



## Economic valuation of liquidity timing <sup>☆</sup>



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### 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 et al., 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.

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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.<sup>1,2</sup> A smart investor can potentially time the market and adjust exposure before liquidity events occur, i.e. time liquidity. Cao et al. (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.<sup>3</sup>

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<sup>1</sup> Amihud (2002), Jones (2002), and Baker and Stein (2004) show this for the U.S. market. Bekaert et al. (2007) find supporting evidence in emerging markets.

<sup>2</sup> 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.

<sup>3</sup> For spread proxies see e.g. Roll (1984), Lesmond et al. (1999), Hasbrouck (2009), and Holden (2009); for price impact measures see e.g. Amihud et al. (1997), Berkman and Eleswarapu (1998), Amihud (2002), and Pástor and Stambaugh (2003), and for turnover see Baker and Stein (2004).

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".<sup>4</sup>

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 et al., 2009), Zeros (Lesmond et al., 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 et al., 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.<sup>5</sup> 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 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.

<sup>4</sup> Other articles, e.g. Goyenko et al. (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.

<sup>5</sup> 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.

This paper contributes to the literature on liquidity proxies comparison. Goyenko et al. (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 et al. (1993) use the mean-variance and quadratic utility setting to rank exchange rate volatility models based on utility gains. Fleming et al. (2001) investigate volatility timing in equity markets. Della-Corte et al. (2008) and Della-Corte et al. (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 et al. (2007) we use autoregressive models to capture the autocorrelation in the liquidity series:

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

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

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

where  $\beta_{0,t} = \delta_0 + \delta_1 \phi_{0,t}$  and  $\beta_{i,t} = \delta_1 \phi_{i,t}$ . We only need estimates for the  $\beta$ -parameters and do not estimate Eq. (1), because we are interested in return predictions generated by Eq. (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 Eq. (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

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