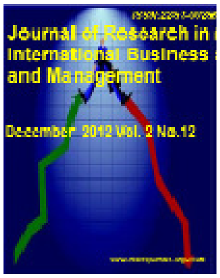

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Full Length Research Paper

Asset pricing and liquidity risk interrelation: an empirical investigation of the Tunisian stock Market

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Abstract

The empirical work on liquidity and stock returns supports the existence of a liquidity effect. Accordingly, this paper empirically analyses whether Tunisian average stock returns vary with liquidity risk factors: The aggregated bid-ask spread and the Amihud (2002) price impact measure. From 2002 through 2007, in contrast to previous works, our empirical results on the emerging Tunisian Stock Market (TSM) show that the liquidity factor is not priced either in portfolio sorting approach neither in cross-section regressions, after adjusting for exposures to the market return as well as size an value. We also found that sorting stocks according to liquidity is not likely to generate average returns greater than those on passive combinations of the mimicking returns for risk factors.

Keywords: Emerging market, asset pricing, liquidity risk, bid-ask spread, price impact measure, abnormal return.

INTRODUCTION

It is widely admitted that liquidity is an important attribute that influences investment decision given its thinly relation with transaction costs. Theoretically, investors buying illiquid stocks require higher returns to be compensated for their risk exposure. The luck of liquidity can thus be considered as an additional risk factor, Pástor and Stambaugh (2003), Martinez et al.(2005), Hearn (2011).

Considering individual stocks, Amihud and Mandelson (1986), Brennan and Subrahmanyam (1996), Brennan et al.(1998), Datar et al.(1998) all found a negative relationship between stock individual characteristics and gross stock returns. Other studies found that individual stock liquidity varies with others, Chordia et al.(2000), Hasbrouk and Seppi (2001) and Huberman and Halka (2001). The communality in stock characteristics raises the question if stock liquidity comprises a risk source that can't be diversified and is therefore compensated by expected stock returns. The stock liquidity thus comprises two components: one specific representing its individual determinants and another systematic integrating stock related characteristics and common to all stocks. The literature concerning the inclusion of liquidity as a priced state variable within a valuation framework is very recent. Pastor and Stambaugh (2003) find strong evidence from US stock data that market-wide liquidity is a priced state variable and that the liquidity premium should be positive. The applied literature dealing with liquidity risk has grown rapidly recently with studies relating to Africa (Hearn, 2010; Hearn and Piesse, 2009, 2010; Hearn et al., 2010), South East Asia (Shum and Tang, 2005) and the Spanish stock market (Martinez et al., 2005). These studies found evidence supporting the use of liquidity factors in valuation.

It should be pointed out, as stated by Martínez et al.(2005), that besides the extensive evidence from the U.S. market, there is limited evidence regarding the importance of illiquidity as a risk factor in other markets. Thus, it is important to report empirical results from other data sets to check the robustness of the available results and to support the conviction that it is not due to a data-snooping problem, Lo and MacKinlay (1990) and Lewellen et al.(2010). In this sense, the Tunisian stock market will shed light on the potential role of illiquidity in stock return valuation on an emerging market. African markets have low levels of liquidity compared with developed world markets, Hearn et al.(2009). This is particularly true in Tunisia, which is one of the smallest

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markets. Besides, risks associated with liquidity are cited as a major concern for overseas institutional investors and hinder participation in emerging stock markets, Kenny and Moss (1998). This market present some degree of risk and illiquidity, which makes it very appropriate for modeling a risk adjusted capital asset pricing model.

In the remainder of the paper, after sorting stocks into portfolios according to liquidity levels, we first test if there is a systematic liquidity risk and examine its magnitude. We also test if average abnormal returns are greater than those on passive combinations of the mimicking returns for risk factors. Finally, we examine if average systematic liquidity is priced in cross- section regressions using the Fama MacBeth (1973) methodology.

Institutional characteristics of the Tunisian market

The Bourse de Tunis was established in 1969. The Principal Market is reserved for the large and high performance companies. Trading is electronic and was introduced in 1996 and all listed securities are traded on the system. Orders entered by brokers at their terminals are forwarded to the central system and matched. The trading system is split into fixing and continuous systems, with the former handling small and illiquid securities and comprised of a series of sequential electronic call auctions (Bourse de Tunis website, 2012). In an effort to further boost listings, a range of tax breaks is offered to firms seeking to raise capital on the local bourse. We note that the number of firms listed on the TSE increased from 13 to 49 between 1990 and 2007. Despite a sharp increase of the volume of trading and capitalization since the implementation of 1989 and 1994 reforms, in 2007, market capitalization represented only 14.55 per cent of GDP and the annual value of trading amounted to 1.6 per cent of GDP, which is very small compared to other emerging markets.

The model

We follow a straightforward portfolio-based approach to create a universe of assets whose liquidity levels are sufficiently disperse: Common stocks are sorted into 5 portfolios every December by their mean monthly liquidity value over the previous 12 months and portfolios are held for the following year. The post-formation returns on these portfolios during the next 12 months are linked across years to form a single return series for each quintile portfolio. The excess returns on those portfolios are then regressed on return-based factors that are commonly used in empirical asset pricing studies. Specifically, each quintile excess return is regressed on the aggregated liquidity factor Lt, the stock market excess return MKT and the Fama and French (1993) risk factors SMB and HML, as in (1):

$$r_{i,t} = \beta_i^0 + \beta_i^L L_t + \beta_i^M MKT_t + \beta_i^S SMB_t + \beta_i^H HML_t + \varepsilon_{i,t} \quad (1)$$

Where $r_{i,t}$ denotes asset's *i* excess return, MKT denotes the excess return on a broad market index, and the other two factors, SMB and HML, are payoffs on long-short spreads constructed by sorting stocks according to market capitalization and book-to-market ratio.

After estimating liquidity beta and various other risk variables for each stock as in (1), the next step is employing these variables as predictors in the cross-section regression. The methodology of testing is similar to that of Fama and MacBeth (1973). The procedure is as follows: In the first step, for each single time period a cross-sectional regression is performed. Then, in the second step, the final coefficient estimates are obtained as the average of the first step coefficient estimates. For the Fama–French model, the basic cross-section relationship is postulated as in (2):

$$\tilde{R}_i = \tilde{\gamma}_{0t} + \tilde{\gamma}_1 \beta_i + \tilde{\gamma}_2 \beta_{iL} + \tilde{\gamma}_3 \beta_{iSMB} + \tilde{\gamma}_4 \beta_{iHML} + \varepsilon_i \quad (2)$$

The method of testing is similar to that of Fama and MacBeth (1973). The statistical significance of the estimated risk premium is tested using a t-statistic given by:

$$t(\bar{\hat{\gamma}}) = \frac{\bar{\hat{\gamma}}}{S(\bar{\hat{\gamma}})/\sqrt{n}} \quad \textbf{(3)}$$

Where $\bar{\hat{\gamma}}$ and $S(\bar{\hat{\gamma}})$ are the average and standard deviation of the estimated coefficient, respectively, and n is the number of months in the study.

Liquidity risk factors

We construct two measures to reflect the aggregate market wide liquidity based on the bid-ask spread and the Amihud (2002) price impact measure.

Measure based on Bid-Ask Spread

As investors wishing to trade immediately may always sell (buy) at the quoted bid (ask) price that includes a concession (premium) for immediate execution, the spread between the bid and the ask prices, which is the sum of concessions and premiums, divided by the midpoint of the spread, is a natural measure of liquidity. The aggregated relative quoted spread is given by:

$$Spread_{m,t} = \frac{1}{N_t D_t} \sum_{i=1}^{N_t} \sum_{d=1}^{D_t} RQS_{i,d,t} \quad (4)$$

Where N_t is the number of firms in month t and D_t is the number of days in month t. Increasing spreads are associated with decreasing liquidity.

Amihud (2002) Price Impact Measure

The Amihud (2002) price impact measure follows Kyle's concept of illiquidity, as the response of price to order flow. Kyle (1985) argues that spreads are an increasing function of the probability of facing an informed trader, and since the market maker cannot distinguish between order flow from informed traders and order flow from noise traders, she sets prices as an increasing function of the order imbalance that may indicate informed trading. The Amihud (2002) price impact measure is defined as the average ratio of the daily absolute return to the (dinar) trading volume on that day. We expect that large positive values induce low liquidity, consistent with the interpretation of the price impact measure. For every stock, we calculate:

$$ILLIQ_{i,t} = \frac{1}{D_n} \sum_{d=1}^{D_n} \frac{|r_{i,d,t}|}{v_{i,d,t}} \times 1000 \quad (5)$$

where:

$r_{i,d,t}$: the return of stock *i* on day *d* in month *t*.

$v_{i,d,t}$: the dollar volume for stock *i* on day *d* in month *t.*

D_n: the number of trading days in month t.

The aggregate measure is the simple average of the individual stock measures. Large values are associated with low liquidity levels.

Asset Pricing Tests

We investigate whether a stock's expected return is related to the sensitivity of its return to the aggregate liquidity, L_t. That sensitivity, denoted for stock *i* by its liquidity beta β_i^L, is the slope coefficient on L_t, in a multiple regression in which the other independent variables are additional factors considered important for asset pricing.We test for the existence of a liquidity risk premium in two ways. First, to the extent that the post-ranking liquidity betas, according to the objective of the sorting procedure, differ from zero and increase across quintiles, β_i^L explains a component of expected returns not captured by exposures to the other factors. We expect that the (5-1) liquidity spread, which goes long quintile 5 (stocks with high liquidity betas) and short quintile 1 (stocks with low liquidity betas) is positive. Then, we estimate the abnormal return to each liquidity sorted quintile portfolio using the three-factor model of Fama and French (1993) and examine the intercepts. The difference in abnormal return between the extreme quintiles provides information about a component of expected returns not captured by the three-factor model. We also test the hypothesis that all 5 alphas are jointly equal to zero, using the test of Gibbons, Ross, and Shanken (1989), denoted by GRS. Under the null hypothesis that liquidity has no effect on expected returns, the intercepts in these regressions are equal to zero. Following Fama and French, we test the null hypothesis using the GRS (1989) statistic, which can be defined as follows. Let there be N time-series observations, *L* portfolios, and *K - 1* explanatory variables (excluding the intercept). Further, let *X* denote the matrix of regressors. Then, the test statistic is given by:

$$F = \left(A'\Sigma^{-1}A\right) \frac{N-K-L+1}{L \times (N-K) \times w_{1.1}} \quad \textbf{(6)}$$

Where *A* is the column vector of the regression intercepts, Σ is the variance-covariance matrix of the residuals from the regressions, and $w_{1,1}$ is the diagonal element of $(X'X)^{-1}$ corresponding to the intercept. Under the null hypothesis this statistic has an F-distribution with *L* and *N - K - L + 1* degrees of freedom.

Data Sources

The sample considered in this study consists of the stocks traded on the Tunisian stock market from January 2002 to December 2007. From a total of 51 listed at the end of 2007, we selected those that were traded for at least 36 months. Our study will thus focus on 35 stocks. Our choice for the 2002-2007 period is designed to avoid the potential impact of the 2007 subprime crisis on the Tunisian economy as well as the drop of liquidity following the 2010 political transition Foreign acquisitions during the 2008 fourth quarter were 390 millions (in dinars), while cessions amounted to 489 millions, (TSE 2008 activity report).Data relative to financial statements, monthly stock returns and firm market equity (number of shares outstanding times the stock price) come from the TSE electronic database. The book value is obtained as the net assets of the firms excluding any preferred stocks. The market return is a value-weighted return computed from the Tunindex index. Risk-free returns are estimated from the "TRE" (rate of return on savings), which is the smallest rate. Book equity is computed as the book value of the stockholder's equity. Daily best bid and offer (BBO) eligible quotes from the open until just prior to the market close are used to calculate the relative quoted spread are recovered from the TSE. Finally, all stock returns are adjusted for stock splits, right offerings and dividend payment. The well known SMB and HML risk factors of Fama and French (1993) are also used in this study.

Series construction

The mimicking portfolio of the size and book to market construction method is similar to Fama and French (1993). The stocks are allocated to two size portfolios (small and large) depending on whether their market equity is above or below the median. A separate sorting of the stocks classifies them into three portfolios formed

Table 1. Correlation matrix

	SPREADM	ILLIQM	SMB	HML	MKT-RF	VOL
SPREADM	1					
ILLIQM	-0.1759	1				
	(0.1424)					
SMB	-0.0865	0.152	1			
	(0.473)	(0.2056)				
HML	-0.0583	0.1353	0.2469	1		
	(0.6293)	(0.2607)	(0.0379)			
MKT-RF	0.0872	-0.2602	-0.1674	-0.1732	1	
	(0.4667)	(0.0284)	(0.1629)	(0.1485)		
VOL	0.4689	-0.2658	-0.0312	-0.1334	0.3162	1
	(0.000)	(0.0251)	(0.7965)	(0.2672)	(0.0068)	

The table reports the pair wise time-series Pearson correlations of the Fama-French (1993) three factors and (i) aggregated liquidity measures; (ii) the equally weighted average percentage change in monthly dollar volume for TSE stocks, VOL. The Fama-French three factors are the market portfolio (excess of risk-free rate), SMB and HML of Fama and French (1993). For aggregated liquidity measures, SPREADM and ILLIQM, they are calculated according to the relative bid-ask spread and the Amihud (2002) price impact measure. *P*-values are reported in parentheses. The sample period is January 2002 to

using the break points of the lowest 30%, middle 40% and the highest 30%. From these independent sorting we construct six portfolios from the intersection of two size and three book to market portfolios (S/L, S/M, S/H, B/L, B/M, B/H). Equally weighted portfolios are constructed for the full sample range. The SMB factor is the return difference between the average returns on the three small firms portfolios; (S/L + S/M + S/H)/3 and the average of the returns on three big firms portfolios; (B/L + B/M + B/H)/3. In a similar way the HML factor is the return difference in each time period between the return of the two high book-to-market portfolios; (S/H + B/H)/2 and the average of the returns on two low book to-market portfolios; (S/L +B/L)/2. The construction in this way ensures that the two constructed factors represent independent dimensions relation to the stock returns.

For the same set of common stocks, we also have daily data on the trading volume. This daily data is employed for the monthly calculation of firms' illiquidity ratios. Once individual illiquidity ratios are estimated, the next step consists in the construction of 5 illiquidity-based sorted portfolios according to the average illiquidity value of each security in the previous year. P1 includes the stocks with the smallest illiquidity ratio within the sample and P5 contains the stocks with the largest illiquidity ratio. Portfolio monthly returns are calculated giving equal weight to each asset within the portfolio (EW) or according to the value of each stock (VW). These are the portfolio returns, which will be employed in testing the illiquidity based asset-pricing models in the next sections.

Descriptive statistics

Table 1 of correlation matrix reports that the aggregated bid-ask spread, SPREADM, is not correlated with the price impact measure, ILLIQM, (-17.6%) and we can't reject the null hypothesis that this correlation is zero. We conclude that the two dimensions of market-wide liquidity are not related. This primary empirical evidence doesn't support the existence of a common factor in liquidity as with Chordia et al.(2000) and Amihud (2002). This relation is illustrated in figure1. While the aggregated price impact measure ILLIQM has an erratic trend showing several spikes, the aggregated bid-ask spread, SPREADM has rather an increasing linear trend. In contrast to the theoretical evidence, the correlation between the aggregated bid-ask spread and the equally weighted average percentage change in monthly dollar volume for TSE stocks is positive, 42.9%, and statistically significant. When the aggregated bid-ask spread widens, trading activity increases as with the drop of liquidity in period of crisis. As stated by Pástor and Stambaugh (2003), although liquid markets are typically associated with high levels of trading activity, it is often the case that volume is high when liquidity is low. Table 1 also reports correlations between the two liquidity measure and the value weighted TUNINDEX index, and the Fama French factors SMB and HML. None of these correlations is statistically significant. The relation between liquidity, value and growth is controversial.

Post-ranking Portfolio Betas

At the end of each year, stocks are sorted by their mean monthly liquidity value over the previous 12 months and assigned to 5 portfolios. Portfolio returns are computed over the following 12 months, after which the estimation/formation procedure is repeated. The

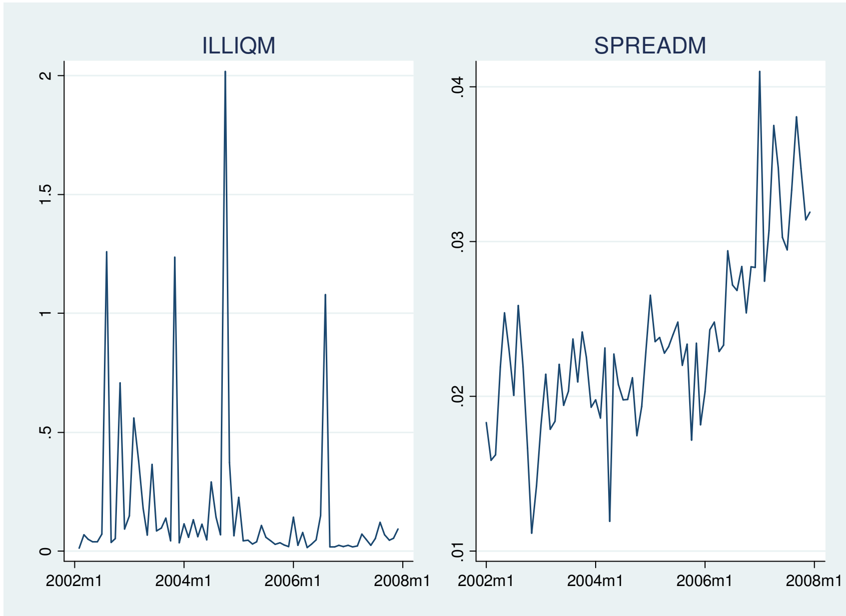

Figure 1. Aggregate liquidity levels
SPREADM is the monthly aggregate liquidity level using the daily average relative quoted spread (RS) for stock *i* on day *d* in month *t* for all stocks. ILLIQM is the monthly aggregate liquidity level using the Amihud (2002) price impact measure defined as the average ratio of the daily absolute return to the (dinar) trading volume on that day.

postranking returns are linked across years, generating a single return series for each quintile covering the period from January 2003 through December 2007.

Table 2 reports the postranking liquidity betas of the quintile portfolios according to the mean monthly RQS value over the previous 12 months when the stocks within each portfolio are value-weighted (VW). The liquidity betas are estimated by running the regression in (1). Annual coefficients are computed as 12 times the monthly estimates. The postranking liquidity betas are not significant and do not increase across quintiles. The (5-1) liquidity spread, which goes long quintile 5 (stocks with high liquidity spread) and short quintile 1 (stocks with low liquidity spread) is rather negative. Table (3) also reports the quintile portfolios'betas with respect to the Fama-French factors, MKT, SMB, and HML. SMB and HML betas of the (5-1) portfolio are statistically significant: 6.8% for SMB and -3.56% for HML. The SMB betas are all positive and confirm the pattern in average capitalizations and the HML betas indicate that the (5-1) portfolio has a tilt toward growth stocks. Table 3 reports the post-ranking liquidity betas according to the Amihud (2002) price impact measure for value-weighted portfolios. The liquidity betas are also insignificant for all quintiles. Only the HML betas are significant. None of the (5-1) portfolio explanatory risk factors is significant. The results for equally weighted portfolios, after sorting stocks according to RQS and Amihud (2002) price impact measure, not reported, are nearly identical. These primary findings show that market liquidity effect on stock returns is problematic. For further investigations, we estimate the abnormal return to each liquidity sorted quintile portfolio using the CAPM and the three-factor model of Fama and French and examine the intercepts.

Alphas

The intercept in the time-series regression of the portfolio's excess return on explanatory returns is the average abnormal return needed to judge whether a manager can beat the market, that is, whether he can use special information about liquidity to generate average returns greater than those on passive combinations of the mimicking returns for risk factors.

If our liquidity risk factor is priced, we should see systematic differences in the average returns of our liquidity-sorted portfolios. After sorting stocks according to the RQS and Amihud (2002) price impact measure, we report the value-weighted and the equally-weighted portfolios' postranking alphas estimated under two different factor specifications. The capital asset pricing model (CAPM) alpha is computed with respect to MKT and the Fama-French alpha with respect to the Fama-French factors. The evidence in table 4 indeed doesn't favor the pricing of liquidity risk. All the quintile intercepts

Table 2. Risk factor sensitivities of portfolios sorted on mean monthly spread (VW)

	1	2	3	4	5	5-1
		$R_{p,t} = \beta_p^0 + \beta_p^L SPREADM_t + \beta_p MKT_t + \beta_p^S SMB_t + \beta_p^H HML_t + \varepsilon_{p,t},$				
MKT beta	1.8	0.372	2.196	2.184	4.368	-0.732
	(0.99)	(0.15)	(0.98)	(0.69)	(1.32)	(-0.27)
SPREADM beta	0.4692	0.5076	-0.4224	0.2208	-0.3588	-1.476
	(0.63)	(0.39)	(-0.66)	(0.13)	(-0.29)	(-1.16)
SMB beta	0.08076	2.616	3.18	4.512	2.808	6.888
	(0.04)	(1.51)	(2.72)	(1.4)	(0.73)	(3.06)
HML beta	-2.376	-3.072	-2.976	-6.912	-6.036	-3.564
	(-1.88)	(-2.51)	(-2.83)	(-2.28)	(-2.57)	(-1.87)
alpha	-0.03936	-0.0396	-0.0252	-0.05472	-0.03	0.0198
	(-1.81)	(-1.20)	(-1.50)	(-1.43)	(-0.98)	(0.63)
R^2	0.133	0.119	0.21	0.198	0.229	0.246

Common stocks are sorted into 5 portfolios every December by their mean monthly bid-ask spread over the previous 12 months and portfolios are held for the following year. The post formation returns on these portfolios during the next 12 months are linked across years to form a single return series for each quintile portfolio. The value-weighted portfolio excess returns on those portfolios are then regressed on return-based factors that are commonly used in empirical asset pricing studies. Specifically, each quintile excess returns is regressed on the aggregated bid-ask spread SPREADM, the stock market excess return MKT and the Fama and French (1993) risk factors SMB and HML. The t-statistics are in parentheses.

Table 3 . Risk factor sensitivities of portfolios sorted on mean monthly Amihud (2002) price-impact measure (VW)

	1	2	3	4	5	5-1
		$R_{p,t} = \beta_p^0 + \beta_p^L ILLIQM_t + \beta_p MKT_t + \beta_p^S SMB_t + \beta_p^H HML_t + \varepsilon_{p,t},$				
MKT beta	1.0584	1.0236	3.828	3.228	-0.5616	-1.62
	(0.52)	(0.51)	(1.4)	(1.45)	(-0.19)	(-0.43)
ILLIQM beta	0.01224	0.00948	0.02772	-0.03768	0.01128	-0.00102
	(1.05)	(0.72)	(2.32)	(-0.73)	(0.86)	(-0.07)
SMB beta	2.628	3.312	2.82	2.064	5.628	3
	(1.2)	(1.14)	(1.59)	(0.89)	(1.35)	(1.09)
HML beta	-4.692	-5.028	-2.028	-4.188	-6.9	-2.208
	(-2.61)	(-2.61)	(-1.98)	(-2.81)	(-2.63	(-0.9)
alpha	-0.00792	-0.00864	-0.00708	0.00516	-0.00708	0.000828
	(-0.85)	(-1.49)	(-0.93)	(0.59)	(-0.89)	(0.07)
R^2	0.233	0.285	0.155	0.184	0.28	0.0461

Common stocks are sorted into 5 portfolios every December by their mean monthly Amihud (2002) price-impact measure over the previous 12 months and portfolios are held for the following year. The postformation returns on these portfolios during the next 12 months are linked across years to form a single return series for each quintile portfolio. The value-weighted portfolio excess returns on those portfolios are then regressed on return-based factors that are commonly used in empirical asset pricing studies. Specifically, each quintile excess returns is regressed on the aggregated price impact measure ILLIQM, the stock market excess return MKT and the Fama and French (1993) risk factors SMB and HML. The t-statistics are in parentheses.

are statistically different from zero but with a negative sign. Sorting stocks according to the historical RQS doesn't offer investors a premium greater than the one offered by the market. Only the 5-1 portfolios CAPM alpha is positive. It is only 0.0276 percent per year (Annual alphas are computed as 12 times the monthly estimates) and not statistically significant (t = 0.02). Concerning the value-weighted portfolios, the (5-1) CAPM extra-premium is rather negative, -0.804%, and statistically insignificant (t=-0.87). The (5-1) Fama-French

Table 4. Alphas of portfolios sorted on historical spread

	Quintile Portfolio					
	1	**2**	**3**	**4**	**5**	**5-1**
	Value-weighted portfolios					
CAPM alpha	-1.944	-1.788	-2.688	-2.772	-1.92	0.0276
	(-3.22)	(-2.46)	(-4.46)	(-2.2)	(-1.78)	(0.02)
Fama-French alpha	-2.784	-2.712	-3.552	-4.932	-3.888	-1.104
	(-4.14)	(-3.38)	(-5.59)	(-3.72)	(-3.42)	(-0.75)
	Equally-weighted portfolios					
CAPM alpha	-1.596	-1.356	-2.4	-2.568	-2.412	-0.804
	(-2.92)	(-2.26)	(-3.17)	(-4)	(-2.66)	(-0.87)
Fama-French alpha	-2.34	-2.424	-3.72	-3.276	-3.996	-1.656
	(-3.88)	(-3.82)	(-5.78)	(-5.05)	(-5.00)	(-1.73)

At the end of each year between 2002 and 2006, eligible stocks are sorted into 5 portfolios according to their mean monthly bid-ask spread value over the previous 12 months. The portfolio returns for the 12 postranking months are linked across years to form one series of postranking returns for each quintile. The table reports the quintile portfolios' postranking alphas, in percentages per year. The alphas are estimated as intercepts from the regressions of value-weighted and equally weighted excess portfolio postranking returns on excess market returns (CAPM alpha) and on the Fama-French factor returns (Fama-French alpha). Annual intercept is computed as 12 times the monthly estimate multiplied by 100.The t-statistics are in parentheses.

Table 5. Alphas of portfolios sorted on historical price impact measure

	Quintile Portfolio					
	1	**2**	**3**	**4**	**5**	**5-1**
	Value-weighted portfolios					
CAPM alpha	0.852	0.816	0.168	1.416	1.512	0.66
	(1.1)	(1.08)	(0.25)	(1.45)	(1.42)	(0.64)
Fama-French alpha	-0.624	-0.744	-0.348	0.0156	-0.552	0.0696
	(-0.78)	(-0.99)	(-0.46)	(0.01)	(-0.53)	(0.06)
	Equally-weighted portfolios					
CAPM alpha	-2.184	-2.664	-2.556	-1.752	-1.224	0.96
	(-3.65)	(-3.56)	(-4.18)	(-2.76)	(-1.48)	(1.15)
Fama-French alpha	-2.34	-2.424	-3.72	-3.276	-3.996	-1.656
	(-5.68)	(-6.5)	(-4.85)	(-4.91)	(-2.52)	(-1.41)

At the end of each year between 2002 and 2006, eligible stocks are sorted into 5 portfolios according to their mean monthly price impact measure value over the previous 12 months. The portfolio returns for the 12 postranking months are linked across years to form one series of postranking returns for each quintile. The table reports the quintile portfolios' postranking alphas, in percentages per year. The alphas are estimated as intercepts from the regressions of value-weighted and equally weighted excess portfolio postranking returns on excess market returns (CAPM alpha) and on the Fama-French factor returns (Fama-French alpha). Annual intercept is computed as 12 times the monthly estimate multiplied by 100.The t-statistics are in parentheses.

alpha is also negative and insignificant.

Table 5 reports the value-weighted and the equally-weighted portfolios' postranking alphas after sorting stocks according to the Amihud price impact measure. The capital asset pricing model (CAPM) and the Fama-French model are used to compute the alphas (abnormal return). All four alphas of the (5-1) portfolio are insignificant. For example, the CAPM value-weighted alpha is 0.66 percent per year (t = 0.64) while the CAPM equally weighted alpha is 0.96 percent per year (1.15).

Annual alphas are computed as 12 times the monthly estimates.

We also test the hypothesis that all 5 alphas are jointly equal to zero, using the test of Gibbons, Ross, and Shanken (1989), GRS. Under the null hypothesis that liquidity has no effect on expected returns the intercepts in these regressions are equal to zero. The finite sample distribution of the GRS test is derived under the assumption of normality of asset returns. To overcome this limitation, we also apply the Generalized Method of Moments (GMM) to test the same hypothesis by simply comparing the restricted and unrestricted model fit with a

Table 6. Joint tests on the regression intercepts

		GRS (1989) test		GMM test	
	Model	**F statistic**	**P-value**	**chi2**	**P-value**
SPREADM	CAPM_VW	0.00017751	1	20.68	0.0009
	CAPM _EW	0.00016294	1	26.99	0.0001
	FF_VW	10.621879	4.59E-07	59.72	0.0000
	FF_EW	14.68136	5.72E-09	102.49	0.0000
ILLIQM	FF_VW	0.22435366	0.95036973	2.74	0.7396
	FF_EW	15.984846	1.61E-09	87.90	0.0000
	CAPM _VW	0.00002739	1	4.76	0.4458
	CAPM _EW	0.00020349	1	21.64	0.0006

The hypothesis that all 5 alphas are jointly equal to zero is tested using the F-statistic of Gibbons, Ross, and Shanken (1989), GRS. We also apply the Generalized Method of Moments (GMM) to test the same hypothesis by comparing the restricted and unrestricted model fit with a Chi-squared test. Under the null hypothesis that liquidity has no effect on expected returns, the intercepts in these regressions are equal to zero. We refer the CAPM and the Fama French three factor (FF) models both augmented with a liquidity factor: aggregated spread, SPREADM, or price impact measure, ILLIQM. We use both equally weighted (EW) and value weighted portfolio. For example, SPREADM_CAPM_VW is the CAPM model adjusted with the aggregated spread effects applied on value weighted portfolios.

Chi-squared test. The results are reported in table (6). After sorting stocks according to the RQS, for both equally-weighted and value-weighted portfolios and for the CAPM and Fama-French models, the hypothesis is rejected at a 1 percent significance level using the GMM method. With the GRS test, the hypothesis is just rejected with the Fama and French model for equally weighted and value-weighted portfolios. For partitioning stocks according to the price impact measure, the F-test just rejects at the 5% and 1% levels the null hypothesis that the intercepts are jointly equal to zero for the Fama-French model with the equally-weighted portfolio. With the Chi-squared test, the same hypothesis is rejected with equally-weighted portfolios for both models. To answer the question of whether liquidity has an impact on stock returns, the interesting result is that only one or more of the five intercepts from the three-factor or CAPM models is much different from zero. In practical terms, liquidity is not rewarded for all portfolios. Rather than dealing with the magnitude of systematic liquidity according to its historical level, after partitioning stocks into quintiles, we investigate in the following section the relationship between liquidity average risk premium and average stock returns.

Fama–MacBeth cross-section regression

Tables 8 and 9 report the benchmark CAPM adjusted with the aggregated liquidity effects containing only the average cross-section coefficients for beta and liquidity risks. Similarly the three Fama–French and liquidity factors consists of only the average factor loading of the three Fama–French factors and the aggregated bid-ask spread or price impact measures. Our asset-pricing tests use the cross-sectional regression approach of Fama and MacBeth (1973). Each month the cross-section of returns on stocks is regressed on variables hypothesized to explain expected returns: the aggregated liquidity factor L_t, the stock market excess return MKT and the Fama and French (1993) risk factors SMB and HML. The time-series means of the monthly regression slopes then provide standard tests of whether different explanatory variables are on average priced.

Table 7 shows that the average coefficient on the aggregated bid-ask spread is negative and significant in the CAPM model (t= -1.98) but it is a marginal 1.78 standard errors from 0 in the Fama–French model. However, its magnitude is just 0.72% and 0.81% per year respectively in the two models which is small compared to transaction costs. Concerning the average premium per unit of market, MKT, it is significant and about 0.88% per month in both models. This is large from an investment perspective (about 10.5 % per year). The average SMB return (the average premium for the size-related factor in returns) is only 0.09% per month (t = -1.76) but the book-to-market factor HML does not produce an additional average premium (t = -1.33).

Table 8 shows that only the average premium per unit of market, MKT, is significant in both models (t= 9.05 and t= 8.99). The hypothesis that average risk premiums associated with the price impact measure is not significant cannot be rejected for both the CAPM (t= -1.58) and the Fama and French (t= -1.65) models. As with the bid-ask spread, the average premium per unit of market, MKT, is significant and about 0.85% per month in

Table 7. Fama-MacBeth Regression Slopes and aggregated bid-ask spread: 2002-2007

Variable		FF_SPREAD	CAPM_SPREAD
MKT-RF	$\bar{\hat{\beta}}^{M}$	0.883 (9.11)	0.879 (8.95)
SPREADM	$\bar{\hat{\beta}}^{SPREAD}$	-0.0597 (-1.78)	-0.0673 (-1.98)
SMB	$\bar{\hat{\beta}}^{S}$	0.0603 (1.76)	
HML	$\bar{\hat{\beta}}^{H}$	-0.0418 (-1.33)	
alpha	$\bar{\hat{\beta}}^{0}$	0.00048 (0.56)	0.00077 (0.90)
R^2		0.0919	0.0881

The table reports the average regression coefficient using the Fama and MacBeth (1973) two steps methodology: In the first step, for each single time period, a cross-sectional regression is performed. Each stock excess returns is regressed on the aggregated bid-ask spread *SPREADM,* the stock market excess return MKT-RF and the Fama and French (1993) risk factors *SMB* and *HML*. Then, in the second step, the final coefficient estimates are obtained as the average of the first step coefficient estimates. This model is labeled *FF_SPREAD*. The table also report *CAPM_SPREAD*, the CAPM model adjusted with the aggregated bid-ask spread. Annual liquidity is computed as 12 times the monthly estimate multiplied by 100. The t-statistics are in parentheses.

Table 8. Fama-MacBeth Regression Slopes and aggregated price impact measure: 2002-2007

Variable		*FF_ILLIQT*	*CAPM_ILLIQ*
MKT-RF	$\bar{\hat{\beta}}^{M}$	0.854 (9.05)	0.855 (8.99)
ILLIQM	$\bar{\hat{\beta}}^{H}$	-0.00056 (-1.65)	-0.00054 (-1.58)
SMB	$\bar{\hat{\beta}}^{ILLIQ}$	0.0678 (1.96)	
HML	$\bar{\hat{\beta}}^{S}$	-0.0378 (-1.20)	
alpha	$\bar{\hat{\beta}}^{0}$	-.00087 (-3.34)	-.00081 (-3.11)
R^2		0.0906	0.0895

The table reports the average regression coefficient using the Fama and MacBeth (1973) two steps methodology: In the first step, for each single time period, a cross-sectional regression is performed. Each stock excess returns is regressed on the aggregated price impact measure ILLIQM, the stock market excess return MKT-RF and the Fama and French (1993) risk factors *SMB* and *HML*. Then, in the second step, the final coefficient estimates are obtained as the average of the first step coefficient estimates. This model is labeled *FF_ILLIQ*. The table also report *CAPM_ILLIQ*, the CAPM model adjusted with the aggregated price-impact measure. Annual liquidity is computed as 12 times the monthly estimate multiplied by 100. The t-statistics are in parentheses.

both models. The average SMB is also significant but the book-to-market factor, HML, is not.

These results push us to conclude that the average systematic liquidity effect is problematic during the January 2002 to December 2007 period. While the Amihud average liquidity premium is not priced in the CAPM and three factor models, the same sensitivity is marginally significant with the RQS. We care that systematic liquidity is negative with both liquidity measures and with both models.

CONCLUSION

The aim of this study was to investigate if market liquidity is a state variable that has to be rewarded in a multifactor asset pricing model in the Tunisian emerging market. The models used to check this assumption are the CAPM and the Fama and French models that, in addition to aggregated liquidity, account for risks related to market, size and book-to-market factors. We used the relative quoted spread, RQS, and the Amihud (2002) price impact measures to account for the market liquidity factor. We tested the relationship between expected returns and liquidity in referring to two methods: (i) Partitioning stocks in portfolios according to historical individual liquidity levels and (ii) using the Fama- MacBeth (1973) approach. In contrast to the objective of the sorting procedure, with the first approach, we found that post-ranking liquidity betas are not significant and do not increase across quintiles for both liquidity measures and for equally weighted and value weighted portfolios. We also found that all four alphas of the (5-1) portfolio are insignificant for the same set of data. We further tested the hypothesis that all 5 alphas (abnormal returns) are jointly equal to zero, using the F-statistic of Gibbons, Ross, and Shanken (1989), GRS and the Generalized Method of Moments (GMM) with a Chi-squared test. Among eight models to check this hypothesis (CAPM and Fama and French models with the aggregated bid-ask spread and price impact measure, for equally weighted and value weighted portfolios), we rejected this hypothesis for four models with the GRS test and for two models with the GMM chi-squared test. To answer the question of whether liquidity can be useful in applications, the result is that only one or some of the 5 quintile portfolios are sensitive to liquidity. Applying the Fama-MacBeth cross-section approach has also shown that average returns are marginally sensitive to aggregated liquidity levels with both CAMP and Fama and French models but the price impact measure is not.

DISCUSSION

The lack of liquidity on the emerging TSE can be considered as a barrier that discriminates the introduction of new listed companies. From macroeconomic and microstructure perspectives, liquidity is indispensable in order to attract investment and foreign capital. Through this paper, we intended to measure to what extent market liquidity is linked to expected stock returns. Our findings show that liquidity is a controversial state variable that is not rewarded. We thus think that our results are affected by return interval. As pointed out by Gilmer (1988), the intervalling effect is the tendency of risk estimates to be different as the holding period changes. Also Handa et al.(1989) found that as the return interval is increased the spread between the betas of low and high-risk securities will increase. Ikbal and Brooks (2007) noted that betas estimated using returns measured over different intervals would also be affected by their different standard errors. The standard error of the beta estimated using longer interval returns would be greater as there are fewer observations available for estimation. Considering this evidence of sensitivity of betas to the return interval, this work should be performed at different other frequencies (daily and weekly). Furthermore, considering the infrequent trading of many stocks on the TSE, the effect of changes in liquidity over time should also be examined. This raises the problem of non-synchronicity. It results from the assumption that multiple time series are sampled simultaneously when in fact the sampling is non-synchronous. For a further work, taking into account this assumption will shed light on an issue not yet examined concerning the interrelation of liquidity and stock returns.

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