Extreme Illiquidity and Cross-Sectional Corporate Bond Expected Returns

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Abstract

Corporate bonds carry a premium of extreme illiquidity (*EIL*). This premium permeates all rating categories and heightens in times of stress and periods with high uncertainty. *EIL* has predictive power in the cross-section for future returns up to a one-year horizon. Active investors like mutual funds prefer low *EIL* bonds that can be easily liquidated in bad times, whereas passive investors overweight high *EIL* bonds to receive the *EIL* premium. Although adding an *EIL* factor constructed from portfolios to the factor models increases explanatory power, its effect is largely subsumed by bond *EIL* characteristic in a horserace regression.

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1. Introduction

A vast literature suggests that liquidity is important for asset pricing. Liquidity has many dimensions, and traditionally researchers have focused on either the effect of liquidity level (Amihud and Mendelson, 1986; Brennan and Subrahmanyam, 1996; Eleswarapu, 1997; Amihud, 2002; Amihud, Hameed, Kang, and Zhang, 2015; Bongaerts, De Jong, and Driessen, 2017; Friewald and Nagler, 2019) or liquidity risk (Pastor and Stambaugh, 2003; Acharya and Pedersen, 2005; Sadka, 2006, 2010; Lee, 2011; Lin, Wang, and Wu, 2011, among others). Illiquidity results in higher transaction costs for investors and therefore, in equilibrium illiquid assets are priced with a discount to provide a premium to compensate investors (Duffie, Garleanu, and Pedersen, 2005, 2007). Covariations in liquidity also induce undiversifiable risk of losing asset value when market liquidity precipitates. A number of studies show that marketwide liquidity is a systematic risk factor priced in both stock and bond markets (Pastor and Stambaugh, 2003; Acharya and Pedersen, 2005; Sadka, 2010; Lin et al., 2011; Kondor and Vayanos, 2019).

Market downturns are often accompanied by liquidity dry up. History has witnessed that liquidity evaporated in many sectors of financial markets in times of stress. In the financial crisis, a downward spiral in financial markets causes flights to liquidity and fire sales (Brunnermeier and Pedersen, 2009; Ellul, Jotikasthira, and Lundblad, 2011; Acharya, Amihud, and Bharath, 2013). Market turmoil strains dealers' inventory-absorption capacity due to a surge in liquidity demand from the public and at the same time a decrease in liquidity supply by market makers in response to heightened uncertainty, tighter funding constraints, and greater market frictions. Karolyi, Lee, and Van Dijk (2012) and Koch, Ruenzi, and Starks (2016) find that institutions' correlated trading increases commonalities in liquidity, and institutionalization of the market intensifies the flight-to-liquidity during market selloffs. It has been shown that extreme illiquidity raises stock returns and that liquidity risk is priced differently in times of stress (Dick-Nielsen, Feldhütter, and Lando, 2012; Nagel, 2012; Chen, Huang, Sun, Yao, and Yu, 2020).

The severity of illiquidity during the subprime crisis has drawn considerable interest in understanding the effect of extreme risk on the pricing of securities. A strand of research finds that heavy-tailed shocks to economic fundamentals can explain certain asset price behavior that has proven otherwise difficult to reconcile with macrofinance theory (Gabaix, 2012; Gourio, 2012; Wachter, 2013). A number of studies have investigated the impacts of tail risk and downside risk on stock returns (see, for example, Kelly and Jiang, 2014; Chabi-Yo, Ruenzi, and Weigert, 2018; Ang, Chen, and Xing, 2006; Lu and Murray, 2019) and equity fund returns (Agarwal, Ruenzi, and Weigert, 2017; Karagiannis and Tolikas, 2019). Extreme illiquidity is one form of heavy-tailed shocks that can significantly affect asset returns. Nagel (2012) shows that expected returns and Sharpe ratios spike during market turmoil and liquidity deterioration.

The corporate bond market provides an ideal setting to study the pricing of extreme illiquidity. Most corporate bonds trade infrequently due to high inventory, search, and bargaining frictions. Illiquidity is thus a much greater concern for participants in the corporate bond market (see Bongaerts et al., 2017; Friewald and Nagler, 2019). Therefore, investigating the effect of extreme illiquidity on corporate bond pricing can provide important insight into the role of tail risk in different asset classes. A unique feature in the corporate bond market is that unlike stocks, firms typically issue bonds with different maturities. Debts maturing in near terms induce rollover risk. He and Xiong (2012) demonstrate a strong interaction effect of illiquidity and rollover risk on firm risk, which are particularly important during the financial crisis. Using a comprehensive data set consisting of bonds with different maturities allows us to ascertain the role of extreme illiquidity in propelling the effect of rollover risk. Exploiting an important insight from Amihud and

Mendelson (1991) on the interaction of maturity and illiquidity, we are able to disentangle the role of extreme illiquidity from day-to-day illiquidity in bond pricing. Moreover, availability of detailed institutional holding data (eMAXX) facilitates an in-depth study on the investment clientele of bonds with high illiquidity to identify a fundamental source of the extreme illiquidity premium and examine its implications for the pricing in the cross-section of corporate bonds.

As in prior research of heavy-tailed risk in stock markets, a significant challenge in our empirical investigation is finding a suitable empirical measure of extreme illiquidity due to the infrequent nature of these events. In this paper, we draw on the idea of value-at-risk (VaR) to obtain a parsimonious extreme illiquidity measure with great explanatory power. In our baseline analysis, we construct a measure of extreme illiquidity using the 5% tail-risk rule commonly adopted in risk management. Given a prominent illiquidity index such as the Amihud (2002) measure (*ILLIQ*), we select an illiquidity level at the 95th percentile as the threshold of extreme illiquidity for an individual bond over a specific period. For a 60-month estimation window, the level of extreme illiquidity (*EIL*) typically falls at the third-highest *ILLIQ* value. This procedure results in an *EIL* series for each individual bond to facilitate pricing tests. Our results are robust to alternative ways of constructing the extreme illiquidity measure, i.e., using the average of the highest 10% illiquidity observations akin to the *expected* shortfall (ES) or loss measure, or using a different length of estimation window.

We find that extreme illiquidity carries a statistically significant premium of 0.56% per month. The predictive power of *EIL* in the cross-section for future bond returns holds up to a one-year horizon. The *EIL* effect is robust to controlling for the standard Amihud illiquidity measure, systematic liquidity risk (beta), and downside risk. The results suggest that extreme illiquidity is priced in the corporate bond market.

The *EIL* premium permeates all bond categories (coupon, size, age, maturity, and ratings), not just concentrating in only a particular segment. There are substantial variations in *EIL* premia across bonds. Consistent with the inference that extreme illiquidity is a greater concern for firms faced with rollover risk, we find that the *EIL* premium is substantially higher for bonds issued by firms with high refinancing risk. In addition, consistent with active investors being more concerned about extreme illiquidity, due to their trading needs, than passive investors, we find a significantly higher *EIL* premium among bonds invested by mutual funds than by insurance companies.

EIL premia are time-varying, larger during periods of high uncertainty or low investment sentiment, and vice versa. The *EIL* premium during the subprime crisis is about 30% higher than that in the normal period. A similar pattern of high *EIL* premia exists when there is high market uncertainty as measured by the indexes of Baker, Bloom, and Davis (2016) and Bekaert, Engstrom, and Xu (2019). On the other hand, the *EIL* premium is low (high) when investor sentiment is high (low) based on the Baker-Wurgler (2006) measure.

Constructing a tradable factor from the high-minus-low *EIL* decile portfolios, we find that the return of this factor compensates the risk of marketwide extreme illiquidity. Conventional risk factors cannot explain the *EIL* factor return. This finding is robust to the uses of alternative test portfolios formed by size/maturity, size/rating, industry, and *EIL*-loadings to ensure sufficient independent variations in factor loadings and to alleviate the concern for low power in standard cross-sectional asset pricing tests warned by Lewellen, Nagel, and Shanken (2010). The results consistently show that incorporating the *EIL* factor into the conventional factor model significantly reduces the pricing error (or alpha) and increases the adjusted R^2 of the factor model.

The finding that the *EIL* factor has explanatory power raises the familiar issue of whether *EIL* as a characteristic or the *EIL* factor loading is more relevant in explaining the cross-section of corporate bond returns. To tackle this issue head-on, we run a horserace regression to evaluate how *EIL* as a characteristic fares against the *EIL* beta in explaining the bond cross-section. Interestingly, we find that the coefficient of *EIL* beta becomes insignificant when we control for the effect of bond-specific *EIL* in the cross-sectional regression. The results show that the *EIL* characteristic is more significantly priced in the cross-section of corporate bonds than the loading of the *EIL* factor.

We conduct additional tests to further differentiate the effect of extreme illiquidity from conventional illiquidity and downside risk effects. We find that both *EIL* and Amihud *ILLIQ* carry a premium of comparable magnitude but they capture the effects of illiquidity in different dimensions. While *ILLIQ* grasps the effect of ordinary illiquidity, *EIL* captures the effect of extraordinary movements in illiquidity on cross-sectional bond returns. Amihud and Mendelson (1991) suggest that for an investor who needs to trade prior to bond maturity, the effect of *ILLIQ* on prices (yields) should be weaker for a longer-maturity bond. However, longer maturity also entails a higher probability of an extreme illiquidity event, in which transaction costs ramp up and persist. Consistent with this inference, we find a significantly negative interaction effect of *ILLIQ* and maturity on bond yield, and an insignificant interaction of EIL and maturity. For downside risk, our results show that neither downside risk as a characteristic nor as a systematic risk factor has a material effect on the *EIL* coefficient in the cross-sectional regression, suggesting that the *EIL* premium is different from the downside risk premium.

Moreover, we find that active investors like mutual funds have a strong preference for bonds with low *EIL*. Although mutual funds sold low *EIL* bonds during the subprime crisis, as it was difficult to trade high *EIL* bonds at that time, we find that after the crisis, they accumulate holdings of low *EIL* bonds and shy away from high *EIL* bonds. Aversion of these active investors to extreme illiquidity drives down the prices of bonds with high *EIL* and increases their premia.

This paper contributes to the literature on the role of extreme illiquidity in asset pricing. Roll and Subrahmanyam (2010) first document an increase in the right skewness of transaction costs in the stock market. Menkveld and Wang (2012) use a Markov regime-switching model to estimate the probability in a prolonged illiquid state and find higher returns for stocks with a greater probability of being trapped in that state. Anthonisz and Putnins (2017) construct the three Acharya-Pedersen (2005) downside liquidity risk measures conditional on negative market returns and find that only the conditional covariance between individual stock liquidity and market returns carries a significant premium. Wu (2019) studies the pricing of stock return exposure to aggregate liquidity tail risk. Ruenzi, Ungeheuer, and Weigert (2020) show that the cross-section of stock returns reflects a premium if a stock's return (liquidity) is low and at the same time, the market liquidity (return) is low. Belkhir, Saad, and Samet (2020) find that stock-level extreme illiquidity increases the cost of equity capital. Although trading costs have been steadily decreasing, extreme illiquidity appears to play an increasingly important role in the recent stock market (see Ruenzi et al., 2020). A related literature also investigates the effect of illiquidity volatility on stock returns (see, for example, Chordia, Subrahmanyam, and Anshuman, 2001; Pereira and Zhang, 2010; Akbas, Petkova, and Armstrong, 2011; Barinov, 2015). Our work complements these studies by investigating the role of extreme illiquidity in the cross-section of corporate bond returns.

Although existing studies of the extreme illiquidity effect focus on the stock market, there are two notable exceptions. Irresberger, Weiß, Gabrysch, and Gabrysch (2018) investigate the relationship between liquidity tail risk and CDS spreads, where the former is represented by the upper tail dependence or the asymptotic probability of a joint surge in the bid-ask spreads of a firm's CDS and the CDS market index. Yan, Hamill, Li, Vigne, and Waterworth (2018) uncover a positive skewness of bid-ask spreads in European sovereign bond markets. Our paper focuses on the corporate bond market. Furthermore, we identify the economic channels of the *EIL* effect from the variation of maturities and the detailed institutional holding data.

This paper is also related to the literature on the pricing of tail risk in the cross-section of security returns (see, for example, Bali, Demirtas, and Levy, 2009; Yan, 2011; Huang, Liu, Rhee, and Wu, 2012; Bégin, Dorion, and Gauthier, 2020). Atilgan, Bali, Demirtas, and Gunaydin (2020) and Bai, Bali, and Wen (2019) use value-at-risk and the expected shortfall of the return distribution to capture downside risk and find that this risk is priced in the stock and bond markets. Our finding for the pricing of extreme illiquidity risk in the corporate bond market adds to a growing literature that shows the tail risk is a systematic risk, which cannot be diversified away (Kelly and Jiang, 2014; Bali, Cakici, and Whitelaw, 2014; Bollerslev, Todorov, and Xu, 2015; Van Oordt and Zhou, 2016; Gao, Lu, and Song, 2019, among others).

The remainder of this paper is organized as follows. Section 2 discusses the data and Section 3 examines the pricing of *EIL* as a bond characteristic. Section 4 introduces the *EIL* factor and compares its explanatory power in the cross-section of bond returns with conventional stock and bond market factors. Section 5 studies the economic channel behind the pricing of *EIL*. Finally, Section 6 summarizes our main findings and concludes the paper.

2. Data

Corporate bond data are from the enhanced Trade Reporting and Compliance Engine (TRACE) database and the Mergent Fixed Income Securities Database (FISD). The enhanced TRACE provides the transaction data of all publicly traded corporate bonds starting from July 2002. The FISD database contains issuance information for all fixed-income securities with a CUSIP number, including bond issue- and issuer-related characteristics, such as the issue date, offering amount, maturity date, first interest date, coupon type, coupon rate, and ratings. The sample covers the period from July 2002 to June 2019.

We merge the transaction records of bonds from the enhanced TRACE with their issuance information from FISD by the CUSIP number. Following the convention in the literature, we use the following procedure to filter bond observations: (1) remove canceled, corrected, commission, and small (below \$10,000) trades;[1] (2) eliminate bond transactions that are labeled as when-issued, locked-in, or have special sales conditions; (3) drop bonds that are callable,[2] puttable, convertible, sinking-fund, or asset-backed and focus on straight bonds; (4) exclude bonds that are issued through private placement or under the 144A rule; and (5) exclude corporate bonds with a maturity of less than 1 year or longer than 30 years (see Dick-Nielsen et al., 2012; Chung et al., 2019).[3]

For a bond, the raw return in month t is

$$r_t^i = \frac{\left(P_t^i + AI_t^i\right) + C_t^i}{P_{t-1}^i + AI_{t-1}^i} - 1 \tag{1}$$

where P_t^i is the price of bond i at the end of month t, AI_t^i is the accrued interest, and C_t^i is the coupon payment if any. We calculate daily prices as the trade size-weighted average of intraday prices during the day. If the last transaction in a month does not fall in the last trading day, we use the interpolated month-end price to calculate the return. Our final sample includes 417,997 bond-month observations for 15,217 bonds issued by 1,786 firms from July 2002 to June 2019. Figure 1 plots the number of sample bonds and firms in each month from July 2002 to June 2019.

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[1] Some studies eliminate trades below \$100,000 rather than \$10,000 (see Bessembinder, Kahle, Maxwell, and Xu, 2009; Chung, Wang, and Wu, 2019). The results with \$100,000 cutoff are quantitatively similar, which are available upon request.

[2] There is a recent trend to include callable bonds, which substantially increases the sample size. While we don't use callable bonds for the main analysis, we show in the Internet Appendix A that our conclusion doesn't change with callable bonds.

[3] Bonds with less than one year of maturity are excluded from most bond indices, which may cause index-tracking investors to change their holding positions and thus distort bond return measures. In addition, bonds with a maturity of less than one year trade infrequently, and return data are very noisy. We also exclude bonds with longer than 30-year maturity as the longest maturity of Treasury is 30 years, which is needed for calculating maturity-matched excess returns.

[Insert Figure 1 around here]

For bond i in each month t, we calculate the monthly Amihud (2002) illiquidity measure

$$ILLIQ_t^i = \frac{1}{days_{it}} \sum_{j=1}^{days_{it}} \frac{|r_{i,j,t}|}{vol_{i,j,t}} \tag{2}$$

where $days_{it}$ is the number of trading days with daily returns, and $vol_{i,j,t}$ is the volume in day j measured in $million. Extreme illiquidity (EIL_t^i) is the third-highest *ILLIQ* of bond i over the past 60-month window. Figure 2 plots the cross-sectional average *EIL* across all corporate bonds in each month from January 2006 to June 2019.[4]

[Insert Figure 2 around here]

The final sample is representative of the corporate bond market, with the average issue size, time to maturity, age, and coupon rate being $0.52 billion, 6.97 years, 6.02 years, and 5.45%, respectively. The median credit rating is A-. The detailed characteristics are reported in Panel A of Table 1, where the numbers represent the time-series average of all cross-sections (months). In most analyses, we control for the conventional stock and bond market factors, whose basic statistics can be found in Panel B of Table 1. We estimate the "beta" of each corporate bond's return to a factor with a rolling 5-year window to be consistent with the calculation of *EIL*. The time-series averages of the cross-sectional statistics for the betas and *EIL* are reported in Panel C of Table 1. As shown in Panel D, time-series averages of the cross-sectional pairwise correlations between *EIL* and other risk betas and bond characteristics are mild, except for *ILLIQ* and size.[5] To investigate the persistence of *EIL*, in each cross-section, we first sort *EIL* into deciles and calculate the transition probability of bonds in deciles over the next month, the next six months,

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[4] In empirical tests, we require a bond to have at least 15 monthly *ILLIQ* observations over this window. The usage of the "third-highest" *ILLIQ* is intended to capture the 95th percentile of the illiquidity level of bonds. Internet Appendix B reports the results for alternative estimation windows and illiquidity percentiles.

[5] Section 5.1.1 shows that *EIL* and *ILLIQ* capture different facets of illiquidity.

and the next year, then we take the average of the transition matrices across all cross-sections. The relative *EIL* rankings across bonds are stable over the next month to one-year horizon, as revealed in the transition matrices in Table 2.

[Insert Tables 1 and 2 around here]

3. Pricing of *EIL* as a characteristic

We begin our analysis by examining the cross-sectional relation between *EIL* and expected returns on corporate bonds using univariate portfolio analysis. To control for standard risk factors and bond characteristics, we perform bivariate portfolio sorts and Fama-MacBeth cross-sectional regressions on individual bond returns. Following this, we explore the variations in the *EIL* premium across securities and over time.

3.1. Univariate portfolio analysis

At the end of each month t, we form equal-weighted decile portfolios by sorting on *EIL*. The first row (*Return*) of Table 3 reports the average portfolio returns the next month in excess of the one-month T-bill rate. The second row (*AdjRet*) adjusts returns for ratings and maturities.[6] Both *Return* and *AdjRet* monotonically increase with *EIL*. The long-short (10-1) portfolio return spread is 0.56% per month (or 6.72% per annum), while the long-short portfolio return spread based on the characteristic-adjusted returns is 0.25% per month. Both are significant at the 1% level.

[Insert Table 3 around here]

To adjust for risk factors, we obtain alphas by running the Black-Jensen-Scholes (1972, BJS) time-series regressions against these risk factors. We control for the Fama-French (1993, FF) five

[6] Specifically, we assign each bond to one of the 4×3 benchmark portfolios by four ratings (AAA/AA, A, BBB, and Junk) and three maturities (Short: < 5 years; Medium: 5~10 years; Long: > 10 years) and calculate the equal-weighted return for each of the twelve benchmark portfolios each month. The *AdjRet* is the bond return minus the return of the corresponding rating/maturity benchmark portfolio to which the bond belongs.

factors:[7] market (*MKT*), size (*SMB*), value (*HML*), default (*DEF*), and term (*TERM*) factors; the Bai-Bali-Wen (2019, BBW) four bond market factors: excess bond market returns (*MKTb*), the downside risk factor (*DRF*), the credit risk factor (*CRF*), and the liquidity risk factor (*LRF*); and the Lin-Wang-Wu (2011) corporate bond market liquidity factor (*LIQ*).[8] We estimate the alphas of both excess returns (*Return*) and rating/maturity adjusted returns (*AdjRet*) relative to these factors.

The middle and bottom panels of Table 3 report the alpha of each *EIL* decile portfolio, and the long-short (10-1) portfolio alpha spread controlling for different sets of risk factors. All alphas increase with *EIL*, and all long-short alpha spreads are significant at the 1% level regardless of the specification of factor models or return measures (*Return* or *AdjRet*). Thus, the positive relation between cross-sectional bond returns and *EIL* cannot be explained by exposure to common risk factors.

3.2. Predictability over longer horizons

Table 4 reports the univariate portfolio results over different time horizons for equal-weighted decile portfolios of *EIL* formed at the end of each month t. For instance, the first column reports the average 10-1 portfolio excess return, characteristic-adjusted return, and alphas relative to different sets of factors in month $t+1$, the second column reports the returns and alphas in month $t+2$, and so on until the last column reporting bond portfolio returns 12 months ahead. The results show that *EIL* has predictive power in the cross-section for corporate bond returns up to at least one-year horizon.

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[7] The *MKT*, *SMB*, and *HML* factors are from Kenneth R. French's data library. The default spread (*DEF*) is the difference between the monthly return of a value-weighted portfolio of all long-term investment-grade bonds in the sample and the return of long-term government bonds. The term spread (*TERM*) is the difference between the monthly return of the long-term government bond and the one-month T-bill rate; both collected from the Federal Reserve Board.

[8] In constructing liquidity risk factor (*LRF*), Bai et al. (2019) use the Bao, Pan, and Wang (2011) measure as the proxy for illiquidity. The liquidity factor (*LIQ*) uses the Amihud (2002) measure following the method of Chung et al. (2019).

[Insert Table 4 around here]

3.3. Controlling for characteristics

Prior research shows that bond characteristics explain cross-sectional variations in bond returns because they capture the effects of missing risk factors (e.g., Gebhardt, Hvidkjaer, and Swaminathan, 2005; Li, Wang, Wu, and He, 2009). There is a concern that the univariate relation could be driven by the correlation between *EIL* and conventional risk factors or bond characteristics. This section provides evidence that alleviates this concern.[9]

3.3.1. Bivariate portfolio analysis

We start with the bivariate portfolio sorts to control for other effects. At the end of each month t, we first sort bonds into quintiles by one of the characteristics (*Maturity*/*Coupon* /*Size*/*Age*/*Rating*/*ILLIQ*) or betas (β_{DRF} or β_{LIQ}). We then form a high-minus-low (5-1) *EIL* portfolio within each characteristic quintile by longing the 20% bonds with the highest *EIL* and shorting the bottom 20% bonds with the lowest *EIL*. If the pricing of *EIL* is driven by its correlation with bond characteristics, the return of the 5-1 *EIL* portfolio within each characteristic quintile would be close to zero since the variation of the characteristics is limited within each quintile.

[Insert Table 5 around here]

The first five columns of Table 5 Panel A report the time-series average returns of the 5-1 *EIL* portfolios from the lowest to the highest characteristic quintile. The *EIL*-sorted portfolio earns significantly positive returns within each characteristic quintile. For example, in column 1 and row 1 in Panel A, 0.41 is the difference between the returns of the highest and lowest *EIL* portfolios for bonds with the shortest maturity. We then form a portfolio (Avg) by taking equal weights on

[9] *EIL* is particularly related to Amihud (2002) illiquidity measure *ILLIQ* and Bai et al. (2019) downside risk measure *DOWN*, for which we conduct detailed comparisons in Section 5.1.

the *EIL*-sorted portfolios in the five quintiles for each characteristic. The last two columns of Panel A report the time-series average return and the *t* value for these equal-weighted portfolios.

All *EIL* portfolio return spreads are significant at the 1% level across characteristic groups, suggesting that the correlation between *EIL* and bond characteristics is not the reason that *EIL* is priced. It is particularly comforting to find consistent results in rating quintiles. Credit ratings are widely used in bond investment selection and portfolio management. As firms with different credit ratings typically have different investment clientele, corporate policies, and regulatory restrictions, their bonds are likely to have different exposure to extreme illiquidity. The *Rating* row in Panel A shows that the pricing of *EIL* is pervasive over different ratings, although the risk premium differs. We will further explore the effect of *EIL* on investment clientele in Section 5.

Finally, Panel B of Table 5 reports the alphas of the portfolios in Panel A relative to the four different factor models described in the previous section. The results show that the *EIL* premium is robust to controlling for risk factors commonly adopted in the literature.

3.3.2. Fama-MacBeth cross-sectional regression tests

The Fama-MacBeth (1973) cross-sectional regression permits joint control for bond characteristics and risk factors. Each month *t*, we run the following cross-sectional regression of individual bond returns:

$$r_{t+1}^{i,e} = \gamma_0 + \gamma_1\beta_{MKT_t}^i + \gamma_2\beta_{SMB_t}^i + \gamma_3\beta_{HML_t}^i + \gamma_4\beta_{DEF_t}^i + \gamma_5\beta_{TERM_t}^i + \gamma_6\beta_{LIQ_t}^i + \gamma_7 EIL_t^i + \delta Z_t^i + \varepsilon_t^i \quad (3)$$

where $r_{t+1}^{i,e}$ is the return of bond i in month $t+1$ in excess of the one-month T-bill rate. Z_t^i is a vector of control variables, including the lagged bond return and Amihud (2002) illiquidity in month *t*, as well as bond characteristics such as coupon rate, issue size, rating, age, and maturity. β_{MKT}, β_{SMB}, β_{HML}, β_{DEF}, β_{TERM}, and β_{LIQ} are estimated from the regression in the five-year rolling window requiring at least 15 monthly return observations.[10] We normalize each variable on the right side of the regression by its cross-sectional standard deviation each month to facilitate consistent comparison of the effect of each variable. The coefficient of each variable can be easily interpreted as the premium per unit of one standard deviation variation in that variable.

[Insert Table 6 around here]

We run the Fama-MacBeth cross-sectional regression first on *EIL* alone, then add different risk factors, and finally include controls for bond characteristics to investigate the role of *EIL* relative to other risk factors and bond characteristics in bond pricing. Table 6 reports the time-series average for each estimated γ, representing the risk premium per standard deviation of each variable, and the corresponding *t* value. Used alone, *EIL* has a positive coefficient (0.16), which is highly significant ($t = 5.18$). In terms of economic magnitude, a one standard deviation increase in *EIL* raises the bond expected return by 16 bps per month (or 1.92% per annum). The coefficient on *EIL* remains significant at the 1% level after controlling for illiquidity, return reversals and all other variables. The results strongly suggest that extreme illiquidity is priced in the cross-section of corporate bond returns.

3.3.3. Firm level analysis

The number of bonds issued by a firm exhibits significant cross-sectional variations. Bonds issued by the same firm are exposed to the same fundamental conditions, information flows, and firm-specific risks. Large firms commonly issue a large number of bonds, which may bias our results in bond-level regressions. As these firms are overweighted, the results may not represent the whole universe of bond issuers.

[10] When estimating betas, we add lagged *LIQ* into the rolling regression and use the sum of the coefficients of two liquidity terms as liquidity risk (beta) to account for the potential nonsynchronous trading effect and lagged response in the corporate bond market which is known to be less liquid. Internet Appendix C repeats the Fama-MacBeth regressions controlling for FF-BBW7 factors. The results are robust.

To address this concern, we construct a firm-level sample by aggregating bonds issued by the same issuer. Each month, we calculate the value-weighted bond returns and characteristics (*ILLIQ*, time to maturity, age, coupon rate, issue size, and rating) using the values of bonds outstanding as weights for all bonds issued by the same firm. Internet Appendix D shows the results of the portfolio and regression analyses using this firm-level sample. We continue to find significant *EIL* premiums in both analyses, suggesting that our finding is robust to sampling at the firm level.

3.4. Variations across securities and over time

In this section, we explore the variation of the *EIL* pricing across securities (with different rollover risk of firms) and over time (periods of normal/crisis, high/low uncertainty, and high/low sentiment).

3.4.1. EIL and issuer's rollover risk

Firms need to refinance or issue debts periodically to continue their operations or to finance new investment projects. Firms may face difficulties in rolling over their maturing debts or obtaining new financing when credit market conditions deteriorate. In the extreme case, when market liquidity dries up, as manifested during the subprime crisis, the funding market can completely shut down. Rollover risk increases not only the liquidity premium of debts but also credit risk (He and Xiong, 2012). When liquidity frictions are high, the likelihood that firms cannot refinance their debt is high or, even if they can refinance it, the new debt will be priced at unfavorable interest rates or contracted with more stringent loan terms. These factors can endogenously increase firms' default probability and losses, which increases the risk premium of their bonds.

To test whether the *EIL* premium varies across securities, we incorporate rollover risk into the cross-sectional regression. We define *Short* as the ratio of firms' debts due within one year to their total assets of the last fiscal year from the Compustat database. We create a dummy variable D_{short} that equals one when a firm's short-term debt ratio is higher than the median (or mean) of the cross-sectional firms each month. We then include an interaction variable $D_{short}\times EIL$ in the regression to explore whether *EIL* has a stronger effect on the bonds issued by firms with higher rollover risk.

[Insert Table 7 around here]

Table 7 reports the cross-sectional regression results. The coefficient of $D_{short}\times EIL$ is 0.05 (0.07) and is significant at the 5% level when the rollover dummy is defined based on the cross-sectional median (mean) in the regression with controls for all risk and characteristic variables. The results suggest that extreme illiquidity can significantly increase expected corporate bond returns through the channel of rollover risk.

3.4.2. EIL pricing for investors with different trading needs

EIL reflects the transaction cost during market liquidity deterioration, which is supposed to be more important for investors who need to trade regularly. Following the literature, we treat mutual funds as active investors and insurance companies as passive investors in the corporate bond market. Active investors trade more frequently than passive investors. We obtain the information of institutional bond investors from the eMAXX database. Using this information, we test the hypothesis that the pricing of *EIL* is more important for mutual funds, which have more trading needs than for insurance companies.

Table 8 reports the results of cross-sectional regression to test the clientele effect. In Panel A, we introduce a dummy variable D_{Mutual} which takes a value of one if a bond is held by mutual funds and zero otherwise. To identify the effect of *EIL* for mutual funds, we include an interaction variable $D_{Mutual}\times EIL$ in the regression. The results show that both *EIL* and $D_{Mutual}\times EIL$ have a significant and positive coefficient. The significantly positive coefficient of the interaction variable suggests that the pricing of *EIL* is more important for active investors like mutual funds, which need to trade even when the market is hit by liquidity shocks. We also find evidence that holding by insurance companies reduces the premium for *EIL*, as in Panel B.

In panel B of Table 8, we run the cross-sectional regression with a similar setup to identify the effect of *EIL* for insurance companies. Here, we set a dummy variable $D_{Insurance}$, which equals one if a bond is held by insurance companies and zero otherwise, and include an interaction variable $D_{Insurance}\times EIL$ in the regression. The results again show that *EIL* commands a significantly positive premium. Consistent with passive investors having less need for trading and therefore being less susceptible to liquidity shocks, the coefficient of the interaction variable $D_{Insurance}\times EIL$ is significantly negative, indicating that the *EIL* premium is less pronounced for inactive investors.

[Insert Table 8 around here]

3.4.3. Normal vs. crisis periods

During a financial crisis, liquidity squeezes and possible fire sales subject investors to potentially much larger losses. Thus, corporate bonds are likely to carry a higher *EIL* premium during a crisis period. In the subprime crisis, market conditions started to deteriorate significantly in December 2007. We set the period from December 2007 to January 2009 as the crisis period and the other months in the sample as the normal period. We then conduct cross-sectional tests for these two subperiods separately.

Panel A of Table 9 reports the results of cross-sectional regressions for the crisis and normal periods, respectively. The size of the *EIL* coefficient for the crisis period is 29% (or 2 percentage points) higher than that for the normal period, consistent with liquidity costs being much higher in the corporate bond market during the subprime crisis (Ellul et al., 2011).

[Insert Table 9 around here]

3.4.4. High uncertainty vs. low uncertainty periods

Policy uncertainty increases the risk premium of assets (Pastor and Veronesi, 2013). When policy uncertainty is high, investors are likely to become more risk-averse to the losses caused by extreme illiquidity and require a larger premium to compensate for this risk. To investigate this possibility, we use the economic policy uncertainty (EPU) index constructed by Baker et al. (2016) to measure policy uncertainty and examine the effect of *EIL* in different regimes. Specifically, we divide the whole sample period into high and low policy uncertainty periods by the median of the EPU index and run the tests for these two periods. Panel B of Table 9 reports the results of cross-sectional regressions for high and low policy uncertainty periods. Consistent with investors being more risk-averse when faced with high uncertainty, the risk premium of extreme illiquidity increases substantially during periods of high policy uncertainty.

Similarly, economic uncertainty can lead to an increase in the risk premium of assets (Bekaert et al., 2021; see also Jurado, Ludvigson, and Ng, 2015). To test whether the risk premium of extreme illiquidity increases during periods of high economic uncertainty, we use the economic uncertainty index constructed by Bekaert et al. (2021) to measure market uncertainty. Again, we use the median of the index series as a cutoff for high and low periods of economic uncertainty. Panel C of Table 9 shows that the *EIL* coefficient in the cross-sectional regression increases from 0.06 to 0.08, or about one-third when economic uncertainty is high. The results suggest that investors require a higher premium to bear the risk of liquidity deterioration when economic conditions become more uncertain.

3.4.5. High sentiment vs. low sentiment periods

Investor sentiment affects asset returns (Baker and Wurgler, 2006; Baker, Wurgler, and Yuan, 2012; Cepni, Guney, Gupta, and Wohar, 2020). During the high sentiment period, investors become less risk-averse even though the prospect for future returns is unlikely to be as high as in the recent past. In a high sentiment period, investors are likely to require a lower *EIL* premium as they think asset prices will continue to increase and there is no liquidation need. To investigate this possibility, we divide the whole sample period into two periods by the median value of the Baker-Wurgler (2006) sentiment index and run the cross-sectional regression for each period separately.[11] Panel D of Table 9 reports the Fama-MacBeth regression results for the high and low sentiment periods. Indeed, the results show that investors require a lower risk premium of extreme illiquidity when market sentiment is high. This finding is consistent with the investor sentiment literature that investors become less risk-averse during high sentiment periods.

4. An *EIL* factor in the corporate bond market

In this section, we construct a tradable *EIL* factor. We first examine whether this factor can be explained by conventional stock and bond market factors. We then investigate the ability of the *EIL* factor to explain the expected returns of test portfolios of corporate bonds following Lewellen et al. (2010). Finally, we run a test of horserace between *EIL* beta and *EIL* to study whether the pricing of *EIL* for corporate bonds is through a systematic risk channel.

4.1. Summary statistics and alphas on the tradable *EIL* factor

Based on the results in Table 3, we construct a tradable *EIL* factor of corporate bonds from the long-short (10-1) portfolios sorted by *EIL*. The mean return of the *EIL* factor is 0.56%, which is significant at the 1% level with a t value of 5.41 (as in Table 3).[12] Panel A of Table 10 provides

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[11] The sentiment index data are downloaded from Jeffrey Wurgler's website https://pages.stern.nyu.edu/~jwurgler/, which ends in December 2018.

[12] We also adopt four alternative methods to construct the *EIL* factor based on the idea of dependent portfolio sort: (1) 5×5 bivariate sorts on liquidity risk (β_{LIQ}) and *EIL*, (2) 3×3×3 tri-variate sorts on liquidity risk (β_{LIQ}), illiquidity (*ILLIQ*), and *EIL*, (3) 4×5 bivariate sorts on rating (AAA/AA, A, BBB, and Junk) and *EIL*, and (4) 4×3×3 tri-variate

summary statistics of the tradable *EIL* factor.

Panel B of Table 10 reports the alphas of the *EIL* factor returns estimated from eleven alternative factor models, which cover all well-known risk factors in the literature.[13] The results show that alphas are highly significant across the board. The results suggest that the *EIL* factor captures an important source of risk in corporate bond returns, which is missing from the conventional factor models.

[Insert Table 10 around here]

4.2. *EIL* as a risk factor

We next examine whether the *EIL* factor is a systematic risk factor priced in the cross-section of corporate bonds. In light of the literature, we evaluate the relative performance of two factor models: (a) the base model, which includes the five stock market factors (*MKT*, *SMB*, *HML*, MOM^{Stock}, and LIQ^{Stock}), and the BBW4 four bond market factors (*MKTb*, *DRF*, *CRF*, and *LRF*), and (b) the base model augmented by the tradable *EIL* factor.

[Insert Table 11 around here]

We first conduct the portfolio sorts independently by size and maturity and use the resulting 5×5 portfolios as test portfolios. Panel A of Table 11 reports various performance measures for the time-series regressions of excess returns on the two different factor models. Incorporating the tradable *EIL* factor reduces the average absolute alpha across the 25 portfolios from 0.199% to 0.113% per month. Although the two models both fail the GRS test (Gibbons, Ross, and Shanken, 1989), the augmented model performs much better. The GRS statistic drops from 8.12 to 5.54 after

sorts on rating (AAA/AA, A, BBB, and Junk), illiquidity (*ILLIQ*), and *EIL*. The details can be found in Internet Appendix E. The results in Section 4 are robust to the *EIL* factors constructed by different methods.

13 The profitability (*RMW*), investment (*CMA*), and momentum (MOM^{Stock}) factors are obtained from Kenneth R. French's data library (Fama and French, 2015). The stock market liquidity factor (LIQ^{Stock}) is obtained from Robert F. Stambaugh's website.

incorporating the *EIL* factor. Figure 3 presents the 95% confidence intervals of the alphas of the 25 test portfolios. Incorporating the *EIL* factor decreases the values of alphas (22 out of 25 portfolios) and generates insignificant alphas for 15 out of 25 portfolios, whereas 21 out of 25 portfolios have significant alphas for the base model.

[Insert Figure 3 around here]

We report three additional model performance measures in Columns (4) to (6) of Table 11. $A|\alpha_i|/A|\bar{r}_i|$ is the average absolute value of the intercepts over the average absolute value of $\bar{r}_i$, which is the average excess return on portfolio i minus the average excess return on the bond market portfolio *MKTb*, and $A\alpha_i^2/A\bar{r}_i^2$ which is the average squared intercept over the average squared value of $\bar{r}_i$. These two ratios are essentially scaling variables that measure the dispersion of the intercept (alpha) relative to the average deviation of portfolio returns from the benchmark bond market returns. A lower value of these ratios signals a better performance of an asset pricing model, as it indicates that the dispersion of intercepts or portfolio returns left unexplained by the model is low relative to the dispersion of portfolio average returns. AR^2 in Column (6) is the average value of regression R^2 adjusted for degrees of freedom, which measures the ability of a model to explain variations in portfolio returns.

The two ratios $A|\alpha_i|/A|\bar{r}_i|$ and $A\alpha_i^2/A\bar{r}_i^2$ have values of 0.71 and 0.63 for the *EIL*-augmented model and 1.25 and 1.55 for the base model. In other words, the two ratios drop by 43% and 59%, respectively. The results indicate that the model with the *EIL* factor delivers superior performance. The AR^2 value increases from 71% to 75%, which also points to a better performance of the *EIL*-augmented model.

Lewellen et al. (2010) point out that characteristic-sorted portfolios may not have sufficient independent variations in the loadings of factors constructed with the same characteristics.

Therefore, the evidence of the strong explanatory power of a newly proposed model from asset pricing tests could be spurious. One solution to this problem is to include additional portfolios sorted by other characteristics, industry, or factor loadings. Based on this idea, we form three alternative sets of test portfolios to investigate the explanatory power of the factor models: 5×5 portfolios sorted independently by size and rating, 12 industry portfolios based on Fama and French (1997) industry classifications, and 25 portfolios sorted by the loadings on the *EIL* factor.

The results show a similar pattern for the test portfolios sorted by size/rating, industry, and *EIL* loadings. In Panel E, in which we include all 87 portfolios, adding the *EIL* factor to the base model decreases the average absolute value of the monthly alpha from 0.173% to 0.110%, and $A|\alpha_i|/A|\bar{r}_i|$ $(A\alpha_i^2/A\bar{r}_i^2)$ drops from 1.30 to 0.82 (from 1.42 to 0.69).

4.3. *EIL* characteristic or beta?

The finding that the *EIL* factor has explanatory power rekindles the issue of "characteristics versus covariances". In the literature, there has been much controversy over whether individual firm characteristics or factor loadings are more relevant in explaining the cross-section of asset returns. Daniel and Titman (1997) argue that firm characteristics are more important than factor loadings in explaining the cross-section of average stock returns, whereas Davis, Fama, and French (2000) contend that firm characteristics such as size and B/M ratios are just proxies of factor loadings (betas) on priced risk factors. In the corporate bond market, Gebhardt et al. (2005) find that betas of bond market factors better explain expected bond returns than characteristics such as duration, ratings, and yields to maturity. Using more recent data, Chung et al. (2019) also find that factor loadings are more important than bond characteristics in explaining expected corporate bond returns in the cross-section.

The mixed evidence in the literature highlights the importance of differentiating the role of

EIL as a characteristic versus a risk factor. In this section, we evaluate how the *EIL* factor loading and *EIL* characteristic fare against one another in explaining the cross-section of bond returns. We estimate β_{EIL} by regressing bond excess returns on the tradable *EIL* factor controlling for ratings over a rolling 60-month window,[14] and compare its explanatory power with that of *EIL* as a characteristic. Table 12 reports the results of regressions with a horserace between β_{EIL} and *EIL* characteristic. Used alone, β_{EIL} is significant at the conventional level. However, once controlling for the effect of *EIL*, β_{EIL} becomes insignificant while *EIL* remains highly significant. The results show that *EIL*, as a characteristic, has higher explanatory power in the cross-section than *EIL* as a covariance risk. It suggests that the persistent difference in the extreme liquidity cost plays a more important role in determining the required return of corporate bonds. We discuss this issue further in Section 5, in which we argue that the difference in transaction costs leads to changes in investor composition, which is the fundamental force driving the *EIL* premium.

[Insert Table 12 around here]

5. Economic channels

The analysis in Sections 3 and 4 shows that *EIL* is priced in the cross-section of corporate bonds. In this section, we explore the economic channel behind *EIL* pricing.

5.1. Comparison with "*ILLIQ*" and "*DOWN*"

The construction of *EIL* renders itself closely related to two characteristics that are found to explain the cross-sectional dispersion in bond returns: *ILLIQ* and *DOWN*.[15] As such, we first rule out the possibility that *EIL* is priced simply due to its correlation with them.

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[14] The tradable *EIL* factor is constructed by 4×5 dependent bivariate sorts of rating (AAA/AA, A, BBB, and Junk) and *EIL*. Complimenting Table 12, Internet Appendix F contains results for the alternative measurement of β_{EIL}, which controls for other sets of common risk factors (FFL6 or FF-BBW7 factors augmented with tradable *EIL* factor) in the rolling estimation. The finding is robust to different specifications.

[15] Based on *ILLIQ* and *DOWN*, the literature proposes two corresponding risk factors, which are *LIQ* and *DRF*. In the following analysis, we also control for the exposure to these risk factors.

5.1.1. Amihud ILLIQ measure

By construction, *EIL* and *ILLIQ* are naturally correlated.[16] As an example, if *ILLIQ* follows an exponential distribution, the 95th percentile of *ILLIQ* will be proportional to its mean. Therefore, *EIL* could (noisily) contain the effect of *ILLIQ*. However, we argue that *EIL* and *ILLIQ* represent different facets of illiquidity: *ILLIQ* measures the average transaction cost, whereas *EIL* captures the unusual trading cost arising from severe deterioration in liquidity. In the preceding analysis, we control for *ILLIQ* and systematic liquidity risk (β_{LIQ}) in portfolio sorts and Fama-Macbeth regressions. The results show that *EIL* commands a premium that is robust to controlling for the routine illiquidity and liquidity risk exposure. However, linear control for a variable is not always sufficient. Below we perform a battery of additional tests to disentangle *EIL* and *ILLIQ* effects.

First, we orthogonalize the effect of *ILLIQ* (month-by-month cross-sectionally) by regressing *EIL* against the most recent *ILLIQ* and the rolling first and second moments of *ILLIQ*. We then use the residual-*EIL* to sort the bonds into deciles. We find that the 10-1 return and alpha spreads continue to be significant.[17] The results suggest that *EIL* contains important information over and beyond *ILLIQ*.

We also conduct a "placebo" test where we use the rolling median *ILLIQ* (instead of the 95th percentile) to calculate *EIL*. If *EIL* is a proxy for *ILLIQ*, the median should contain much less noise than the 95th percentile. On the contrary, we find that the median-*EIL* is no longer significant in the Fama-MacBeth regression when controlling for *ILLIQ*.[18] This finding is heartening and reaffirms that *EIL* contains important information in the right tail of transaction cost distribution.

Our "smoking gun" evidence is an economic test that takes advantage of the finite maturity

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[16] The Spearman/Pearson correlation coefficient is 0.69/0.48 as in Table 1 Panel D.

[17] The average excess return of the 10-1 portfolio is 0.20% (t = 2.68), and the alphas are 0.18% (t = 2.39), 0.17% (t = 2.25), 0.15% (t = 2.42), and 0.16% (t = 2.47) relative to FF5, FFL6, BBW4, and FF-BBW7 factor models, respectively.

[18] *ILLIQ* is still significantly positive at the 5% level. The results are available upon request.

of corporate bonds. Consider an investor who may need to sell a bond at some point before its maturity. If the bond has a long maturity, the effect of normal illiquidity *ILLIQ* on the per-period return (i.e., yield) should be lower because the transaction cost is averaged out, as argued by Amihud and Mendelson (1991). However, if there is a probability that transaction costs may increase sharply and remain elevated, this probability is greater when bond maturity is longer. Therefore, the effect of extreme illiquidity *EIL* on yields may not be a decreasing function of maturity. Formally, we run the following regression:

$$Yield_t^i = a_1 \cdot ILLIQ_t^i + a_2 \cdot \frac{ILLIQ_t^i}{Maturity_t^i} + b_1 \cdot EIL_t^i + b_2 \cdot \frac{EIL_t^i}{Maturity_t^i} + \delta Z_t^i + \varepsilon_t^i,$$

where $Yield_t^i$ is the yield to maturity of bond i.[19] In Table 13 Panel A, we find that $a_2 > 0$, which is consistent with the argument of Amihud and Mendelson (1991). On the other hand, b_2 is not significant. The results show that the effect of *EIL* does not decrease with bond maturity.[20] This finding highlights the economic difference between *EIL* and *ILLIQ* in affecting bond prices.

[Insert Table 13 around here]

5.1.2. Downside risk

The literature has also suggested that downside risk "*DOWN*" is a determinant of corporate bond returns. Bai et al. (2019) use the 5% VaR rule[21] similar to ours to construct the *DOWN* measure. We could use the same orthogonal method as in the case of *ILLIQ* to control for the effect of *DOWN*. But we find that downside risk is essentially orthogonal to the pricing of *EIL*. In Table 13 Panel B1, we conduct 5×5 bivariate sorts first on *DOWN* and then on *EIL*. We see a clear

[19] Since the left-hand side now is yield, which is more persistent than return, we use 12-lag Newey-West adjustment.
[20] In Table 13, each regressor is normalized by the cross-sectional standard deviation each month. Our results are robust if we don't scale the variables.
[21] Bai et al. (2019) use the second-lowest monthly return observation over the past 36 months. We use the third-lowest return over the past 60 months to be consistent with the construction of *EIL*. The results are similar if we use Bai et al. (2019) definition. Bai et al. (2019) include callable bonds which do not materially change our results.

monotonic relationship between return and *EIL* within *each DOWN* quintile. On the other hand, the return is also increasing with *DOWN*, consistent with Bai et al. (2019) [22]. In Panel B2, we run the Fama-MacBeth regressions with controls for downside risk both as characteristic (*DOWN*) and systematic risk (β_{DRF}). The results show that neither of them materially affects the coefficient on *EIL* and *EIL* continues to carry a significant premium. Thus, the *EIL* effect is not a proxy for the downside risk effect.

5.2. The clientele channel

We show earlier that the *EIL* characteristic is priced and the *EIL* premium is more pronounced if the bond is held by mutual funds. In this section, we formally test the clientele channel for the *EIL* pricing economic mechanism. We argue that active investors dislike bonds with extreme illiquidity, which lowers the price and increases the required return of a bond with high *EIL*.

We use the eMAXX dataset, which covers holdings of over 7,000 buy-side firms with more than $USD 19 trillion in assets under management by North American and European insurance companies, pension funds, and mutual funds. Following Dass and Massa (2014), we use the managing firm-level classification provided in eMAXX to determine the type of institutional investors in our sample. Specifically, mutual funds are identified by the classification code MUT, while insurance companies are identified by the classification codes ILF, IMD, IND, IPC, and REI.

Figure 4 compares the average mutual fund holdings[23] of low and high *EIL* bonds versus insurance companies. Mutual funds show a clear preference for low *EIL* bonds, which they can

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[22] In Table 5, we also report the 5×5 bivariate sort results first on downside risk exposure (β_{DRF}) and then on *EIL*. β_{DRF} is estimated by regressing bond excess returns on the *DRF* factor in the 5-year rolling window. The results show that all the 5-1 and Avg portfolio returns/alphas are positive and highly significant.

[23] To calculate mutual fund (insurance company) holding, for each quarter, we sum up the amounts held by all mutual funds (insurance companies) for a bond in each quarter, divided by the bond's total outstanding value. If a bond in one quarter doesn't have holding records in eMAXX by either a mutual fund or insurance company, we delete the observation.

easily dispose of in times of stress. The difference is even starker after 2010 when mutual funds gradually increase the holding of low *EIL* bonds while shy away from high *EIL* bonds years afterward.[24]

[Insert Figure 4 around here]

Tables 14 and 15 formally test the clientele channel, controlling for the common characteristics and covariances. The dependent variable in Table 14 is the amount held by mutual funds divided by the bond's total outstanding value (in percentage points). We find quantitatively similar results using the Fama-MacBeth method and pooled OLS method, which suggest that *EIL* discourages mutual fund holdings. Indeed, the magnitude is broadly in line with Figure 4.

[Insert Tables 14 and 15 around here]

We also use three alternative measures of an institutional investor's holdings. In Table 15, we use (1) *Investor's Portfolio-Weighted Dummy*, which is a dummy variable indicating whether an investor holds this bond in a given quarter; (2) *Investor's Portfolio Weight*, which is the rating adjusted percentage of an institutional investor's portfolio invested in a bond in a given quarter,[25] and (3) *Investor's Overweighting*, which is the difference between the weight that an investor assigns to a bond in its portfolio within the same rating category and the market weight of the bond in a portfolio consisting of all outstanding bonds within the same rating category.[26] When using the dummy dependent variable, we estimate the coefficients with a logistic regression model. Otherwise, we conduct a pooled OLS regression. The errors are clustered at the institutional investor level with a quarter-fixed effect. We repeat the analysis using these three measures for

[24] Internet Appendix G repeats a similar analysis by rating and by size. We find the same pattern for all ratings except for junk bonds and that the effect concentrates in large bonds, consistent with the ideas of flight-to-quality and flight-to-liquidity.

[25] It is calculated every quarter as the ratio (in percentage points) of the investment by an institutional investor in a bond to all the bonds in the same rating category that this investor holds in the portfolio; it is defined only when the institutional investor's bond holding is positive.

[26] It is defined only when the investor's bond holding is positive.

both mutual funds (Panel A) and insurance companies (Panel B). Both the results for mutual funds and insurance companies are significant and consistent with our clientele channel hypothesis. Active investors, such as mutual funds, avoid holding bonds with high *EIL*, which results in lower prices and higher expected returns for these bonds. On the other hand, passive investors overweight high *EIL* bonds to benefit from the higher illiquidity premium.

6. Conclusion

In this paper, we document evidence that corporate bonds carry a significant premium of extreme illiquidity. The premium is time-varying, which increases during the financial crisis and periods of high economic uncertainty and low investor sentiment. Extreme illiquidity is priced in all rating categories and bonds of different characteristics, suggesting that its effect is not limited to a particular segment of the corporate bond universe. The effect of extreme illiquidity on expected bond returns is robust to controlling for stock and bond market risk factors and bond characteristics. This effect is stronger when firms face rollover risk.

Constructing a tradable factor based on *EIL*, we find that conventional stock and bond market factors cannot explain the *EIL* factor variation. Adding the *EIL* factor to an inclusive factor model significantly improves its explanatory power in the cross-section for corporate bond returns. However, we find that the coefficient of *EIL* beta becomes insignificant when we control for the effect of bond-specific *EIL* in a horserace cross-sectional regression.

EIL contains different information than conventional illiquidity and downside risk measures. The effect of *EIL* is robust to controlling for these variables. Moreover, we find that active investors such as mutual funds avoid holding bonds which may become difficult to trade when liquidity deteriorates. The lower demand for high *EIL* bonds decreases their prices, leading to a higher *EIL* premium for these bonds.

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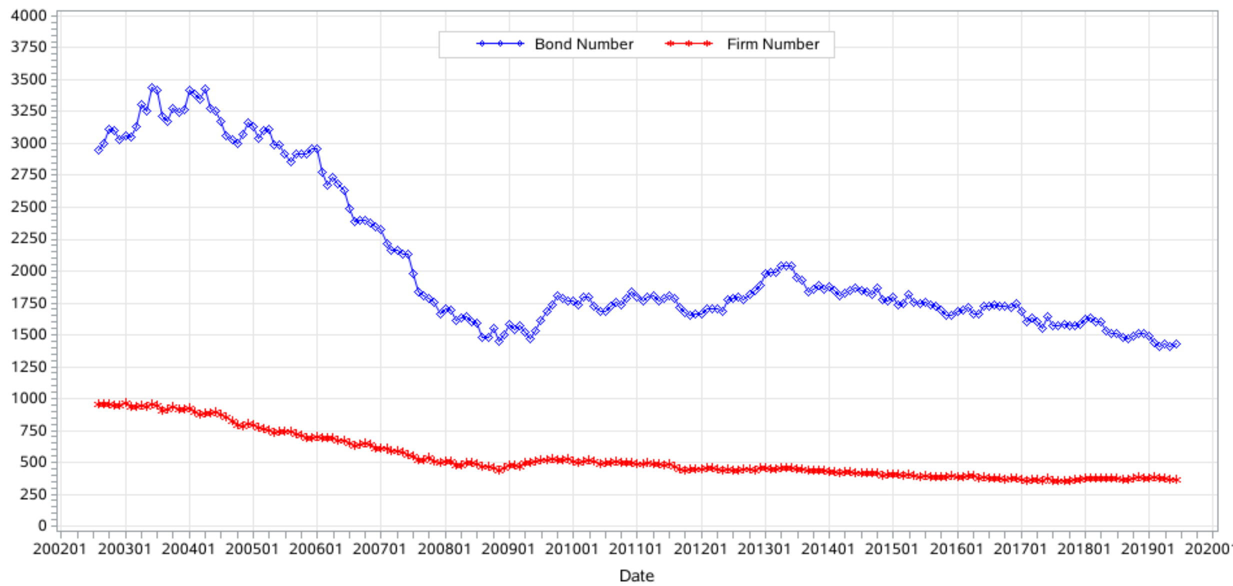


Figure 1. Numbers of bonds and firms for the full sample (July 2002 – June 2019)
This figure plots the monthly time series of the number of bonds and firms in the sample period from July 2002 to June 2019.

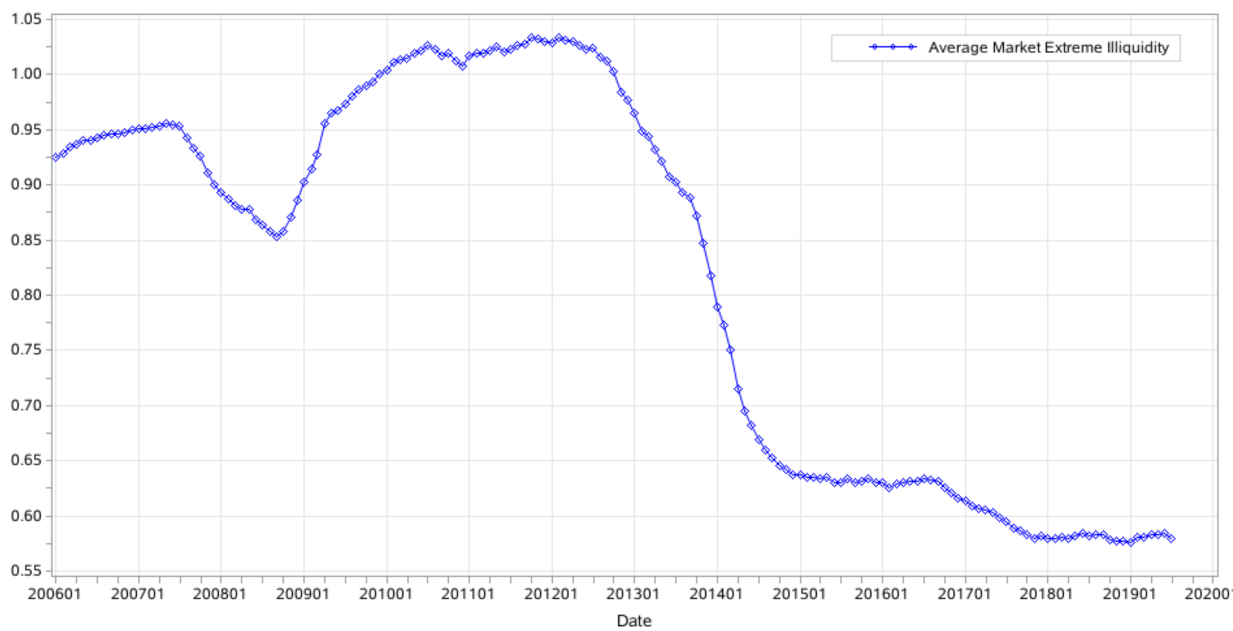


Figure 2. Average extreme illiquidity across all bonds from January 2006 to June 2019
This figure plots the average extreme illiquidity (*EIL*) across all bonds in each month from January 2006 to June 2019. The *EIL* is measured by the third-highest monthly Amihud (2002) illiquidity over the past 5 years.

Alphas of 25-size/maturity-sorted bond portfolios

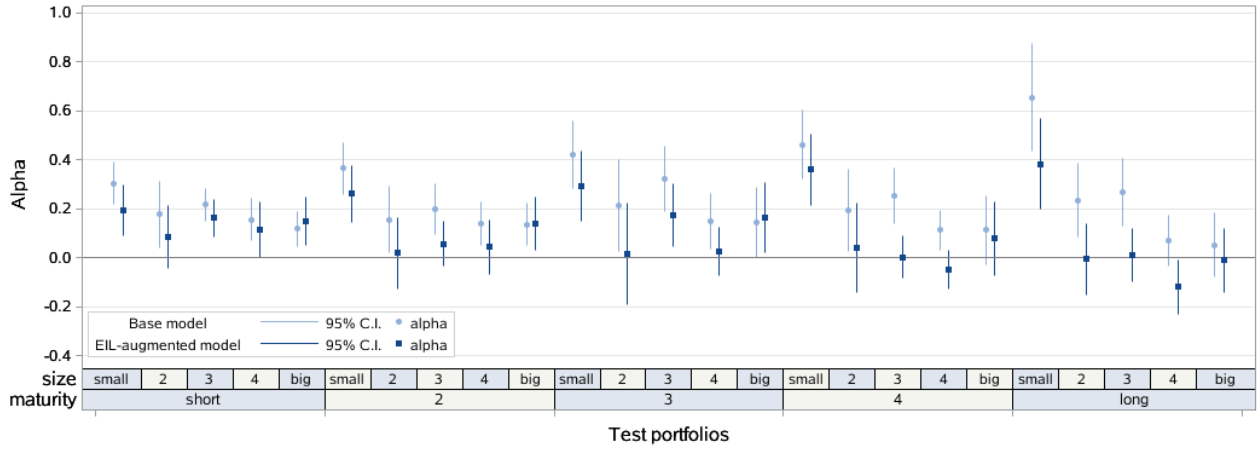
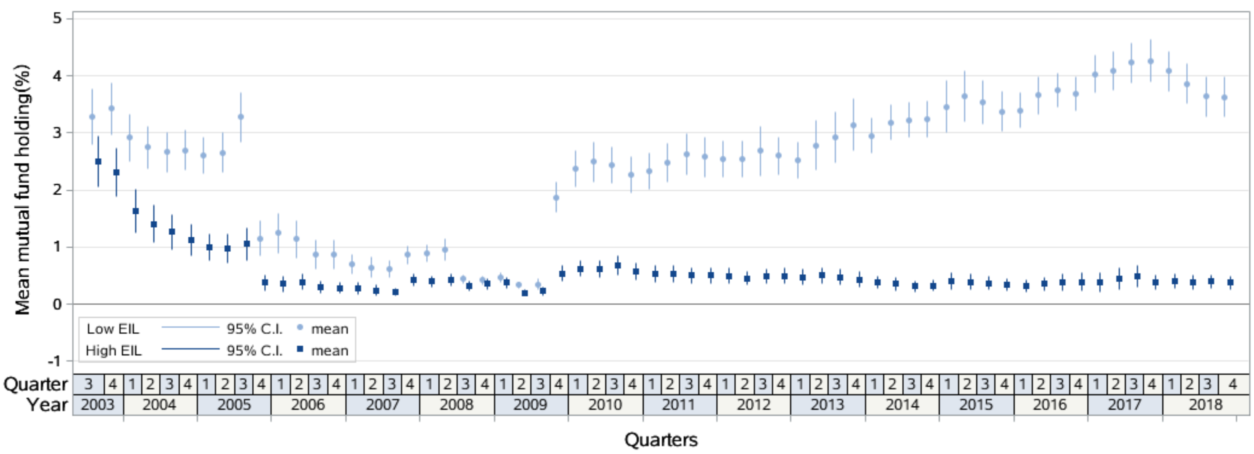


Figure 3. Alphas of alternative test portfolios

This figure presents the 95% confidence interval of alphas of an alternative set of test portfolios, which are 5×5 independently sorted by bond issue size and maturity, relative to the two different factor models in Table 11.

Panel A: Mean mutual fund holdings for high and low *EIL* bonds



Panel B: Mean insurance company holdings for high and low *EIL* bonds

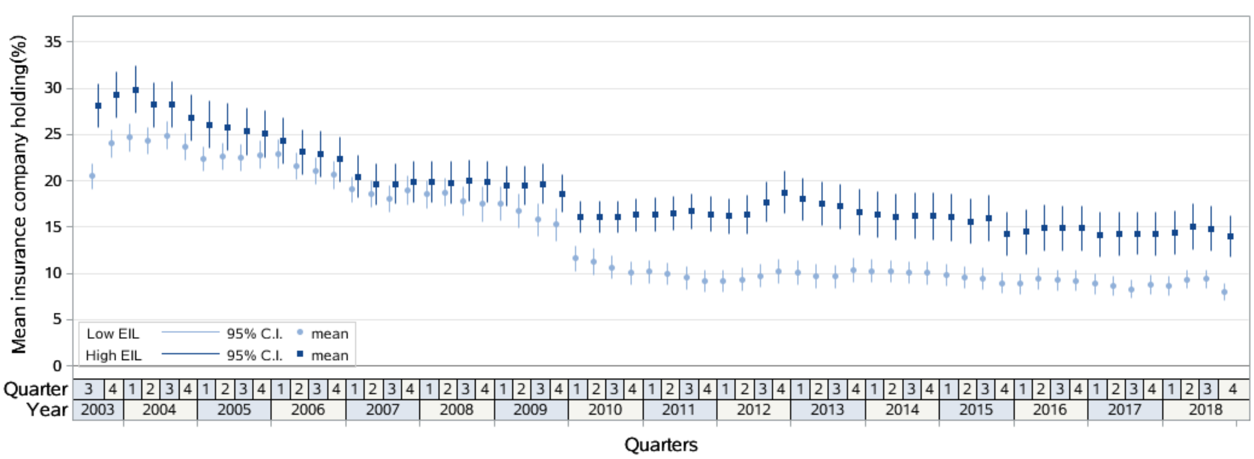


Figure 4. Investors' holdings for high and low *EIL* bonds

This figure presents the 95% confidence interval of mean holdings for high and low *EIL* bond groups in each quarter. Panel A: Mutual funds; Panel B: Insurance companies.

Table 1. Summary statistics and correlations

Panel A reports the time-series averages of the cross-sectional statistics of corporate bond characteristics. *Coupon* is the coupon rate. *Size* is the issue size in billions of dollars. *Rating* is the Moody's bond rating (Aaa=0, Aa+=1, …, C=20, and D=21), and if the Moody's rating is unavailable, we use the S&P rating whenever possible. *Age* is the number of years since issuance. *Maturity* is years to maturity. Panel B reports summary statistics for the monthly risk factors. *MKT, SMB,* and *HML* are the Fama-French three factors downloaded from Kenneth French's data library. The default factor (*DEF*) is the difference between the return of a value-weighted portfolio of all long-term investment-grade bonds in the sample and the return of long-term government bonds. The term factor (*TERM*) is the difference between the long-term government bond return and the one-month T-bill rate. *LIQ* is the Amihud corporate bond liquidity factor based on Lin, Wang, and Wu (2019). Panel C summarizes the cross-sectional statistics of bond returns, extreme illiquidity (*EIL*), which is the third-highest monthly illiquidity over the past rolling 5 years, and betas for individual bonds obtained from time-series regression of excess returns on risk factors using a five-year rolling window. *Return* is the bond monthly *Raw Return* in excess of one-month T-bill rates. Panel D reports the time-series average of the cross-sectional pairwise correlations (upper triangle: Pearson correlations; lower triangle: Spearman correlations). *REV* is the return and *ILLIQ* is the Amihud (2002) illiquidity measure in the end month of the rolling window. The factors and returns are in percentage points. The sample period is from July 2002 to June 2019 from the enhanced TRACE database.

Panel A: Summary statistics of bond characteristics

	Mean	Std. Dev.	Median	Q1	Q3
Coupon	5.45	1.71	5.29	4.29	6.50
Size	0.52	4.47	0.12	0.01	0.49
Rating	6.07	3.36	5.72	3.83	7.58
Age	6.02	5.46	4.12	2.07	7.93
Maturity	6.97	6.18	4.86	2.55	9.03

Panel B: Summary statistics of conventional factors

	Mean	Std. Dev.	Median	Q1	Q3
MKT	0.73	4.18	1.18	-1.43	3.24
SMB	0.14	2.43	0.17	-1.45	1.79
HML	-0.07	2.46	-0.23	-1.40	1.29
DEF	0.29	1.72	0.29	-0.64	1.37
TERM	0.32	1.99	0.19	-0.77	1.41
LIQ	0.00	0.06	0.01	-0.02	0.03

Panel C: Summary statistics of returns, extreme illiquidity, and betas

	Mean	Std. Dev.	Median	Q1	Q3
Raw Return	0.62	2.08	0.50	-0.40	1.58
Return	0.52	2.08	0.40	-0.50	1.48
EIL	0.82	0.78	0.67	0.21	1.17
β_{MKT}	0.02	0.22	0.02	-0.07	0.10
β_{SMB}	0.02	0.24	0.00	-0.10	0.12
β_{HML}	0.01	0.27	0.00	-0.11	0.11
β_{DEF}	0.16	0.51	0.08	-0.13	0.40
β_{TERM}	0.41	0.39	0.35	0.17	0.62
β_{LIQ}	0.29	2.09	0.21	-0.67	1.17

Panel D: Correlations

S \ P	β_{MKT}	β_{SMB}	β_{HML}	β_{DEF}	β_{TERM}	β_{LIQ}	*EIL*	*REV*	*ILLIQ*	*Coupon*	*Size*	*Rating*	*Age*	*Maturity*
β_{MKT}		-0.28	0.11	-0.35	0.04	-0.09	-0.02	0.00	-0.05	0.12	0.14	0.23	0.07	-0.01
β_{SMB}	-0.27		0.01	0.07	0.08	0.03	0.08	0.00	0.06	0.03	-0.10	0.08	0.03	-0.02
β_{HML}	0.06	0.01		-0.18	0.08	0.03	0.08	0.00	0.05	0.06	-0.05	0.16	0.03	0.01
β_{DEF}	-0.32	0.06	-0.15		0.00	-0.08	0.11	0.05	0.05	0.14	-0.02	0.29	0.01	0.18
β_{TERM}	0.06	0.08	0.05	-0.01		-0.08	-0.05	0.00	-0.04	0.19	0.25	-0.11	0.13	0.47
β_{LIQ}	-0.07	0.02	0.01	-0.07	-0.06		0.13	0.01	0.09	0.10	-0.12	0.19	0.09	0.01
EIL	-0.10	0.10	0.06	0.16	-0.01	0.16		0.09	0.48	0.31	-0.54	0.28	0.35	0.24
REV	-0.01	0.01	0.01	0.06	0.03	0.01	0.09		0.05	0.05	-0.05	0.08	0.02	0.06
ILLIQ	-0.11	0.08	0.06	0.10	-0.01	0.16	0.69	0.08		0.13	-0.37	0.13	0.12	0.20
Coupon	0.08	0.04	0.04	0.17	0.23	0.13	0.31	0.05	0.19		0.07	0.42	0.75	0.29
Size	0.15	-0.12	-0.06	-0.06	0.27	-0.15	-0.71	-0.06	-0.63	0.04		0.01	0.08	0.00
Rating	0.13	0.11	0.13	0.33	-0.03	0.19	0.23	0.08	0.15	0.41	-0.04		0.28	0.07
Age	0.03	0.04	-0.01	0.06	0.15	0.10	0.40	0.02	0.20	0.75	-0.03	0.25		0.18
Maturity	-0.01	-0.03	-0.01	0.14	0.52	0.04	0.30	0.09	0.31	0.34	-0.03	0.07	0.14	

Table 2. *EIL* transition matrices

The extreme illiquidity (*EIL*) is the third-highest monthly Amihud (2002) illiquidity over the past 60 months. This table reports the transition matrix of *EIL* over the next month (Panel A), the next six months (Panel B), and the next year (Panel C). In each cross-section, we first sort *EIL* into deciles and calculate transition matrices over the period and then take the average of the transition matrices.

Panel A: Transition matrix of *EIL* over the next month

EIL decile	*EIL* decile in month $t+1$									
in month t	1	2	3	4	5	6	7	8	9	10
1	0.98	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	0.01	0.97	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3	0.00	0.02	0.96	0.02	0.00	0.00	0.00	0.00	0	0.00
4	0.00	0.00	0.03	0.94	0.02	0.00	0.00	0.00	0.00	0.00
5	0.00	0.00	0.00	0.04	0.93	0.03	0.00	0.00	0.00	0.00
6	0.00	0.00	0.00	0.00	0.04	0.92	0.03	0.00	0.00	0.00
7	0.00	0.00	0.00	0.00	0.01	0.04	0.92	0.03	0.00	0.00
8	0.00	0.00	0.00	0.00	0.00	0.01	0.04	0.93	0.03	0.00
9	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.03	0.94	0.02
10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.97

Panel B: Transition matrix of *EIL* over the next six months

EIL decile	*EIL* decile in month $t+6$									
in month t	1	2	3	4	5	6	7	8	9	10
1	0.91	0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	0.04	0.86	0.09	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3	0.00	0.07	0.84	0.08	0.01	0.00	0.00	0.00	0.00	0.00
4	0.00	0.00	0.11	0.79	0.08	0.01	0.01	0.00	0.00	0.00
5	0.00	0.00	0.01	0.14	0.73	0.10	0.02	0.01	0.00	0.00
6	0.00	0.00	0.00	0.02	0.15	0.69	0.11	0.02	0.01	0.00
7	0.00	0.00	0.00	0.01	0.03	0.14	0.68	0.11	0.02	0.01
8	0.00	0.00	0.00	0.00	0.01	0.04	0.13	0.70	0.10	0.02
9	0.00	0.00	0.00	0.00	0.01	0.01	0.03	0.12	0.74	0.08
10	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.02	0.10	0.87

Panel C: Transition matrix of *EIL* over the next year

EIL decile	*EIL* decile in month $t+12$									
in month t	1	2	3	4	5	6	7	8	9	10
1	0.85	0.14	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	0.06	0.77	0.15	0.01	0.00	0.00	0.00	0.00	0.00	0.00
3	0.00	0.10	0.74	0.13	0.01	0.00	0.00	0.00	0.00	0.00
4	0.00	0.01	0.15	0.67	0.12	0.02	0.01	0.01	0.00	0.00
5	0.00	0.00	0.03	0.19	0.58	0.14	0.03	0.01	0.01	0.00
6	0.00	0.00	0.01	0.05	0.20	0.52	0.15	0.04	0.02	0.01
7	0.00	0.00	0.00	0.02	0.07	0.19	0.51	0.16	0.04	0.01
8	0.00	0.00	0.00	0.01	0.03	0.07	0.17	0.53	0.16	0.03
9	0.00	0.00	0.00	0.01	0.01	0.03	0.06	0.16	0.60	0.13
10	0.00	0.00	0.00	0.00	0.01	0.01	0.02	0.04	0.14	0.78

Table 3. Univariate portfolio sorts

This table reports mean excess returns, characteristic-adjusted returns, and alphas for each decile portfolio sorted by extreme illiquidity (*EIL*). *Return* is the average monthly returns (in percentage) of individual bonds in excess of one-month T-bill rates. *AdjRet* is the excess returns adjusted for rating and maturity. Alphas are calculated from four factor models: (1) FF5: Fama-French (1993) 5-factors (*MKT*, *SMB*, *HML*, *DEF*, and *TERM*); (2) FFL6: FF5 factors and Amihud corporate bond market liquidity factor (*LIQ*); (3) BBW4: Bai-Bali-Wen (2019) four bond market factors, i.e., the excess bond market return (*MKTb*), the downside risk factor (*DRF*), the credit risk factor (*CRF*), and the liquidity risk factor (*LRF*); (4) FF-BBW7: Fama-French three factors (*MKT*, *SMB*, and *HML*) and BBW4 factors. The last two columns report the average return/alpha of the high-minus-low (10-1) *EIL* portfolios and Newey-West adjusted *t*-statistics. The signs *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	1 (Lowest)	2	3	4	5	6	7	8	9	10 (Highest)	10-1	*t-stat*
Return	0.24	0.29	0.35	0.37	0.44	0.44	0.49	0.52	0.56	0.81	0.56^{***}	(5.41)
AdjRet	-0.09	-0.09	-0.08	-0.07	-0.02	-0.02	0.02	0.03	0.05	0.17	0.25^{***}	(7.44)
Return Alpha												
FF5	-0.01	0.02	0.05	0.07	0.15	0.14	0.20	0.22	0.25	0.46	0.46^{***}	(5.76)
FFL6	-0.00	0.03	0.07	0.10	0.17	0.17	0.23	0.24	0.28	0.49	0.49^{***}	(5.85)
BBW4	0.02	0.03	0.05	0.09	0.15	0.16	0.23	0.22	0.25	0.45	0.43^{***}	(5.17)
FF-BBW7	0.01	0.03	0.04	0.08	0.14	0.15	0.22	0.21	0.24	0.43	0.42^{***}	(5.11)
AdjRet Alpha												
FF5	-0.12	-0.12	-0.11	-0.08	-0.01	-0.01	0.04	0.04	0.07	0.18	0.30^{***}	(8.32)
FFL6	-0.13	-0.13	-0.11	-0.08	-0.02	-0.00	0.04	0.04	0.07	0.19	0.32^{***}	(8.36)
BBW4	-0.10	-0.10	-0.10	-0.06	0.00	0.00	0.05	0.02	0.04	0.16	0.26^{***}	(7.22)
FF-BBW7	-0.11	-0.10	-0.10	-0.06	-0.00	0.00	0.06	0.03	0.04	0.16	0.27^{***}	(7.86)

Table 4. Longer horizon tests

This table reports the average excess and characteristic-adjusted returns and alphas of the high-minus-low (10-1) *EIL*-sorted portfolios, 1 to 12 months ahead after estimating betas and *EIL* in month t. For example, the first column reports the average 10-1 portfolio returns and alphas in month $t+1$, and the last column presents the return/alpha spreads in month $t+12$. The Newey-West adjusted t-statistics are reported in the parenthesis. The signs *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	# of months ahead											
	1	2	3	4	5	6	7	8	9	10	11	12
Return	0.56***	0.55***	0.53***	0.52***	0.50***	0.49***	0.48***	0.47***	0.47***	0.45***	0.45***	0.45***
	(5.41)	(5.34)	(5.13)	(5.00)	(4.78)	(4.89)	(4.91)	(4.88)	(5.15)	(4.84)	(4.76)	(4.83)
AdjRet	0.25***	0.24***	0.24***	0.23***	0.22***	0.21***	0.21***	0.20***	0.21***	0.19***	0.20***	0.21***
	(7.44)	(7.19)	(6.87)	(6.64)	(6.31)	(6.22)	(6.19)	(5.70)	(5.61)	(4.77)	(4.64)	(4.95)
Return Alpha												
FF5	0.46***	0.44***	0.43***	0.42***	0.41***	0.40***	0.40***	0.40***	0.40***	0.39***	0.39***	0.39***
	(5.76)	(5.62)	(5.48)	(5.44)	(5.17)	(5.16)	(5.19)	(5.17)	(5.46)	(5.16)	(5.03)	(5.00)
FFL6	0.49***	0.47***	0.46***	0.45***	0.43***	0.43***	0.43***	0.43***	0.43***	0.42***	0.42***	0.42***
	(5.85)	(5.73)	(5.61)	(5.60)	(5.42)	(5.40)	(5.43)	(5.46)	(5.74)	(5.52)	(5.52)	(5.60)
BBW4	0.43***	0.42***	0.41***	0.40***	0.40***	0.41***	0.41***	0.40***	0.40***	0.39***	0.39***	0.40***
	(5.17)	(5.15)	(5.13)	(5.06)	(4.95)	(4.96)	(4.94)	(4.84)	(4.92)	(4.74)	(4.73)	(4.79)
FF-BBW7	0.42***	0.41***	0.40***	0.39***	0.39***	0.40***	0.40***	0.39***	0.40***	0.38***	0.38***	0.39***
	(5.11)	(5.14)	(5.12)	(5.06)	(4.93)	(4.90)	(4.89)	(4.82)	(4.89)	(4.75)	(4.72)	(4.76)
AdjRet Alpha												
FF5	0.30***	0.28***	0.29***	0.28***	0.27***	0.27***	0.27***	0.27***	0.28***	0.27***	0.27***	0.28***
	(8.32)	(7.90)	(7.97)	(7.79)	(7.35)	(7.39)	(7.70)	(7.52)	(7.97)	(7.09)	(7.03)	(7.24)
FFL6	0.32***	0.30***	0.30***	0.29***	0.29***	0.29***	0.29***	0.29***	0.30***	0.28***	0.29***	0.30***
	(8.36)	(7.91)	(7.89)	(7.80)	(7.49)	(7.45)	(7.65)	(7.59)	(8.08)	(7.50)	(7.66)	(8.07)
BBW4	0.26***	0.25***	0.25***	0.25***	0.24***	0.25***	0.25***	0.25***	0.26***	0.25***	0.26***	0.27***
	(7.22)	(6.92)	(6.96)	(6.74)	(6.79)	(6.95)	(7.14)	(6.92)	(7.21)	(6.67)	(6.64)	(6.88)
FF-BBW7	0.27***	0.26***	0.26***	0.25***	0.25***	0.26***	0.26***	0.26***	0.26***	0.26***	0.26***	0.27***
	(7.86)	(7.65)	(7.57)	(7.16)	(7.10)	(7.31)	(7.54)	(7.36)	(7.59)	(6.94)	(6.84)	(7.11)

Table 5. Bivariate portfolio sorts

At the end of each month t, we sort bonds into quintiles using one of the characteristics or betas. We then form a high-minus-low (5-1) *EIL* portfolio within each quintile, and another portfolio (Avg) which is the average of *EIL* portfolios across the five quintiles. The Newey-West adjusted *t*-statistics in the last column are for the average. Panel A reports excess returns of the *EIL* portfolios, and Panel B reports alphas controlling for four different factor models: (1) FF5 factors: *MKT*, *SMB*, *HML*, *DEF*, and *TERM*; (2) FFL6: the FF5 factors and the bond market liquidity factor (*LIQ*); (3) BBW4 factors: *MKTb*, *DRF*, *CRF*, and *LRF*; (4) FF-BBW7: Fama-French three-factors (*MKT*, *SMB*, and *HML*) and BBW4 factors. All portfolios are rebalanced monthly, and the bonds are equally weighted. Returns and alphas of each portfolio are expressed in monthly percentage terms. The signs *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: *EIL* portfolio excess returns

control variable	Low	2	3	4	High	Avg	*t*-stat
Maturity	0.41***	0.35***	0.36***	0.29***	0.29***	0.34***	(5.28)
Coupon	0.31***	0.35***	0.41***	0.34***	0.37***	0.35***	(5.61)
Size	0.27***	0.37***	0.36***	0.42***	0.47***	0.38***	(3.85)
Age	0.38***	0.40***	0.36***	0.41***	0.44***	0.40***	(5.18)
Rating	0.25***	0.21***	0.36***	0.29***	0.51***	0.32***	(7.87)
β_{DRF}	0.34***	0.34***	0.36***	0.32***	0.49***	0.37***	(5.34)
β_{LIQ}	0.43***	0.26***	0.39***	0.41***	0.34***	0.36***	(5.11)
ILLIQ	0.24***	0.24***	0.17***	0.17***	0.32***	0.23***	(4.46)

Panel B: Alphas of *EIL* portfolio excess returns

control variable	Low	2	3	4	High	Avg	*t*-stat	Low	2	3	4	High	Avg	*t*-stat
	FF5							**FFL6**						
Maturity	0.33***	0.30***	0.39***	0.33***	0.51***	0.37***	(6.26)	0.35***	0.32***	0.42***	0.36***	0.54***	0.40***	(6.56)
Coupon	0.26***	0.35***	0.39***	0.33***	0.39***	0.34***	(6.17)	0.27***	0.35***	0.42***	0.36***	0.39***	0.36***	(6.30)
Size	0.13**	0.25***	0.26***	0.19***	0.24**	0.22***	(3.53)	0.15**	0.27***	0.27***	0.20***	0.25**	0.23***	(3.57)
Age	0.29***	0.30***	0.32***	0.32***	0.43***	0.34***	(5.60)	0.32***	0.33***	0.32***	0.35***	0.44***	0.36***	(5.78)
Rating	0.17***	0.18***	0.38***	0.27***	0.49***	0.29***	(6.87)	0.19***	0.19***	0.38***	0.28***	0.51***	0.30***	(7.13)
β_{DRF}	0.35***	0.25***	0.26***	0.28***	0.57***	0.34***	(5.59)	0.39***	0.28***	0.30***	0.30***	0.60***	0.37***	(5.88)
β_{LIQ}	0.45***	0.18***	0.30***	0.33***	0.36***	0.32***	(5.23)	0.48***	0.20***	0.31***	0.34***	0.38***	0.34***	(5.41)
ILLIQ	0.21***	0.24***	0.18***	0.13**	0.28***	0.21***	(4.71)	0.22***	0.25***	0.19***	0.13*	0.30***	0.22***	(4.83)
	BBW4							**FF-BBW7**						
Maturity	0.23***	0.25***	0.30***	0.30***	0.41***	0.29***	(5.83)	0.22***	0.24***	0.31***	0.30***	0.40***	0.29***	(5.95)
Coupon	0.21***	0.26***	0.36***	0.27***	0.33***	0.28***	(5.62)	0.21***	0.26***	0.36***	0.26***	0.33***	0.28***	(5.68)
Size	0.08	0.22***	0.27***	0.22***	0.21**	0.20***	(3.53)	0.07	0.21**	0.27***	0.21***	0.19**	0.19***	(3.54)
Age	0.18**	0.25***	0.26***	0.31***	0.40***	0.28***	(5.01)	0.18**	0.24***	0.25***	0.30***	0.40***	0.27***	(4.96)
Rating	0.21***	0.21***	0.35***	0.26***	0.49***	0.29***	(6.39)	0.20***	0.21***	0.36***	0.26***	0.50***	0.30***	(6.41)
β_{DRF}	0.35***	0.23***	0.26***	0.24***	0.50***	0.31***	(5.20)	0.35***	0.22***	0.25***	0.23***	0.51***	0.31***	(5.16)
β_{LIQ}	0.40***	0.19***	0.25***	0.34***	0.33***	0.30***	(4.97)	0.41***	0.18***	0.25***	0.34***	0.33***	0.29***	(5.04)
ILLIQ	0.21***	0.24***	0.23***	0.16**	0.26***	0.22***	(4.54)	0.20***	0.24***	0.24***	0.17**	0.25***	0.22***	(4.69)

Table 6. Fama-MacBeth cross-sectional regressions

In each cross-section, we run the following regression:

$$r_{t+1}^{i,e} = \gamma_0 + \gamma_1 \beta_{MKT_t}^i + \gamma_2 \beta_{SMB_t}^i + \gamma_3 \beta_{HML_t}^i + \gamma_4 \beta_{DEF_t}^i + \gamma_5 \beta_{TERM_t}^i + \gamma_6 \beta_{LIQ_t}^i + \gamma_7 EIL_t^i + \delta Z_t^i + \varepsilon_t^i,$$

where $r_{t+1}^{i,e}$ is the (potentially extrapolated) return of bond i in month $t+1$ in excess of the one-month T-bill rate. β_{MKT}, β_{SMB}, β_{HML}, β_{DEF}, β_{TERM}, and β_{LIQ} are estimated by regressing bond monthly excess returns on risk factors over a rolling 60-month window. Extreme illiquidity (*EIL*) is the third-highest monthly illiquidity over the past 60 months. *REV* is the return in month t. *ILLIQ* is Amihud (2002) illiquidity measure in month t. *Coupon* is the coupon rate. *Size* is the issue size. *Rating* is the Moody's bond rating (Aaa=0, Aa+=1, …, C=20, and D=21), and if the Moody's rating is unavailable, we use the S&P rating whenever possible. *Age* is the number of years since issuance. *Maturity* is years to maturity. The regression results are for the sample from July 2002 to June 2019. Each regressor is normalized by the cross-sectional standard deviation each month. The numbers in parentheses are Newey-West adjusted *t*-statistics. The signs *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Intercept	β_{MKT}	β_{SMB}	β_{HML}	β_{DEF}	β_{TERM}	β_{LIQ}	*EIL*	*REV*	*ILLIQ*	*Coupon*	*Size*	*Rating*	*Age*	*Maturity*	Adj.R^2
0.28***							0.16***								0.020
(2.86)							(5.18)								
0.26***	0.02	-0.01	-0.01				0.16***								0.050
(2.76)	(0.84)	(-0.44)	(-0.63)				(5.05)								
0.21***	0.05	0.00	0.01	0.09**	0.01		0.14***								0.101
(2.87)	(1.41)	(0.05)	(0.57)	(2.05)	(0.36)		(5.34)								
0.19***	0.07*	-0.00	0.01	0.10**	0.01	0.07***	0.13***								0.112
(2.66)	(1.70)	(-0.06)	(0.40)	(2.21)	(0.44)	(2.94)	(5.39)								
0.06	-0.00	-0.01	-0.00	0.02	0.02	0.02*	0.08***			0.01	-0.02	0.15**	-0.04*	0.06	0.165
(0.81)	(-0.01)	(-0.44)	(-0.13)	(0.93)	(1.19)	(1.70)	(4.07)			(0.56)	(-1.36)	(2.37)	(-1.88)	(1.62)	
0.02	-0.01	-0.01	-0.02	0.03	0.03	-0.01	0.07***	-0.45***	0.05***	0.01	-0.01	0.17***	-0.04	0.07*	0.233
(0.19)	(-0.28)	(-0.43)	(-0.87)	(0.99)	(1.23)	(-0.39)	(3.24)	(-10.22)	(3.06)	(0.34)	(-0.41)	(2.74)	(-1.59)	(1.77)	

Table 7. The effect of rollover risk

In each cross-section, we run the following regression:

$$r_{t+1}^{i,e} = \gamma_0 + \gamma_1\beta_{MKT_t}^{i} + \gamma_2\beta_{SMB_t}^{i} + \gamma_3\beta_{HML_t}^{i} + \gamma_4\beta_{DEF_t}^{i} + \gamma_5\beta_{TERM_t}^{i} + \gamma_6\beta_{LIQ_t}^{i} + \gamma_7 EIL_t^i + \gamma_8 EIL_t^i \times D_{Short_t^i} + \delta Z_t^i + \varepsilon_t^i,$$

where $r_{t+1}^{i,e}$ is the (potentially extrapolated) return of bond i in month $t+1$ in excess of the one-month T-bill rate. β_{MKT}, β_{SMB}, β_{HML}, β_{DEF}, β_{TERM}, and β_{LIQ} are estimated by regressing bond monthly excess returns on risk factors over a rolling 60-month window. Extreme illiquidity (*EIL*) is the third-highest monthly illiquidity over the past 60 months. *Short* is the proportion of a firm's debt due within one year in its total assets reported for the last fiscal year, which measures the rollover risk of the issuer. D_{short} is a dummy equal to one (zero) when *Short* is higher (lower) than its median or mean of each month. *REV* is the lagged bond return and *ILLIQ* is Amihud (2002) illiquidity measure in month t. *Coupon* is the coupon rate. *Size* is the issue size. *Rating* is the Moody's bond rating (Aaa=0, Aa+=1, …, C=20, and D=21), and if the Moody's rating is unavailable, we use the S&P rating whenever possible. *Age* is the number of years since issuance. *Maturity* is years to maturity. The sample period runs from July 2002 to June 2019. Each regressor is normalized by the cross-sectional standard deviation each month. The numbers in parentheses are Newey-West adjusted *t*-statistics. The signs *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

D_{short} equals one (zero) when *Short* is higher (lower) than its cross-sectional median																
Intercept	β_{MKT}	β_{SMB}	β_{HML}	β_{DEF}	β_{TERM}	β_{LIQ}	*EIL*	D_{Short}×*EIL*	*REV*	*ILLIQ*	*Coupon*	*Size*	*Rating*	*Age*	*Maturity*	Adj.R^2
0.23***	0.04	-0.01	0.04	0.10**	-0.01	0.04	0.09***	0.06**								0.112
(3.05)	(1.01)	(-0.35)	(1.22)	(2.34)	(-0.14)	(1.51)	(3.25)	(2.14)								
0.25***	0.03	-0.01	0.05	0.12**	0.02	-0.00	0.08***	0.06**	-0.46***	0.05***						0.186
(3.39)	(0.48)	(-0.22)	(1.45)	(2.40)	(0.34)	(-0.00)	(3.17)	(2.03)	(-10.66)	(3.64)						
0.10	0.00	-0.01	0.03	0.07**	0.00	-0.01	0.05**	0.05*	-0.52***	0.04***	0.03***	-0.03*	0.10*	-0.03	0.09**	0.252
(1.20)	(0.11)	(-0.39)	(0.96)	(2.46)	(0.06)	(-0.17)	(2.46)	(1.82)	(-13.44)	(3.28)	(2.65)	(-1.90)	(1.90)	(-1.26)	(2.06)	
D_{short} equals one (zero) when *Short* is higher (lower) than its cross-sectional mean																
Intercept	β_{MKT}	β_{SMB}	β_{HML}	β_{DEF}	β_{TERM}	β_{LIQ}	*EIL*	D_{Short}×*EIL*	*REV*	*ILLIQ*	*Coupon*	*Size*	*Rating*	*Age*	*Maturity*	Adj.R^2
0.23***	0.04	-0.01	0.04	0.10**	-0.00	0.04	0.08***	0.07***								0.112
(3.02)	(1.01)	(-0.36)	(1.17)	(2.35)	(-0.11)	(1.52)	(3.18)	(2.86)								
0.25***	0.03	-0.01	0.05	0.12**	0.02	0.00	0.08***	0.08***	-0.46***	0.05***						0.186
(3.36)	(0.50)	(-0.24)	(1.35)	(2.41)	(0.36)	(0.00)	(3.10)	(3.03)	(-10.60)	(3.63)						
0.09	0.00	-0.01	0.02	0.07**	0.00	-0.01	0.04*	0.07**	-0.52***	0.04***	0.03***	-0.03	0.09*	-0.03	0.09**	0.252
(1.16)	(0.09)	(-0.44)	(0.87)	(2.50)	(0.01)	(-0.16)	(1.66)	(2.48)	(-13.39)	(3.30)	(2.66)	(-1.65)	(1.83)	(-1.16)	(2.06)	

Table 8. *EIL* pricing for different investment clientele

In each cross-section, we run the following regression:

$$r_{t+1}^{i,e} = \gamma_0 + \gamma_1\beta_{MKT_t}^{i} + \gamma_2\beta_{SMB_t}^{i} + \gamma_3\beta_{HML_t}^{i} + \gamma_4\beta_{DEF_t}^{i} + \gamma_5\beta_{TERM_t}^{i} + \gamma_6\beta_{LIQ_t}^{i} + \gamma_7 EIL_t^i + \gamma_8 EIL_t^i \times D_{Mutual_t^i}(D_{Insurance_t^i}) + \delta Z_t^i + \varepsilon_t^i,$$

where $r_{t+1}^{i,e}$ is the (potentially extrapolated) return of bond i in month $t+1$ in excess of the one-month T-bill rate. β_{MKT}, β_{SMB}, β_{HML}, β_{DEF}, β_{TERM}, and β_{LIQ} are estimated over a rolling 60-month window ending in month t. Extreme illiquidity (*EIL*) is the third-highest monthly illiquidity over the past 60 months. D_{Mutual} is a dummy equal to one if a bond is held by mutual funds and zero, otherwise; $D_{Insurance}$ is a dummy equal to one if a bond is held by insurance companies and zero, otherwise. *REV* is the lagged bond return and *ILLIQ* is Amihud (2002) illiquidity measure in month t. *Coupon* is the coupon rate. *Size* is the issue size. *Rating* is the Moody's bond rating (Aaa=0, Aa+=1, …, C=20, and D=21), and if the Moody's rating is unavailable, we use the S&P rating whenever possible. *Age* is the number of years since issuance. *Maturity* is years to maturity. The sample period runs from July 2002 to December 2018. Each regressor is normalized by the cross-sectional standard deviation each month. The numbers in parentheses are Newey-West adjusted *t*-statistics. The signs *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: D_{Mutual} equals one if a bond is held by mutual funds

Intercept	β_{MKT}	β_{SMB}	β_{HML}	β_{DEF}	β_{TERM}	β_{LIQ}	*EIL*	$D_{Mutual}\times EIL$	*REV*	*ILLIQ*	*Coupon*	*Size*	*Rating*	*Age*	*Maturity*	Adj.R^2
0.19**	0.08*	0.01	0.01	0.10**	-0.01	0.06***	0.09***	0.06**								0.136
(2.38)	(1.73)	(0.23)	(0.39)	(2.10)	(-0.17)	(2.92)	(3.67)	(2.07)								
0.20**	0.07	0.00	0.01	0.12**	0.00	0.02	0.09***	0.07**	-0.36***	0.06***						0.182
(2.53)	(1.08)	(0.10)	(0.35)	(2.17)	(0.10)	(0.55)	(4.10)	(2.28)	(-8.17)	(2.95)						
0.05	0.01	-0.01	-0.02	0.04	0.01	-0.01	0.07***	0.04**	-0.41***	0.05***	-0.00	0.00	0.16**	-0.03	0.05	0.239
(0.50)	(0.31)	(-0.35)	(-0.81)	(1.45)	(0.52)	(-0.25)	(2.89)	(1.99)	(-9.38)	(2.82)	(-0.08)	(0.10)	(2.30)	(-1.27)	(1.16)	

Panel B: $D_{Insurance}$ equals one if a bond is held by insurance companies

Intercept	β_{MKT}	β_{SMB}	β_{HML}	β_{DEF}	β_{TERM}	β_{LIQ}	*EIL*	$D_{Insurance}\times EIL$	*REV*	*ILLIQ*	*Coupon*	*Size*	*Rating*	*Age*	*Maturity*	Adj.R^2
0.19**	0.08*	0.01	0.01	0.11**	-0.00	0.07***	0.61**	-0.51**								0.137
(2.37)	(1.75)	(0.32)	(0.40)	(2.14)	(-0.07)	(2.92)	(2.56)	(-2.17)								
0.20**	0.07	0.01	0.01	0.12**	0.01	0.03	0.73**	-0.63**	-0.36***	0.06***						0.182
(2.53)	(1.12)	(0.19)	(0.36)	(2.22)	(0.21)	(0.61)	(2.48)	(-2.14)	(-8.27)	(2.86)						
0.03	0.01	-0.01	-0.02	0.04	0.01	-0.01	0.42**	-0.20**	-0.41***	0.05***	-0.00	0.01	0.16**	-0.03	0.05	0.240
(0.30)	(0.37)	(-0.29)	(-0.79)	(1.56)	(0.60)	(-0.20)	(2.32)	(-2.30)	(-9.60)	(2.72)	(-0.22)	(0.44)	(2.31)	(-1.05)	(1.22)	

Table 9. Subperiod analysis

This table reports the results of different subperiod tests. Panel A reports the results of Fama-MacBeth (1973) regressions of normal and crisis periods. The crisis period is from December 2007 to January 2009; other months from July 2002 to June 2019 are normal periods. In Panel B, the high uncertainty period refers to the months when the economic policy uncertainty index (Baker, Bloom, and Davis, 2016) is higher than its median level from July 2002 to June 2019. In Panel C, the high uncertainty period is when Bekaert-Engstrom-Xu (2021) economic uncertainty index is higher than its median level from July 2002 to June 2019. In Panel D, the high sentiment period is the months in which Baker-Wurgler (2006) investor sentiment index is higher than its median level from July 2002 to December 2018. Each regressor is normalized by the cross-sectional standard deviation each month. The numbers in parentheses are Newey-West adjusted t-statistics. The signs *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Normal vs. crisis periods

	Intercept	β_{MKT}	β_{SMB}	β_{HML}	β_{DEF}	β_{TERM}	β_{LIQ}	*EIL*	*REV*	*ILLIQ*	*Coupon*	*Size*	*Rating*	*Age*	*Maturity*	Adj.R^2
Crisis	0.62	-0.32	-0.21*	-0.15**	-0.10	-0.07	-0.40	0.09**	-1.00***	-0.02	0.01	-0.09	-0.31	0.07	-0.32***	0.218
	(1.16)	(-1.60)	(-1.91)	(-2.22)	(-0.89)	(-0.78)	(-1.50)	(2.00)	(-3.20)	(-0.77)	(0.22)	(-1.46)	(-1.34)	(0.61)	(-3.00)	
Normal	-0.03	0.02	0.00	-0.01	0.04	0.04*	0.02	0.07***	-0.40***	0.06***	0.01	-0.00	0.21***	-0.04**	0.11***	0.234
	(-0.43)	(0.57)	(0.13)	(-0.30)	(1.41)	(1.66)	(1.12)	(2.92)	(-16.28)	(3.33)	(0.32)	(-0.03)	(3.71)	(-2.05)	(2.75)	

Panel B: High vs. low uncertainty periods classified by the policy uncertainty index

	Intercept	β_{MKT}	β_{SMB}	β_{HML}	β_{DEF}	β_{TERM}	β_{LIQ}	*EIL*	*REV*	*ILLIQ*	*Coupon*	*Size*	*Rating*	*Age*	*Maturity*	Adj.R^2
High	0.01	-0.05	-0.07**	-0.03	0.05	0.06	-0.05	0.09***	-0.49***	0.09***	-0.01	0.03	0.24**	-0.04	0.08	0.224
	(0.06)	(-0.84)	(-2.38)	(-1.03)	(1.10)	(1.45)	(-0.88)	(2.83)	(-5.88)	(3.31)	(-0.34)	(1.22)	(2.12)	(-1.24)	(1.43)	
Low	0.03	0.03	0.04	-0.00	0.00	-0.00	0.03	0.05**	-0.40***	0.01	0.02	-0.05**	0.10**	-0.03	0.07	0.242
	(0.24)	(0.71)	(0.96)	(-0.08)	(0.16)	(-0.12)	(1.08)	(2.00)	(-12.59)	(0.96)	(1.16)	(-2.38)	(2.58)	(-1.33)	(1.21)	

Panel C: High vs. low uncertainty periods measured by the economic uncertainty index

	Intercept	β_{MKT}	β_{SMB}	β_{HML}	β_{DEF}	β_{TERM}	β_{LIQ}	*EIL*	*REV*	*ILLIQ*	*Coupon*	*Size*	*Rating*	*Age*	*Maturity*	Adj.R^2
High	0.16	-0.02	-0.06**	-0.04	0.07	0.04	-0.06	0.08***	-0.52***	0.07**	0.01	-0.02	0.14	-0.04	0.06	0.238
	(1.20)	(-0.31)	(-2.40)	(-1.07)	(1.34)	(0.88)	(-0.89)	(3.05)	(-6.56)	(2.49)	(0.48)	(-0.58)	(1.43)	(-0.90)	(0.89)	
Low	-0.12	-0.00	0.04	0.00	-0.01	0.02	0.03	0.06**	-0.38***	0.04**	0.00	0.00	0.21***	-0.04	0.09*	0.228
	(-1.55)	(-0.07)	(0.75)	(0.17)	(-0.24)	(1.07)	(1.35)	(2.01)	(-13.65)	(2.44)	(0.05)	(0.14)	(3.00)	(-1.63)	(1.74)	

Panel D: High vs. low sentiment periods

	Intercept	β_{MKT}	β_{SMB}	β_{HML}	β_{DEF}	β_{TERM}	β_{LIQ}	*EIL*	*REV*	*ILLIQ*	*Coupon*	*Size*	*Rating*	*Age*	*Maturity*	Adj.R^2
High	-0.02	0.02	0.05	-0.01	-0.01	0.01	0.00	0.07***	-0.40***	0.03*	0.02	-0.02	0.09	-0.04*	0.01	0.238
	(-0.14)	(0.55)	(1.00)	(-0.44)	(-0.17)	(0.50)	(0.18)	(2.92)	(-10.97)	(1.84)	(1.10)	(-0.98)	(1.59)	(-1.85)	(0.12)	
Low	-0.07	-0.03	-0.07**	-0.00	0.04	0.03	-0.05	0.10***	-0.51***	0.08**	-0.01	0.02	0.30***	-0.03	0.13**	0.217
	(-0.60)	(-0.43)	(-2.21)	(-0.07)	(0.86)	(0.75)	(-0.70)	(4.31)	(-6.33)	(2.63)	(-0.36)	(0.85)	(2.64)	(-0.93)	(2.32)	

Table 10. Summary statistics and alphas for the tradable *EIL* factor

The tradable *EIL* factor is measured by the time-series returns of high-minus-low (10-1) portfolio sorted by *EIL*. Panel A reports the summary statistics of the tradable *EIL* factor for the full sample. Panel B reports the intercepts (alphas) and their *t*-statistics from time-series regressions of the tradeable *EIL* factor on the commonly used stock and bond market factors. Newey-West adjusted *t*-statistics are shown in parentheses. Eleven alternative factor models are considered. The tradable *EIL* factor covers the period from October 2003 to June 2019.

Model 1: $MKT + SMB + HML + DEF + TERM$

Model 2: $MKT + SMB + HML + DEF + TERM + LIQ^{Bond}$

Model 3: $MKTb + DRF + CRF + LRF$

Model 4: $MKT + SMB + HML + MKTb + DRF + CRF + LRF$

Model 5: $MKT + SMB + HML + MOM^{Stock} + LIQ^{Stock}$

Model 6: $MKT + SMB + HML + RMW + CMA$

Model 7: $MKTb + DEF + TERM + LIQ^{Bond}$

Model 8: $MKT + SMB + HML + MOM^{Stock} + LIQ^{Stock} + MKTb + DEF + TERM + LIQ^{Bond}$

Model 9: $MKT + SMB + HML + RMW + CMA + MKTb + DEF + TERM + LIQ^{Bond}$

Model 10: $MKT + SMB + HML + MOM^{Stock} + LIQ^{Stock} + MKTb + DRF + CRF + LRF$

Model 11: $MKT + SMB + HML + RMW + CMA + MKTb + DRF + CRF + LRF$

Panel A: Summary statistics

	Mean	*t*-stat	Std.dev.	Median	Q1	Q3
Tradable *EIL*	0.56***	5.41	0.96	0.54	0.02	1.03

Panel B: Alphas on the tradeable *EIL* factor

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
Alpha	0.46***	0.49***	0.49***	0.48***	0.52***	0.52***	0.49***	0.51***	0.50***	0.46***	0.48***
t-stat	(5.76)	(5.85)	(5.60)	(5.43)	(5.87)	(5.79)	(5.74)	(5.98)	(5.89)	(5.20)	(5.70)
Adj.R^2	0.21	0.25	0.14	0.22	0.15	0.12	0.23	0.29	0.25	0.25	0.22

Table 11. Explanatory power of alternative factor models for bond portfolios

In Panel A, the 25 test portfolios are formed by independently sorting corporate bonds into 5×5 quintile portfolios on issue size and maturity, and then constructed from the intersections of the size and maturity quintiles. In Panel B, the 25 test portfolios are formed by independently sorting corporate bonds into 5×5 quintile portfolios on issue size and credit ratings, and then constructed from the intersections of the size and rating quintiles. In Panel C, the test portfolios are formed by sorting bonds into 12 industry portfolios on Fama-French industry classifications. In Panel D, the test portfolios are formed by sorting bonds into 25 portfolios on loadings of the tradable EIL factor estimated in the previous 5-year rolling windows. In Panel E, the test portfolios include all the above. Following Fama and French (2016), we report: (1) GRS statistic testing whether the intercepts for the test portfolios are jointly zero; (2) the p-value for the GRS statistic; (3) the average absolute value of the intercepts $A|\alpha_i|$; (4) $A|\alpha_i|/A|\bar{r}_i|$, the average absolute value of the intercepts over the average absolute value of $\bar{r}_i$, which is the average excess return on portfolio i minus the average excess return on the bond market portfolio *MKTb*; (5) $A\alpha_i^2/A\bar{r}_i^2$, the average squared intercept over the average squared value of $\bar{r}_i$; (6) AR^2, the average value of regression R^2 adjusted for degrees of freedom.

The base model: Stock and bond market factors

($MKT + SMB + HML + MOM^{Stock} + LIQ^{Stock}$) + ($MKTb + DRF + CRF + LRF$)

The EIL-augmented model: The base model that adds the tradable EIL factor

($MKT + SMB + HML + MOM^{Stock} + LIQ^{Stock}$) + ($MKTb + DRF + CRF + LRF$) + tradable EIL

	(1) GRS	(2) p(GRS)	(3) $A\|\alpha_i\|$	(4) $A\|\alpha_i\|/A\|\bar{r}_i\|$	(5) $A\alpha_i^2/A\bar{r}_i^2$	(6) AR^2
Panel A: 25-size/maturity-sorted bond portfolios						
Base	8.12	0.000	0.199	1.25	1.55	0.71
EIL-augmented	5.54	0.000	0.113	0.71	0.63	0.75
Panel B: 25-size/rating-sorted bond portfolios						
Base	10.68	0.000	0.190	1.29	1.53	0.71
EIL-augmented	8.11	0.000	0.130	0.89	0.89	0.76
Panel C: 12-industry-sorted bond portfolios						
Base	2.49	0.006	0.160	1.46	1.47	0.67
EIL-augmented	2.77	0.002	0.105	0.96	0.83	0.72
Panel D: 25-*EIL* loading-sorted bond portfolios						
Base	2.05	0.006	0.138	1.30	1.02	0.68
EIL-augmented	1.80	0.021	0.087	0.82	0.44	0.70
Panel E: All 87 portfolios						
Base	5.25	0.000	0.173	1.30	1.42	0.70
EIL-augmented	4.19	0.000	0.110	0.82	0.69	0.73

Table 12. Horserace regressions with both tradable *EIL* factor loading and *EIL*

In each cross-section, we run the following regression:

$$r_{t+1}^{i,e} = \gamma_0 + \gamma_1 \beta_{EIL_t}^{i} + \gamma_2 EIL_t^i + \delta Z_t^i + \varepsilon_t^i,$$

where $r_{t+1}^{i,e}$ is the (potentially extrapolated) return of bond i in month $t+1$ in excess of the one-month T-bill rate. β_{EIL} is estimated by regressing bond excess returns on tradable *EIL* factor controlling for rating over a rolling 60-month window. Extreme illiquidity (*EIL*) is the third-highest monthly illiquidity over the past 60 months. *REV* is the return in month t. *ILLIQ* is Amihud (2002) illiquidity measure in month t. *Coupon* is the coupon rate. *Size* is the issue size. *Rating* is the Moody's bond rating (Aaa=0, Aa+=1, …, C=20, and D=21), and if the Moody's rating is unavailable, we use the S&P rating whenever possible. *Age* is the number of years since issuance. *Maturity* is years to maturity. The regression results are for the sample from July 2002 to June 2019. Each regressor is normalized by the cross-sectional standard deviation each month. The numbers in parentheses are Newey-West adjusted *t*-statistics. The signs *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Intercept	β_{EIL}	*EIL*	*REV*	*ILLIQ*	*Coupon*	*Size*	*Rating*	*Age*	*Maturity*	Adj.R^2
0.41***	0.06**									0.023
(3.16)	(1.97)									
0.29***		0.17***								0.020
(2.77)		(5.04)								
0.25**	0.02	0.16***								0.041
(2.40)	(0.59)	(4.26)								
0.05	0.01	0.09***			0.02	-0.01	0.14**	-0.04*	0.06	0.141
(0.59)	(0.39)	(3.72)			(1.14)	(-1.00)	(2.05)	(-1.92)	(1.46)	
0.03	0.02	0.07***	-0.43***	0.06***	0.02	-0.01	0.16**	-0.05**	0.08*	0.208
(0.30)	(0.51)	(3.01)	(-13.86)	(3.13)	(1.31)	(-0.51)	(2.04)	(-2.09)	(1.66)	

Table 13. Tests separating the effect of *EIL* from *ILLIQ* and *DOWN*

Panel A reports the results of Fama-MacBeth regressions separating the effect of *EIL* from *ILLIQ*. In each cross-section, we run the following regression:

$$Yield_t^i = a_1 \cdot ILLIQ_t^i + a_2 \cdot ILLIQ_t^i \cdot \frac{1}{Maturity_t^i} + b_1 \cdot EIL_t^i + b_2 \cdot EIL_t^i \cdot \frac{1}{Maturity_t^i} + \delta Z_t^i + \varepsilon_t^i,$$

where $Yield_t^i$ is the yield to maturity of bond i at the end of month t, extreme illiquidity (*EIL*) is the third-highest monthly illiquidity over the past 60 months ended in month t, *ILLIQ* is Amihud (2002) illiquidity measure in month t, and *Maturity* is years to maturity at the end of month t. Z_t^i is the control variable which includes *Coupon*, *Size*, *Rating*, *Age*, and *Maturity*. Panel B reports the results for bivariate portfolio sorts (Panel B1) and Fama-MacBeth regressions (Panel B2) controlling for individual bonds' downside risk. *DOWN* is the individual bond's downside risk, which is defined as the third-lowest monthly return observation over the past 5 years. The original *DOWN* measure is multiplied by -1 so that a higher value indicates a higher downside risk. At the end of each month t, we first sort bonds into quintiles on their downside risk, then further into quintiles on *EIL*. We also form a high-minus-low (5-1) *EIL* portfolio within each *DOWN* group. Excess returns for the above portfolios are expressed in monthly percentage terms. All portfolios are rebalanced monthly, and the bonds are equally weighted. The sample is from July 2002 to June 2019. Each regressor in this table is normalized by the cross-sectional standard deviation each month. Newey-West adjusted *t*-statistics for the 5-1 portfolios and regression coefficients are in the parenthesis. The signs *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Fama-MacBeth regressions separating the effect of *EIL* from *ILLIQ*

Intercept	*ILLIQ*	*ILLIQ/Maturity*	*EIL*	*EIL/Maturity*	*Maturity*	*Age*	*Coupon*	*Size*	*Rating*	Adj.R^2
0.04***	0.00	0.01***	0.01***	-0.00						0.161
(8.33)	(1.49)	(3.15)	(8.65)	(-0.89)						
-0.01*	0.00*	0.00***	0.01***	-0.00	0.00***	-0.00***	-0.00	0.00***	0.03***	0.414
(-1.79)	(1.82)	(3.23)	(6.19)	(-0.15)	(3.22)	(-2.96)	(-0.62)	(3.53)	(4.19)	

Panel B: Tests controlling for individual bonds' downside risk

Panel B1: Bivariate portfolio sorts

Downside risk	Low *EIL*	2	3	4	High *EIL*	5-1	*t*-stat
Low *DOWN*	0.16	0.14	0.22	0.34	0.49	0.33***	(7.08)
2	0.26	0.24	0.35	0.42	0.46	0.20***	(4.87)
3	0.33	0.40	0.42	0.47	0.55	0.22***	(5.89)
4	0.42	0.48	0.54	0.56	0.62	0.20***	(3.51)
High *DOWN*	0.65	0.66	0.71	0.84	1.05	0.39***	(3.18)

Panel B2: Fama-MacBeth regressions

Intercept	β_{MKT}	β_{SMB}	β_{HML}	β_{DEF}	β_{TERM}	β_{LIQ}	β_{DRF}	*EIL*	*REV*	*ILLIQ*	*DOWN*	*Coupon*	*Size*	*Rating*	*Age*	*Maturity*	Adj.R^2
0.20***											0.18***						0.046
(3.23)											(3.05)						
0.13**								0.12***			0.14**						0.058
(2.15)								(5.88)			(2.42)						
0.17***	0.03	-0.00	-0.00	0.07*	-0.03	0.05***	0.04*	0.12***			0.10*						0.129
(2.85)	(0.95)	(-0.03)	(-0.21)	(1.78)	(-0.79)	(2.91)	(1.86)	(5.80)			(1.86)						
0.10	-0.00	-0.01	-0.01	0.02	0.01	0.02	0.02*	0.08***			0.05	0.00	-0.03**	0.13**	-0.03	0.04	0.176
(1.18)	(-0.02)	(-0.50)	(-0.52)	(0.68)	(0.46)	(1.44)	(1.74)	(4.00)			(1.54)	(0.29)	(-2.04)	(2.05)	(-1.38)	(1.14)	
0.06	-0.02	-0.02	-0.03	0.02	0.02	-0.02	0.02	0.06***	-0.46***	0.05***	0.05	0.00	-0.01	0.16**	-0.03	0.05	0.243
(0.68)	(-0.38)	(-0.53)	(-1.31)	(0.60)	(0.83)	(-0.50)	(1.13)	(3.03)	(-9.35)	(2.70)	(1.55)	(0.04)	(-0.84)	(2.37)	(-1.20)	(1.24)	

Table 14. Mutual fund holdings and extreme illiquidity

This table reports the results of regressing mutual fund holding on extreme illiquidity. The mutual fund holding is the bond amount held by mutual funds divided by the bond's total outstanding value (in percentage). The extreme illiquidity (*EIL*) is the third-highest monthly Amihud (2002) illiquidity over the past 60 months. In Panel A, we run Fama-MacBeth regressions of mutual fund holding on *EIL*, controlling for betas and common bond characteristics. The standard error is Newey-West adjusted with four lags. In Panel B, we run pooled OLS regressions with the same variables, adding a quarter-fixed effect while clustering the standard error by the issuer.

Panel A: Fama-MacBeth regressions

Intercept	β_{MKT}	β_{SMB}	β_{HML}	β_{DEF}	β_{TERM}	β_{LIQ}	*EIL*	*REV*	*ILLIQ*	*Coupon*	*Size*	*Rating*	*Age*	*Maturity*	Adj.R^2
2.85***	0.59*	0.28	-0.24*	-0.02	-0.37***	-0.10***	-1.45***								0.151
(7.40)	(1.71)	(1.29)	(-1.97)	(-0.07)	(-2.88)	(-3.69)	(-4.90)								
3.01***	0.28**	-0.07	-0.34***	0.05	0.32*	-0.07***	-1.09***			-0.17**	0.09*	0.08**	-0.03**	-0.03***	0.191
(5.00)	(2.56)	(-0.36)	(-4.13)	(0.63)	(1.75)	(-3.44)	(-5.38)			(-2.38)	(1.90)	(2.64)	(-2.25)	(-4.03)	
3.03***	0.23**	-0.05	-0.34***	0.03	0.28	-0.07***	-1.00***	-0.01	-0.45***	-0.16**	0.08*	0.08**	-0.03**	-0.03***	0.194
(5.00)	(2.30)	(-0.26)	(-4.36)	(0.35)	(1.56)	(-3.49)	(-5.33)	(-1.20)	(-4.36)	(-2.34)	(1.87)	(2.66)	(-2.34)	(-3.85)	

Panel B: Pooled OLS regressions

Intercept	β_{MKT}	β_{SMB}	β_{HML}	β_{DEF}	β_{TERM}	β_{LIQ}	*EIL*	*REV*	*ILLIQ*	*Coupon*	*Size*	*Rating*	*Age*	*Maturity*	Adj.R^2
2.60***	1.32***	0.16	0.25	0.65***	-0.35***	-0.11***	-1.07***								0.139
(14.95)	(4.35)	(0.74)	(1.16)	(4.24)	(-2.87)	(-4.52)	(-13.83)								
3.17***	0.82**	-0.04	0.11	0.46***	0.32*	-0.11***	-0.84***			-0.21***	-0.00	0.11***	-0.04	-0.03***	0.168
(11.04)	(2.49)	(-0.18)	(0.54)	(2.96)	(1.90)	(-4.47)	(-7.80)			(-3.24)	(-0.98)	(3.62)	(-1.57)	(-3.37)	
3.17***	0.83**	-0.03	0.10	0.45***	0.32*	-0.11***	-0.80***	-0.02***	-0.10***	-0.21***	-0.00	0.11***	-0.04	-0.03***	0.169
(11.08)	(2.51)	(-0.12)	(0.50)	(2.95)	(1.88)	(-4.51)	(-7.94)	(-2.92)	(-2.68)	(-3.25)	(-0.99)	(3.66)	(-1.59)	(-3.30)	

Table 15. Alternative measures of holdings by institutional investors

This table shows the impact of bonds' extreme illiquidity (*EIL*) on the mutual funds' (Panel A) or insurance companies' (Panel B) demand for them. The institutional investors' demand is proxied by three different measures which are defined as follows. *Investor's Portfolio-Weighted Dummy* is a dummy variable indicating whether a fund holds this bond in a given quarter. *Investor's Portfolio Weight* is the percentage of a mutual fund's portfolio invested in a bond in a given quarter; it is calculated every quarter as the ratio (in percentage) of the investment by a fund in a bond to all the bonds in the same rating category that this fund holds in the portfolio; it is defined only when the fund's bond holding is positive. *Investor's Overweighting* is the difference (in percentage) between the weight that a mutual fund assigns to a bond in its portfolio within the same rating category and the market weight of the bond in a portfolio consisting of all outstanding bonds within the same rating category; it is defined only when the fund's bond holding is positive. We conduct the analyses using a logistic regression model for the dummy as the dependent variable and a pooled OLS regression for the other two variables. The errors are clustered at the institutional investor level with a quarter-fixed effect.

Panel A: Mutual fund holdings

Intercept	β_{MKT}	β_{SMB}	β_{HML}	β_{DEF}	β_{TERM}	β_{LIQ}	*EIL*	*REV*	*ILLIQ*	*Coupon*	*Size*	*Rating*	*Age*	*Maturity*	Pseudo R^2
Dependent variable: *Investor's Portfolio-Weighted Dummy*															
-3.20***	0.41***	0.11**	0.07	0.16***	-0.06	-0.01	-0.22***	-0.01***	-0.07**	0.02	-0.00	0.07***	-0.03***	0.00	0.025
(-7.80)	(2.99)	(2.15)	(1.44)	(3.81)	(-1.02)	(-1.41)	(-4.04)	(-2.87)	(-1.96)	(0.78)	(-0.49)	(3.87)	(-3.15)	(0.50)	
Dependent variable: *Investor's Portfolio Weight*															
6.95***	4.52***	-0.60	0.63	0.56*	-1.52**	-0.14**	-1.06***	0.14***	-0.18	0.23**	0.02	-0.25**	-0.15***	-0.01	0.026
(2.98)	(6.92)	(-1.16)	(1.57)	(1.96)	(-2.09)	(-2.57)	(-3.77)	(4.53)	(-0.99)	(2.10)	(1.63)	(-2.01)	(-4.02)	(-0.32)	
Dependent variable: *Investor's Overweighting*															
6.89***	4.39***	-0.63	0.61	0.57**	-1.44**	-0.14**	-1.03***	0.14***	-0.17	0.23**	-0.09***	-0.25**	-0.15***	-0.01	0.025
(2.94)	(6.78)	(-1.22)	(1.52)	(2.01)	(-1.99)	(-2.47)	(-3.70)	(4.40)	(-0.96)	(2.05)	(-7.85)	(-2.02)	(-3.94)	(-0.42)	

Panel B: Insurance company holdings

Intercept	β_{MKT}	β_{SMB}	β_{HML}	β_{DEF}	β_{TERM}	β_{LIQ}	*EIL*	*REV*	*ILLIQ*	*Coupon*	*Size*	*Rating*	*Age*	*Maturity*	Pseudo R^2
Dependent variable: *Investor's Portfolio-Weighted Dummy*															
-0.24*	-0.50***	-0.09***	-0.02	-0.10***	0.21***	0.00	0.36***	0.00	0.11***	-0.02*	-0.00**	-0.04***	0.05***	-0.00	0.053
(-1.75)	(-8.11)	(-3.39)	(-0.72)	(-4.22)	(6.71)	(1.62)	(13.70)	(0.20)	(8.59)	(-1.77)	(-2.32)	(-8.84)	(9.40)	(-0.64)	
Dependent variable: *Investor's Portfolio Weight*															
7.40***	5.15***	1.30***	2.97***	1.41***	-2.09***	0.16***	0.37**	0.11***	0.03	-0.61***	0.02***	0.43***	0.06***	-0.04**	0.032
(10.21)	(8.56)	(4.17)	(9.45)	(7.45)	(-7.31)	(4.71)	(2.32)	(7.40)	(0.43)	(-7.54)	(3.29)	(8.02)	(2.63)	(-2.14)	
Dependent variable: *Investor's Overweighting*															
7.35***	5.14***	1.34***	2.97***	1.42***	-2.05***	0.16***	0.39**	0.11***	0.04	-0.61***	-0.11***	0.42***	0.06***	-0.04**	0.035
(10.13)	(8.52)	(4.29)	(9.45)	(7.51)	(-7.18)	(4.77)	(2.44)	(7.24)	(0.45)	(-7.54)	(-17.61)	(7.98)	(2.65)	(-2.24)	