Idiosyncratic risk, returns and liquidity in the London Stock Exchange: a spillover approach[1]

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Abstract

In the light of recent evidence that liquidity and idiosyncratic risk may be priced factors in the cross section of expected stock returns and that market capitalization significantly affects investor behavior and liquidity, we explore the interactions between liquidity, idiosyncratic risk and return across time as well as across size-based portfolios of stocks listed in the London Stock Exchange. In a Vector Autoregressive (VAR) analytical framework, we find that volatility spills over from large cap stocks to small cap stocks and vice versa. Volatility shocks can be predicted by illiquidity shocks in both large cap as well as in the small cap portfolios. Illiquidity can be predicted by return shocks in small cap stocks. Finally, we document some evidence of asymmetric liquidity spillovers, from large cap stocks to small cap ones, supporting the intuition that common information is first incorporated in the trading behavior of large-cap investors and the liquidity of large cap stocks and is then transmitted in the trading of small stocks.

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1. INTRODUCTION

Systematic as well as idiosyncratic risk affects liquidity in the London Stock Exchange (LSE) (Menyah and Paudal, 1996), liquidity affects expected returns (Galariotis and Giouvris, 2007b) and returns are determined by idiosyncratic risk (Angelidis and Tessaromatis, 2008). The dynamic, causal relation between idiosyncratic risk, liquidity and returns motivated our effort to investigate the properties of liquidity in the LSE, in association with variations in idiosyncratic risk, return and market capitalization. In this paper, we study the time series as well as the cross section determinants of the liquidity of stocks traded in the LSE. We explore bidirectional causal relations between shocks in (il)liquidity, returns and idiosyncratic risk. Our sample is –to the best of our knowledge- the largest sample used in a liquidity study for the LSE: we use 20 years of daily data on trading activity, returns and volatility in a period of significant institutional changes in the LSE, such as the transition from the SEAQ to the SETS.

So far, the literature for the liquidity in the London LSE is mostly spread in five directions: i) the estimation of the components of the bid-ask spread (Sapporta et al.,1999, Menyah and Paudal 1996, Menyah and Paudal 2000, Levin and Wright 2004), ii) intraday time series properties of spreads, volatility and volume (Abhyankar et al. 1997, Cai et al., 2004) iii) the effect of the transition from the SEAQ to the SETS (Taylor et. al, 2000, Cheeley-Steeley 2005, Ellul et al., 2005, Lai 2007, Galariotis and Giouvris 2007a), iv) the characteristics of the interdealer market (Hansch et al., 1998, Reiss and Werner 1998, Reiss and Werner, 2005), and v) the characteristics of large trades (Gemmil 1996, Snell and Tonks 2003, Bernhardt et al., 2005).

The decomposition of the bid-ask spread into its components, for stocks traded in the LSE was the contribution of Sapporta et al. (1999). They found that the adverse selection and inventory costs constitute a small portion of the bid-ask spread and that spreads decrease with trade size and hence concluded that order-processing costs are a decisive determinant of the bid-ask spread. Menyah and Paudal (2000) studied the determinants of the bid-ask spread in the LSE. Using intraday data for 819 stocks traded in the LSE over a 12-month period, they discovered that the three components of the bid-ask spread (inventory, order-processing and asymmetric information) vary with the liquidity of the stocks, measured with the minimum amount of shares the market makers are obliged to trade (NMS). In excess of these three components of the bid-ask spread, Levin and Wright (2004) investigated the profit markup component of the spreads. They applied Nash-Cournot microeconomic analysis in order to derive a model for the economic profit of market makers. Their empirical evidence on stocks that constituted the FTSE100 index showed an 11% profit markup component.

At the origins of our time series approach on liquidity in the LSE, the time series properties of liquidity, returns, volume and volatility for the stocks listed in the LSE were studied on an intraday basis by Abhyankar et.al. (1997). Working with a three-month sample they documented a U-shaped pattern for intraday spreads and volatility, a double-humped pattern for trading volume that varied with the extent of trading activity. Cai et al. (2004) extended the work of Abhyankar et al. (1997) to a larger sample and to multiple trading settings (SETS and SEAQ). They discovered the same intraday patterns for volatility and volume and roughly similar ones for the bid-ask spread.

Closest to our ambition to investigate the cross sectional and the time series properties of liquidity is the work of Menyah and Paudyal (1996). They produced evidence that the bid-ask spread is affected by (systematic and unsystematic) risk, share price and trading volume and -for some years- the level of competition in market-making was also important. In the time series dimension, they examined the adjustment of the spread due to deviations from its normal value (normal spread taken as a time series average). They found that roughly the same factors that explained the cross section also explained the time series of the adjustment to the normal spread (competition of market makers can be more important in this case). We extend this approach by studying the interactions between idiosyncratic risk, return, liquidity in a far richer data set, including -in a VAR framework- a cross sectional as well as a time series across size portfolios. Explicitly accounting for a market-capitalization factor, we study spillover relations between liquidity, idiosyncratic risk and returns.

So far, time series analysis on liquidity of the LSE has been mostly confined to an intraday setting (Cai et al., 2004 and Abhyankar et al., 2004) and the cross section analysis has been oriented towards the commonality features of the liquidity. Recent theoretical and empirical work on the dynamics of the bid-ask spread has demonstrated the need for a comprehensive approach, incorporating causal relations between liquidity, trading activity, returns and volatility.

Based on evidence that market capitalization is significant in explaining variations in liquidity (Chordia et al., 2000, Huberman and Halka 2001, Brockman et al., 2006) as well as trading activity (Chordia et al., 2007), we organize our sample into size-based portfolios and study liquidity interactions (spillovers) between large cap and small cap stocks. Our spillover analysis also extends to volatility and return interactions between small-cap and large-cap stocks, drawing on the findings of Lo and MacKinlay (1990), Conrad et al. (1990) and, recently, Chordia et al. (2006) and Harris and Pisedtasalasai (2006). On the liquidity-volatility relation, we build our case on evidence that volatility is a factor that significantly affects liquidity (Benston and Hagerman 1974, Stoll 1978, Menyah and Paudyal 1996, Chordia et al., 2000). Our investigation on the liquidity-return relation is motivated by microeconomic arguments (Amihud and Mendelson 1986, Holmstrom and Tirole 2001) as well empirical evidence (e.g. Brennan and Subrahmanyam 1996, Brennan et al., 1998, Amihud 2002, Liu 2006) that liquidity is a priced factor in the cross section of expected stock returns but also on evidence that liquidity itself is affected by stock returns (Brockman et al., 2006, Chordia et al., 2006). Our case for a causal dependence of liquidity on returns and risk can also be supported by evidence that while liquidity depends on trading activity (Menyah and Paudyal, 1996, Chordia et al., 2000), trading activity itself depends on risk and returns (Chordia et al, 2007) and return and volatility spillovers are affected by spillovers of trading activity across size portfolios (Chordia et al., 2006). We adopt the modeling approach of Chordia et al. (2006) and apply their VAR approach (also found in Huang and Masulis, 1999 and Bekaert et al., 2007) in exploring spillovers of liquidity, trading activity, volatility and returns across capitalization-based portfolios. Our largely quote-driven sample (SEAQ was the trading setting to the majority of the stocks in our sample) provides the opportunity to see whether their results are affected by considerations on the structure of the trading system. In the following section we describe our sample selection approach, justify our choice for a measure of (il)liquidity and present the time series properties of illiquidity in the sample. Section 3 lays out our adjustment regressions aiming at removing calendar and systematic market effects from our results on the dynamics of return and idiosyncratic risk of stocks traded in the LSE during the sample period. In section 4 we construct a VAR econometric mechanism in order to explore the relation between idiosyncratic risk, return and liquidity in the

LSE and discuss the information flows and investing behaviors suggested by our results. Section 5 concludes the paper, summarizing our findings and pointing out directions for further research.

2. THE SAMPLE

Our data set has been obtained from Datastream and covers all listed and de-listed stocks in the London stock Exchange from 31/12/1987 to 31/05/2007 (a total of 4825 observations). Datastream covered, approximately, 2300 (1500) securities in 2007 (1988). We impose some filters to minimize the risk of data errors in order to exclude the following categories of stocks from the analysis and to account for potential peculiarities of the UK data[2]:

1. All the foreign companies and the investment trusts due to the fact that maybe they are exhibited different trading behavior
2. To avoid the influence of either high or low priced stocks, we set the price to a missing value for that day if it was greater than 999.99 or lower than 0.1 pounds.
3. If the daily return of a stock is greater than 100% or lower than -90% it was set to a missing value.

Kyle (1985) argued that the term "liquidity" is composed by three different aspects: (a) tightness, which refers to the cost of liquidating a small position, due mainly to the bid–ask spread, (b) depth, which describes the ability to buy or sell any amount of stock beyond the posted bid–ask spread and (c) resiliency, which describes the time and the speed prices need to return to their equilibrium level. Given this multi-aspect nature of liquidity, it is not feasible to create a single measure that captures all these aspects and hence more than one measure must be used in order the liquidity to best be described, as correctly was pointed out by Amihud (2002).

Our approach to illiquidity is in the spirit of Amihud (2002), examining the relation between daily absolute returns and the daily pound trading volume. The Amihud illiquidity measure is defined as:

[2] These filters removed less than 5% of observation during the sample period.

$$I_{i,t} = \frac{|r_{i,t}|}{Vol_{i,t}}$$

where $Vol_{i,t}$ and $|r_{i,t}|$ are the trading pound volume and the absolute return on stock i on day t, respectively.

When compared to other liquidity approximations, (e.g. Hasbrouck, 2005), the Amihud ratio is highly correlated to other liquidity measures based on microstructure data. However, as correctly pointed out by Hwang and Lu (2006), Amihud's (2002) illiquidity ratio has two shortcomings: Given that the Amihud measure uses the trading pound volume, the illiquidity ratio increases when the stock price increases, even if the liquidity remained constant. Moreover, the Amihud illiquidity ratio can turn out to be correlated with market capitalization, since trading volume is related to the market capitalization of traded stock (Nagel, 2005, Lo and Wang, 2000) which, in turn, is also known to affect liquidity (e.g. Chordia et al., 2000). Hwang and Lu (2006), following the proposal of Lo and Wang (2000), used as proxy of illiquidity the natural log of the ratio between absolute return to turnover to minimize the effect of outliers that are commonly observed during periods of low trading activity and the turnover in the attempt to be free of the market capitalization

$$\Psi_{i,t} = \ln \frac{|r_{i,t}|}{Turnover_{i,t}}.$$

Adopting the reasoning of Hwang and Lu (2000) on the desirable properties of an illiquidity measure, we employ $\Psi_{i,t}$ as a measure for the illiquidity of stocks traded in the LSE. In calculating an illiquidity measure for the entire stock market, we can either use a value-weighted or an equally weighted (e.g. Galariotis and Giouvris 2007a) index.

In order to investigate more closely the time series and the cross section of liquidity spillovers in the LSE, we create 10 portfolios based on the market capitalization of the previous year end. For these portfolios we calculate the daily value weighted and equally weighted returns and liquidity measures. Table 1 presents summary statistics for the illiquidity measures. For the smallest capitalization stocks equals 0.000227 ($e^{-8.39}$) while for the largest stocks reaches to

0.000030 ($e^{-10.43}$) and hence there are indications that the largest stocks are the most liquid, a finding that is consistent with the work of Chordia et al. (2006) who reported that the proportional spreads of the smallest NYSE stocks are substantial higher than that of the largest implying that they are more illiquid. In addition, the risk that is associated to the illiquidity exhibits a U-shaped pattern, as it decreases for the first eight portfolios and then start to increase. However, the standard deviation of the largest capitalization companies is lower than that of the smallest ones. Furthermore, the equally weighed illiquidity measure is lower than that of the value weighted since the later measure resembles that of the largest capitalization companies. Specifically, the null hypothesis of equality of the two measures is rejected at any commonly used confidence level, as the t-statistic equals 82.22.

As it is expected, the illiquidity measures are positively correlated and thus an increase of illiquidity in any portfolio affects, contemporaneously, all the others. The relation is statistically significant only between either the smallest or the largest stocks since the correlation coefficient between the largest and the smallest securities is equal to 0.01 which is statistically insignificant. The two market wide illiquidity measures are correlated as the coefficient equals 0.50 and hence they move in tandem. The detailed results are given in Table 2.

Figure 1 plots the time series of the two market wide illiquidity measures and that of the two extreme portfolios. The equally weighted illiquidity index increased over the sample period and this implies an increase in the illiquidity of the smallest stocks, since an equally weighted calculation gives more weight on the smallest stocks. On the other hand, time series evidence indicates that the largest companies became more liquid as the value of the illiquidity measure is lower in 2007 than it was in 1988. The smallest stocks become more illiquid as at the beginning (end) of the sample the illiquidity ratio equals 0.00003 (0.00017) which corresponds to an approximate increase of 600%! On the other hand, the corresponding values of the largest capitalization stocks are 0.00004 and 0.000007. Therefore, the liquidity of the smallest portfolios increased throughout our sample period, contrary to the findings of Chordia et al. (2006) who reported a decrease especially after the changes in tick size that occurred in 1997 and 2001. A different picture is revealed when we examine the largest stocks, as there are indications that become more liquid consistent with the findings of Chordia et al. (2006).

Visual inspection of the graphs reveals evidence of trends in all illiquidity measures. Table 3 shows the reports the ordinary least-squared (OLS) regression results of the various liquidity measures on a constant and a linear time trend. The trend coefficient (β) is positive and statistically significant for almost all the smallest capitalization portfolios a finding that is also confirmed by the coefficient of the equally weighted illiquidity measure. Therefore, the smallest stocks are less liquid than they were in 1988. On the other hand, the largest capitalization stocks (portfolio 9 and 10) are more liquid as the trend coefficient is negative and statistically significant. To conclude, the statistical evidence in Table 3 confirms the conclusion based on visual inspection of the time series of volatilities: the liquidity of the largest (smallest) stocks show significant positive (negative) trend during the 1988-2007 period.

3. TIME SERIES ADJUSTMENTS

Chordia et al (2005) estimate the volatility for each size portfolio as the absolute value of the residuals of the following equation:

$$R_{i,t} = \alpha_1 + \sum_{j=1}^{4} \alpha_{2,j} D_j + \sum_{j=1}^{12} \alpha_{3,j} R_{i,t-j} + \varepsilon_{i,t} \text{ (1),}$$

where D_j is a dummy variable for the day of the week and R_{it} is the value-weighted for the size-based portfolio *i*. Yet, the residuals obtained from the previous regression do not capture only the volatility effect of the decile but also the market effect. Recent evidence on the LSE suggests that idiosyncratic risk is a significant priced factor, especially for small cap stocks (Angelidis and Tessaromatis, 2008). In order to capture the idiosyncratic effect of each decile, we estimate the following regression:

$$R_{i,t} = \alpha_1 + \sum_{j=1}^{4} \alpha_{2,j} D_j + \sum_{j=1}^{12} \alpha_{3,j} R_{i,t-j} + \beta R_{m,t} + \sum_{j=1}^{12} \beta_j R_{m-j} + \varepsilon_{i,t} \text{ (2),}$$

where R_{mt} is the value weighted market return. Chordia et al. (2005) approximated volatility with the absolute value of e_{it}. Volatility, however, is time varying and may well exhibit an asymmetric effect. Drawing on these arguments and following the work of Spiegel and Wang

(2005) who modeled the time variations in the variance of stock returns, it is plausible to estimate Nelson's (1991) EGARCH(1,1) model that captures the leverage effect:

$$\ln(\sigma_t^2) = a_0 + a_1(|\varepsilon_{t-1}/\sigma_{t-1}| - E|\varepsilon_{t-1}/\sigma_{t-1}|) + \gamma_1(\varepsilon_{t-1}/\sigma_{t-1}) + b_1 \ln(\sigma_{t-1}^2) \quad (3)$$

Our logarithmic transformation ensures that the forecasts of the variance are non-negative. The parameters γ_1 allow for the asymmetric effect. If $\gamma_1 = 0$ then a positive surprise, ($\varepsilon_t > 0$), has the same effect on volatility as a negative surprise, ($\varepsilon_t < 0$). The presence of leverage effect can be investigated by testing the hypothesis that $\gamma_1 < 0$. Table 4 presents the estimated parameters of the model. In both cases (smallest-largest stocks) the parameters of the variance equation are statistically significant, a result that supports the modeling procedure.

In order to explore the dynamic interdependence of idiosyncratic risk, return and liquidity across size-based portfolios in the LSE, we have to disentangle calendar as well as autocorrelation regularities from our time series data. In the spirit of Gallant et al. (1992) and Chordia et al (2005) we adopted an adjustment model, which can be compactly described as:

$$\begin{aligned} &w = x'B + u \\ &\log(u^2) = x'\gamma + v \qquad (4) \\ &w_{adjusted} = a + b(\hat{u}/e^{(x'\gamma/2)}) \end{aligned}$$

where w is the series to be adjusted and x are the four day-of-the-week dummies for Monday through Thursday, the 11 month dummies for February through December, a time trend, a square of the time trend and twelve lags values of w to capture any time dependence of the series[3]. a and b are chosen in a way that both the mean and the variance of the adjusted and the unadjusted data are the same. The results presented in this paper as well as the subsequent analysis, will be based on the adjusted time series or return, idiosyncratic risk and liquidity.

4. VAR ESTIMATION AND DISCUSSION OF THE RESULTS

[3] For the illiquidity series we also included the equally weighted market wide measure as an extra control variable. For the return series we include the value weighted market return.

In order to investigate the relation and the positive and the negative spillover between the various measures of volatility, liquidity and returns, we estimate a GARCH(1,1) VAR model which is commonly used for forecasting systems of interrelated time series. VAR is represented as:

$$y_t = A_1 y_{t-1} + \varepsilon_t \quad (5),$$

where y_t is a k vector of endogenous variables and ε_t is a vector that is assumed to distributed normally with mean zero and conditional covariance H_t :

$$\mathrm{H}_t = \Omega + \mathrm{A} \otimes \varepsilon_{t-1}\varepsilon_{t-1}' + \mathrm{B} \otimes \mathrm{H}_{t-1}$$

Table 5 below presents the results from our VAR analysis. Table 6 shows contemporaneous correlation results on the variables studied in our VAR.

The results from our VAR analysis show, that, in small cap portfolios, returns are significant in the prediction of illiquidity. This evidence is supported by the assumption that past returns shape expectations about future returns (Chordia et al. 2001). Shocks in stock returns can generate investor interest and increase trading activity, thus resulting in a decrease of illiquidity. A negative relation between illiquidity and returns has also been documented in Goyenko and Ukhov (2007). We also found some evidence (at a 10% significance level) that liquidity shocks in the large cap stocks have a negative effect on small cap liquidity. This spillover finding is in agreement with recent US evidence that trading activity may flow from large cap stocks to small cap ones (Chordia et al., 2006). The reasons for a negative sign however, can be found in Table 6 that shows negative contemporaneous correlation between small cap and large cap stock returns. As positive large cap return shocks increase trading activity and decrease illiquidity, simultaneous negative shocks in the small cap stocks decrease trading activity and liquidity. Furthermore, our VAR results show that liquidity shocks persist in both large cap and small cap firms. This evidence is in accordance with US (Acharya and Pedersen, 2005) and international (Bekaert, Harvey and Lundbland, 2007) research findings on the persistence of liquidity shocks.

In the volatility front, we see that volatility shocks from large cap portfolios spill over to small cap portfolios. Bidirectional volatility spillovers have also been documented by Chordia et al (2006) for the US and by Pardo and Torro (2007) for Portugal. Our spillover findings agree with the results of Harris and Pisedtasalasai (2006) with respect to the effect of large stocks on small stocks. Our different results with respect to the significance of volatility spillover effects from small cap stocks to large cap stocks may be attributed to the differences in the structure of our data set.

Shocks in small cap returns predict shocks in small cap volatility of opposite sign, thus providing evidence of an asymmetric volatility effect in small cap stocks. We also see from Table XX that volatility can also be predicted by illiquidity shocks in both large cap and small cap portfolios. This result complements evidence provided by Tse and Xiang (2005) on the FTSE100 futures that documented a causal relation between illiquidity and volatility, attributed to asymmetric volatility effects.

Finally, with respect to the time series properties of stock returns, we found persistent shocks in stock returns for large-cap stocks and also with reversals in the returns of small cap stocks. Our findings for stocks in the large-cap portfolio are in the same spirit with the findings of Chelley-Steely (2005), who studied the time series of FTSE 100 and FTSE 30 returns (a mainly large-cap sample). As for the reversals and the overreaction in small cap stocks, the source of this phenomenon can be attributed to the fact that in our sample, the small cap stocks were more illiquid, compared to the large cap stocks. Small cap stocks mostly attract non-informational liquidity traders, whose preferences result in a downward sloping demand curve, for illiquid, small cap stocks and it is this demand curve that generates reversals in returns (Avramov et al., 2006).

5. CONCLUSIONS AND SUGGESTIONS FOR FUTURE RESEARCH

Our analysis on the spillover of idiosyncratic risk, return and liquidity across size portfolios in the LSE has shown significant volatility spillovers from large cap stocks to small cap ones and vice versa. Illiquidity shocks in the LSE are persistent and can predict shocks in volatility and we also produced some evidence that illiquidity shocks transmit from the large cap stocks to the small cap ones.

Our work can be extended in multiple directions. A direct extension of the work presented here, would be the investigation of the interactions between liquidity, volatility, return and firm size on an intraday level. Moreover, our VAR modeling approach could adopt the bid-ask spread as a proxy for liquidity and decompose it into its order-processing, adverse selection and inventory holding cost components. These decompositions, along with our decomposition of risk into its systematic and idiosyncratic components, could help determine the component of the bid-ask spread as well as the components of risk that are responsible for the spillover effects that are documented in this paper.

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Table 1. Descriptive Statistics for equally weighted and value-weighted liquidity measures												
	Portfolios										Market	
	1	2	3	4	5	6	7	8	9	10	Equal	Value
Mean	-8.39	-8.89	-9.15	-9.35	-9.49	-9.66	-9.91	-10.18	-10.41	-10.43	-9.57	-10.36
Median	-8.29	-8.79	-9.10	-9.30	-9.46	-9.67	-9.94	-10.19	-10.36	-10.36	-9.58	-10.30
Maximum	-6.26	-6.74	-7.09	-7.13	-6.99	-7.19	-7.31	-7.23	-7.29	-7.85	-7.54	-7.83
Minimum	-11.31	-11.54	-11.58	-11.69	-12.02	-11.64	-11.50	-11.87	-11.80	-12.24	-11.28	-11.95
Std. Dev.	0.73	0.68	0.62	0.61	0.59	0.54	0.45	0.46	0.52	0.56	0.43	0.51
Skewness	-1.08	-0.85	-0.57	-0.54	-0.28	0.12	0.58	0.52	0.01	-0.29	0.04	-0.29
Kurtosis	4.64	3.96	3.88	3.86	3.92	3.96	5.08	5.38	3.72	3.14	4.21	3.37
Jarque-Bera	1474.69	769.49	417.10	384.73	233.40	196.46	1144.43	1351.73	103.58	70.75	296.85	93.03

This table presents summary statistics for the illiquidity measures for the 10 portfolios based on the market capitalization of the previous year end and the market wide illiquidity measures. The illiquidity is calculated as $\Psi_{i,t} = \ln \frac{|r_{i,t}|}{Turnover_{i,t}}$, where and $|r_{i,t}|$ is the absolute return on stock i on day t. The sample runs from 31/12/1987 to 31/05/2007.

Table 2. Correlation Analysis of the Illiquidity Measures

		Portfolios										Market	
		1	2	3	4	5	6	7	8	9	10	Equal	Value
Portfolios	1	1.00											
	p value	-											
	2	0.79	1.00										
	p value	0.00	-										
	3	0.77	0.83	1.00									
	p value	0.00	0.00	-									
	4	0.75	0.80	0.81	1.00								
	p value	0.00	0.00	0.00	-								
	5	0.70	0.78	0.79	0.82	1.00							
	p value	0.00	0.00	0.00	0.00	-							
	6	0.62	0.72	0.75	0.77	0.79	1.00						
	p value	0.00	0.00	0.00	0.00	0.00	-						
	7	0.52	0.60	0.66	0.71	0.73	0.75	1.00					
	p value	0.00	0.00	0.00	0.00	0.00	0.00	-					
	8	0.35	0.40	0.45	0.50	0.53	0.56	0.63	1.00				
	p value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-				
	9	0.04	0.06	0.14	0.24	0.27	0.33	0.46	0.68	1.00			
	p value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-			
	10	0.01	0.01	0.08	0.16	0.19	0.24	0.36	0.61	0.83	1.00		
	p value	0.43	0.36	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-		
Market	Equal	0.77	0.82	0.85	0.88	0.88	0.86	0.84	0.72	0.49	0.42	1.00	
	p value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-	
	Value	0.07	0.09	0.16	0.24	0.27	0.32	0.44	0.69	0.89	0.98	0.50	1.00
	p value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-

This table presents the bivariate correlations between the illiquidity measures for the 10 portfolios based on the market capitalization of the previous year end and the market wide illiquidity measures. The sample runs from 31/12/1987 to 31/05/2007.

Table 3. Trend Analysis

Portfolios	α	β	R^2-Adjusted
1	-0.46	0.000013	0.76
	0.00	0.00	
2	-0.55	0.000016	0.76
	0.00	0.00	
3	-0.64	0.000015	0.72
	0.00	0.00	
4	-0.67	0.000014	0.70
	0.00	0.00	
5	-0.72	0.000014	0.67
	0.00	0.00	
6	-1.01	0.000015	0.56
	0.00	0.00	
7	-1.43	0.000012	0.44
	0.00	0.00	
8	-1.09	-0.000003	0.48
	0.00	0.37	
9	-0.84	-0.000016	0.63
	0.00	0.00	
10	-0.85	-0.000019	0.62
	0.00	0.00	
Equal	-0.49	0.000005	0.73
	0.00	0.04	
Value	-0.69	-0.000014	0.67
	0.00	0.00	

This table reports the ordinary least-squared (OLS) regression results of the two illiquidity measures on a constant and a linear time trend. The model can be represented as: $Illiq_t = a + \beta * Time + \sum_{j=1}^{12} c_j Illiq_{t-j} + \varepsilon_t$, where $Illiq_t$ is the corresponding illiquidity measure. The second row for each regression gives the Newey-West (1987) adjusted p-values. The last column reports the adjusted R2 values. The sample runs from 31/12/1987 to 31/05/2007.

Table 4. Volatility Estimation				
	Portfolio 1		Portfolio 10	
	Coefficient	p value	Coefficient	p value
α_1	0.0014	0.00	-0.0001	0.03
$\alpha_{2,1}$	-0.0001	0.87	0.0003	0.00
$\alpha_{2,2}$	-0.0011	0.02	0.0001	0.34
$\alpha_{2,3}$	-0.0040	0.00	0.0004	0.00
$\alpha_{2,4}$	-0.0028	0.00	0.0001	0.29
$\alpha_{3,1}$	0.2092	0.00	0.0678	0.00
$\alpha_{3,2}$	0.0793	0.00	0.0061	0.69
$\alpha_{3,3}$	0.0634	0.00	0.0386	0.01
$\alpha_{3,4}$	0.0344	0.03	0.0054	0.71
$\alpha_{3,5}$	0.0250	0.09	0.0023	0.87
$\alpha_{3,6}$	0.0496	0.00	-0.0093	0.52
$\alpha_{3,7}$	0.0046	0.76	-0.0135	0.34
$\alpha_{3,8}$	0.0500	0.00	0.0048	0.74
$\alpha_{3,9}$	0.0303	0.04	0.0122	0.42
$\alpha_{3,10}$	0.0636	0.00	0.0205	0.15
$\alpha_{3,11}$	-0.0030	0.84	0.0268	0.06
$\alpha_{3,12}$	0.0187	0.17	-0.0064	0.65
β	0.7984	0.00	1.1425	0.00
β_1	0.1516	0.00	-0.1274	0.00
β_2	0.0329	0.13	-0.0290	0.10
β_3	0.0865	0.00	-0.0646	0.00
β_4	0.0485	0.03	-0.0209	0.23
β_5	0.0798	0.00	-0.0172	0.30
β_6	0.0101	0.65	0.0018	0.92
β_7	-0.0042	0.86	0.0052	0.76
β_8	-0.0352	0.12	-0.0119	0.48
β_9	0.0032	0.89	-0.0267	0.13
β_{10}	0.0134	0.54	-0.0296	0.08
β_{11}	-0.0333	0.13	-0.0356	0.04
β_{12}	0.0209	0.33	0.0046	0.78

Table 5 (Continued). Variance Equation				
α_0	-0.2081	0.00	-0.2353	0.00
α_1	0.1256	0.00	0.1366	0.00
γ_1	-0.0180	0.00	0.0389	0.00
b_1	0.9877	0.00	0.9894	0.00
Adjusted R-squared	43.62%		94.68%	

This table presents, for the two extreme portfolios, the estimates of an EGARCH(1,1) model:

$$R_{i,t} = \alpha_1 + \sum_{j=1}^{4} \alpha_{2,j} D_j + \sum_{j=1}^{12} \alpha_{3,j} R_{i,t-j} + \beta R_{mt} + \sum_{j=1}^{12} \beta_j R_{m-j} + \varepsilon_{i,t},$$

$$\ln\left(\sigma_t^2\right) = a_0 + a_1\left(\left|\varepsilon_{t-1}/\sigma_{t-1}\right| - E\left|\varepsilon_{t-1}/\sigma_{t-1}\right|\right) + \gamma_1\left(\varepsilon_{t-1}/\sigma_{t-1}\right) + b_1 \ln\left(\sigma_{t-1}^2\right)$$

where D_j is a dummy variable for the day of the week, R_{it} is the value-weighted for the size-based portfolio i and R_{mt} is the value weighted market return. The sample runs from 31/12/1987 to 31/05/2007.

			Volatility		Illiquidity		Return	
			Portfolios					
			1	10	1	10	1	10
Volatility	Portfolios	1	-0.01271	0.00881	-0.02407	-3.99511	0.13561	-0.03243
		p value	0.46	0.00	0.99	0.13	0.06	0.47
		10	0.17251	-0.01061	-21.69992	-16.65879	0.31753	-0.08526
		p value	0.00	0.48	0.14	0.14	0.17	0.68
Illiquidity		1	0.00040	0.00002	0.03958	-0.00785	0.00009	-0.00038
		p value	0.00	0.18	0.01	0.48	0.75	0.03
		10	-0.00002	0.00019	-0.03550	0.07141	0.00007	0.00002
		p value	0.84	0.00	0.07	0.00	0.84	0.92
Return		1	-0.02815	0.00049	-1.81632	0.36950	-0.06084	-0.00577
		p value	0.00	0.44	0.01	0.49	0.00	0.49
		10	0.00727	0.03191	-1.69853	-0.65970	0.01016	0.11153
		p value	0.09	0.00	0.12	0.43	0.62	0.00
		Constant	0.01439	0.00428	-8.38626	-9.68253	0.00046	-0.00218
		p value	0.00	0.00	0.00	0.00	0.92	0.48

Table 5.Garch VAR

This table presents the estimates of a GARCH(1,1) which is represented as: $y_t = A_1 y_{t-1} + \varepsilon_t$ where y_t is a k vector of endogenous variables and ε_t is a vector that is assumed to distributed normally with mean zero and conditional covariance $\mathrm{H}_t : \mathrm{H}_t = \Omega + \mathrm{A} \otimes \varepsilon_{t-1}\varepsilon_{t-1}{}' + \mathrm{B} \otimes \mathrm{H}_{t-1}$ The sample runs from 31/12/1987 to 31/05/2007.

Table 6. Correlation Analysis of the Adjusted Series								
			Volatility		Illiquidity		Return	
			Portfolios					
			1	10	1	10	1	10
Volatility	Portfolios	1	1					
		p value	-					
		10	0.10	1				
		p value	0.00	-				
Illiquidity		1	-0.01	-0.02	1			
		p value	0.78	0.10	-			
		10	-0.03	-0.04	-0.12	1		
		p value	0.02	0.01	0.00	-		
Return		1	0.05	0.01	-0.11	0.02	1	
		p value	0.00	0.55	0.00	0.24	-	
		10	-0.00	0.02	0.04	0.01	-0.24	1
		p value	0.96	0.15	0.00	0.43	0.00	-

This table presents the bivariate correlations between the illiquidity, volatility and returns of the two extreme portfolios. The series are adjusted based on the following procedure:

$$w = x'B + u$$

$$\log(u^2) = x'\gamma + v$$

$$w_{adjusted} = a + b(\hat{u}/e^{(x'\gamma/2)})$$

where w is the series to be adjusted and x are the four day-of-the-week dummies for Monday through Thursday, the 11 month dummies for February through December, a time trend, a square of the time trend and twelve lags values of w to capture any time dependence of the series. a and b are chosen in a way that both the mean and the variance of the adjusted and the unadjusted data are the same. The sample runs from 31/12/1987 to 31/05/2007.

Figure 1. Time Series of the Illiquidity measures

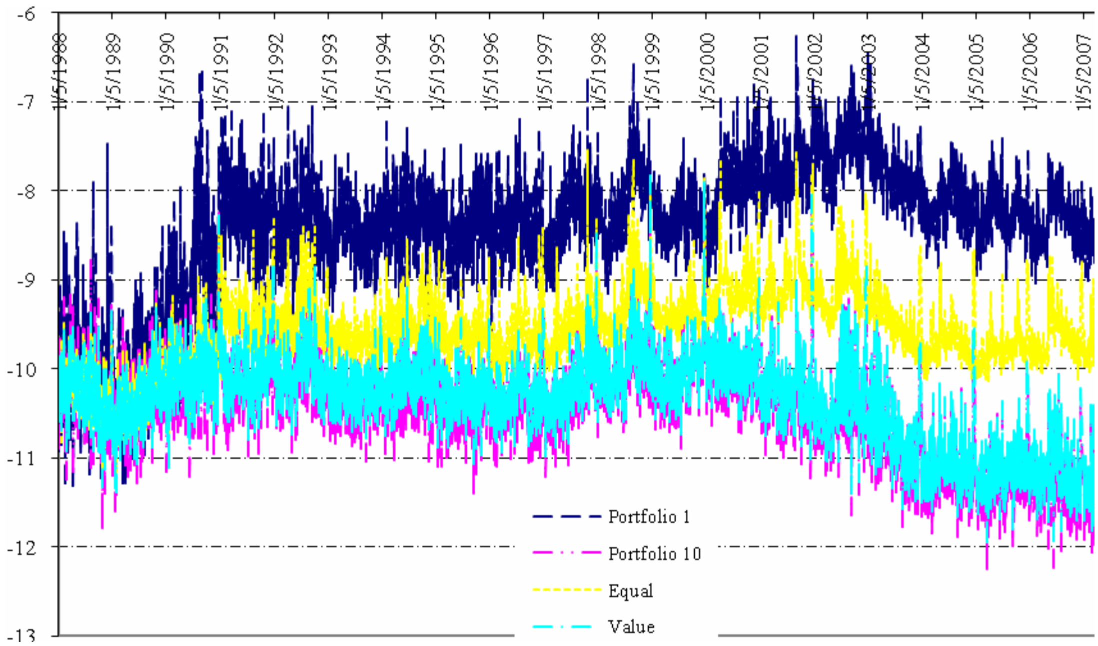

Figure 1 plots the time series of the two market wide illiquidity measures and that of the two extreme portfolios. The sample runs from 31/12/1987 to 31/05/2007.