Marketwide Liquidity and Another Look at Liquidity Risk

ABSTRACT

We re-investigate the importance of liquidity as an additional priced risk factor in a standard three-factor asset pricing model. Recent empirical findings reporting a high premium due to liquidity risk motivate another look at its effects using an alternative measure of (aggregate) market liquidity. We follow previous studies in defining liquidity risk as the sensitivity of portfolio returns to market liquidity fluctuations. We contribute to the empirical literature by constructing a time-series of market liquidity innovations (liquidity factor) based on microstructure models of trading costs, and estimated with intraday data. We test a standard factor model specification including the liquidity factor, for 25 portfolios sorted by size and book-to-market. We show that liquidity risk is not able to significantly explain the cross-sectional variation in returns for this choice of portfolios. There is a weak improvement in the fit, but the liquidity risk premium is not statistically or economically significant.

1   Introduction

The relationship between liquidity and asset prices has been extensively investigated and discussed in the literature. At first, the empirical literature focused on the effects of liquidity levels on the cross-section of expected returns. Overall, the findings suggest a positive relationship between expected stock returns and alternative proxies for individual illiquidity levels (as in Amihud and Mendelson (1986), Brennan and Subrahmanyan (1996), Brennan et al. (1998), Datar et al. (1998), among many others). Next, the focus changed to the time-series properties of aggregate liquidity measures, suggesting the existence of predictability and commonality in liquidity (as in Chordia, Roll and Subrahmanyam (2001), Hasbrouck and Seppi (2001), Amihud (2002), Jones (2002), and Huberman and Halka (2001)).

More recently, motivated by the time-series evidence, another aspect of liquidity and its importance for asset pricing has been the object of attention in the literature. Additionally to liquidity levels, the systematic component of liquidity has been investigated as a potential source of priced risk. The literature is still mostly empirical, motivated by the idea behind models of, for example, solvency constraints (as in Lustig (2001)). The intuition is that investors prefer a stock with higher returns when marketwide liquidity drops.

The empirical findings to date suggest that liquidity risk is an important priced source of risk when the model is fitted to U.S. equity data (Pastor and Stambaugh (2003), Acharya and Pedersen (2005), Sadka (2005)). The magnitude of the premium due to liquidity risk varies among the studies, but overall the findings suggest that liquidity risk is statistically and economically significant. In particular, Pastor and Stambaugh (2003) report a very high estimated premium for holding a high liquidity risk portfolio (a 7.5% annualized premium).

However, the magnitude of the liquidity premium varies across studies, as well as the proxies for marketwide liquidity. Moreover, the fact that the current U.S. equity market is highly liquid, with very infrequent severe illiquidity shocks, puts into question the existence of such a high premium for liquidity risk, and even the motivation based on solvency constraints.

Therefore, further investigation on the subject is important, either as a robustness check for previous findings or as a test of an alternative hypothesis of a non-priced liquidity risk factor.

In this paper, we re-evaluate the importance of liquidity risk for asset pricing, using a measure of marketwide liquidity that has not yet been used in the literature and that has important features.

Our measure is constructed by aggregating firm-level measures of trading costs, as in Piqueira (2004). This measure is based on microstructure models of trading costs (as in Glosten and Harris (1988)) and estimated with high frequency data. Hence, it has a clear economic interpretation and it is estimated with high precision. More importantly, it does not depend on daily trading volume data or daily return reversals, which might be capturing other effects rather than liquidity. Finally, our measure also includes NYSE and NASDAQ stocks, while most of the literature uses only NYSE stocks. We think that these are desirable features for a more precise proxy of marketwide liquidity, as a measure of the actual costs of trading.

We first construct the marketwide illiquidity innovation series from firm-level measures of trading costs. We present the main time-series properties, relating the series fluctuations with the main liquidity-related events observed during the sample period. We then use this measure in cross-sectional asset pricing tests for portfolios sorted by size and book-to-market. We allow for a liquidity risk factor in addition to the standard three Fama and French (1993) factors.

Our results show that liquidity risk is not able to significantly explain the cross-sectional variation in returns for the considered portfolio. There is a weak improvement in the R-square, but the liquidity premium is not statistically or economically significant, especially when compared to previous findings.

We interpret these results as some evidence not supportive of the hypothesis of a significant and priced liquidity risk for the U.S. equity market in the considered sample period.

The rest of the paper is organized as follows. In section 2 we discuss related literature. In section 3 we describe the construction of the liquidity risk factor, as well as its empirical features. In section 4 we describe the data and method for the asset pricing test and analyze our findings. Conclusions are presented in section 5.

2   Related Literature

This paper is related to recent empirical studies that investigate the effects of liquidity risk on asset prices. Alternative measures of liquidity[1] are constructed in order to define a measure of innovations in liquidity, and liquidity betas are estimated and analyzed. The importance of liquidity risk as a priced source of risk is evaluated by testing the contribution of liquidity beta(s) in standard asset pricing models.

In Acharya and Pedersen (2005), a theoretical asset pricing model with liquidity risk is introduced. They derive and test the implications of a liquidity-adjusted CAPM for a sample of NYSE and AMEX stocks from 1963 to 1999. The assumptions on their model imply that expected returns increase with the expected level of illiquidity and with what they call "net beta" (since the restrictions on their model imply a single risk premium). The "net beta" is decomposed into the usual market beta and three additional betas, reflecting liquidity risk. The illiquidity betas capture commonality in liquidity, the sensitivity of portfolio[2] returns to marketwide illiquidity and the sensitivity of portfolio illiquidity to market returns.

They first estimate a portfolio-level illiquidity measure as in Amihud (2002). This measure is based on the movements of daily returns in response to daily trading volume, defining an illiquid stock if its price moves excessively in response to small levels of trading volume. They construct portfolios based on firm characteristics and illiquidity levels, then estimate the corresponding illiquidity betas. They test the fit of their liquidity-adjusted

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[1]In this section, we refer to "liquidity" or "illiquidity" as it is used in the mentioned papers. The following sections refer to "illiquidity" measures.

[2]or firm.

CAPM model in cross-sectional regressions. They first show that their model significantly improves the performance of a standard CAPM model for most of the considered portfolios. Their findings also suggest that liquidity risk is a significant source of risk, with an estimated annualized premium of 1.1%. The premium is decomposed into the three sources of liquidity risk (under the model restrictions), showing that the most important source is the sensitivity of portfolio illiquidity to market returns (0.82%).

Pastor and Stambaugh (2003) focus on the sensitivity of portfolio returns to fluctuations in marketwide liquidity as the source of liquidity risk. The idea is that investors prefer assets that are less likely to require liquidation when illiquidity is low and hence, assets with higher liquidity betas command higher expected returns. They estimate monthly firm-level liquidity measures for NYSE and AMEX stocks (1962-1999), defining marketwide liquidity as the cross-sectional mean. The firm-level measure is based on estimates of daily return reversals induced by order flow, i.e. a more illiquid stock is associated with a higher reversal. They estimate liquidity betas for a large sample of NYSE and AMEX stocks (1962-1999), and construct and analyze zero-cost liquidity beta portfolios. They perform asset pricing tests without controlling for liquidity levels. Their findings suggest that high liquidity beta portfolios (i.e. high liquidity risk) substantially outperform low liquidity beta portfolios (7.5% a year), after controlling for the usual factors and for momentum.

The approach of Sadka (2005) is the closest to our paper. Firm-level measures of illiquidity costs are constructed with intraday data, for a large sample of NYSE and AMEX stocks (1983-2001). He estimates a microstructure model of trading costs similar to the one presented in this paper. He analyzes the empirical features of marketwide liquidity, interpreting liquidity risk as in Pastor and Stambaugh (2003). However, he only considers the variable informational component of trading costs as the relevant marketwide liquidity measure, while we use total illiquidity costs. He tests the importance of the liquidity factor by running cross-sectional regressions for two sets of portfolios. His results suggest that there is a considerable improvement in the Fama-French three factor model when the liquidity

factor is included, especially for the portfolios sorted by momentum and (non-informational) trading costs.

There is also a recent study by De Jong and Driessen (2004) in which the effect of liquidity risk on expected returns for corporate bonds is investigated. They consider two types of liquidity factors, one related to marketwide equity liquidity and the other related to marketwide liquidity in the treasury bond market. They construct the equity measure as in Amihud (2002) for a large sample of NYSE stocks (1993-2002). They show that the liquidity factors help to explain expected variation in returns for corporate bonds. They also investigate the implications of liquidity premium (estimated from corporate bond returns) for the cross section of stock returns, which is more related to our paper as an out-of-sample test of liquidity risk. Their findings suggest that for portfolios sorted by size and book-to-market, there is a weak improvement of the CAPM model when the liquidity factors are included.

We contribute to this recent empirical literature by re-investigating the effects of liquidity risk on cross-sectional returns, but using an alternative marketwide illiquidity measure. Our measure has the advantage of being strongly based on theoretical microstructure models and estimated at firm-level with intraday data. Hence, our measure does not capture any volume-related effect or return reversals that might be caused by reasons other than liquidity. Even though trading volume is used in the literature as a proxy for liquidity, there is recent theoretical and empirical literature relating excessive trading volume and turnover with for example, models of divergence of opinion.[3] The use of intraday data instead of daily volume data minimizes this potential source of noise.

Moreover, the measure of marketwide illiquidity constructed in this paper is based on the overall costs of trading, since we think that this is more consistent with the motivation of liquidity risk based on solvency constraints. Finally, our measure is constructed by aggregating firm-level measures of not only NYSE but also NASDAQ stocks, which are

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[3]See for example Scheinkman and Xiong (2004) and Lee and Swaminathan (2000).

excluded from all papers mentioned above. We also compare our results to previous findings and we provide an alternative interpretation for the illiquidity beta estimates and for the importance of liquidity risk as a priced systematic risk.

3   The Illiquidity Measure

3.1   Data and Methodology

We construct a measure of marketwide illiquidity by aggregating firm-level measures of illiquidity costs, based on microstructure models. We start with the firm-level measures constructed and described in Piqueira (2004), in which three versions of a trade indicator model, as in Glosten and Harris (1988), are estimated with intraday data.[4] The model allows for permanent (adverse selection costs) and transitory (order processing costs/market makers' profits) components of trading costs, assuming a linear specification for both.

The trade indicator variable D_k is defined as in Lee and Ready (1991): each transaction is assigned as a buyer-initiated transaction ($D_k = 1$) or a seller-initiated transaction ($D_k = -1$) by comparing the transaction price with the mid-quote. The model implies that the price change from transaction $k-1$ to transaction k depends linearly on the trade indicator and on the signed trade size, $D_k q_k$:

$$\triangle P_k = \lambda_1 D_k q_k + \lambda_2 D_k + \varphi_1(D_k - D_{k-1}) + \varphi_2(D_k q_k - D_{k-1} q_{k-1}) + e_k \qquad (1)$$

The three illiquidity measures in Piqueira (2004) differ in their assumptions about the structure of the permanent and the temporary costs, i.e. on the constraints on the parameters in (1). At each month t, the three versions of (1) are estimated by OLS for each firm i separately. The parameter estimates are collected, multiplied by the average trade size for firm i, $\overline{q}(i,t)$, and normalized by the average price $\overline{P}(i,t)$, in order to define a measure

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[4]We refer the reader to Piqueira (2004) for details on the estimation, data filtering and the cross-sectional properties of these measures. The model is presented in the Appendix.

comparable to the actual costs of trading.

The firm-level illiquidity costs measures are then defined as:

$$ILLIQ(1)_{(i,t)} := 2 * \left[\frac{\widehat{\lambda_1}(i,t) * \overline{q}(i,t) + \widehat{\varphi_1}(i,t)}{\overline{P}(i,t)} \right] \tag{2}$$

$$ILLIQ(2)_{(i,t)} := 2 * \left[\frac{\widehat{\lambda_2}(i,t) + \widehat{\varphi_1}(i,t)}{\overline{P}(i,t)} \right] \tag{3}$$

$$ILLIQ(3)_{(i,t)} := 2 * \left[\frac{\widehat{\lambda_1}(i,t) * \overline{q}(i,t) + \widehat{\lambda_2}(i,t) + \widehat{\varphi_1}(i,t) + \widehat{\varphi_2}(i,t) * \overline{q}(i,t)}{\overline{P}(i,t)} \right] \tag{4}$$

There are alternative ways of proxying for illiquidity, since it is an unobservable characteristic[5] with many dimensions.[6] We focus on the dimension related to the costs of immediacy. As explained in Piqueira (2004), the measures defined by $(2) - (4)$ are based on theoretical models of adverse selection and temporary trading costs. Moreover, the estimation with intraday data provides a more precise and meaningful proxy for the actual trading costs faced by investors. Hence, when we aggregate illiquidity for the entire market, we are considering a measure of the average costs of trading with strong theoretical and empirical appeal.

Most of the empirical papers on liquidity risk use measures that relate daily returns with daily trading volume, instead of constructing measures of trading costs from intraday data. The main reason is the availability of daily volume data for a longer horizon. Pastor and Stambaugh (2003) construct a measure of daily return reversals induced by daily trading volume, while Acharya and Pedersen (2005) and De Jong and Driessen (2004) use the Amihud (2002) measure, based on the proportional daily variation in returns with respect to movements in daily trading volume.

Although these measures also have a strong liquidity interpretation and they are able to empirically capture some of the observed market illiquidity crisis, it is possible that volume-

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[5]For a discussion, see O'Hara (2003).
[6]For a survey on the aspects of trading costs, see for example Pagano and Roell (2003).

related effects other than liquidity are also captured.[7] Hence, some of the fluctuations in marketwide illiquidity in these studies might be in fact due to trading volume fluctuations, not necessarily reflecting liquidity shocks. The use of intraday data provides a more precise measure of illiquidity fluctuations, interpreted as fluctuations in the total costs of trading.

Sadka (2005) also constructs a measure of trading costs based on intraday data and microstructure models and his analysis is the closest to our paper. However, he only considers the variable permanent (informational) component when constructing marketwide illiquidity. We consider the total illiquidity costs in this paper, since we think that the exposure to illiquidity risk is due to the overall costs of trading, especially in terms of marketwide illiquidity risk. Our measure is also constructed from a larger sample of NYSE-listed and NASDAQ-listed stocks, while the studies mentioned above consider only NYSE-listed stocks and disregard a considerable set of the available stocks.

3.2 Marketwide Illiquidity

Marketwide illiquidity is defined by averaging $(2) - (4)$ cross-sectionally, at each month t. Following the liquidity risk literature, we use equal-weighted averages.[8] Denoting by N_t the total number of stocks in the sample at month t, the level of marketwide illiquidity is defined, for each model $m = 1, 2, 3$ as:

$$ILLIQ_t(m) := \frac{1}{N_t} \sum_{i=1}^{N_t} ILLIQ(m)_{(i,t)} \qquad t = 1, 2, ..T \qquad (5)$$

We have a large sample of NYSE and NASDAQ stocks from January 1993 to December 2002, including all CRSP stocks with share codes 10 and 11, after the required filtering for the intraday estimates. On average, the sample includes 1,179 NYSE-listed stocks and 2,018 NASDAQ-listed stocks per month.

We report summary statistics for the level of marketwide illiquidity in Table 1, Panel

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[7]Although Amihud (2002) provides some evidence that his measure is positively related to measures of price impact.

[8]See Acharya and Pedersen (2005) for an explanation.

A. We show that the three measures are very similar in aggregate levels,[9] with a time-series mean of around 2% and standard deviation of 0.65%. In this paper, we will focus on the time-series properties and on the effects of $ILLIQ(2)$. As explained in Piqueira (2004), this measure is a better approximation of the unrestricted version of model (1), while $ILLIQ(1)$ might be underestimated due to the inclusion of signed trade size only for permanent costs.

In Figure 1 we plot the evolution of marketwide illiquidity levels for the three considered measures. We first observe a decreasing trend, expected from institutional changes during 1993-2002 and the increasing competition among exchanges. In particular, we observe significant declines after June 1997 and during the second half of 2000. The level of marketwide illiquidity decreases from 2.3% on June 1997 to 1.9% in October 1997, possibly due to the reduction of the minimum tick size on NYSE and NASDAQ (as in Chordia, Roll and Subramanyam (2001)) and the implementation of new order handling rules on NASDAQ (as in Barclay et al. (1999) and Bessembinder (1999)). Illiquidity drops from 1.81% in August 2000 to 1.38% in February 2001, responding to the decimalization process gradually implemented from August 2000 to January 2001.

Some of the events characterized as liquidity crises are captured by Figure 1: a peak of 2.7% in April 1997, possibly related to the Asian crisis, and a persistent increase in September and October 1998 (from 1.9% in August to 2.2% and 2.14%, respectively in September and October) caused possibly by the Long-Term Capital Management episode. We also observe a peak in September 2001, followed by a steady decreasing trend.

3.3 Innovations in Illiquidity

It is clear in Figure 1 that marketwide illiquidity is non-stationary, and it is persistent along a decreasing time trend. In Figure 2 we plot the linear trend for $ILLIQ(2)$, showing that even the detrended series is persistent.

In order to construct a valid measure of liquidity risk to be included in asset pricing

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[9]For an analysis of NYSE and NASDAQ separately, see Piqueira (2004).

tests, we cannot simply use the series of marketwide illiquidity levels in Figure 1. First, we need to transform it in a stationary series, in order to avoid the possibility of cointegration in the regressions. Second, we need to transform the stationary series in an approximation to a white noise process, defining liquidity risk only from the unexpected component of illiquidity.

We first detrend the series, choosing a linear trend since it results in the best fit. However, a white noise test for the detrended series is strongly rejected (as expected from Figure 2) and there is still an auto-correlation coefficient of 0.74. A white noise test for an AR(2) specification with a linear time trend is not rejected, resulting in a stationary series with low autocorrelation (-0.0068). The inclusion of higher lags does not significantly improve the model.

Hence, we define innovations in illiquidity as the residual of an AR(2) regression model with a linear time trend. Denoting by $\xi(m)$ the innovation in illiquidity, we run the following time series regression for $m = 1, 2, 3$:

$$ILLIQ_t(m) = \alpha t + \rho_1 ILLIQ_{t-1}(m) + \rho_2 ILLIQ_{t-2}(m) + e_t \tag{6}$$

$$\xi_t(m) := ILLIQ_t(m) - \widehat{ILLIQ_t}(m) \tag{7}$$

where $\widehat{ILLIQ}(m)$ is the fitted value of (6) and $\{\xi_t(m)\}_{t=1}^T$ is the corresponding time-series of residuals.

We report summary statistics for the illiquidity innovation series defined by (7) for the three illiquidity models in Table 1. The innovations in illiquidity range from -0.321% to 0.130% with a mean of 0.0026%.

In Figure 3 we plot the evolution of this measure over time, for $m = 2$.[10] First, we see that the series is clearly stationary and, as in the liquidity risk literature, we are only considering innovations in marketwide illiquidity. Next, we notice that the effects of regu-

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[10]From now on, we will consider only $\xi(2)$ in the analysis, without loss of generality.

lation changes during the sample period are still captured by the series: $\xi(2)$ decreases (i.e. liquidity increases) from 0.02% in July 1997 to -0.29% in September 1997 and from 0.08% in September 2000 to -0.23% by the end of the decimalization process in February 2001.

We also observe the upward peaks related to episodes characterized as liquidity crises: in April 1997 (Asian crisis), $\xi(2)$ reached 0.36%, from a 0.09% level in March. From -0.07% in July 1998, $\xi(2)$ reached 0.23% in September 1998, remained high during October (0.15%) and decreased abruptly in November to -0.32%. There is a peak in September 2001, when $\xi(2)$ jumped from -0.015% in August to 0.34% in September.

In summary, the time-series features of $\xi(2)$ are able to capture the main liquidity-related events observed in the considered sample period. We do observe peaks related to liquidity crisis episodes, but since our measure is intended to capture systematic variation in market illiquidity and since it is a monthly measure (i.e. using all transactions in a given month in the estimation), the results for illiquidity innovations are somehow less dramatic than the ones displayed in Acharya and Pedersen (2005) and Pastor and Stambaugh (2003). In these papers, the innovation series, constructed with daily data, seems to be noisier with more abrupt jumps.[11]

Next, we investigate the correlation of $\xi(2)$ with the market factor and with the Fama-French factors. Ideally, an additional factor that would improve the performance of the asset pricing model should be orthogonal to the other factors. We check if this is the case for the illiquidity factor $\xi(2)$ in Table 1, Panel B.

We first notice the low correlation (-0.14) between $\xi(2)$ and the market excess returns MKT, showing that the movements in marketwide illiquidity innovations are not necessarily followed or caused by market movements. The low correlation also provides more evidence for the validity of our measure of illiquidity.[12]

We contrast the evolution of the market excess return series and the illiquidity innovation

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[11]See Figure 1 in Pastor and Stambaugh (2003) and Figure 1 in Acharya and Pedersen (2005).

[12]If, for example, $\xi(2)$ was capturing only variation in prices, the correlation with market returns would be higher in absolute value.

series in Figure 4. We notice that there is an asymmetry in the co-movement of the two series, i.e. the co-movement between market return and illiquidity appears to be significant only during market downturns. We confirm this asymmetry by calculating the correlation of $\xi(2)$ with $MKT+$ and $MKT-$, where $MKT+$ ($MKT-$) denotes the market excess returns if the returns are positive (negative). Interestingly, the correlation of illiquidity innovations with $MKT-$ is -0.22, while the correlation with $MKT+$ is close to zero.

Hence, it seems that the co-movement between market returns and illiquidity is mostly restricted to market downturns. This result might be linked to commonality in liquidity and its effects on returns. If there is an important common factor in illiquidity, this result is in line with the prediction of Acharya and Pedersen (2005) model about the covariance between portfolio-level illiquidity and market returns.[13] According to their model, the investors are willing to accept a lower return on stocks that are liquid on market downturns. Further research would help to explain the link between the correlation illustrated in Figure 4 and Acharya and Pedersen (2005) findings.

The correlation of $\xi(2)$ with SMB is -0.21, showing that even though illiquidity levels are smaller for larger firms, when we consider innovations in illiquidity we are not using it solely as a proxy for SMB. We will explore this in detail in the following section. Also, the correlation with HML is close to zero (-0.027). Overall, the results of Table 1, Panel B show that the additional illiquidity factor is not proxying for any of the usual risk factors and we can include it in the asset pricing tests without further filtering.

4   Asset Pricing Tests

In this section we investigate the importance of liquidity risk as a priced factor. We first clarify the meaning and interpretation of the illiquidity factor loading, and we describe the data and methodology of our analysis. We then show the results for a set of standard portfolios, comparing our findings with previous literature in terms of the statistical and

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[13]β^4 in their model.

economic significance of liquidity risk.

4.1 Defining Liquidity Risk

We first define liquidity risk in the context of this paper. In principle, assumptions on the underlying asset pricing model are required to identify the main sources of liquidity risk.

The theoretical model of Acharya and Pedersen (2005) identifies three potential sources of liquidity risk affecting expected returns: the covariance between portfolio-level illiquidity and market illiquidity (commonality in liquidity); the covariance between portfolio-level returns and market illiquidity; and the covariance between portfolio-level illiquidity and market returns. They estimate all components under strong assumptions on a liquidity CAPM-type model, allowing them to work with a single risk premium for all three sources of liquidity risk and for the market risk.

Pastor and Stambaugh (2003) and Sadka (2005) consider only the source of liquidity risk defined by the covariance between marketwide illiquidity and firm-level (or portfolio-level) returns.[14] The intuition and motivation for choosing this particular source of risk is also mentioned in Pastor and Stambaugh (2003, page 1), based on models of solvency constraints as in Lustig (2001). The main implication is that investors require a higher expected return for a portfolio with a high (low) covariance between its return and market liquidity (illiquidity). Hence, a higher (lower) liquidity (illiquidity) loading should be observed for a stock with higher exposure to marketwide liquidity fluctuations, i.e. higher liquidity risk.

We follow these two authors and we focus in this particular effect, i.e. liquidity risk in the context of this paper is defined as the covariance between marketwide illiquidity innovations and portfolio returns $(cov(\ \xi_t(2), R_t^p))$. This would allow us to (i) perform standard factor model tests; (ii) compare our findings to the above mentioned papers.

Moreover, the identification and empirical estimates of all sources of liquidity risk require strong assumptions in a theoretical model of asset pricing with illiquidity costs, and this is

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[14]β^4 in Acharya and Pedersen (2004).

beyond the scope of this paper. Still, it is surely an important area of future research.

4.2 Data and Methodology

We re-investigate the effects of liquidity risk for the set of Fama-French 25 value-weighted portfolios, sorted by size and book-to-market (BK/MKT). We use data on portfolio returns and factor returns from January 1993 to December 2002, downloadable from Kenneth French's website.[15]

Because of the relatively short horizon of our sample, we do not estimate firm-level illiquidity betas[16] and hence, we do not replicate the methodology proposed by Pastor and Stambaugh (2003). They sort all stocks in the sample by their estimates of firm-level liquidity betas, constructing and analyzing a zero-cost portfolio based on these estimates (long on high betas and short on low betas). Nevertheless, we are still able to compare our findings with their empirical results in sub-section 4.5.

Instead, we use the standard two-step procedure, as in Black, Jensen and Scholes (1972) and Fama and MacBeth (1973). We first estimate the loadings for the usual factors (MKT, SMB, HML), and the illiquidity factor $\xi(2)$ for each of the 25 portfolios $p = \{1, 2..., 25\}$ through the following time-series regression:

$$R_t^p = \alpha^p + B^{p'} F_t + \varepsilon_t^p \qquad t = 1, 2, .., T \tag{8}$$

where R_t^P is the excess (to the risk-free rate) return for portfolio p at month t, $B^{p'} := [\beta_{F1}^p, \beta_{F2}^p, \beta_{F3}^p, \beta_{\xi(2)}^p]$ is the vector of factor loadings, including the illiquidity factor loading, and $F_t := [F1, F2, F3, \xi(2)]'$ is the vector of the three Fama-French factors and the illiquidity factor.

In the second step of the procedure, we run a cross-sectional regression for alternative specifications of a factor model, at each month t. We regress expected excess portfolio

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[15] We thank Kenneth French for making this data available on his website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[16] As noted by Sadka (2005).

returns (proxied by average excess portfolio returns) on the estimated factor loadings, as in:

$$R^p = \gamma + \lambda' \widehat{B^p} + v^p \qquad p = 1, 2, .., 25 \qquad (9)$$

We denote by $\widehat{\lambda_t'}$ the vector of risk premium estimates at each month t. We calculate time-series means and standard errors for the monthly estimates $\widehat{\lambda_t'}$ as in Fama and Macbeth (1973). We test three alternative specifications of model (9).

Before presenting the results, we should make a few remarks about the illiquidity factor loading and the illiquidity premium. First, we are talking about illiquidity, instead of liquidity: according to our definition and motivation, an asset with a higher illiquidity loading is preferred by investors, since it has high return when the market is illiquid. Henceforth, a high illiquidity beta is interpreted as low liquidity risk.[17]

Moreover, if liquidity risk is priced, this also implies a negative premium, i.e. a negative $\lambda_{\xi(2)}$. Since a higher beta is preferred by investors, they are willing to accept a lower future return for portfolios with higher beta. Finally, in the following sub-section we present the illiquidity factor loadings divided by 10, in order to simplify the presentation of the results.

4.3   Results

In Table 2 we report summary statistics and the estimates for the standard factor loadings (MKT, SMB, HML) and the illiquidity factor loading for each of the 25 portfolios. We first notice that there is considerable variation in excess returns, as required for this methodology.

It is interesting to compare the factor loadings estimates across portfolios, in particular the illiquidity beta. The illiquidity beta has mean -0.004 and standard deviation 0.217. We first observe that controlling for size, the illiquidity beta increases from high BK/MKT portfolios to low BK/MKT portfolios. According to this finding and under our underlying motivation about liquidity risk, excess returns of glamour stocks are less likely to be

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[17]As opposed to the definition in Pastor and Stambaugh (2003), in which a high beta implies high liquidity risk.

negatively affected by variations in marketwide illiquidity. For value stocks, the loadings are negative, meaning that these stocks have a higher sensitivity to illiquidity shocks in the market.

Controlling for book-to-market, we do not observe a monotonic pattern across size groups. Still, the largest stocks (size quintile 5) have smaller loadings than the smallest stocks (size quintile 1), except for value stocks (BK/MKT quintile 5). In fact, the loadings for the smallest stocks are mostly positive while they are mostly negative for the largest firms. This result suggests that the largest firms are more exposed to fluctuations in marketwide illiquidity, i.e. the largest stocks tend to have lower returns when the market is more illiquid (higher liquidity risk).

Even though at first this result might seem counterintuitive, Pastor and Stambaugh (2003) also document a similar finding in the first part of their paper (Table 3, section 3.A).[18] They report that the lowest-beta portfolio (corresponding to high illiquidity betas in this paper) includes stocks of smaller firms, with an average market cap of $2.83 billion, compared to a market cap of $14.28 billion for the highest-beta portfolio (our lowest illiquidity betas). They also show that the stocks with higher illiquidity betas are less liquid, in terms of firm-level proxies of liquidity levels. However, they have contradictory results when sorting all stocks by size (Table 9, section 3.C): if the sorting is made according to all stocks' breakpoints, the result is that smaller (and more illiquid) stocks have the highest betas, while the sorting by NYSE breakpoints results in flat betas across size deciles.

Still, high liquidity risk (i.e. low illiquidity betas) is not necessarily associated with high illiquidity levels or small market size.[19] The results in Table 2 suggest that for this particular sample period, higher liquidity risk is in fact associated with the largest firms. The intuition behind this finding is the following (a "flight-to-quality" type of explanation):

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[18]Table 4 in Sadka (2005) also reports this pattern for the 5x5 Fama-French portfolios. On the other hand, Acharya and Pedersen (2005) find the opposite result, i.e. they show in Table 1 that a more illiquid stock has also higher illiquidity risk.

[19]In fact, Pastor and Stambaugh (2003) explicitly make this point in their paper, despite their results in section 3.C.

when the market becomes more illiquid, investors tend to reallocate a proportion of their assets from equity markets to bond markets. In order to minimize trading costs, they sell the more liquid stocks in their portfolios, since these stocks have lower firm-level illiquidity costs. At the same time, the illiquid stocks are not necessarily affected by the illiquidity shock, since they are already illiquid and hence, not traded very often. Therefore, an increase in market illiquidity (such as an illiquidity shock) would be more likely to affect the returns of highly liquid and large stocks. Our results suggest that for this particular sample period, this might be the case.

Next, we analyze the results of cross-sectional regressions. In Table 3, we report the results for the regression model defined in (9) for three alternative factor specifications. We first test the CAPM specification using only MKT as a risk factor. We then include the loadings of the two Fama-French factors SMB and HML. Finally, we include the illiquidity beta.

We first confirm the poor performance of the CAPM in explaining the differences in returns for the 25 size/book-to-market portfolios. The average R^2 is 20.85% and the t-statistic for the market factor is -1.9. The inclusion of the SMB and HML factor loadings highly improves the predictive power of the model, as expected. The average R^2 increases to 60.3%, even though the t-statistics are low (which might be due to this particular sample period)[20] and we actually observe a negative risk premium for HML and again for the market.

Finally, we analyze the model specification including all three factors and the illiquidity factor loading. We notice that there is a weak improvement in fit, i.e. the average R^2 increases from 60.3% to 66% when we include the illiquidity factor loading. Since we show in Table 1 that the illiquidity innovation has a small correlation with the other factors, we would expect that if liquidity risk is priced, the increase in R^2 would be higher.[21]

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[20]See, for example Easley et al. (2002).

[21]Sadka (2005) actually reports an increase in R^2 that is higher than our findings: he shows that it increases from 61% from the single factor specification to 75% when all factors are included. We think that this is possibly related to the choice of the sample, since the R^2 of

Moreover, even though the liquidity premium has the expected negative sign in line with the liquidity risk motivation, the t-statistic for the illiquidity factor loading is extremely small (-0.00159). In fact, we think that the small magnitude of the t-statistic cannot be explained only by sample horizon problems. Therefore, this result suggests that liquidity risk is not statistically significant and hence, it cannot explain cross-sectional returns for this particular set of portfolios. Acharya and Pedersen (2005, Table 6B) document a similar finding, showing that their liquidity-adjusted CAPM model fails to explain the book-to-market effect.

4.4 Results with Other Measures of Liquidity Innovation

We consider two alternative measures of illiquidity in this sub-section, in order to test the robustness of our results to the definition of illiquidity innovation. First, we consider a measure of marketwide illiquidity based on a standard measure of trading costs widely used in the literature, the bid-ask spread. Even though the bid-ask spread is not considered an adequate proxy for cross-sectional liquidity variation,[22] in aggregate terms this measure provides a standard approximation for marketwide illiquidity.

We collect firm-level monthly averages for the proportional bid-ask spread ($PQSPR$) as in Piqueira (2004) and we consider the cross-sectional averages as in (5). We construct innovations for marketwide bid-ask spread as in $(6) - (7)$, denoted by $\xi(S)$. We use this measure instead of $\xi(2)$ in cross-sectional regressions $(8) - (9)$.

Factor loading estimates for each portfolio are reported in Table 4[23] and the regression results in Table 5. The R^2 increases to 65.6%, similar to the results with $\xi(2)$. But the liquidity premium is still not significant, with a t-statistic of -0.042. This result provides

the CAPM seems to be too high, given all evidence about its poor performance in explaining book-to-market/size returns. In De Jong and Driessen (2004), the liquidity risk premium is estimated from the bonds market for a range of values assumed as good proxies for the market risk premium. They find that the inclusion of the illiquidity factor weakly increases the R^2. For example, for an equity premium of 2%, it increases from 25% to 38.2%. (Table 5, line 1).

[22] See Piqueira (2004).

[23] We report only the illiquidity factor loadings.

additional evidence against the pricing of liquidity risk, since the bid-ask spread is the most standard measure of illiquidity in the literature, and in aggregate terms it can be considered a reasonable approximation for the costs of trading.

Next, we construct a value-weighted measure of $ILLIQ(2)$, including market capitalization weights in (5). The liquidity risk literature justifies the use of equal-weighted illiquidity as a way of compensating for not considering the "true market portfolio in the economy",[24] since the sample of stocks does not include other illiquid assets (e.g. bonds, real state) usually held by investors. However, we think that it is important to analyze the effects of value-weighted illiquidity in the equity market, since many investors only look at the behavior of the largest stocks as the relevant marketwide illiquidity measure. The correlation between $\xi(W2)$ and $\xi(2)$ is 0.47.

We define $\xi(W2)$ as the measure of value-weighted marketwide illiquidity innovations, constructed as in $(6) - (7)$. We use this measure in the cross-sectional regressions as the relevant illiquidity factor. Factor loading estimates for this measure are presented in Table 4 and the cross-sectional regression results in Table 5. We show that this measure is not able to capture any systematic effect as defined in the literature, since the coefficient on $\xi(W2)$ is not significantly different from zero and in fact it is positive, as opposed to the liquidity risk hypothesis.

We interpret these results as further evidence against the liquidity risk hypothesis, and we think that the weak improvement in R^2 does not imply that liquidity risk is important for asset pricing, since the illiquidity coefficient is not significantly different from zero for the three considered measures and it is actually positive if we consider a value-weighted measure.

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[24]Acharya and Pedersen (2005), Section 4.2.

4.5 Economic Significance and Comparison with Previous Findings

In this sub-section we discuss the economic significance of liquidity risk. Although the results in Tables 3 and 5 suggest that liquidity risk is not statistically significant for the considered set of portfolios, we still would like to investigate the magnitude of its effect. Henceforth, we calculate the annual return premium required to hold a low illiquidity beta (i.e. high liquidity risk) instead of a high illiquidity beta (i.e. low liquidity risk) portfolio. We use the maximum and minimum values for the illiquidity betas in Tables 2 and 4 and the illiquidity risk premium estimates in Tables 3 and 5, defining the return premium as follows:

$$\text{Return Premium} := 12 * \widehat{\lambda_{\xi(2)}} * (\beta_{\xi(2)}^{MIN} - \beta_{\xi(2)}^{MAX})$$

The required return premium is approximately 0.0068% a year, i.e. very close to zero. If we use $\xi(S)$, the premium is 0.197% a year, still very small especially when compared with previous findings.

Even though there are significant differences in methodology, sample size and liquidity measures, we still can compare this estimate of return premium with the ones found in previous papers.

The return premium computed above is much smaller than the one found in Pastor and Stambaugh (2003), in which higher liquidity risk portfolios outperform lower liquidity risk portfolios by 7.5% a year. Acharya and Pedersen (2005), also report a higher premium, 1.1%.[25] Sadka (2005) does not explicitly calculate the required premium, although the magnitude of his estimates and liquidity betas suggests a much higher premium than the one reported here. In fact, he reports the sharpe ratio of the illiquidity premium, which is close to the one calculated in Pastor and Stambaugh (2003), suggesting a similar (to 7.5%) magnitude of the required premium.

Overall, our results show that for portfolios sorted by size and book-to-market and

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[25]In fact, if we consider only the component of liquidity risk correspondent to our definition (beta 3), the required premium reported in Acharya and Pedersen (2005) is 0.16%.

for the particular sample period (1993-2002), liquidity risk is not statistically significant, while the economic significance seems to be very small especially when compared with previous findings. Moreover, we did not find a considerable improvement in the (in sample) performance of the three-factor model when the liquidity risk factor is included. These findings suggest that liquidity risk does not seem to be priced. There are other possible interpretations though, and we discuss some of them below.

First, it is possible that liquidity risk is actually priced, but not able to explain cross-sectional variation in returns for size/book-to-market portfolios, in line with Acharya and Pedersen (2005) findings. Second, it is possible that liquidity risk matters, but not the component/interpretation assumed in this paper (and in Pastor and Stambugh (2003) and Sadka (2005)), i.e. the sensitivity of portfolio returns to marketwide illiquidity fluctuations. This interpretation is in line with Acharya and Pedersen (2005) decomposition of the estimated required return premium for each liquidity risk component. They report that the most important component of liquidity risk is, in fact the sensitivity of portfolio level illiquidity to market returns, accounting for 0.82% of the total 1.1% liquidity risk premium.

Although the above interpretations are plausible, we think that our results go to the direction that liquidity as a systematic source of risk is not actually priced, or at least not economically significant. Even though we show (Figure 3) that illiquidity innovation varies over time, there is no *a priori* reason to believe that this will necessarily affect returns as a source of systematic risk. This will be the case only if (i) liquidity drops significantly below a certain threshold, and (ii) there is considerable commonality in liquidity.

The solvency models that motivate the empirical liquidity risk literature imply that returns respond to illiquidity shocks only if there is a considerable liquidity drop in an already illiquid market, in order to liquidation to occur and hence affect returns. In other words, liquidity risk will be a source of systematic risk, only if we start with a market that is already highly illiquid and hence, closer to the illiquidity threshold after which further jumps would affect returns. We think that this is an unreasonable conjecture for the current U.S.

equity market investigated in this paper, given the increasing level of liquidity and the high competition among exchanges. On the other hand, the above mentioned studies investigate a longer sample (including the 1987 crash), and the high significance of liquidity risk might be the result of a noisier marketwide illiquidity measure, constructed with daily trading volume data.

Further research relating commonality in liquidity, market downturns in illiquid markets and the propagation of these shocks into more liquid markets is required to derive stronger conclusions about the importance of liquidity risk as a priced state variable.

5 Conclusions

This paper re-investigates the importance of liquidity risk as an additional priced factor in a standard three-factor model. Recent empirical findings reporting a high premium due to liquidity risk motivate another look at its effects using an alternative measure of marketwide illiquidity. We follow previous papers (Pastor and Stambaugh (2003) and Sadka (2005)) when defining liquidity risk as the sensitivity of returns to marketwide illiquidity. However, we use an alternative measure of marketwide illiquidity.

We contribute to the liquidity risk literature by defining liquidity risk through a marketwide illiquidity measure of trading costs with strong theoretical and empirical appeal. We construct the measure by aggregating firm-level measures of trading costs estimated in Piqueira (2004). This measure is based on a microstructure model of trading costs as in Glosten and Harris (1988). Three versions of the model are estimated with intraday data, resulting in an illiquidity measure with a more precise definition in terms of the actual costs of trading. Moreover, we consider not only NYSE-listed but also a large proportion of NASDAQ stocks.

We present the empirical properties of the illiquidity factor, defined as the innovation in marketwide illiquidity. We show that this measure is consistent with the main liquidity-related events observed in the market during the sample period covered in this

paper (January 1993 to December 2002).

Our results for portfolios sorted by size and book-to-market do not provide evidence supporting the hypothesis of a priced liquidity risk factor. The fit of a three factor model improves weakly, but the illiquidity premium is not statistically significant with marginal economic significance when compared to previous findings. Moreover, the results also hold if we use a measure of marketwide bid-ask spread or if we use a value-weighted measure.

We interpret these results as some counterevidence to the hypothesis of a priced liquidity risk factor. Further empirical research is needed to evaluate the importance of this additional risk factor in more illiquid markets, especially during market downturns.

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6 Appendix: The Model for Illiquidity Costs

We follow Glosten and Harris (1988) in deriving the price impact of a trade, as described in (1). Trading costs due to adverse selection are permanent trading costs since they affect the dynamics of the expected value of the security for the uninformed market maker (the "true price process"). Trading costs related to order processing costs and market makers' profits are transitory trading costs since they only affect the level of actual prices.

Let D_k be a buyer-seller indicator variable that equals $+1(-1)$ if transaction k is buyer-initiated (seller-initiated), q_k be the order flow of transaction k and e_k be a public signal. The market maker's expected value of the security given the available information is defined as: $E[v_{k+1}|D_k, q_k, e_k] := v_k$ (the "true price process" in Glosten and Harris (1988)).

The model considers a linear specification for the expected value and a linear specification for permanent and transitory costs. Permanent costs (denoted as Z_k) are decomposed into a fixed (λ_2) and a variable (λ_1) component. Transitory costs (denoted as C_k) are decomposed into a fixed (φ_1) and a variable (φ_2) component as follows:

$$v_k = v_{k-1} + e_k + D_k Z_k \tag{A1}$$

$$Z_k = \lambda_2 + \lambda_1 q_k \tag{A2}$$

$$C_k = \varphi_1 + \varphi_2 q_k \tag{A3}$$

The observed transaction price includes transitory costs, while adverse selection costs are permanently incorporated into the updated beliefs of the market maker, i.e:

$$P_k = v_k + D_k C_k \tag{A4}$$

Equations (A1)-(A4) imply that the price changes from transaction $k-1$ to transaction k,

$\triangle P_k = P_k - P_{k-1}$ is given by:

$$\triangle P_k = \lambda_1 D_k q_k + \lambda_2 D_k + \varphi_1(D_k - D_{k-1}) + \varphi_2(D_k q_k - D_{k-1} q_{k-1}) + e_k \qquad (1)$$

Evaluating (1) for $D_{k-1} = 1$ and $D_k = -1$, we have the round-trip price change for a sale that immediately follows a purchase of equal size.

FIGURE 1: Marketwide Illiquidity (levels)
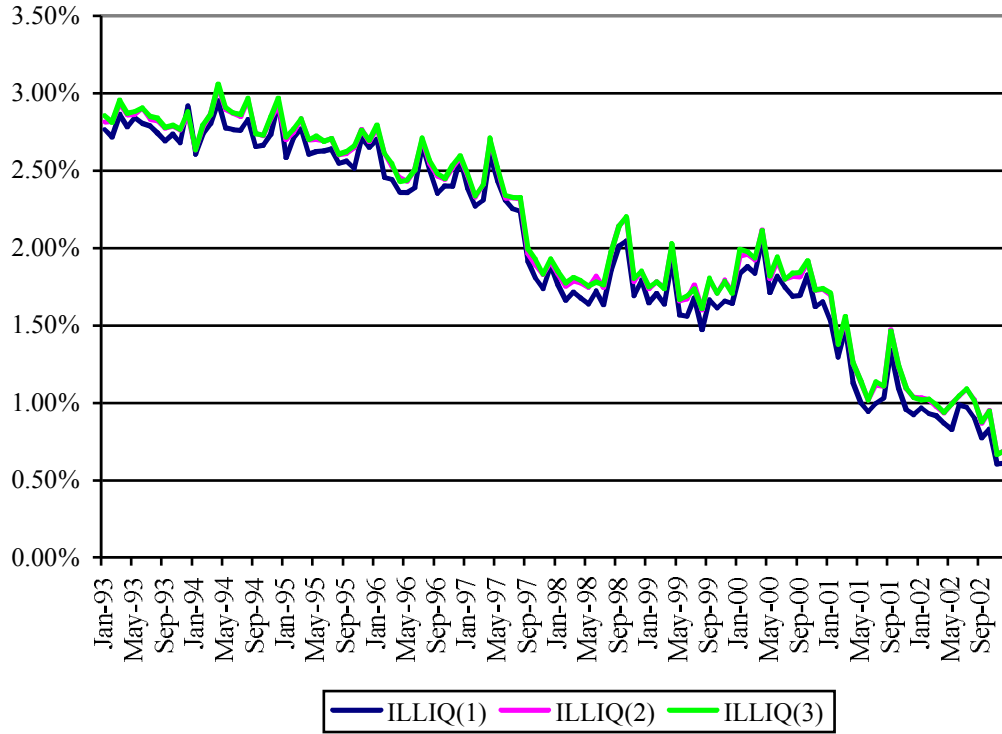
FIGURE 2: Marketwide Illiquidity - Time Trend (ILLIQ(2))
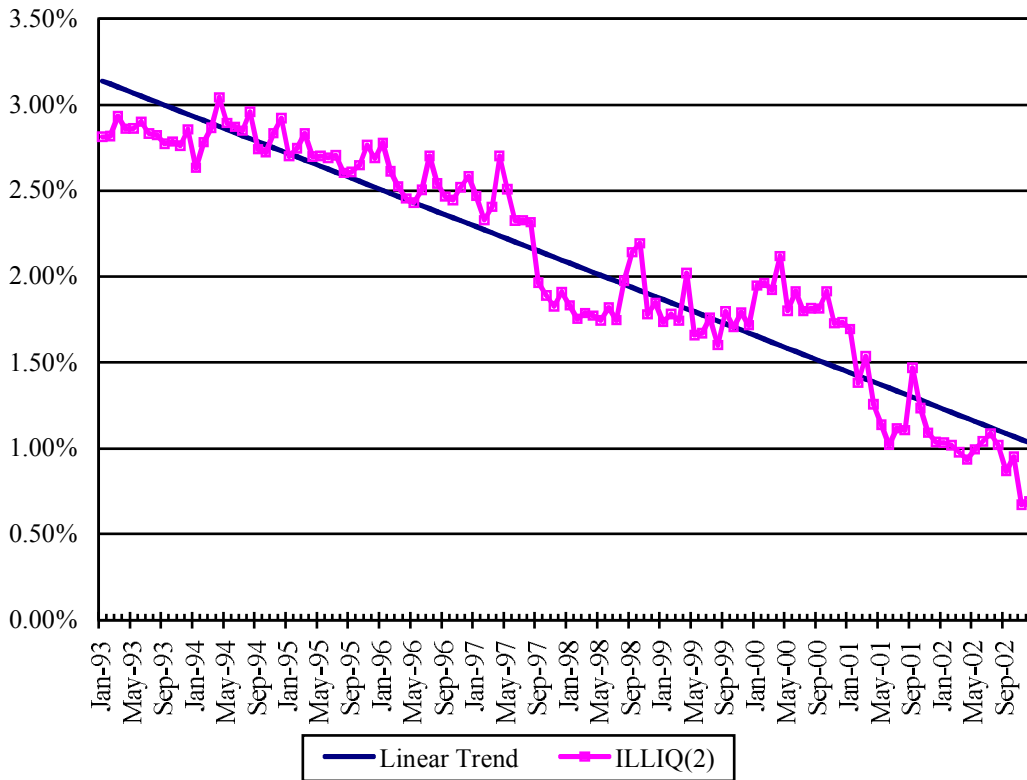
FIGURE 3: Marketwide Illiquidity Innovation - $\xi(2)$

$\xi(2)$
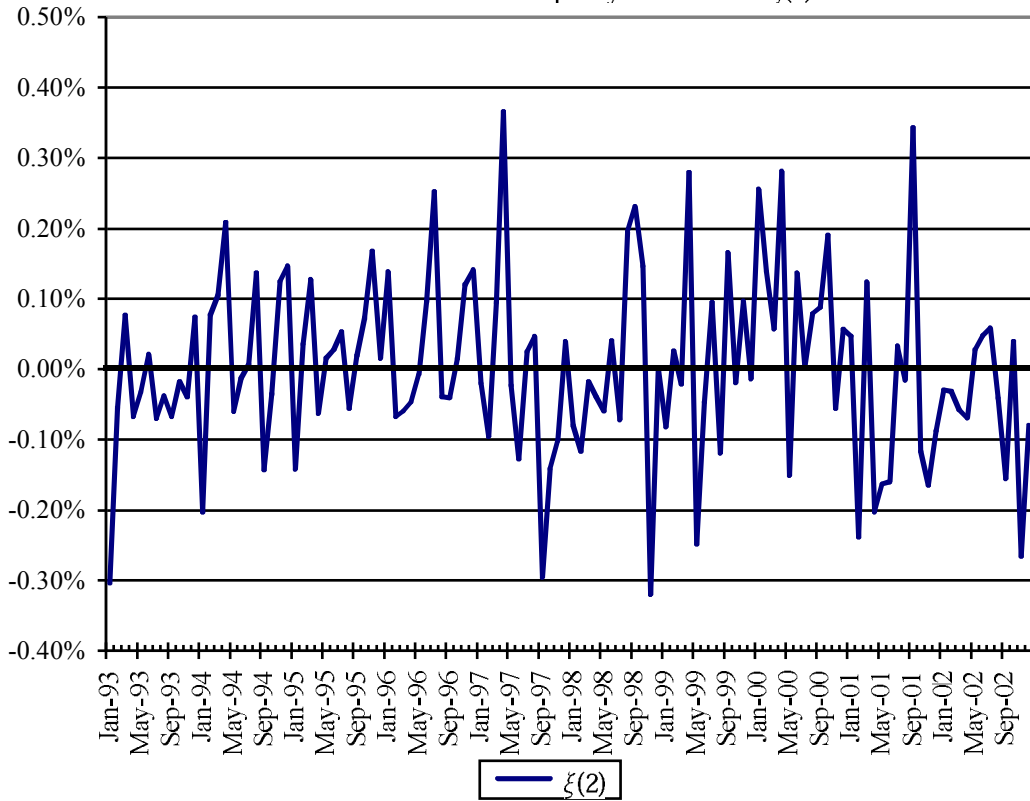
FIGURE 4: Marketwide Illiquidity Innovations ($\xi(2)$) and Excess Market Returns

Rm- Rf $\xi(2)$
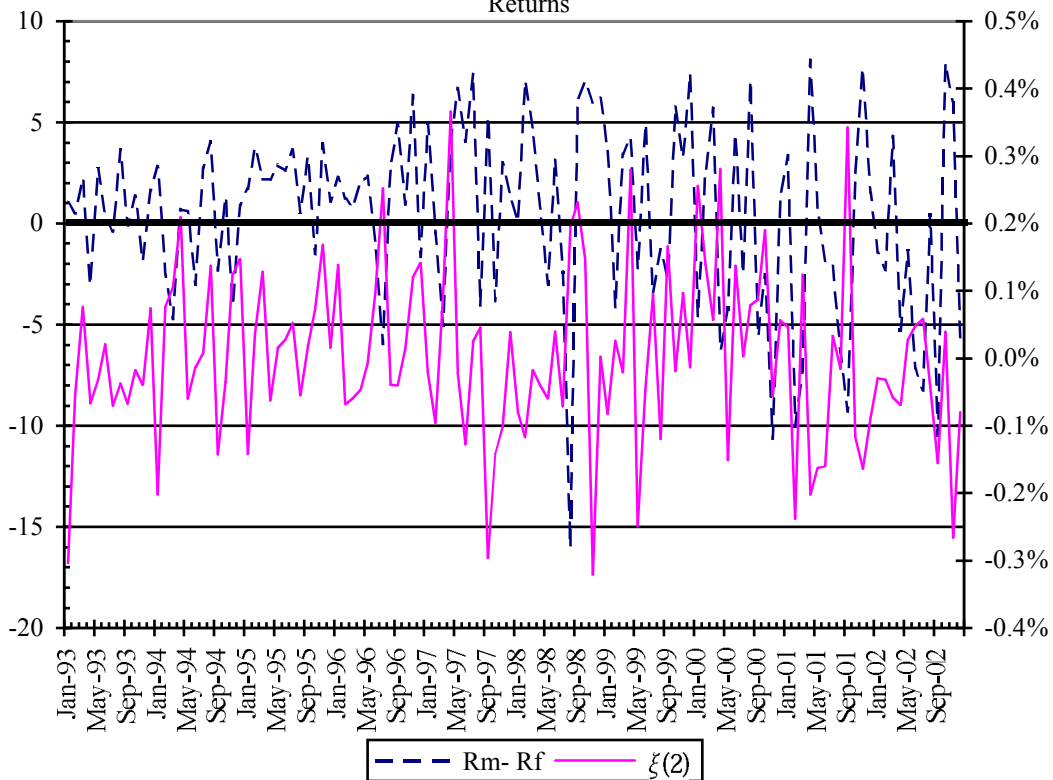
TABLE 1: Marketwide Illiquidity - Summary Statistics

PANEL A: Means and standard deviations

	Mean	Max.	Min.	Std. Dev.
ILLIQ(1)	2.000%	2.950%	0.605%	0.661%
ILLIQ(2)	2.085%	3.042%	0.670%	0.648%
ILLIQ(3)	2.093%	3.059%	0.668%	0.651%
$\zeta(1)$	0.0028%	0.363%	-0.290%	0.135%
$\zeta(2)$	0.0026%	0.366%	-0.321%	0.130%
$\zeta(3)$	0.0025%	0.372%	-0.308%	0.131%

PANEL B: Correlations

	$\zeta(2)$	MKT	SMB	HML
$\zeta(2)$		-0.140	-0.207	-0.027
MKT			0.168	-0.342
SMB				-0.415
HML				

Time-series summary statistics are reported in Panel A and correlations across time are reported in Panel B. The sample includes monthly data from 1/1993 to 12/2002. Marketwide illiquidity measures are constructied from a large sample of NYSE and NASDAQ stocks. ILLIQ(i), i=1,2,3 are the measures of marketwide illiquidity levels (cross-sectional means) for each trade indicator model described by (2)-(4) in the text. $\zeta(i)$, i=1,2,3 are the measures of marketwide innovations in illiquidity, constructed as in (6)-(7) in the text. MKT, SMB and HML are the Fama-French factors, available from Kenneth's French website.

TABLE 2: Portfolios sorted by Size/Book-to-Market (5x5):
Summary Statistics and Factor Loadings

	BK/MKT	SIZE				
		Size =1 (Small)	Size =2	Size =3	Size =4	Size =5 (Large)
Excess *Returns*	BK/MKT=1 (Glamour)	-0.280	0.075	0.081	0.494	0.479
	BK/MKT=2	0.820	0.449	0.516	0.698	0.646
	BK/MKT=3	1.008	0.734	0.671	0.746	0.687
	BK/MKT=4	1.290	0.806	0.574	0.705	0.664
	BK/MKT=5 (Value)	1.130	0.711	0.933	0.578	0.418
B(MKT)	BK/MKT=1 (Glamour)	1.193	1.220	1.161	1.170	1.028
	BK/MKT=2	0.875	0.882	0.967	0.944	0.962
	BK/MKT=3	0.680	0.745	0.845	0.902	0.930
	BK/MKT=4	0.628	0.758	0.765	0.806	0.798
	BK/MKT=5 (Value)	0.679	0.790	0.849	0.864	0.870
B(SMB)	BK/MKT=1 (Glamour)	1.555	1.260	1.006	0.633	-0.239
	BK/MKT=2	1.408	0.935	0.526	0.220	-0.218
	BK/MKT=3	1.030	0.706	0.307	0.072	-0.125
	BK/MKT=4	0.875	0.716	0.300	0.098	-0.290
	BK/MKT=5 (Value)	0.855	0.761	0.360	0.012	-0.334
B(HML)	BK/MKT=1 (Glamour)	-0.247	-0.134	-0.239	-0.252	-0.155
	BK/MKT=2	-0.179	0.137	0.251	0.291	0.238
	BK/MKT=3	-0.017	0.256	0.352	0.404	0.387
	BK/MKT=4	0.085	0.360	0.415	0.334	0.439
	BK/MKT=5 (Value)	0.225	0.373	0.540	0.488	0.440
B(ζ(2))	BK/MKT=1 (Glamour)	0.189	0.358	0.333	0.276	0.069
	BK/MKT=2	0.106	0.081	0.335	0.098	-0.132
	BK/MKT=3	0.093	0.107	0.065	-0.030	-0.063
	BK/MKT=4	-0.075	-0.006	-0.013	-0.124	-0.317
	BK/MKT=5 (Value)	-0.444	-0.234	-0.292	-0.137	-0.343

The sample includes 25 value-weighted portfolios sorted by size and book-to-market as described in Kenneth French's website, from 01/1993 to 12/2002. We report average excess (to the risk-free rate) returns for each portfolio. We report the factor loadings B(F) for each portfolio, estimated in time-series regressions as in (8), where F= MKT, SMB, HML and ζ(2). MKT, SMB and HML are the Fama-French factors, available at Kenneth's French website. ζ(2) is the measure of marketwide innovations in illiquidity, constructed as in (6)-(7) for the second illiquidity measure. We report B(ζ(2)) divided by 10.

TABLE 3: Portfolios sorted by Size/Book-to-Market (5x5):
Cross- Sectional Regression Results

	Intercept	B(MKT)	B(SMB)	B(HML)	B(ξ(2))	R-Square
Coefficient	2.164	-1.723				20.8%
t-statistic	7.363	-1.932				
Coefficient	2.480	-1.951	-0.108	-0.310		60.3%
t-statistic	5.974	-3.302	-0.306	-0.540		
Coefficient	2.480	-1.950	-0.108	-0.310	-0.00066	66.0%
t-statistic	5.960	-3.253	-0.299	-0.504	-0.00159	

The sample includes 25 value-weighted portfolios sorted by size and book-to-market as described in Kenneth French's website, from 01/1993 to 12/2002. The cross-sectional regression model of expected excess portfolio returns on factor loadings as in (9) is tested for three alternative factor specifications. We report the Fama-Macbeth (1973) average of the monthly risk premium estimates and the corresponding t-statistics. The average R-square for each specification is reported.

TABLE 4: Portfolios sorted by Size/Book-to-Market (5x5):
Illiquidity factor loadings

		SIZE				
	BK/MKT	Size =1 (Small)	Size =2	Size =3	Size =4	Size =5 (Large)
B(ζ(S))	BK/MKT=1 (Glamour)	0.108	0.310	0.326	0.292	0.121
	BK/MKT=2	0.074	-0.010	0.197	-0.099	-0.220
	BK/MKT=3	-0.086	-0.105	-0.200	-0.129	-0.239
	BK/MKT=4	-0.345	-0.129	-0.220	-0.182	-0.400
	BK/MKT=5 (Value)	-0.589	-0.300	-0.428	-0.055	-0.537
B(ζ(W2))	BK/MKT=1 (Glamour)	-3.775	4.471	5.970	5.363	-2.786
	BK/MKT=2	-3.131	0.367	7.056	-0.027	-3.630
	BK/MKT=3	-5.788	2.385	1.811	1.225	-2.818
	BK/MKT=4	-6.987	0.414	0.890	-1.135	-4.567
	BK/MKT=5 (Value)	-7.217	-2.981	-4.297	1.556	-4.791

The sample includes 25 value-weighted portfolios sorted by size and book-to-market as described in Kenneth French's website, from 01/1993 to 12/2002. We report only the illiquidity loadings B(ζ(k)) for each portfolio, estimated in time-series regressions as in (8) for the four-factor model specification. k=S, W2 are measures of marketwide illiquidity. S is the monthly equally-weighted cross-sectional average for the proportional quoted bid-ask spread and W2 is the monthly value-weighted cross-sectional average for ILLIQ(2). ζ(k) are measures of marketwide innovations for illiquidity measure k, constructed as in (6)-(7). We report B(ζ(k)) divided by 10.

TABLE 5: Portfolios sorted by Size/Book-to-Market (5x5):
Cross-Sectional Regression Results

	Int.	B(MKT)	B(SMB)	B(HML)	B(ζ(S))	B(ζ(W2))	R-Square
Coefficient	2.452	-1.994	-0.079	-0.193	-0.0019		65.6%
t-statistic	5.346	-3.188	-0.220	-0.298	-0.0419		
Coefficient	2.481	-1.961	-0.113	-0.261		0.0009	67.7%
t-statistic	5.286	-3.144	-0.311	-0.494		0.4026	

The sample includes 25 value-weighted portfolios sorted by size and book-to-market as described in Kenneth French's website, from 01/1993 to 12/2002. ζ(k) are the measures of marketwide innovations for illiquidity measures k=S,W2, constructed as in (6)-(7). The cross-sectional regression model of expected excess portfolio returns on factor loadings as in (9) is tested for three alternative factor specifications. We report the Fama-Macbeth (1973) average of the monthly risk premium estimates and the corresponding t-statistics. The average R-square for each specification is reported.