit crisis, such as the March 2008 Bear Sterns failure and the September 2008 Lehman collapse. Both Dick-Nielsen, Feldhütter and Lando (2009) and Bao, Pan and Wang (2010) report similar illiquidity spikes in 2008.

Following equation (1), Table 1 also reports results of univariate and multivariate regressions of bond returns on various factors: (i) equity market (S&P500) returns, (ii) volatility shocks, measured by innovations in the VIX index, and (iii) systematic bond liquidity shocks (market-wide level of corporate bond transaction costs). We see that corporate bonds have significant equity market exposure, which by itself explains on average 50% of the time-series variation. We also see that corporate bond returns have significant negative exposure to systematic liquidity shocks, measured by innovations in the market-wide level of corporate bond transaction costs. This exposure explains alone on average about 26% of the time-series return variation. Turning to volatility risk, we see a strong negative exposure, as expected, which explains 53% of the time-series variation. Hence, volatility risk is even more important as a time-series determinant of corporate bond returns than equity returns. When we look at the multivariate betas,

we see that the equity and volatility betas both become substantially smaller, which is due to the strong negative correlation between equity returns and volatility shocks (the "leverage effect"). The average time-series R^2 for this multivariate regression is 62%.

Finally, Table 1 reports the returns, costs and betas of high-liquidity and low-liquidity portfolios. Recall that our portfolios are first sorted on rating or EDF, and then on one of the three liquidity proxies, bond age, amount issued and volume. For each rating level or EDF quintile, we thus have a high-liquidity and low-liquidity portfolio for each liquidity proxy (except for the AAA and CCC ratings). Table 1 reports averages across all rating-based or EDF-based portfolios and across the three liquidity proxies. We see that low-liquidity portfolios have higher expected returns and higher estimated transaction costs, suggesting an effect of transaction costs on expected returns. In contrast, there is little difference in equity or volatility betas, which shows that, once we sort on rating or EDF, the liquidity sort is indeed capturing liquidity effects and not differences in market or volatility risk exposure. We also see that the liquidity betas of the low-liquidity portfolios are closer to zero than those of the high-liquidity portfolios. There is substantial variation in liquidity betas across portfolios however: the bond market liquidity exposures range from -1.8 to about -8.9 (or -0.1 to -7.6 for the multivariate betas) across portfolios (non-tabulated), so that our data should be informative about the presence of a liquidity risk premium.

5.2   Asset pricing tests: Risk-factor approach

5.2.1   Benchmark results

In this subsection we focus on the first asset pricing approach where we include equity market returns and systematic liquidity shocks in the corporate bond market as factors,

and the expected transaction costs as portfolio characteristic (equations (1) and (2)). In robustness checks, we include volatility shocks (innovations in VIX), risk-free interest rate shocks (3-month T-bill rate) and equity market liquidity shocks (innovation in equity-market ILLIQ measure) as additional factors.

Then, to test the pricing of corporate bonds, we run a cross-sectional regression of the average expected excess returns on the estimated risk factor exposures and the average expected transaction costs. The averages and the betas are estimated over the full sample period 2005-2008. As the betas and the expected costs contain estimation noise, the standard errors of the regression are calculated using an extension of the method by Shanken (1992).[10] Notice that the regressions do not contain an intercept, which is consistent with the model in equation (2).

Table 2 shows that, in univariate regressions, the equity beta and expected cost have a positive coefficient (specifications (1) and (3)). The liquidity cost beta has a negative coefficient, as expected (specification (2)): given the negative liquidity betas, the product of the liquidity beta and liquidity premium is positive. All estimates are strongly significant, although liquidity risk has low cross-sectional explanatory power: it has a negative cross-sectional R^2, which implies that the model with priced liquidity risk explains less of the expected return variation than a model with a constant term only.

Of course, the more important question is whether the corporate bond prices are affected by both expected transaction costs and liquidity risk. This is investigated in multiple regressions, where the equity beta is always included (specifications (4) and (5)). With all three variables included, the liquidity beta coefficient has a positive sign. This implies a counter-intuitive negative contribution to the risk premium. However, the effect

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[10]The Internet Appendix of BDD provides more details on the procedure.

is economically small: for example, when we add liquidity risk to the model with equity risk only, the cross-sectional R^2 does not increase (R^2 of 47.2% in both specifications (1) and (4)). Expected liquidity continues to have a positive and significant impact when we control for liquidity risk and equity risk: adding expected liquidity increases the R^2 from 47.2% to 65.5%. The coefficient on expected liquidity can be related to the trading frequency of bonds. The coefficient of 1.189 in specification (5) corresponds to a turnover frequency of about 10 months, which seems reasonable.[11]

When we include additional risk factors such as volatility risk, interest rate risk and equity market illiquidity shocks (see the multivariate regression specifications (6)–(8)), we see that the effect of expected liquidity remains positive and significant. In fact, the coefficient on expected liquidity is very stable across specifications (between 1.19 and 1.40). In contrast, the bond liquidity risk premium changes sign across specifications and is economically small. Of the additional factors, we find evidence for a large and significant volatility risk premium: bonds with higher (i.e. more negative) volatility exposure have higher expected returns.[12] The exposure to equity market liquidity risk is also significantly priced with the "correct" sign. Finally, note that the estimated equity premium is always significantly positive and reasonable in size (between 3% and 5.2% per year).

Figure 2 graphs the fitted values of the risk premium according to specification (7), for the portfolios sorted on rating and liquidity proxies (Panel A) and for the sorts on EDFs and liquidity (Panel B). The graphs present the average across the three liquidity proxies per rating/EDF category and show that the equity risk premium and the ex-

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[11]Note that this should not be interpreted as the equally-weighted average turnover across bonds. Since we use transaction data, bonds that trade more often have a higher weight in our sample. Hence, the expected liquidity coefficient captures some trade-frequency weighted average of turnover across bonds.

[12]Such a volatility risk premium has also been found in the cross-section of stock returns (see Ang, Hodrick, Xing and Zhang (2006)) and for index options (see e.g. Bollerslev, Tauchen and Zhou (2009)).

pected liquidity premium together explain most of the observed credit spreads, with a smaller contribution of volatility risk and a negligible effect of liquidity risk.

These results shed light on the credit spread puzzle. Huang and Huang (2003) show that structural models of default risk generate credit spreads well below observed credit spread levels. We find similar results using our asset pricing approach. Equity market and volatility risk exposure explain only a part of the level of expected bond returns. In particular, equity and volatility betas of high-rated bonds are very low, so that only with extremely high equity and volatility risk premia it would be possible to explain the relatively high expected returns on these bonds. However, such high market risk premia would (i) be inconsistent with premia observed in for example equity markets, and (ii) imply too high expected returns on lower-rated bonds, given that these bonds have high exposure to market and volatility risk. Incorporating liquidity effects, mainly expected liquidity, resolves this puzzle. As shown in Figure 2, a substantial part of the expected return of high-rated bonds is due to expected liquidity. The model provides a very good fit of expected bond returns across all portfolios, and does not underestimate the expected return on high-rated bonds. In fact, for high-rated bonds the model predicts expected returns that are slightly higher than the observed average returns.

So far, all results are based on the full sample (2005-2008). However, our forward-looking approach of calculating expected returns can be done on a weekly basis. Similarly, expected costs are also estimated each week. This makes a Fama-MacBeth estimation of the model on a weekly basis possible. However, the right hand side betas cannot be calculated with only one week of data. Therefore, we use the following procedure: we estimate betas using 52-week (backward-looking) rolling windows, and the second-step equations are estimated using four-week rolling windows.

Figure 3 graphs the results for the model including the equity, volatility and transac-

tion cost betas, and expected costs. The left-hand panels of Figure 3 show the estimated betas and transaction costs. For each week, the graphs show the cross-sectional average over all portfolios. We see that all betas increase (in absolute value) from the start of the financial crisis in mid-2007. The transaction costs also increase from that period onwards, and increase very substantially around the Lehman collapse in September 2008. The middle panels show the estimated coefficients from the weekly second step regressions. The coefficients are remarkably stable over time. The right-hand panels show the implied equity, volatility and liquidity risk premiums (top-right panel), and the expected liquidity premium (bottom-right panel), obtained by multiplying the betas with the estimated coefficients from the second step regressions. These graphs clearly show an increase in the equity and volatility risk premiums from mid-2007. The liquidity risk premium is small and unstable, though. The expected liquidity premium increases from 80 basis points to around 2.5 percent for the average portfolio.

The average weekly estimates and their Newey-West t-stats are reported in the column labeled "FB" in Table 2. The average estimated equity premium is around 5 percent, the volatility and liquidity risk premia are significantly negative, although the liquidity risk premium is economically negligible. The estimated coefficient of transaction costs is in the same order of magnitude as in the full sample estimates. In sum, these time-varying results support our main finding that expected liquidity has a strong effect on bond prices, while the effect of liquidity risk is very small.

5.2.2 Sorting on liquidity betas

The results above indicate that the effects of liquidity risk on corporate bond prices are economically small. However, this finding may be caused by a lack of cross-sectional variation in liquidity betas making estimation of a risk premium difficult. Therefore,

similar to Pastor and Stambaugh (2003) we now construct test assets that are also sorted on liquidity betas. This requires liquidity beta estimates at the individual bond level. The challenge here is that many bonds do not trade very frequently and estimation of individual betas for these assets is problematic. Moreover, beta estimates for individual instruments can be rather unstable and sensitive to outliers.

To deal with these issues, we use a Bayesian approach. Our liquidity beta for each bond is calculated as a weighted average of the direct regression estimate (obtained by regressing individual bond returns on the liquidity factor) and a portfolio-based beta. This portfolio beta is obtained by using the liquidity beta of the portfolios to which the bond was assigned in the analysis above. The liquidity beta of these portfolios is our "best guess" (or, in Bayesian terms, "prior") of the true liquidity beta of the bond in case insufficient trading data for this bond is available. The more precisely we can estimate the individual bond liquidity beta from transaction data, the less weight we want to give to these portfolio betas. This is exactly what our Bayesian solution here achieves.

More specifically, we estimate the portfolio liquidity betas and their standard errors from a regression of bond portfolio excess returns on market liquidity innovations for all double sorted portfolios across quality (rating and EDF) and liquidity (age, issue size, trading volume) as well as the AAA and CCC rated portfolio. We do this on a weekly basis using a one-year rolling window. For each portfolio we then create quarterly betas and standard errors by averaging the betas over all weeks in the quarter and calculating the appropriate covariances. Next we average for each bond-quarter the betas and standard errors[13] of all portfolios in which that bond was contained.

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[13]This implicitly implies a correlation of one between beta estimates of different portfolios; betas are typically highly correlated across liquidity sorts. If anything, this would put too little weight on the portfolio betas.

For each bond, we also estimate the direct liquidity beta. To this end, we estimate a beta and standard error from the univariate regression of the individual bond excess returns on market liquidity innovations. We again do this on a weekly basis using the last trade available every week on a one-year rolling window, where we require at least 25 observations and where the smallest and largest observation are winsorized.

When constructing the portfolios for a given quarter, say Q2 2006, the one-year rolling window used to estimate these betas includes this quarter, hence we use data from Q3-Q4 2005 and Q1-Q2 2006 in this example. We thus essentially use a mixture of the pre-ranking and post-ranking betas to form portfolios. This has the advantage that it generates more variation in the liquidity betas used to estimate the asset pricing model. The disadvantage is that these portfolios are not ex-ante tradable portfolios, but this is not an issue for estimating and testing asset pricing models.[14]

Having obtained the portfolio beta and the direct beta we can now use the standard Bayesian formula to calculate our posterior beta

$$\beta_{liq}^{post} = \frac{var(\hat{\beta}_{liq}^{port})^{-1}\hat{\beta}_{liq}^{port} + var(\hat{\beta}_{liq}^{direct})^{-1}\hat{\beta}_{liq}^{direct}}{var(\hat{\beta}_{liq}^{port})^{-1} + var(\hat{\beta}_{liq}^{direct})^{-1}}. \tag{16}$$

Portfolio double sorts are then conducted again as before using a sequential sort, first on credit quality (rating or EDF) and then on liquidity beta.

Table 2 - specification LB (which stands for liquidity beta) shows the cross-sectional results when we add these liquidity-beta portfolios to our cross-section of portfolios. Comparing these results with specification (7), we see that adding liquidity-beta portfolios hardly affects the estimates for the risk premia and expected liquidity. In particular, the liquidity risk premium still has the "wrong" sign, it even becomes slightly more positive, and its economic impact remains very small. Even when we only use the

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[14]When we use pre-ranking betas, we find very similar results (not reported).

liquidity-beta portfolios for the cross-sectional estimation, we find a small and positive coefficient for the liquidity risk premium (non-tabulated).

5.3 Asset pricing tests: Liquidity-CAPM approach

In the analysis above we focused on one liquidity risk exposure, the covariance between portfolio returns and market-wide liquidity shocks. However, the liquidity CAPM of Acharya and Pedersen (2005) suggests that other liquidity risk covariances may also matter. We therefore now focus on the second asset pricing approach, as described in section 3 (equation (7)). We focus on the extension of the liquidity CAPM in Bongaerts, de Jong and Driessen (BDD, 2011), incorporating exposure to other risk factors.

Table 3 presents summary statistics on the different betas in this model. Most notably, we see that the different liquidity betas have the expected sign: β^{rc} and β^{cr} are negative on average: low returns coincide with higher transaction costs. Also, the average β^{cc} is positive, suggesting the presence of commonality in liquidity.

Turning to the cross-sectional regressions, we estimate a variety of specifications for the BDD model in equation (7). All specifications include the equity beta, volatility beta and the expected transaction costs. In addition, either the 'net' beta or all or some of its components (β^{rr}, β^{rc}, β^{cr}, and β^{cc}) are in the regression. The equity beta and the transaction cost have positive and significant coefficients in every specification, and the volatility risk premium is significantly negative in all specifications, in line with the results above. The magnitudes of the equity risk premium and the transaction cost premium are fairly stable across specifications. Together, expected liquidity and the equity and volatility risk premia explain 73% of the cross-sectional variation in expected returns.

Without additional variables, the estimated equity risk premium is 3.9% per year, and the estimated turnover rate of bonds is 0.932 per year. Adding the corporate bond market risk premium (orthogonalized for the equity risk) in Table 4, specification (2) gives similar results with exposure to β^{rr} not significant.

Next we add various liquidity risk factors. In specifications (3) and (4), the exposure of bond returns to corporate bond market transaction costs β^{rc} is added. This factor is significant and has a counter-intuitive positive sign, implying a negative liquidity risk premium (as β^{rc} is negative for every portfolio), but the economic effect is small as the cross-sectional R^2 increases only marginally. Even when we add all components of liquidity risk with separate coefficients in specification (5) the cross-sectional R^2 does not increase substantially, and multicollinearity across the different liquidity betas leads to "wrongly-signed" coefficients on some of the liquidity betas. When we impose the restriction that all coefficients on the liquidity betas are the same ($\beta^{other} = -\beta_i^{rc} - \beta_i^{cr} + \beta_i^{cc}$, specification (6)), we again find the "wrong" sign for this liquidity risk premium, and again the effect is economically small. Finally, when we include the total 'net' beta as the regressor in equation (7), $\beta_i^{net} = \beta_i^{rr} - \beta_i^{rc} - \beta_i^{cr} + \beta_i^{cc}$, this net beta has a negative but insignificant coefficient (specification (7)). In sum, even when we allow for various forms of liquidity risk exposure, we do not find that liquidity risk is priced in the cross-section of corporate bond portfolios. The effect of expected liquidity is remarkably constant over all specifications, though, with a coefficient around one.

5.4   Why is liquidity risk not priced?

Our results show that expected liquidity has a strong effect on corporate bond prices, while liquidity risk exposure does not. In contrast, several articles have found evidence that liquidity risk is priced in equity markets (Acharya and Pedersen (2005), Pastor and

Stambaugh (2003)). To understand these empirical findings, first note that US equities are typically much more liquid than US corporate bonds. Then consider an investor holding both liquid (low-cost) assets (US equities) and illiquid (high-cost) assets (US corporate bonds). There are various reasons why investors trade these assets over time, such as rebalancing, risk-shifting, satisfying regulatory capital requirements, exogenous liquidity needs, etc. In the presence of transaction costs, the investor then faces a trade-off between having an optimally diversified portfolio and minimizing trading costs, see for example Constantinides (1986).

In Appendix B we formalize such a setup using a simple two-period asset pricing model. In this model, a mean-variance investor can invest in two assets, a low-cost asset and high-cost asset. After one period, the investor is forced to liquidate part of his portfolio due to an exogenous liquidity shock. If the difference between transaction costs of the two assets is sufficiently high, it is optimal for the investor to absorb the liquidity shock by selling only low-cost assets and avoid trading in the high-cost asset. In equilibrium, this implies that the risk of shocks to the liquidity of the high-cost asset is not priced. Only exposure to the liquidity risk of the low-cost asset is priced. Applying this result to our setting, it would imply that corporate bond liquidity risk is not priced, which is in line with our empirical findings, while exposure to equity market liquidity risk should be priced. This is also in line with our empirical findings: in Table 2 we find that exposure to equity market illiquidity has a significant risk premium with the expected sign. Alternatively, if the difference between transaction costs is sufficiently small, our simple model predicts that both assets are used to absorb the liquidity shock, although the low-cost asset is still used relatively more. In this case, shocks to transaction costs of both assets are priced.

This simple model can be used to generate some additional testable hypotheses. First, the model predicts higher turnover for the low-cost asset. Second, the pricing of

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liquidity and the turnover levels may be different in normal times versus crisis periods. To see this, consider the case where, in normal times, transaction costs on both assets are sufficiently small so that both assets will be used for trading. In this case, liquidity risk on both the low-cost asset (equity) and high-cost asset (corporate bonds in our case) is priced. However, in normal times the variation in transaction costs is quite small (see Figure 1) and hence the effect of liquidity risk on prices may be negligible. Then consider a crisis period during which transaction costs on the high-cost asset increase substantially so that in equilibrium this asset will not be used to absorb liquidity shocks. The model then predicts that trading in the liquid asset actually increases when moving from normal times to crisis periods, while trading in the illiquid asset decreases.

To support these claims, we study turnover patterns in equity and corporate bond markets. We test two implications. First, turnover in liquid markets should be higher than turnover in illiquid markets. Second, as markets become less liquid and/or prices go down, turnover in the illiquid market decreases, while turnover in the liquid market increases.

For our 2005-2008 sample period we calculate monthly turnover for each stock in the CRSP database and each bond in our TRACE sample, by dividing monthly dollar trading volume by the dollar value of the market capitalization (or amount issued in bond markets). We first focus on the value-weighted average turnover levels in both markets. We indeed find that equity market turnover is much higher than corporate bond turnover. For stocks, the value-weighted average turnover level equals 68.3% per quarter, while for corporate bonds the corresponding number is 6.6% per quarter.

Subsequently, we study the dynamics of turnover. Figure 4 graphs the time series of the value-weighted mean and the median turnover across stocks and bonds, respectively. We see that, as the crisis unfolds, equity turnover increases while corporate bond

turnover goes down. To analyze these time series in more detail, we perform two sets of regressions. First, we regress monthly changes in the value-weighted average equity turnover on the equity market return and the change in Amihud's (2002) ILLIQ measure. This ILLIQ measure is calculated for each stock, and we then use the change in the value-weighted average ILLIQ across stocks as regressor. Results in Table 5 show that a decrease in liquidity or decrease in the stock market index level imply an increase in equity market turnover. Both effects are significant in these univariate regressions. Given that the change in ILLIQ and the equity market return have a correlation of -81%, a multivariate regression suffers from multicollinearity issues, as shown in Table 5. These results show that equity market turnover increases in bad, illiquid times. As discussed above, this may be because investors are essentially forced to trade despite the higher transaction costs.

The second regression focuses on corporate bond turnover. In this case, we perform a panel regression of the monthly change in individual bond turnover on the change in the market-wide level of corporate bond transaction costs, as constructed in this paper, and the change in the average credit spread across all bonds. The results in Table 6 show that corporate bond turnover decreases when the market becomes less liquid and when credit spreads increase. A more subtle implication of the hypothesis put forward here is that, within the corporate bond market, the reported decrease in turnover in bad times should be larger for less liquid bonds. We analyze this by interacting the liquidity and credit spread variables with a dummy that equals one when a bond is rated AAA or AA, since these high-rated bonds are typically the most liquid among all corporate bonds, especially in crisis periods (see Acharya, Amihud and Bharath (2010)). The results of the turnover regression in Table 6 show that the turnover decrease in bad times is indeed larger for low-rated (and hence less liquid) corporate bonds

In sum, these results shows that stocks have much higher turnover than corporate

bonds, and that this difference is larger when prices go down and when markets are overall less liquid. Hence, in line with our hypothesis, when transaction costs increase investors prefer to trade the relatively more liquid assets and avoid trading in less liquid assets.

6   Conclusion

This paper explores the asset pricing implications of expected liquidity and liquidity risk for expected corporate bond returns. We measure liquidity using a Bayesian estimation of Roll's effective cost model. We then construct liquidity levels and liquidity innovations for a set of corporate bond portfolios. Several asset pricing models, including Acharya and Pedersen's liquidity CAPM, are then estimated using the cross-section of corporate bond portfolios. Overall, we find a strong effect of expected liquidity, while there is little evidence that liquidity risk covariances explain expected corporate bond returns, even during the recent financial crisis. We show that incorporating expected liquidity effects goes a long way in explaining the high returns on high-rated corporate bonds (the "credit spread puzzle"). We also find that equity risk and volatility risk (exposure to VIX shocks) are priced in the cross-section of corporate bonds.

A Gibbs sampler for the Roll model

Estimation of the coefficients of the Roll model is done by means of the Gibbs sampling method developed by Hasbrouck (2009), combined with the repeat sales methodology. In the Gibbs sampler, the parameters c and σ_u^2 and the latent series ΔM_t and r are simulated step-by-step from their Bayesian posterior distributions. In every step, one set of parameters or latent variables is simulated, conditional on the values of the other parameters and latent variables from the previous simulation round. Each step then is a relatively simple application of Bayesian regression.

Simulating q

The first step in each iteration of the Gibbs sampler is the simulation of the trade indicators q. In Hasbrouck's model, these can take only two values, $+1$ and -1. The prior is equal probabilities, i.e. $Pr[q_{i,t_{ik}} = 1] = 1/2$. After observing p, the posterior odds are

$$\frac{Pr[q_{i,t_{ik}} = 1]}{Pr[q_{i,t_{ik}} = -1]} = \frac{f(e_{t_{ik}}|q_{i,t_{ik}} = 1)f(e_{t_{i,k+1}}|q_{i,t_{ik}} = 1)}{f(e_{t_{ik}}|q_{i,t_{ik}} = -1)f(e_{t_{i,k+1}}|q_{i,t_{ik}} = -1)}$$

where

$$f(e_{t_{ik}}|q_{i,t_{ik}} = q) = \phi\left(\frac{CS_{i,t_{ik}} - CS_{i,t_{i,k-1}} - \sum_{s=t_{i,k-1}+1}^{t_{ik}} z_i \Delta M_s - c_{t_{ik}} q + c_{t_{i,k-1}} q_{i,t_{i,k-1}}}{\sigma_u^2 \sum_{s=t_{i,k-1}+1}^{t_{i,k}} v_s^2}\right)$$

and

$$f(e_{t_{i,k+1}}|q_{i,t_{ik}} = q) = \phi\left(\frac{CS_{i,t_{i,k+1}} - CS_{i,t_{ik}} - \sum_{s=t_{ik}+1}^{t_{i,k+1}} z_i \Delta M_s - c_{t_{i,k+1}} q_{i,t_{i,k+1}} + c_{t_{ik}} q}{\sigma_u^2 \sum_{s=t_{i,k-1}+1}^{t_{i,k}} v_s^2}\right)$$

From the posterior odds ratio, the posterior probabilities for $q = 1, -1$ are easily calculated.

Simulating c

The liquidity cost of a particular week $w = t_{i,k}$ realized in a particular trade k shows up in two credit-spread equations:

$$CS_{i,t_{ik}} - CS_{i,t_{i,k-1}} - \sum_{s=t_{i,k-1}+1}^{t_{ik}} z_i \Delta M_s = c_{t_{ik}} q_{i,t_{ik}} - c_{t_{i,k-1}} q_{i,t_{i,k-1}} + e_{it_{ik}}, \qquad (17)$$

$$CS_{i,t_{i,k+1}} - CS_{i,t_{i,k}} - \sum_{s=t_{i,k}+1}^{t_{ik+1}} z_i \Delta M_s = c_{t_{ik+1}} q_{i,t_{ik+1}} - c_{t_{i,k}} q_{i,t_{i,k}} + e_{it_{ik+1}} \qquad (18)$$

The posterior mean for c_w is found from a linear regression of the two return equations stacked on top of each other.

Let us first work out equation (17). If both t_{ik} and $t_{i,k-1}$ fall in the same week w_{ik}, the equation is

$$CS_{i,t_{ik}} - CS_{i,t_{i,k-1}} - \sum_{s=t_{i,k-1}+1}^{t_{ik}} z_i \Delta M_s = c_{w_{ik}} (q_{i,t_{ik}} - q_{i,t_{i,k-1}}) + e_{it_{ik}} \qquad (19)$$

If $t_{i,k-1}$ happens to be in an earlier week, we write

$$CS_{i,t_{ik}} - CS_{i,t_{i,k-1}} - \sum_{s=t_{i,k-1}+1}^{t_{ik}} z_i \Delta M_s + \widehat{c}_{w_{i,k-1}} q_{i,t_{i,k-1}} = c_{w_{ik}} q_{i,t_{ik}} + e_{it_{ik}} \qquad (20)$$

where $\widehat{c}_{w_{i,k-1}}$ is the most recent simulation of the earlier week's transaction cost.

Working out equation (18), we get again that if both t_{ik} and $t_{i,k+1}$ fall in the same week w_{ik}, the equation is

$$CS_{i,t_{ik+1}} - CS_{i,t_{i,k}} - \sum_{s=t_{i,k}+1}^{t_{ik+1}} z_i \Delta M_s = c_{w_{ik}} (q_{i,t_{ik+1}} - q_{i,t_{i,k}}) + e_{it_{ik+1}} \qquad (21)$$

If $t_{i,k+1}$ happens to be in a later week, we write

$$CS_{i,t_{ik+1}} - CS_{i,t_{i,k}} - \sum_{s=t_{i,k}+1}^{t_{ik+1}} z_i \Delta M_s - \widehat{c}_{w_{i,k+1}} q_{i,t_{i,k+1}} = -c_{w_{ik}} q_{i,t_{ik}} + e_{it_{ik+1}} \qquad (22)$$

where $\widehat{c}_{w_{i,k+1}}$ is the simulation of the subsequent week's transaction cost from the pre-vious iteration. Estimation of the posterior mean of c_w is then done by stacking these equations. Formally, we estimate $y = Xc_w + e$ with

$$y = \begin{pmatrix} y^{cont} \\ y^{fut} \end{pmatrix} \qquad (23)$$

$$y_{ik}^{cont} = CS_{i,t_{ik}} - CS_{i,t_{i,k-1}} - \sum_{s=t_{i,k-1}+1}^{t_{ik}} z_i \Delta M_s + (1 - I_{w_{ik}=w_{i,k-1}})\widehat{c}_{w_{i,k-1}} q_{i,t_{i,k-1}}) \qquad (24)$$

$$y_{ik}^{fut} = CS_{i,t_{ik+1}} - CS_{i,t_{i,k}} - \sum_{s=t_{i,k}+1}^{t_{ik+1}} z_i \Delta M_s - (1 - I_{w_{ik}=w_{i,k+1}})\widehat{c}_{w_{i,k+1}} q_{i,t_{i,k+1}}) \qquad (25)$$

and

$$x = \begin{pmatrix} x^{cont} \\ x^{fut} \end{pmatrix} \qquad (26)$$

$$x_{ik}^{cont} = q_{i,t_{ik}} - I_{w_{ik}=w_{i,k-1}} q_{i,t_{i,k-1}} \qquad (27)$$

$$x_{ik}^{fut} = -(q_{i,t_{ik}} - I_{w_{ik}=w_{i,k-1}} q_{i,t_{i,k+1}}) \qquad (28)$$

for all $w_{ik} = w$ and is estimated using all data in that week. Notice that the error term e_{it} is a sum $u_{it} v_t$ for $t = t_{i,k-1}$ to $t = t_{i,k}$ and therefore heteroskedastic. So, the posterior distribution of c_w is

$$c_w \sim N((X'\Sigma_e^{-1}X)^{-1}X'\Sigma_e^{-1}y, \ (X'\Sigma_e^{-1}X)^{-1}) \qquad (29)$$

with Σ_e a diagonal matrix with elements $\sigma_u^2 \sum_{s=t_{i,k-1}+1}^{t_{i,k}} v_s^2$

Simulating ΔM

The most complex step is the simulation of the latent portfolio-level changes in credit spreads ΔM_t. This step is absent in Hasbrouck's model but necessary here as Δm consists of two components (simulating u is not necessary as it follows immediately from the observed values of CS and the simulated values of q, c and ΔM). We draw ΔM from a normal distribution with mean $\widehat{\Delta M}$ and variance $\widehat{V}$, where $\widehat{\Delta M}$ is the OLS estimate of a repeat sales regression

$$y = X\Delta M + e \tag{30}$$

with the matrixes y and X have rows

$$y_{ik} = CS_{i,t_{ik}} - CS_{i,t_{i,k-1}} - c_{t_{ik}} q_{i,t_{ik}} + c_{t_{i,k-1}} q_{i,t_{i,k-1}} \tag{31}$$

and

$$x_{ik} = (0'..z_{ik}\iota'..0') \tag{32}$$

for $k = 1, .., K(i)$ and $i = 1, .., N$ stacked, where $K(i)$ denotes the total number of transactions for bond i and N is the number of bonds allocated to the portfolio. ι is a vector of ones with length $t_{ik} - t_{i,k-1}$. The OLS estimator then is $\widehat{\Delta M} = (X'X)^{-1}X'y$ with variance $\widehat{V} = (X'X)^{-1}X'\Sigma_e X(X'X)^{-1}$. We neglect any serial correlation in credit spread changes, and thus take the diagonal of $\widehat{V}$ to draw ΔM. This procedure occasionally has 'gaps' i.e. periods with no or too few transactions. In such case, adjoining periods are clustered and the procedure estimates the cumulative return over the clustered periods.

36

B Model

In this appendix we derive a simple asset pricing model that helps to explain why liquidity risk is not priced in the corporate bond market. The model has two assets, a liquid asset a (equity) with low transaction costs c_a and an illiquid asset b (corporate bond) with high costs c_b. We assume two investment periods, starting at time $t = 0$ and $t = 1$ and ending at $t = 2$. We first study the decision problem at time $t = 1$. Let N_a and N_b be the positions in assets a and b, fixed at time $t = 0$, with prices of the assets normalized to 1 a time 1. The investor faces a liquidity problem at $t = 1$ and is forced to liquidate an amount D of his risky asset holdings. This can be done by selling either asset a, asset b or both. The amounts sold are denoted by $\Delta N_a \geq 0$ and $\Delta N_b \geq 0$, where the amounts sold must add up to D, so that $\Delta N_a + \Delta N_b = D$. Selling the assets gives rise to transaction costs $c_a \Delta N_a + c_b \Delta N_b$. The wealth after the sale is therefore

$$W_1 = N_a - \Delta N_a + N_b - \Delta N_b - \Delta N_a c_a - \Delta N_b c_b. \tag{33}$$

The wealth at time $t = 2$ then is given by

$$W_2 = (N_a - \Delta N_a)R_a + (N_b - \Delta N_b)R_b - \Delta N_a c_a - \Delta N_b c_b, \tag{34}$$

where R_a and R_b are the gross returns on the assets. Substituting the restriction $\Delta N_a + \Delta N_b = D$ we can write this as

$$W_2 = \Delta N_a(R_b - R_a + c_b - c_a) + N_a R_a + (N_b - D)R_b - Dc_b. \tag{35}$$

Applying a mean-variance optimization, taking c_a and c_b as known at time $t = 1$, we find the optimal amount to be sold for asset a. If there is an interior solution with $\Delta N_a > 0$

and $\Delta N_b > 0$, the first order condition is

$$(\mu_b - \mu_a + c_b - c_a) - \alpha Var(R_b - R_a)\Delta N_a - \alpha Cov(N_a R_a + (N_b - D)R_b, R_b - R_a) = 0, \quad (36)$$

which gives the optimal amount ΔN_a to be sold

$$\Delta N_a = \frac{\mu_b - \mu_a + c_b - c_a}{\alpha Var(R_b - R_a)} + \frac{Cov(N_a R_a + (N_b - D)R_b, R_b - R_a)}{Var(R_b - R_a)}. \quad (37)$$

This amount is increasing in the difference in transaction costs between asset b and asset a. However, if the cost difference becomes very large, at some point the optimal N_a will exceed the amount to be liquidated D. In that case, $\Delta N_a = D$ and $\Delta N_b = 0$ will be optimal and the wealth at time $t = 1$ after the sale will be

$$W_1 = N_a + N_b - D - Dc_a. \quad (38)$$

Now we turn to the optimization problem at time $t = 0$. Suppose it is known in advance to the investor that in the case of a forced liquidation of assets, there will be a corner solution with $\Delta N_a = D$. Then we can find the $t = 2$ wealth as seen from $t = 0$ as

$$W_2 = N_a R_a + N_b R_b - D - Dc_a, \quad (39)$$

where R_a and R_b now denote the two-period return, i.e. the return from time 0 to time 2. A simple mean-variance problem, without leverage constraints, produces the optimal investments

$$N = \alpha^{-1}\Sigma^{-1}(\mu - r_f) + D\Sigma^{-1}Cov(R, c_a), \quad (40)$$

with $N = (N_a, N_b)'$ etcetera.

Now consider the equilibrium implications in a setting with several investors, which

may differ in terms of the size of the liquidity shock D. The equilibrium depends on which traders are forced to liquidate assets and how many end up at the corner solution $\Delta N_a = D$. In order to provide intuition for the outcome, assume that all traders are at this corner solution, where each investor has to liquidate an amount D_i. In equilibrium, then, with common α, μ and Σ we find

$$\bar{N} = \alpha^{-1}\Sigma^{-1}(\mu - r_f) + \bar{D}\Sigma^{-1}Cov(R, c_a), \tag{41}$$

where $\bar{D}$ is the average of the individual amounts to be liquidated. The equilibrium risk premiums then are

$$\mu - r_f = \alpha\Sigma\bar{N} - \alpha\bar{D}Cov(R, c_a). \tag{42}$$

The risk premiums are the sum of a usual market risk premium, plus a liquidity premium for the covariance between the asset returns and the transaction cost on the (more liquid) asset c_a. We see that there is no risk premium for correlation with the transaction cost of the less liquid asset, c_b. Notice that μ_b may contain a liquidity risk premium for the covariance between the illiquid asset return R_b and the transaction costs on the liquid asset c_a, but there is no liquidity risk premium for the covariance between the illiquid asset return R_b and its own transaction cost c_b.

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Table 1: **Expected returns, costs and betas**
The table presents descriptive statistics of the data. The sample period is 2005 to 2008 and the portfolios are based on various sequential sorts; first, the portfolios are sorted on rating or EDF, then each rating/EDF portfolio (except the AAA and CCC rating portfolios) is sorted on the basis of trading activity, average bond age or issue size. In total, there are 62 portfolios. The first three columns present the average values across all portfolios. The second and third column present the average t-statistic and average R^2 of the first step regressions. The final two columns show the average values for low liquidity and the high liquidity portfolios (excluding the AAA and CCC rating portfolios). Annualized expected returns are denoted by $E(r)$ and average transaction costs by $E(c)$, both in percentages. The betas capture exposure of corporate bond returns to equity market returns (β^{eq}), corporate bond liquidity shocks (β^{cost}), and shocks to VIX.

rating	average	t-stat	R^2	low liq	high liq
$E(r)$	1.868	[4.801]		1.938	1.778
$E(c)$	0.833	[6.152]		0.933	0.712
univariate					
β^{eq}	0.380	[14.62]	0.498	0.358	0.399
β^{cost}	-4.194	[-8.52]	0.263	-3.805	-4.522
β^{vix}	-0.281	[-15.50]	0.526	-0.264	-0.299
multivariate					
β^{eq}	0.162	[2.46]		0.164	0.148
β^{cost}	-2.033	[-5.16]		-1.752	-2.240
β^{vix}	-0.134	[-3.46]	0.618	-0.121	-0.157

Table 2: **Risk-factor model: Cross-sectional regression estimates**

This table present estimates of the risk factor model in equation (2). The sample period is 2005 to 2008 and the portfolios are based on various sequential sorts; first, the portfolios are sorted on rating or EDF, then each rating/EDF portfolio (except the AAA and CCC rating portfolios) is sorted on the basis of trading activity, firm size or issue size. In total, there are 62 portfolios. Shanken (1992) t-statistics are given in square brackets. The column (FB) shows Fama-MacBeth estimates based on four week rolling regressions with betas estimated on a 52-week rolling window. The column (LB) shows the results for an additional portfolio sort based on the liquidity beta, as explained in section 5.2.2.

model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	FB	LB
β^{eq}	4.743			4.725	3.056	5.192	3.592	2.959	4.923	3.751
	[5.29]			[5.55]	[5.78]	[5.31]	[6.78]	[5.10]	[6.694]	[7.25]
β^{cost}		-0.397		-0.115	0.044	-0.120	0.044	0.081	-0.066	0.054
		[-5.19]		[-3.89]	[2.59]	[-4.11]	[2.55]	[3.60]	[-3.65]	[2.59]
β^{vix}						-5.235	-2.598	-2.363	-5.042	-2.827
						[-4.37]	[-3.54]	[-2.89]	[-5.53]	[-3.96]
β^{rf}								-0.002		
								[-1.13]		
β^{illiq}								-0.229		
								[-5.88]		
$E(c)$			2.194		1.189		1.234	1.405	1.363	1.380
			[4.05]		[4.04]		[4.21]	[5.09]	[12.96]	[3.52]
R^2	0.472	-0.328	0.168	0.472	0.655	0.492	0.687	0.712		0.687

Table 3: **Market and liquidity betas across corporate bond portfolios**
The table presents average betas (across all portfolios) of the Bongaerts, de Jong and Driessen (2009) model in equation (7). We have $\beta^{eq} = \beta^{r,eq} - \zeta_0 \beta^{c,eq}$ and $\beta^{vix} = \beta^{r,vix} - \zeta_0 \beta^{c,vix}$, with $\zeta_0 = 1.189$. The other betas are defined in equations (4) and (5).

$\beta^{r,eq}$	0.158
$\beta^{r,vix}$	-0.165
$\beta^{c,eq}$	-0.013
$\beta^{c,vix}$	0.018
β^{eq}	0.174
β^{vix}	-0.187
β^{rr}	0.760
β^{rc}	-0.098
β^{cr}	-0.127
β^{cc}	0.044
β^{other}	0.268
β^{net}	1.029

Table 4: **BDD model: Cross-sectional regression estimates**
This table present estimates of the Bongaerts, de Jong and Driessen (2009) model in equation (7). The sample period is 2005 to 2008. t-statistics are given in square brackets.

model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
β^{eq}	3.902	3.844	3.844	2.969	2.354	3.286	3.955
	[6.95]	[7.03]	[7.03]	[3.78]	[3.17]	[3.95]	[5.94]
β^{vix}	-2.149	-2.154	-2.195	-1.500	-1.718	-1.943	-2.220
	[-3.18]	[-2.51]	[-3.08]	[-1.69]	[-1.93]	[-2.13]	[-2.67]
$E(c)$	0.932	0.933	1.043	1.067	1.112	1.156	0.961
	[4.36]	[3.62]	[3.95]	[4.12]	[4.85]	[4.90]	[3.58]
β^{rr}		-0.004		0.598	0.569	0.427	
		[-0.02]		[3.12]	[2.59]	[1.84]	
β^{rc}			0.906	2.927	0.471		
			[1.55]	[5.27]	[0.92]		
β^{cr}					-5.169		
					[-3.37]		
β^{cc}					-19.02		
					[-4.92]		
β^{other}						-1.380	
						[-4.07]	
β^{net}							-0.044
							[-0.38]
R^2	0.728	0.728	0.733	0.745	0.777	0.739	0.728

Table 5: **Equity Turnover Regressions**

The table contains estimates of a linear regression of monthly changes in the value-weighted mean of log turnover across stocks on the value weighted equity market excess return and changes in the value-weighted ILLIQ across stocks, corrected for inflation. Data runs from Jan 2005 to Dec 2008. t-statistics are in brackets.

model	(1)	(2)	(3)
$d(Equity\,market\,illiquidity)$	0.140		-0.004
	[1.93]		[-0.03]
$Equity\,market\,return$		-1.725	-1.755
		[-2.51]	[-1.53]
$Constant$	0.001	0.001	0.001
	[0.32]	[0.33]	[0.34]
N	47	47	47
R^2	0.076	0.123	0.123

Table 6: **Corporate bond turnover regressions**

The table contains estimates of a linear panel regression of quarterly changes in individual bond log turnover on changes of our market-wide liquidity cost measure for the corporate bond market and changes in mean credit spreads. We also include interactions between a high quality dummy (equal to one for bonds rated AAA or AA) and the change in cost index or mean credit spread respectively. Bond-specific fixed effects are included and standard errors are clustered by quarter. Sample period is from 2005Q1 to 2008Q4 and contains data on the same sample of bonds as is used in the previous tables. Bond turnover is winsorized at 5% top and 5% bottom. t-statistics are in brackets.

model	(1)	(2)	(3)	(4)	(5)
$d(Corporate\,bond$	-0.149***		-0.118***	-0.144***	-0.119***
$market\,illiquidity)$	[-7.29]		[-7.62]	[-6.63]	[-7.88]
$d(Credit\,spread)$		-7.844**	-3.440**	-3.526**	-5.327**
		[-2.45]	[-2.31]	[-2.36]	[-2.67]
$d(Corporate\,bond$				0.0841**	
$market\,illiquidity)$				[2.71]	
$*HQ\,dummy$					
$d(Credit\,spread)$					5.965**
$*HQ\,dummy$					[2.46]
$HQ\,dummy\,(AAA/AA)$				0.0173	0.00632
				[0.31]	[0.11]
$Constant$	-0.0371*	-0.0279	-0.0275	-0.0326	-0.0295
	[-1.93]	[-1.45]	[-1.42]	[-1.32]	[-1.20]
N	113776	113776	113776	113776	113776
R^2	0.049	0.048	0.050	0.050	0.050
N_clust	15	15	15	15	15

Figure 1: **Time series of expected bond returns and transaction costs**
The figure shows weekly time series of the expected corporate bond returns (top line)
and transaction costs obtained by the Gibbs sampler (bottom line), averaged across all
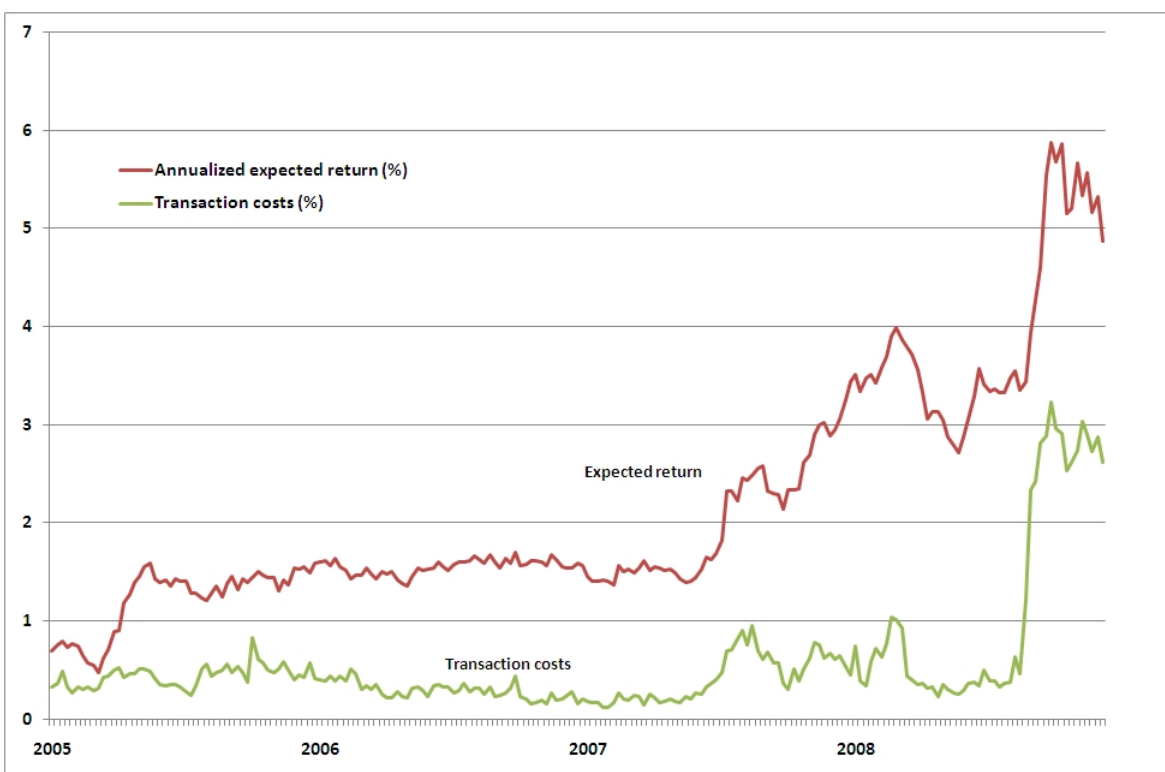portfolios. The sample period is 2005 to 2008.

Figure 2: **Risk-factor model: Fit of expected returns**
The figure shows the fitted values of the expected bond returns, obtained by multiplying the estimated coefficients in Table 2, specification (7) with the estimated expected cost and the estimated betas. Alpha is the pricing error as defined in equation (2). The fit is presented for portfolios across rating categories / EDFs and liquidity proxies, averaged across liquidity proxies. For example, "AA-hi" refers to the high-liquidity AA portfolios, while "AA-lo" refers to the low-liquidity AA portfolios.
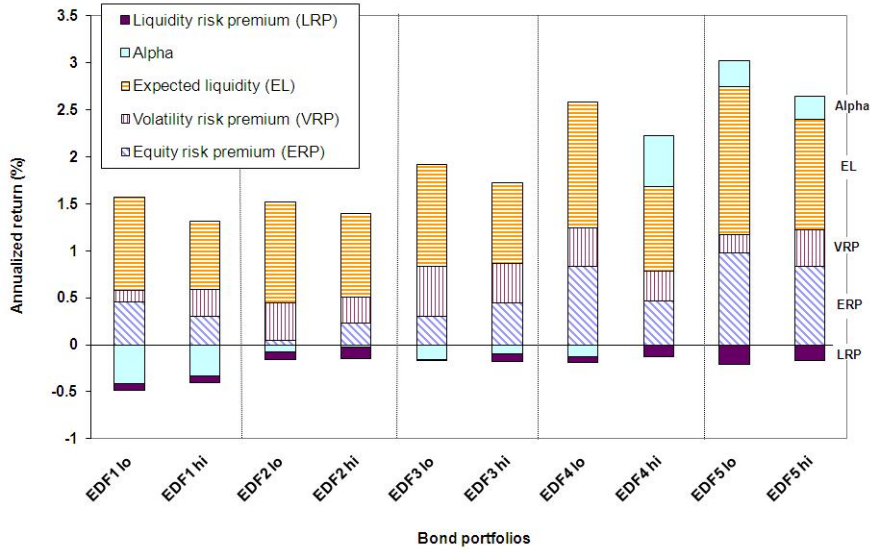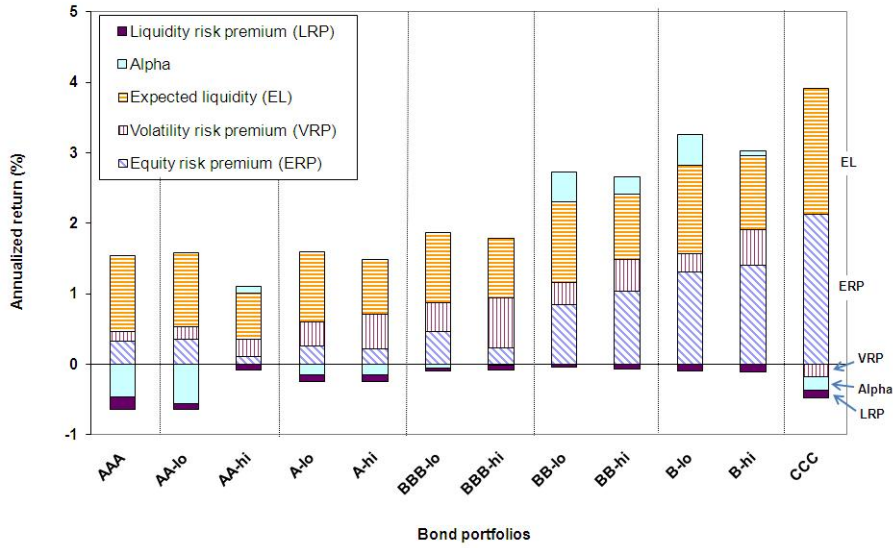
Figure 3: **Time-varying estimates**

The top panels of this figure show the estimated betas, second step regression coefficients and implied risk premiums for the equity return (solid line), VIX innovations (short dashed line) and liquidity innovations (long dashed line). The bottom panels show the same items for the expected liquidity. The estimates are obtained from four weeks of expected return and cost data, with a 52-week rolling estimate of the betas. To improve legibility, the liquidity beta has been divided by 10 and the liquidity price of risk (lambda) multiplied by 10. The resulting risk premium is unaffected by this.
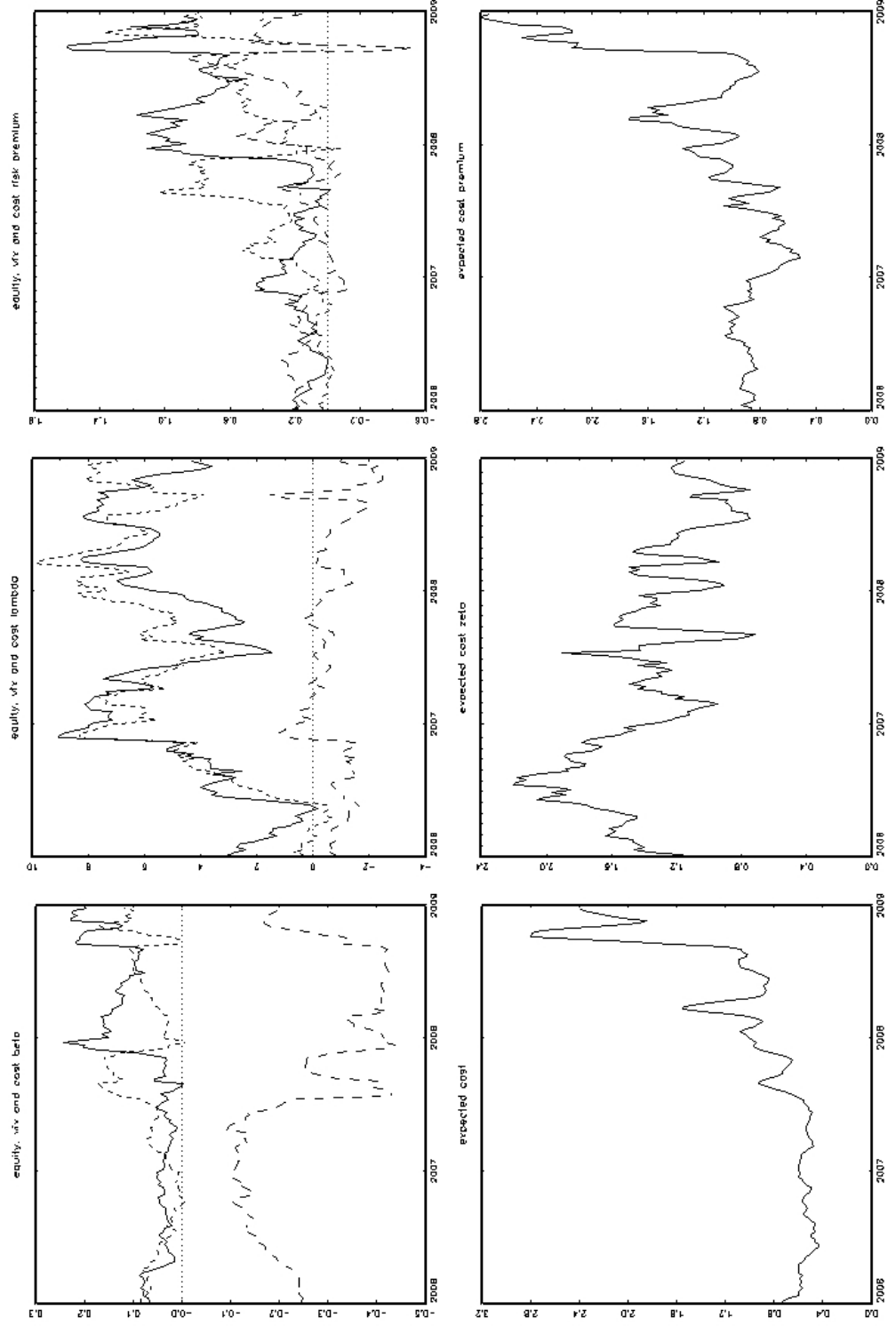
Figure 4: **Turnover in equity and corporate bond markets**
The figure shows quarterly turnover in the equity and corporate bond market. For the
equity market, the time series of both the value-weighted mean and median of quarterly
turnover across all CRSP stocks is shown. Similarly, for corporate bonds the time series
of the value-weighted mean and median of quarterly bond turnover across all TRACE
bonds is shown.