The Pricing of the Illiquidity Factor's Conditional Risk with Time-varying Premium

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This version: February 2019

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We received useful comments from participants of the following events and institutes: the Conference on Financial Friction at the Copenhagen Business School, the Midwest Finance Association Annual Conference, the National Bureau of Economic Research Microstructure Conference, the Liquidity Conference at Corvinus University, Stern School-NYU, Baruch College, Hebrew University, ESMT Berlin, Humboldt University, Bar Ilan University, Ben Gurion University, the University of Utah, the University of St. Gallen, Moscow School of Economics, WHU, the University of Konstanz, Case Western Reserve University, Ohio University, the Market-microstructure course at Emory University, and Korea University.

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Abstract

We test the pricing of the systematic risk (β) of a traded illiquidity factor, the return premium on illiquid-minus-liquid (*IML*) stock portfolios, whose risk-adjusted return is positive and significant. We find that the risk premium of β_{IML} is time-varying being higher in times of expected financial distress. In our main analysis, we find a positive and significant risk premium on *conditional* β_{IML} that rises in times of financial distress, measured by the corporate bond yield spread, TED spread, or broker–dealer loans (including margin loans). The positive pricing of the conditional β_{IML} remains significant after controlling for the unconditional and conditional βs of other commonly used pricing factors and liquidity-based factors and for common firm characteristics, including size and illiquidity.

1. Introduction

Illiquidity is known to be priced both as a *characteristic* and as a *systematic risk*.[1] This paper studies the pricing of the conditional systematic risk of a *traded* liquidity premium factor of Illiquid-Minus-Liquid stock portfolios, denoted *IML*, which is time-varying. The mean risk-adjusted *IML* is positive and significant for our sample period of January 1947 through December 2017.[2] We test two hypotheses on the pricing of *IML* systematic risk, denoted β_{IML}. The first hypothesis is that the risk premium on β_{IML} is time-varying, being higher in times of anticipated financial distress. The second and main hypothesis is that investors demand a positive premium on the *conditional* β_{IML}, the systematic risk of *IML* that varies as a function of market conditions, being higher in times of financial distress.

These predictions follow from Brunnermeier and Pedersen's (2009) theory that higher funding illiquidity and binding financial conditions raise both market illiquidity and the shadow price of liquidity. Investors who become financially constrained must liquidate their holdings and are willing to bear higher costs of illiquidity or pay more for liquidity. This raises illiquidity – the price impact in liquidation – and the shadow price of liquidity rises.[3] We propose that investors thus demand a risk premium on stocks with greater exposure to – or β of – the illiquidity premium factor *IML* in times of financial distress, when both illiquidity and the price of illiquidity are higher. This is analogous to the theory and findings of Lettau and Ludvigson (2001, henceforth LL) that investors price the conditional β of the market factor in times of higher risk or risk aversion captured by higher consumption/asset ratio denoted *cay*. We adopt the estimation and test methodology of Cochrane (1996, 2005) and LL who allow the market factor's β and its risk premium to be conditioned on a variable that forecasts the market return premium.[4] Our conditioning variable is the yield spread between BAA- and AAA-rated corporate bonds, denoted *SP*, a known proxy for financial distress which also forecasts *IML*.

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[1] Amihud and Mendelson (1986) and Brennan and Subrahmanyam (1996) find that stock expected return increases in stock illiquidity and Pastor and Stambaugh (2003) and Acharya and Pedersen (2005) find that the expected return is an increasing function of illiquidity systematic risk, using a non-traded illiquidity factor. See a review of research on the pricing of liquidity and liquidity risk in Amihud, Mendelson and Pedersen (2005, 2013).
[2] The *IML* was found to be positive and significant across 45 countries (Amihud, Hameed, Kang, and Zhang, 2015).
[3] Acharya, Amihud, and Bharath (2013) find that illiquidity shocks affect corporate bond returns in times of financial and economic distress.
[4] Similar models of the market factor's conditional β using macroeconomic conditioning variables are proposed by Shanken (1990), Ferson and Schadt (1996), Jagannathan and Wang (1996), and Ferson and Harvey (1999). Ferson,

We test our first hypothesis that the risk premium of β_{IML} is varying over time, increasing in times of anticipated financial distress. This test follows the methodology of Ferson and Harvey (1991) and Chordia, Goyal, and Shanken (2015) who estimate changing premiums of factors' βs by time-series regressions of the monthly cross-sectional regression estimates on lagged predictive variables. First we estimate the β_{IML} for each stock together with the β coefficients of the return factors of Fama and French (1993) and Carhart (1997) (henceforth, FFC). Then, we do monthly cross-stock Fama-Macbeth (1973) regressions and estimate the slope coefficient of β_{IML} controlling for the FFC βs and for six commonly-used stock characteristics: illiquidity, size, book-to-market ratio, return volatility, and two variables based on past returns. Finally, we regress the monthly series of the estimated slope coefficients of β_{IML} on lagged *SP* which proxies for anticipated financial distress. We find that the slope coefficient of β_{IML} is an increasing function of lagged *SP*. In particular, the premium on β_{IML} is positive and significant following higher values of *SP* while it is insignificant otherwise. The results suggest that when investors anticipate funding illiquidity they price stocks with greater exposure to the *IML* factor so as to earn higher expected returns on them.

Our second and main test is of the pricing of the *conditional* β_{IML} that varies as a function of anticipated financial distress. That is, consider two stocks, one with constant exposure to *IML* and the other has its exposure to *IML* rising in time of greater anticipated financial distress, when both illiquidity and its expected premium are higher. We propose that the expected return on the second stock is higher than the first one. Our methodology follows Cochrane (1996, 2005) and LL in estimating and testing a cross-sectional model of stock expected returns as functions of *conditional* β_{IML}, the systematic risk of the *IML* factor scaled by lagged *SP*. This procedure allows both β_{IML} and its risk premium to vary as functions of the state of the market, being higher in times of anticipated financial distress.

Our main finding is that there is a positive and significant pricing of the conditional β_{IML} in the cross-section of stock returns, meaning that expected returns are higher for stocks with greater exposure to the illiquidity factor *IML* in times of financial distress when investors' aversion to illiquidity is higher. This result holds for our entire sample period of 66 years, 1952-2017, and it consistently holds for each of the two equal subperiods of 33 years. At the same

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Sarkissian, and Simin (2008) show that asset pricing models that employ conditional betas estimated from conditional asset pricing regressions are robust to data mining and that the pricing result is not spurious.

time, we find that the unconditional β_{IML} is not significantly priced in the cross-section. This result is similar to the findings of Cochrane (1996) and LL on the significant pricing of the conditional β of their pricing factors scaled by instruments that forecast the corresponding factor premiums while the unconditional β is not priced.[5]

The selection of our scaling instrument *SP*, the corporate bond yield spread, follows Cochrane (1996) and LL who use scaling instruments that forecast their pricing factors.[6] We find that *SP* forecasts the illiquidity premium factor *IML*. *SP* is a known indicator of financial distress and suitably represents the state of funding illiquidity in Brunnermeier and Pedersen (2009) which instigates a rise in the shadow price of illiquidity. Importantly, the corporate bond yield spread reflects an illiquidity premium in addition to the default premium, see Chen, Lesmond, and Wei (2007), Dick-Nielsen, Feldhutter, and Lando (2012), and Bongaerts, de Jong, and Driessen (2017). The corporate bond yield spread is also found to forecast adverse economic conditions. Fama and French (1989, p. 43) suggest that the default spread is "higher when times are poor" and Gilchrist and Zakrajšek (2012) find that the BAA-AAA corporate bond yield spread significantly forecasts increase in unemployment and decline in industrial production.[7] In addition to *SP*, we employ two alternative conditioning variables that proxy for financial distress and funding constraint: the TED spread (the Eurodollar rate minus the U.S. T-bill rate) with several maturities and the series of broker-dealer loans that importantly includes margin loans, which is the basis for the Brunnermeier and Pedersen (2009) analysis, relative to total loans. The results are similar for all three measures of funding illiquidity: the conditional β_{IML} on funding illiquidity is positively and significantly priced in the cross-section of individual stock returns in times of anticipated financial distress.

Our illiquidity return premium factor *IML* is constructed based on two widely used measures of illiquidity: Amihud's (2002) *ILLIQ*, the average of daily ratio of absolute return to dollar trading volume that measures the price impact, and Lesmond, Ogden, and Trzcinka's

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[5] In general, Cochrane (1996, p. 617) concludes that "[T]he scaled factor models typically perform substantially better than the nonscaled factor models." Watanabe and Watanabe (2008) too find that the β of innovations in illiquidity (a non-traded factor) is priced only in times of elevated trading volume but not otherwise.

[6] Cochrane's (1996) reasons the selection of his scaling variables – the term yield spread on Treasury bonds, the dividend/price ratio and the corporate bond default spread which we denote *SP* – in that they forecast stock returns factor in that "[T]hese instruments are popular forecasters of stock returns" (p. 588). Lettau and Ludvigson (2001) employ a scaling variable *cay*, the consumption/asset ratio, which forecasts the market return factor. They say (p. 1243) that *cay* "has striking forecasting power for excess returns on aggregate stock market indexes." Ferson and Harvey (1999) include *SP* among their instrumental variables that proxy for time variation in expected return.

[7] Schwert (1989) finds that the default spread predicts stock return volatility.

(1999) *ZERO*, the proportion of days with zero returns or no trade which is a general proxy measure of trading cost.[8] *ZERO* presents an aspect of illiquidity that is different from *ILLIQ* since it does not employ information on return, price, and volume used in calculating *ILLIQ*. We find that *IML*'s risk-adjusted mean, *alpha*, is about 4% annually under the FFC four-factor model, which is consistent with the evidence that illiquidity is priced.

We conduct two sets of robustness tests of our finding of significant positive pricing of the conditional β_{IML}, the β of *IML* that rises in times of financial distress. First, we test the pricing of the conditional β_{IML} in a model that includes the conditional βs of any of the four FFC factors. We find that the significant positive pricing of the conditional β is unique to *IML*. None of the conditional βs of the FFC factors is priced significantly in the same way as we find for *IML*.[9] In the second set of tests, we add to our model other liquidity-related factors proposed by Pastor and Stambaugh (2003), Liu (2006), and Korajczyk and Sadka (2008) and test the pricing of the conditional β_{IML} controlling for their unconditional and conditional βs. We find that the pricing of conditional β_{IML} remains positive and significant in the presence of the βs of the other liquidity-based factors.

Notably, our β_{IML} is different from the illiquidity betas studied by Pastor and Stambaugh (2003) and by Acharya and Pedersen (2005), denoted β_{IL}. *IML* is a traded return factor which represents the *return premium* on illiquidity while Pastor and Stambaugh (2003) and Acharya and Pedersen (2005) use non-traded factors of innovations in the *level of market (il)liquidity*. To illustrate the difference between these two βs by the standard CAPM, our β_{IML} is analogous to the β of the risk premium factor *RMrf*, while β_{IL} is analogous to the β of innovations in the level of market volatility (risk) studied by Ang, Hodrick, Xing, and Zhang (2006).

We use as test assets *individual* stocks instead of the often-used stock portfolios because of the well-known potential pitfalls in using portfolios for testing asset pricing models.[10] Lewellen, Nagel, and Shanken (2010) show that using test portfolios sorted on characteristics can impart a strong factor structure across them, providing a hurdle that is too low for testing

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[8] Lesmomd et al. (1999) suggest that given the cost of trading, the marginal investor may reduce trading or refrain from trading when the information signal is low causing a zero return or no trade day. Thus, a stock with higher transaction costs will have more zero returns days.

[9] In Section 4.3, we present evidence, which is not robust, that the premium of the conditional β of *HML* scaled by *SP* is positive and significant at the 10% significance level. This does not reduce the robust and significant pricing of conditional β_{IML} in times of financial distress.

[10] For a review of the problems in using stock portfolios in tests of asset pricing models, see Jegadeesh, Noh, Pukthuanthong, Roll, and Wang (2018) and Gagliardini, Ossola, and Scaillet (2016).

whether factor risks are priced. In addition, the estimated pricing of the factor risks may be sensitive to a subjective choice of sorting variables.[11] The drawback of employing individual stocks as test assets is the well-known errors-in-variables (EIV) bias. We attend to this problem by employing the EIV bias correction procedure of Litzenberger and Ramaswamy (1979) and Chordia, Goyal, and Shanken (2015). Our test results are qualitatively similar when we estimate the pricing model without correcting for the EIV bias and when we employ a weighted least square method that accounts for a bias resulting from market microstructure noise.

Earlier studies on the pricing of conditional liquidity-based systematic risk include those of Martinez, Nieto, Rubio, and Tapia (2005), Watanabe and Watanabe (2008), and Acharya, Amihud, and Bharath (2013). They all use non-traded illiquidity factors and present evidence that the β of illiquidity shocks is priced conditional on the state of the market and the economy.[12] In contrast, in our model with time-varying risk premium, the conditional β_{IML} employs a *traded* return factor that captures the return premium on illiquid stocks over liquid ones. Jensen and Moorman (2010) show that monetary expansion or contraction, which affects funding illiquidity, affects stock illiquidity and also affects the return spread between illiquid and liquid stocks. Our study is on the pricing of the conditional β_{IML} in bad times when funding illiquidity is high.

We proceed as follows. In Section 2, we introduce the *IML* illiquidity return premium factor and examine its risk-adjusted mean, its relation to other factors, and its behavior over time. Section 3 presents our main results on the pricing of the systematic risk of conditional *IML* under the FFC four-factor model. In Section 4, we present a number of robustness tests and show that the pricing of the conditional β_{IML} remains positive and significant in all these tests. Concluding remarks are presented in Section 5.

[11] Also, the power of an asset pricing test becomes lowered by the low dimensionality issue that can occur when employing stock portfolios and including a number of systematic risks and characteristics in the model. This problem can hinder identifying priced systematic risks significantly.
[12] Also, the early studies use stock portfolios as test assets while our tests employ individual stocks.

2. *IML*, the return on *Illiquid-Minus-Liquid* stocks

2.1. The construction of *IML*

We construct a return factor *IML* of *Illiquid-Minus-Liquid* stocks, which we expect to have a positive risk-adjusted return. This follows Amihud and Mendelson's (1986) proposition that stock illiquidity is positively priced across stocks, and the evidence since then (see summary in Amihud, Mendelson, and Pedersen, 2005, 2013). The construction of *IML* follows Fama and French's (1993) procedure in constructing the return factors *SMB* (small-minus-big firm size) and *HML* (high-minus-low book-to-market ratio), after having found that the characteristics size and book-to-market ratio are priced across stocks. We employ NYSE/AMEX[13] stocks with codes 10 and 11 (common stocks). The sample period covers 71 years, January 1947 through December 2017, 852 months in total. We begin the sample period in 1947 because book values of stocks (to calculate book-to-market ratios) which we need in the cross-sectional analysis are available on Compustat since the middle of 1951, and we need 60 months before that to estimate the β coefficient of *IML*.[14]

To construct the *IML*, we employ two illiquidity measures, *ILLIQ* and *ZERO*, proposed respectively by Amihud (2002) and by Lesmond, Ogden, and Trzcinka (1999). The first measure is based on the full information on return, price, and trading volume and the second one relies on the counts of days with zero returns or no trading. These measures are found by Hasbrouck (2009) and by Goyenko et al. (2009) to be strongly correlated with high-frequency (intraday) measures of price impact and the bid-ask spread, respectively.[15] $ILLIQ_{j,t}$ and $ZERO_{j,t}$ are calculated for each stock j over a rolling twelve-month window that ends in month t. $ILLIQ_{j,t}$ is the average daily values of $ILLIQ_{j,d} = |return_{j,d}|/dollar\ volume_{j,d}$ (in \$million). We delete stock-days with trading volume below 100 shares or with return of less than -100% and we also

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[13] These are the New York Stock Exchange and American Stock Exchange, where trading could be done directly between investors with the intermediation of specialists. The convention in the literature is to exclude Nasdaq stocks because, during much of the sample period, Nasdaq trading was conducted through market makers so the trading volume was counted twice (e.g., see Amihud (2002); Ben Rephael, Kadan, and Wohl (2013)).

[14] Also, since 1947, we have more than 40 stocks on average in each of the three high-*ILLIQ* and three low-*ILLIQ* portfolios. While there is no rule for the minimum number of stocks, it is clear that the efficiency and accuracy of the analysis are lower with a smaller number of stocks. For example, in May 1933 which is in the middle of the Great Depression there are only 10 stocks in each of the three high-*ILLIQ* and low-*ILLIQ* portfolios.

[15] *ILLIQ* is found by Hasbrouck (2009) and by Goyenko et al. (2009) as the best low-frequency proxy for Kyle's (1985) price impact measure that is estimated from intraday data. *ZERO* is found Lesmond et al. (1999) and by Goyenko et al. (2009) to be highly correlated with realized spread. Goyenko et al. (2009, p. 155) state that "… in more recent years, during the decimals regime, the performance of all measures deteriorates with the exception of Zeros and the Amihud measures." *ZERO* is used by Lesmond (2005) and by Bekaert, Harvey, and Lundblad (2007) to measure illiquidity in global markets.

delete the highest daily value of $ILLIQ_{j,d}$ in each twelve-month period. A stock is included if its price remains between $5 and $1000 and it has more than 200 days of valid return and volume data during the twelve-month period. $ZERO_{j,t}$ is the ratio of the number of days with zero returns or no trade divided by the total number of days in the rolling twelve-month window, which is used to calculate $ILLIQ_{j,t}$. Notably, *ZERO* is not based on trading volume or volatility which are components of *ILLIQ*. Finally, for each month t, we delete the stocks with the highest 1% values of $ILLIQ_{j,t}$ or $ZERO_{j,t}$.

Using $ILLIQ_{j,t}$ and $ZERO_{j,t}$, we construct two return factors $IML_{ILLIQ,t}$ and $IML_{ZERO,t}$ separately, employing the same methodology and the same sample of stocks. We sort stocks first by return volatility and then by each illiquidity measure in order to mitigate a possible confounding between their effects given the positive illiquidity-volatility correlation (Stoll, 1978) and the evidence on the effect of volatility on expected returns.[16] Stocks are sorted into three portfolios by $StdDev_{j,t}$, the standard deviation of daily returns, and within each volatility portfolio we sort stocks into five portfolios by either $ILLIQ_{j,t}$ or $ZERO_{j,t}$, all calculated over a period of twelve months. This produces 15 (3×5) portfolios for each illiquidity measure.[17] We calculate the month-t value-weighted average return of the stocks included in the portfolio on month t-2 (i.e., skipping month t-1) in order to avoid the effect of short-term reaction of stock returns following unusually large shocks of illiquidity or volatility.[18] We adjust returns by Shumway's (1997) method to correct for delisting bias.[19] $IML_{ILLIQ,t}$ and $IML_{ZERO,t}$ are the averages of the returns on the highest-illiquidity quintile portfolios minus the averages of the returns on the lowest-illiquidity quintile portfolios across the three corresponding *StdDev* portfolios. Finally, we calculate IML_t for each month t as the average of $IML_{ILLIQ,t}$ and $IML_{ZERO,t}$.

[16] Levy (1978) and Merton (1987) propose that expected stock return is *positively* related to idiosyncratic volatility because of limited diversification, while Amihud (2002), and Ang, Hodrick, Xing, and Zhang (2006, 2009) find a negative effect of (idiosyncratic) volatility on expected return.

[17] This procedure follows the procedure in Fama and French (1993) when constructing their *HML* factor. They first sort stocks by size and then by book-to-market ratio within each size portfolio.

[18] This follows Brennan, Chordia, and Subrahmanyam (1998) and Brennan, Chordia, Subrahmanyam, and Tong (2012), who discuss the merit of skipping one month. Fu (2009) notes the effect of return reversal on the relation between stock return and lagged idiosyncratic volatility.

[19] The last month return of a delisted stock is either the last return available from the Center for Research in Security Prices (CRSP), RET, or the delisting return DLRET, if available. If both are available, the calculated last month return proposed by CRSP is (1+RET)*(1+DLRET)-1. If neither the last return nor the delisting return is available and the deletion code is in the 500s—which includes 500 (reason unavailable), 520 (became traded over the counter), 551–573 and 580 (various reasons), 574 (bankruptcy), 580 (various reasons), and 584 (does not meet exchange financial guidelines)—the delisting return is assigned to be -30%. If the delisting code is not in the 500s, the last return is set to -1.0.

2.2. Analysis of *IML*

INSERT TABLE 1

Table 1 presents statistics for the *IML* return series for the entire sample period of 71 years or 852 months, from January 1947 to December 2017. For robustness, we also present results for two equal subperiods of 35.5 years, 1/1947-6/1982 and 7/1982-12/2017. In Panel A, the average monthly *IML* is 0.319%, nearly 4% a year, and it is statistically significant with t = 3.43. The median is 0.277% and the fraction of months with positive *IML* values is 0.550, which is significantly greater than 0.50, the chance result. The mean *IML* is positive and significant in both subperiods.

Panel B presents $alpha_{IML}$, the risk-adjusted *IML* after controlling for the FFC risk factors, estimated from the following model:

$$IML_t = alpha_{IML} + \beta_{RMrf}*RMrf_t + \beta_{SMB}*SMB_t + \beta_{HML}*HML_t + \beta_{UMD}*UMD_t + \varepsilon_t \,. \quad (1)$$

RMrf, *SMB*, *HML*, and *UMD* are, respectively, the market excess return over the T-bill rate, and the returns on small-minus-big firms (size factor), high-minus-low book-to-market ratio firms (value-growth factor), and winner-minus-loser stocks (momentum factor).

We find that $alpha_{IML}$ is positive and significant for the entire sample period of 1947 through 2017 and for each of the two subperiods. For the entire period, $alpha_{IML}$ is 0.341% with t = 5.47 and for the first and second subperiods, it is 0.441% with t = 4.94 and 0.288% with t = 3.33, respectively.[20] The positive and significant $alpha_{IML}$ after controlling for *SMB*, whose slope coefficient is positive and highly significant, means that the illiquidity premium is in excess of the size premium, which itself is partially due to small stocks' illiquidity. *HML*'s positive slope coefficient suggests a positive relation between illiquidity and the book-to-market ratio. This is consistent with the finding of Fang, Noe, and Tice (2009) on the negative relation between illiquidity and the inverse of book-to-market ratio.

Panel C presents *out-of-sample* estimates of one-month-ahead $alpha_{IML,t}$. We first estimate the coefficients of Model (1) over a rolling window of past 60 months up to month t - 1 and then use the estimated factors' coefficients β_{t-1} to calculate $alpha_{IML,t}$ using the realized factors returns in month t:

[20] The decline in the illiquidity premium over time is shown in Amihud (2002) and Ben Refael, Kadan, and Wohl (2015).

$$alpha_{IML,t} = IML_t - [\beta_{RMrf,t-1}*RMrf_t + \beta_{SMB,t-1}*SMB_t + \beta_{HML,t-1}*HML_t + \beta_{UMD,t-1}*UMD_t] .$$

This procedure is repeated by rolling forward the 60-month estimation window one month at a time. The statistics of the series $alpha_{IML,t}$ are presented for January 1952 through December 2017 since the first five years are used to estimate the first set of β values. The mean of out-of-sample $alpha_{IML,t}$ is 0.356%, with t = 5.87. For the first and second subperiods, the mean $alpha_{IML,t}$ is 0.487% with t = 5.36 and 0.242% with t = 3.00, respectively, all statistically significant. The medians are close to the means, and the fraction of positive values of $alpha_{IML,t}$ is significantly greater than 0.50, the chance result, for the entire period and for each of the two subperiods. Figure 1 presents a plot of the 12-month moving average of the monthly time-series of the out-of-sample $alpha_{IML,t}$.

INSERT FIGURE 1

In Panel D we estimate Model (1) separately for each of the two illiquidity factors, $IML_{ILLIQ,t}$ and $IML_{ZERO,t}$. The respective risk-adjusted returns are $alpha_{ILLIQ}$ = 0.391% (t = 6.00) and $alpha_{ZERO}$ = 0.291% (t = 4.03), both highly significant, for the entire sample period. The estimated $alpha_{ILLIQ}$ and $alpha_{ZERO}$ are also positive and significant for each of the two subperiods. This result indicates that the positive and significant risk-adjusted *IML* return is not confined into one particular measure of illiquidity.[21]

3. The pricing of *IML* systematic risks, β_{IML}

In this section, we study two research questions on the pricing of β_{IML}, the systematic risk of the illiquidity premium factor *IML*. The first is whether the risk premium on β_{IML} is higher in periods of anticipated financial distress and thus it is time-varying. The second is whether investors require higher expected returns on stocks whose β_{IML}s rise in times of higher anticipated funding illiquidity and distress. These predictions follow from Brunnermeier and Pedersen's (2009) proposition that the opportunity cost of illiquidity rises in times of funding illiquidity or financing constraints.

[21] Our main empirical results are robust to choosing $IML_{ILLIQ,t}$, $IML_{ZERO,t}$, or their average, i.e., IML_t.

3.1. The effect of expected financial distress on the risk premium of *IML*'s $\boldsymbol{\beta}$

3.1.1. The risk premium of unconditional $\boldsymbol{\beta_{IML}}$

The test procedure is as follows. First, we estimate for each stock *j* the factors' β coefficients from a time-series model using monthly returns over a rolling window of past 60 months that ends in month *s*-1:

$$(r_j - rf)_t = \beta_{0j} + \beta_{RMrf,j}*RMrf_t + \beta_{SMB,j}*SMB_t + \beta_{HML,j}*HML_t + \beta_{UMD,j}*UMD_t$$
$$+ \boldsymbol{\beta_{IML,j}*IML_t}\,. \qquad (2)$$

Next, we employ the Fama-Macbeth (1973) procedure and estimate in each month *s* a cross-sectional regression of stock excess return $(r_j - rf)_s$ on lagged factors' β coefficients that were estimated by Model (2). The model also includes stock characteristics[22] to accommodate Daniel and Titman's (1997) concern on whether it is the risks or the characteristics that are priced. (Below, we also estimate a cross-sectional model that includes only the factors' βs.)

$$(r_j - rf)_s = \gamma_{0,s} + \gamma_{RMrf,s}*\beta_{RMrf,j,s-2} + \gamma_{SMB,s}*\beta_{SMB,j,s-2} + \gamma_{HML,s}*\beta_{HML,j,s-2} + \gamma_{UMD,s}*\beta_{UMD,j,s-2}$$
$$+ \boldsymbol{\gamma_{IML,s}*\beta_{IML,j,s-2}} + \delta_{1,s}*ILLIQma_{j,s-2} + \delta_{2,s}*StdDev_{j,s-2} + \delta_{3,s}*BM_{j,s-2}$$
$$+ \delta_{4,s}*Size_{j,s-2} + \delta_{5,s}*R12lag_{j,s-2} + \delta_{6,s}*R1lag_{j,s-1}. \qquad (3)$$

The six stock characteristics included in the model are: **(1)** *ILLIQma*, the mean-adjusted stock illiquidity. This variable is the *ILLIQ* value of stock *j* calculated over a twelve-month period divided by the mean of all stocks' *ILLIQ* values for that period.[23] **(2)** *StdDev*, return volatility, measured by the standard deviation of daily stock returns over a twelve month period. Volatility is known to be positively correlated with *ILLIQ* and it has its own effect on the cross-section of stock returns (Amihud, 2002; Ang et al., 2006). For the calculation of *ILLIQ* and *StdDev*, we require to have more than 200 days of valid return and volume data, as we did in the construction of *IML*. **(3)** *BM* (in logarithm), the book-to-market ratio, using the book value from the firm's annual financial report (data are from Compustat) known as of the end of the previous fiscal year and the market value as of December of the year before the year of analysis. Following Fama and French (1992), we exclude stocks with negative book values. **(4)** *Size*, the logarithm of market capitalization. **(5)** *R12lag*, the lagged return over eleven months from month *s*-2 to month *s*-12 to

[22] As we do in the construction of *IML*, the lag skips one month (except for *R1lag*).

[23] This adjustment keeps the mean of *ILLIQma* stable at 1.0 in all months. See Amihud (2002), and Amihud, Hameed, Kang, and Zhang (2015).

capture the momentum effect. **(6)** *R1lag*, the stock return in month s-1 to capture the short-term reversal effect.

We employ individual stocks as test assets because using stock portfolios to test the pricing of the factors' βs may have potential pitfalls; see Lewellen, Nagel, and Shanken (2010). Model (2) is estimated over the sample period from January 1947 through December 2017 and Model (3) is estimated over the sample period from January 1952 through December 2017 since the first 60 months are used to estimate the first set of β coefficients. Data on book values of companies begin in the middle of 1951 on Compustat. We employ NYSE/AMEX-listed stocks that satisfy our data requirements. They have data for all the variables in Model (3) and their prices in month s-1 are between \$5 and \$1000. We then trim stocks whose *ILLIQ* is in the extreme 1% or whose estimated βs are in the 0.5% of each tail of the distribution (for each β). We end up having 718.8 stocks on average for the monthly cross-sectional regressions in Model (3) with the number of stocks for each month ranging between 174 and 1084. Stock returns in the monthly cross-sectional regressions are corrected for potential bias due to delisting (or survivorship) using Shumway's (1997) procedure.

The monthly estimation of Model (3) provides five time-series of monthly risk premiums on the unconditional factor βs: $\gamma_{RMrf,s}$, $\gamma_{SMB,s}$, $\gamma_{HML,s}$, $\gamma_{UMD,s}$, and $\gamma_{IML,s}$. The means and t-statistics of these γ coefficients are as follows. For $\gamma_{RMrf,s}$: 0.210 (t = 2.44). For $\gamma_{SMB,s}$: 0.618 (t = 1.22). For $\gamma_{HML,s}$: 0.093 (t = 1.94). For $\gamma_{UMD,s}$: -0.039 (t = -0.58). For $\gamma_{IML,s}$: 0.043 (t = 0.94), which is positive but insignificant.

3.1.2. The effect of financial distress on γ_{IML}, the risk premium of β_{IML}

We hypothesize that investors require greater premium on β_{IML} when they anticipate financial distress. To test that, we employ the methodology of Ferson and Harvey (1991, Section IV.A) and Chordia, Goyal, and Shanken (2015, Section V) who test the predictability of the risk premiums of factors' βs by regressing the series of estimated monthly premiums on lagged predictive variables. Here, we test our hypothesis by investigating whether γ_{IML}, the monthly premium of β_{IML} estimated by Model (3), is greater in times of higher value of lagged *SP*, the spread between the yields on BAA-rated and AAA-rated corporate bonds. (This time series is available for the entire sample period of January 1947 through December 2017 from the St. Louis Federal Reserve Bank database.) We estimate the following time-series model: in month t,

$$\gamma_{IML,t} = a0 + a1*DumSP_{t-1} + a2*RMrf_t\ , \tag{4}$$

where $DumSP_t = 1$ if SP_t is above the median and zero otherwise. Given the persistence of $DumSP_t$ – its autocorrelation is 0.88 – its high value in one month predicts a high value in the following month. In this model, *a1* measures the additional risk premium on β_{IML} demanded by investors in times of anticipated financial distress over the premium in "good" times, measured by *a0*, and $RMrf_t$ controls for general market conditions.

INSERT TABLE 2

The estimation results of Model (4), presented in Table 2, show that the risk premium of β_{IML} is positive and significant in times of anticipated financial distress and it is insignificant otherwise. In column (1), $a1$ = 0.189 with t = 2.13 which is significant, while $a0$ = -0.021 with t = -0.34, insignificant. When $RMrf_t$ is excluded (column (2)), $a1$ = 0.172 with t = 1.89, significant at 10% level, and $a0$ = -0.048 with t = -0.75, insignificant. The results imply a positive pricing of the systematic risk of *IML* in times of anticipated financial distress with an annualized premium that exceeds 2%, while this risk is not priced in "good" times. These results are consistent with the prediction of Brunnermeier and Pedersen's (2009) model in which the shadow price of illiquidity is strictly positive only when the financing constraint is binding following adverse financial shocks. When the funding constraint is not binding, the shadow price of illiquidity is zero. The empirical results are also consistent with the findings of Acharya, Amihud, and Bharath (2013) that illiquidity shocks are priced in corporate bond returns in months of anticipated adverse economic conditions while in other months their effect is mostly insignificant.

The estimation of *a1* in Model (4) may be subject to the finite sample bias problem given the high autocorrelation in the predictive variable, see Stambaugh (1999). We correct for the potential bias by Amihud and Hurvich's (2004) method and we find that the bias-corrected estimate of *a1* remains practically unchanged.

Next, we estimate Model (4) over a *rolling* window of 60 months where $DumSP_{t-1} = 1$ if it exceeds the median SP_t for that window. The estimation starts with the 60-month period of 1/1952 to 12/1956 and rolls forward one month at a time producing 733 monthly estimates of $a0_t$ and $a1_t$. Defining $Sum_t = a0_t + a1_t$, the *combined* risk premium of β_{IML} when $DumSP_{t-1} = 1$, we expect positive means of both $a1_t$ and Sum_t. We find that the proportions of estimated positive values of $a0_t$, $a1_t$, and Sum_t are, respectively, 0.46, 0.65, and 0.72. Figure 2 plots the series $a0_t$,

$a1_t$, and Sum_t over time. The estimated values of $a1_t$ and Sum_t are mostly positive and they are particularly high following the recent financial crisis.

INSERT FIGURE 2

We calculate the means of the coefficients $a0_t$ and $a1_t$ and their t-statistics which employ standard errors calculated by the Newey-West (1986) procedure with 12 lags. We find – the results are presented in column (3) of Table 2 – that the mean of $a1_t$ is 0.133 with t = 3.10, which is significant, and the mean of $a0_t$ is 0.033 with t = 1.09, insignificant. In column (4) where $RMrf_t$ is excluded, the means of $a1_t$ and $a0_t$ are, respectively, 0.085 (t = 2.56) and 0.008 (t = 0.29). We employ again Amihud and Hurvich's (2004) bias-correction method to the estimation in column (4) since the small sample size in the rolling 60-month regression window exacerbates the finite sample bias problem. We find that the mean of the corrected $a1_t$ rises from 0.085 to 0.101 with t = 2.39, which is significant, while the mean of corrected $a0_t$ is -0.0002 with t = -0.005.

We also test whether the mean of $Sum_t = a0_t + a1_t$ is significantly positive given that the estimated series $a0_t$ and $a1_t$ are negatively correlated. For the model in column (3) we find that the mean of Sum_t is 0.166 with t = 5.37, highly significant, and for the model in column (4) that excludes $RMrf_t$, the mean of Sum_t is 0.093 with t = 3.91, again highly significant. Using the bias-correction method for the latter model, we find that the mean of Sum_t = 0.102 with t = 3.37, again highly significant. We thus conclude that the risk premium on β_{IML} varies over time and it is positive and significant following months when SP_t exceeds its median, while β_{IML} is not priced following months when SP_t is below its median.

Columns (5) and (6) of Table 2 present the test results of Model (4) with log(SP_{t-1}) replacing $DumSP_{t-1}$. In column (5), $a1$ = 0.386 with t = 2.69 and $a0$ = 0.125 with t = 2.40, and in column (6) we find that $a1$ = 0.365 (t = 2.63) and $a0$ = 0.167 (t = 1.66). Again, since the predictor series log(SP_{t-1}) has high serial correlation of 0.98, we re-estimate the model in column (6) by Amihud and Hurvich's (2004) bias correction method. The corrected slope coefficient of log(SP_{t-1}) slightly rises from 0.365 to 0.374. The results show again that the risk premium on β_{IML} is time-varying and it becomes significant in times of anticipated financial distress proxied by higher lagged yield spread of corporate bonds.

When we repeat the same analysis in this section by excluding firm characteristics in the estimation of Model (3), we obtain results that are qualitatively similar to those in Table 2. We present these results Table A.1 of the Appendix.

Our results show that the premium on β_{IML} exhibits significant variation over time. We find that investors require significantly higher risk premium on β_{IML}, the systematic risk of the illiquidity return premium factor *IML*, when they anticipate financial distress which is signified by a higher value of lagged corporate bond yield spread.

3.2. The pricing of the conditional systematic risk of *IML*: Methodology

We now turn to our main test of whether investors price the conditional β_{IML} that is a function of lagged *SP*. A positive pricing of the conditional β_{IML} means that expected return is higher on stocks whose exposure to the liquidity return factor *IML* rises in times of anticipated financial distress when liquidity is more valuable. We follow the methodology of Cochrane (1996; 2005, Ch. 8) and LL, which estimates and test asset pricing models with conditioning information proxied by a lagged instrument variable.[24] These studies propose the following conditional asset pricing model:

$$\begin{aligned} \mathrm{E}_{t-1}[(r - rf)_t] &= a_{t-1} + b_{t-1}*\mathrm{E}_{t-1}[F_t] = a_0 + \beta_z*\mathrm{z}_{t-1} + (\beta_F + \beta_{Fz}*\mathrm{z}_{t-1})*\mathrm{E}_{t-1}[F_t] \\ &= a_0 + \beta_z*\mathrm{z}_{t-1} + \beta_F*\mathrm{E}_{t-1}[F_t] + \beta_{Fz}*\mathrm{E}_{t-1}[z_{t-1}*F_t], \end{aligned}$$

where r_t is the asset return, F_t is the pricing factor, a_{t-1} and b_{t-1} are parameters that can vary over time and are modeled to depend on z_{t-1}, a conditioning variable that summarizes the investors' information set in time *t-1*, and $\mathrm{E}_{t-1}[\ \cdot\ ] = \mathrm{E}[\ \cdot \mid z_{t-1}]$ is the conditional expectation on z_{t-1}. Then the conditional risk premium of the pricing factor F_t, i.e., $\mathrm{E}_{t-1}[F_t]$, is also assumed to be a function of z_{t-1}. This model replaces a one-factor model with time-varying coefficients by a three-factor model of z_{t-1}, F_t, and $z_{t-1}*F_t$ with fixed coefficients, where $z_{t-1}*F_t$ is a *scaled factor*.[25] The scaling instrument z_{t-1} is selected from among variables that forecast the pricing factor F_t and enter into the model significantly. For z_t, Cochrane (1996) and Ferson and Harvey (1999) employ the dividend/price ratio, the term spread of interest rates, and the corporate bond default yield spread

[24] See also Ferson and Schadt (1996), Jagannathan and Wang (1996), and Ferson and Harvey (1999).

[25] Cochrane (2005, p. 144) proposes: "To express the conditional implications of a given model, all you have to do is include some well-chosen scaled … portfolio returns… [y]ou can just add new factors, equal to the old factors scaled by the conditioning variables and … forget that you ever heard about conditioning information."

(similar to our *SP*), and LL employ *cay*, the consumption/asset ratio, which significant forecast market excess return.

The conditional asset pricing model above implies the following unconditional model:

$$E[(r_j - rf)] = \gamma_0 + \gamma_z * \beta_{z,j} + \gamma_F * \beta_{F,j} + \gamma_{Fz} * \beta_{Fz,j},$$

where γ_0 is the expected excess return on a zero-beta portfolio, and $\beta_{z,i}$, $\beta_{F,j}$, and $\beta_{Fz,j}$ are the slope coefficients from a time-series regression of stock *j*'s excess return $(r_j - rf)_t$ on z_{t-1}, F_t, and $z_{t-1} * F_t$, respectively. The test of the conditional asset pricing model above amounts to testing whether γ_F and γ_{Fz} are positive and significant. As Cochrane (2005) points out, the pricing of an unconditional factor model implies the pricing of the associated conditional factor model, while the pricing of a conditional factor model does not necessarily imply the pricing of its unconditional version. If a bad state is signified by $z_{t-1}>0$, a high value of $\beta_{Fz,j}$ implies a high value of $\beta_{Fz,j} * z_{t-1}$ in the bad state. Thus the positive coefficient of $\beta_{Fz,j}$ implies the positive pricing of $\beta_{Fz,j} * z_{t-1}$ in bad states, which captures the conditional exposure to the pricing factor F_t. With $z_t = cay_t$ and $F_t = RMrf_t$, LL find that γ_{Fz} is positive and significant in the cross-section of portfolio returns while γ_F is not significant, concluding that their conditional version of the CAPM empirically outperforms the unconditional CAPM.

As do Cochrane (2005) and LL, we select a conditioning variable which forecasts the factor whose systematic risk (β) is being studied and which is observed by investors when making their pricing decision. We find that our scaling instrument *SP*, the BAA-AAA corporate bond yield spread (in percent points), significantly forecasts the illiquidity factor *IML*. In a regression of IML_t on SP_{t-1} controlling for $RMrf_t$, the slope coefficient of SP_{t-1} is 0.732 with t = 3.65 for our sample period of January 1947 through December 2017. The positive effect of SP_{t-1} on the expected illiquidity premium is consistent with its forecasting of adverse economic conditions, see Gilchrist and Zakrajšek (2012). It is also consistent with Brunnermeier and Pedersen's (2009) proposition that in financial distress and lower funding liquidity, the market illiquidity and its shadow price or premium rise. Our scaling variable SP_{t-1} is observed by investors thus satisfying Cochrane's (2005, p. 143) requirement that the conditioning variable should be a part of the investors' information set in time *t-1*.

Extending the methodology explained above to our analysis, we now test whether the conditional β_{IML} that varies linearly in *SP* is significantly priced in times of financial distress across individual stocks. In the first stage, we estimate the following time-series factor model, an extension of Model (2), for each stock j over a rolling window of 60 months beginning with the period of January 1947 to December 1951: In month t,

$$(r_j - rf)_t = \beta_{0j} + \beta_{RMrf,j}*RMrf_t + \beta_{SMB,j}*SMB_t + \beta_{HML,j}*HML_t + \beta_{UMD,j}*UMD_t$$
$$+ \boldsymbol{\beta_{IML,j}*IML_t + \beta_{IMLZ1,j}*IML_t*Z1_{t-1} + \beta_{Z1,j}*Z1_{t-1}}, \qquad (5)$$

where the model includes the scaled factor IML_t*Z1_{t-1} to capture the time-variations in β_{IML} and its risk premium. In the second stage, in each month s that follows the 60-month estimation window, we employ the Fama-Macbeth (1973) procedure of estimating a cross-sectional regression of stock excess returns $(r_j - rf)_s$ on the seven β coefficients that are estimated in Model (5) and on six lagged stock characteristics (see details following Model (3)):

$$(r_j - rf)_s = \gamma_{0,s} + \gamma_{RMrf,s}*\beta_{RMrf,j,s-2} + \gamma_{SMB,s}*\beta_{SMB,j,s-2} + \gamma_{HML,s}*\beta_{HML,j,s-2} + \gamma_{UMD,s}*\beta_{UMD,j,s-2}$$
$$+ \boldsymbol{\gamma_{IML,s}*\beta_{IML,j,s-2} + \gamma_{IMLZ1,s}*\beta_{IMLZ1,j,s-2} + \gamma_{Z1,s}*\beta_{Z1,j,s-2}}$$
$$+ \delta_{1,s}*ILLIQma_{j,s-2} + \delta_{2,s}*StdDev_{j,s-2} + \delta_{3,s}*BM_{j,s-2}$$
$$+ \delta_{4,s}*Size_{j,s-2} + \delta_{5,s}*R12lag_{j,s-2} + \delta_{6,s}*R1lag_{j,s-1}. \qquad (6)$$

Our hypothesis is that γ_{IMLZ1} is positive, implying that stock expected return increases in its conditional exposure (β_{IML}) to the *IML* factor in times of financial distress. LL (p. 1266) suggest that the pricing of the *beta* of the scaled market factor "… may be attributable to time variation in risk aversion… or time variation in risk itself." Similarly, in our model the pricing of β_{IMLZ1} can be attributable to the time variation in illiquidity premium or variation in illiquidity risk itself.

Model (6) is estimated over 66 years or 792 months, January 1952 through December 2017. We employ three estimation methods:

(1) Ordinary least squares (OLS), which is commonly used in Fama–Macbeth regressions.

(2) CGS, the method of Chordia, Goyal, and Shanken (2015) that corrects for the bias in the estimation of the γ coefficients which is due to the errors-in-the-variable (EIV) problem by the estimated β coefficients.[26]

[26] This method follows the bias-correcting method of Litzenberger and Ramaswamy (1979) and Shanken and Zhou (2007). It relies on White's (1980) heteroscedasticity-consistent covariance matrix estimator for the OLS estimates of the β values and corrects for the EIV-induced bias in the OLS cross-sectional estimates of the γ values. In a single-factor model, the EIV problem induces downward bias in the (absolute) value of the γ coefficient. In a multifactor model, the directions of the EIV-induced biases depend not only on the variances of the β estimation errors but also on their covariances. Our estimation involves the covariance matrix of the estimated β values.

(3) Weighted least squares (WLS), following Asparouhova et al. (2010), to account for possible bias due to microstructure noise which inflates the average return of illiquid stock. The weights are proportional to the prior month's gross return, $1 + r_{j,s-1}$.

The scaling variable is $Z1_t = maSP_t$, the mean-adjusted SP_t[27] using the mean over of the preceding ten years. Table 3 presents summary statistics for the 13 explanatory variables —seven β coefficients and six stock characteristics—that are used in Model (6). In the left two columns, we present the average of the monthly means and monthly standard deviations that are calculated across all stocks in each month *s* over the 792 months of our sample period, 1952-2017. The right panel presents the averages of the monthly pairwise correlations across all stocks among some variables in each month *s*.

INSERT TABLE 3

3.3. Results for the pricing of the conditional β_{IML}

The tests of Model (6) that is estimated by the three methods—OLS, CGS, or WLS—employ the following two statistics:

(i) The mean of the monthly slope coefficients and its *t*-statistic

(ii) The precision-weighted mean and the respective *t*-statistic. The weights are proportional to the reciprocal of the standard errors of the slope coefficients from the monthly cross-sectional regressions, thus more precisely estimated monthly slope coefficients have greater weights.[28] Ferson and Harvey (1999) propose this weighting method to improve the efficiency of the slope coefficients estimated by the Fama-Macbeth procedure and mitigate the problem of heteroskedasticity.

INSERT TABLE 4

The results in Table 4 show that γ_{IMLZ1} is positive and highly significant, supporting our hypothesis that the investors price the *conditional IML* systematic risk in times of financial distress. That is, expected return is higher on a stock whose exposure to *IML* (the illiquidity return premium factor) rises in times of financial distress. At the same time, the unconditional

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[27] Lettau and Ludvigson's (2001) use the mean-adjusted value of their scaling variable *cay* and Cochrane (1996, p. 588) also transforms his scaling variable, the dividend/price series.

[28] For the weighted mean of the monthly slope coefficients estimated by the CGS method, we use as weights the reciprocals of the standard errors of monthly OLS cross-sectional regressions. Chordia et al. (2015) find, through simulations, that the Fama–MacBeth standard error estimates by OLS method are practically identical to the true standard deviations of the EIV-corrected slope coefficients by the CGS method.

β_{IML} is not significantly priced – the mean of γ_{IML} is positive but statistically insignificant. This is similar to the findings of Cochrane (1996) and LL that the *conditional* market βs enter into their pricing models significantly while the unconditional market βs do not. We also find that illiquidity as a characteristic is priced: the slope coefficient δ_1 of *ILLIQma* is positive and significant. These results hold under all three estimation methods: OLS, CGS, and WLS.

We find that the OLS estimated mean of γ_{IMLZ1} is 0.062% (t = 3.17) and its precision-weighted mean is 0.040% (t = 3.20). For the CGS method, the mean and precision-weighted mean of γ_{IMLZ1} are 0.060% (t = 3.52) and 0.043% (t = 3.72), respectively. For the WLS method, the mean and precision-weighted mean of γ_{IMLZ1} are close to those under the OLS method.

The economic significance of our test results is illustrated as follows. For each month s, we first compute $\gamma_{IMLZ1,s}*StdDev_c(\beta_{IMLZ1,j,s-2})$, which is the same as the risk premium on the *conditional* β_{IML} for that month,[29] where $StdDev_c$ is the cross-sectional standard deviation, and then we average it across all months. Using the CGS estimate, a stock whose $\beta_{IMLZ1,j,s-2}$ is one standard deviation greater has on average an annual expected return that is higher by 1.51% (= 12*0.126%) with t = 4.04, which is highly significant. This figure may have a large effect on stock prices. To illustrate, a rise of 1.51% in the discount rate of a perpetuity asset whose value is 15 lowers its value to 12.53.

As for the other variables, none of the four FFC β coefficients is significantly priced while the coefficients of all stock characteristics are significant with their predicted signs as has been observed in earlier studies. By the OLS estimate, the coefficient δ_1 of *ILLIQma* is 0.041% with t = 2.58 and the slope coefficients of *StdDev*, *BM*, *Size*, *R12lag*, and *R1lag* are -27.935% (t = -4.25), 0.098% (t = 2.45), -0.086% (t = -3.82), 1.116% (t = 6.77), and -5.047% (t = -14.99), respectively.

We conclude that across individual stocks, there is a positive and significant risk premium on the conditional systematic risk of the illiquidity return factor *IML* which rises in times of financial distress. We find this result, after controlling for the β coefficients of the four FFC factors and for six commonly-used firm characteristics, including illiquidity itself, which are priced in the cross-section. This means that expected returns are higher on stocks with greater sensitivities to the illiquidity return factor *IML* in times of financial distress.

[29] For each month s, $\gamma_{IMLZ1,s}*StdDev_c(\beta_{IMLZ1,j,s-2})$ is the same as the cross-sectional standard deviation of the conditional β_{IML} (= $StdDev_c(\beta_{IMLZ1,j,s-2}*Z1_{s-3})$) times its risk price (=$\gamma_{IMLZ1,s}/Z1_{s-3}$).

4. Robustness tests

We present seven robustness tests of the positive pricing of the conditional β_{IML} that rises in times of financial distress.

1) Using the baseline Model (6), we examine whether the results are consistent over time by splitting the sample period of 66 years into two non-overlapping subperiods of 33 years each and testing our hypothesis separately in each subperiod.

2) We test whether the results are robust to the measure of illiquidity by separately testing whether γ_{IMLZ1} is positive and significant when doing the analysis with either IML_{ILLIQ} or IML_{ZERO},

3) We expand the baseline model with the FFC factors, conditioning each factor's β and risk premium on $Z1_{t-1}$ as we do for *IML*.

4) We test whether the pricing of conditional β_{IML} remains positive and significant after expanding the baseline model with four liquidity-based factors that were proposed in earlier studies, allowing their βs and risk premiums to be conditional on $Z1_{t-1}$.

Next, we do three tests in which we replace the scaling variable $Z1_t$ by other scaling variables that are related to financial distress and re-estimate the baseline models of Table 4. We use the following scaling variables:

5) We use as a conditioning variable $Z2_t = dSP_t^+$, the positive change or the rise in SP_t. Then, the positive and significant coefficient of β_{IMLZ2} implies the pricing of the conditional systematic risk of *IML* when financial conditions worsen.

6) We use $Z3_t$ = the TED spread, a known indicator of financial distress or funding illiquidity.

7) We use $Z4_t$ = the broker-dealer loans series that includes their margin loans in excess of total loans. This choice of scaling variable is motivated by Brunnermeier and Pedersen's (2009) theory which is based on the effect of margin loan constraint on the rise in illiquidity and in its premium.

In all these robustness tests, we find that the slope coefficient of β_{IMLZ} is positive and highly significant as we find it to be for the baseline model in Table 4, indicating that the pricing of conditional β_{IML} in times of financial distress or funding illiquidity is fairly robust.

4.1 Testing our baseline model over subperiods.

We test whether the positive and significant slope coefficient of β_{IMLZ1} is consistent over time. We split the sample period of 66 years (January 1952 through December 2017) into two equal subperiods of 33 years and repeat our tests for each subperiod separately. This can be viewed as an out-of-sample test of the pricing of conditional β_{IML} over the second subperiod after having observed its pricing in the first subperiod. The test results for γ_{IMLZ1} are presented in Table 5 using the CGS bias-correcting method. We find that in both subperiods, the means and precision-weighted means of γ_{IMLZ1} are positive and significant. Notably, the magnitude of these coefficients is similar in both subperiods indicating consistency over time in the pricing of β_{IMLZ1}. Naturally, the power of the subperiod tests is lower than it is when we use the entire sample period.

INSERT TABLE 5

4.2. Separate tests using IML_{ILLIQ} or IML_{ZERO}.

We replace IML_t in Model (5) by $IML_{ILLIQ,t}$ or by $IML_{ZERO,t}$ and employ each of these estimated βs in Model (6). The test results are qualitatively similar to those reported in Table 4, that is, we find positive and significant slope coefficients of β_{IMLZ1} with either IML_{ILLIQ} or IML_{ZERO}. For example, under the CGS method, for IML_{ILLIQ}, the mean γ_{IMLZ1} is 0.054% (t = 3.06) and its precision-weighted mean is 0.047% (t = 3.87). For IML_{ZERO}, the mean γ_{IMLZ1} is 0.060% (t = 3.18) and its precision-weighted mean is 0.037% (t = 2.82). We find that the slope coefficients of β_{IMLZ1} are also positive and significant for each of the two subperiods.

4.3. Tests using the conditional βs of the four FFC factors

This section provides two tests. First, we test whether the conditional β_{IML} remains positively and significantly priced in the presence of the conditional βs of any of the four FFC factors that are estimated in the same way as we estimate β_{IMLZ1}. Second, we test whether the conditional βs of the FFC factors are significantly priced or whether the pricing of conditional β with *SP* as a conditioning variable is unique to the *IML* factor.

The test is conducted as follows. For each factor F, F = *RMrf*, *SMB*, *HML*, or *UMD*, we add to Model (5) the term $\beta_{FZ1}*F_t*Z1_{t-1}$ and estimate β_{FZ1} together with all the other βs. Then, we add β_{FZ1} to Model (6) and estimate its slope coefficient γ_{FZ1} together with all the other variables in Model (6). We test whether the slope coefficient of β_{IMLZ1} is positive and significant and whether the slope coefficients of β_{FZ1} are positive and significant as well.

We have two important findings. First, the means of γ_{IMLZ1} remain positive and highly significant regardless of which of the FFC factors' *conditional* βs is added to Model (6). For example, in the models that include the conditional βs of $F = RMrf$, *SMB*, *HML*, or *UMD*, under the CGS method the precision-weighted means of γ_{IMLZ1} are 0.039% (t = 3.28), 0.043% (t = 3.66), 0.042% (t = 3.55), and 0.041% (t = 3.49), respectively. Second, none of the means of the γ_{FZ1} coefficients is consistently significant. We find these results both in the entire sample period and in each of the two subperiods. Under the CGS method, for the entire sample period, the precision-weighted means are γ_{RMrfZ1} = -0.041% (t = -1.47) for β_{RMrfZ1}, γ_{SMBZ1} = 0.010% (t = 0.91) for β_{SMBZ1}, γ_{HMLZ1} = 0.021% (t = 1.79) for β_{HMLZ1}, and γ_{UMDZ1} = -0.008% (t = -0.50) for β_{UMDZ1}, respectively. Thus, the significant pricing of the conditional β is unique to *IML* where the conditioning variable indicates financial distress. This supports our proposed link between the pricing of exposure to the illiquidity factor *IML* and financial distress or funding illiquidity, following Brunnermeier and Pedersen (2009).

We focus on the model which includes SMB_t*Z1_{t-1} given the strong relation between illiquidity and size. For this model, under the CGS method, the precision-weighted mean of γ_{IMLZ1} is 0.043% with t = 3.66, which is similar to what we find in Table 4. For the two subperiods, the precision-weighted means for γ_{IMLZ1} and γ_{SMBZ1} are, respectively, 0.033% (t = 2.12) and -0.006% (t = 0.40) for the first subperiod, and those are, respectively, 0.052% (t = 3.01) and 0.026% (t = 1.54) for the second subperiod. We also find that the means of both γ_{IML} and γ_{SMB} are positive but insignificant.

We also report that γ_{HMLZ1} is positive and significant at the 10% level. However, this result is not robust across the two subperids. Under the CGS method, the precision-weighted means of γ_{HMLZ1} are 0.006% (t = 0.39) and 0.034% (t = 1.87) for the first and second subperiods, respectively. At the same time, those of γ_{IMLZ1} are 0.034% (t = 2.14) and 0.050% (t = 2.84), respectively, both positive and significant.

We conclude that the pricing of the conditional β_{IML} in times of financial distress remains positive and significant in the presence of the conditional βs of the FFC factors and that this pricing of conditional β is unique to *IML*.

4.4. The pricing of the conditional β_{IML} and the conditional βs of other liquidity factors

We add to our model liquidity-based factors that were used in earlier studies and test whether the pricing of the conditional β_{IML} remains positive and significant in the presence of these factors' βs, both unconditional and conditional.[30]

For each of the liquidity-based factors that we use, denoted LF_t, we add to Model (5) $\beta_{LF}*LF_t + \beta_{LFZ1}*LF_t*Z1_{t-1}$. We estimate this augmented model over a rolling 60-month period, add the estimated coefficients β_{LF} and β_{LFZ1} to the cross-sectional regression in Model (6). Finally, we estimate the slope coefficients of these βs, γ_{LF} and γ_{LFZ1}, together with the slope coefficients of all the other βs and characteristic variables in Model (6).

We use four liquidity-based factors. The first two are traded factors that represent a liquidity-based return premium as does *IML*, and the other two are non-traded factors that represent shocks to market-wide (il)liquidity. The four liquidity factors are:

(i) *PS*, a traded liquidity risk factor due to Pastor and Stambaugh (2003). It is the value-weighted average return on the high-minus-low decile portfolios obtained by sorting stocks on the β values which are obtained from a regression of each stock return series on innovations in the aggregate liquidity index that they propose. This factor has a positive and significant excess return. *PS*, available from Lubos Pastor's homepage,[31] begins on January, 1968.

(ii) *LIU*, a traded illiquidity premium factor proposed by Liu (2006). It is the differential return between illiquid and liquid stocks, using Liu's liquidity measure that is based on non-trading days and turnover. The time series of *LIU*, kindly provided by the author, is available from January, 1947 to December, 2014. The correlation of *LIU* and *IML* is 0.46. While both *IML* and *LIU* measure the return premium on illiquid-minus-liquid stocks, they differ not only in underlying illiquidity measures but also in their construction. Compared to *IML*, *LIU* reflects the returns on more extremely illiquid and liquid stocks without controlling for stock return volatility (*StdDev*).[32]

[30] Notably, while we use individual stocks as test assets, earlier studies employ as test assets stock *portfolios* sorted on some characteristics.

[31] http://faculty.chicagobooth.edu/lubos.pastor/research/liq_data_1962_2017.txt

[32] *LIU* is based on extreme decile portfolios sorted on his illiquidity measure with equally weighted returns, while *IML* is based on quintile portfolios double sorted on *ILLIQ* and *StdDev* with value-weighted returns. The mean return of *LIU* is nearly halved when using *value*-weighted returns, see Liu (2006, p. 642).

(iii) *dMILLIQ*, the first-order difference of the logarithm of monthly market illiquidity *MILLIQ*, a non-traded factor. *MILLIQ* is the average over the days of each month of the value-weighted average of daily *ILLIQ* across the stocks that satisfy our data requirements.[33] This series is available for the entire sample period of our analysis. Testing whether the systematic risk of market-wide illiquidity shocks is priced is related to the analyses of Pastor and Stambaugh (2003) and Acharya and Pedersen (2005).

(iv) *KS*, the innovation in the market-wide liquidity measure of Korajczyk and Sadka (2008), a non-traded factor. *KS* combines several liquidity measures by employing the principal component analysis, given the considerable commonality among them. Data for *KS* begin on September 1983. Hence the cross-sectional regressions are run over the sample period from October 1988 to December 2000 (147 months).

INSERT TABLE 6

We find that γ_{IMLZ1} is positive and highly significant in all model specifications with any of the alternative liquidity factors. Table 6 presents the test results of the slope coefficient of β_{IMLZ1} in the presence of β_{LF} and β_{LFZ1}, the βs of the other liquidity factors, $LF = PS$, LIU, *dMILLIQ*, or *KS*. To save space we present the results only under the CGS method for the slope coefficients of the liquidity-related βs. The cross-sectional regression models include all the other βs and stock characteristics in Model (6).

In summary, we find that the positive and significant pricing of the conditional β_{IML} in times of financial distress survives a "horse race" with the unconditional and conditional βs of other liquidity-based factors.

4.5. Using as a conditioning variable the positive change in *SP*

We employ a different scaling variable, the *rise* in SP_t which indicates worsening of a financial and economic state. Denoting by dSP_t the first-order difference in the SP_t, the new conditioning variable is $Z2_t = dSP_t^+$, which equals dSP_t when $dSP_t > 0$ and zero otherwise. We estimate Models (5) and (6) using this scaling variable. The associated test results on the pricing

[33] The value weighting employs the stock capitalization at the end of the preceding month. Included are common stocks (codes 10 and 11) that trade on NYSE/AMEX whose price is between \$5 and \$1,000 at the end of the preceding month. For each day, we delete the 1% of stocks with the highest *ILLIQ*, which are possible outliers.

of the conditional systematic risk β_{IML}, presented in Table 7, Panel A, are qualitatively similar to those in Table 4 with $Z1_t$.[34]

Under the OLS method, the mean of γ_{IMLZ2} is 0.014% (t = 3.26) and its precision-weighted mean is 0.005% (t = 2.57). Under the CGS method, the mean and precision-weighted mean of γ_{IMLZ2} are 0.013% (t = 3.50) and 0.005% (t = 2.56), respectively. Under the WLS method, the mean and precision-weighted mean are similar to those under the OLS method. In summary, with this scaling variable that proxies for worsening financial distress, the pricing of the conditional β_{IML} is positive and significant.

INSERT TABLE 7

4.6. Using the TED spread series as a conditioning variable

We now use as a conditioning variable the TED spread which has been defined as "a measure of liquidity strains on the banking system," quoting Cornett, McNutt, Strahan, and Tehranian (2011, p. 299) since it usually widens in time of financial distress. Brunnermeier (2009, p. 85) also suggests: "The TED spread provides a useful basis for gauging the severity of the current liquidity crisis." We construct the monthly TED spread as the difference between the Eurodollar rate and U.S. T-bill rate, both with one month to maturity. (We also use three or six months to maturity.) The series are available from the Federal Reserve Bank of St. Louis. Data on the Eurodollar rate begin in 1971. We find that TED_t and SP_t are positively correlated with a coefficient of 0.335 which is significant at the 1% level. We estimate Models (5) and (6) above replacing the conditioning variable $Z1_t$ by $Z3_t$ which equals the demeaned TED_t. The cross-sectional regressions in Model (6) are estimated over 488 months (about 41 years) from March 1976 through October 2016.[35]

We find that γ_{IMLZ3}, the slope coefficient of β of IML scaled by the TED spread, is positive and significant under all estimation methods. The results are reported in Table 7, Panel B for γ_{IML} and γ_{IMLZ3} (to save space). Under OLS, CGS, and WLS, the mean of γ_{IMLZ3} is 0.221% (t = 2.78), 0.152% (t = 2.19), and 0.215% (t = 2.73), respectively. The results mean that expected returns are higher on stocks with greater exposure to IML in times of financial distress which is

[34] Employing both dSP_t^+ and dSP_t^- as conditioning variables does not affect the significance of the slope coefficient of β_{IMLZ2}, while the slope coefficient of conditional β_{IML} based on dSP_t^- is insignificant.
[35] The series of TED spread was discontinued on October 2016 in the Federal Reserve Bank of St. Louis.

signified by high values of TED spread. This is consistent with our earlier results when using the BAA-AAA corporate bond yield spread as a proxy for funding illiquidity. The results on γ_{IMLZ3} being positive and significant are similar when we replace the TED spread with one month to maturity by the TED spread with three or six months to maturity. As before, the γ coefficients of the Fama-French factors' βs (not reported in the table) are insignificantly different from zero except for γ_{HML} whose mean is significantly positive at the 10% level under the OLS estimation method.

4.7. Using broker-dealer loans series as a conditioning variable

We employ a proxy measure of funding illiquidity or financial constraint based on loans made by brokers and dealers that include margin loans. The use of this proxy is motivated by Brunnermeier and Pedersen (2009, p. 2202) who link margin requirements and dealer funding to market liquidity. Here, funding illiquidity is indicated by a decline in broker-dealer loans, which include margin loans, relative to a benchmark series of total loans of brokers and dealers. We use the following series, available from the Federal Reserve Bank of St. Louis. *S1* is the series "Security brokers and dealers; other loans and advances; assets" (SBDOLAA)[36] that includes "margin accounts at brokers and dealers." *S2* is a benchmark loan series, defined as "Security brokers and dealers; loans; liability" (series SBDLL). These series are quarterly, available for the period Q1/1952 to Q4/2017. They are generally upward trending with a sharp decline at the end of 2008 during the financial crisis. The mean ratio *S1*/*S2* is 0.604, the median ratio is 0.619, and the interquartile range is 0.447 to 0.741. The series is highly persistent with a first-order serial correlation of 0.88.

We construct a series of the quarterly change in the ratio of these two series: $dS12_q = (S1/S2)_q - (S1/S2)_{q-1}$ in quarter q. Next, we examine the economic significance of this series by relating it to other economic series. We find the following results. First, $dS12_q$ is negatively correlated with dSP_q, the quarterly change in the yield spread between BAA- and AAA-rated corporate bonds (using the average spread over the quarter). In a regression of $dS12_q$ on dSP_q, the slope coefficient is -0.087 with t = -3.92. This means that in times of financial distress, the series that includes broker-dealer margin loans declines relative to the benchmark loan series. Second,

[36] The definitions are available in the web site of the Federal Reserve Bank of St. Louis for the respective series. The components of the series SBDOLAA are available from this web site https://www.federalreserve.gov/apps/fof/SeriesAnalyzer.aspx?s=FL663069005&t=

broker-dealer margin loans increase (decrease) following a rise (fall) in stock prices. In a regression of $dS12_q$ on $RMrf_{q-1}$, the quarterly market excess return, (and an intercept), the slope coefficient is 0.192 with t = 3.60. Finally, lagged $dS12_q$ negatively and significantly forecasts IML_q, the quarterly compounded monthly IML_t. Regressing IML_q on $dS12_{q\text{-}1}$ (and an intercept), the slope coefficient is -0.119 with t = -2.90 and when adding to the model $RMrf_q$ as a control, the slope coefficient of $dS12_{q\text{-}1}$ is -0.112 with t = -2.72. This suggests that a decline in broker-dealer margin loans, which indicates financing constraint, forecasts a rise in the expected illiquidity premium. These results are consistent with Brunnermeier and Pedersen's (2009) theory on the effect of the margin loans and financial constraint on the shadow price of liquidity and on the effect of shock to market prices on subsequent margin loans.

We now estimate Model (5) replacing $Z1_{t-1}$ by $Z4_{t-1}$ = $-dS12_{q-1}$, the value of the series in the quarter that precedes the quarter of month t. We multiply $dS12$ by -1 to make $Z4$ positively related to funding illiquidity and financial distress as are $Z1$, $Z2$, and $Z3$ above. Since the data on $S1$ and $S2$ are available from Q1/1952, the cross-sectional monthly estimation of Model (6) is conducted over the period of August 1957 through December 2017 (725 months). We expect that γ_{IMLZ4} is positive as are γ_{IMLZ1}, γ_{IMLZ2}, and γ_{IMLZ3} in previous analyses.

The results in Table 7, Panel C for γ_{IML} and γ_{IMLZ4} from Model (6) show that γ_{IMLZ4} is positive and significant.[37] The mean and precision-weighted mean of γ_{IMLZ4} under CGS are, respectively, 0.019% with t = 2.15 and 0.012% with t = 2.02. Under the OLS method, the mean and precision-weighted mean of γ_{IMLZ4} are 0.018% (t = 2.13) and 0.012% (t = 2.03), respectively. The results are similar under the WLS method. As for γ_{IML}, the slope coefficient of the unconditional β_{IML}, its mean under the CGS method is 0.088% with t = 1.85, which is significant at the 10% level.

In conclusion, using a loan-based conditioning variable that includes broker-dealer's margin loans, we find that the conditional systematic risk of IML is positively and significantly priced in times of financial distress and funding illiquidity, which is consistent with its pricing evidence when using the corporate bond yield spread and the TED spread as conditioning variables.

[37] Regarding the pricing of the other factors' βs, we find that only the means and precision-weighted means of γ_{HML} are positive and marginally significant at the 10% level under all three estimation methods.

5. Conclusion

This paper tests whether the market is pricing the *conditional* systematic risks of the illiquidity return premium factor, denoted *IML*. The *IML* systematic risk, β_{IML}, and its premium are modeled to be conditional on financial distress and funding illiquidity using as a proxy the yield differential between BAA- and AAA-rated corporate bonds. We find that expected returns are higher for stocks with greater sensitivity to the illiquidity return premium factor *IML* in times of greater financial distress and funding illiquidity. This pricing evidence of conditional β_{IML} remains robustly significant after controlling for the conditional and unconditional βs of the Fama-French-Carhart return factors. Further, we find that the pricing of the conditional β_{IML} is positive and significant in the presence of the conditional and unconditional βs of several commonly used illiquidity-based factors and of stock characteristics including size and illiquidity. Our finding also holds when using other proxies for financial distress and funding illiquidity: the TED spread and the (negative of the) difference between the loans made by brokers and dealers, which include their margin loans, and a benchmark of their total loans. In all, greater exposure to the illiquidity return factor in times of financial distress is positively and significantly priced.

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Table 1: Time-series estimation results for the illiquidity return premium factor *IML* (*Illiquid-Minus-Liquid)*

IML is the differential return between the highest-illiquidity and lowest-illiquidity quintile portfolios of stocks. We sort stocks by either one of the two measures of illiquidity: (1) *ILLIQ*, the average daily values of |return|/dollar volume, or (2) *ZERO*, the proportion of zero-return or no-trading days. Both measures are calculated over a rolling window of twelve months. In each month, stocks are first sorted into three portfolios by the standard deviation (*StdDev*) of their daily returns, and within each tercile portfolio, stocks are sorted into five portfolios by *ILLIQ* or by *ZERO*. This produces 15 (3x5) portfolios for each illiquidity measure. Value-weighted average returns are calculated for each portfolio for each month *t* using the ranking done in month *t*-2 (i.e., skipping one month after the portfolio formation period). The *IML* for each illiquidity measure is the average return on the three highest-illiquidity quintile portfolios (across the volatility portfolios) minus the average return on the three lowest-illiquidity quintile portfolios. This produces IML_{ILLIQ} and IML_{ZERO}. Finally, we define $IML = (IML_{ILLIQ} + IML_{ZERO})/2$. The returns are in monthly percentage points. We use NYSE/AMEX stocks and apply some filters (details are provided in the text). Estimations are performed for the entire sample period of 71 years (852 months), January 1947 to December 2017, and for each of its two equal subperiods.

Panel A: Statistics on *IML* returns. The *p*-values are from tests of whether the fraction of positive returns is 0.50, the result due to chance. All other numbers in parentheses (in all panels) are *t*-statistics, employing robust standard errors.

Panel B: The intercept $alpha_{IML}$ and the β coefficients of the FFC factors obtained from the regression model

$$IML_t = alpha_{IML} + \beta_{RMrf}*RMrf_t + \beta_{SMB}*SMB_t + \beta_{HML}*HML_t + \beta_{UMD}*UMD_t + \varepsilon_t\,, \quad (1)$$

RMrf is the market return in the excess of the risk-free rate, *SMB* and *HML* are the Fama and French (1993) factors of size and the book-to-market (BE/ME) ratio, and *UMD* is the Carhart (1997) momentum factor (We denote them as FFC factors.). The calculation of *t*-statistics (in parentheses) employs robust standard errors (White, 1980).

Panel C: Out-of-sample, one-month-ahead rolling $alpha_{IML,t}$. Model (1) is estimated over a rolling window of 60 months beginning in January 1947. For month 61, $alpha_{IML,t} = IML_t - [\beta_{RMrf,t-1}*RMrf_t + \beta_{SMB,t-1}*SMB_t + \beta_{HML,t-1}*HML_t + \beta_{UMD,t-1}*UMD_t]$, using the β values estimated from the previous 60-month estimation window. The values of the out-of-sample $alpha_{IML,t}$ begin in January 1952.

Panel D: Estimates of Model (1) separately for IML_{ILLIQ} and IML_{ZERO}.

	1947–2017	1947-6/1982	7/1982–2017
Panel A: Statistics on *IML*			
Mean	0.319 (3.43)	0.385 (2.77)	0.254 (2.05)
Median	0.277	0.295	0.227
Fraction positive	0.550	0.549	0.552
Serial correlation	-0.057	-0.040	-0.079
N	852	426	426
Panel B: Regression of *IML* on the FFC factors			
$\boldsymbol{alpha_{IML}}$	**0.341 (5.47)**	**0.441 (4.94)**	**0.288 (3.33)**
β_{RMrf}	-0.287 (-15.59)	-0.328 (-13.00)	-0.234 (-10.08)
β_{SMB}	0.606 (18.87)	0.595 (13.56)	0.574 (12.88)
β_{HML}	0.404 (12.34)	0.468 (8.02)	0.366 (10.00)
β_{UMD}	-0.078 (-3.77)	-0.206 (-5.37)	-0.006 (-0.26)
R^2	0.61	0.66	0.61
Panel C: One-month-ahead rolling $alpha_{IML,t}$			
Mean $\boldsymbol{alpha_{IML,t}}$	**0.356 (5.87)**	**0.487 (5.36)**	**0.242 (3.00)**
Median	0.330	0.480	0.293
Fraction positive	0.587	0.617	0.561
Serial correlation	0.073	0.124	0.017
N	792	366	426
Panel D: Estimated intercepts (*alpha*) of Model (1) for IML_{ILLIQ} and IML_{ZERO}			
$alpha_{ILLIQ}$	0.391 (6.00)	0.500 (5.66)	0.328 (3.57)
$alpha_{ZERO}$	0.291 (4.03)	0.382 (3.75)	0.247 (2.41)
Both include FFC factors	Yes	Yes	Yes

Table 2: The effect of the corporate bond yield spread on γ_{IML}, the risk premium of $\boldsymbol{\beta_{IML}}$

This table presents the effect of the corporate bond yield spread between BAA-rated and AAA-rated bonds, denoted SP_t, on γ_{IML}, the risk premium of β_{IML}, the systematic risk of *IML*, the illiquid-minus-liquid return premium factor (see Table 1 for details). The data period is January 1947 through December 2017. In the first stage, β coefficients are estimated from the following time-series model over a rolling window of 60 months for each stock *j*, with the first estimation window being January 1947 to December 1951:

$$(r_j\text{-}rf)_t = \beta_{0j} + \beta_{RMrf,j}*RMrf_t + \beta_{SMB,j}*SMB_t + \beta_{HML,j}*HML_t + \beta_{UMD,j}*UMD_t + \boldsymbol{\beta_{IML,j}*IML}. \qquad (2)$$

The dependent variable is the monthly return on stock *j*, $r_{j,t}$, in excess of the risk-free rate, rf_t. The first four factors are those of Fama and French (1993) and Carhart (1997) (see Table 1). In the second stage, for each month *s* in the period of January 1952 through December 2017, we estimate a cross-sectional regression of individual stock excess returns $(r_j - rf)_s$ on their β coefficients estimated by Model (2) and on six stock characteristics:

$$\begin{aligned}(r_j - rf)_s = {} & \gamma_{0,s} + \gamma_{RMrf,s}*\beta_{RMrf,j,s-2} + \gamma_{SMB,s}*\beta_{SMB,j,s-2} + \gamma_{HML,s}*\beta_{HML,j,s-2} + \gamma_{UMD,s}*\beta_{UMD,j,s-2} \\ & + \boldsymbol{\gamma_{IML,s}*\beta_{IML,j,s-2}} + \delta_{1,s}*ILLIQma_{j,s-2} + \delta_{2,s}*StdDev_{j,s-2} + \delta_{3,s}*BM_{j,s-2} \\ & + \delta_{4,s}*Size_{j,s-2} + \delta_{5,s}*R12lag_{j,s-2} + \delta_{6,s}*R1lag_{j,s-1}. \qquad (3)\end{aligned}$$

The stock characteristics are: *ILLIQma* is stock illiquidity (see Table 1), mean adjusted by division by the mean of *ILLIQ* values across all stocks used in the monthly cross-sectional regression, and *StdDev* is return volatility, measured by the standard deviation of daily returns. Both *ILLIQ* and *StdDev* are calculated from daily data over a twelve-month rolling window. The variable *BM* (in logarithm) is the book-to-market ratio, using the book value from the firm's annual financial report known as of the end of the previous fiscal year and the market value as of December of the year before the year of analysis. The variable *Size* (in logarithm) is the market capitalization and *R12lag* is the lagged cumulative stock return over past eleven months. These stock characteristics are lagged, skipping one month, except for the variable *R1lag* which is the one-month lagged stock return.

The table presents the results in columns (1)-(4) of the following time-series regression model:

$$\gamma_{IML,t} = a0 + a1*DumSP_{t-1} + a2*RMrf_t\ , \qquad (4)$$

where $DumSP_t$ = 1.0 if SP_t is above its median value (zero otherwise). Columns (5)-(6) present results of Model (4) replacing $DumSP_t$ by log(SP_t). Columns (1)-(2) and (5)-(6) present the regression results for the entire sample period. Columns (3)-(4) present the average slope coefficients of regressions estimated over 60-month rolling windows with $DumSP_t$ calculated relative to the medians of those windows. The *t*-statistics in columns (1)-(2) and (5)-(6) employ robust standard errors following White (1980) and those in columns (3)-(4) employ Newey-West (1986) standard errors with 12 lags.

	Regressions over the entire sample period		Regressions over rolling 60 months		Regressions over the entire sample period	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	-0.021 (-0.34)	-0.048 (-0.75)	0.033 (1.09)	0.008 (0.29)	0.125 (2.40)	0.167 (1.66)
$DumSP_{t-1}$	0.189 (2.13)	0.172 (1.89)	0.133 (3.10)	0.085 (2.56)		
log(SP_{t-1})					0.386 (2.69)	0.365 (2.63)
$RMrf_t$	-0.060 (-4.65)		-0.068 (-7.49)		-0.060 (-4.71)	
R^2	0.044	0.004	0.096	0.017	0.053	0.013

Table 3: Summary statistics of the variables

This table presents summary statistics for the seven β coefficients and six characteristics that are calculated for each stock for each month over 66 years, from January 1952 through December 2017. The β coefficients are estimated from the following time-series regression model over a rolling window of 60 months for each stock *j*, with the first window being January 1947 to December 1951:

$$(r_j\text{-}rf)_t = \beta_{0j} + \beta_{RMrf,j}*RMrf_t + \beta_{SMB,j}*SMB_t + \beta_{HML,j}*HML_t + \beta_{UMD,j}*UMD_t + \boldsymbol{\beta_{IML,j}*IML_t}$$

$$+ \boldsymbol{\beta_{IMLZ1,j}*IML_t*Z1_{t-1} + \beta_{Z1,j}*Z1_{t-1}}. \qquad (5)$$

The dependent variable is the monthly return on stock *j*, $r_{j,t}$, in excess of the risk-free rate rf_t. The first four factors are those of Fama and French (1993) and Carhart (1997) (see Table 1). The variable *IML* is the return on the illiquid-minus-liquid portfolios (see Table 1); $Z1_t$ is the differential yield between BAA- and AAA-rated corporate bonds in excess of the moving average over the preceding ten years. As for stock characteristics, *ILLIQma* is stock illiquidity (see Table 1), mean adjusted by division by the mean of *ILLIQ* values across all the stocks used in the monthly cross-sectional regressions, and *StdDev* is return volatility, measured by the standard deviation of daily returns. Both *ILLIQ* and *StdDev* are calculated from daily data over a twelve-month rolling window. The variable *BM* (in logarithm) is the book-to-market ratio, using the book value from the firm's annual financial report known as of the end of the previous fiscal year and the market value as of December of the year before the year of analysis. The variable *Size* (in logarithm) is the market capitalization and *R12lag* is the lagged cumulative stock return over past eleven months. These stock characteristics are lagged, skipping one month, so that, e.g., the observation for January, 1952 is obtained from the period that ends on November, 1951. The variable *R1lag* is the one-month lagged stock return.

The table presents the averages of the monthly cross-stock mean and standard deviation, and of the monthly pairwise cross-stock correlations among the variables that are used in that month's cross-sectional regression. For the right panel, we focus on the three liquidity-based variables: β_{IML}, β_{IMLZ1}, and *ILLIQma*.

	Average of cross-sectional…		Average of cross-sectional pairwise correlations between…		
Variable	Mean	Std. Dev.	β_{IML}	β_{IMLZ1}	*ILLIQma*
β_{RMrf}	1.023	0.426	0.261	0.030	-0.056
β_{SMB}	0.355	0.926	-0.587	-0.006	0.186
β_{HML}	0.199	0.727	-0.394	-0.017	0.050
β_{UMD}	-0.055	0.430	0.175	-0.054	-0.011
β_{IML}	0.024	1.104	1.000	0.070	0.080
β_{IMLZ1}	0.054	2.378	0.070	1.000	0.015
β_{Z1}	0.000	0.053	0.016	-0.136	-0.016
ILLIQma	1.000	1.757	0.080	0.015	1.000
StdDev	0.019	0.006	-0.195	0.015	0.214
BM	-0.439	0.629	0.046	0.013	0.231
Size	20.295	1.450	-0.058	-0.018	-0.642
R12lag	0.131	0.240	0.016	0.015	0.014
R1lag	0.011	0.077	0.003	0.011	0.012

Table 4: Pricing of stock systematic risks and characteristics in the cross-section

This table presents the test results of the Fama-Macbeth monthly cross-sectional regressions of Model (6) with individual stock returns. For each month *s*, we estimate a cross-sectional regression of stock excess returns $(r_j - rf)_s$ on the seven β coefficients that are estimated by Model (5) and on the six stock characteristics (see Table 3):

$$(r_j - rf)_s = \gamma_{0,s} + \gamma_{RMrf,s}*\beta_{RMrf,j,s-2} + \gamma_{SMB,s}*\beta_{SMB,j,s-2} + \gamma_{HML,s}*\beta_{HML,j,s-2} + \gamma_{UMD,s}*\beta_{UMD,j,s-2} + \boldsymbol{\gamma_{IML,s}*\beta_{IML,j,s-2}} + \boldsymbol{\gamma_{IMLZ1,s}*\beta_{IMLZ1,j,s-2}} + \boldsymbol{\gamma_{Z1,s}*\beta_{Z1,j,s-2}} + \delta_{1,s}*ILLIQma_{j,s-2} + \delta_{2,s}*StdDev_{j,s-2} + \delta_{3,s}*BM_{j,s-2} + \delta_{4,s}*Size_{j,s-2} + \delta_{5,s}*R12lag_{j,s-2} + \delta_{6,s}*R1lag_{j,s-1}. \quad (6)$$

The model is estimated across stocks over the period from January 1952 through December 2017, that is, 792 months. We present the mean of each slope coefficient and the precision-weighted ("wtd") mean where the weight is the reciprocal of the standard error of the slope coefficient. We employ three estimation methods: (1) ordinary least squares (OLS), (2) the bias-correcting method of Chordia, Goyal and Shanken (2015) (CGS), and (3) weighted least square (WLS), following Asparouhova et al. (2010). The slope coefficients are in percentages. The corresponding *t*-statistics are presented in parentheses. The *Avg adj.* R^2 is the average of monthly *adjusted* R^2 values of cross-sectional regressions.

	Estimation method					
	OLS		CGS		WLS	
Coefficient of	Mean	Wtd mean	Mean	Wtd mean	Mean	Wtd mean
β_{RMrf}	0.206 (1.33)	0.138 (0.72)	0.163 (0.99)	0.111 (0.47)	0.203 (1.31)	0.135 (0.69)
β_{SMB}	0.048 (0.92)	0.033 (0.73)	0.079 (1.62)	0.052 (1.23)	0.049 (0.92)	0.032 (0.71)
β_{HML}	0.082 (1.74)	0.071 (1.72)	0.080 (1.75)	0.075 (1.84)	0.071 (1.51)	0.063 (1.54)
β_{UMD}	-0.027 (-0.40)	0.009 (0.16)	0.020 (0.29)	0.034 (0.61)	-0.020 (-0.30)	0.014 (0.25)
β_{IML}	0.011 (0.23)	0.005 (0.13)	0.039 (0.89)	0.026 (0.65)	0.005 (0.12)	0.001 (0.03)
$\boldsymbol{\beta_{IMLZ1}}$	**0.062 (3.17)**	**0.040 (3.20)**	**0.060 (3.52)**	**0.043 (3.72)**	**0.062 (3.21)**	**0.041 (3.26)**
β_{Z1}	-0.330 (-0.49)	-0.572 (-1.31)	-0.441 (-1.15)	-0.333 (-0.89)	-0.221 (-0.33)	-0.517 (-1.19)
ILLIQma	0.041 (2.58)	0.029 (2.52)	0.040 (2.57)	0.029 (2.51)	0.036 (2.30)	0.025 (2.23)
StdDev	-27.935 (-4.25)	-29.989 (-4.98)	-27.536 (-4.12)	-29.931 (-4.93)	-26.834 (-4.07)	-29.002 (-4.81)
BM	0.098 (2.45)	0.090 (2.52)	0.093 (2.32)	0.083 (2.29)	0.107 (2.68)	0.097 (2.71)
Size	-0.086 (-3.82)	-0.077 (-3.67)	-0.081 (-3.61)	-0.074 (-3.48)	-0.087 (-3.85)	-0.079 (-3.70)
R12lag	1.116 (6.77)	0.946 (6.16)	1.036 (6.31)	0.874 (5.80)	1.149 (6.99)	0.976 (6.36)
R1lag	-5.047 (-14.99)	-4.811 (-15.15)	-5.151 (-15.48)	-4.884 (-15.44)	-4.907 (-14.68)	-4.650 (-14.87)
Avg adj. R^2	10.96%		10.52%		10.98%	

Table 5: Pricing over two subperiods of stock systematic risks and characteristics
This table replicates the asset pricing tests presented in Table 4 with the statistics for the slope coefficients presented separately for two equal subperiods. The results are based on the estimations according to the CGS bias-correcting method. The slope coefficients are in percentages and their *t*-statistics are presented in parentheses. The variables and the estimation procedure are the same as those in Table 4 and are explained in the legend there.

	Subperiod I: 1952 through 1984		**Subperiod II:** 1985 through 2017	
Coefficient of	Mean	Wtd mean	Mean	Wtd mean
β_{IML}	0.034 (0.51)	0.013 (0.25)	0.044 (0.77)	0.038 (0.64)
$\boldsymbol{\beta_{IMLZ1}}$	**0.051** **(2.00)**	**0.037** **(2.38)**	**0.069** **(3.07)**	**0.049** **(2.86)**
Avg adj. R^2	11.00%		10.42%	

Table 6: Pricing of the conditional $\boldsymbol{\beta_{IML}}$ in the presence of other liquidity-related $\boldsymbol{\beta}$s

This table presents the test results of Fama–MacBeth monthly cross-sectional regressions of stock returns. We first add to Model (5) $\beta_{LF}*LF_t + \beta_{LFZ1}*LF_t*Z1_{t-1}$ where LF_t is one of the following four liquidity-based factors: (1) *PS*, the traded factor of Pastor and Stambaugh (2003) (available from Lubos Pastor's homepage), the value-weighted average return on stocks with high exposure to innovations in their aggregate liquidity relative to stocks with low exposure (using decile portfolios); (2) *LIU*, the traded factor of the return premium on high-minus-low illiquidity portfolio using Liu's (2006) measure based on non-trading days and turnover and obtained from the author; (3) *dMILLIQ*, a non-traded factor of the first-order changes in the monthly value-weighted market illiquidity (in logarithm); and (4) *KS*, the innovation in a non-traded liquidity factor that combines the cross-sections of several measures of liquidity, constructed by Korajczyk and Sadka (2008) and obtained from them. Then, we add to Model (6) β_{LF} and β_{LFZ1} and estimate their slope coefficients γ_{LF} and γ_{LFZ1} in cross-sectional regressions.

To save space, the table presents only the slope coefficients that are related to the liquidity βs. The estimation of those slope coefficients includes all the other βs and six stock characteristics in Model (6). The estimation employs the CGS bias-correcting method. Explanations of the estimation method and the test statistics are given in the legend of Table 4.

	Coefficient of	Mean	Wtd mean
$LF_t = PS_t$. Data period: 2/1973–2017	β_{IML}	0.059 (1.15)	0.046 (1.03)
	$\boldsymbol{\beta_{IMLZ1}}$	**0.087 (3.83)**	**0.059 (3.54)**
	B_{LF}	-0.076 (-0.96)	-0.064 (-0.90)
	$\boldsymbol{B_{LFZ1}}$	**-0.039 (-1.29)**	**-0.028 (-1.30)**
$LF_t = LIU_t$. Data period: 1952–2014	β_{IML}	0.014 (0.31)	0.002 (0.05)
	$\boldsymbol{\beta_{IMLZ1}}$	**0.055 (3.13)**	**0.042 (3.49)**
	B_{LF}	-0.045 (-0.74)	-0.020 (-0.40)
	$\boldsymbol{B_{LFZ1}}$	**0.012 (0.57)**	**0.026 (2.12)**
$LF_t = dMILLIQ_t$. Data period: 1952–2017	β_{IML}	0.041 (0.90)	0.029 (0.71)
	$\boldsymbol{\beta_{IMLZ1}}$	**0.062 (3.42)**	**0.042 (3.48)**
	B_{LF}	-0.348 (-1.08)	-0.177 (-0.60)
	$\boldsymbol{B_{LFZ1}}$	**-0.057 (-0.55)**	**-0.052 (-0.71)**
$LF_t = KS_t$. Data period: 10/1988–2000	β_{IML}	-0.221 (-2.31)	-0.226 (-3.07)
	$\boldsymbol{\beta_{IMLZ1}}$	**0.077 (2.60)**	**0.079 (2.93)**
	B_{LF}	-0.012 (-0.47)	-0.020 (-1.09)
	$\boldsymbol{B_{LFZ1}}$	**0.004 (0.50)**	**0.006 (1.01)**

Table 7: Pricing of *IML* systematic risks with three alternative conditioning variables
This table presents the test results of Fama–MacBeth monthly cross-sectional regressions using three alternative conditioning variables that replace *Z1* in Models (5) and (6) described in the legend of Table 4.
Panel A: $Z2_t = dSP_t^+$, the positive value of $dSP_t = SP_t - SP_{t-1}$ (it is zero otherwise) where SP_t is the yield spread between BAA- and AAA-rated corporate bonds.
Panel B: $Z3_t$ is the monthly TED spread (the Eurodollar rate minus the U.S. T-bill rate, both of which are with one month to maturity) in the excess of its average. These series begin in 1971 and are discontinued in 2016. Accordingly, the cross-sectional regressions are run over a period of about 41 years (488 months) from March 1976 through October 2016.
Panel C: $Z4_q = -dS12_q = -((S1/S2)_q - (S1/S2)_{q-1})$, the change in the ratio of two quarterly loan series for quarter *q*. $S1_q$ is broker-dealers loans that include their margin loans (SBDOLAA) and $S2_q$ is the benchmark loans (SBDLL). These series are available since Q1/1952.
The data source for all series is the Federal Reserve Bank of St. Louis. To save space, we present only the test results for the slope coefficients of the βs of *IML*-related variables.

	Estimation method					
	OLS		CGS		WLS	
Coefficient of	Mean	Wtd mean	Mean	Wtd mean	Mean	Wtd mean
Panel A: $Z2_t = dSP_t^+$, the value of the rise in the corporate bond yield spread.						
β_{IML}	0.040 (0.85)	0.030 (0.74)	0.033 (0.69)	0.017 (0.42)	0.031 (0.66)	0.024 (0.59)
$\boldsymbol{\beta_{IMLZ2}}$	**0.014 (3.26)**	**0.005 (2.57)**	**0.013 (3.50)**	**0.005 (2.56)**	**0.014 (3.20)**	**0.005 (2.41)**
Avg Adjusted R^2	11.04%		10.63%		11.07%	
Panel B: $Z3_t$ is the monthly TED spread in excess of its average						
β_{IML}	0.020 (0.35)	0.020 (0.36)	0.013 (0.24)	0.014 (0.26)	0.012 (0.21)	0.012 (0.23)
$\boldsymbol{\beta_{IMLZ3}}$	**0.221 (2.78)**	**0.171 (2.67)**	**0.152 (2.19)**	**0.116 (2.06)**	**0.215 (2.73)**	**0.167 (2.64)**
Avg adj. R^2	10.38%		10.09%		10.37%	
Panel C: $Z4_q$ is the (negative of the) change in broker-dealers loans that include their margin loans relative to the benchmark of broker-dealer all loans series.						
β_{IML}	0.084 (1.79)	0.066 (1.59)	0.088 (1.85)	0.070 (1.69)	0.079 (1.67)	0.062 (1.50)
$\boldsymbol{\beta_{IMLZ4}}$	**0.018 (2.13)**	**0.012 (2.03)**	**0.019 (2.15)**	**0.012 (2.02)**	**0.018 (2.12)**	**0.012 (2.02)**
Avg adj. R^2	10.82%		10.44%		10.83%	

Figure 1: 12-month moving average of one-month-ahead rolling $alpha_{IML,t}$

The monthly one-month-ahead $alpha_{IML,t}$ is calculated as

$$alpha_{IML,t} = IML_t - [\beta_{RMrf} * RMrf_t + \beta_{SMB} * SMB_t + \beta_{HML} * HML_t + \beta_{UMD} * UMD_t],$$

where the β values are estimated over 60 months preceding month t from the regression Model (1). The sample period is January 1947 through December 2017 and $alpha_{IML,t}$ begins on January 1952. The figure presents a twelve-month moving average of $alpha_{IML,t}$. The numbers on the y-axis are monthly returns in percentage.

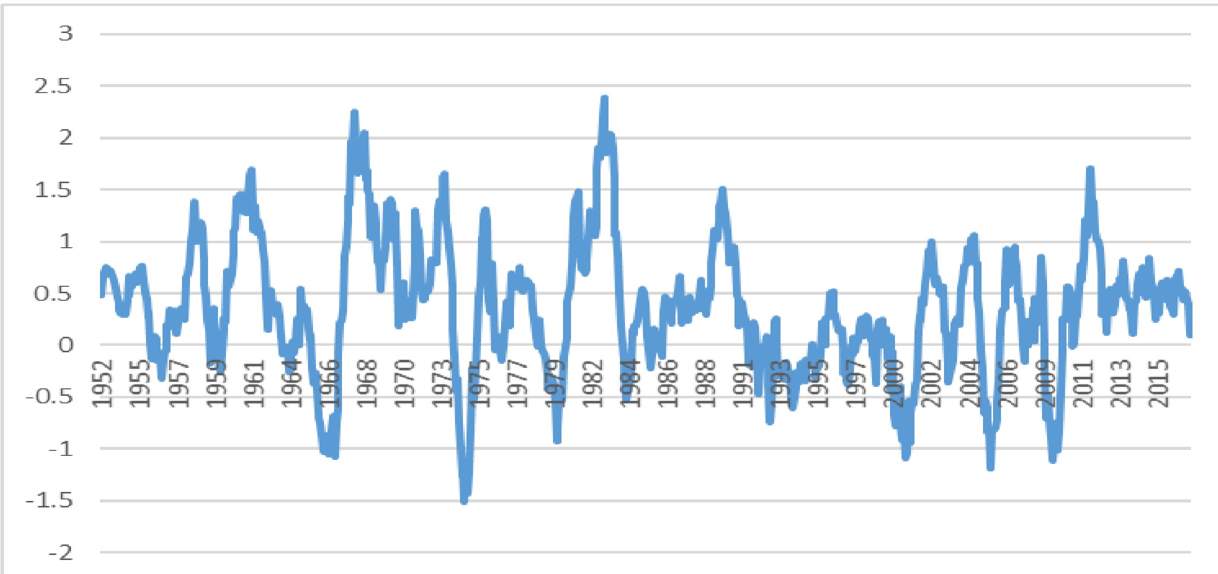

Figure 2: The effect of corporate bond yield spread on the premium on β_{IML}, the *IML* systematic risk

Following the procedure in the legend of Table 2, we regress $\gamma_{IML,t}$, the monthly estimate (using Model (3)) of the premium of *IML's* systematic risk β_{IML}, on $DumSP_{t-1}$ which equals 1 if the corporate bond yield spread between BAA-rated and AAA-rated bonds exceeds its median (zero otherwise), and on $RMrf_t$. The model is estimated over a 60-month rolling window that begins with the period of January 1952 through December 1956 and then moves forward by one month at a time. We denote the intercept by $a0_t$ and the slope coefficient of $DumSP_{t-1}$ by $a1_t$ and we define $Sum_t = a0_t + a1_t$.

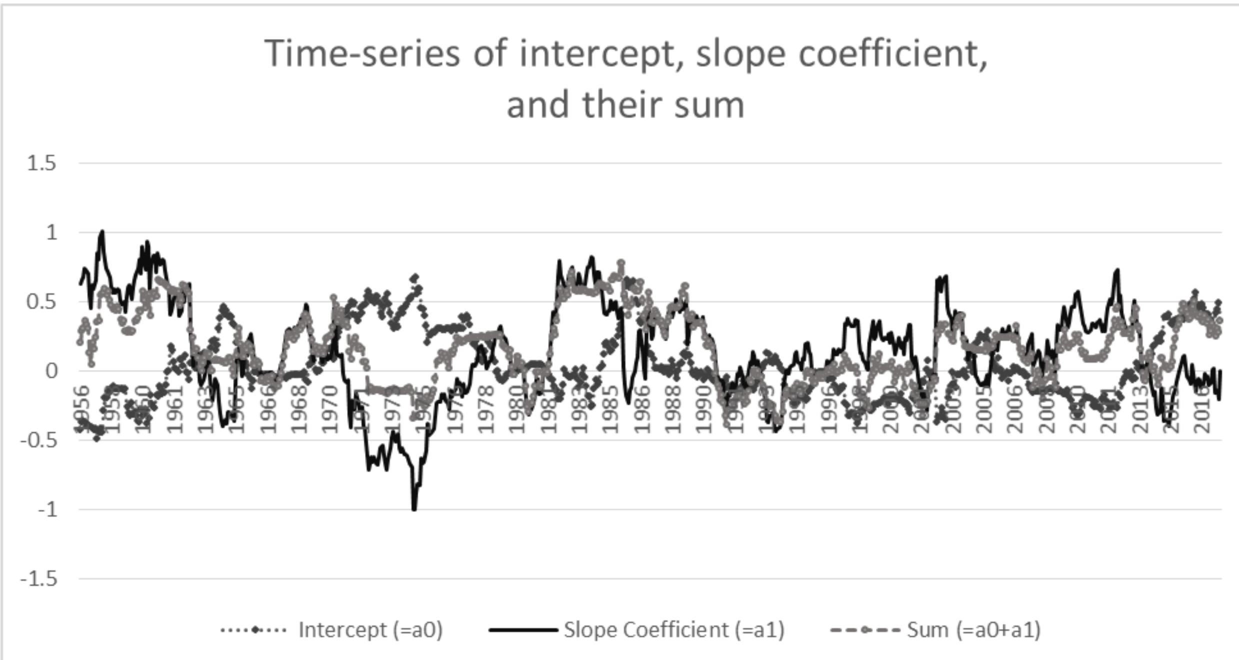

Table A.1: The effect of the corporate bond yield spread on γ_{IML}, the risk premium of β_{IML}, estimated from a cross-sectional regression model that excludes firm characteristics

The legend of this table is the same as that of Table 2 except that γ_{IML} is estimated from a cross-sectional regression model that includes only the β coefficients of the Fama-French-Carhart factors and *IML*: for month *s*,

$$(r_j - rf)_s = \gamma_{0,s} + \gamma_{RMrf,s} * \beta_{RMrf,j,s-2} + \gamma_{SMB,s} * \beta_{SMB,j,s-2} + \gamma_{HML,s} * \beta_{HML,j,s-2} + \gamma_{UMD,s} * \beta_{UMD,j,s-2} + \boldsymbol{\gamma_{IML,s} * \beta_{IML,j,s-2}}.$$

SP is the yield spread between BAA- and AAA-rated corporate bonds. $DumSP_t$ equals 1.0 if SP_t is above its median value (zero otherwise). Columns (1)-(2) and (5)-(6) present the regression results for the entire sample period. Columns (3)-(4) present the average slope coefficients of regressions estimated over 60-month rolling windows with $DumSP_t$ calculated relative to the medians of those windows. The *t*-statistics in columns (1)-(2) and (5)-(6) employ robust standard errors following White (1980) and those in columns (3)-(4) employ Newey-West (1986) standard errors with 12 lags.

	Regressions over the entire sample period		Regressions over rolling 60 months		Regressions over the entire sample period	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.138 (1.85)	0.087 (1.07)	0.137 (4.05)	0.113 (2.68)	0.309 (4.41)	0.235 (3.31)
$DumSP_{t-1}$	0.215 (1.86)	0.182 (1.50)	0.260 (5.30)	0.155 (3.34)		
$\log(SP_{t-1})$					0.490 (2.63)	0.451 (2.48)
$RMrf_t$	-0.114 (-5.35)		-0.115 (-8.72)		-0.115 (-5.39)	
R^2	0.083	0.002	0.141	0.016	0.092	0.011