Duisenberg school of finance - Tinbergen Institute Discussion Paper

TI 13-156 /IV/ DSF 64

# Economic Valuation of Liquidity Timing

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July 1, 2013

**Abstract**

This paper conducts a horse-race of different liquidity proxies using dynamic asset allocation strategies to evaluate the short-horizon predictive ability of liquidity on monthly stock returns. We assess the economic value of the out-of-sample power of empirical models based on different liquidity measures and find three key results: liquidity timing leads to tangible economic gains; a risk-averse investor will pay a high performance fee to switch from a dynamic portfolio strategy based on various liquidity measures to one that conditions on the Zeros measure (Lesmond, Ogden, and Trzcinka, 1999); the Zeros measure outperforms other liquidity measures because of its robustness in extreme market conditions. These findings are stable over time and robust to controlling for existing market return predictors or considering risk-adjusted returns.

*JEL classification*: G11; G12; G17.
*Keywords*: Liquidity; forecasting; expected returns; economic valuation.

*The authors thank participants at the SMU-ESSEC Symposium on Empirical Finance & Financial Econometrics 2012, the 18th International Conference on Computing in Economics and Finance, the 5th Erasmus Liquidity Conference, the 66th European Meeting of the Econometric Society, and the 6th Financial Risks International Forum on Liquidity Risk for useful comments and suggestions. Sojli gratefully acknowledges the financial support of the European Commission Grant PIEF-GA-2008-236948. Tham gratefully acknowledges the financial support of the European Commission Grant PIEF-GA-2009-255330. Michel van der Wel is grateful to Netherlands Organisation for Scientific Research (NWO) for a Veni grant; and acknowledges support from CREATES, funded by the Danish National Research Foundation.

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# 1 Introduction

There is ample evidence that liquidity, the ease with which financial assets can be bought and sold, is important in explaining variations in asset prices. When market liquidity is expected to be low expected returns are higher.[1,2] A smart investor can potentially time the market and adjust exposure before liquidity events occur, i.e. time liquidity. Cao, Chen, Liang, and Lo (2013) provide evidence that many hedge fund managers behave like liquidity timers, adjusting the market exposure of their portfolios based on equity-market liquidity. However there is no guidance on empirical models and measures that one could use for liquidity timing, and this paper addresses these issues.

The literature approximates the unobserved liquidity of a financial asset using various liquidity measures. A large number of proxies for liquidity exists because liquidity has multiple aspects (e.g. width, depth, immediacy, or resiliency). Examples of liquidity proxies are spread proxies, measures of price impact, and turnover.[3] However it is unclear what liquidity measure an investor should use for liquidity timing and how it should be implemented.

In this paper we examine which proxy a liquidity timer should use. We do so, by measuring the economic value of liquidity forecasts using different liquidity proxies, from the perspective of investors who engage in short-horizon asset allocation strategies. We focus on the economic valuation of liquidity because it is relevant from an investor's point of view. Moreover it allows us to compare the performance of different liquidity measures, which might be capturing different aspects of liquidity, under the same "unit".[4]

[1] Amihud (2002), Jones (2002), and Baker and Stein (2004) show this for the U.S. market. Bekaert, Harvey, and Lundblad (2007) find supporting evidence in emerging markets.

[2] Amihud and Mendelson (1986) and Vayanos (1998) argue that investors anticipate future transaction costs and discount assets with higher transaction costs more. Baker and Stein (2004) relate liquidity to irrational investors who under-react to information in order flow. These investors are restricted by short-sales constraints and only participate in the market when they overvalue the market relative to rational investors. Hence when the market is more liquid, it is overvalued and expected returns are lower.

[3] For spread proxies see e.g. Roll (1984), Lesmond, Ogden, and Trzcinka (1999), Hasbrouck (2009), and Holden (2009); for price impact measures see e.g. Amihud, Mendelson, and Lauterbach (1997), Berkman and Eleswarapu (1998), Amihud (2002), and Pástor and Stambaugh (2003), and for turnover see Baker and Stein (2004).

[4] Other articles, e.g. Goyenko, Holden, and Trzcinka (2009) and Hasbrouck (2009), compare liquidity measures to a benchmark. Their set-up only allows to compare proxies that approximate the same aspect of liquidity, e.g. price impact or effective spread.

We consider the following five low-frequency liquidity measures for liquidity timing: illiquidity ratio (ILR) (Amihud, 2002), Roll (Roll, 1984), Effective Tick (Holden, 2009, Goyenko, Holden, and Trzcinka, 2009), Zeros (Lesmond, Ogden, and Trzcinka, 1999), and High-Low (Corwin and Schultz, 2012). Using these liquidity measures, we form conditional expectations about stock returns for the next period. Building on previous research (e.g. West, Edison, and Cho, 1993), we employ mean-variance analysis as a standard measure of portfolio performance and apply quadratic utility to examine and to compare the economic gains of the different measures. We use the Sharpe ratio (SR) and performance fee to evaluate the economic gains.[5] In addition, we also calculate the break-even transaction cost, which is the transaction cost that would remove any economic gain from a dynamic asset allocation strategy.

Based on NYSE-listed stocks for the period 1947-2008, we find evidence of economic value in liquidity timing. The Zeros measure outperforms the other measures: ILR, Roll, Effective Tick, and High-Low. The Zeros measure achieves a Sharpe ratio of 0.51, followed by the ILR with a Sharpe Ratio of 0.27. The SR of a buy and hold strategy over the same period is 0.28. A risk-averse investor with quadratic utility would pay an annual fee of more than 250 basis points to switch from the other liquidity proxies to condition on the Zeros liquidity measure. The alpha of the Zeros strategy is 7.01% after controlling for exposure to the three Fama and French (1993) factors, the Carhart (1997) momentum factor, and the Pástor and Stambaugh (2003) liquidity factor. The results are not driven by correlations with other return predictors such as the dividend yield or the book-to-market ratio (Welch and Goyal, 2008). Furthermore, the outperformance is not specific to a particular period and is robust to different subsamples, weight restrictions, and target volatility and risk aversion parameters.

We document that the Zeros measure shows positive performance under all market conditions. Its returns remain very high throughout both bull and bear periods and its

[5]The Sharpe ratio is the most common measure of performance evaluation employed in financial markets to assess the success or failure of active asset managers; it is calculated as the ratio of the average realized portfolio excess returns to their variability. The performance fee measures how much a risk-averse investor is willing to pay for switching from one strategy to another.

weights remain quite stable. Additionally, we show that the return predictions of the Zeros strategy are of good quality. We do this by restricting the weights in the asset allocation to be nonnegative. Jagannathan and Ma (2003) show that imposing nonnegativity restrictions in an asset allocation problem, reduces the estimation error in the return prediction parameters and gives similar effects as shrinking the return predictions. However, if the quality of the predictions is already good and cannot simply be improved by shrinkage, the strategy performance will deteriorate when restrictions are imposed. We find that weight restrictions lower the performance of the Zeros strategy, while they increase the performance of the other strategies.

This paper contributes to the literature on liquidity proxies comparison. Goyenko, Holden, and Trzcinka (2009) investigate how well low frequency liquidity measures approximate true transaction costs for market participants, which are measured by high-frequency benchmarks. They find that Effective Tick is the best low frequency measure for effective and realized spread, and ILR is the best measure for price impact. However, the best proxy for transaction costs is not necessarily the proxy that an investor should use for liquidity timing. In contrast, this paper investigates which measure can be used to time the market. Effective Tick shows no economic value, despite its ability to approximate high frequency transaction costs well and the Zeros measure is the most relevant for liquidity timing.

This paper contributes also to the literature on portfolio allocation. West, Edison, and Cho (1993) use the mean-variance and quadratic utility setting to rank exchange rate volatility models based on utility gains. Fleming, Kirby, and Ostdiek (2001) investigate volatility timing in equity markets. Della-Corte, Sarno, and Thornton (2008) and Della-Corte, Sarno, and Tsiakas (2009) apply the approach to short-term interest rates and predictability in the foreign exchange market. Thornton and Valente (2012) investigate the economic value of long-term forward interest rate information to predict bond returns. Differently from these papers, we evaluate the economic value of liquidity timing in equity markets.

# 2 Methodology

We examine whether liquidity timing leads to economic benefits and which liquidity proxy should be used, following three steps. First, we form conditional expectations of returns based on different liquidity measures. Second, we construct dynamically rebalanced mean-variance portfolios based on these return predictions. Third, we evaluate the performance of these strategies. In this section we focus on the methodology, while implementation details are presented when discussing the results.

## 2.1 Forecasting Liquidity and Expected Returns

We start by modeling liquidity in order to estimate expected liquidity in the next period. Following Amihud (2002), Acharya and Pedersen (2005), and Bekaert, Harvey, and Lundblad (2007) we use autoregressive models to capture the autocorrelation in the liquidity series:

$$LIQ_{k,t} = \phi_0 + \sum_{i=1}^{p} \phi_i LIQ_{k,t-i} + \eta_{k,t}, \tag{1}$$

where $LIQ_{k,t}$ is the liquidity of asset $k$ at time $t$, and $p$ is the order of the autoregressive model. Iterating forward Equation (1), liquidity predictions for the next period are given by $E_t\left[LIQ_{k,t+1}\right] = \phi_{0,t} + \sum_{i=1}^{p} \phi_{i,t} LIQ_{k,t-i}$. Adding expected liquidity in a model for conditional expected excess returns that is solely driven by liquidity, gives:

$$\begin{aligned} E_t\left[r_{k,t+1} - r_{f,t}\right] &= \delta_0 + \delta_1 E_t\left[LIQ_{k,t+1}\right] \\ &= \delta_{0,t} + \delta_{1,t}\left(\phi_{0,t} + \sum_{i=1}^{p} \phi_{i,t} LIQ_{k,t-i}\right) \\ &= \beta_{0,t} + \sum_{i=1}^{p} \beta_{i,t} LIQ_{k,t-i}, \end{aligned} \tag{2}$$

where $\beta_{0,t} = \delta_0 + \delta_1 \phi_{0,t}$ and $\beta_{i,t} = \delta_1 \phi_i$. We only need estimates for the $\beta$-parameters and do not estimate Equation (1), because we are interested in return predictions generated by Equation (2). The coefficients $\beta_{0,t}$ and $\beta_{i,t}$ are allowed to vary over time and are estimated using a rolling window of length $L$. If liquidity is beneficial for forecasting expected returns, it can be used in a 'liquidity timing' strategy. We estimate the parameters in Equation (2) using a window length of 10 years ($L = 120$ monthly observations). To minimize the effect of possible structural breaks on the results, Pesaran and Pick (2011) suggest to average predictions generated using different rolling window lengths. We take the average of three different predictions based on a window length of 5, 10, and 20 years ($L = 60, 120$, and 240 monthly observations).

To allow for a long enough sample to cover the longest moving window of 20 years, the first return prediction is made for January 1967. For the 10 year moving window, we estimate the regression in Equation (2) using data from January 1957 to December 1966. Using the estimated coefficients we make a forecast for next month, January 1967. Then we shift the window one period ahead. Thus the second estimation window runs from February 1957 to January 1967, and we make a prediction for February 1967. This procedure is repeated for all months $t$ = Jan 1967, Feb 1967, ... , Dec 2008 and all assets $k = 1, 2, \ldots, K$, for each liquidity measure. For the 5 year moving window, the first window is January 1962 to December 1966 and for the 20 years, the first window is January 1947 to December 1966.

## 2.2 Asset Allocation

We use mean-variance dynamic trading strategies to assess the economic value of liquidity timing. An investor invests every month in the $K$ risky assets and one riskless U.S. Treasury bill ($r_{f,t}$). She chooses the weights to invest in each risky asset by constructing a dynamically re-balanced portfolio that maximizes the conditional expected return subject to a target conditional volatility. Her optimization problem is given by

$$\max_{w_t} \left\{ r_{s,t+1|t} = w_t' r_{k,t+1|t} + (1 - w_t' \mathbf{1}) r_{f,t} \right\} \quad (3)$$
$$\text{s.t.} \quad (\sigma_s^*)^2 = w_t' \Sigma_{t+1|t} w_t,$$

where $r_{s,t+1|t}$ is the conditional expected return of strategy $s$, $w_t$ is the vector of weights of the risky assets, $r_{k,t+1|t}$ is the vector of conditional risky asset return predictions, $\sigma_s^*$

is the target level of risk for the strategy, and $\Sigma_{t+1|t}$ is the variance-covariance matrix of the risky assets. $\Sigma_{t+1|t}$ is estimated recursively as the investor updates return predictions and dynamically balances her portfolio every month. The solution to this maximization problem yields the risky asset investment weights:

$$w_t = \frac{\sigma_s^*}{\sqrt{Q_t}} \Sigma_{t+1|t}^{-1} \left( r_{k,t+1|t} - \mathbf{1} r_{f,t} \right),$$

where $Q_t = \left( r_{k,t+1|t} - \mathbf{1} r_{f,t} \right)' \Sigma_{t+1|t}^{-1} \left( r_{k,t+1|t} - \mathbf{1} r_{f,t} \right)$ and $r_{k,t+1|t} - \mathbf{1} r_{f,t}$ is the conditional excess return. The weight invested in the risk free asset is $1 - w_t' \mathbf{1}$. The covariance matrix is estimated by the sample covariance matrix over a 10 year rolling window, thus, the covariance matrix is time-varying.[6]

## 2.3 Evaluation

We employ mean-variance analysis as a standard measure of portfolio performance to calculate Sharpe ratios (SR). Assuming quadratic utility, we also measure how much a risk-averse investor is willing to pay for switching from one liquidity measure to another. For each of these economic evaluation metrics, we obtain one ranking of all investigated liquidity measures.

### Sharpe Ratio

The first economic criterion we employ is the Sharpe ratio, or return-to-variability ratio, which measures the risk-adjusted returns from a portfolio or investment strategy and is widely used by investment banks and asset management companies to evaluate investment and trading performance. The ex-post SR is defined as:

$$SR = \frac{\overline{r_s - r_f}}{\sigma_s},$$

[6]Our results are similar when we carry out the out-of-sample asset allocation problem with the covariance matrix predicted by a multivariate GARCH(1,1) model or with the covariance matrix kept constant over time.

where $\overline{r_s - r_f}$ is the average (annualized) excess strategy return over the risk free rate, and $\sigma_s$ is the (annualized) standard deviation of the investment returns. This measure is commonly used to evaluate performance in the context of mean-variance analysis. However, Marquering and Verbeek (2004) and Han (2006) show that the SR can underestimate the performance of dynamically managed portfolios. This is because the SR is calculated using the average standard deviation of the realized returns, which overestimates the conditional risk (standard deviation) faced by an investor at each point in time. For this reason we use the performance fee as an additional economic criterion to quantify the economic gains from using the liquidity models considered.

**Performance Fees Under Quadratic Utility**

The second economic significance evaluation metric is based on the performance fee. Specifically, we calculate the maximum performance fee a risk-averse investor is willing to pay to switch from the strategy based on liquidity measure A to an alternative strategy that is based on liquidity measure B. This measure is based on mean-variance analysis with quadratic utility (West, Edison, and Cho, 1993, Fleming, Kirby, and Ostdiek, 2001, Rime, Sarno, and Sojli, 2010). Under quadratic utility, at the end of period $t+1$ the investor's utility of wealth can be represented as:

$$U\left(W_{t+1}\right) = W_{t+1} - \frac{\varrho}{2} W_{t+1}^2 = W_t \left(1 + r_{s,t+1}\right) - \frac{\varrho}{2} W_t^2 \left(1 + r_{s,t+1}\right)^2,$$

where $W_{t+1}$ is the investor's wealth at $t+1$; $r_{s,t+1}$ is the gross strategy return; and $\varrho$ determines her risk preference. To quantify the economic value of each model the degree of relative risk aversion (RRA) of the investor is set to $\delta = \frac{\varrho W_t}{1-\varrho W_t}$, and the same amount of wealth is invested every day. Under these conditions, West, Edison, and Cho (1993) show that the average realized utility ($\overline{U}$) can be used to consistently estimate the expected utility generated from a given level of initial wealth. The average utility for an investor with initial wealth $W_0 = 1$ is:

$$\overline{U} = \frac{1}{T}\sum_{t=0}^{T-1}\left(1 + r_{s,t+1} - \frac{\delta}{2\left(1+\delta\right)}\left(1 + r_{s,t+1}\right)^2\right).$$

At any point in time, one set of estimates of the conditional returns is better than a second set if investment decisions based on the first set leads to higher average realized utility, $\overline{U}$. Alternatively, the optimal model requires less wealth to yield a given level of $\overline{U}$ than a suboptimal model. Following Fleming, Kirby, and Ostdiek (2001), we measure the economic value of liquidity by equating the average utilities for selected pairs of portfolios. Suppose, for example, that holding a portfolio constructed using the optimal weights based on liquidity measure A yields the same average utility as holding the optimal portfolio implied by the liquidity measure B that is subject to daily expenses $\Phi$, expressed as a fraction of wealth invested in the portfolio. Since the investor would be indifferent between these two strategies, we interpret $\Phi$ as the maximum performance fee she will pay to switch from strategy A to strategy B. In other words, this utility-based criterion measures how much a mean-variance investor is willing to pay for conditioning on a particular liquidity measure for the purpose of forecasting stock returns. The performance fee will depend on the investor's degree of risk aversion. To estimate the fee, we find the value of $\Phi$ that satisfies:

$$\sum_{t=0}^{T-1}\left\{1 + r^A_{s,t+1} - \frac{\delta}{2\left(1+\delta\right)}\left(1 + r^A_{s,t+1}\right)^2\right\} = \sum_{t=0}^{T-1}\left\{\left(1 + r^B_{s,t+1} - \Phi\right) - \frac{\delta}{2\left(1+\delta\right)}\left(1 + r^B_{s,t+1} - \Phi\right)^2\right\},$$

where $r^A_{s,t+1}$ is the strategy return obtained using forecasts based on the liquidity measure $A$, $\Phi$ is the maximum performance fee an investor wants to pay to switch from strategy A to strategy B, and $\delta$ is the degree of relative risk aversion (RRA) of the investor.

**Transaction Costs**

In dynamic investment strategies, where the investor rebalances the portfolio every month, transaction costs can play a significant role in determining returns and comparative utility gains. However, traders charge transaction costs according to counter-party types and trade size. Thus, instead of assuming a fixed cost, we compute the break-even transaction cost $\tau$, which is the minimum monthly proportional cost that cancels the utility advantage of a given strategy. A similar measure of transaction costs has been used by Han (2006), Marquering and Verbeek (2004), and Della-Corte, Sarno, and Tsiakas (2009). We assume that transaction costs at time $t$ equal a fixed proportion $\tau$ of the amount traded in asset $k$:

$$\tau \sum_{k=1}^{K} A_{k,t} \left| w_{k,t} - w_{k,t-1} \left( \frac{1 + r_{k,t} + r_{f,t-1}}{1 + r_{s,t}} \right) \right|,$$

where $k = 1, \ldots, K$ refers to the risky assets and $A_{k,t} = \frac{costs_{k,t}}{costs_{K,t}}$ is a scaling factor that expresses the break-even transaction costs $\tau$ in terms of asset $K$. The scaling factor takes into account the difference in trading costs between the different assets. To quantify the transaction cost we use the Effective Tick estimates: $costs_{k,t} = \textit{Eff. Tick}_{k,t}$. The choice for Effective Tick is based on Goyenko, Holden, and Trzcinka (2009) who find that this measure is the best proxy for effective spread, which is an estimate of the execution cost actually paid by the investor. Previous articles assume that the transaction costs of all assets in their analysis is the same, i.e. $A_{k,t} = 1$. We cannot make that assumption because we focus on the liquidity differences between assets, which implies that the transaction costs of the different assets are unlikely to be the same.

# 3 Data

We use daily data of common stocks listed on the New York Stock Exchange (NYSE) from 1947-2008. All data are obtained from the Center for Research in Security Prices (CRSP). We use the daily data to construct the monthly variables. Using daily data, instead of high frequency data, enables us to investigate a longer sample period. Following the literature (see e.g. Chordia, Roll, and Subrahmanyam, 2000, Hasbrouck, 2009, Goyenko, Holden, and Trzcinka, 2009), we include only stocks that have sharecode 10 or 11 and do not change ticker symbol, CUSIP, or primary exchange over the sample period. Days with unusually low volume due to holidays are removed. Our final sample includes 16,083,228 stock/day observations.

The dependent variable in all our regressions is monthly excess returns. All monthly stock returns are adjusted for delisting bias following Shumway (1997).[7] Excess returns $r_{i,t}^e$ are calculated above the 1-month Treasury bill rate from Ibbotson Associates as provided on Kenneth French's website.[8]

## 3.1 Portfolio Construction

We use liquidity and excess return series of size portfolios instead of individual stocks in the regressions. The aggregation of individual stocks into portfolios is necessary to reduce the number of assets in the asset allocation. It also deals with issues related to individual stocks that enter and leave the sample, due to delistings and IPOs. Before aggregating the individual stocks into portfolios, we filter the individual observations based on the level of the stock price, the number of daily observations within the month, and the availability of size, liquidity, and return information.[9] Stock $i$ is included in a portfolio in month $t$ if it satisfies the following criteria:

(1) The preceding month-end stock price is between \$5 and \$1,000 $\left(5 < p_{i,t-1,D_{i,t-1}} < 1000\right)$, where $p_{i,t-1,D_{i,t-1}}$ is the stock price of stock $i$ on day $D_{i,t-1}$ in month $t-1$. This rules out returns that are affected by the minimum tick size.

(2) The preceding month-end market capitalization information $(M_{i,t-1})$ is available, which we need for sorting.

[7]For all delistings we use the delisting returns available in CRSP. If this return is not available and the delisting code is 500, 520, 551-574, 580, or 584, we follow Shumway (1997) and use a return of $-30\%$.

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

[9]The filtering criteria are in line with Amihud (2002), Pástor and Stambaugh (2003), Acharya and Pedersen (2005), and Ben-Rephael, Kadan, and Wohl (2010).

(3) $LIQ_{i,t-1}$ is available and is computed using at least 15 daily observations to ensure the quality of the measure.

(4) After excluding individual monthly observations that do not satisfy conditions (1) to (3), we winsorize each month across all remaining stocks to the top and bottom 1% of the liquidity variables to avoid outliers.

After filtering, the sample consists of 4,348 stocks. We sort these stocks based on previous end-of-month market capitalization in $K = 10$ size portfolios. The portfolio liquidity and return series are simply the cross-sectional averages of the included individual stocks.

Directly sorting on the liquidity measure of interest is not possible because we analyze various liquidity measures, which would lead to different rankings and different portfolio components for each measure. If we construct different portfolios for each individual liquidity measure, we will not be able to disentangle whether performance differences are due to the composition of the portfolio or to the better predictive quality of the liquidity measure. Furthermore, Amihud (2002) finds that the effect between liquidity and expected returns is stronger for small firms than for large firms. By creating portfolios based on size we take this into account in the econometric framework.

## 3.2 Liquidity Variables

The liquidity variables are the explanatory variables in the regressions. We consider a variety of monthly liquidity measures which together capture all aspects of liquidity: Roll, Effective Tick, Zeros, High-Low, and Illiquidity Ratio (ILR).[10] The first four measures proxy for the bid-ask spread and the fifth measure is a proxy for price impact. All liquidity variables measure illiquidity, i.e. higher estimates correspond to lower liquidity.

[10]Some liquidity measures that we leave out are: the measures developed in Chordia, Huh, and Subrahmanyam (2009) because they require analyst data, and the Sadka (2006) measure based on high-frequency data.

**Roll**

Roll (1984) shows that trading costs lead to a negative serial correlation in subsequent price changes. In other words, the effective bid-ask spread is inversely related to the covariance between subsequent price changes. The Roll measure is calculated as:

$$Roll_{i,t} = \begin{cases} 2\sqrt{-Cov\left(\Delta p_{i,t,d};\Delta p_{i,t,d-1}\right)}, & \text{if } Cov\left(\Delta p_{i,t,d};\Delta p_{i,t,d-1}\right) < 0, \\ 0, & \text{if } Cov\left(\Delta p_{i,t,d};\Delta p_{i,t,d-1}\right) \geq 0. \end{cases}$$

where $\Delta p_{i,t,d}$ is the price change for stock $i$ in month $t$ on day $d$ with $d = 1, 2, \ldots, D_{i,t}$ and $D_{i,t}$ the total number of trading days of stock $i$ in month $t$.

**Effective Tick**

Holden (2009) and Goyenko, Holden, and Trzcinka (2009) jointly develop a liquidity measure based on price clustering, which builds on the findings of Harris (1991) and Chrisie and Schultz (1994). If one assumes that the spread size is the only cause of price clustering, observable price clusters can be used to infer the spread. If prices are exclusively quoted on even eight increments $\left(\$\frac{1}{4}, \$\frac{1}{2}, \$\frac{3}{4}, \$1\right)$ the spread must be $\$\frac{1}{4}$ or larger. However when prices are also quoted on odd eight increments $\left(\$\frac{1}{8}, \$\frac{3}{8}, \$\frac{5}{8}, \$\frac{7}{8}\right)$ the spread must be $\$\frac{1}{8}$. If the minimum tick size is $\$\frac{1}{8}$, there are $J = 4$ possible spreads: $s_1 = \$\frac{1}{8}; s_2 = \$\frac{1}{4}; s_3 = \$\frac{1}{2}; s_4 = \$1$. The observed fraction $F_j$ of odd $\$\frac{1}{8}, \$\frac{1}{4}, \$\frac{1}{2}, \$1$ prices can be used to estimate the probability $\gamma_j$ of a certain spread $s_j$. The unconstrained probability $U_{i,t,j}$ of the $j^{th}$ spread $s_j$ for stock $i$ in month $t$ is:

$$U_{i,t,j} = \begin{cases} 2F_{i,t,j} & \text{if } j = 1 \\ 2F_{i,t,j} - F_{i,t,j-1} & \text{if } j = 2, 3, \ldots, J_t - 1 \\ F_{i,t,j} - F_{i,t,j-1} & \text{if } j = J_t, \end{cases}$$

where $F_{i,t,j}$ is the observed fraction of trades on prices corresponding to the $j^{th}$ spread for stock $i$ in month $t$: $F_{i,t,j} = \frac{N_{i,t,j}}{\sum_{j=1}^{J_t} N_{i,t,j}}$ for $j = 1, 2, \ldots, J_t$. with $N_{i,t,j}$ the number of positive volume days in month $t$ that correspond to the $j^{th}$ spread. The unconstrained probabilities $U_{i,t,j}$ can be below zero or above one, so we add restrictions to make sure the $\gamma_{i,t,j}$'s are real probabilities:

$$\gamma_{i,t,j} = \begin{cases} \min[\max(U_{i,t,j}, 0), 1] & \text{if } j = 1 \\ \min[\max(U_{i,t,j}, 0), 1 - \sum_{m=1}^{j-1} \gamma_{i,t,m}] & \text{if } j = 2, 3, \ldots, J_t. \end{cases}$$

The effective tick measure is the expected spread scaled by the average price over that month.

$$Eff.\ Tick_{i,t} = \frac{\sum_{j=1}^{J_t} \gamma_{i,t,j} s_{i,t,j}}{\overline{p}_{i,t}}.$$

**Zeros**

Lesmond, Ogden, and Trzcinka (1999) develop a liquidity measure based on the proportion of days with zero returns. In a day with zero return, the value of trading on information does not exceed transaction costs for an investor on that day. A less liquid asset with high transaction costs is less often traded than a more liquid asset, and the less liquid asset has a higher proportion of days with zero returns. Zeros is measured as:

$$Zeros_{i,t} = \frac{\sum_{d=1}^{D_{i,t}} I_{\{r_{i,t,d}=0\}}}{D_{i,t}},$$

where $I_{\{r_{i,t,d}=0\}}$ is an indicator function that takes the value 1 if the return of stock $i$ on day $d$ in month $t$ is zero.

**High-Low**

Corwin and Schultz (2012) develop a liquidity measure based on daily high and low prices. It is likely that the highest price on a particular day is against the ask quote while the lowest price is against the bid quote. The high-low ratio therefore reflects both a stock's variance and its bid-ask spread. To disentangle the variance and the spread component, we make use of multiple time intervals since the variance is proportional to the length of the interval, while the spread component is not. Hence, the liquidity measure is written as a function of one-day and two-day high-low ratios:

$$High\text{-}Low_{i,t} = \frac{2\left(\exp^{\alpha} - 1\right)}{1 + \exp^{\alpha}},$$

where $\alpha = \frac{\sqrt{2\beta} - \sqrt{\beta}}{3 - 2\sqrt{2}} - \sqrt{\frac{\gamma}{3 - 2\sqrt{2}}}$, $\beta = \log\left(\frac{H_{i,t}}{L_{i,t}}\right)^2 + \log\left(\frac{H_{i,t-1}}{L_{i,t-1}}\right)^2$, $\gamma = \log\left(\frac{H_{i,t-1,t}}{L_{i,t-1,t}}\right)^2$, $H_{i,t}\left(L_{i,t}\right)$ is the high (low) price on day $t$ for asset $i$, and $H_{i,t-1,t}\left(L_{i,t-1,t}\right)$ is the high (low) price over the two days $t-1$ and $t$ for asset $i$.

**Illiquidity Ratio**

The measure developed in Amihud (2002) proxies for the price impact of a trade. Price impact refers to the positive relation between transaction volume and price change. The measure is defined as the ratio between the absolute daily return over dollar volume, averaged over the month:

$$ILR_{i,t} = \frac{1}{D_{i,t}} \sum_{d=1}^{D_{i,t}} \frac{|r_{i,t,d}|}{V_{i,t,d}},$$

where $V_{i,t,d}$ is the dollar volume of traded stocks $i$ (in millions) on day $d$ and $D_{i,t}$ is the number of trading days in month $t$. To be able to compare the ILR over time, we correct it for inflation and the increased size of financial markets. When adjusting the series we cannot use future information that is not available to a real-time investor. We follow Acharya and Pedersen (2005) and Pástor and Stambaugh (2003) and scale the liquidity measure by a ratio of market capitalizations:

$$ILR_{i,t}^{adj} = ILR_{i,t} \frac{M_{m,t-1}}{M_{m,1}},$$

where $ILR_{i,t}$ is the illiquidity ratio in month $t$ of stock $i$ and $M_{m,t-1}$ is the market capitalization in month $t-1$ and $M_{m,1}$ is the market capitalization in January 1947. In the remainder of this paper we drop the superscript and refer to the adjusted Amihud illiquidity ratio with *ILR*.

## 3.3 Preliminary Statistics

Table 1 presents the liquidity characteristics for the market and three size portfolios. Panel A shows the liquidity characteristics for the market portfolio. Panels B, C, and D show the liquidity characteristics for the size portfolios. The portfolio with small firms (Panel B) is the least liquid and has the most variability over time. The bottom three panels (E - G) show market liquidity over three subperiods of 20 years. The ILR measure shows that price impact is the lowest in the post-war sub-period (1947-1967) with a value of 2.537 and has the lowest volatility of 0.725. In contrast, Zeros shows that liquidity has increased over time.

[insert Table 1 here]

Figure 1 shows the time series of the liquidity measures. The Roll and High-Low liquidity measures are quite stable and fluctuate around means of 0.01 and 0.006 respectively. Both measures show low liquidity around 1975 (oil crisis), 2000 (burst of internet bubble), and 2007-2008 (global financial crisis). The Effective Tick and Zeros measures exhibit a decreasing trend. There are two permanent shocks in these series that coincide with the two minimum tick changes: on June 24, 1997, the minimum tick decreases from $\frac{1}{8}$ to $\frac{1}{16}$, and on January 29, 2001, it decreases from $\frac{1}{16}$ to 0.01. The last measure, ILR, shows periods of illiquidity in 1970, 1975, in the beginning of the 90's, in 2000, and in 2008. The figure shows that it is important to allow the relation between liquidity and conditional expected returns to vary over time by using rolling estimation windows.

[insert Figure 1 here]

Table 2 shows the descriptive statistics for the market portfolio excess returns and three size portfolios, over the entire sample and three subsamples: 1947-1967, 1968-1988, and 1989-2008. In line with Fama and French (1992), we find that small firms have both more volatile and higher average returns compared to the returns for large firms. The different subsamples show that returns vary considerably over time. The preliminary statistics provide initial evidence of a possible link between liquidity and returns.

[insert Table 2 here]

# 4 Results

We now turn to the results of our main analysis. Here, all liquidity series are modeled using an autoregressive model of order two. The optimal number of lags is based on the Akaike Information Criterion and the Bayesian information Criterion. In this section, all switching fees are based on a relative risk aversion coefficient $\delta = 5$, and the ex-ante target volatility is set to $\sigma_s^* = 10\%$. In Section 6 we examine the robustness of the results to these settings.

## 4.1 Main Results

Table 3 shows the performance of the liquidity timing strategies. We present the following performance measures: the Sharpe ratio (SR, column 1), the relative performance expressed in switching fees (columns 2-5), transaction costs (columns 6-7), the excess return and volatility (columns 8-9), and the Manipulation-proof Performance Measure (MPPM, column 10) of Goetzmann, Ingersoll, Spiegel, and Welch (2007). Each row corresponds to the characteristics of a strategy that conditions on a particular liquidity measure. The results in Panel A indicate that it is possible to use liquidity timing to earn positive returns, and that the Zeros measure performs best. The SR of the Zeros strategy is 0.38 and is higher than the SR of ILR (0.13), Roll (-0.04), Effective Tick (-0.07), and High-Low (-0.16).[11]

The Zeros strategy performs best as indicated by the positive switching fees of all variables towards Zeros. A risk-averse investor would pay 287.3 basis points per year to switch from the ILR strategy to a strategy that conditions on Zeros. The High-Low strategy has the worst performance because a risk-averse investor does not want to pay a

[11]The differences in SR are not only economically but also statistically significant. According to the SR test of Ledoit and Wolf (2008), the SR of the Zeros strategy is significantly higher than the other SRs, except for the SR of the ILR strategy.

positive fee to switch to the High-Low strategy.[12] The Zeros break-even transaction costs ($\tau_1$) are 4.2 basis points, if we assume that transaction costs are the same for all risky assets. When we incorporate the cost differences and express the break-even transaction costs in terms of the most liquid asset, we find $\tau_A = 2.0$ basis points. The next two columns show the excess returns and their volatilities. The excess return of Zeros is the highest, 4.55%.

Recently, Goetzmann, Ingersoll, Spiegel, and Welch (2007) show that performance measures of active management can be gamed. They propose a manipulation-proof measure (MPPM), which accounts for non-linear payoffs in the return-risk relation. For robustness, we also show the results using this measure in column (10). The ranking using MPPM is the same as with the other measures.[13]

Panel B shows the strategy characteristics when the return predictions are based on the average return prediction using three different rolling windows (5, 10, and 20 years). The Zeros strategy has both the highest excess return (6.04%) and SR (0.51). The positive switching fees for the Zeros strategy show that a risk-averse investor always wants to pay a positive fee to switch to condition on the Zeros measure. Compared to Panel A, the excess returns in Panel B are higher for four of the five measures and the return volatilities remain similar. Averaging the return predictions of different rolling windows seems to deliver better performance, which could be related to more accurate return forecasts, in line with Pesaran and Pick (2011).

[insert Table 3 here]

Figure 2 shows the cumulative returns of all five strategies based on the 10 year rolling window predictions. The best performing strategies are based on the ILR and the Zeros measures. The outperformance of the Zeros strategy is not generated during a particular period, since its returns steadily increase over the entire sample period. The ILR strategy

[12] The break-even transaction costs are not computed for the Effective Tick, Roll, and High-Low strategy because their excess returns are negative.

[13] Results using MPPM generate the same ranking as the other measures, in all the rest of the empirical work. We do not present these results to conserve space, but they are available from the authors upon request.

performs very well and tracks the Zeros strategy until 1995, but it decreases substantially between 1995 and 1998 and never recovers. The decline in performance of the ILR strategy is in line with Ben-Rephael, Kadan, and Wohl (2010), who argue that the profitability of trading strategies based on volume related liquidity proxies declined over the past four decades. Both the Roll and High-Low strategies show good performance until 1980, but they become loss-making afterwards. Finally, the Effective Tick strategy loses money until 1990, it sharply increases until 2001, and in the final years of the sample its performance is flat.

[insert Figure 2 here]

## 4.2 Control Variables

This section deals with the possibility that an omitted variable, which is correlated with the liquidity measures, is driving the results. Welch and Goyal (2008) examine the predictive ability of several market return predictors suggested in the existing literature.[14] We use only the Welch and Goyal (2008) predictors that are publicly available for the entire sample period (1947-2008).[15] All variables are constructed for the market and not for the individual size portfolios.

Adding the control variables to Equation (2), with $p = 2$ yields:

$$E_t\left[r_{k,t+1} - r_{f,t}\right] = \beta_{0,t} + \beta_{1,t}LIQ_{k,t} + \beta_{2,t}LIQ_{k,t-1} + \sum_{n=1}^{N}\gamma_{n,t}f_{n,t}, \tag{4}$$

where $LIQ_{k,t}$ is the liquidity of asset $k$ at time $t$ and $f_{n,t}$ are the $n = 1, 2, \ldots, N$ control variables: dividend yield, earnings price ratio, dividend payout ratio, stock variance, book-to-market ratio, net equity expansion, term-spread, default yield spread, default return spread, and inflation. We estimate the $\beta$- and $\gamma$-parameters in the same way as in the main analysis. Some of the control variables, especially the dividend price ratio and

[14]They investigate the dividend price ratio, dividend yield, earnings price ratio, dividend payout ratio, stock variance, cross-sectional premium, book-to-market ratio, net equity expansion, percent equity issuing, term-spread, default yield spread, default return spread, inflation, and investment to capital ratio.

[15]We exclude percent equity issuing and investment to capital ratio because they are not publicly available. All available data are from Amit Goyal's website `http://www.hec.unil.ch/agoyal/`.

dividend yield, are highly correlated. Hence, we run separate regressions for each control variable and one regression where we include all control variables, excluding the dividend price ratio to avoid singularity issues.[16]

We test whether any of the control variables yield better predictions compared to the model with also a liquidity term. In this set-up we first estimate a model where expected excess returns are only driven by a constant and one of the control variables. Second, we estimate a model where expected excess returns are driven by a constant, one of the control variables, and a liquidity variable. We then check if the added liquidity variable increases performance, compared to the first case.

The results are presented in Table 4. Columns (1) - (3) show the SR and break-even transaction costs if the model consists of a constant and one control variables. Columns (4) - (8) show the SR when liquidity is added to predict returns. The highest SR in column (1) in Panel A is 0.21, which is lower than the highest SR of a strategy conditioning only on liquidity (0.38 from the Zeros strategy in Table 3). Comparing column (7) with column (1), shows that adding the Zeros measure always increases the SR. The only exception is when we add Zeros to a strategy consisting of all control variables, in which case the SR only improves in Panel B. The Zeros measure is followed by the ILR measure, which increases the SR in 6 out of 12 cases. In Panel B the best control variable also underperforms the best liquidity strategy, the SR is 0.28 versus 0.51. The last rows of both Panel A and B show the performance of the net equity expansion variable (ntis). In contrast to the other 10 controls, this variable performs really well with an SR of 0.42 in both panels. According to Baker and Stein (2004) this variable is related to liquidity. Hence, this supports our idea that liquidity has predictive ability for returns.

[insert Table 4 here]

To summarize, the addition of alternative return predictors shows that the results are not driven by an omitted variable bias. When we condition only on one individual control variable, we do not find a strategy that gets close to the best liquidity strategy in terms

[16] We include the dividend yield because it shows the highest SR on an individual basis (see Table 4). Furthermore, replacing the dividend yield by the dividend price ratio gives similar results.

of SR. Furthermore, the Zeros liquidity measure always increases the performance of a strategy that conditions on one control variable.

### 4.3 Cross-sectional Predictors

We extend the analysis in the previous section with cross-sectional predictors, i.e. the three Fama-French factors and the Carhart momentum factor. Fama and French (1993) and Carhart (1997) show that these factors can explain cross-sectional return differences. The data are from Wharton Research Database Services (WRDS).

In line with Equation (4), we get:

$$E_t\left[r_{k,t+1} - r_{f,t}\right] = \beta_{0,t} + \beta_{1,t} LIQ_{k,t} + \beta_{2,t} LIQ_{k,t-1} + \sum_{n=1}^{M} \kappa_{m,t} h_{m,t},$$

where $LIQ_{k,t}$ is the liquidity of asset $k$ at time $t$ and $h_{m,t}$ are the $m = 1, 2, \ldots, M$ control variables: excess market return, Small-minus-Big, High-minus-Low, and momentum. Table 5 shows the results of the strategies when conditioning on only a constant and one control variable and when conditioning on a constant, a control variable, and a liquidity variable. The SR of the excess market return strategy in column (1) of Panel A is 0.41, which is higher than the SR of the Zeros strategy. When we include all four control variables in one strategy, the SR is 0.47. All Sharpe ratios increase when we add the Zeros liquidity measure in Column (7). In other words, the Zeros liquidity measure contains relevant information that increases the quality of the return predictions. The cross-sectional predictors in Panel B do not outperform the Zeros strategy in terms of SR. In addition the SR of the "all strategy" increases when we add the Zeros liquidity measure.

[insert Table 5 here]

### 4.4 Risk Adjusted Returns

Until now, we have compared the different liquidity measures based on excess returns. It is possible that some of the strategies load more on risk than others, and therefore achieve higher returns. In this section we adjust the returns of the strategies for their exposure to the three Fama-French factors, the Carhart Momentum factor, and the Pastor and Stambaugh liquidity factor. Then, we compare the liquidity strategies based on alpha.

The methodology to compute alphas is similar to Brennan, Chordia, and Subrahmanyam (1998), Chordia, Subrahmanyam, and Anshuman (2001), and Ben-Rephael, Kadan, and Wohl (2010). In the first step we estimate the sensitivity ($\beta^i$) of the strategy returns to each risk factor:

$$r_{s,t} - r_{f,t} = \alpha_{s,t} + \sum_i \beta^i_{s,t} F^i_t + \varepsilon_{s,t},$$

where $r_{s,t} - r_{f,t}$ is the excess return at time $t$ of strategy $s$, $\alpha_{s,t}$ is the risk adjusted return, $\beta^i_{s,t}$ is the sensitivity to risk factor $i$, and $F^i_t$ are the risk factors. The factor loadings are estimated over the preceding 60 months: $t-60$ to $t-1$. Next, we calculate the alpha as the excess return of the strategy $s$ in month $t$ minus the just estimated loadings on the risk factors multiplied with the realized returns in month $t$ on the risk factors:

$$\alpha_{s,t} = r_{s,t} - r_{f,t} - \widehat{\beta}^{MKT}_{s,t} r_{MKT,t} - \widehat{\beta}^{SMB}_{s,t} r_{SMB,t} - \widehat{\beta}^{HML}_{s,t} r_{HML,t} - \widehat{\beta}^{UMD}_{s,t} r_{UMD,t} - \widehat{\beta}^{LIQ}_{s,t} r_{LIQ,t}. \quad (5)$$

Table 6 shows the risk-adjusted results of all liquidity strategies. In both Panel A and B the alpha of the Zeros strategy is the highest, $\alpha = 5.79\%$ and $\alpha = 7.01\%$ respectively. The Zeros strategy is followed by the ILR strategy with an alpha of 1.64% in Panel A and 3.36% in Panel B. Also both these alphas are significantly different from zero. The Effective Tick, Roll, and High-Low strategy have alphas that are either zero or negative.

[insert Table 6 here]

The alphas of the Zeros and ILR strategies are higher than the excess returns in Table 3, which implies that these strategies do not load on these risk factors. In the end, the ranking of the strategies remains the same: Zeros shows the best performance, followed by the ILR strategy.

# 5 Why Zeros Performs Best?

In all previous analyses we find that the Zeros strategy outperforms other liquidity strategies. In this section we examine why the liquidity timing strategy based on the Zeros measure outperforms the strategies using other liquidity measures.

## 5.1 Performance Conditional on Market Returns

To get a better understanding of the differences in performance between the liquidity strategies, we investigate how the strategies perform in extreme market conditions. We sort the market returns of the past 50 years and condition on particular quantiles of their empirical distribution. Table 7 shows the performance of the liquidity strategies conditional on the worst or best x% market returns. In both Panel A and B, only the Zeros strategy achieves positive returns in all cases. This implies that even if the market is decreasing, the Zeros strategy goes long and short in the right assets and makes a profit. In contrast, the ILR strategy shows negative performance when the market is decreasing but shows larger profits when the market is going up. Concluding, the Zeros measure outperforms the other liquidity strategies because it is the only strategy that achieves positive performance in both bull and bear markets.

[insert Table 7 here]

## 5.2 Quality of Predicted Returns

Jagannathan and Ma (2003) show that restricting the weights in an asset allocation problem to be nonnegative, reduces the estimation error in the return prediction parameters. Hence, nonnegativity restrictions should improve the quality of the return predictions, which will increase the performance of the optimal portfolios. The rationale behind improved prediction quality due to nonnegativity constraints is that it has similar effects as shrinking the return predictions. However, if the quality of the predictions is already good and cannot simply be improved by shrinkage, the strategy performance will deteriorate when restrictions are imposed. Thus, by imposing the weights in the asset allocation to be nonnegative, we expect to find that shrinkage effects improve strategy performance based on return predictions of low quality and deteriorate strategy performance using predictions of high quality.

The results in Table 8 show that imposing nonnegativity constraints on the asset weights lead to higher excess returns, lower return volatility, and higher SRs for all strategies, except the Zeros strategy. This implies that the quality of the underlying return predictions is improved for all strategies, except the Zeros strategy. Possibly, the quality of Zeros' return predictions was already high and shrinkage lowers the informational quality. Combining these results with the findings in the previous section, we can say that the positions of the Zeros strategy are often right and the strategy is constrained when introducing short selling restrictions. Although the Zeros strategy no longer shows the best performance when weights are restricted to be positive, it is actually a sign of its ability to long and short the right assets in the unrestricted case.

Instead of restricting the weights of individual assets, DeMiguel, Garlappi, Nogales, and Uppal (2009a) propose to constrain the norm of the asset-weight vector. This generalization nests as special case the approach of Jagannathan and Ma (2003) but at the same time allows for more flexibility. We find qualitatively similar results when we restrict the weights using norm restrictions instead of short-sale restrictions.[17]

[insert Table 8 here]

# 6 Robustness

## 6.1 Benchmarks

In this section we show whether the liquidity timing strategies are related to other timing strategies, which we refer to as benchmarks. The first group of benchmarks predicts returns by conditioning on past return information: (i) the historical average return (Prevailing mean strategy) and (ii) the historical average return and a lagged return

[17] We do not present these results to conserve space, but they are available from the authors upon request.

term (Lagged return strategy). The second group of benchmarks consists of an equally weighted, a volatility timing, and a minimum variance strategy.

Some of the benchmarks that we use are related to existing literature. The prevailing mean model is used in Welch and Goyal (2008) and Campbell and Thompson (2008). A simple extension to the prevailing mean model is the addition of a lagged return term. If monthly returns are correlated over time this term would improve the quality of return predictions. Both benchmarks closely follow the methodology of the liquidity strategies, only the expression in Equation (2) does not contain liquidity variables.

The benchmarks in the second group obtain weights using a different optimization problem than in Equation (3). The equally weighted strategy simply gives all risky assets the same weight. Hence, this strategy is long-only and closely resembles the market portfolio. DeMiguel, Garlappi, and Uppal (2009b) show that sample-based mean-variance models have difficulties outperforming such a naive 1/N portfolio.

The second is a volatility timing strategy, similar to Fleming, Kirby, and Ostdiek (2001). This strategy minimizes the portfolio variance, subject to an ex-ante target portfolio return. To eliminate possible predictive power from the return predictions, we set these predictions equal to a constant, i.e. the sample average return of the risky assets. This ensures that the variation in investment weights of this strategy is fully determined by changes in the conditional covariance matrix. Note that we introduce a look-ahead bias by using the average return over the entire sample, which should improve the performance of this benchmark. The last benchmark is a minimum variance strategy. Similar to the volatility timing strategy, the asset weights depend only on the conditional covariance matrix.

Table A.1 in the Appendix shows that the SR of the benchmarks is lower than the SR of the best performing liquidity strategies in Table 3. The prevailing mean model has a low SR, which is in contrast to the findings of Welch and Goyal (2008). This difference can possibly be explained by the differences in data. We use a shorter data sample and we predict the returns of size portfolios, not of the market portfolio. Furthermore, we make use of a rolling window approach whereas they use an expanding window. The addition of a lagged return term leads to a higher SR in Panels A and B.

Panel C shows the performance of the three strategies that obtain investment weights in a different way. The good performance of the equally weighted strategy is in line with the findings in DeMiguel, Garlappi, and Uppal (2009b). Its SR is 0.28 and its turnover is lower than that of the other strategies, as reflected by the high break-even transaction costs. The results of the volatility timing strategy are worse than the liquidity timing strategies. The last row indicates that minimizing volatility also gives lower performance, hence in the main analysis we are really improving on the quality of the return predictions and are not timing volatility.

## 6.2 Sensitivity Analysis

All previous results are based on target conditional volatility $\sigma_s^* = 10\%$ and Relative Risk Aversion (RRA) $\delta = 5$. Tables A.2 and A.3 in the Appendix provide some sensitivity analysis. Table A.2 in the Appendix shows the results for target conditional volatility equal to 15% and 20%. The SRs decrease slightly but the ranking of the strategies remains the same. The switching fees between the strategies are larger, in absolute value, because the strategies are more volatile, which a risk-averse investor dislikes.

The sensitivity results of the RRA parameter $\delta$ are also presented in Table A.3 in the Appendix. The RRA is set to $\delta = 1$ in Panel A and $\delta = 10$ in Panel B. Similar RRA values are used in Fleming, Kirby, and Ostdiek (2001) and Della-Corte, Sarno, and Tsiakas (2009). The target conditional volatility is $\sigma_s^* = 10\%$ as in the main analysis.

When an investor is less risk averse, Panel A, she is willing to pay a higher switching fee to switch to the high return Zeros strategy. For example, the switching fee from the Roll strategy to the Zeros strategy in column (7) increases to 706.9 basis points per year from 480 in Table 3. When an investor is more risk averse, Panel B, she favors less volatile strategies. The ranking based on economic value remains the same: Zeros performs the best, followed by ILR, Roll, Effective Tick, and High-Low.

### 6.3 Bias Adjustment

It is possible that market microstructure noise affects the analysis of observed returns, see Asparouhova, Bessembinder, and Kalcheva (2010, 2012) . They argue that "*Temporary deviations of trade prices from fundamental values impart bias to estimates of mean returns to individual securities, to differences in mean returns across (equally weighted) portfolios, and to parameters estimated in return regressions.*" To correct for this bias we can either weigh returns by their prior gross return (return-weighted) or by their prior firm value (value-weighted). The return-weighted approach places equal weights on all securities while the value-weighted approach gives more weight to large firms. Since our stocks are equally weighted within the portfolios, the natural choice is the return-weighted approach. Table A.4 in the Appendix shows that the main results remain unchanged when stocks within the portfolios are return weighted instead of equally weighted.

## 7 Conclusion

In this paper we examine which proxy a liquidity timer should use. We build on the findings of Amihud (2002), Jones (2002), Baker and Stein (2004), and Bekaert, Harvey, and Lundblad (2007) who show that liquidity is predictable and that liquidity significantly predicts future excess returns. We investigate liquidity timing by measuring the economic value of liquidity forecasts from different liquidity proxies for investors, who engage in short-horizon asset allocation strategies. The following five low-frequency liquidity measures are considered in our liquidity timing analysis: illiquidity ratio (ILR) (Amihud, 2002), Roll (Roll, 1984), Effective Tick (Holden, 2009, Goyenko, Holden, and Trzcinka, 2009), Zeros (Lesmond, Ogden, and Trzcinka, 1999), and High-Low (Corwin and Schultz, 2012).

In line with Cao, Chen, Liang, and Lo (2013), we find that liquidity timing leads to tangible economic gains. The best performing strategy is based on the Zeros measure of Lesmond, Ogden, and Trzcinka (1999). Its Sharpe ratio is 0.51, over the sample period January 1947 - December 2008. The positive switching fees indicate that a risk-inverse investor will pay a high performance fee to switch from a strategy based on the ILR, Roll, Effective Tick, or High-Low measure to the Zeros strategy. The performance of the liquidity strategies is not driven by an alternative return predictor that is correlated with liquidity. Furthermore the performance of the strategies is not related to a certain subperiod and the ranking based on economic value is robust to different specifications and parameter settings.

The Zeros measure outperforms the other liquidity measures due to its robustness. It achieves positive performance even when the market is going down. The performance of the Zeros measure decreases when restricting the asset allocation weights and shrinking the return predictions. This implies that also the most extreme weights of the Zeros strategy are based on return predictions that are in the right direction.

Our ranking based on economic value differs from the ranking of Goyenko, Holden, and Trzcinka (2009), which is based on statistical criteria. They find that Effective Tick is good in measuring effective and realized spread and ILR is good in measuring price impact. We find that Zeros is the best proxy to use for liquidity timing in contrast to Effective Tick, which seems not relevant for predicting excess returns. This implies that low frequency measures that are a good proxy for high frequency transaction costs do not necessarily lead to the highest economic value in a liquidity timing strategy.

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## Table 1
## Liquidity statistics for size portfolios

The table presents time series characteristics for monthly liquidity series. The sample period is January 1947 to December 2008. Size portfolios are formed based on previous month market capitalization ($M_{i,t-1}$). The liquidity measures are: ILR (Amihud, 2002), Roll (Roll, 1984), Effective Tick (Holden, 2009, Goyenko et al., 2009), Zeros (Lesmond et al., 1999), and High-Low (Corwin and Schultz, 2012). Panel A shows the liquidity characteristics of the equally weighted market portfolio over the entire sample period. Panel B, C, and D show the liquidity characteristics for size portfolio 1, 5, and 10, respectively, where portfolio 1 consists of the smallest firms and portfolio 10 of the largest firms. Panel E, F, and G show the liquidity characteristics of the equally weighted market portfolio for three subperiods.

| | ILR | Eff. Tick | Roll | Zeros | High-Low |
|---|---|---|---|---|---|
| *Panel A: Market portfolio* | | | | | |
| Average | 2.904 | 0.0077 | 0.0090 | 0.151 | 0.0065 |
| Median | 2.641 | 0.0082 | 0.0083 | 0.169 | 0.0062 |
| Volatility | 1.358 | 0.0031 | 0.0028 | 0.061 | 0.0014 |
| *Panel B: Size portfolio 1, small firms* | | | | | |
| Average | 13.294 | 0.0147 | 0.0128 | 0.227 | 0.0101 |
| Median | 11.868 | 0.0160 | 0.0124 | 0.249 | 0.0101 |
| Volatility | 6.628 | 0.0055 | 0.0032 | 0.082 | 0.0023 |
| *Panel C: Size portfolio 5* | | | | | |
| Average | 1.562 | 0.0074 | 0.0089 | 0.152 | 0.0063 |
| Median | 1.386 | 0.0079 | 0.0083 | 0.168 | 0.0059 |
| Volatility | 0.977 | 0.0031 | 0.0031 | 0.065 | 0.0015 |
| *Panel D: Size portfolio 10, large firms* | | | | | |
| Average | 0.118 | 0.0034 | 0.0062 | 0.092 | 0.0047 |
| Median | 0.106 | 0.0036 | 0.0053 | 0.098 | 0.0044 |
| Volatility | 0.100 | 0.0014 | 0.0034 | 0.045 | 0.0017 |
| *Panel E: Market portfolio (1947-1967)* | | | | | |
| Average | 2.537 | 0.0089 | 0.0085 | 0.183 | 0.0061 |
| Median | 2.388 | 0.0083 | 0.0080 | 0.181 | 0.0059 |
| Volatility | 0.725 | 0.0018 | 0.0024 | 0.029 | 0.0009 |
| *Panel F: Market portfolio (1968-1988)* | | | | | |
| Average | 3.258 | 0.0092 | 0.0086 | 0.172 | 0.0067 |
| Median | 2.743 | 0.0090 | 0.0083 | 0.171 | 0.0064 |
| Volatility | 1.752 | 0.0018 | 0.0018 | 0.028 | 0.0010 |
| *Panel G: Market portfolio (1989-2008)* | | | | | |
| Average | 2.916 | 0.0049 | 0.0098 | 0.096 | 0.0068 |
| Median | 2.910 | 0.0049 | 0.0086 | 0.080 | 0.0061 |
| Volatility | 1.296 | 0.0033 | 0.0038 | 0.074 | 0.0020 |

## Table 2
## Excess return statistics for size portfolios

The table presents descriptive characteristics for monthly excess returns. All reported values are annualized. The sample period is January 1947 to December 2008 and is divided into three subperiods. Size portfolios are formed based on previous month market capitalization ($M_{i,t-1}$). Panel A shows the characteristics of the equally weighted market portfolio. Panel B, C, and D show the characteristics for size portfolio 1, 5, and 10, respectively, where portfolio 1 consists of the smallest firms and portfolio 10 of the largest firms.

| | Entire Sample | 1947-1967 | 1968-1988 | 1989-2008 |
|---|---|---|---|---|
| *Panel A: Market portfolio* | | | | |
| Average | 7.50 % | 12.28 % | 4.98 % | 5.30 % |
| Median | 12.58 % | 17.17 % | 5.23 % | 10.03 % |
| Volatility | 17.06 % | 14.22 % | 20.45 % | 15.82 % |
| *Panel B: Size portfolio 1, small firms* | | | | |
| Average | 8.42 % | 13.72 % | 9.24 % | 2.32 % |
| Median | 12.29 % | 16.10 % | 12.03 % | 7.22 % |
| Volatility | 20.47 % | 17.86 % | 24.50 % | 18.21 % |
| *Panel C: Size portfolio 5* | | | | |
| Average | 7.75 % | 12.28 % | 5.14 % | 5.90 % |
| Median | 11.56 % | 17.86 % | 5.85 % | 10.14 % |
| Volatility | 18.12 % | 14.98 % | 21.56 % | 17.18 % |
| *Panel D: Size portfolio 10, large firms* | | | | |
| Average | 5.19 % | 10.24 % | 1.51 % | 3.96 % |
| Median | 10.17 % | 13.85 % | 4.01 % | 9.45 % |
| Volatility | 14.35 % | 12.18 % | 16.65 % | 13.77 % |

## Table 3
## Performance of dynamic asset allocation strategies

The table presents dynamic strategy results for the different liquidity measures. The dynamic asset allocation strategies are based on a mean-variance framework where the investor maximizes the conditional expected return subject to a target conditional volatility ($\sigma_s^* = 10\%$). The return predictions of the risky assets in Panel A are based on a 10-year rolling window and in Panel B are based on the average prediction of a 5, 10, and 20 year rolling window. The weights of the risky assets are not restricted. The sample period is January 1947 to December 2008, and the strategies start trading in January 1967. The liquidity measures are: ILR (Amihud, 2002), Roll (Roll, 1984), Effective Tick (Holden, 2009, Goyenko et al., 2009), Zeros (Lesmond et al., 1999), and High-Low (Corwin and Schultz, 2012). All numbers are annual, except for the break-even costs $\tau_1$ and $\tau_A$ that are reported in basis points per trade. The switching fee is the maximum performance fee a risk-averse investor is willing to pay to switch from one strategy to another. It is expressed in annual basis points and is computed based on a relative risk aversion parameter of 5. $\tau_1$ shows the break-even costs under the assumption that all assets have the same transaction costs. $\tau_A$ shows the break-even costs in terms of large firms, whereby the liquidity differences between small and large firms are taken into account. If the excess return of a strategy is negative we do not compute break-even transaction costs and report the symbol "-". The Manipulation-proof Performance Measure (MPPM) shows the strategies' premium return after adjusting for risk and can be interpreted as the annualized continuously compounded excess return certainty equivalent of the strategy (Goetzmann et al., 2007).

| | | Switching fee | | | | | | Excess | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | SR | ILR | Eff. Tick | Roll | Zeros | $\tau_1$ | $\tau_A$ | return | Volatility | MPPM |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| *Panel A. 10Y window* | | | | | | | | | | |
| ILR | 0.13 | | | | | 1.4 | 0.6 | 1.50 % | 11.88 % | 0.08 % |
| Eff.Tick | -0.07 | -206.3 | | | | - | - | -0.79 % | 11.41 % | -2.09 % |
| Roll | -0.04 | -192.2 | 13.8 | | | - | - | -0.49 % | 11.77 % | -1.86 % |
| Zeros | 0.38 | 287.3 | 494.1 | 480.0 | | 4.2 | 2.0 | 4.55 % | 12.05 % | 3.00 % |
| High-Low | -0.16 | -349.7 | -143.7 | -157.5 | -637.5 | - | - | -1.94 % | 11.99 % | -3.38 % |
| *Panel B. Combination of windows* | | | | | | | | | | |
| ILR | 0.27 | | | | | 2.8 | 1.3 | 3.14 % | 11.54 % | 1.76 % |
| Eff.Tick | -0.13 | -477.7 | | | | - | - | -1.54 % | 11.81 % | -2.95 % |
| Roll | 0.06 | -245.6 | 232.5 | | | 0.8 | 0.4 | 0.72 % | 11.69 % | -0.63 % |
| Zeros | 0.51 | 264.8 | 742.5 | 510.0 | | 5.5 | 2.6 | 6.04 % | 11.79 % | 4.47 % |
| High-Low | -0.09 | -455.6 | 22.5 | -210.0 | -720.0 | - | - | -1.15 % | 12.15 % | -2.63 % |

## Table 4
## Performance of dynamic asset allocation strategies for single control variables

The table presents dynamic strategy results for the different control variables. Columns (1) - (3) show results of strategies that condition on a constant and only one of the 11 control variables: dividend price ratio (d/p), dividend yield (d/y), earnings price ratio (e/p), dividend payout ratio (d/e), stock variance (svar), book-to-market ratio (b/m), term-spread (tms), default yield spread (dfy), default return spread (dfr), inflation (infl), and net equity expansion (ntis). The last strategy (all) contains all control variables, except the dividend price ratio. Columns (4) - (8) show Sharpe ratios of strategies that condition both on a constant, one control variable, and one liquidity variable. The dynamic asset allocation strategies are based on a mean-variance framework where the investor maximizes the conditional expected return subject to a target conditional volatility ($\sigma_s^* = 10\%$). The return predictions of the risky assets in Panel A are based on a 10-year rolling window and in Panel B are based on the average prediction of a 5, 10, and 20 year rolling window. The weights of the risky assets are not restricted. The sample period is January 1947 to December 2008, and the strategies start trading in January 1967. All numbers are annual, except for the break-even costs $\tau_1$ and $\tau_A$ that are reported in basis points per trade. $\tau_1$ shows the break-even costs under the assumption that all assets have the same transaction costs. $\tau_A$ shows the break-even costs in terms of large firms, whereby the liquidity differences between small and large firms are taken into account.

| | without liquidity | | | with liquidity | | | | |
|---|---|---|---|---|---|---|---|---|
| | SR<br>(1) | $\tau_1$<br>(2) | $\tau_A$<br>(3) | ILR<br>(4) | Eff. Tick<br>(5) | Roll<br>(6) | Zeros<br>(7) | High-Low<br>(8) |
| *Panel A. 10Y window* | | | | | | | | |
| d/p | 0.13 | 4.7 | 2.2 | 0.21 | -0.12 | -0.10 | 0.19 | -0.22 |
| d/y | 0.19 | 7.1 | 3.3 | 0.23 | -0.11 | -0.06 | 0.21 | -0.14 |
| e/p | 0.08 | 3.0 | 1.4 | 0.15 | 0.06 | -0.13 | 0.26 | -0.23 |
| d/e | 0.14 | 5.1 | 2.3 | 0.16 | -0.05 | -0.06 | 0.42 | -0.20 |
| svar | 0.04 | 1.3 | 0.6 | 0.16 | 0.06 | -0.09 | 0.22 | -0.30 |
| b/m | 0.02 | 0.9 | 0.4 | 0.08 | 0.04 | -0.13 | 0.25 | -0.14 |
| tms | 0.21 | 6.9 | 3.2 | 0.11 | -0.12 | -0.08 | 0.36 | -0.26 |
| dfy | 0.21 | 7.1 | 3.3 | 0.18 | 0.04 | 0.00 | 0.26 | -0.11 |
| dfr | 0.17 | 2.9 | 1.3 | 0.17 | -0.05 | 0.00 | 0.39 | -0.12 |
| infl | 0.11 | 2.3 | 1.1 | 0.06 | -0.03 | -0.04 | 0.37 | -0.17 |
| ntis | 0.42 | 14.5 | 6.7 | 0.22 | -0.01 | 0.14 | 0.47 | -0.02 |
| all | 0.30 | 4.6 | 2.2 | 0.27 | -0.05 | 0.02 | 0.21 | -0.23 |
| *Panel B. Combination of windows* | | | | | | | | |
| d/p | 0.19 | 6.7 | 3.1 | 0.20 | -0.13 | -0.08 | 0.42 | -0.18 |
| d/y | 0.28 | 9.5 | 4.4 | 0.28 | -0.05 | -0.02 | 0.43 | -0.10 |
| e/p | 0.15 | 5.0 | 2.3 | 0.29 | 0.07 | -0.07 | 0.44 | -0.21 |
| d/e | 0.09 | 3.6 | 1.7 | 0.33 | -0.05 | 0.06 | 0.54 | -0.16 |
| svar | 0.06 | 1.9 | 0.9 | 0.27 | -0.04 | 0.03 | 0.34 | -0.24 |
| b/m | 0.07 | 2.7 | 1.3 | 0.16 | -0.04 | -0.12 | 0.47 | -0.12 |
| tms | 0.18 | 5.8 | 2.7 | 0.29 | -0.07 | 0.03 | 0.45 | -0.20 |
| dfy | 0.26 | 8.3 | 3.8 | 0.22 | -0.03 | 0.06 | 0.44 | -0.07 |
| dfr | 0.15 | 2.5 | 1.2 | 0.29 | -0.11 | 0.07 | 0.46 | -0.07 |
| infl | 0.14 | 3.2 | 1.5 | 0.24 | -0.11 | 0.06 | 0.47 | -0.10 |
| ntis | 0.42 | 13.6 | 6.2 | 0.40 | -0.03 | 0.24 | 0.62 | -0.02 |
| all | 0.25 | 3.6 | 1.7 | 0.21 | 0.10 | -0.01 | 0.30 | -0.24 |

## Table 5
## Performance of dynamic asset allocation strategies for single cross-sectional control variables

The table presents dynamic strategy results for the different control variables. Columns (1) - (3) show results of strategies that condition on a constant and only one of the 4 cross-sectional control variables: excess market return (Mkt-Rf), Small-minus-Big (SMB), High-minus-Low (HML), and momentum (Mom). The last strategy (all) contains all control variables. Columns (4) - (8) show Sharpe ratios of strategies that condition both on a constant, one control variable, and one liquidity variable. The dynamic asset allocation strategies are based on a mean-variance framework where the investor maximizes the conditional expected return subject to a target conditional volatility ($\sigma_s^* = 10\%$). The return predictions of the risky assets in Panel A are based on a 10-year rolling window and in Panel B are based on the average prediction of a 5, 10, and 20 year rolling window. The weights of the risky assets are not restricted. The sample period is January 1947 to December 2008, and the strategies start trading in January 1967. All numbers are annual, except for the break-even costs $\tau_1$ and $\tau_A$ that are reported in basis points per trade. $\tau_1$ shows the break-even costs under the assumption that all assets have the same transaction costs. $\tau_A$ shows the break-even costs in terms of large firms, whereby the liquidity differences between small and large firms are taken into account. If the excess return of a strategy is negative we do not compute break-even transaction costs and report the symbol "-".

| | without liquidity | | | with liquidity | | | | |
|---|---|---|---|---|---|---|---|---|
| | SR | $\tau_1$ | $\tau_A$ | ILR | Eff. Tick | Roll | Zeros | High-Low |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *Panel A. 10Y window* | | | | | | | | |
| Mkt-Rf | 0.41 | 7.4 | 3.4 | 0.32 | 0.20 | 0.04 | 0.57 | -0.13 |
| SMB | 0.21 | 4.2 | 1.9 | 0.13 | -0.03 | -0.02 | 0.37 | -0.22 |
| HML | 0.08 | 1.8 | 0.8 | 0.18 | -0.12 | -0.10 | 0.37 | -0.20 |
| Mom | 0.34 | 6.9 | 3.2 | 0.11 | -0.05 | 0.03 | 0.47 | -0.14 |
| all | 0.47 | 6.0 | 2.8 | 0.31 | 0.20 | 0.11 | 0.59 | -0.15 |
| *Panel B. Combination of windows* | | | | | | | | |
| Mkt-Rf | 0.38 | 7.1 | 3.2 | 0.36 | 0.12 | 0.16 | 0.72 | -0.01 |
| SMB | 0.15 | 3.2 | 1.4 | 0.24 | -0.07 | 0.09 | 0.50 | -0.13 |
| HML | -0.03 | - | - | 0.36 | -0.16 | 0.01 | 0.48 | -0.10 |
| Mom | 0.28 | 5.8 | 2.7 | 0.25 | -0.07 | 0.13 | 0.55 | -0.08 |
| all | 0.37 | 5.0 | 2.3 | 0.34 | 0.14 | 0.22 | 0.68 | -0.03 |

## Table 6
## Risk-adjusted results

The table presents the risk-adjusted results for the different liquidity strategies. The dynamic asset allocation strategies are based on a mean-variance framework where the investor maximizes the conditional expected return subject to a target conditional volatility ($\sigma_s^* = 10\%$). The return predictions of the risky assets in Panel A are based on a 10-year rolling window and in Panel B are based on the average prediction of a 5, 10, and 20 year rolling window. The weights of the risky assets are not restricted. The sample period is January 1947 to December 2008, and the strategies start trading in January 1967. The liquidity measures are: ILR (Amihud, 2002), Roll (Roll, 1984), Effective Tick (Holden, 2009, Goyenko et al., 2009), Zeros (Lesmond et al., 1999), and High-Low (Corwin and Schultz, 2012). We calculate the alpha as the excess return of the strategy minus the estimated loadings on the risk factors multiplied with the realized returns on the risk factors, see Equation 5 on page 21. The sensitivity of the strategy returns to each risk factor is estimated over the preceding 60 months. The risk factors that we take into account are: the excess market return, the SMB factor, the HML factor, the Carhart (1997) momentum factor, and the Pástor and Stambaugh (2003) traded liquidity factor. All numbers are annualized.

| | Alpha<br>(1) | Volatility<br>(2) | t-stat<br>(3) |
|---|---|---|---|
| *Panel A. 10Y window* | | | |
| ILR | 1.64 % | 12.94 % | 2.65 |
| Eff.Tick | -1.14 % | 11.80 % | -2.01 |
| Roll | -0.75 % | 12.47 % | -1.25 |
| Zeros | 5.79 % | 12.72 % | 9.50 |
| High-Low | -3.58 % | 12.62 % | -5.92 |
| *Panel B. Combination of windows* | | | |
| ILR | 3.36 % | 12.48 % | 5.62 |
| Eff.Tick | -2.12 % | 12.40 % | -3.56 |
| Roll | 0.70 % | 12.43 % | 1.17 |
| Zeros | 7.01 % | 12.63 % | 11.59 |
| High-Low | -2.98 % | 12.72 % | -4.90 |

## Table 7
## Performance of liquidity strategy conditional on market returns

The table presents the monthly return performance of the dynamic asset allocation strategies conditional on a particular quantile of the market returns empirical distribution. We obtain the market returns empirical distribution by sorting the market returns of the past 50 years. We investigate the performance of the liquidity strategies for the months where the market returns belong to the top and bottom quantiles of their empirical distribution. All presented numbers are monthly.

| | bottom 1% (1) | bottom 5% (2) | bottom 10% (3) | top 10% (4) | top 5% (5) | top 1% (6) |
|---|---|---|---|---|---|---|
| *Panel A. 10Y window* | | | | | | |
| ILR | -3.18 % | -2.22 % | -0.94 % | 0.83 % | 2.20 % | 3.27 % |
| Eff.Tick | -0.54 % | -1.32 % | -0.42 % | 0.36 % | 0.35 % | 0.68 % |
| Roll | -3.09 % | -2.09 % | -0.08 % | 0.40 % | 0.77 % | 0.49 % |
| Zeros | 1.04 % | 0.26 % | 0.70 % | 0.54 % | 1.29 % | 2.30 % |
| High-Low | -1.97 % | -0.29 % | 0.30 % | 0.58 % | 0.78 % | 0.57 % |
| *Panel B. Combination of windows* | | | | | | |
| ILR | -1.35 % | -0.79 % | -0.42 % | 1.00 % | 1.64 % | 2.14 % |
| Eff.Tick | -0.02 % | -1.59 % | -0.72 % | 0.41 % | 0.20 % | -0.13 % |
| Roll | -2.67 % | -1.50 % | 0.18 % | 0.21 % | 0.63 % | 0.46 % |
| Zeros | 2.50 % | 1.22 % | 1.11 % | 0.56 % | 1.14 % | 1.76 % |
| High-Low | -1.43 % | -0.12 % | 0.42 % | 0.47 % | 0.96 % | 1.45 % |

## Table 8
## Performance of dynamic asset allocation strategies with nonnegative weights

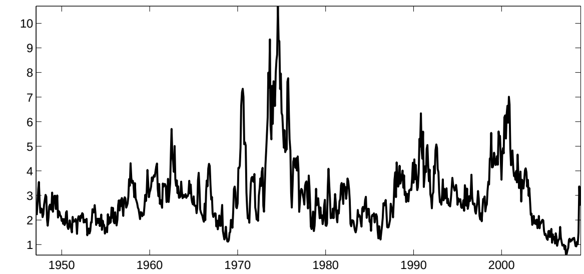
The table presents dynamic strategy results for the different liquidity measures. The dynamic asset allocation strategies are based on a mean-variance framework where the investor maximizes the conditional expected return subject to a target conditional volatility ($\sigma_s^* = 10\%$). The return predictions of the risky assets in Panel A are based on a 10-year rolling window and in Panel B are based on the average prediction of a 5, 10, and 20 year rolling window. The weights of the risky assets are restricted to be between $0 < w < 1$. The sample period is January 1947 to December 2008, and the strategies start trading in January 1967. The liquidity measures are: ILR (Amihud, 2002), Roll (Roll, 1984), Effective Tick (Holden, 2009, Goyenko et al., 2009), Zeros (Lesmond et al., 1999), and High-Low (Corwin and Schultz, 2012). All numbers are annual, except for the break-even costs $\tau_1$ and $\tau_A$ that are reported in basis points per trade. The switching fee is the maximum performance fee a risk-averse investor is willing to pay to switch from one strategy to another. It is expressed in annual basis points and is computed based on a relative risk aversion parameter of 5. $\tau_1$ shows the break-even costs under the assumption that all assets have the same transaction costs. $\tau_A$ shows the break-even costs in terms of large firms, whereby the liquidity differences between small and large firms are taken into account.

| | | Switching fee | | | | | | Excess | |
|---|---|---|---|---|---|---|---|---|---|
| | SR | ILR | Eff. Tick | Roll | Zeros | $\tau_1$ | $\tau_A$ | return | Volatility |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| *Panel A. 10Y window* | | | | | | | | | |
| ILR | 0.35 | | | | | 42.2 | 16.9 | 3.89 % | 11.03 % |
| Eff.Tick | 0.24 | -109.7 | | | | 30.0 | 12.2 | 2.53 % | 10.54 % |
| Roll | 0.26 | -92.8 | 17.1 | | | 29.5 | 12.1 | 2.80 % | 10.75 % |
| Zeros | 0.26 | -91.9 | 18.3 | 1.2 | | 33.4 | 14.0 | 2.78 % | 10.69 % |
| High-Low | 0.27 | -84.4 | 25.5 | 7.5 | 7.0 | 31.1 | 13.8 | 2.83 % | 10.63 % |
| *Panel B. Combination of windows* | | | | | | | | | |
| ILR | 0.34 | | | | | 40.7 | 15.9 | 3.74 % | 10.87 % |
| Eff.Tick | 0.24 | -97.5 | | | | 30.1 | 12.3 | 2.57 % | 10.49 % |
| Roll | 0.28 | -69.4 | 27.7 | | | 32.0 | 13.0 | 2.95 % | 10.72 % |
| Zeros | 0.29 | -50.6 | 47.3 | 18.7 | | 35.6 | 14.6 | 3.14 % | 10.69 % |
| High-Low | 0.29 | -57.2 | 40.1 | 11.2 | -7.5 | 33.1 | 14.1 | 3.06 % | 10.69 % |

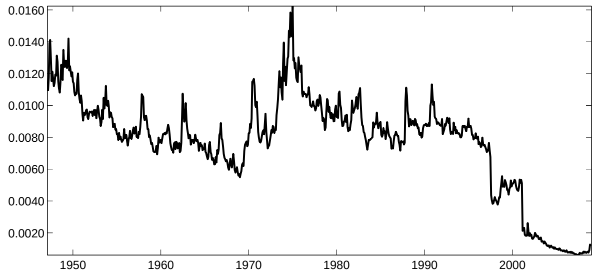
# Figure 1
# Liquidity measures

The figure shows the liquidity measures for the market over time. The market series is computed as the cross-sectional equally-weighted average of individual stock liquidity measures. The sample period is January 1947 to December 2008. The low-frequency liquidity measures are: ILR (Amihud, 2002), Roll (Roll, 1984), Effective Tick (Holden, 2009, Goyenko et al., 2009), and Zeros (Lesmond et al., 1999), and High-Low (Corwin and Schultz, 2012).

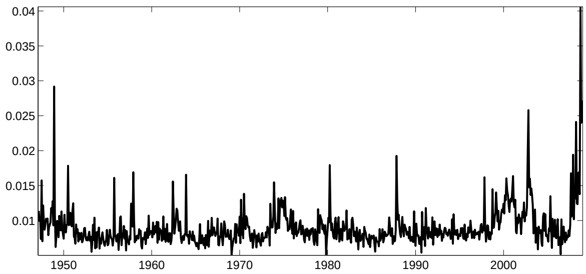
**(a) Illiquidity ratio**



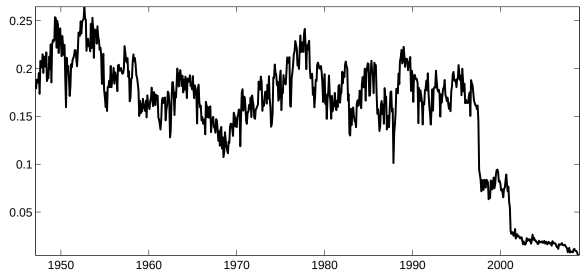

**(b) Effective Tick**



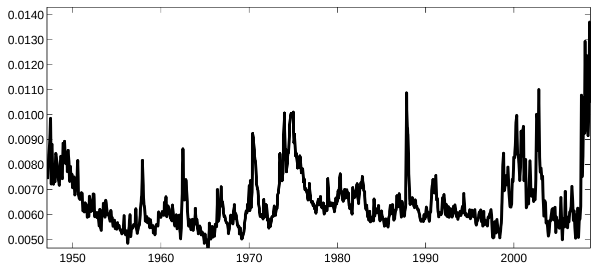

**(c) Roll**




**(d) Zeros**

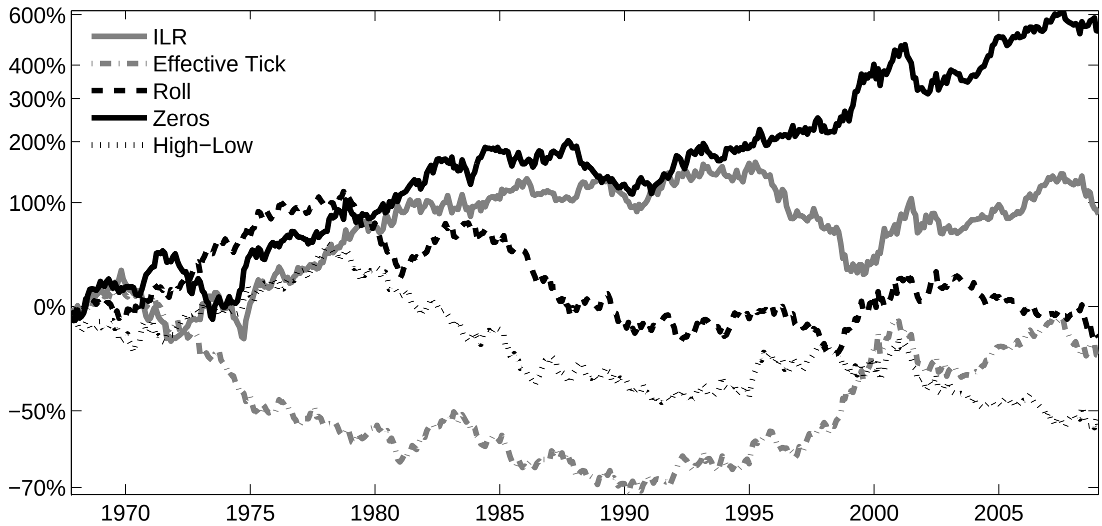



**(e) High-Low**



## Figure 2
## Cumulative returns of dynamic asset allocation strategies

The figure shows the cumulative log returns of the dynamic asset allocation strategies that use liquidity information to predict excess returns. The low-frequency liquidity measures are: ILR (Amihud, 2002), Roll (Roll, 1984), Effective Tick (Holden, 2009, Goyenko et al., 2009), Zeros (Lesmond et al., 1999), and High-Low (Corwin and Schultz, 2012). The dynamic asset allocation strategies are based on a mean-variance framework where the investor maximizes the conditional expected return subject to a target conditional volatility. The return predictions of the risky assets are based on a 10-year rolling window.



# Appendix

**Table A.1**
**Benchmark results**

The table presents the performance of the benchmark strategies. These strategies do not condition on liquidity information to obtain investment weights. The strategies in Panel A and B condition on past return information using either a 10 year rolling window or a combination of three rolling windows, respectively. The strategies in Panel C solve a different optimization problem to obtain the risky asset weights. The Equally weighted strategy gives all available stocks the same weight. Volatility timing minimizes the conditional expected portfolio variance subject to a target conditional return ($\mu_s^* = 10\%$), i.e. $\min_{w_t} \left\{ \sigma^2_{s,t+1|1} = w_t' \Sigma_{t+1|t} w_t \right\}$ s.t. $\mu_s^* = w_t' r_{k,t+1|t} + (1 - w_t' \mathbf{1}) r_{f,t}$. The "return predictions" $\left( r_{k,t+1|t} \right)$ are set equal to their unconditional averages, such that the weights only depend on the conditional covariance matrix. The minimum variance portfolio finds the portfolio with the lowest possible variance, again the investment weights only depend on the conditional covariance matrix. The weights of the risky assets are in all strategies unrestricted and all strategies start trading in January 1967.

| | SR (1) | $\tau_1$ (2) | $\tau_A$ (3) | Excess return (4) | Volatility (5) |
|---|---|---|---|---|---|
| *Panel A. 10Y window* | | | | | |
| Prevailing mean | 0.15 | 6.2 | 2.8 | 1.74 % | 11.63 % |
| Lagged return | 0.18 | 2.0 | 0.9 | 2.19 % | 12.46 % |
| *Panel B. Combination of windows* | | | | | |
| Prevailing mean | 0.06 | 3.2 | 1.5 | 0.76 % | 11.97 % |
| Lagged return | 0.17 | 2.0 | 0.9 | 2.07 % | 12.49 % |
| *Panel C. Alternative optimization function* | | | | | |
| Equally weighted | 0.28 | 454.2 | 207.2 | 5.14 % | 18.30 % |
| Volatility timing | 0.16 | 15.1 | 6.8 | 1.88 % | 12.05 % |
| Minimum variance | 0.15 | 15.8 | 7.5 | 2.37 % | 15.36 % |

## Table A.2
## Different target conditional volatility

The table presents dynamic strategy results for the different liquidity measures. The dynamic asset allocation strategies are based on a mean-variance framework where the investor maximizes the conditional expected return subject to a target conditional volatility ($\sigma_s^*$). In Panel A $\sigma_s^* = 15\%$ and in Panel B $\sigma_s^* = 20\%$. The return predictions of the risky assets are based either on a 10-year rolling window or on the average prediction of a 5, 10, and 20 year rolling window. The weights of the risky assets are not restricted. The sample period is January 1947 to December 2008, and the strategies start trading in January 1967. The liquidity measures are: ILR (Amihud, 2002), Roll (Roll, 1984), Effective Tick (Holden, 2009, Goyenko et al., 2009), Zeros (Lesmond et al., 1999), and High-Low (Corwin and Schultz, 2012). All numbers are annual, except for the break-even costs $\tau_1$ and $\tau_A$ that are reported in basis points per trade. The switching fee is the maximum performance fee a risk-averse investor is willing to pay to switch from one strategy to another. It is expressed in annual basis points and is computed based on a relative risk aversion parameter of 5. $\tau_1$ shows the break-even costs under the assumption that all assets have the same transaction costs. $\tau_A$ shows the break-even costs in terms of large firms, whereby the liquidity differences between small and large firms are taken into account. If the excess return of a strategy is negative we do not compute break-even transaction costs and report the symbol "-".

| | SR (1) | Switching fee ILR (2) | Eff. Tick (3) | Roll (4) | Zeros (5) | $\tau_1$ (6) | $\tau_A$ (7) | Excess return (8) | Volatility (9) |
|---|---|---|---|---|---|---|---|---|---|
| **Panel A. Target conditional volatility $\sigma_s^* = 15\%$** | | | | | | | | | |
| *10Y window* | | | | | | | | | |
| ILR | 0.10 | | | | | 1.1 | 0.5 | 1.72 % | 17.81 % |
| Eff.Tick | -0.10 | -288.3 | | | | - | - | -1.67 % | 17.12 % |
| Roll | -0.07 | -283.1 | 5.6 | | | - | - | -1.25 % | 17.65 % |
| Zeros | 0.35 | 422.8 | 712.5 | 706.9 | | 3.9 | 1.9 | 6.32 % | 18.08 % |
| High-Low | -0.19 | -530.6 | -240.9 | -247.5 | -953.4 | - | - | -3.43 % | 17.99 % |
| *Combination of windows* | | | | | | | | | |
| ILR | 0.24 | | | | | 2.5 | 1.1 | 4.23 % | 17.31 % |
| Eff.Tick | -0.16 | -729.4 | | | | - | - | -2.83 % | 17.71 % |
| Roll | 0.03 | -374.5 | 353.7 | | | 0.5 | 0.2 | 0.57 % | 17.54 % |
| Zeros | 0.49 | 386.2 | 1114.7 | 759.4 | | 5.2 | 2.4 | 8.62 % | 17.69 % |
| High-Low | -0.12 | -711.6 | 18.5 | -335.6 | -1098.0 | - | - | -2.28 % | 18.23 % |
| **Panel B. Target conditional volatility $\sigma_s^* = 20\%$** | | | | | | | | | |
| *10Y window* | | | | | | | | | |
| ILR | 0.07 | | | | | 0.8 | 0.4 | 1.57 % | 23.75 % |
| Eff.Tick | -0.13 | -357.0 | | | | - | - | -2.88 % | 22.82 % |
| Roll | -0.10 | -371.3 | -13.6 | | | - | - | -2.35 % | 23.53 % |
| Zeros | 0.32 | 552.7 | 912.2 | 925.3 | | 3.6 | 1.7 | 7.73 % | 24.11 % |
| High-Low | -0.22 | -714.4 | -355.8 | -342.2 | -1267.5 | - | - | -5.25 % | 23.99 % |
| *Combination of windows* | | | | | | | | | |
| ILR | 0.22 | | | | | 2.2 | 1.0 | 4.97 % | 23.08 % |
| Eff.Tick | -0.19 | -988.4 | | | | - | - | -4.44 % | 23.61 % |
| Roll | 0.00 | -508.8 | 478.6 | | | 0.2 | 0.1 | 0.07 % | 23.38 % |
| Zeros | 0.46 | 497.8 | 1485.9 | 1007.3 | | 4.8 | 2.3 | 10.89 % | 23.59 % |
| High-Low | -0.15 | -987.9 | 4.7 | -476.5 | -1486.9 | - | - | -3.76 % | 24.31 % |

## Table A.3
## Different relative risk aversion parameter

The table presents the switching fees of the dynamic strategies based on the different liquidity measures. The dynamic asset allocation strategies are based on a mean-variance framework where the investor maximizes the conditional expected return subject to a target conditional volatility ($\sigma_s^* = 10\%$). The weights of the risky assets are not restricted. The sample period is January 1947 through December 2008, and the strategies start trading in January 1967. The liquidity measures are: ILR (Amihud, 2002), Roll (Roll, 1984), Effective Tick (Holden, 2009, Goyenko et al., 2009), Zeros (Lesmond et al., 1999), and High-Low (Corwin and Schultz, 2012). The switching fee is the maximum performance fee a risk-averse investor is willing to pay to switch from one strategy to another. It is expressed in annual basis points and requires a value for the relative risk aversion (RRA) parameter (in the main results it is set equal to 5). In Panel A the RRA is equal to 1 and in Panel B it is equal to 10.

**Panel A. RRA parameter $\delta = 1$**

| | Switching fee | | | |
|---|---|---|---|---|
| | ILR | Eff. Tick | Roll | Zeros |
| *10Y window* | | | | |
| ILR | | | | |
| Eff.Tick | -227.8 | | | |
| Roll | -197.3 | 30.5 | | |
| Zeros | 296.0 | 523.9 | 493.6 | |
| High-Low | -344.5 | -116.6 | -146.9 | -640.8 |
| *Combination of windows* | | | | |
| ILR | | | | |
| Eff.Tick | -465.1 | | | |
| Roll | -238.0 | 226.9 | | |
| Zeros | 276.6 | 742.0 | 514.9 | |
| High-Low | -425.9 | 39.3 | -187.8 | -703.1 |

**Panel B. RRA parameter $\delta = 10$**

| | Switching fee | | | |
|---|---|---|---|---|
| | ILR | Eff. Tick | Roll | Zeros |
| *10Y window* | | | | |
| ILR | | | | |
| Eff.Tick | -178.6 | | | |
| Roll | -187.5 | -7.5 | | |
| Zeros | 275.6 | 455.6 | 463.1 | |
| High-Low | -358.1 | -177.7 | -171.6 | -633.8 |
| *Combination of windows* | | | | |
| ILR | | | | |
| Eff.Tick | -494.1 | | | |
| Roll | -254.1 | 239.1 | | |
| Zeros | 249.4 | 743.0 | 503.9 | |
| High-Low | -494.1 | 2.3 | -240.0 | -743.4 |

## Table A.4
## Strategy performance based on bias adjustment

This table shows the counterpart of the main results table. The only difference is that all individual stocks are weighted (within the 10 size portfolios) by their previous month gross return, instead of equally weighted. This adjustment is suggested in Asparouhova, Bessembinder, and Kalcheva (2013) to deal with noisy security prices.

| | | Switching fee | | | | | | Excess | |
|---|---|---|---|---|---|---|---|---|---|
| | SR | ILR | Eff. Tick | Roll | Zeros | $\tau_1$ | $\tau_A$ | return | Volatility |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| *Panel A. 10Y window* | | | | | | | | | |
| ILR | 0.08 | | | | | 0.9 | 0.4 | 0.96 % | 11.88 % |
| Eff.Tick | 0.02 | -31.6 | | | | 0.3 | 0.2 | 0.27 % | 11.08 % |
| Roll | -0.02 | -113.2 | -80.6 | | | - | - | -0.24 % | 11.73 % |
| Zeros | 0.33 | 286.4 | 318.7 | 400.3 | | 3.7 | 1.8 | 3.98 % | 12.03 % |
| High-Low | -0.15 | -267.2 | -234.4 | -150.0 | -553.1 | - | - | -1.74 % | 11.78 % |
| *Panel B. Combination of windows* | | | | | | | | | |
| ILR | 0.23 | | | | | 2.3 | 1.1 | 2.66 % | 11.61 % |
| Eff.Tick | -0.08 | -348.3 | | | | - | - | -0.87 % | 11.57 % |
| Roll | 0.11 | -139.9 | 208.4 | | | 1.2 | 0.6 | 1.28 % | 11.69 % |
| Zeros | 0.45 | 247.3 | 595.8 | 387.2 | | 4.8 | 2.3 | 5.27 % | 11.69 % |
| High-Low | -0.08 | -371.7 | -23.4 | -230.6 | -619.0 | - | - | -0.98 % | 11.83 % |

## Table A.5
## Performance of dynamic asset allocation strategies with control variables

The table presents dynamic strategy results for the different liquidity measures. All strategies condition besides liquidity information on 10 control variables: dividend yield, earnings price ratio, dividend payout ratio, stock variance, book-to-market ratio, net equity expansion, term-spread, default yield spread, default return spread, and inflation. Note that the dividend price ratio is excluded to avoid singularity issues. The dynamic asset allocation strategies are based on a mean-variance framework where the investor maximizes the conditional expected return subject to a target conditional volatility ($\sigma_s^* = 10\%$). The return predictions of the risky assets in Panel A are based on a 10-year rolling window and in Panel B are based on the average prediction of a 5, 10, and 20 year rolling window. The weights of the risky assets are not restricted. The sample period is January 1947 to December 2008, and the strategies start trading in January 1967. The liquidity measures are: ILR (Amihud, 2002), Roll (Roll, 1984), Effective Tick (Holden, 2009, Goyenko et al., 2009), Zeros (Lesmond et al., 1999), and High-Low (Corwin and Schultz, 2012). All numbers are annual, except for the break-even costs $\tau_1$ and $\tau_A$ that are reported in basis points per trade. The switching fee is the maximum performance fee a risk-averse investor is willing to pay to switch from one strategy to another. It is expressed in annual basis points and is computed based on a relative risk aversion parameter of 5. $\tau_1$ shows the break-even costs under the assumption that all assets have the same transaction costs. $\tau_A$ shows the break-even costs in terms of large firms, whereby the liquidity differences between small and large firms are taken into account. If the excess return of a strategy is negative we do not compute break-even transaction costs and report the symbol "-".

| | | Switching fee | | | | | | Excess | |
|---|---|---|---|---|---|---|---|---|---|
| | SR | ILR | Eff. Tick | Roll | Zeros | $\tau_1$ | $\tau_A$ | return | Volatility |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| *Panel A. 10Y window* | | | | | | | | | |
| ILR | 0.27 | | | | | 3.0 | 1.4 | 3.25 % | 12.10 % |
| Eff.Tick | -0.05 | -337.5 | | | | - | - | -0.60 % | 11.13 % |
| Roll | 0.02 | -279.4 | 55.1 | | | 0.2 | 0.1 | 0.26 % | 11.81 % |
| Zeros | 0.21 | -51.1 | 282.2 | 227.3 | | 2.1 | 1.0 | 2.32 % | 11.28 % |
| High-Low | -0.25 | -606.3 | -272.1 | -326.3 | -555.0 | - | - | -2.96 % | 11.85 % |
| *Panel B. Combination of windows* | | | | | | | | | |
| ILR | 0.21 | | | | | 2.3 | 1.1 | 2.57 % | 12.10 % |
| Eff.Tick | 0.10 | -110.4 | | | | 0.9 | 0.4 | 1.17 % | 11.54 % |
| Roll | -0.01 | -269.1 | -157.5 | | | - | - | -0.15 % | 12.10 % |
| Zeros | 0.30 | 123.7 | 233.4 | 391.6 | | 2.9 | 1.4 | 3.39 % | 11.19 % |
| High-Low | -0.26 | -577.5 | -467.3 | -309.1 | -701.7 | - | - | -3.18 % | 12.14 % |

## Table A.6
## Performance of dynamic asset allocation strategies with restricted weights

The table presents dynamic strategy results for the different liquidity measures. The dynamic asset allocation strategies are based on a mean-variance framework where the investor maximizes the conditional expected return subject to a target conditional volatility ($\sigma_s^* = 10\%$). The return predictions of the risky assets in Panel A are based on a 10-year rolling window and in Panel B are based on the average prediction of a 5, 10, and 20 year rolling window. The weights of the risky assets are restricted to be between $-1 < w < 2$. The sample period is January 1947 to December 2008, and the strategies start trading in January 1967. The liquidity measures are: ILR (Amihud, 2002), Roll (Roll, 1984), Effective Tick (Holden, 2009, Goyenko et al., 2009), and Zeros (Lesmond et al., 1999). All numbers are annual, except for the break-even costs $\tau_1$ and $\tau_A$ that are reported in basis points per trade. The switching fee is the maximum performance fee a risk-averse investor is willing to pay to switch from one strategy to another. It is expressed in annual basis points and is computed based on a relative risk aversion parameter of 5. $\tau_1$ shows the break-even costs under the assumption that all assets have the same transaction costs. $\tau_A$ shows the break-even costs in terms of large firms, whereby the liquidity differences between small and large firms are taken into account. If the excess return of a strategy is negative we do not compute break-even transaction costs and report the symbol "-".

| | | Switching fee | | | | | | Excess | |
|---|---|---|---|---|---|---|---|---|---|
| | SR | ILR | Eff. Tick | Roll | Zeros | $\tau_1$ | $\tau_A$ | return | Volatility |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| *Panel A. 10Y window* | | | | | | | | | |
| ILR | 0.21 | | | | | 2.6 | 1.1 | 2.44 % | 11.56 % |
| Eff.Tick | -0.16 | -398.9 | | | | - | - | -1.79 % | 11.07 % |
| Roll | -0.03 | -281.3 | 118.1 | | | - | - | -0.40 % | 11.56 % |
| Zeros | 0.31 | 106.6 | 506.2 | 388.1 | | 3.7 | 1.7 | 3.64 % | 11.76 % |
| High Low | -0.24 | -516.6 | -117.4 | -235.1 | -623.0 | - | - | -2.76 % | 11.47 % |
| *Panel B. Combination of windows* | | | | | | | | | |
| ILR | 0.29 | | | | | 3.3 | 1.4 | 3.34 % | 11.37 % |
| Eff.Tick | -0.17 | -528.8 | | | | - | - | -1.95 % | 11.46 % |
| Roll | 0.04 | -296.3 | 233.0 | | | 0.6 | 0.3 | 0.46 % | 11.66 % |
| Zeros | 0.43 | 145.3 | 674.5 | 442.5 | | 4.8 | 2.2 | 4.87 % | 11.40 % |
| High Low | -0.18 | -538.1 | -8.2 | -241.9 | -683.2 | - | - | -2.04 % | 11.44 % |