Market Illiquidity and Conditional Equity Premium

Hui Guo, Sandra Mortal, Robert Savickas, and Robert Wood*

First Version: May 2008
This Version: September 2016

*Hui Guo is Briggs Swift Cunningham professor of finance at Carl H. Lindner College of Business, University of Cincinnati; email: hui.guo@uc.edu. Sandra Mortal is associate professor of finance at Fogelman College of Business & Economics, University of Memphis; email: scmortal@memphis.edu. Robert Savickas is associate professor of finance at School of Business, George Washington University; email: savickas@gwu.edu. Robert Wood is Professor Emeritus of finance at Fogelman College of Business & Economics, University of Memphis; email: rawood11@gmail.com. The paper formerly circulated under the title “Uncovering the Relation between Aggregate Stock Illiquidity and Expected Excess Market Returns”. We thank the anonymous referee, Yakov Amihud, Turan Bali, Shmuel Baruch, Eric Chang, Rene Garcia, Brian Hatch, Pankaj Jain, Abraham Lioui, Marc Lipson, Buhui Qiu, Michael Schill, Steve Slezak, Masa Watanabe, Ivo Welch, and the seminar participants at Hong Kong University, EDHEC Business School, the Central University of Finance and Economics, the Chicago Quantitative Alliance 2009 Spring Meetings in Las Vegas, and the FMA 2010 meetings in New York City for comments. We are grateful to Nagpurmanand Prabhala, Buhui Qiu, Yufeng Han, and Amit Goyal for providing data.
Market Illiquidity and Conditional Equity Premium

Abstract

We examine the time-series relation between aggregate bid-ask spreads and conditional equity premium. We document that average market-wide relative effective bid-ask spreads forecast aggregate market returns only when controlling for average idiosyncratic variance. This control allows us to document the otherwise elusive relation between illiquidity and returns. The reason is that idiosyncratic variance correlates positively with spreads but has a negative effect on conditional equity premium, causing an omitted variable bias. Our results are robust to standard return predictors, alternative illiquidity measures, and out of sample tests. These findings are important because they provide strong support for the literature’s conjecture that market-wide liquidity is an important asset-pricing risk factor.
1. **Introduction**

Chordia, Roll, and Subrahmanyam (2000), Hasbrouck and Seppi (2001), Huberman and Halka (2001), Lo and Wang (2000), and others document strong commonality in stock-level liquidity. Pastor and Stambaugh (2003) and Acharya and Pedersen (2005) conjecture that liquidity is a systematic risk factor because they find that covariances with market-wide liquidity help explain the cross-section of stock returns.¹ For this inference to be validated, according to Campbell’s (1993) ICAPM, we need a time series relation—that decreased market liquidity predicts higher future market returns.² The relation, however, is rather weak over the post-World War II sample. In this paper, we explore the possibility that the relation between aggregate idiosyncratic risk and both aggregate returns and liquidity is such, that omitting this variable confounds the time-series relation between aggregate liquidity and conditional equity premium.

Using direct transaction cost measures for a long but cross-sectionally restricted sample of Dow Jones firms, Jones (2002) uncovers a positive relation between aggregate illiquidity and future market returns over the 1900 to 2000 period but not in the post-1950 sample. Using indirect measures of illiquidity for a large set of firms, Amihud (2002) and Baker and Stein (2004) document a positive illiquidity-return relation as well; Fujimoto (2003), however, shows that these illiquidity measures have negligible predictive power over the 1966 to 2002 period.


² Jones (2002) proposes two specific channels through which aggregate illiquidity correlates with conditional equity premium. First, illiquidity is a measure of information asymmetry, which correlates positively with the expected stock returns (e.g., Glosten and Milgrom (1985)). Second, illiquidity moves closely with market makers’ financial constraints, which tend to change countercyclically across time. Moreover, Baker and Stein (2004) argue that variation in illiquidity reflects waves of investors’ excessive optimism and pessimism.
We document a positive and significant relation between aggregate effective bid-ask spreads and future excess stock market returns only when including aggregate idiosyncratic variance as a control. This suggests the lack of predictive power in earlier studies is partly due to an omitted-variable bias. There are two necessary conditions for the omitted-variable bias. First, aggregate illiquidity and aggregate idiosyncratic variance correlate closely with each other. Indeed, their correlation coefficient is positive and over 40%. Second, aggregate idiosyncratic variance correlates with conditional equity premium in a way that is opposite to that of aggregate illiquidity, i.e. the relation between average idiosyncratic variance and future market returns is negative. Guo and Savickas (2008) document such a negative relation in G7 countries.

The underlying relation between liquidity and returns as well as the confounding relation between idiosyncratic variance and both liquidity and returns are all suggested by existing economic theories and empirical findings. Constantinides (1986) argues that transaction costs per se have a negligible effect on equity premium because investors choose optimally to rebalance their portfolios infrequently to avoid high trading costs. Jang, Koo, Liu, and Loewenstein (2007) and Lynch and Tan (2009), however, point out that the effect of liquidity risk on equity premium can be economically significant when there is a strong demand for hedging against changes in investment opportunities. That is, both liquidity risk and hedging risk are important determinants of conditional equity premium.

Guo and Savickas (2008) document a negative relation between value-weighted aggregate idiosyncratic variance and conditional equity premium, using quarterly data. They argue that this is because, by construction, idiosyncratic variance correlates closely with the
variance of an omitted hedging risk factor. Specifically, Guo and Savickas find (1) that aggregate idiosyncratic variance correlates closely with the variance of the value premium—the most commonly used proxy for the hedging risk factor in empirical asset pricing research, and (2) that the two variances have similar forecasting power for excess market returns. Similarly, we document that the relation between aggregate bid-ask spreads and future excess market returns becomes significantly positive when we replace idiosyncratic variance with the variance of the value premium. In other words, both idiosyncratic variance and the variance of the value premium have similar effects on the relation between aggregate bid-ask spreads and conditional equity premium. Our results suggest that the effect of idiosyncratic variance on the illiquidity/conditional equity premium relation is due to its relation to the hedging risk factor.

Aggregate idiosyncratic variance correlates positively with aggregate bid-ask spreads because an increase in uncertainty about investment opportunities, e.g., the value premium, likely leads to more information asymmetry and higher inventory costs and hence larger bid-ask spreads. For firm-level idiosyncratic variance, a relation with spreads is consistent with the information speculation paradigm of Kyle (1985) and Admati and Pfleiderer (1988). They argue that a firm’s liquidity depends on the chances of a market maker losing money to an informed trader. Idiosyncratic risk reflects the stock’s response to firm specific information and is positively related to insider’s opportunities to profitably trade against dealers (Benston and Hagerman (1974)). A relation between idiosyncratic risk and spreads is also consistent with the inventory paradigm of Demsetz (1968) and Stoll (1978). They argue that a firm’s liquidity

---

3 Recent studies, e.g., Chen and Petkova (2012), Duarte, Kamara, Siegel, and Sun (2014), and Herskovic, Kelly, Lustig, and Nieuwerburgh (2015), document strong commonality in stock-level idiosyncratic variance and show that innovations in aggregate idiosyncratic variance are priced in the cross-section of stock returns.

4 Fama and French (1996) interpret the value premium as a hedging risk factor. Campbell and Vuolteenaho (2004) show that the value premium is a proxy for changes in discount rates in Campbell’s (1993) ICAPM. Guo, Savickas, Wang, and Yang (2009) show that the negative relation between the variance of the value premium and conditional equity premium is consistent with Campbell’s ICAPM.
depends on the factors that influence the risk of holding inventory, such as volatility of returns. A positive relation between firm-level idiosyncratic risk and illiquidity suggests a positive relation at the aggregate level as well. Aggregate idiosyncratic risk is time-varying, reflecting common variation in idiosyncratic risk across individual stocks. Periods of high idiosyncratic risk among a group of stocks should result in high levels of illiquidity in those same stocks, suggesting a positive correlation between idiosyncratic risk and illiquidity at the aggregate level.

Our main finding, that bid-ask spreads forecast market returns once we control for idiosyncratic variance, is robust to a number of tests and specifications. Results are qualitatively similar for alternative illiquidity measures. For example, we find that the Pastor and Stambaugh (2003) liquidity measure does not forecast market returns in univariate regressions despite its significant explanatory power for the cross-section of stock returns, but does predict market returns when in conjunction with aggregate idiosyncratic variance. Our regressions have true forecasting power using out of sample forecasting tests, and our results are robust to including standard predictive variables found in the literature to forecast market returns. The results are also robust to changing the period of analysis from quarterly to monthly frequency. Interestingly, the effect of aggregate bid-ask spreads on conditional equity premium is stronger during business recessions than during business expansions. Lastly, we estimate a variant of Merton (1973) or Campbell’s (1993) ICAPM using DCC-GARCH model proposed by Bali and Zhou (2016) and find that aggregate illiquidity is priced in the cross-section of stock returns.

Idiosyncratic variance computed from daily return data is subject to measurement error due to market microstructure noise (see, e.g., Andersen, Bollerslev, Diebold, and Labys (2003)). Therefore, the predictive power of effective bid-ask spreads for market returns when in

---

5 Although our results are robust to using alternative measures of illiquidity, the effect of bid-ask spreads on conditional equity premium always subsumes the information content of the less precise, low frequency measures of illiquidity. This is consistent with bid-ask spreads being a more precise measure of illiquidity.
conjunction with idiosyncratic variance may reflect the correlation of effective bid-ask spreads with microstructure noise. We show that microstructure noise does not account for our main findings. Asparouhova, Bessembinder, and Kalcheva (2010) point out that liquidity biases are much larger for small stocks than for big stocks. To alleviate the bias, we use value-weighted instead of equal-weighted aggregate idiosyncratic variance in our empirical analysis. Our results remain unchanged when we use aggregate options-implied variance instead of realized idiosyncratic variance. Moreover, our results are robust to computing idiosyncratic variance from closing mid-quotes as in Han and Lesmond (2011) and Lesmond and Zhao (2015).

Stock prices fell sharply in 2008 as both funding liquidity and market liquidity dried up on the Lehman Brothers bankruptcy announcement; however, the stock market recovered with a big rally in 2009 when liquidity conditions improved following the debacle. In retrospect, this rare event unequivocally illustrates profound effects of market illiquidity and funding illiquidity on asset prices, as we argue in this paper. Nevertheless, excluding this event from our empirical analysis does not affect our main findings in any qualitative manner. We circulated previous drafts of this paper before the 2008 financial market crisis using data ending in 2007.

In contrast to the elusive evidence in the U.S. data, Bekaert, Harvey, and Lundblad (2007) document a significantly positive relation between illiquidity and conditional equity premium using a panel of eighteen emerging markets. These authors suggest that the difference partly reflects the fact that illiquidity has stronger effects on asset prices in emerging markets than in developed markets. We complement their argument by showing that, when controlling for aggregate illiquidity’s correlation with aggregate idiosyncratic variance, aggregate illiquidity is an important determinant of conditional equity premium in the U.S. market—arguably the most liquid market in the world.
Amihud and Mendelson (1989), Spiegel and Wang (2005), Bali, Cakici, Yan, and Zhang (2005), Han and Lesmond (2011), and Lesmond and Zhao (2015) have investigated the asset pricing implications of the strong positive relation between illiquidity and idiosyncratic variance. These authors emphasize a *multicollinearity* problem that illiquidity and idiosyncratic variance have similar explanatory power for expected stock returns. For example, Lesmond and Zhao (2015) find that the positive relation between equal-weighted aggregate idiosyncratic variance and future market returns documented by Goyal and Santa-Clara (2003) disappears when controlling for equal-weighted aggregate illiquidity measures. In contrast, our paper highlights the existence of an *omitted-variable* problem and shows that value-weighted aggregate idiosyncratic variance and value-weighted effective bid-ask spreads jointly have significant forecasting power for market returns although not individually.\(^6\)

Chordia, Roll, and Subrahmanyam (2005) find that order imbalances forecast intraday returns at the stock level, and Hendershott and Seasholes (2008) show that non-informational order imbalances forecast daily market returns. By contrast, we uncover significant predictive power of aggregate illiquidity for market returns at business cycle frequencies. The illiquidity premium, the return difference between stocks with high and low illiquidity, appears to have diminished over the past two decades (e.g., Ben-Rephael, Kadan, and Wohl (2015)). Nevertheless, we show that aggregate illiquidity remains an important determinant of conditional equity premium in recent data.

The remainder of this paper proceeds as follows. We discuss data in Section 2 and present empirical results obtained using transaction data in Section 3. We analyze several

\(^6\) While the multicollinearity problem and the omitted-variable problem are both due to correlation among independent variables, we can easily distinguish them by comparing univariate regression results with multivariate regression results. Specifically, t-values and adjusted R\(^2\) are higher in multivariate regressions than in univariate regressions for the omitted-variable problem, as we document in this paper. The opposite is true for the multicollinearity problem, as shown in Lesmond and Zhao (2015).
standard illiquidity measures constructed from daily data in Section 4 and present cross-sectional
results in Section 5. We offer some concluding remarks in Section 6.

2. Data

We measure illiquidity in a number of different ways and focus mainly on measures of
illiquidity built with high frequency ISSM and TAQ data (Section 3). Our main variable of
interest is relative effective bid-ask spread, as it is a direct measure of trading costs. For
robustness and comparison, we also consider proxies for illiquidity built from lower frequency
data in our empirical analysis (Section 4). We use the measures of illiquidity proposed by
Amihud (2002) and Pastor and Stambaugh (2003), and the measures of funding liquidity
proposed by Adrian, Etula, and Muir (2014) and Adrian, Moench, and Shin (2014). The main
advantage of using high frequency measures, as compared with their low frequency counterparts,
is that they are more accurate and have smaller measurement errors (e.g., Amihud (2002), Baker
and Stein (2004), and Fujimoto (2003)). On the other hand, many low frequency measures are
reasonably reliable, are available for much longer sample periods, and are easy to construct (e.g.,
Hasbrouck (2009) and Goyenko, Holden, Trzcinka (2009)). Overall, we find that while high
frequency measures have stronger predictive power for excess market returns, results are
qualitatively similar for low frequency measures, especially in longer sample periods.

Relative effective bid-ask spread is computed as

$$\frac{2 |Price - Quote Midpoint|}{Quote Midpoint},$$

where $Price$ is the transaction price and $Quote Midpoint$ is the average of the ask and bid quotes. We use the
relative spread instead of the dollar spread because a given dollar spread implies different
illiquidity levels for stocks with different prices. Following McInish and Wood (1992), we
calculate the daily time-weighted spread for each stock in the ISSM and TAQ databases over the
1983 to 2009 period. We then aggregate the relative effective spread using value weights across all common stocks in the CRSP database with market capitalization data.

Figure 1 shows that over the January 1983 to December 2009 period, daily aggregate relative effective spreads (solid line) occasionally have drastic spikes. To alleviate potential outlier effects, we use log spreads (dashed line), LRES, in the empirical analysis. Consistent with previous studies, e.g. Chordia, Roll, and Subrahmanyam (2001), and Jones (2002), we document a strong secular downward trend in aggregate bid-ask spreads. It is not obvious that the trend in trading costs affects stock market prices in any particular manner. We, however, expect a positive correlation of cyclical variation in trading costs with conditional equity premium, given that market illiquidity can hinder investors’ ability to hedge for changes in investment opportunities (e.g., Jang, Koo, Liu, and Loewenstein (2007) and Lynch and Tan (2009)) or dry up financial intermediaries’ funding liquidity (e.g., Brunnermeier and Pedersen (2009)). This is our main refutable hypothesis.

For robustness, we remove the trend from aggregate bid-ask spreads using two standard approaches. First, we run a regression of daily LRES on a constant and a linear time trend, and use the residual, LRES_LD, as a linearly detrended illiquidity measure. Second, we use the difference between daily LRES and its average in the recent three years, LRES_ST, as a stochastically detrended illiquidity measure. We convert the daily LRES_LD and LRES_ST into monthly data using their observations on the last business day of the month, and average monthly measures across each quarter to obtain quarterly data. Figure 2 shows that quarterly LRES_LD (solid line) and LRES_ST (dashed line) move closely to each other. Specifically, both illiquidity measures increase sharply during the 1987 stock market crash, the 1991 liquidity

---

7 In previous drafts, we convert daily aggregate relative effective spreads into monthly (quarterly) data by using their average in a month (quarter), and find qualitatively similar results.
crunch, the 1998 Russia sovereign debt default, the 2001 dotcom bubble crash, and the 2008 global financial market crisis.

We follow Goyal and Santa-Clara (2003) and Guo and Savickas (2008) in the construction of quarterly aggregate realized idiosyncratic variance using CRSP data. In each quarter, we run a regression of a stock’s daily returns on a constant and daily value-weighted market returns, and use the sum of squared residuals as a measure of that stock’s realized idiosyncratic variance. We require a minimum of 45 daily return observations in the regression, and the aggregate idiosyncratic variance is the value-weighted realized idiosyncratic variance across the 500 biggest stocks. We use value weights instead of equal weights because the former is less susceptible to liquidity biases (e.g., Asparouhova, Bessembinder, and Kalcheva (2010)).

As in Merton (1980), Andersen, Bollerslev, Diebold, and Labys (2003), and others, the quarterly realized stock market variance is the sum of squared daily excess market returns in a quarter. We construct quarterly realized value premium variance in a similar fashion. Daily excess stock market return data and daily value premium data are from Ken French at Dartmouth College.\(^8\) Over the 1986Q1 to 2009Q4 period, we construct options-implied market variance using VIX obtained from the Chicago Board Options Exchange (CBOE). We use its closing price on the last business day in quarter \(t\) as a measure of quarter \(t+1\) market volatility. Because CBOE reports VIX as annualized standard deviation, we divide the squared VIX by four to get quarterly conditional market variance. For the 1983Q4 to 1985Q4 period, we obtain options-implied market volatility from Christensen and Prabhala (1998).\(^9\) Overall, quarterly options-implied market variance data span the 1983Q4 to 2009Q4 period.

---

\(^8\) [http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html](http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html)

\(^9\) We thank Nagpurunanand Prabhala at the University of Maryland for providing the data.
In Figure 3, realized value premium variance (dashed line) and aggregate idiosyncratic variance (solid line) move very closely to each other. In the next section, we find that these two variables have similar predictive power for excess market returns. Figure 4 plots options-implied market variance (dashed line) along with realized market variance (solid line). Similar to aggregate illiquidity measures shown in Figure 2, both market variance measures increase sharply during major financial market turmoil. Especially, for the 1987 stock market crash and the 2008 global financial market crisis, realized market variance has a drastic spike that is twice as large as that of options-implied market variance. To partially address potential outlier effects of these two extreme observations, we use log realized market variance instead of the level in empirical analysis. However, as we discuss in the next section, using the level does not change our main finding of a positive illiquidity-return relation in any qualitative manner.

Guo and Qiu (2014) construct value-weighted aggregate variance using options-implied variance from OptionMetrics. As a forward-looking variable, options-implied variance is potentially a better measure of conditional variance than is realized variance, although it is potentially a biased measure due to variance risk premium (e.g., Bollerslev, Tauchen, and Zhou (2009) and Drechsler and Yaron (2011)). Indeed, Guo and Qiu (2014) find that the market return predictive power of the options-implied variance is similar to, but stronger than, that of realized idiosyncratic variance. For example, unlike aggregate realized idiosyncratic variance, aggregate options-implied variance forecasts excess market returns at the monthly frequency. This is in line with our results in the next section, where we show that the correlation of the aggregate bid-ask spread with one-month-ahead excess market returns becomes significantly positive when in conjunction with aggregate options-implied variance but remains weak when in conjunction with
aggregate realized idiosyncratic variance. Because aggregate options-implied variance data are available for a short sample period starting from 1996, we mainly use quarterly aggregate realized idiosyncratic variance in our empirical analysis.

We obtain the monthly value-weighted market return and the monthly risk-free rate over the 1926 to 2009 period from the Center for Research in Stock Prices (CRSP). We convert monthly returns into quarterly, semiannual, and annual returns through simple compounding. The excess market return is the difference between market returns and the risk-free rate. We construct daily average number of trades using the ISSM and TAQ databases; Amihud’s (2002) daily illiquidity measure using daily CRSP return and trading volume data; and daily turnover using daily CRSP trading volume data. We aggregate the number of trades, Amihud’s measure, and turnover across stocks using value weights, and then convert them into quarterly data in a way similar to that for relative effective bid-ask spreads. We obtain Pastor and Stambaugh’s (2003) monthly aggregate illiquidity measure (constructed from daily stock return data) from Lubos Pastor at the University of Chicago. Following Adrian, Moench, and Shin (2014), we construct quarterly brokers and market makers’ book leverage using the flow of funds data from the Federal Reserve Board. Lastly, we obtain commonly used market return predictors from Amit Goyal at the University of Lausanne.

Table 1 reports summary statistics of selected variables. To avoid any confusion, we use only illiquidity measures in our empirical analysis: If a variable originally measures liquidity, we convert it into a measure of illiquidity by multiplying it by -1. Appendix contains a description of the acronyms used in the paper. LRES_LD (LRES_SD) is linearly (stochastically) detrended aggregate relative effective spread. ERET is the excess market return. IV is aggregate realized idiosyncratic variance. LMV is log realized market variance. VIX is options-implied market

---

10 We thank Buhui Qiu at Rotterdam School of Management for providing aggregate options-implied variance data.
Amihud is the linearly detrended Amihud (2002) illiquidity measure. We use the negative value of the Pastor and Stambaugh (2003) liquidity measure to obtain an illiquidity measure, PS. Following Adrian, Moench, and Shin (2014), we use the difference between brokers and market makers’ book leverage and its average in the recent four quarters as a funding liquidity measure. Again, we use the negative value of the Adrian, Moench, and Shin liquidity measure to get an illiquidity measure, LEV_SD. LRES_ST is available over the 1986Q1 to 2009Q4 period; VIX is available over the 1983Q4 to 2009Q4 period; and the other variables are available over the 1983Q1 to 2009Q4 period. LRES_LD correlates closely with LRES_ST, with a correlation coefficient of 66%, and we focus mainly on LRES_LD for brevity.

Stoll (2000) and many others document a strong positive relation between a stock’s bid-ask spread and the stock’s volatility. This result is consistent with the conventional wisdom that an increase in idiosyncratic volatility leads to more information asymmetry and higher inventory costs. If there is a systematic movement in stock-level idiosyncratic variance, we expect a similar relation at the aggregate level across time. Indeed, Table 1 reveals a strong positive relation between LRES_LD and IV, with a correlation coefficient of 43%. Consistent with Chung and Chuwonganant’s (2014) finding that VIX is an important source of commonality in stock illiquidity, LRES_LD correlates closely with VIX as well, with a correlation coefficient of 37%. To investigate whether IV and VIX are both important determinants of aggregate trading costs, we run a multivariate regression of LRES_LD on these two variables along with log average number of trades, LNT (untabulated). Consistent with Stoll’s (2000) cross-sectional finding, LRES_LD depends negatively and significantly on LNT, while the coefficients on IV and VIX are significantly positive. Similarly, IV correlates positively with other standard illiquidity measures such as Amihud and PS. Therefore, our results suggest that aggregate
idiosyncratic variance is an important determinant of commonality in stock illiquidity. To the best of our knowledge, this finding is novel.\textsuperscript{11} In the next section, we show that this new stylized fact is important to uncover the positive aggregate illiquidity-return relation.

3. Aggregate Relative Effective Bid-Ask Spread and Conditional Equity Premium

To the best of our knowledge, only two empirical studies investigate whether aggregate bid-ask spreads, a direct trading cost measure, forecast excess market returns, and these studies document mixed empirical evidence for the post-world war II sample. Jones (page 26; 2002) finds that although aggregate bid-ask spreads predict stock market returns before 1950, after 1950, spreads and turnover do not reliably predict stock market returns; for example, the spread variable has a $p$-value of 33% (65%) in the univariate (multivariate) regressions in his Table 4. By contrast, Fujimoto (page 3; 2003) shows that an increase in the proportional spread predicts a higher excess market return in the following period based on monthly and quarterly data over the 1966-2002 period. Because Fujimoto (2003) includes contemporaneous shocks to aggregate bid-ask spreads as an additional explanatory variable, her results are not directly comparable with those reported in Jones (2002), in that hers are not true predictive regressions. In this section, we show that aggregate bid-ask spreads correlate positively and significantly with future market returns when in conjunction with aggregate idiosyncratic variance, although aggregate bid-ask spreads have negligible predictive power in univariate regressions.

In Table 2, we investigate whether aggregate bid-ask spreads forecast one-quarter-ahead excess market returns. As in Jones (2002) and Baker and Stein (2004), but unlike in Fujimoto

\textsuperscript{11} Chordia, Roll, and Subrahmanyam (2001) investigate the relation between aggregate bid-ask spreads with market variance and other macrovariables. However, they do not consider aggregate idiosyncratic variance, as we do in this paper. Moreover, we find that aggregate idiosyncratic variance correlates positively with aggregate bid-ask spreads even when controlling for market variance.
(2003), we use only *ex-ante* information in forecasting regressions. Panel A reports estimation results for the linearly detrended spread measure, LRES_LD, over the 1983Q2 to 2009Q4 period. Row 1 confirms Jones’ (2002) post-World War II findings. In the univariate forecasting regression, LRES_LD correlates positively with future excess market returns; the relation, however, is statistically insignificant at the 10% level. The weaker relation in the post-World War II sample partly reflects the fact that *there is considerably more variation* (in aggregate bid-ask spreads) *in the first third of the 1900’s than in the period since then* (Jones (page 25; 2002)).

Below, we propose and investigate the omitted-variable problem as an alternative explanation.

Specifically, as we discuss in the previous section, aggregate trading costs correlate positively with aggregate idiosyncratic variance; and Guo and Savickas (2008) show that the latter correlates *negatively* with conditional equity premium. In contrast, aggregate illiquidity is expected to be positively related to conditional equity premium (Koo, Liu, and Loewenstein (2007) and Lynch and Tan (2009)). The weak aggregate bid-ask spread-return relation, when idiosyncratic variance is omitted from the analysis, reflects the fact that aggregate bid-ask spreads and idiosyncratic variance have opposing effects on conditional equity premium.

To illustrate this point clearly, we adopt a textbook example of the omitted-variable problem from Greene (1997, p. 402). Suppose the excess market return is the dependent variable, IV is the omitted variable with the true parameter $B1$, and LRES_LD is the included variable with the true parameter $B2$. As we verify in the empirical analysis below, $B1$ is negative and $B2$ is positive. In the univariate regression, the point estimate of the coefficient on LRES_LD is $\hat{B2} = B2 + \frac{\text{cov}(\text{LRES}_LD, IV)}{\text{VAR}(\text{LRES}_LD)} \cdot B1$. Because LRES_LD correlates positively with IV (Table 1), the bias due to the omitted-variable problem $\frac{\text{Cov}(\text{LRES}_LD, IV)}{\text{Var}(\text{LRES}_LD)} \cdot B1$ is negative.
and thus lowers the estimated coefficient on LRES_LD downward towards zero. In a similar
vein, omitting aggregate illiquidity from the analysis when investigating the IV-market returns
relation biases the estimated coefficient on IV upward to zero. Because correlated independent
variables can lead to either the omitted-variable problem or the multicollinearity problem, it is
important to understand their differences. In general, $t$-values and adjusted $R^2$ are higher in
multivariate regressions than in univariate regressions in the former situation, while the opposite
is true in the latter situation.

We address the omitted-variable problem by adding IV to the forecasting regression
along with LRES_LD in row 2 of Table 2. As conjectured, the estimated coefficient on
LRES_LD increases substantially to 0.058 in the bivariate regression from 0.022 in the
univariate regression (row 1). Moreover, the positive effect of LRES_LD on conditional equity
premium becomes statistically significant at the 5% level. The coefficient on IV is significantly
negative at the 1% level in row 2. Similarly, the coefficient on IV in the bivariate regression is
over 40% higher in magnitude than is its univariate counterpart reported in row 3. Moreover,
adjusted $R^2$ in the bivariate regression is 8.4%, compared with -0.2% and 4.8% for univariate
regressions on LRES_LD or IV, respectively. To summarize, LRES_LD and IV jointly forecast
excess market returns, and this result is unlikely due to multicollinearity.

As a robustness check, we use two alternative measures of idiosyncratic variance. The
first alternative measure we use is realized idiosyncratic variance computed from closing mid-
quote returns, $\text{IV}_{\text{QR}}$, that Lesmond and Zhao (2015) and Han and Lesmond (2011) propose to
alleviate liquidity biases.\textsuperscript{12} Our results remain unchanged. Row 4 of Table 2 shows that the
coefficient of LRES_LD is positive and statistically significant at the 1% level when we control

\textsuperscript{12} We thank Yufeng Han for providing the data on idiosyncratic variance computed from closing mid-quote returns.
See Han and Lesmond (2011) for details on how to compute this variable.
for IV_QR. The coefficient of IV_QR is significantly negative at the 1% level. The second alternative measure of aggregate idiosyncratic variance is options-implied variance, IV_O, proposed by Guo and Qiu (2014). This measure is also less susceptible to microstructure noise. Results are qualitatively similar despite the relatively short sample period (1996Q2 to 2009Q4) during which we have IV_O data. Row 5 shows that LRES_LD correlates positively and significantly with one-quarter-ahead excess market returns at the 5% level when in conjunction with IV_O, which itself has significantly negative effects on conditional equity premium at the 1% level. By contrast, untabulated results show that LRES_SD again has negligible predictive power in the univariate regression over the 1996Q2 to 2009Q4 period.

Jones (2002) points out that aggregate bid-ask spreads forecast market returns possibly because of their close correlation with market variance—an important determinant of conditional equity premium in Merton’s (1973) ICAPM. Row 6 of Table 2 shows that the log of realized market variance, LMV, correlates positively and significantly with one-quarter-ahead excess market returns at the 1% level when in conjunction with IV. To address Jones’ (2002) concern, we include LMV as a predictor in the forecasting regression along with LRES_LD and IV. Row 7 shows that both LRES_LD and LMV correlate positively and significantly with future excess market returns at the 5% level, while the coefficient on IV remains significantly negative at the

---


14 Economic theories, e.g., Merton (1973), suggest that we should use the level rather than the log of market variance as a market return predictor, although both specifications are standard in empirical studies. The level, however, has negligible predictive power for excess market returns in our sample. This is mainly because of outlier effects from its two drastic spikes in the 1987 stock market crash and the 2008 global financial market crisis. Using the log seems more appropriate because it alleviates outlier effects while capturing cyclical variations in market variance. Nevertheless, using the stock market variance level as a control variable does not affect our main finding of a positive aggregate stock market spread-return relation in any qualitative manner (untabulated). This result is not surprising because the stock market variance level has negligible predictive power for market returns and thus does not account for the positive aggregate stock market spread-return relation. That is, the log provides a more stringent test for the maintained hypothesis than does the log.
1% level. Therefore, our results indicate that aggregate bid-ask spreads and market variance have distinct effects on conditional equity premium.

A negative relation between aggregate realized idiosyncratic variance and conditional equity premium is puzzling because most of extant economic theories suggest the relation is either zero (e.g., CAPM) or positive (e.g., Merton (1987)). One possible explanation is that IV forecasts excess market returns because of its correlation with the variance of an omitted hedging risk factor. A full-fledge investigation is beyond the scope of this paper. However, we illustrate our main point through a simple exercise. Specifically, we use the value premium from the commonly used Fama and French (1996) three-factor model as a proxy for the hedging risk factor. Consistent with visual inspection of Figure 3, realized value premium variance, V_HML, correlates closely with IV, with a correlation coefficient of 90% over the 1983Q1 to 2009Q4 period (untabulated). To address our conjecture formally, in row 8 of Table 2, we include V_HML instead of IV as an explanatory variable in the forecasting regression, while we use IV as an instrumental variable for V_HML. Interestingly, we uncover a significantly positive relation between LRES_LD and conditional equity premium when controlling for V_HML, which, like IV, correlates negatively and significantly with one-quarter-ahead excess market returns at the 1% level.

The novel finding of the interaction between LRES_LD and V_HML is consistent with theoretical models proposed by Jang, Koo, Liu, and Loewenstein (2007) and Lynch and Tan

15 Fama and French (1996) suggest that the value premium is a proxy for changes in investment opportunities, as in Merton’s (1973) ICAPM. Gomes, Kogan, and Zhang (2003), Zhang (2005), and Lettau and Wachter (2007) have developed equilibrium models to investigate the link between the value premium and investment opportunities. Consistent with this conjuncture, recent empirical studies, e.g., Campbell and Vuolteenaho (2004), Brennan, Wang, and Xia (2004), Hahn and Lee (2006), and Petkova (2006), document a close relation between the value premium and discount rate shocks. Other authors, e.g., Lakonishok, Shleifer, and Vishny (1994) and Barberis and Shleifer (2003), however, suggest that the value premium reflects mispricing.

16 HML is an empirical risk factor, and V_HML arguably is subject to measurement error. We use IV as an instrumental variable for V_HML to alleviate the attenuation effect of measurement errors in our regression.
These authors emphasize that by contrast with the Constantinides (1986) model, illiquidity can have a first order effect on asset prices when unexpected changes in investment opportunities or human capital make investors rebalance their portfolios frequently. Specifically, a big shock to investment opportunities leads to (1) an increase in \( V_{HML} \) and (2) an increase in trading costs when investors have asymmetric information about the shock. This simple example explains the positive relation between \( LRES_{LD} \) and \( V_{HML} \) (untabulated) despite their opposing effects on conditional equity premium.

Because both \( IV \) and \( V_{HML} \) are measures of realized variances constructed using daily return data, they might have measurement errors due to market microstructure noise (see, e.g., Andersen, Bollerslev, Diebold, and Labys (2003)). Therefore, the predictive power of \( LRES_{LD} \) for market returns when in conjunction with \( IV \) or \( V_{HML} \) may reflect the correlation of \( LRES_{LD} \) with market microstructure noise. That said, as Andersen, Bollerslev, Diebold, and Labys (2003) point out, while market microstructure noise can have sizeable effects when we estimate realized volatility using transaction data, its effects are likely to be small when we use daily data, as we do in this study. Nevertheless, we show that microstructure noise does not account for our main findings in three ways. First, we use two different measures of idiosyncratic variance that mitigate microstructure noise: idiosyncratic variance computed from mid-quote returns and options-implied variance. In table 2 we show that our results are qualitatively similar when using \( IV_{QR} \) (row 4) and \( IV_{O} \) (row 5) instead of \( IV \) or \( V_{HML} \). Second, we orthogonalize \( LRES_{LD} \) by a constant and \( IV \), and find that the relation between the orthogonalized \( LRES_{LD} \) and future market returns is significantly positive at the 5% level (untabulated). Last, \( LRES_{LD} \) remains statistically insignificant when in conjunction with
realized market variance constructed using daily return data (untabulated), which, similar to \( V_{HML} \) or IV, is also potentially susceptible to market microstructure noise.

In panel B of Table 2, we use stochastically detrended aggregate relative effective bid-ask spread, \( LRES_{SD} \), as an alternative illiquidity measure and find qualitatively similar results. \( LRES_{SD} \) does not forecast excess market returns in the univariate regression (row 9). Its correlation with one-quarter-ahead excess market returns, however, becomes significantly positive at least at the 5% level when in conjunction with IV (rows 10 and 13), IV_QR (row 11), IV_O (row 12), or \( V_{HML} \) (row 14). The positive relation between \( LRES_{SD} \) and conditional equity premium is robust to controlling for market variance (rows 13 and 14). For brevity, we use only \( LRES_{LD} \) as the forecasting variable in the remainder of the paper.

In Table 3, we investigate whether the effect of \( LRES_{LD} \) on conditional equity premium is asymmetric.\(^{17}\) Following the methodology proposed by Bali (2000), we partition the economy into good versus bad states. Specifically, as in Allen, Bali, and Tang (2012), the economy is in the good state at time \( t \) if the Chicago Fed National Activity Index (CFNAI\(_t\)) is greater than zero and is in the bad state otherwise. We run the following regression:

\[
R_{m,t+1} = \alpha + \beta^+ \cdot LRES_{LD} + \beta^- \cdot LRES_{LD} - \varepsilon_{m,t+1},
\]

where

\[
LRES_{LD}^+ = \begin{cases} LRES_{LD}, & \text{if CFNAI}_t > 0 \\ 0, & \text{if CFNAI}_t \leq 0 \end{cases} \quad \text{and} \quad LRES_{LD}^- = \begin{cases} 0, & \text{if CFNAI}_t > 0 \\ LRES_{LD}, & \text{if CFNAI}_t \leq 0 \end{cases}.
\]

Row 1 of Table 3 shows that neither \( LRES_{LD}^+ \) nor \( LRES_{LD}^- \) is statistically significant in the bivariate regression forecasting one-quarter-ahead excess market returns. In row 2, we control for aggregate idiosyncratic variance and find that the effect of \( LRES_{LD}^- \) on

\(^{17}\) We thank an anonymous referee for this suggestion.
conditional equity premium is significantly positive at the 5% level, while the effect of 
$LRES\_LD_i^+$ is insignificant. These results are consistent with the conventional wisdom that 
illiquidity has larger effects on stock prices during business recessions that during business 
expansions. The results are qualitatively similar when we include LMV as an additional 
predictive variable (row 3). Untabulated results show that the asymmetric effect is robust (1) 
when we allow for asymmetric effects of IV and/or LMV on conditional equity premium and (2) 
when we use excess market returns, LMV, and LRES_LD as the conditioning variables.\(^{18}\)

We conduct comprehensive robustness checks. For brevity, we do not tabulate these 
results in the paper but they are available on request. First, we find that LRES_LD correlates 
positively and significantly with the one-month-ahead excess market return when in conjunction 
with aggregate options-implied variance, IV_O.\(^{19}\) We find qualitatively similar results using 
semianual and annual data as well. Second, as in Lettau and Ludvigson (2001), we conduct 
formal out-of-sample tests using the test statistic proposed by Clark and McCracken (2001). To 
address the omitted-variable problem, we include both aggregate bid-ask spreads and aggregate 
Idiosyncratic variance as predictors in the forecasting model. Alternatively, we run a regression 
of aggregate bid-ask spreads on a constant and aggregate idiosyncratic variance, and use the 
orthogonalized aggregate bid-ask spreads as the predictor. In both cases, we find that aggregate 
bid-ask spreads have significant out-of-sample forecasting power for excess stock market 
returns. Third, we control for additional standard market return predictors, including the

\(^{18}\) The economy is in the good state when the market return is greater than zero, LMV is lower than its sample 
median, or LRES_LD is lower than its sample median. The economy is in the bad state when the market return is 
less than zero, LMV is higher than its sample median, or LRES_LD is higher than its sample median.

\(^{19}\) The relation between LRES_LD and conditional equity premium, however, is weak when we use aggregate 
realized idiosyncratic variance as the control variable. These results likely reflect the fact that the forward-looking 
options-implied variance is a better measure of conditional variance than is the backward-looking realized variance 
(e.g., Christensen and Prabhala (1998) and Fleming (1998)). For example, Guo and Qiu (2014) find that the former 
always drives the latter in the forecast of excess market returns.
consumption-wealth ratio (CAY), the dividend yield (DY), the earnings-price ratio (EP), the default premium (DEF), the term premium (TERM), and the stochastically detrended risk-free rate (RREL). We find that the information content of aggregate bid-ask spreads for future market returns is distinct from that contained in commonly used market return predictors. Fourth, results are qualitatively similar when we use equal-weighted relative effective bid-ask spread and relative quoted bid-ask spread as measures of illiquidity to forecast excess market returns. Fifth, Amihud (2002) argues that if aggregate illiquidity correlates positively with future market returns, an unanticipated increase in aggregate illiquidity should lower the market index immediately because it implies higher expected market returns. Consistent with this conjecture, we find a significantly negative relation between unexpected changes in aggregate bid-ask spreads and contemporaneous excess market returns. Sixth, aggregate bid-ask spreads and aggregate realized idiosyncratic variance have relatively strong serial correlation, and both variables correlate with excess market returns (Table 1). Therefore, the OLS estimator is potentially biased in small samples (see, e.g., Stambaugh (1999) for univariate regressions and Amihud and Hurvich (2004) and Amihud, Hurvich, and Wang (2009) for multivariate regressions). We find that correcting for the small sample bias has a rather negligible effect on our inference. These results are not surprising because our forecasting variables are much less persistent than the variables cautioned against by Stambaugh (1999), e.g., the dividend yield. Last, consistent with earlier studies, e.g., Amihud (2002) and Baker and Stein (2004), aggregate bid-ask spreads have stronger predictive power for equal-weighted market returns than for value-weighted market returns. These results are not surprising because small stocks are not as liquid as big stocks and thus are more sensitive to changes in aggregate illiquidity (e.g., Amihud and
Mendelson (1986)). To summarize, we find that aggregate bid-ask spreads have strong forecasting power for excess market returns.

4. Alternative Illiquidity Measures

In this section, we consider two market illiquidity measures proposed by Amihud (2002) and Pastor and Stambaugh (2003) and two funding illiquidity measures advocated by Nagel (2012) and Adrian, Moench, and Shin (2014). The Amihud measure is a gauge of price impact—a measure of adverse selection due to information asymmetry. Pastor and Stambaugh (2003) measure liquidity associated with temporary price reversal induced by order flow, and we can view it as a measure of market making costs. These two measures capture two key aspects of bid-ask spreads, or trading costs, because bid-ask spreads are market makers’ compensation for adverse selection and market making costs. Indeed, both alternative illiquidity measures correlate positively with aggregate bid-ask spreads (Table 1).

In the Brunnermeier and Pederson (2009) model, market makers and brokers’ book leverage is a measure of funding liquidity. Adrian, Moench, and Shin (2014) find that this funding liquidity measure predicts excess market returns and explains the cross-section of stock returns. Recent studies, e.g., Nagel (2012) and Chung and Chuwonganant (2014), show that VIX is a measure of both funding illiquidity and market illiquidity. Indeed, Table 1 shows that VIX correlates positively with both (1) the Adrian, Moench, and Shin (2014) funding illiquidity and (2) market illiquidity measures such as aggregate bid-ask spreads. These results are consistent with Brunnermeier and Pedersen’s (2009) model, which highlights a strong interaction between funding illiquidity and market illiquidity in explaining drastic asset price volatility. Note that
VIX forecasts stock market returns also because of its strong correlation with conditional market variance—an important determinant of conditional equity premium in Merton’s (1973) ICAPM.

In Table 4, we investigate whether these market illiquidity and funding illiquidity measures forecast excess market returns over the 1983Q2 to 2009Q4 period, over which we have high frequency spread data. We find that the predictive power of the Amihud (2002) measure, the Pastor and Stambaugh measure, and VIX is qualitatively similar to that of aggregate bid-ask spreads. Specifically, these illiquidity measures correlate positively with one-quarter-ahead excess market returns but the relation is statistically insignificant in univariate regressions. Their positive effects on conditional equity premium become statistically significant at least at the 10% level when in conjunction with aggregate idiosyncratic variance. Moreover, the predictive power of alternative illiquidity measures becomes insignificant when we control for aggregate bid-ask spreads and realized market variance in the forecasting regression, suggesting that the information content of alternative illiquidity measures about future excess market returns is similar to that of aggregate bid-ask spreads. These results should not be surprising because as we explain above, the Amihud (2002) and Pastor and Stambaugh (2003) measures capture two important components of aggregate bid-ask spreads. Similarly, VIX forecasts market returns because it is a key driver of commonality in stock illiquidity and a proxy for market variance.

Row 13 of Table 4 replicates Adrian, Moench, and Shin’s (2014) main finding that the funding illiquidity constructed using market makers’ and brokers’ book leverage, LEV_SD, correlates positively and significantly with one-quarter-ahead excess market returns at the 5% level. Its effect becomes moderately more significant when in conjunction with IV (row 14). Interestingly, LEV_SD becomes insignificant when we control for realized market variance and aggregate bid-ask spreads (rows 15), suggesting that funding illiquidity and market
illiquidity/volatility have similar effects on conditional equity premium. To the best of our knowledge, this finding is novel.

To summarize, we find a positive aggregate illiquidity-return relation using standard low frequency illiquidity measures. While aggregate high frequency spreads appear to have stronger market return predictive power than do low frequency illiquidity measures, the latter have an important advantage because they are available over a much longer sample period.

5. Aggregate bid-ask spreads and the Cross-Section of Stock Returns

We argue that aggregate bid-ask spreads forecast excess stock market returns because illiquidity is a pervasive state variable. Pastor and Stambaugh (2003) and Acharya and Pedersen (2005) have shown that indirect measures of trading costs—(1) temporal price reversal induced by order flow and (2) the price impact, respectively—is significantly priced in the cross-section of stock returns. In this section, we formally investigate whether our direct measure of trading costs, LRES_LD, is a priced risk factor.20

Specifically, we estimate a variant of Merton (1973) or Campbell’s (1993) ICAPM using excess market returns, \( R_{m,t+1} \), and shocks to the aggregate relative effective bid-ask spread, \( LRES\_LD_{t+1}^{shock} \), as the risk factors:

\[
(2) \quad R_{i,t+1} = \alpha_i + A \cdot \text{cov}_t(R_{i,t+1}, R_{m,t+1}) + B \cdot \text{cov}_t(R_{i,t+1}, LRES\_LD_{t+1}^{shock}) + \epsilon_{i,t+1}.
\]

Where \( R_{i,t+1} \) is the excess portfolio return, \( \alpha_i \) is the intercept, and \( \epsilon_{i,t+1} \) is the residual term. As in Bali (2008) Bali and Zhou (2016), we regress \( LRES\_LD_{t+1}^{shock} \) on its one-period lag and a constant, and use the residual as a proxy for \( LRES\_LD_{t+1}^{shock} \). We use a panel of 41 assets.

---

20 We thank the anonymous referee for suggesting this to us.
including 10 size portfolios, 10 B/M portfolios, 10 momentum portfolios, 10 industry portfolios, and the market portfolio. Following Bali and Zhou (2016), we regress each of the portfolio returns, including the market portfolio, on its own one-period lag and use the residual to estimate the covariance terms in equation (2) with the bivariate DCC-GARCH(1,1) model.

We then estimate equation (2) using a SUR model that takes into account serial correlation, cross-correlation, and heteroskedasticity in the residual term, \( \varepsilon_{i,t+1} \). Table 5 reports the estimates of the market risk price (A) and the illiquidity risk price (B). For the quarterly data spanning the 1983Q2 to 2009Q4 period, we find that both market risk and illiquidity risk are significantly priced at least at the 5% level. Consistent with ICAPM, the price of market risk is positive. Illiquidity risk usually increases during bad times such as the 2008 financial crisis when investment opportunities deteriorate. Stocks that comove positively with illiquidity risk provide a hedge for investment opportunities; therefore, they should have a lower illiquidity risk premium than do stocks that comove negatively with illiquidity risk (e.g., Pastor and Stambaugh (2003)). Consistent with this conjecture, we find that the price of illiquidity risk is negative. Results are qualitatively similar for the monthly data spanning the 1983M2 to 2009M12. The price of illiquidity risk is significantly negative at the 1% level.

To summarize, consistent with the conjecture that aggregate bid-ask spread is a systematic risk factor, we find that illiquidity risk is negatively priced in the cross-section of stock returns.

6. Conclusion

We conduct a comprehensive investigation on the relation between aggregate illiquidity and future market returns and document three novel empirical results. First, aggregate bid-ask
spreads, a direct measure of trading costs, correlate positively and significantly with future excess market returns when controlling for their positive correlation with aggregate idiosyncratic variance. Aggregate idiosyncratic variance has a negative effect on conditional equity premium (the opposite effect from aggregate illiquidity). When aggregate idiosyncratic variance is omitted from the analysis, aggregate illiquidity also picks up the effect of aggregate idiosyncratic variance, and because of the conflicting effects between these two variables, the effect of aggregate illiquidity on conditional equity premium is biased towards zero. The elusive empirical findings documented in previous studies reflect an omitted-variable problem. Second, consistent with extant economic theories, we document a strong relation between aggregate illiquidity and market variance. Nevertheless, these two risk factors have distinct effects on conditional equity premium. Last, consistent with Brunnermeier and Pedersen’s (2009) model, we document a strong interaction between market illiquidity and funding liquidity: They have similar predictive power for excess market returns.

The interplay between aggregate illiquidity and aggregate idiosyncratic variance is consistent with the conjecture that the latter is a proxy for the variance of an omitted hedging risk factor. Specifically, aggregate idiosyncratic variance correlates closely with realized variance of the value premium—a hedging risk factor in the prominent Fama and French (1996) three-factor model. Moreover, we uncover a positive aggregate bid-ask spread-return relation when controlling for realized value premium variance instead of aggregate idiosyncratic variance. This novel finding is consistent with the recent theoretical works by Jang, Koo, Liu, and Loewenstein (2007) and Lynch and Tan (2009). These authors show that aggregate illiquidity has a first-order effect on asset prices because changes in investment opportunities or labor income make investors rebalance their portfolios rather frequently. Our new empirical findings
lend support for O’Hara’s (2003) conjecture of important interaction between microstructure and aggregate financial markets. In future studies, it will be interesting to explain these findings using general equilibrium models.
References


### Appendix

#### Table A1
**Description of Acronyms Used in the Paper**

<table>
<thead>
<tr>
<th>Acronym</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>AMIHUD</td>
<td>aggregate illiquidity measure proposed by Amihud (2002)</td>
</tr>
<tr>
<td>CAY</td>
<td>consumption wealth ratio</td>
</tr>
<tr>
<td>DEF</td>
<td>yield spread between Baa-rated and Aaa-rated corporate bonds</td>
</tr>
<tr>
<td>DY</td>
<td>dividend yield</td>
</tr>
<tr>
<td>EP</td>
<td>earnings price ratio</td>
</tr>
<tr>
<td>ERET</td>
<td>excess stock market return</td>
</tr>
<tr>
<td>IV</td>
<td>aggregate idiosyncratic variance</td>
</tr>
<tr>
<td>IV_O</td>
<td>aggregate options-implied variance constructed using OptionMetrics data</td>
</tr>
<tr>
<td>LEV_SD</td>
<td>aggregate funding illiquidity from Adrian, Moench, and Shin’s (2014)</td>
</tr>
<tr>
<td>IV_QR</td>
<td>aggregate realized idiosyncratic variance computed from closing mid-quote returns as in Han and Lesmond (2011)</td>
</tr>
<tr>
<td>LMV</td>
<td>log of realized stock market variance</td>
</tr>
<tr>
<td>LRES</td>
<td>log of relative effective spread</td>
</tr>
<tr>
<td>LRES_LD</td>
<td>log of relative effective spread, linearly detrended</td>
</tr>
<tr>
<td>LRES_SD</td>
<td>log of relative effective spread, stochastically detrended</td>
</tr>
<tr>
<td>MV</td>
<td>realized stock market variance</td>
</tr>
<tr>
<td>PS</td>
<td>aggregate liquidity measure proposed by Pastor and Stambaugh (2003)</td>
</tr>
<tr>
<td>RREL</td>
<td>stochastically detrended risk-free rate</td>
</tr>
<tr>
<td>TERM</td>
<td>yield spread between long-term Treasury bonds and short-term Treasury bills</td>
</tr>
<tr>
<td>V_HML</td>
<td>realized value premium variance</td>
</tr>
<tr>
<td>VIX</td>
<td>conditional market variance constructed using options on the market index</td>
</tr>
</tbody>
</table>
Figure 1
Daily Level (Solid Line) and Log (Dashed Line) of Relative Effective Spreads: January 1, 1983 to December 31, 2009

Figure 2
Quarterly Linearly (Solid Line) and Stochastically (Dashed Line) Detrended Relative Effective Spread: 1983Q1 to 2009Q4
Figure 3
Quarterly Realized Value Premium Variance (Dashed Line) and Aggregate Idiosyncratic Variance (Solid Line): 1983Q1 to 2009Q4

Figure 4
Quarterly Options-Implied Market Variance (Dashed Line) and Realized Market Variance (Solid Line): 1983Q1 to 2009Q4
Table 1 Summary Statistics

<table>
<thead>
<tr>
<th></th>
<th>LRES LD</th>
<th>LRES SD</th>
<th>ERET</th>
<th>IV</th>
<th>LMV</th>
<th>VIX</th>
<th>Amihud</th>
<th>PS</th>
<th>LEV SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.020</td>
<td>-0.081</td>
<td>0.017</td>
<td>0.023</td>
<td>-5.292</td>
<td>0.012</td>
<td>0.000</td>
<td>-0.033</td>
<td>0.000</td>
</tr>
<tr>
<td>SD</td>
<td>0.351</td>
<td>0.221</td>
<td>0.086</td>
<td>0.019</td>
<td>0.809</td>
<td>0.010</td>
<td>0.531</td>
<td>0.068</td>
<td>0.002</td>
</tr>
<tr>
<td>Autocorrelation</td>
<td>0.844</td>
<td>0.571</td>
<td>0.038</td>
<td>0.798</td>
<td>0.616</td>
<td>0.557</td>
<td>0.676</td>
<td>0.299</td>
<td>0.648</td>
</tr>
</tbody>
</table>

Note: The table reports summary statistics for selected quarterly variables. LRES_LD is the linearly detrended log aggregate relative effective spread. LRES_SD is the stochastically detrended log aggregate relative effective spread. ERET is the excess stock market return. IV is the aggregate realized idiosyncratic variance. LMV is the log realized stock market variance. VIX is the options-implied market variance. Amihud is the linearly detrended log aggregate Amihud (2002) illiquidity measure. PS is Pastor and Stambaugh’s (2003) aggregate illiquidity measure. LEV_SD is Adrian, Moench, and Shin’s (2014) aggregate funding illiquidity measure. Data are available over the 1986Q1 to 2009Q4 period for LRES_SD, 1983Q4 to 2009Q4 period for VIX, and 1983Q1 to 2009Q4 period for all other variables.
Table 2 Aggregate bid-ask spreads and One-Quarter-Ahead Excess Market Returns

<table>
<thead>
<tr>
<th></th>
<th>LRES_LD</th>
<th>LRES_SD</th>
<th>IV</th>
<th>IV_QR</th>
<th>IV_O</th>
<th>LMV</th>
<th>V_HML</th>
<th>Adj. R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.022</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.002</td>
</tr>
<tr>
<td></td>
<td>(0.842)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>0.058**</td>
<td>-1.502***</td>
<td>(2.920)</td>
<td>-3.529</td>
<td></td>
<td></td>
<td></td>
<td>0.084</td>
</tr>
<tr>
<td></td>
<td>(2.290)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>0.086***</td>
<td>-1.059***</td>
<td>(3.536)</td>
<td>-3.269</td>
<td></td>
<td></td>
<td></td>
<td>0.048</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>0.074**</td>
<td>-1.929***</td>
<td>(2.448)</td>
<td>-4.638</td>
<td></td>
<td></td>
<td></td>
<td>0.141</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>0.074**</td>
<td>-3.965***</td>
<td>(2.448)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.072</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>0.096***</td>
<td>-1.928***</td>
<td>(2.531)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.076</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>0.086**</td>
<td>-2.302***</td>
<td>(2.531)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.108</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>0.075**</td>
<td>-1.492***</td>
<td>(2.531)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.038</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Panel A: Linearly Detrended Log Relative Effective Spreads

<table>
<thead>
<tr>
<th></th>
<th>LRES_LD</th>
<th>LRES_SD</th>
<th>IV</th>
<th>IV_QR</th>
<th>IV_O</th>
<th>LMV</th>
<th>V_HML</th>
<th>Adj. R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>9</td>
<td>0.034</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.003</td>
</tr>
<tr>
<td></td>
<td>(0.887)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>0.096***</td>
<td>-1.492***</td>
<td>(3.139)</td>
<td>-4.127</td>
<td></td>
<td></td>
<td></td>
<td>0.085</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>0.086**</td>
<td>-1.490***</td>
<td>(2.571)</td>
<td>-3.634</td>
<td></td>
<td></td>
<td></td>
<td>0.086</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>0.106***</td>
<td>-4.384***</td>
<td>(2.942)</td>
<td>-3.614</td>
<td></td>
<td></td>
<td></td>
<td>0.087</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>0.075**</td>
<td>-2.085***</td>
<td>(2.217)</td>
<td>-4.432</td>
<td></td>
<td></td>
<td></td>
<td>0.098</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>14</td>
<td>0.083**</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.037</td>
</tr>
<tr>
<td></td>
<td>(2.47)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Panel B: Stochastically Detrended Log Relative Effective Spreads

Note: The table reports the OLS estimation results of forecasting one-quarter-ahead excess stock market returns. LRES_LD is the linearly detrended log aggregate relative effective spread. LRES_SD is the stochastically detrended log aggregate relative effective spread. IV is the aggregate realized idiosyncratic variance. IV_QR is the aggregate realized idiosyncratic variance computed from closing mid-quote returns as in Han and Lesmond (2011). IV_O is the aggregate options-implied variance. LMV is the log realized market variance. V_HML is the realized value premium variance. The data are available over the 1986Q1 to 2009Q4 period for LRES_SD, the 1982Q4 to 2008Q4 period for IV_QR, the 1996Q1 to 2009Q4 period for IV_O, and 1983Q1 to 2009Q4 period for all other variables. We calculate Newey-West t-values using four lags and report them in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. In rows 7 and 12 we use IV as an instrumental variable for V_HML.
Table 3: Asymmetric Effects of Aggregate bid-ask spreads

<table>
<thead>
<tr>
<th></th>
<th>LRES LD⁺</th>
<th>LRES LD⁻</th>
<th>IV</th>
<th>LMV</th>
<th>Adjusted R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-0.003</td>
<td>0.040</td>
<td>-0.004</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.082)</td>
<td>(1.232)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>0.030</td>
<td>0.074**</td>
<td>-1.476***</td>
<td>0.080</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.038)</td>
<td>(2.262)</td>
<td>(-3.544)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>0.031</td>
<td>0.068**</td>
<td>-2.240***</td>
<td>0.026**</td>
<td>0.102</td>
</tr>
<tr>
<td></td>
<td>(1.179)</td>
<td>(2.020)</td>
<td>(-5.589)</td>
<td>(2.326)</td>
<td></td>
</tr>
</tbody>
</table>

Note: The table reports the OLS estimation results of forecasting one-quarter-ahead excess stock market returns:

$LRES_{LD}^+ = \begin{cases} LRES_{LD} & \text{if CFNAI}_t > 0 \\ 0 & \text{if CFNAI}_t \leq 0 \end{cases}$ and $LRES_{LD}^- = \begin{cases} 0 & \text{if CFNAI}_t > 0 \\ LRES_{LD} & \text{if CFNAI}_t \leq 0 \end{cases}$, where LRES_LD is the linearly detrended log aggregate relative effective bid-ask spread, CFNAI is the Chicago Fed National Activity Index. IV is the aggregate realized idiosyncratic variance. LMV is the log realized stock market variance. The data are available over the 1983Q1 to 2009Q4 period for LRES_LD. We calculate Newey-West t-values using four lags and report them in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.
<table>
<thead>
<tr>
<th></th>
<th>Amihud</th>
<th>PS</th>
<th>VIX</th>
<th>LEV_SD</th>
<th>IV</th>
<th>LMV</th>
<th>LRES_LD</th>
<th>Adj. R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.016</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>(1.335)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>0.026*</td>
<td></td>
<td>-1.225***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.064</td>
</tr>
<tr>
<td></td>
<td>(1.838)</td>
<td></td>
<td>(-3.664)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>0.013</td>
<td></td>
<td>-2.282***</td>
<td>0.025**</td>
<td>0.049*</td>
<td></td>
<td></td>
<td>0.105</td>
</tr>
<tr>
<td></td>
<td>(0.889)</td>
<td></td>
<td>(-5.298)</td>
<td>(2.577)</td>
<td>(1.798)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>0.113</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.002</td>
</tr>
<tr>
<td></td>
<td>(0.706)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>0.237*</td>
<td></td>
<td>-1.302***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.067</td>
</tr>
<tr>
<td></td>
<td>(1.895)</td>
<td></td>
<td>(-4.364)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>0.145</td>
<td></td>
<td>-2.279***</td>
<td>0.022*</td>
<td>0.053**</td>
<td></td>
<td></td>
<td>0.109</td>
</tr>
<tr>
<td></td>
<td>(1.095)</td>
<td></td>
<td>(-5.528)</td>
<td>(1.675)</td>
<td>(2.107)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>0.428</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.007</td>
</tr>
<tr>
<td></td>
<td>(0.353)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>2.975***</td>
<td>2.057***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.114</td>
</tr>
<tr>
<td></td>
<td>(2.730)</td>
<td></td>
<td>(-4.852)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>2.442</td>
<td></td>
<td>-2.436***</td>
<td>0.005</td>
<td>0.050*</td>
<td></td>
<td></td>
<td>0.131</td>
</tr>
<tr>
<td></td>
<td>(1.392)</td>
<td></td>
<td>(-5.556)</td>
<td>(0.277)</td>
<td>(1.750)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>8.445**</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.033</td>
</tr>
<tr>
<td></td>
<td>(2.085)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>14</td>
<td>9.720**</td>
<td>-1.181***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.095</td>
</tr>
<tr>
<td></td>
<td>(2.307)</td>
<td></td>
<td>(-4.193)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>6.712</td>
<td>-2.072***</td>
<td>0.019**</td>
<td>0.049**</td>
<td></td>
<td></td>
<td></td>
<td>0.122</td>
</tr>
<tr>
<td></td>
<td>(1.394)</td>
<td></td>
<td>(-5.134)</td>
<td>(2.133)</td>
<td>(2.146)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: The table reports the OLS estimation results of forecasting one-quarter-ahead excess stock market returns. Amihud is the linearly detrended log aggregate Amihud (2002) illiquidity measure. PS is Pastor and Stambaugh’s (2003) aggregate illiquidity measure. VIX is the options-implied market variance. LEV_SD is Adrian, Moench, and Shin’s (2014) aggregate funding illiquidity measure. IV is the aggregate realized idiosyncratic variance. LMV is the log realized stock market variance. LRES_LD is the linearly detrended log aggregate relative effective spread. The data are available over the 1983Q1 to 2009Q4 period for LRES_LD. We calculate Newey-West $t$-values using four lags and report them in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.
Table 5 Aggregate Bid-Ask Spread and the Cross Section of Stock Returns

<table>
<thead>
<tr>
<th>Data Frequency</th>
<th>( \text{cov}(R_{i,t+1}, R_{m,t+1}) )</th>
<th>( \text{cov}(R_{i,t+1}, LRES_{LD\text{Shock}}) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Quarterly</td>
<td>1.419*** (7.141)</td>
<td>-0.849** (-2.414)</td>
</tr>
<tr>
<td>2 Monthly</td>
<td>0.192 (0.878)</td>
<td>-0.259*** (-3.534)</td>
</tr>
</tbody>
</table>

Note: We estimate a variant of Merton (1973) or Campbell’s (1993) ICAPM using excess market returns, \( R_{m,t+1} \), and shocks to the aggregate relative effective bid-ask spread, \( LRES_{LD\text{Shock}} \), as the risk factors:

\[
R_{i,t+1} = \alpha_i + A \cdot \text{cov}(R_{i,t+1}, R_{m,t+1}) + B \cdot \text{cov}(R_{i,t+1}, LRES_{LD\text{Shock}}) + \epsilon_{i,t+1}.
\]

Where \( R_{i,t+1} \) is the excess portfolio return, \( \alpha_i \) is the intercept, and \( \epsilon_{i,t+1} \) is the residual term. We regress \( LRES_{LD_{t+1}} \) on its one-period lag and a constant, and use the residual as a proxy for \( LRES_{LD_{t+1}} \). We use a panel of 41 assets, including 10 size portfolios, 10 B/M portfolios, 10 momentum portfolios, 10 industry portfolios, and the market portfolio. We regress each of the portfolio returns, including the market portfolio, on its own one-period lag and use the residual to estimate the covariance terms in equation (2) with the bivariate DCC-GARCH(1,1) model. We then estimate equation (2) using a SUR model that takes into account serial correlation, cross-correlation, and heteroskedasticity in the residual term, \( \epsilon_{i,t+1} \). The table reports the estimates of the market risk price (A) and the illiquidity risk price (B). T-statistics are in parenthesis. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. We use the quarterly data spanning the 1983Q2 to 2009Q4 period in row 1 and use the monthly data spanning the 1983M2 to 2009M12 period in row 2.