Internet Appendix to: "Micro(structure) before Macro? The Predictive Power of Aggregate Illiquidity for Stock Returns and Economic Activity"

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This document provides additional discussion, results and robustness checks associated with the paper "Micro(structure) before Macro? The Predictive Power of Aggregate Illiquidity for Stock Returns and Economic Activity."

Section 1 provides details regarding data sources and the construction of various illiquidity and other variables considered in the paper. Section 2 provides an approximate analytical decomposition result for the Amihud illiquidity measure similar to decomposition results for the FHT and Roll measures that appear in Section 3.2 of the main paper. Section 3 provides technical details related to estimation, filtering, break-adjustment and bootstrap procedures applied in the paper. Section 4 discusses additional empirical results and robustness tests.

1 Data Sources and Construction of Measures

1.1 Aggregate liquidity and price delay measures

Low-frequency market liquidity and price delay measures are constructed using daily data from the University of Chicago's Center for Research in Security Prices (CRSP) over the period 1926-2015. We restrict the sample to common shares (CRSP share code of 10, 11, or 12) of NYSE-listed stocks. We construct the various measures for each stock i over each time interval t (monthly or quarterly intervals) and then compute the equally-weighted mean across securities for each time interval.[1]

Roll measure (*ROLL*) The Roll (1984) liquidity measure is an estimate of the relative ef-

[1] In addition to the proxies listed below, we also compute a bid-ask spread measure as the difference between the closing ask and bid quotes reported by CRSP, scaled by the average of the ask and bid quotes. Chung and Zhang (2014) find that this CRSP-based spread is highly correlated across stocks with the spread based on high-frequency (TAQ) data. However, the CRSP-based spread is not continuously available, due to the fact that CRSP ask and bid quotes for NYSE stocks are unavailable for certain portions of our sample period. Consequently, our empirical analysis focuses on other spread proxies.

fective bid-ask spread based on the serial covariance of successive price movements. We compute the measure using Eq. (5) from the main paper. The $ROLL$ proxy is undefined whenever the first-order serial covariance of returns is positive. Researchers have adopted one of three conventions to address this issue: (1) set the Roll proxy to zero, (2) treat the observation as missing, or (3) reverse the sign of the sample autocovariance, and multiply the resulting spread proxy by negative one, which yields a negative spread estimate. The latter approach suggests a negative trading cost, which seems undesirable. On the other hand, the first two approaches impart an upward bias to the cross-sectional average of the spread. Results in the main paper set the Roll proxy to zero when the first-order sample covariance is positive. Our main conclusions regarding Granger causality continue to obtain under the alternative approaches.

Corwin and Schultz measure (CS) The Corwin and Schultz (2012) liquidity measure uses high and low daily price quotes to estimate bid-ask spreads. Daily high prices are almost always buyer-initiated orders while daily low prices are almost always seller-initiated orders, which suggests that the ratio of high to low prices reflects both the stock's variance and its spread. The variance component grows proportionately with the time interval but the spread component does not, allowing one to derive a spread estimator of high-low ratios over one and two day windows. See Corwin and Schultz (2012) for details regarding the derivation of the proxy. We construct the variable following Eqs. (14) and (18) from Corwin and Schultz (2012). We closely follow Corwin and Schultz's implementation procedures, including the suggestion to adjust the measure to 0 if the spread estimate is negative.

Fong, Holden, and Trzcinka measure (FHT) We compute the Fong, Holden, and Trzcinka (2016) liquidity measure at the firm level based on Eq. (4) from the main paper. The FHT measure represents a simplification of the Lesmond, Ogden, and Trzcinka (1999) (LOT) measure. Fong et al. (2016) find that the FHT measure outperforms both the LOT measure and a variation of the LOT measure, the LOT Y-split measure, proposed in Goyenko, Holden, and Trzcinka (2009).

Effective tick measure ($TICK$) Holden (2009) and Goyenko et al. (2009) propose the effective tick measure, a relative effective spread measure based on observable price clustering. $TICK$ is constructed under the assumption that price clustering is completely determined by spread size. This implies that the simple frequency in which closing prices occur in particular price clusters can be used to estimate spread probabilities. Using these estimated probabilities, firm i's effective tick measure is a weighted average of its estimated spreads over period t. See Holden (2009) and Craig Holden's website[2] for further details on variable construction.

We construct $TICK$ using daily prices from positive-volume days only. An alternative measure, $TICK2$, is computed in the same manner as $TICK$ except that $TICK2$ uses daily prices from all trade days. We rely on $TICK$ in our empirical analysis, but our main conclusions continue to hold if we alternatively use $TICK2$. We construct the effective tick measure using a 1/8 fractional price grid from 1926 up until 1997 when the NYSE implemented a 1/16 tick size. We use a 1/16 fractional price grid from 1997-2000. In 2001, the NYSE implemented decimal pricing and we use a decimal price grid from 2001 until the end of our sample period.

[2] http://www.kelley.iu.edu/cholden/examples.pdf

Zeros measure ($ZEROS$) This liquidity measure, proposed by Lesmond et al. (1999), is the proportion of zero-return trading days in time interval t. The $ZEROS$ measures serve as liquidity proxies because zero-return days often occur when transaction costs keep marginal investors from trading. The frequency of zero returns are increasing in transaction costs. As a robustness check, we also constructed a variation of the zeros measure, proposed by Goyenko et al. (2009), computed as the number of positive volume days with zero return divided by the number of trade days. Key results are robust to the particular version of the measure used.

Amihud illiquidity measure (AMI) Amihud (2002) proposes a price impact measure that captures the sensitivity of stock price movements to trading volume level. AMI is computed using daily data and aggregated over time interval t and is constructed as follows

$$AMI_{i,t} = \frac{1}{D_{i,t}} \times \sum_{d=1}^{D_{i,t}} \frac{|R_{i,d,t}|}{DVOL_{i,d,t}}, \tag{A.1}$$

where $D_{i,t}$ is the number of trading days for stock i during interval t, $|R_{i,d,t}|$ is the absolute value of return for stock i on day d during time interval t, and $DVOL_{i,d,t}$ is the respective dollar trading volume. Brennan, Huh, and Subrahmanyam (2013) construct a version of the Amihud measure based on the ratio of absolute daily returns to daily turnover, calculated as daily share volume divided by total shares outstanding ($AMITO$).

To correct for inflation effects on dollar trading volume, we compute AMI in real terms. Specifically, each month, we multiply dollar volume by a CPI adjustment factor where the base CPI period is January of 1926, and US CPI data is collected from the US Bureau of Labor and Statistics. We require that daily dollar trading volume exceeds \$1000 in the computation of the firm-level AMI measure and that daily volume exceeds 100 shares in the construction of the $AMITO$ measure. Finally, we multiply AMI by a scaling factor of 10^6.

Pastor and Stambaugh measure (PS) Pástor and Stambaugh (2003) propose a price impact measure based on the following regression:

$$RET^e_{i,d+1,t} = \theta_{i,t} + \phi_{i,t} RET_{i,d,t} + \gamma_{i,t} sign(RET^e_{i,d,t}) DVOL_{i,d,t} + \epsilon_{i,d+1,t}, \tag{A.2}$$

where $RET_{i,d,t}$ is the return for stock i on day d in time interval t, $RET^e_{i,d,t}$ is the return in excess of the CRSP value-weighted market index, and $DVOL_{i,d,t}$ is dollar volume. The $\gamma_{i,t}$ estimate is the liquidity proxy. The intuition is as follows: volume signed by the stock return in excess of the market return is a proxy for order flow and should be followed by a return reversal in the future if the stock is less than perfectly liquid. The greater the reversal, the lower the liquidity, and thus the more negative the $\gamma_{i,t}$ estimate.

Following Pástor and Stambaugh (2003), we adjust for stock market growth by multiplying the γ_t estimate by m_t/m_0 where m_t is the CRSP market index value at time t and m_0 is the market index value at August, 1962 (the date used by Pastor and Stambaugh). We exclude observations if less than 15 days of price data in a month are available, if the stock price is below \$5 or above \$1000, or if dollar volume is less than or equal to \$1000. Importantly, we multiply the above-described estimate of $\gamma_{i,t}$ by -1, which converts the measure from one of liquidity to one of *illiquidity*.

Hou and Moskowitz measure (HM) Hou and Moskowitz (2005) propose an annual price delay measure that captures the speed of adjustment of prices to market news. We create an analogous measure at quarterly and monthly intervals. Specifically, we regress individual stock returns on contemporaneous and 5 days of lagged market returns over each (quarterly or monthly) time interval:

$$RET_{i,d,t} = \alpha_{i,t} + \beta_{i,t} RET_{m,d,t} + \sum_{n=1}^{5} \delta_{i,t}^{(-n)} RET_{m,d-n,t} + \epsilon_{i,d,t}, \tag{A.3}$$

where $RET_{i,d,t}$ is the return for stock i on day d during time interval t, $RET_{m,d,t}$ is the corresponding return on the NYSE value-weighted index, and n represents the number of lags. The regression A.3 represents a modification of Hou and Moskowitz's approach as we compute quarterly or monthly price delay measures using daily, rather than weekly, returns. Additionally, we include 5 rather than 4 lags, though our main conclusions continue to hold if we only include 4 lags. This modified framework closely follows the approach taken in Boehmer and Wu (2013).

The regression estimates are then used to construct the price delay measure. Price delay is the fraction of variation of individual stock returns explained by lagged market returns:

$$HM = 1 - \frac{R^2_{\text{(restricted model)}}}{R^2_{\text{(unrestricted model)}}}, \tag{A.4}$$

where $R^2_{\text{(unrestricted model)}}$ is the R^2 from regression A.3 and $R^2_{\text{(restricted model)}}$ is the R^2 from regression A.3 restricting all of the lagged $\delta_{i,t}$ coefficients to equal 0. If stock i promptly responds to market news then $\beta_{i,t}$ should be different from zero but the lagged $\delta_{i,t}$ coefficients should all be insignificant. However, if stock i responds to news with a delay then some or all of the lagged $\delta_{i,t}$ coefficients will be different from zero.

Effective spread (high-frequency) A common measure of the cost dimension of market liquidity using high-frequency (intradaily) trading data is the relative effective spread, defined as

$$ESPD = 2\,\frac{|P_k - M_k|}{M_k}, \tag{A.5}$$

where P_k represents the price of the k-th trade, and M_k represents the midpoint of the best bid and offer (BBO) prevailing at the time of the k-th trade. At the firm or asset level, this measure is aggregated over some unit of time (trading day, month, quarter) by computing the dollar-volume-weighted average of the percent effective spread for the time interval. The effective spread represents an estimate of the round trip cost of trading over the corresponding interval. We obtained this measure for all NYSE firms over the period 1993–2007 as a benchmark for evaluating the performance of the various low-frequency spread proxies.[3]

1.2 Financial and macroeconomic variables

Our empirical analysis incorporates a number of financial variables. Each variable is constructed at monthly and quarterly frequencies from 1926-2015.

Term spread $TERM$ is the difference between long-term US government bond yields and the 3-month T-bill yield. Data are sourced from Goyal and Welch (2008), available at Amit Goyal's website.[4]

[3] We thank Ekkehart Boehmer and Julie Wu for providing these data.

[4] http://www.hec.unil.ch/agoyal/

Credit spread $CRED$ is the yield on BAA-rated corporate bonds less the yield on long-term US bonds. Data are sourced from Goyal and Welch (2008).

Default spread DEF is defined as the yield on BAA-rated corporate bonds minus the yield on AAA-rated corporate bonds. Data are sourced from Goyal and Welch (2008).

Net equity issuance $NTIS$ is the 12-month moving sum of net issuance by NYSE listed stocks divided by the total end-of-year market capitalization of NYSE stocks. This variable is sourced from Goyal and Welch (2008).

Book-to-market $BMKT$ is defined as the ratio of book value to market value for the Dow Jones Industrial Average. This variable is sourced from Goyal and Welch (2008).

Earnings yield ep is the difference of the log of earnings and the log of prices for the S&P 500 index. This variable is sourced from Goyal and Welch (2008).

Dividend yield dp denotes the difference of the log of dividends and the log of prices for the S&P 500 index. This variable is sourced from Goyal and Welch (2008).

Commercial paper spread $CPSP$ is the 3-month commercial paper yield less the 3-month T-bill yield. Both series are obtained from the Federal Reserve Statistical Release H.15 beginning in 1971. Prior to 1971, the commercial paper rate is based on the New York commercial paper rate from the NBER macro-history database.

Excess market return Log market return (ret) is the log of one plus NYSE value-weighted return with distributions minus the log of one plus the 3-month T-bill rate. Stock return data are sourced from CRSP and the T-bill rates are sourced from Goyal and Welch (2008).

Volatility Aggregate volatility (vol) is the cross-sectional average of the natural logarithm of the sample standard deviation of returns, where firm-level standard deviations are computed using daily returns over the corresponding month or quarter. This measure is constructed using U.S. common stocks listed on the NYSE.

We also collect macroeconomic variables at both monthly and quarterly frequencies.

Output We collect two output measures. The first, real gross domestic product (GDP), is available at a quarterly frequency from 1947-2015. The second output measure, industrial production growth (IP), is available at a monthly frequency from 1926-2015. Both measures are seasonally-adjusted.

Unemployment We collect the seasonally-adjusted overall unemployment rate (UE) at both quarterly and monthly frequencies from 1948-2015.

Investment Our investment measure (INV) is real, seasonally-adjusted gross private domestic investment, available at a quarterly frequency from 1947-2015.

Consumption The consumption measure ($CONS$) is real, seasonally-adjusted personal consumption expenditures, available at a quarterly frequency from 1947-2015.

We collect all macroeconomic variables, except for the unemployment rate, from the St. Louis Federal Reserve (FRED2) website. The unemployment rate is collected at the U.S. Bureau of Labor and Statistics.

2 Extracting a Volatility Component from the Amihud Illiquidity Measures

Under certain assumptions, it is possible to analytically derive a log-linear volatility component from Amihud-type measures. Amihud-type measures take the form:

$$AMI_{i,t} = \frac{1}{D_{i,t}} \times \sum_{t=1}^{D_{i,t}} \frac{|R_{i,d,t}|}{X_{i,d,t}}, \tag{A.6}$$

where $D_{i,t}$ is the number of trading days for the i-th stock in time interval t, $R_{i,d,t}$ is the day d return on the i-th stock, and $X_{i,d,t}$ represents a generic, strictly positive normalization factor, e.g., dollar volume or share turnover. $AMI_{i,t}$ in Eq. (A.6) is the sample analog of the population quantity $E\left[|R_{i,d,t}|\, X_{i,d,t}^{-1}\right]$. Under the assumption that daily returns are mean-zero Gaussian random variables, $|R_{i,d,t}|$ follows a folded-normal distribution with expectation $E\left[|R_{i,d,t}|\right] = \sigma_{i,t}\sqrt{\frac{2}{\pi}}$, where $\sigma_{i,t}$ is the variance of $R_{i,d,t}$ (assumed to be constant over time interval t). Imposing an additional assumption that $\mathrm{Cov}\left(|R_{i,d,t}|,\, X_{i,d,t}^{-1}\right) = 0$ implies that

$$E\left[|R_{i,d,t}|\, X_{i,d,t}^{-1}\right] = \sigma_{i,t}\sqrt{\frac{2}{\pi}} E\left[X_{i,d,t}^{-1}\right]. \tag{A.7}$$

Replacing population quantities in Eq. (A.7) with sample analogs, taking logs, and averaging across firms gives:

$$ami_t^{*} = (1/2)\ln(2/\pi) + vol_t + \overline{\ln\left(\overline{X_{i,d,t}^{-1}}\right)}, \tag{A.8}$$

where $\overline{X_{i,d,t}^{-1}} = (1/N_{d,t}) \sum X_{i,d,t}^{-1}$. The notation ami_t^{*} emphasizes that the expression on the right-hand side of Eq. (A.8) is not precisely equal to $ami_t = \ln(AMI_t)$, where AMI_t is the cross-sectional average of the Amihud measure of Eq. (A.6). The link between the two involves the population relationship of Eq. (A.7) under the specified assumptions.

The decomposition in Eq. (A.8) implies that volatility-adjusted Amihud measures are cross-sectional averages of a nonlinear transformation of the normalizing variable X, e.g., of dollar volume. Of course, the assumptions used to derive Eq. (A.8) are unlikely to strictly hold. Daily stock returns are not Gaussian (nor exactly mean zero, presumably), and it is likely that $\mathrm{Cov}\left(|R_{i,d,t}|,\, X_{i,d,t}^{-1}\right) \neq 0$. In the latter case, Taylor series arguments can be used to continue to motivate Eq. (A.8) as an approximate decomposition.

3 Estimation, Filtering, Break-Adjustment and Bootstrap Procedures

This section of the Internet Appendix provides additional details regarding estimation, filtering and bootstrap procedures applied in the paper. To describe these procedures, first consider the following time series model that imposes the null of no predictability:

$$
\begin{aligned}
\phi_y(L)(y_t - \mu_y) &= \epsilon_{1,t} \\
\phi_x(L)(1-L)^d(x_t - \mu_{x,t}) &= \theta_x(L)\,\epsilon_{2,t},
\end{aligned}
\tag{A.9}
$$

where $\phi_y(z) = 1 - \phi_{y,1}\,z - \cdots - \phi_{y,p_y}\,z^{p_y}$, $\phi_x(z) = 1 - \phi_{x,1}z - \cdots - \phi_{p_x}z^{p_x}$, and $\theta_x(z) = 1 + \theta_{x,1}a + \cdots + \theta_{x,q}z^q$ are polynomials in the lag operator with roots strictly outside the unit circle. $(1-L)^d$ is the fractional difference operator defined by the binomial expansion:

$$
(1-L)^d \equiv \sum_{s=0}^{\infty} \frac{\Gamma(s-d)}{\Gamma(-d)\Gamma(s+1)}\,L^s, \tag{A.10}
$$

where $\Gamma(\cdot)$ indicates the gamma function. The shocks $\epsilon_t = (\epsilon_{1,t}, \epsilon_{2,t})' \sim$ i.i.d. $N(0, \Sigma)$, with Σ is a symmetric, positive definite 2×2 matrix with (potentially) nonzero off-diagonal elements. The contemporaneous correlation between shocks is $\rho = \Sigma_{12}/\sqrt{\Sigma_{11}\Sigma_{22}}$.

The first equation in the system of Eq. (A.9) specifies the dynamics of the forecasting target variable (stock returns or a measure of economic activity), which is assumed to follow a standard autoregressive model with p_y lags under the null of no predictability. The second equation of (A.9) specifies that the predictor variable x_t (generally a measure of illiquidity) follows an autoregressive fractionally integrated moving average process – or ARFIMA(p_x, d, q) process. This model permits both long memory dynamics, through the parameter d, as well as standard short memory dynamics of an ARMA form. The model also permits a time-varying mean for x_t according to the specification $\mu_{x,t} = \beta' \, z_t$, where z_t is a set of deterministic variables. This feature is incorporated to address structural instability in various illiquidity measures (see the main paper and further discussion below).[5]

3.1 Estimation details

The y_t equation of the system (A.9) is estimated via OLS, following standard empirical practice for AR models. The x_t equation of the system (A.9) is estimated using the so-called 'conditional sum of squares' (CSS) method (Beran (1995)). The CSS estimator is a parametric estimator in the time domain. For a given sample size T, the CSS parameter estimates maximize the conditional log likelihood function, given by

$$L_C(d, \phi_x, \theta_x, \beta) = -\frac{T}{2} \ln \left[\sum_{t=1}^{T} \left(\frac{\phi_x(L)}{\theta_x(L)} (1-L)^d (x_t - z_t' \beta) \right)^2 \right]. \tag{A.11}$$

[5] Our x_t specification could be termed an 'ARFIMAX' model given the inclusion of a time-varying mean driven by deterministic (and therefore exogenous) inputs z_t.

The 'CSS' terminology in the literature comes from the fact that maximizing L_C is equivalent to minimizing the usual (conditional) sum of squares:

$$CSS(d, \phi_x, \theta_x, \beta) = \frac{1}{T} \sum_{t=1}^{T} \left(\frac{\phi_x(L)}{\theta_x(L)} (1-L)^d (x_t - z_t' \beta) \right)^2 . \tag{A.12}$$

Estimation is performed via numerical optimization in Matlab using Matlab's nonlinear least squares optimization routine ('lsqnonlin'). The numerical optimization routine requires starting values for model parameters, which are obtained as follows. Starting values for β, denoted β_0, are based on OLS estimates of the regression of y_t on z_t. (In implementations without structural breaks, $z_t = 1$ and the series y_t is simply de-meaned.) To obtain a starting value for the parameter d, we apply the bias reduced log-periodogram regression (BRLPR) estimator proposed by Andrews and Guggenberger (2003) to the series $\tilde{y}_t \equiv y_t - \beta_0' z_t$.[6] Let $\breve{y}_t = (1-L)^{d_0}\, \tilde{y}_t$, i.e., the residuals after de-meaning and applying the fractional differencing operator using corresponding parameter starting values. Starting values for the AR parameter(s) ϕ_x are based on OLS estimates of the corresponding AR specification applied to the series $\breve{y}_t$. Finally, starting values for any MA parameters θ_x are simply set to zero.

The variance-covariance matrix associated with the CSS parameter estimates is computed as the inverse of minus the numerical second derivative of the criterion function Eq. (A.11). In particular, an estimate of the asymptotic variance is based on

$$\hat{V}_T = \hat{\sigma}_T^2 \left(\nabla_\varphi \nabla_\varphi' \right)^{-1}, \tag{A.13}$$

[6] The BRLPR estimator is a semiparametric estimator that implements a bias correction relative to the original log periodogram estimator proposed by Geweke and Porter-Hudak (1983). An advantage of using a semiparametric estimator to obtain starting values for the parameter d is that we do not need to specify the short memory dynamics for y_t. Following Nielsen and Frederiksen (2005), we set the polynomial order to $R = 1$ in our implementation of the BRLPR estimator. We set the bandwidth parameter m equal to $T^{0.6}$. See Andrews and Guggenberger (2003) and Nielsen and Frederiksen (2005) for details.

where $\hat{\sigma}_T^2 = \sum_{t=1}^T \hat{e}_t^2$.

A particular implementation of the model of Eq. (A.9) involves specifying the order of various short memory components (e.g., the choice of lag order p_y for y_t and the orders p_x and q for the AR and MA components of x_t), the nature of z_t (a constant or a specification allowing structural shifts), etc.

3.2 Shock correlation estimates in Table 1

Table 1 of the main paper reports estimates of the correlation between shocks to various illiquidity measures and stock returns or growth in industrial production. These correlation estimates are computed as the sample correlation for shocks based on an estimated version of the model of Eq. (A.9), with stock returns (or IP growth) as y_t and the corresponding illiquidity measure as x_t. Parameters are estimated following the procedures described in Section 3.1. Results reported in Table 1 of the main paper set $p_x = 1$, $q = 0$, and $z_t = 1$ for the illiquidity measure, i.e., an ARFIMA$(1, d, 0)$ specification without level shifts.[7] The y_t AR model specification includes zero lags for stock returns (so that shocks are simply innovations relative to the mean) and 4 lags for growth in industrial production.

3.3 Break-adjusted illiquidity series

We consider a variety of methods for adjusting illiquidity measures for structural breaks or shifts that appear to occur following tick-size reductions in 1997 and (especially) 2001. Let $z_t = (1, D_{t,t_1}, D_{t,t_2})'$, where $D_{t,t_1} \equiv 1_{t \geq t_1}$ and $D_{t,t_2} \equiv 1_{t \geq t_2}$ represent dummy variables indicating periods following two hypothesized breakpoints, denoted t_1 and t_2, with the convention that

[7] Note that the estimation sample is restricted to 1948–1997 to avoid potential subsequent level shifts from influencing correlation estimates.

$t_1 < t_2$.

Let x_t denote some illiquidity measure. A first, relatively simple approach to 'real time' break adjustment involves recursively estimating the following regression for time periods $j \in [t_1 + 1, t_2]$:

$$x_t = 1 + \delta D_{t,t_1} + e_t, \tag{A.14}$$

where the regression is based on data for periods $1, \ldots, j$. This regression yields recursive estimates $\hat{\delta}_j$ of the break magnitude parameter δ. We then compute the break-adjusted series value for each period as $\tilde{x}_j = x_j - \hat{\delta}_j$. Following the second hypothesized breakpoint, we estimate the regression model for $j \in [t_2 + 1, T]$:

$$x_t = 1 + \delta_1 D_{t,t_1} + \delta_2 D_{t,t_2} + e_t. \tag{A.15}$$

The associated break-adjusted values is then computed as $\tilde{x}_j = x_j - \hat{\delta}_{1,j} - \hat{\delta}_{2,j}$.

The break-adjustment procedure discussed above is 'real time' in the sense that break-adjusted quantities for each period are based only on data available at that point in time. As time passes, the estimated break magnitude and corresponding adjustment evolve.[8] The adjustment procedure implicitly assumes that the forecaster is aware in real time of the existence of each breakpoint. This assumption is plausible in our context, since the hypothesized break dates coincide with the onset of tick-size reductions, which were known well in advance of implementation. This procedure results in series that we denote as break-adjusted using the 'alternative real time (RT)' approach. Series denoted as break-adjusted using the real time

[8] Our break-adjusted series is in fact conservative with respect to the use of available information, in the sense that we do not update previously adjusted values as the estimated break magnitude evolves over time.

(RT) approach incorporate an additional testing feature as discussed immediately below.

3.3.1 Real time break-adjustment with a break test

It is reasonable to conjecture that there was ex ante uncertainty regarding whether and to what extent tick-size reductions would alter various illiquidity metrics. Consequently, we implement a variation on the previously described break-adjustment procedure that adjusts series following hypothesized break dates only when estimated break magnitudes are statistically significant. Just as with the previous real time break-adjustment approach, it is assumed that there exist particular, known dates when structural breaks *potentially* occur (associated with tick-size reduction times in our implementation). In this case, however, there is an implicit null hypothesis that the true break size is zero ($\delta_i = 0$ for $i = 1, 2$ in our notation). Adjustment therefore occurs only if there is sufficient statistical evidence that $\delta_i \neq 0$.

To explain the approach more precisely, let the notation $p\text{-val}(\hat{\delta}_j)$ indicate the p-value associated with the standard regression-based test of the null hypothesis that $\delta = 0$ in the model of Eq. (A.14) computed at time $j \in [t_1 + 1, t_2]$. Due to the likely presence of serial correlation in the error term e_t of Eq. (A.14), $p\text{-val}(\hat{\delta}_j)$ is computed using Newey-West standard errors with 18 lags. The break adjustment in each period is then

$$\tilde{x}_j = x_j - \hat{\delta}_j \, 1(p\text{-val}(\hat{\delta}_j) < \alpha), \;\; j \in [t_1 + 1, t_2], \tag{A.16}$$

where $1(\cdot)$ denotes the indicator function and α is a specified significance level. Break adjustment proceeds analogously following the second hypothesized break date. In particular, (potential) series adjustment is based on the regression model of Eq. (A.15) and the associated

p-values:

$$\tilde{x}_j = x_j - \hat{\delta}_{1,j}\,1(p\text{-val}(\hat{\delta}_{1,j}) < \alpha) - \hat{\delta}_{2,j}\,1(p\text{-val}(\hat{\delta}_{2,j}) < \alpha),\ \ j \in [t_2+1, T]. \tag{A.17}$$

Several remarks concerning this break-adjustment procedure are in order. First, similar to the previous real time adjustment procedure without break testing, we do not refine or update earlier break adjustments as additional information becomes available. Again, this is likely suboptimal from a forecasting perspective, but should bias *against* finding evidence of predictability. Second, we do not impose any sort of 'time-smoothness' in terms of the break adjustments. It is possible, for example, that a significant break test leads to an adjustment in one period, but that additional data cause the associated p-value to rise above the threshold so that no adjustment is made for subsequent periods, only for yet more data to again lead to a rejection of the null and corresponding adjustments, etc. (In the data, this sort of behavior is rare and adjustments tend to be fairly smooth.) Finally, following the second hypothesized break date (t_2), it is possible to have no adjustment, an adjustment for one significant break ($\delta_1 \neq 0$ or $\delta_2 \neq 0$), or adjustments for two significant breaks.

3.3.2 Ex post or 'full sample' break adjustment

This section describes the full sample (FS) break-adjustment procedure referenced in the main paper. This procedure estimates the regression model of Eq. (A.15) over the full sample of data, producing (full sample) break magnitude estimates $\hat{\delta}_1$ and $\hat{\delta}_2$. The break-adjusted series is then computed as:

$$\tilde{x}_t = x_t - \hat{\delta}_1\,1(t > t_1) - \hat{\delta}_2\,1(t > t_1). \tag{A.18}$$

3.3.3 Stochastic detrending

As an alternative to the aforementioned adjustments for structural instability, we also consider a 'stochastic detrending' approach, in which the adjusted series is defined as the raw series less a moving average of past values with a specified window length. The stochastically detrended series is defined as

$$\tilde{x}_t \equiv x_t - (1/W) \sum_{w=1}^{W} x_{t-w+1}, \tag{A.19}$$

where W denotes the moving average window length. It is relatively common to stochastically detrend highly persistent forecasting variables in predictive regressions for stock returns. For example, many studies stochastically detrend the short-term Treasury bill rate, following Campbell (1991). As Campbell (1991) notes, the stochastically detrended series is equivalent to a backward-looking triangular moving average of changes in the underlying series. Consequently, if the series is difference (covariance) stationary, then the stochastically detrended series is also covariance stationary. Loosely speaking, stochastic detrending can be viewed as an intermediate approach between modeling a potentially nonstationary series in levels and differencing the series. The approach avoids the necessity of detecting or specifying particular times when structural shifts occur. A potential disadvantage is that the stochastically detrended series only gradually adapts to a sudden break in the series level. In addition, it is necessary to specify the length of the moving average window (W in Eq. (A.19)). Results in the main paper apply a window length of 2 years ($W = 24$ months).

3.4 Bootstrap procedure details

Section 4.1 of the main paper describes a bootstrap procedure applied to conduct inference for certain predictive regressions in the paper. The model described by Eq. (10) in the main paper represents a special case of the more general model Eq. (A.9).

The bootstrap procedure involves generating bootstrap samples of data under the null of no predictability. To do so, we first estimate the system of Eq. (A.9) following the procedures described in Section 3.1 of this Internet Appendix. Denote as $\hat{\epsilon}_t$ the associated estimated residuals. We then draw a bootstrap sample of shocks ϵ_t^* from the sample of estimated residuals $\hat{\epsilon}_t$. This process preserves the contemporaneous correlation between $\epsilon_{1,t}$ and $\epsilon_{2,t}$. Using the sample of shocks ϵ_t^* and parameter estimates under the null we create a bootstrap sample $(y_t^*, x_t^*)'$ of size T using Eq. (A.9). In generating bootstrap samples, we employ a burn-in sample of size 400. For each bootstrap sample under the null $(y_t^*, x_t^*)'$ we estimate the following predictive regression using OLS:

$$y_{t+1}^* = \alpha + \sum_{j=1}^{J} \rho_j y_{t+1-j}^* + \beta x_t^* + \nu_{t+1}. \tag{A.20}$$

The resulting estimate $\hat{\beta}^*$ for the bootstrap sample is then recorded. We then draw another bootstrap sample and again record the estimate $\hat{\beta}^*$, continuing this fashion for B bootstrap replications. One- and two-sided bootstrap-based p-values reported in the paper are computed by comparing the bootstrap estimates $\hat{\beta}_i^*$ for $i = 1, ..., B$ with the OLS estimate $\hat{\beta}$ in the data. Results in the main paper are based on $B = 2,500$ replications.

4 Additional Results and Robustness Checks

4.1 Time series properties of aggregate illiquidity measures

The section presents additional evidence on the time series properties of aggregate illiquidity.

Figure A1 presents time series plots of alternative spread measures from 1993-2015. The spread proxies diverge in recent years. The FHT and $TICK$ measures appear to shift downward in the late 1990s and again in the early 2000s. Interestingly, the $ROLL$ and CS proxies do not exhibit a clear downward break at this time. The aggregate effective spread computed using intraday TAQ data ($ESPD$) conforms closely to the FHT and $TICK$ proxies throughout this period. In contrast, $ROLL$ and CS are upward-biased measures of the aggregate effective spread from the late 1990s onward.

Figure A2 presents time series plots of alternative versions of the log zeros measure (top panel) and log Amihud (bottom panel) illiquidity measures. The $zeros$ illiquidity measure is not explicitly a measure of the spread, although the logic behind the measure suggests that it should co-move with the spread. The $zeros$ measure exhibits two particularly sharp downward structural breaks, one following June 1997 and the other following January 2001 - dates coinciding with minimum tick-size reductions for the NYSE. The alternative $zeros$ measures, which omits trading days with zero volume, closely follows the original $zeros$ measure.

Panel B of Figure A2 presents time series plots of the traditional Amihud measure (ami) along with plots for the turnover-based measure ($amito$). The traditional Amihud measure, adjusted for inflation, trends downward over time. In addition to the downward trend, the aggregate Amihud measure tends to increase around economic recessions and financial crises. For example, the aggregate price impact measure increases noticeably during the Great Depression and the recent financial crisis. The turnover-based measure *amito* does not exhibit an obvious downward trend until the turn of the century, coinciding with the decrease in the effective spread around this time (see Figure A1). The turnover-based measure also tends to rise during recessions and increases significantly around the recent financial crisis.

Figure A3 plots time series for the PS and hm illiquidity measures. The PS measure represents an alternative measure of price impact. The top panel of Figure A3 shows that this measure is less persistent than other illiquidity measures. It does not exhibit an obvious trend, although level shifts might be difficult to detect due to the high volatility of the series.[9] The bottom panel of Figure A3 shows the time series for hm measure. The measure shifts downward at the end of the 1990s, similar to many of the illiquidity measures. This evidence suggests that the early 2000s represents a period of reduced market frictions in a broader sense, i.e., not simply with respect to the liquidity component of frictions.

Figure A4 illustrates the effects of alternative volatility adjustment methods. Panel A plots time series for volatility adjusted $roll$ and Panel B plots time series for volatility adjusted fht. We consider three alternative volatility adjustment methods: 1) an analytical method that subtracts the quantity vol_t from the corresponding illiquidity measure; 2) the OLS projection approach that constructs volatility-adjusted measures as the residuals from an OLS regression of the measure on the series vol_t; and 3) a variation of the projection approach that estimates the slope coefficient using the narrow-band least squares (NBLS) method. For each illiquidity measure, the alternative volatility-adjusted series are highly correlated, and the choice of volatility adjustment method does not have a significant impact on key results.

[9] Smoothed and/or filtered versions of the raw PS measure reveal underlying cyclical structure.

4.2 Extensions and robustness tests

This section briefly discusses results from various robustness tests and extensions of analyses in the main paper.

Table A1 presents one-month-ahead predictive regressions for stock returns for additional sets of break- and/or volatility-adjusted aggregate illiquidity measures. Panels A and C present results for break-adjusted measures using an alternative real time ('RT') approach that does not test for a break, but rather assumes breaks occur at tick-size reduction dates and estimates the new break level recursively (see section 3.3 of this Internet Appendix). The measures in Panel A are break-adjusted and the measures in Panel C are break- and volatility-adjusted. These results are very similar to results in Table 4 of the main paper under the 'RT approach,' and indicates that testing for breaks in real time is not crucial for our main findings. Panel B provides results for the decomposition into volatility and residual components for break adjusted measures using the full-sample ('FS') approach. These results are generally similar to the results from the 'RT' approach (see Panel E of Table 4 in the main paper). This illustrates that there is strong evidence that volatility-adjusted aggregate illiquidity forecasts stock returns irrespective of whether adjustment for breaks is made on an ex post basis or in real time.

Table A2 presents one-month-ahead predictive regressions for excess stock returns on the CRSP value-weighted index (including distributions). This analysis employs an identical methodology to that in Table 4 of the main paper, except that stock returns in Table A2 are computed from an index consisting of NYSE, AMEX, and NASDAQ stocks as opposed to an index that only includes NYSE stocks. The results in Table A2 are very similar to those in Table 4 of the main paper.

Table A3 shows results for longer horizon predictive regressions for stock returns using alternative measures of break- and volatility-adjusted illiquidity. The predictive regressions include volatility (vol_t) as a control variable. We present results at 3-, 6-, and 12-month horizons. The results for longer-horizon regressions are similar to those at the one-month horizon. Because the regression involves overlapping observations, we base inference on Newey-West standard errors employing $H + 2$ lags. These inference results are likely imperfect due to the long memory characteristic of illiquidity measures. We prefer to rely on previously presented one-step ahead test results for Granger causality questions. Our interest in longer horizon regressions lies in characterizing the economic significance of predictive relations. The economic significance of the predictive power afforded by the illiquidity measures increases with the forecast horizon: R^2-values show marked improvements at longer horizons. These horizon effects are similar to long-run stock return forecasts for other persistent predictors in the literature, most notably financial ratios such as the the dividend yield and book-to-market ratio.

Table A4 presents one-month-ahead predictive regressions for stock returns using various measures of break-adjusted (but not volatility-adjusted) aggregate illiquidity along with volatility (vol_t) as a control variable. This table relates to footnote 18 in the main paper, which briefly discusses the alternative strategy of controlling for volatility in predictive regressions rather than adjusting illiquidity measures for volatility. We report results for three methods of break-adjustment: the full-sample (FS) approach, the real-time (RT) approach, and the alternative real-time method. Estimated slope coefficients, inference, and R^2 values for specifications in which volatility is separately included as a control variable (Table A4) are similar to those for specifications in which illiquidity is decomposed into a volatility and a residual component (See, e.g., Panel E of Table 4 in the main paper).

Table A5 presents results from monthly predictive regressions for stock returns and economic activity using the first principal component extracted from the full set of break- and volatility-adjusted illiquidity measures. We report results for three methods of break-adjustment applied to the underlying illiquidity measures: the full-sample (FS) approach, the real-time (RT) approach, and stochastic detrending (SD) procedure. Panel A presents results for models that exclude controls z_t. Panels B and C present results for models with the specified controls z_t included.

There is generally strong evidence that aggregate illiquidity forecasts stock returns. For the FS and RT approaches, the slope coefficients on the principal component extracted from the illiquidity measures are significant for each specification and the monthly ΔR^2 values range from 0.74 to 1.18. The stock return forecasting results using the SD break-adjustment approach are less pronounced but still provide evidence that aggregate illiquidity is positively related to future stock returns. The forecasts of economic activity (Δip and Δue) provide mixed evidence. For the FS and RT approaches, the principal component does not forecast economic activity in the univariate model. However, there is evidence that the principal component forecasts the macro variables once additional controls are added to the specification. The results are particularly strong under the FS approach where the full set of controls are added to the predictive regression: ΔR^2 values range from 1.05 to 1.57. Regardless of predictive regression model specification, there is significant evidence that the principal component forecasts economic activity under the SD break-adjustment approach.

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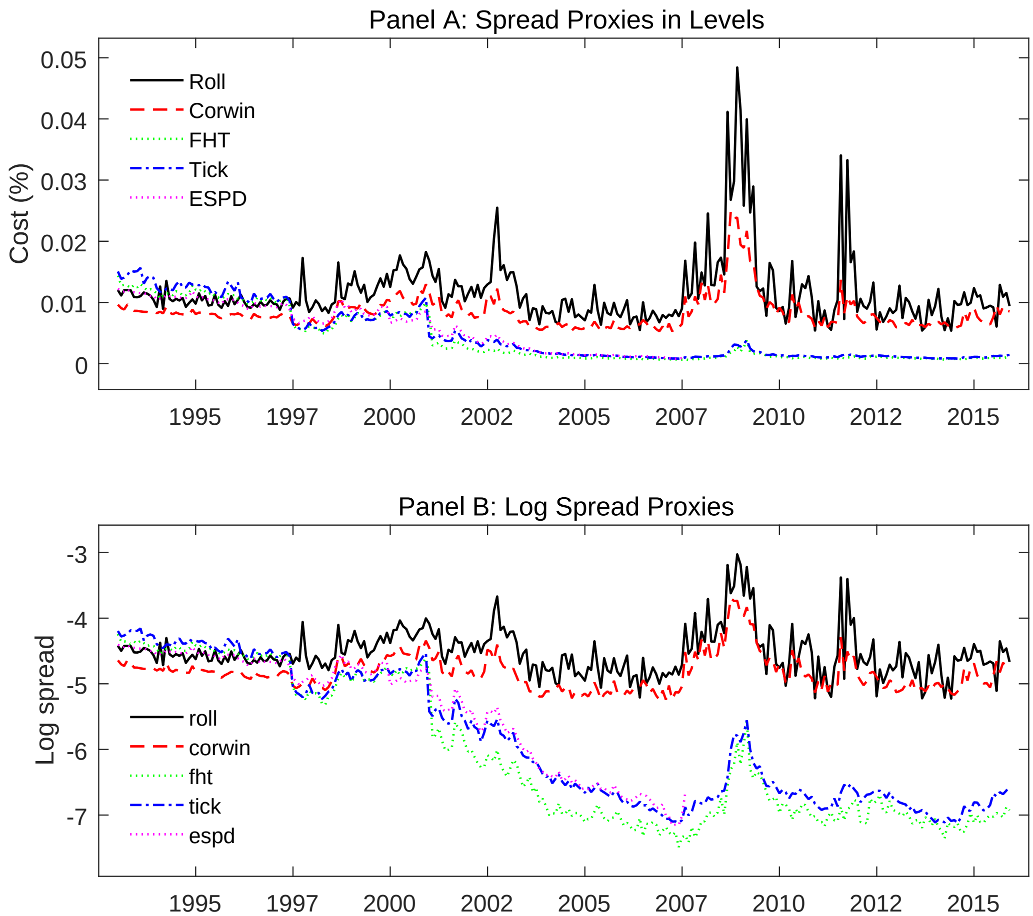

Figure A1: Alternative effective spread proxies: 1993-2015. This figure shows monthly time series for various proxies for the aggregate effective spread over the period 1993.1–2015.12. The top panel shows the spread proxies in levels, while the bottom panel plots log versions of the series. $ROLL$ is the proxy of Roll (1984). CS is the proxy proposed by Corwin and Schultz (2012). FHT is the proxy proposed by Fong et al. (2016). $TICK$ is the effective tick measure proposed by Holden (2009). $ESPD$ is the effective spread computed from high-frequency data. Log versions of series are denoted using lowercase letters (e.g., $roll$).

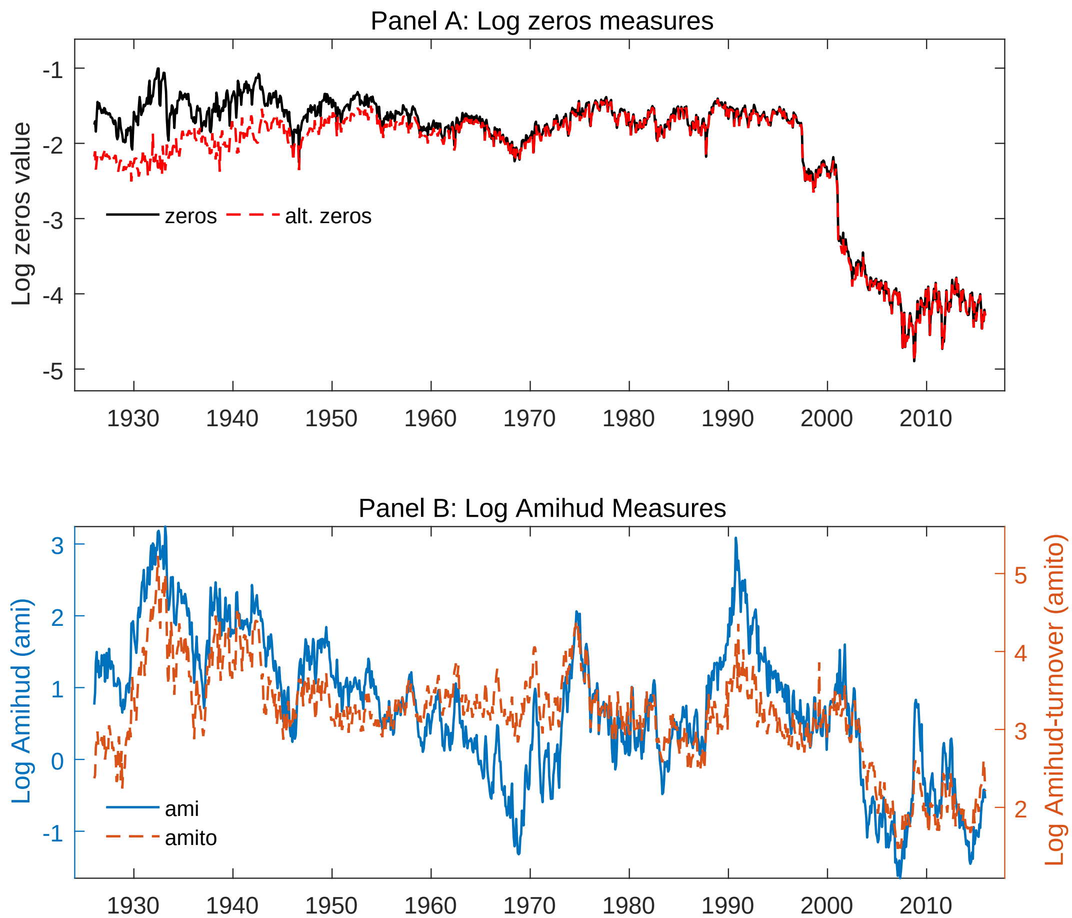

Figure A2: Zeros and Amihud illiquidity measures

This figure shows monthly time series plots for several illiquidity measures considered in the paper. The top panel shows a time series plot for the *zeros* illiquidity measure, as well as an alternative variation that omits trading days with zero volume. The bottom panel plots the natural logarithm of the traditional Amihud illiquidity measure (ami_t) and the Amihud turnover measure studied by Brennan et al. (2013) ($amito_t$). The sample period is 1926–2015.

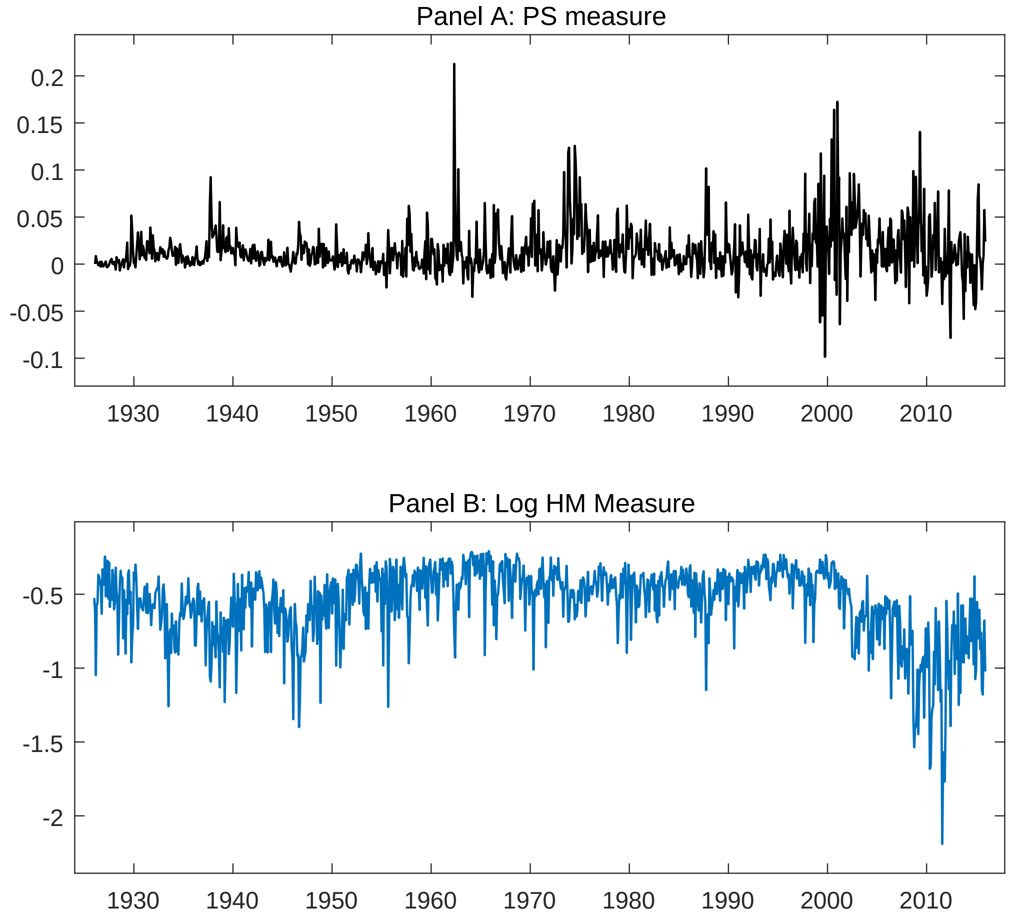

Figure A3: PS and Hou-Moskowitz illiquidity measures

This figure shows monthly time series plots for the PS illiquidity measure (top panel) and the natural logarithm of the Hou-Moskowitz illiquidity measure (hm, bottom panel). The sample period is 1926–2015.

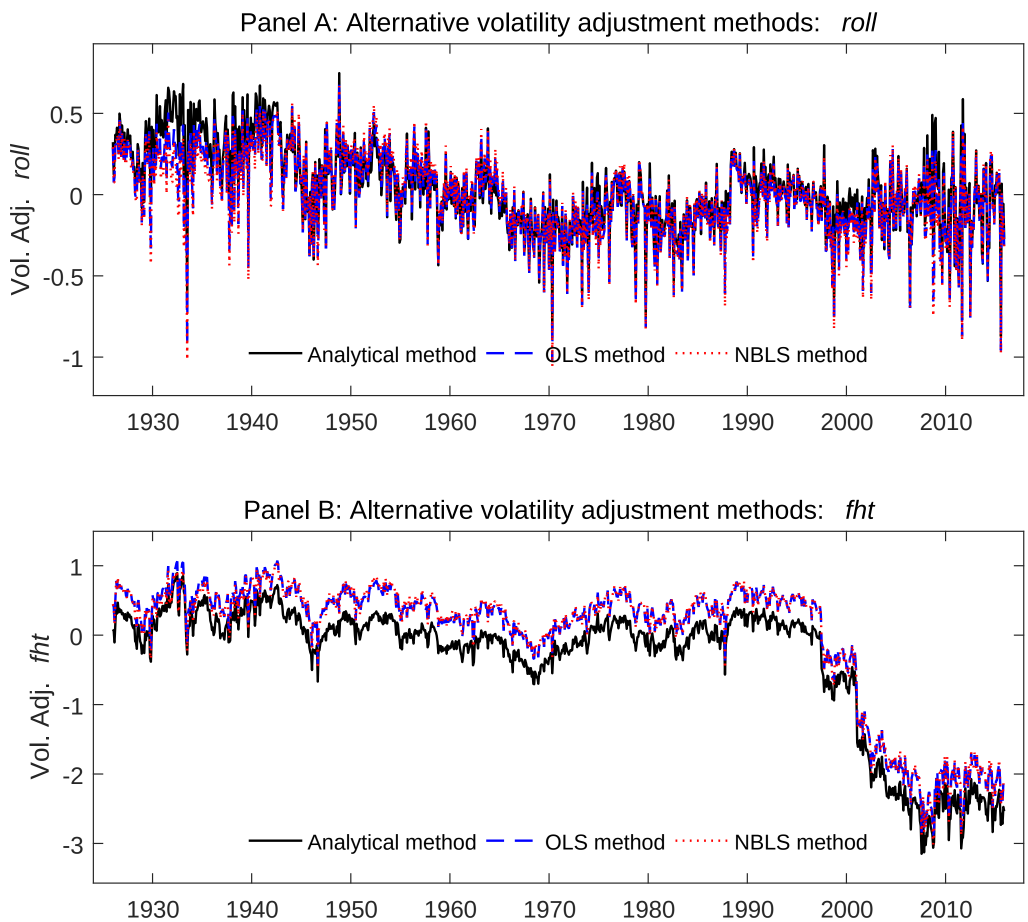

Figure A4: Alternative volatility adjustment methods

This figure shows monthly time series plots for volatility-adjusted illiquidity measures using three alternative approaches: 1) the 'analytical adjustment' that subtracts the quantity vol_t from the corresponding illiquidity measure; 2) the OLS projection approach that constructs volatility-adjusted measures as the residuals from an OLS regression of the measure on the series vol_t; and 3) a variation of the projection approach that estimates the slope coefficient using the narrow-band least squares (NBLS) method. Panel A shows results for the Roll measure ($roll$) and Panel B shows results for the FHT measure (fht). The sample period is 1926–2015.

Table A1: **Monthly forecasting regressions for stock returns: Alternative adjustment approaches**

The table presents results for one-month-ahead predictive regressions for excess stock returns on the NYSE index using various measures of aggregate illiquidity. The table reports results from regressions of the form

$$ret_{t+1} = \alpha + \beta x_t + \epsilon_{t+1},$$

where ret_{t+1} is the monthly NYSE excess return and x_t represents the forecasting variable. For each forecasting variable, the table presents OLS and bootstrap estimates. The OLS estimates include the slope coefficient $\hat{\beta}$, the associated Newey-West standard error, a one-sided p-value (p-val$_{1s}$), a two-sided p-value (p-val$_{2s}$), and an R^2 value. The bootstrap estimates include the slope coefficient $\hat{\beta}$ and the one-sided p-value (p-val$_{1s}$) and two-sided p-value (p-val$_{2s}$). Panel A presents results for break-adjusted measures using an alternative 'RT' approach that does not test for a break but rather assumes breaks occur at tick-size reduction dates and estimates the new break level recursively. Panel B provides results for the decomposition into volatility and residual components for break adjusted measures using the full-sample ('FS') approach. Panel C presents results for the decomposition into volatility and residual components for break-adjusted measuring using the alternative 'RT' approach described above. The sample period is 1948–2015. See Section 2 of the paper for variable definitions.

	OLS					Bootstrap		
	$\hat{\beta}$	SE	p-val$_{1s}$	p-val$_{2s}$	R^2	$\hat{\beta}^*$	p-val$_{1s}$	p-val$_{2s}$
Panel A: Break-adjusted illiquidity measures (Alt. RT approach)								
$roll$	-0.33	0.85	0.65	0.69	0.06	-0.42	0.82	0.47
cs	-0.03	0.72	0.52	0.96	0.00	-0.21	0.73	0.92
fht	0.82	0.59	0.08	0.16	0.34	0.67	0.04	0.04
$tick$	0.87	0.48	0.04	0.07	0.43	0.69	0.03	0.03
$zeros$	2.28	0.91	0.01	0.01	1.16	2.40	0.00	0.01
ami	0.52	0.23	0.01	0.02	0.71	0.44	0.01	0.01
$amito$	0.24	0.53	0.33	0.65	0.04	0.08	0.37	0.46
PS	-6.75	6.58	0.85	0.30	0.21	-6.91	0.92	0.17
hm	-0.51	1.04	0.69	0.62	0.06	-0.39	0.69	0.51
Panel B: Decomp. of illiquidity into volatility and residual (FS approach)								
vol	-0.67	0.86	0.78	0.44	0.17	-0.81	0.97	0.16
$roll$	0.45	0.74	0.27	0.55	0.05	0.44	0.29	0.56
cs	0.73	0.58	0.10	0.21	0.24	0.81	0.05	0.15
fht	2.22	0.69	0.00	0.00	1.42	2.31	0.00	0.00
$tick$	2.18	0.66	0.00	0.00	1.49	2.21	0.00	0.00
$zeros$	2.60	0.91	0.00	0.00	1.13	2.69	0.00	0.00
ami	0.80	0.24	0.00	0.00	1.38	0.77	0.00	0.00
$amito$	0.63	0.69	0.18	0.36	0.18	0.54	0.09	0.12
PS	-5.08	6.75	0.77	0.45	0.11	-5.16	0.83	0.35
hm	-1.65	0.93	0.96	0.08	0.44	-1.58	0.96	0.06
Panel C: Decomp. of illiquidity into volatility and residual (Alt. RT approach)								
vol	-0.67	0.86	0.78	0.44	0.17	-0.81	0.97	0.15
$roll$	0.31	0.86	0.36	0.71	0.02	0.31	0.35	0.70
cs	0.75	0.67	0.13	0.26	0.17	0.81	0.14	0.33
fht	2.18	0.68	0.00	0.00	1.45	2.28	0.00	0.00
$tick$	1.82	0.63	0.00	0.00	1.36	1.84	0.00	0.01
$zeros$	2.28	0.91	0.01	0.01	1.16	2.40	0.00	0.01
ami	0.73	0.23	0.00	0.00	1.19	0.68	0.00	0.00
$amito$	0.58	0.60	0.17	0.34	0.24	0.51	0.09	0.14
PS	-6.18	6.56	0.83	0.35	0.16	-6.25	0.88	0.26
hm	-1.00	0.99	0.84	0.31	0.19	-0.90	0.84	0.26

Table A2: **Monthly forecasting regressions for CRSP value-weighted stock returns**

The table presents results for one-month-ahead predictive regressions for excess returns on the CRSP market index using various measures of aggregate illiquidity. The table reports results from regressions of the form

$$ret_{t+1} = \alpha + \beta x_t + \epsilon_{t+1},$$

where ret_{t+1} is the monthly CRSP value weighted excess return (including distributions) and x_t represents the specified forecasting variable. For each forecasting variable, the table presents OLS and bootstrap estimates. The presented OLS estimates include the slope coefficient $\hat{\beta}$, the associated Newey-West standard error, a one-sided p-value (p-val$_{1s}$), a two-sided p-value (p-val$_{2s}$), and an R^2 value. The presented bootstrap estimates include the slope coefficient $\hat{\beta}$ and the associated one-sided p-value (p-val$_{1s}$) and two-sided p-value (p-val$_{2s}$). The sample period is 1948–2015. See Section 2 of the paper for variable definitions. See Section 3 of the paper for further details on the alternative break-adjustment approaches.

	OLS					Bootstrap		
	$\hat{\beta}$	SE	p-val$_{1s}$	p-val$_{2s}$	R^2	$\hat{\beta}^*$	p-val$_{1s}$	p-val$_{2s}$
Panel A: Raw illiquidity measures								
$roll$	-0.18	0.86	0.58	0.84	0.01	-0.27	0.71	0.72
cs	0.29	0.87	0.37	0.74	0.03	0.11	0.34	0.41
fht	0.15	0.16	0.17	0.34	0.12	0.08	0.31	0.42
$tick$	0.18	0.17	0.14	0.28	0.14	0.06	0.30	0.32
$zeros$	0.15	0.18	0.20	0.39	0.12	0.21	0.18	0.49
ami	0.37	0.17	0.01	0.03	0.52	0.29	0.04	0.04
$amito$	0.12	0.30	0.34	0.68	0.03	-0.03	0.50	0.65
PS	-8.48	7.03	0.89	0.23	0.32	-8.74	0.95	0.11
hm	-0.62	0.83	0.77	0.45	0.13	-0.50	0.75	0.41
Panel B: Break-adjusted illiquidity measures (FS approach)								
$roll$	-0.09	0.86	0.54	0.92	0.00	-0.18	0.63	0.86
cs	0.14	0.75	0.42	0.85	0.01	-0.01	0.45	0.63
fht	1.00	0.68	0.07	0.14	0.46	0.86	0.03	0.03
$tick$	1.08	0.62	0.04	0.08	0.58	0.87	0.01	0.01
$zeros$	2.60	0.93	0.00	0.01	1.06	2.71	0.00	0.00
ami	0.59	0.25	0.01	0.02	0.83	0.51	0.00	0.00
$amito$	0.34	0.66	0.30	0.60	0.06	0.17	0.30	0.35
PS	-7.22	7.21	0.84	0.32	0.22	-7.58	0.93	0.17
hm	-1.22	1.00	0.89	0.22	0.28	-1.14	0.92	0.14
Panel C: Break-adjusted illiquidity measures (RT approach)								
$roll$	-0.17	0.85	0.58	0.84	0.01	-0.28	0.72	0.73
cs	0.31	0.76	0.34	0.69	0.04	0.12	0.34	0.45
fht	0.91	0.61	0.07	0.14	0.39	0.76	0.03	0.03
$tick$	0.95	0.51	0.03	0.06	0.48	0.76	0.02	0.02
$zeros$	2.27	0.93	0.01	0.01	1.07	2.36	0.00	0.01
ami	0.50	0.23	0.01	0.03	0.66	0.42	0.02	0.02
$amito$	0.18	0.51	0.36	0.72	0.02	0.00	0.47	0.59
PS	-7.90	6.76	0.88	0.24	0.27	-8.02	0.94	0.14
hm	-0.60	1.04	0.72	0.56	0.08	-0.50	0.74	0.44

(Table A2 continued from previous page)

	OLS					Bootstrap		
	$\hat{\beta}$	SE	p-val$_{1s}$	p-val$_{2s}$	R^2	$\hat{\beta}^*$	p-val$_{1s}$	p-val$_{2s}$
Panel D: Break-adjusted illiquidity measures (SD approach)								
$roll$	-0.85	0.96	0.81	0.38	0.23	-0.91	0.93	0.17
cs	-1.04	1.29	0.79	0.42	0.19	-1.25	0.98	0.11
fht	0.93	1.07	0.19	0.39	0.23	0.81	0.04	0.05
$tick$	0.74	1.08	0.25	0.50	0.13	0.50	0.10	0.10
$zeros$	1.87	0.95	0.02	0.05	0.60	1.96	0.00	0.01
ami	-0.09	0.46	0.58	0.84	0.01	-0.21	0.84	0.67
$amito$	-0.23	0.71	0.63	0.74	0.02	-0.41	0.85	0.58
PS	-9.46	7.06	0.91	0.18	0.35	-9.63	0.96	0.09
hm	0.26	1.07	0.41	0.81	0.01	0.34	0.35	0.77
Panel E: Decomp. of illiquidity into volatility and residual (RT approach)								
vol	-0.62	0.89	0.76	0.49	0.14	-0.79	0.96	0.21
$roll$	0.38	0.87	0.33	0.67	0.03	0.33	0.35	0.66
cs	0.69	0.69	0.16	0.32	0.14	0.78	0.17	0.39
fht	2.22	0.71	0.00	0.00	1.40	2.33	0.00	0.00
$tick$	1.86	0.65	0.00	0.00	1.32	1.88	0.00	0.01
$zeros$	2.27	0.93	0.01	0.01	1.07	2.38	0.00	0.01
ami	0.70	0.23	0.00	0.00	1.06	0.64	0.00	0.00
$amito$	0.51	0.59	0.20	0.39	0.18	0.46	0.12	0.19
PS	-7.87	6.93	0.87	0.26	0.24	-8.17	0.92	0.17
hm	-1.03	0.98	0.85	0.29	0.19	-0.90	0.85	0.25
Panel F: Decomp. of illiquidity into volatility and residual (SD approach)								
vol	-0.62	0.89	0.76	0.49	0.14	-0.78	0.96	0.20
$roll$	-0.85	1.04	0.79	0.41	0.11	-0.88	0.83	0.35
cs	-0.62	1.36	0.68	0.65	0.03	-0.56	0.69	0.59
fht	1.96	0.90	0.02	0.03	0.76	2.02	0.00	0.00
$tick$	1.84	1.02	0.04	0.07	0.59	1.85	0.00	0.01
$zeros$	1.87	0.95	0.02	0.05	0.60	1.99	0.00	0.01
ami	0.05	0.46	0.45	0.91	0.00	-0.01	0.50	0.83
$amito$	0.21	0.71	0.38	0.77	0.01	0.13	0.41	0.71
PS	-9.49	7.20	0.91	0.19	0.33	-9.46	0.94	0.11
hm	0.04	1.09	0.49	0.97	0.00	0.09	0.47	0.97

Table A3: **Long horizon return forecasting regressions**

The table presents long-horizon predictive regressions for excess returns on the NYSE index (ret) using aggregate illiquidity along with volatility vol_t as a control variable. The predictive regression model takes the form:

$$ret_{t,t+H} = \alpha + \beta x_t + \gamma vol_t + \epsilon_{t,t+H},$$

where $ret_{t,t+H} \equiv \sum_{h=1}^{H} ret_{t+h}$ denotes H-period cumulative log excess stock returns, x_t indicates a break- and volatility-adjusted aggregate illiquidity measure of interest, and vol_t represents volatility. We consider three choices for the return horizon H: 3 months, 6 months, and 12 months. For each forecasting variable, the table presents the estimated slope coefficient $\hat{\beta}$, the associated t-statistic based on Newey-West standard errors including $H+2$ lags, and ΔR^2, defined as the increase in R^2-value relative to a similar regression that excludes x_t (the above model with $\beta = 0$). Panel A presents results for break- and volatility-adjusted illiquidity measures using the real time (RT) approach. Panel B presents results for break- and volatility-adjusted measures using the stochastic detrending (SD) approach. The sample period is 1948–2015. See Section 1 of the Internet Appendix for variable definitions.

	$H = 3$ months			$H = 6$ months			$H = 12$ months		
	$\hat{\beta}$	t-stat	ΔR^2	$\hat{\beta}$	t-stat	ΔR^2	$\hat{\beta}$	t-stat	ΔR^2
Panel A: Break- and volatility-adjusted illiquidity measures (RT approach)									
$roll$	1.89	1.07	0.28	4.60	1.30	0.77	8.73	1.42	1.39
cs	1.80	0.95	0.32	3.84	0.99	0.68	8.52	1.16	1.66
fht	5.29	2.89	2.53	10.28	2.97	4.40	20.43	2.95	8.67
$tick$	4.40	2.76	2.33	8.97	2.86	4.47	17.60	2.95	8.55
$zeros$	6.26	2.57	2.28	12.32	2.73	4.08	24.76	2.69	8.20
ami	2.04	3.54	2.93	4.20	3.91	5.77	8.47	4.15	11.64
$amito$	1.00	0.61	0.20	2.67	0.89	0.65	5.62	1.08	1.43
PS	8.08	0.78	0.08	1.29	0.07	0.00	10.06	0.32	0.03
hm	-5.18	-3.06	1.50	-10.08	-3.87	2.62	-14.61	-2.82	2.74
Panel B: Break- and volatility-adjusted illiquidity measures (SD approach)									
$roll$	-0.96	-0.64	0.05	-0.94	-0.35	0.02	-2.75	-0.61	0.09
cs	-2.91	-0.90	0.20	-4.93	-0.79	0.26	-6.89	-0.67	0.25
fht	3.70	1.53	0.86	7.53	1.81	1.63	16.14	2.49	3.73
$tick$	2.73	1.10	0.41	6.28	1.40	1.01	13.95	1.88	2.48
$zeros$	4.13	1.57	0.88	8.51	1.90	1.72	18.45	2.43	4.01
ami	0.35	0.30	0.03	1.37	0.66	0.21	4.18	1.24	0.97
$amito$	-0.18	-0.10	0.00	0.83	0.27	0.03	4.33	0.80	0.38
PS	4.52	0.51	0.02	-8.92	-0.60	0.04	-4.89	-0.18	0.01
hm	-3.83	-1.82	0.52	-8.32	-2.18	1.13	-9.77	-1.97	0.78

Table A4: **Monthly predictive regressions for stock returns with volatility as control variable**

The table presents one-month-ahead predictive regressions for excess returns on the NYSE index (ret) for various break-adjusted illiquidity measures. The predictive regression model takes the form:

$$ret_{t+1} = \alpha + \beta x_t + \gamma vol_t + \epsilon_{t+1},$$

where ret_{t+1} denotes excess stock returns and x_t indicates a break-adjusted (but not volatility-adjusted) aggregate illiquidity measure of interest. All regressions include the volatility measure vol_t as a control variable. For each forecasting variable, the table presents the estimated slope coefficient $\hat{\beta}$, the associated t-statistic based on Newey-West standard errors, and ΔR^2, defined as the increase in R^2-value relative to a similar regression that excludes x_t (the above model with $\beta = 0$). Results are reported for three methods of break-adjustment: the full-sample (FS) approach, the real-time (RT) approach, and the alternative real-time method. The sample period is 1948–2015. See Section 1 of the Internet Appendix for variable definitions. See Section 3.3 of both the main paper and the Internet Appendix for details regarding alternative break-adjustment methods.

	FS Break-adj.			RT Break-adj.			Alt. RT Break-adj.		
	$\hat{\beta}$	t-stat	ΔR^2	$\hat{\beta}$	t-stat	ΔR^2	$\hat{\beta}$	t-stat	ΔR^2
$roll$	0.53	0.55	0.07	0.19	0.19	0.01	0.43	0.46	0.04
cs	0.99	1.34	0.28	0.73	0.94	0.15	1.37	1.85	0.41
fht	2.42	3.60	1.56	2.09	3.21	1.27	2.09	3.21	1.27
$tick$	2.26	3.59	1.60	1.74	2.99	1.17	1.74	2.99	1.17
$zeros$	2.55	2.83	0.96	2.29	2.64	0.99	2.29	2.64	0.99
ami	0.82	3.46	1.43	0.74	3.19	1.22	0.71	3.20	1.16
$amito$	0.64	0.91	0.19	0.45	0.73	0.12	0.38	0.66	0.09
PS	-3.83	-0.60	0.06	-5.38	-0.85	0.12	-4.64	-0.76	0.09
hm	-1.93	-2.25	0.60	-1.23	-1.38	0.27	-1.23	-1.39	0.27

Table A5: **Forecasting regressions based on principal component extracted from illiquidity measures: monthly data**

The table presents one-month-ahead predictive regressions for excess returns on the NYSE index (ret), growth in industrial production (Δip) and growth in unemployment (Δue) incorporating the first principal component extracted from the full set of monthly break- and volatility-adjusted illiquidity measures. The predictive regression model takes the form:

$$y_{t+1} = \alpha + \beta PC_t + \sum_{j=1}^{J} y_{t+1-j} + \gamma' z_t + \epsilon_{t+1},$$

where y_{t+1} denotes the forecasting target variable (e.g., excess stock returns) and PC_t indicates the principal component extracted from the illiquidity measures. We include four lags of the dependent variable on the right hand side of the predictive regression for Δip and Δue and zero lags for ret. For each forecasting variable, the table presents the estimated slope coefficient $\hat{\beta}$, the associated t-statistic based on Newey-West standard errors, and ΔR^2, defined as the increase in R^2-value relative to a similar regression that excludes PC_t (the above model with $\beta = 0$). Results are reported for three methods of break-adjustment applied to the underlying illiquidity measures: the full-sample (FS) approach, the real-time (RT) approach, and stochastic detrending (SD) procedure. Panel A presents results for models that exclude controls z_t. Panels B and C present results for models with specified controls z_t included. The sample period is monthly 1948–2015. See Section 1 of the Internet Appendix for variable definitions. See Section 3.3 of both the main paper and the Internet Appendix for details regarding alternative break-adjustment methods.

	$y_{t+1} = ret_{t+1}$			$y_{t+1} = \Delta ip_{t+1}$			$y_{t+1} = \Delta ue_{t+1}$		
Break Adj.	$\hat{\beta}$	t-stat	ΔR^2	$\hat{\beta}$	t-stat	ΔR^2	$\hat{\beta}$	t-stat	ΔR^2
Panel A: z_t omitted									
FS	0.23	2.92	1.12	-0.00	-0.05	0.00	0.05	0.63	0.05
RT	0.26	2.94	1.18	-0.00	-0.01	0.00	0.07	0.96	0.12
SD	0.11	1.27	0.24	-0.03	-1.97	0.30	0.16	2.51	0.59
Panel B: $z_t = (vol_t, ret_t)'$									
FS	0.21	2.79	0.84	-0.03	-1.77	0.31	0.14	2.15	0.43
RT	0.23	2.96	0.92	-0.02	-1.25	0.15	0.15	2.19	0.44
SD	0.09	1.01	0.15	-0.05	-3.56	0.92	0.22	3.38	1.13
Panel C: $z_t = (vol_t, ret_t, TBL_t, TERM_t, DEF_t, CPSP_t)'$									
FS	0.21	2.51	0.74	-0.06	-3.02	1.05	0.29	4.07	1.57
RT	0.24	2.87	0.92	-0.03	-1.77	0.32	0.21	3.04	0.81
SD	0.14	1.65	0.34	-0.03	-1.95	0.29	0.20	2.80	0.74