Financial Management

Market Illiquidity and Conditional Equity Premium

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We examine the time-series relation between aggregate bid-ask spreads and conditional equity premium. We document that average marketwide 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 marketwide liquidity is an important asset pricing risk factor.

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 marketwide liquidity help explain the cross-section of stock returns.[1] For this inference to be validated, according to Campbell's (1993) intertemporal capital asset pricing model (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 article, we explore the possibility that aggregate idiosyncratic risk confounds the time-series relation between aggregate liquidity and conditional equity premium.

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 Nagpurnanand Prabhala, Buhui Qiu, Yufeng Han, and Amit Goyal for providing data. The paper formerly circulated under the title "Uncovering the Relation between Aggregate Stock Illiquidity and Expected Excess Market Returns."

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[1] Næs, Skjeltorp, and Ødegaard (2011) and Jensen and Moorman (2010) show that aggregate illiquidity and illiquidity premium change countercyclically across time. Amihud and Mendelson (1986) investigate whether expected stock returns are related to the level of illiquidity as opposed to illiquidity covariance risk. Bali et al. (2014) find that expected stock returns are related to illiquidity shocks in addition to the level of illiquidity.

[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.

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 in a 1900 to 2000 sample but not in a 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 1966 to 2002. 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; that is, 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 both 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 et al. (2007) and Lynch and Tan (2011), 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.[3] Specifically, Guo and Savickas (2008) find that (1) aggregate idiosyncratic variance correlates closely with value premium variance—the most commonly used proxy for the hedging risk factor in empirical asset pricing research—and (2) the two variances have similar forecasting power for excess market returns.[4] Similarly, we document that the relation between aggregate bid-ask spreads and future excess market returns becomes positive and significant when we replace idiosyncratic variance with value premium variance. In other words, both idiosyncratic variance and value premium variance 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, for example, 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

[3] Recent studies (e.g., Chen and Petkova 2012; Duarte et al., 2014; Herskovic et al., 2016), 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 et al. (2009) show that the negative relation between value premium variance and conditional equity premium is consistent with Campbell's (1993) *ICAPM*.

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 Demtsetz (1968) and Stoll (1978). They argue that a firm's liquidity 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.[5] 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 analysis period 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. Finally, we estimate a variant of Merton's (1973) or Campbell's (1993) ICAPM using the DCC-GARCH (dynamic conditional correlation-generalized autoregressive conditional heteroskedasticity) 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 et al., 2003). Therefore, the predictive power of effective bid-ask spreads for market returns when in 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 article. Nevertheless, excluding this event from our empirical analysis does not affect our main findings in any qualitative manner. We circulated previous drafts of this article before the 2008 financial market crisis using data ending in 2007.

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[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.

In contrast to the elusive evidence in the US data, Bekaert, Harvey, and Lundblad (2007) document a positive and significant relation between illiquidity and conditional equity premium using a panel of 18 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 the correlation between aggregate illiquidity and aggregate idiosyncratic variance, aggregate illiquidity is an important determinant of conditional equity premium in the US market—arguably the most liquid market in the world.

Amihud and Mendelson (1989), Spiegel and Wang (2005), Bali et al. (2005), Han and Lesmond (2011), and Lesmond and Zhao (2015) investigate 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 article 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, though 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 noninformational 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.

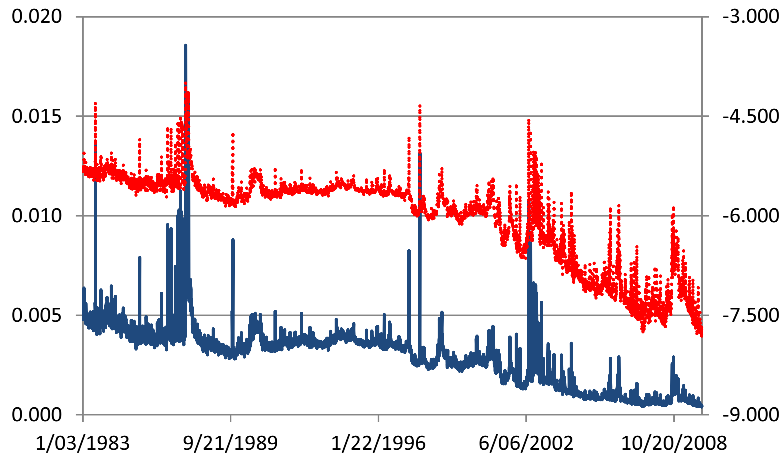
The remainder of this article proceeds as follows. We discuss data in Section I and present empirical results obtained using transaction data in Section II. We analyze several standard illiquidity measures constructed from daily data in Section III and present cross-sectional results in Section IV. We offer some concluding remarks in Section V.

I. Data

We measure illiquidity in a number of different ways and focus on measures of illiquidity built with high-frequency ISSM (Institute for the Study of Security Markets) and TAQ (Trade and Quote) data (Section II). 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 low-frequency data in our empirical analysis (Section III). 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- versus low-frequency measures is that they are

[6] Although 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^2s are higher in multivariate regressions than in univariate regressions for the omitted-variable problem, as we document in this article. The opposite is true for the multicollinearity problem, as shown in Lesmond and Zhao (2015).

Figure 1. Daily Level (Solid Line) and Log (Dashed Line) of Relative Effective Spreads: January 1, 1983 to December 31, 2009



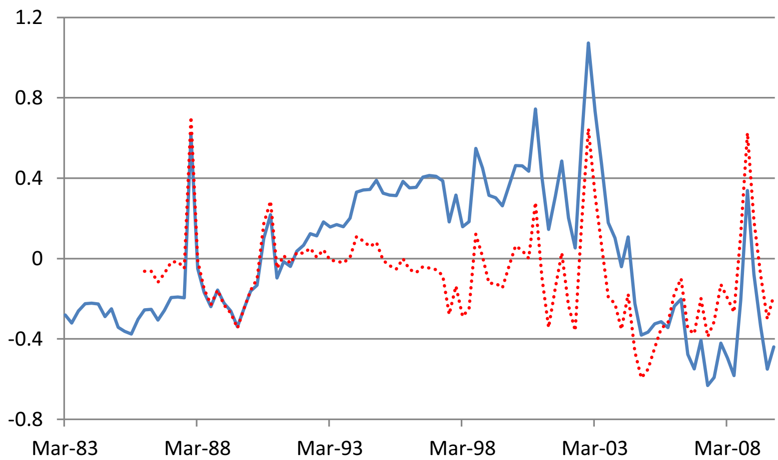
more accurate and have smaller measurement errors (e.g., Amihud, 2002; Fujimoto, 2003; Baker and Stein, 2004). Conversely, many low-frequency measures are reasonably reliable, available for much longer sample periods, and easy to construct (e.g., Goyenko, Holden, and Trzcinka, 2009; Hasbrouck, 2009). Overall, we find that although 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 1983 to 2009. We then aggregate the relative effective spread using value weights across all common stocks in the Center for Research in Security Prices (CRSP) database with market capitalization data.

Figure 1 shows that from January 1983 to December 2009, 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; 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 et al., 2007; Lynch and Tan, 2011) 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

Figure 2. Quarterly Linearly (Solid Line) and Stochastically (Dashed Line) Detrended Relative Effective Spread: 1983Q1 to 2009Q4



the difference between daily *LRES* and its average in the recent three years, *LRES_SD*, as a stochastically detrended illiquidity measure. We convert the daily *LRES_LD* and *LRES_SD* 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.[7] Figure 2 shows that quarterly *LRES_LD* (solid line) and *LRES_SD* (dashed line) move closely to each other. Specifically, both illiquidity measures increase sharply during the 1987 stock market crash, the 1991 liquidity crunch, the 1998 Russia sovereign debt default, the 2001 dot.com bubble crash, and the 2008 global financial market crisis.

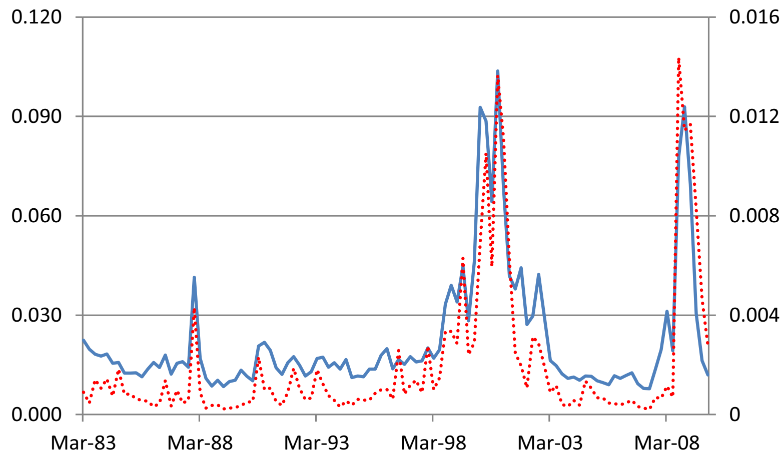
We follow Goyal and Santa-Clara (2003) and Guo and Savickas (2008) in the construction of quarterly aggregate realized idiosyncratic variance using CRSP data. In each quarter, we run a regression of a stock's daily returns on a constant and daily value-weighted market returns, and use the sum of squared 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 are less susceptible to liquidity biases (e.g., Asparouhova et al., 2010).

As in Merton (1980), Andersen et al. (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] For 1986Q1 to 2009Q4, 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

[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.

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

Figure 3. Quarterly Realized Value Premium Variance (Dashed Line) and Aggregate Idiosyncratic Variance (Solid Line): 1983Q1 to 2009Q4



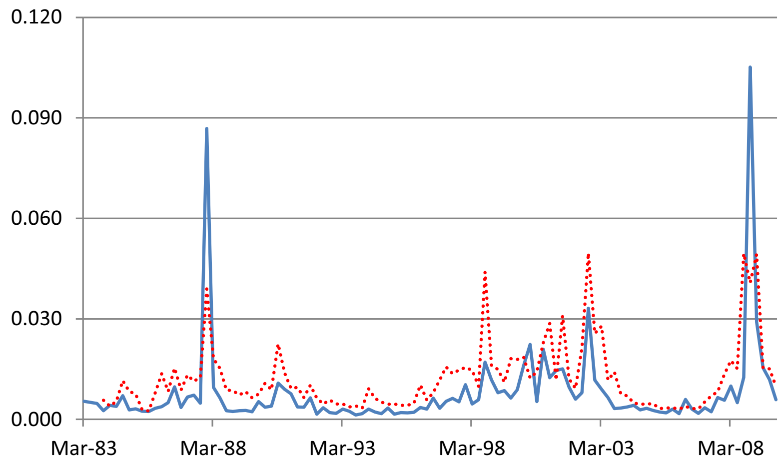
of quarter $t + 1$ market volatility. Because CBOE reports *VIX* as annualized standard deviation, we divide the squared *VIX* by four to get quarterly conditional market variance. For 1983Q4 to 1985Q4, we obtain options-implied market volatility from Christensen and Prabhala (1998).[9] Overall, quarterly options-implied market variance data span 1983Q4 to 2009Q4.

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 because of variance risk premium (e.g., Bollerslev, Tauchen, and Zhou, 2009; 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

[9] We thank Nagpurnanand Prabhala at the University of Maryland for providing the data.

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



one-month-ahead excess market returns becomes positive and significant when in conjunction with aggregate options-implied variance but remains weak when in conjunction with aggregate realized idiosyncratic variance.[10] 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 for 1926 to 2009 from 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 (2002) 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 et al. (2014), we construct quarterly brokers and market makers' book leverage using the flow of funds data from the Federal Reserve Board. Finally, we obtain commonly used market return predictors from Amit Goyal at the University of Lausanne.

Table I 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. *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

[10] We thank Buhui Qiu at Rotterdam School of Management for providing aggregate options-implied variance data.

Table I. Summary Statistics

This 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 et al.'s (2014) aggregate funding illiquidity measure. Data are available from 1986Q1 to 2009Q4 for *LRES_SD*, 1983Q4 to 2009Q4 for *VIX*, and 1983Q1 to 2009Q4 for all other variables.

	LRES_LD	LRES_SD	ERET	IV	LMV	VIX	AMIHUD	PS	LEV_SD
LRES_LD	1.000								
LRES_SD	0.663	1.000							
ERET	−0.155	−0.316	1.000						
IV	0.432	0.448	−0.382	1.000					
LMV	0.336	0.502	−0.380	0.714	1.000				
VIX	0.365	0.529	−0.500	0.642	0.809	1.000			
AMIHUD	0.327	0.510	−0.271	0.228	0.287	0.374	1.000		
PS	0.230	0.325	−0.352	0.372	0.477	0.539	0.191	1.000	
LEV_SD	0.156	0.244	0.181	0.102	0.336	0.242	0.141	0.153	1.000
Mean	0.020	−0.081	0.017	0.023	−5.292	0.012	0.000	−0.033	0.000
SD	0.351	0.221	0.086	0.019	0.809	0.010	0.531	0.068	0.002
Autocorrelation	0.844	0.571	0.038	0.798	0.616	0.557	0.676	0.299	0.648

options-implied market variance. *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 et al. (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 et al. (2014) liquidity measure to get an illiquidity measure, *LEV_SD*. *LRES_SD* is available over 1986Q1 to 2009Q4, *VIX* is available over 1983Q4 to 2009Q4, and the other variables are available over 1983Q1 to 2009Q4. *LRES_LD* correlates closely with *LRES_SD*, 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 I 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*, whereas the coefficients on *IV* and *VIX* are positive and significant. 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.[11] In the next section, we show that this new stylized fact is important to uncover the positive aggregate illiquidity-return relation.

II. 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 (2002, p. 26) 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 Jones's (2002) table IV. By contrast, Fujimoto (2003, p. 3) 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 1966 to 2002. 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 her results 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 II, 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 (2003), we use only ex ante information in forecasting regressions. Panel A reports estimation results for the linearly detrended spread measure, *LRES_LD*, over 1983Q2 to 2009Q4. Row 1 confirms Jones's (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 1900s than in the period since then (Jones, 2002, p. 25). 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 (Jang et al., 2007; Lynch and Tan, 2011). 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, 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 $\widehat{B2} = B2 + \frac{\mathrm{Cov}(LRES\_LD, IV)}{\mathrm{Var}(LRES\_LD)} B1$.

[11] Chordia et al. (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 article. Moreover, we find that aggregate idiosyncratic variance correlates positively with aggregate bid-ask spreads even when controlling for market variance.

Table II. Aggregate Bid-Ask Spreads and One-Quarter-Ahead Excess Market Returns

This table reports the ordinary least squares 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 from 1986Q1 to 2009Q4 for *LRES_SD*, 1982Q4 to 2008Q4 for *IV_QR*, 1996Q1 to 2009Q4 for *IV_O*, and 1983Q1 to 2009Q4 for all other variables. We calculate Newey West's (1987) *t*-values using four lags and report them in parentheses. In rows 8 and 14, we use *IV* as an instrumental variable for *V_HML*.

	LRES_LD	***LRES_SD***	***IV***	***IV_QR***	***IV_O***	***LMV***	***V_HML***	**Adj. R^2**
	Panel A. Linearly detrended log relative effective spreads							
1	0.022							−0.002
	(0.842)							
2	0.058**		−1.502***					0.084
	(2.290)		(−3.529)					
3			−1.059***					0.048
			(−3.269)					
4	0.086***			−1.929***				0.141
	(3.536)			(−4.638)				
5	0.074**				−3.965***			0.072
	(2.448)				(−3.025)			
6			−1.928***			0.029***		0.076
			(−4.644)			(2.694)		
7	0.055**		−2.302***			0.027**		0.108
	(2.289)		(−5.775)			(2.509)		
8	0.059**					0.008	−12.189***	0.038
	(2.531)					(1.079)	(−3.443)	
	Panel B. Stochastically detrended log relative effective spreads							
9		0.034						−0.003
		(0.887)						
10		0.096***	−1.492***					0.085
		(3.139)	(−4.127)					
11		0.086**		−1.490***				0.086
		(2.571)		(−3.634)				
12		0.106***			−4.384***			0.087
		(2.942)			(−3.614)			
13		0.075**	−2.085***			0.023**		0.098
		(2.217)	(−4.432)			(1.966)		
14		0.083**				0.007	−11.327***	0.037
		(2.470)				(0.752)	(−3.781)	

***Significant at the 0.01 level.
**Significant at the 0.05 level.

Because *LRES_LD* correlates positively with *IV* (Table I), the bias due to the omitted-variable problem $\frac{\mathrm{Cov}(LRES\_LD, IV)}{\mathrm{Var}(LRES\_LD)} B1$ is negative and thus biases the estimated coefficient on *LRES_LD* downward toward 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 toward 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^2s are higher in multivariate regressions than in univariate regressions in the former situation, whereas 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 II. 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 to −0.2% and 4.8% for univariate regressions on *LRES_LD* and *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 is realized idiosyncratic variance computed from closing mid-quote returns, *IV_QR*, that Lesmond and Zhao (2015) and Han and Lesmond (2011) propose to alleviate liquidity biases.[12] Our results remain unchanged. Row 4 of Table II shows that the coefficient of *LRES_LD* is positive and statistically significant at the 1% level when we control for *IV_QR*. The coefficient of *IV_QR* is negative and significant 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 negative and significant effects on conditional equity premium at the 1% level. By contrast, untabulated results show that *LRES_LD* again has negligible predictive power in the univariate regression over 1996Q2 to 2009Q4.

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.[13] Row 6 of Table II 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*.[14] To address Jones's (2002) concern, we

[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.

[13] Financial economists have investigated intensively stock market variance-return relation—arguably the first fundamental law of finance. A partial list of previous empirical studies includes Merton (1980), Campbell (1987), French, Schwert, and Stambaugh (1987), Whitelaw (1994), Glosten, Jagannathan, and Runkle (1993), Scruggs (1998), Guo and Whitelaw (2006), Ghysels, Santa-Clara, and Valkanov (2005), Lundblad (2007), Ludvigson and Ng (2007), and Pastor, Sinha, and Swaminathan (2008).

[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

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, whereas the coefficient on *IV* remains negative and significant at the 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 article. 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.[15] Consistent with visual inspection of Figure 3, realized value premium variance, *V_HML*, correlates closely with *IV*, with a correlation coefficient of 90% over 1983Q1 to 2009Q4 (untabulated). To address our conjecture formally, in row 8 of Table II, we include *V_HML* instead of *IV* as an explanatory variable in the forecasting regression, and we use *IV* as an instrumental variable for *V_HML*.[16] Interestingly, we uncover a positive and significant 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 et al. (2007) and Lynch and Tan (2011). These authors emphasize that in contrast to 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 et al., 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 et al. (2003) point out, although market microstructure noise can have sizable effects when realized volatility is estimated using transaction data, its effects are likely to be small when daily data are used, 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

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.

[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) develop equilibrium models to investigate the link between the value premium and investment opportunities. Consistent with this conjuncture, recent empirical studies (e.g., Brennan, Wang, and Xia, 2004; Campbell and Vuolteenaho, 2004; Hahn and Lee, 2006; Petkova, 2006) document a close relation between the value premium and discount rate shocks. Other authors (e.g., Lakonishok, Shleifer, and Vishny, 1994; 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.

Table III. Asymmetric Effects of Aggregate Bid-Ask Spreads

This table reports the ordinary least squares estimation results of forecasting one-quarter-ahead excess stock market returns:

$$LRES\_LD_t^+ = \begin{Bmatrix} LRES\_LD_t & \text{if } CFNAI_t > 0 \\ 0 & \text{if } CFNAI_t \leq 0 \end{Bmatrix} \quad \text{and} \quad LRES\_LD_t^- = \begin{Bmatrix} 0 & \text{if } CFNAI_t > 0 \\ LRES\_LD_t & \text{if } CFNAI_t \leq 0 \end{Bmatrix},$$

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 from 1983Q1 to 2009Q4 for *LRES_LD*. We calculate NeweyWest's (1987) t-values using four lags and report them in parentheses.

	$LRES\_LD^+$	$LRES\_LD^-$	IV	LMV	Adjusted R^2
1	−0.003	0.040			−0.004
	(−0.082)	(1.232)			
2	0.030	0.074**	−1.476***		0.080
	(1.038)	(2.262)	(−3.544)		
3	0.031	0.068**	−2.240***	0.026**	0.102
	(1.179)	(2.020)	(−5.589)	(2.326)	

***Significant at the 0.01 level.
**Significant at the 0.05 level.

two measures of idiosyncratic variance that mitigate microstructure noise: idiosyncratic variance computed from mid-quote returns and options-implied variance. In Table II, 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 positive and significant at the 5% level (untabulated). Finally, *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 II, 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 positive and significant 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 article.

In Table III, 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:

$$R_{m,t+1} = \alpha + \beta^+ \cdot LRES\_LD_t^+ + \beta^- \cdot LRES\_LD_t^- + \varepsilon_{m,t+1}, \tag{1}$$

[17] We thank an anonymous referee for this suggestion.

where

$$LRES\_LD_t^+ = \begin{Bmatrix} LRES\_LD_t & \text{if } CFNAI_t > 0 \\ 0 & \text{if } CFNAI_t \leq 0 \end{Bmatrix} \text{ and}$$

$$LRES\_LD_t^- = \begin{Bmatrix} 0 & \text{if } CFNAI_t > 0 \\ LRES\_LD_t & \text{if } CFNAI_t \leq 0 \end{Bmatrix}.$$

Row 1 of Table III 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 conditional equity premium is positive and significant at the 5% level, whrereas the effect of $LRES\_LD^+$ is insignificant. These results are consistent with the conventional wisdom that illiquidity has larger effects on stock prices during business recessions than 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 when (1) we allow for asymmetric effects of *IV* and/or *LMV* on conditional equity premium and (2) 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 article 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 semiannual 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 consumption-wealth ratio (CAY), dividend yield (DY), earnings-price ratio (EP), default premium (DEF), term premium (TERM), and 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 negative and significant 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,

[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; Fleming, 1998). For example, Guo and Qiu (2014) find that the former always drives the latter in the forecast of excess market returns.

and both variables correlate with excess market returns (Table I). Therefore, the ordinary least squares estimator is potentially biased in small samples; see, for example, 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 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). Finally, consistent with earlier studies (e.g., Amihud, 2002; 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.

III. 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 et al. (2014). The Amihud (2002) 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 I).

In the Brunnermeier and Pederson (2009) model, market makers and brokers' book leverage is a measure of funding liquidity. Adrian et al. (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; Chung and Chuwonganant, 2014), show that *VIX* is a measure of both funding illiquidity and market illiquidity. Indeed, Table I shows that *VIX* correlates positively with both (1) the Adrian et al. (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 IV, we investigate whether these market illiquidity and funding illiquidity measures forecast excess market returns over 1983Q2 to 2009Q4, for which we have high-frequency spread data. We find that the predictive power of the Amihud (2002) measure, the Pastor and Stambaugh (2003) 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

Table IV. Alternative Illiquidity Measures

This table reports the ordinary least squares estimation results of forecasting one-quarter-ahead excess stock market returns. *AMIHUD* is the linearly detrended log aggregate Amihud's (2002) illiquidity measure. *PS* is Pastor and Stambaugh's (2003) aggregate illiquidity measure. *VIX* is the options-implied market variance. *LEV_SD* is Adrian et al.'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 from 1983Q1 to 2009Q4 for *LRES_LD*. We calculate Newey West's (1987) *t*-values using four lags and report them in parentheses.

	AMIHUD	*PS*	*VIX*	*LEV_SD*	*IV*	*LMV*	*LRES_LD*	Adj. R^2
1	0.016							0.001
	(1.335)							
2	0.026*				−1.225***			0.064
	(1.838)				(−3.664)			
3	0.013				−2.282***	0.025**	0.049*	0.105
	(0.889)				(−5.298)	(2.577)	(1.798)	
5		0.113						−0.002
		(0.706)						
6		0.237*			−1.302***			0.067
		(1.895)			(−4.364)			
7		0.145			−2.279***	0.022*	0.053**	0.109
		(1.095)			(−5.528)	(1.675)	(2.107)	
9			0.428					−0.007
			(0.353)					
10			2.975***		−2.057***			0.114
			(2.730)		(−4.852)			
11			2.442		−2.436***	0.005	0.050*	0.131
			(1.392)		(−4.556)	(0.277)	(1.750)	
13				8.445**				0.033
				(2.085)				
14				9.720**	−1.181***			0.095
				(2.307)	(−4.193)			
15				6.712	−2.072***	0.019**	0.049**	0.122
				(1.394)	(−5.134)	(2.133)	(2.146)	

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

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 IV replicates Adrian et al. (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.

Table V. Aggregate Bid-Ask Spread and the Cross-Section of Stock Returns

We estimate a variant of Merton's (1973) or Campbell's (1993) intertemporal capital asset pricing model using excess market returns, $R_{m,t+1}$, and shocks to the aggregate relative effective bid-ask spread, $LRES\_LD^{shock}_{t+1}$, as the risk factors:

$$R_{i,t+1} = \alpha_i + A \cdot \text{cov}_t(R_{i,t+1}, R_{m,t+1}) + B \cdot \text{cov}_t(R_{i,t+1}, LRES\_LD^{shock}_{t+1}) + \varepsilon_{i,t+1},$$

where $R_{i,t+1}$ is the excess portfolio return, α_i is the intercept, and $\varepsilon_{i,t+1}$ 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 $LRES\_LD^{shock}_{t+1}$. We use a panel of 41 assets, including 10 size portfolios, 10 book-to-market 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, $\varepsilon_{i,t+1}$. This table reports the estimates of the market risk price (A) and the illiquidity risk price (B). The *t*-statistics are in parentheses. We use quarterly data from 1983Q2 to 2009Q4 in row 1 and monthly data from 1983M2 to 2009M12 in row 2.

	Data Frequency	A	B
1	Quarterly	1.419***	−0.849**
		(7.141)	(−2.414)
2	Monthly	0.192	−0.259***
		(0.878)	(−3.534)

***Significant at the 0.01 level.
**Significant at the 0.05 level.

To summarize, we find a positive aggregate illiquidity-return relation using standard low-frequency illiquidity measures. Although 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.

IV. 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) show that indirect measures of trading costs—(1) temporal price reversal induced by order flow and (2) the price impact, respectively—are 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's (1973) or Campbell's (1993) ICAPM using excess market returns, $R_{m,t+1}$, and shocks to the aggregate relative effective bid-ask spread, $LRES\_LD^{shock}_{t+1}$, as the risk factors:

$$R_{i,t+1} = \alpha_i + A \cdot \text{cov}_t(R_{i,t+1}, R_{m,t+1}) + B \cdot \text{cov}_t(R_{i,t+1}, LRES\_LD^{shock}_{t+1}) + \varepsilon_{i,t+1}, \tag{2}$$

[20] We thank the anonymous referee for suggesting this to us.

where $R_{i,t+1}$ is the excess portfolio return, α_i is the intercept, and $\varepsilon_{i,t+1}$ is the residual term. As in Bali (2008) and Bali and Zhou (2016), we regress $LRES\_LD_{t+1}$ on its one-period lag and a constant, and use the residual as a proxy for $LRES\_LD_{t+1}^{shock}$. We use a panel of 41 assets, including 10 size portfolios, 10 book-to-market 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 seemingly unrelated regression model that takes into account serial correlation, cross-correlation, and heteroskedasticity in the residual term, $\varepsilon_{i,t+1}$. Table V reports the estimates of the market risk price (coefficient A in Equation (2)) and the illiquidity risk price (coefficient B). For the quarterly data spanning 1983Q2 to 2009Q4, 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 1983M2 to 2009M12. The price of illiquidity risk is negative and significant 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.

V. 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 toward 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. Finally, 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 value premium variance—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 et al. (2007) and Lynch and Tan (2011). 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 frequently. Our new empirical findings lend support for O'Hara's (2003) conjecture of an important interaction between microstructure and aggregate financial markets. In future studies, it will be interesting to explain these findings using general equilibrium models.

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