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Resiliency and Stock Returns: evidence from the London Stock Exchange

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Abstract.

Literature has provided evidence of liquidity as a predictor of expected returns. However, resiliency, as one of its dimensions, has not been extensively studied. The resiliency measure introduced here assumes that liquidity shocks occur during the trading activity and that, in the opening of the following day, the reversals to the new fundamental value is completed. No significant evidence was found for a measure of resiliency that considers the trading day return and the consecutive overnight return, both for equally-weighted and value-weighted portfolios. Also, even considering a sample without micro-cap stocks, illiquidity premium is not significant. (*JEL*: G10, G11, G12, G14)

Keywords: resiliency, liquidity, stock returns, illiquidity premium

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1. Introduction

Traditionally, in asset pricing theory, academics have considered risk as the main key determinant of returns. However, more recent academic papers have shown that liquidity also a determinant of the fair value of assets. Therefore, it is worth defining what a liquid market means. Black (1971) defined a liquid market as a continuous and efficient one where an agent can trade securities at very near the current price. It can also be thought of as a frictionless market where trading an appreciable quantity, in a short time period, does not make an investor incurring in a large transaction cost and, therefore, does not create an adverse price impact. From a firm's perspective, liquidity is extremely correlated with the cost of capital, and that is why it is so relevant to measure how liquid the market is. Bernstein (1987) argues that, for a liquid market, it is necessary depth, breadth, and resiliency[1]. The first two dimensions have been extensively studied in the literature, being the main methods the Amihud's measure and the bid-ask spread. However, surprisingly, there is not much research about resiliency, both in defining the term and studying its implications for the overall market liquidity. Given that fundamental values are not observable, it provides a key insight to market participants and regulators: less resilient stocks bring greater risk attached when an investor trades on the assumption that the current price is signalling the true value.

It was first argued by Amihud & Mendelson (1986) that, using the bid-ask spread as a measure of liquidity, average returns observed in the market are an increasing function of illiquidity, indicating that investors demand a premium for less liquid assets. Later, Amihud (2002) developed an illiquidity measure as the daily ratio of absolute stock return to its dollar volume, averaged over some period; that is, it measures the daily price impact account for a

[1] Harris (2002) explains these concepts in more detail: "depth" refers to the size that investors can trade at a given price, while "breadth" refers to the price at which investors can trade a given size. For instance, "breadth" can be captured by the quote-based bid-ask spread or the trade-based effective spread, whereas "depth" can be proxied by the price impacts.

unit of trading volume. Hence, price impact could be captured with this measure. It was also shown, in this case, that expected stock returns are an increasing function of expected illiquidity. Given its simplicity, it has been widely used by practitioners: better measures of illiquidity require microstructure data that may not be easily available, or may not cover long time periods. Later research has also established a cross-sectional positive return-illiquidity relationship (see Amihud, Mendelson, & Pedersen (2005)). These results, however, are all US-centric. Amihud, Hameed, Kang, & Zhang (2015) were the first to provide international evidence of illiquidity premium using Amihud's illiquidity measure, with portfolios composed of illiquid stocks generating significantly higher risk-adjusted returns compared to the ones with the most liquid assets, in all the different markets.

The literature has provided some definitions of what resiliency means. Kyle (1985) refers to it as the speed of price recovery resulting from an uninformative order-flow shock. Harris (2002) defines it as the quickness that an asset's price reverts to equilibrium value after large order flow imbalances created by an uninformed trader, and that it would be guaranteed by informed traders trying to earn profits. Therefore, in a market not perfectly liquid, an asset would be more resilient if the price impact resulting from a liquidity shock is small, and it is quickly repaired when a deviation occurs (see also Black (1971), Kyle (1985), Llorente, Michaely, Saar, & Wang (2002)). Hence, resiliency could be considered as the time dimension of liquidity. In a case where price discovery is slow, investors would demand higher returns due to greater price uncertainty. Orders causing persistent price dislocations in a market lacking resiliency can make the fundamental value take more time to be revealed, reducing information efficiency and creating an additional source of price uncertainty. Some resiliency measures have been suggested in recent studies[2], and the empirical results have suggested that there is, indeed, a negative relation between resiliency and stock returns.

A recent and relevant measure was presented by Hua, Peng, Schwartz, & Alan (2018), which incorporates both the price impact of a liquidity shock and its persistence. Their resiliency measure, denominated by *RES*, captures a return reversal triggered by a liquidity shock in a not perfectly liquid market, and, with intervals properly chosen, it can be used to compare resiliency between different stocks. Assuming that the opening half-hour is the most critical period of the trading day, the authors described *RES* as the covariance between the returns of the first thirty minutes with the remainder of the day, standardized by the daily return variance. Therefore, a more negative *RES* would mean that the transitory component in the prices after thirty minutes is larger than at the opening or closing time, indicating a higher degree of irresiliency. Theoretically, higher values of *RES* would be associated with higher expected results, and the empirical results support this idea: long-short portfolios composed by US stocks based on *RES* deciles yield a nonresiliency premium ranging from 33 to 57 bps per month for equal-weighted and value-weighted portfolios, respectively.[3] Given its simplicity, it can be easily implemented and used to compare stocks in terms of their liquidity. However, it is worth comparing this measure with some other commonly used, namely, the Amihud's price impact measure and the bid-ask spread. The Amidud's price impact measure (Amihud, 2002) would indicate a market to be illiquid when it faces a large change in the prices and low trading volume, even if this happens due to information efficiency that leads to a new fundamental value. The bid-ask spread is a good measure if we are talking about small

[2] See, among others, (Dong, Kempf, & Yadav, 2007), (Anand, Irvine, Puckett, & Venkataraman, 2013), and (Kempf, Mayston, & Yadav, 2011). The first defines resiliency as the mean reversion parameter of a stock's intraday pricing-error process. The second suggests that it can be measured by the average percentage of months that trading costs exceed two-standard deviation thresholds relative to the pre-crisis period. Finally, the third defines it as the mean reversion parameter of a trading cost flow using intraday data.

[3] As (Hua et al., 2018) point out, *RES* works best if the price adjustment finishes in the trading day, before the market closes. Otherwise, it would bias the results. There is a possibility that the best time interval depends on the characteristics of the stock and the shock.

and uncorrelated orders; however, it does not reflect the higher transaction costs suffered by large traders (even if they split the order into several small orders) nor the impact that it creates to the following orders. A negative externality can be created on subsequent orders by earlier ones because of persistence (meaning that orders are somehow correlated). *RES*, not only account for the price impact, but also for persistence, which makes it a better measure than the bid-ask spread. At the same time, unlike Amihud's one, it also differentiates better the changes in permanent and transitory prices. Comparing these measures empirically has suggested that *RES* could capture additional dimensions of liquidity.

RES relies on intraday data that are not easily accessible to practitioners and/or researchers, and without international evidence of its significance, it looks bold to assume that it can be applied to markets other than the US. Considering the conditions described in the main model and the available data, this paper aims to study the effect of resiliency on expected returns as the standardized covariance between the returns of the trading activity and the consecutive overnight returns. This way, liquidity shocks still occur during the first period, and the second period gives time to repair to the new fundamental value. However, there is the risk that the transitory component has vanished by time *t* and that it can capture other dimensions that are not related to liquidity. In order to test the effectiveness of this new setting, it was performed univariate and bivariate portfolio analyses, as well as Fama-MacBeth cross-sectional regressions. Control variables that have shown to predict future returns were included in the analyses. No evidence was found that this new measure actually works and can be applied.

The paper proceeds as follows. Section 2 presents the resiliency measure, *RES*, as described by Hua et al. (2018), as well as the modifications introduced. Section 3 describes the data, the variables. Section 4 investigates the effect of resiliency on expected returns. Finally, the conclusions are presented in section 5.

2. Resiliency as a Measure of Liquidity

Liquidity shocks provoke movements in prices that can be decomposed on their equilibrium and transitory components, assuming the market is not perfectly liquid. In this situation, the transitory change takes time to disappear, and it could be argued that a more resilient market is one with a transitory change that dissipates as quickly as possible. Given that objective of this paper, we proceed with a brief description of the model proposed by Hua et al. (2018) and the changes considered in this application.

2.1. The Model (Hua et al., 2018)

Consider that both liquidity and information shocks can occur in a time interval from 0, the market's opening, to T, the market's closing. Moreover, the fundamental value at time 0, V_0, equals the stock price in the opening of the market. A liquidity shock occurs at time 1 due to an order arrival with size ε_1, and the impact on the transitory price is captured by $\kappa\sigma_v\varepsilon_1$, being κ the coefficient of the price impact, σ_v the price volatility resulting from fundamental information change, and $\varepsilon_1 \sim N(0,1)$. Therefore, the price impact per share can be represented as $\kappa\sigma_v$. Further, the price impact is dissipated at a rate γ, $0 \leq \gamma \leq 1$. *Ceteris paribus*, in a resilient market, a liquidity shock leads to a small price impact (that is, a small κ), which is quickly dissipated (meaning, a small γ). At last, assume that an *i.i.d.* information shock, $\eta_t \sim N(0, \sigma_v^2)$, affects the asset's price. Because the goal is to focus on liquidity shocks, assume information shocks follow a random walk. Therefore,

$$\begin{aligned} P_1 &= V_0 + \kappa\sigma_v\varepsilon_1 + \eta_1 \\ P_2 &= V_0 + \kappa\sigma_v\varepsilon_1 + \eta_1 + \eta_2 \end{aligned} \tag{1}$$

At time 2, the price of the asset is analyzed so that we can understand whether the effects of the liquidity shock have been repaired. As we want the price at time T to be clean from the effects that these shocks create, it is necessary to set time T to be far enough from time 2. Hence, there is a negative relation between adjacent return $P_2 - P_0$ and $P_T - P_2$:

$$Cov(P_2 - P_0, P_T - P_2) = -\kappa^2\gamma^2\sigma_v^2 \tag{2}$$

As defined in the introduction, our resiliency measure (*RES*) can be written as:

$$RES = \frac{Cov(P_2 - P_0, P_T - P_2)}{\sigma_v^2} = -\kappa^2\gamma^2 \tag{3}$$

One can clearly observe that both *COV* and *RES* are negative and decreasing with respect to κ and γ. As long as price reverts to its equilibrium value by time *T*, both measures have negative signals. *RES* cleans the effect that fundamental volatility could create on *COV*, considering that expected returns are also affected by volatility in ways that are not related to liquidity.

The selection of times *t* and *T* should be set considering that liquidity shocks occur between time 0 and time *t*, while by time *T* reparations are completed for all stocks. However, at time *t*, it should be possible to compare stocks based on their reparation levels. Based on these conditions for a good empirical implementation, as the first thirty minutes represent the most challenging period of a trading day activity for price discovery, the authors set the first interval as the opening half-hour and the second as the remainer of the day.[4] Thus, the second period should allow for full recovery of the transitory prices. As a measure of fundamental volatility, they used the daily return variance.

[4] Hua et al. (2018) provide evidence of illiquidity premia for different time spans. It is presented a more general model allowing for multiple liquidity shocks and other choices of times *t* and *T*. However, it was suggested that *T* can be set to a point after the closing time and no test was performed.

Regarding information shocks, they may undershoot or overshoot prices, resulting in continuations or reversals that affect *RES* positively or negatively.[5] Thus, information shocks and firm characteristics that may create under/overreactions were included as control variables. Variables like analyst coverage and institutional ownership, the probability of informed trading (Easley & O'Hara, 2004), the magnitude of earnings surprises and the event of earnings announcement, the monthly averages of overnight returns and its absolute value were included in the original study. Volume information was also included in their analysis because, they argue, it could help to identify periods affected mainly by liquidity shocks from the ones that are affected by information shocks.

2.2. Considerations about the model

Even though *RES* provides a simple empirical implementation, it requires a huge amount of data that is not accessible to most investors and/or researchers. For instance, in platforms like Bloomberg and Thomson Reuters Eikon, one can only obtain data for the last 240 days (140 days if data is downloaded) or the last 3 months, respectively. Implementing *RES,* as described by the authors, in markets other than the US may not be appropriate, as there is no evidence that it actually works. Therefore, it was decided to adapt this measure to the available data in these platforms, and test its significance.[6]

As suggested by Hua et al. (2018), the model could be applied to other time periods, choosing different t and T, as long as the conditions discussed before were met. Given the limitations of data, the model tested in this paper considers that liquidity shocks occur between the opening and the closing of the market (within the trading day activity), and that until the opening of

[5] For instance, private information that is used for speculative trading can generate return continuations, (Llorente et al., 2002). Behavioural biases can also induce overreactions after information shocks (Daniel, Hirshleifer, & Subrahmanyam, 1998).

[6] Unfortunately, there is no database similar to CRSP for other countries than the US. With such database, one could investigate this question with quality guaranteed.

the following trading day, no more liquidity shocks occur. That is, the closing price is still affected by the shocks, and the opening price of the following day is no longer influenced by the transitory impact. This opening price would be considered as the new fundamental value of the stocks, meaning that all reparations have been completed by then. Therefore, our new resiliency measure for stock *i* in the month *m* of year *y* is:

$$RES_{my} = \frac{Cov\left(P_{my,d}^{close} - P_{my,d}^{open}, P_{my,d+1}^{open} - P_{my,d}^{open}\right)}{\sigma_{my}^{2}} \tag{4}$$

where $P_{my,d}^{open}$ and $P_{my,d}^{close}$ represent the opening and closing daily prices of month m of year *y*, respectively; $P_{my,d+1}^{open}$ represents the opening price of the following trading day of month *m* of year *y*; and σ_{my}^{2} the daily return variance in month *m* of year *y*.

3. Data, Variable Descriptions, and Summary Statistics

The study includes all common stocks that constituted the FTSE All-Share Index as of November 20, 2019, which results from the aggregation of the FTSE 100, FTSE 250 and FTSE Small Cap Indices. It represents approximately 98% of the UK market capitalization of listed shares on the London Stock Exchange. All the data were extracted from the Bloomberg terminal, for the time period from January 2007 to December 2017, with the exception of the daily and monthly Fama and French data that were provided by the University of Exeter (Gregory, Tharyan, & Christidis, 2013).[7]

Following the discussion in Section 1, instead of using intraday data as suggested by Hua et al. (2018), the stock's monthly resiliency is based on the covariance of two consecutive return (that is, the return resulting from the trading day and the consecutive overnight return) divided by the variance of daily returns.

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[7] Available at: http://business-school.exeter.ac.uk/research/centres/xfi/famafrench/files/.

Control variables are separated into two groups. The first refers to the *liquidity variables*, which include the Amihud's measure, the average bid-ask spread, the high-low spread measure, Roll's covariance spread, and sensitivities to Pastor & Stambaugh (2003), while the second refers to the *fundamental variables*, namely the market beta from the Fama and French, the logarithm of market capitalization, and the logarithm of the book-to-market ratio. Moreover, the following variables were also included due to their potential to predict returns: momentum, monthly return reversal, idiosyncratic volatility, maximum daily return, share turnover, and long-term return volatility.

Following Amihud (2002), the illiquidity (*ILLIQ*) measure is the monthly average of the daily stock's absolute return divided by its daily dollar trading volume. The bid-ask spreads are the monthly average of the daily quoted bid-ask spreads (*SPR*). Corwin & Schultz (2012) developed a simple way to estimate spreads using the daily high and low prices (*HLSPR*):

$$S = \frac{2(e^{\alpha} - 1)}{1 + e^{\alpha}} \tag{5}$$

with $\alpha = \frac{\sqrt{2\beta} - \sqrt{\beta}}{3 - 2\sqrt{2}} - \sqrt{\frac{\gamma}{3 - 2\sqrt{2}}}$, $\beta = E\left\{\sum_{j=0}^{1}\left[\ln\left(\frac{H_{t+j}^{0}}{L_{t+j}^{0}}\right)\right]^{2}\right\}$, and $\gamma = \left[\ln\left(\frac{H_{t,t+1}^{0}}{L_{t,t+1}^{0}}\right)\right]^{2}$, where α represents the difference between the adjustments of a single day and a 2-day period, β the sum for two consecutive days of the square of the high-low log ratio, and γ the square of the high-low log-ratio over the two days[8].

Roll (1984) spread estimator is obtained by the serial covariance in price changes:

$$S_{im} = 2\sqrt{-cov\left(\Delta P_{i,d,m}, \Delta P_{i,d-1,m}\right)} \tag{6}$$

[8] For this calculation, some assumptions were required, as suggested in the literature: observable high and low prices are required for two consecutive days, daily high is a buyer-initiated trade and daily low price is a seller-initiated trade.

where $P_{i,d,m}$ is the closing price of stock i on day d of month m, and $\Delta P_d = P_d - P_{d-1}$[9].

Pastor & Stambaugh (2003) developed a liquidity measure for each month using daily data within that month, and proved that innovations in liquidity also predict returns. The sensibilities to innovations in liquidity were also included.

For the set of *fundamental control variables*, the market beta of individual stocks ($BETA$) is calculated following Fama & French (1992), using the previous 60 monthly returns. The stock's size (*LNME*) is the logarithm of the stock's market capitalization (in million pounds). The book-to-market ratio (*LNBM*) is also transformed in the logarithmic form.

Additionally, the momentum return (*MOM*) is calculated as the cumulative returns over a period of 11 months, ending one month before the measurement month, as described in Jegadeesh & Titman (1993). Also, in Jegadeesh (1990), monthly return reversal (*REV*) is referred to as the monthly return of the previous month. The monthly idiosyncratic volatility is obtained, as in Ang, Hodrick, Xing, & Zhang (2006), through the standard deviation of the residuals from the Fama and French market model, estimated using daily returns[10]. The maximum daily return in a month was suggested by T. G. Bali, Cakici, & Whitelaw (2010). Share turnover (*TURN*) is calculated as the number of shares traded in a day divided by the number of shares outstanding, and averaged for each month. At last, the long-term return volatility ($RET5VOL$) can be described as the standard deviation of the previous 60 monthly returns.

Summary statistics are reported, for all our variables, in Panel A of Table 1. Looking to our variable of interest, RES, which denominates the resilience measure of stocks in a specific month, one can observe an average monthly mean of -0.029, with a median value of -0.022,

[9] When the covariance yields a positive value, most practitioners add a negative sign to the covariance. Therefore, we avoid the failure of the Roll's model.
[10] As described by the authors, it was imposed a restriction of at least 17 observations in a month.

and a standard deviation of 0.117. Finally, the average skewness and kurtosis are -0.566 and 2.990, respectively.

Panel B and C of Table 1 report the time-series averages of the cross-sectional Pearson correlation coefficients; that is, the correlations are computed for each time period, and then a time-series average is performed. Panel B refers to correlations between liquidity variables, showing that *RES* is negatively correlated with *ILLIQ*, *SPR*, and *HLSPR*, corresponding to -11%, -12%, and -5%, respectively. These results have the appropriate signs, and suggest that this measure (*RES*) adds some value to the study of liquidity, in the sense that it captures another dimension of liquidity. The correlations with the remaining variables can be found in Panel C.

Fama & Macbeth (1973) methodology was also applied to test the relation between *RES* and some variables, with the results available in Table 2. The outcomes suggest that there is a positive relation between *RES* with highly traded and bigger stocks, and a negative relation with liquidity (thus, suggesting a lower value of *RES*). Later, this methodology will also be applied when studying the effects of *RES* in the expected returns.

4. Effect of *RES* on Expected Returns

The study of the effect of *RES* on expected returns was divided into three approaches, as suggested in the original paper: univariate portfolio analysis, bivariate dependent portfolio analysis, and Fama-MacBeth regressions. The results do not provide evidence of an illiquidity premium between *RES* and 1-month forward stock returns, which will be explained in the following subsections.

Table 1 Descriptive statistics

A. *Summary statistics*

	Mean	Median	SD	Skewness	Kurtosis
RES	-0.029	-0.022	0.117	-0.566	2.990
Liquidity variables					
ILLIQ	0.013	0.000	0.156	16.065	305.070
SPR(%)	0.992	0.614	1.320	4.949	61.764
PS	-2.459	-0.193	105.003	-0.554	41.842
HLSPR(%)	0.566	0.518	0.405	1.081	2.235
ROLL	1.335	1.153	0.907	1.974	8.778
Firm characteristics					
RET	0.749	0.664	6.678	0.187	4.019
BETA	0.823	0.864	0.741	-1.214	17.486
LNME	6.836	6.687	1.638	0.436	0.889
LNBM	0.081	-0.428	1.961	0.808	0.565
MOM	1.089	1.065	0.269	1.250	8.449
REV	0.722	0.628	6.683	0.198	4.084
IVOL	1.300	1.138	0.784	2.377	13.773
MAX	3.668	3.115	2.551	3.231	25.934
TURN	0.644	0.175	5.353	19.763	425.304
RET5VOL	0.720	0.540	0.626	1.779	4.291

B. *Correlations of RES and liquidity variables*

	RES	ILLIQ	SPR	PS	HLSPR
ILLIQ	-0.111				
SPR	-0.120	0.258			
PS	0.092	0.023	0.002		
HLSPR	-0.051	-0.073	-0.207	-0.058	
ROLL	0.026	0.069	0.118	-0.024	0.450

C. *Correlations of RES and other variables*

	RES	RET	BETA	LNME	LNBM	MOM	REV	IVOL	MAX	TURN
RET	-0.013									
BETA	0.060	0.009								
LNME	0.118	-0.016	0.146							
LNBM	0.044	-0.023	-0.102	-0.486						
MOM	0.005	0.083	0.032	0.075	-0.142					
REV	-0.008	0.033	0.001	0.019	-0.043	0.299				
IVOL	0.028	0.005	0.110	-0.266	0.203	-0.087	-0.046			
MAX	0.055	0.008	0.131	-0.157	0.118	-0.074	-0.053	0.793		
TURN	0.052	-0.006	0.032	0.014	0.010	-0.021	-0.010	0.070	0.056	
RET5VOL	0.034	0.027	0.247	-0.229	0.190	0.052	0.026	0.601	0.518	0.065

Panel A reports the main characteristics of the variables used in this paper, namely the mean, standard deviation, skewness, and excess kurtosis. They were obtained as the time-series averages of the cross-sectional characteristics. Panels B and C report the time-series averages of the monthly cross-sectional correlations between liquidity variables and firm characteristics, respectively. Only *RET* is computed for 1 month forward (that is, for $t+1$), while the others were computed for the respective month. *RES* is the monthly covariance between the daily and the overnight return, scaled by the monthly variance of daily returns. *BETA* represents the market beta, while *LNME* and *LNBM* represent the logarithm of market capitalization and the logarithm book-to-market ratio, respectively. *MOM* denotes the momentum return. *REV* is the previous month returns. *IVOL* denotes the idiosyncratic volatility from the market model. *MAX* is the maximum daily return in a month. *TURN* is the average share turnover. *RET5VOL* is the volatility of monthly returns over the previous 5 years. These results cover the period from January 2007 to December 2017, for the full sample of 626 companies.

Table 2 *RES* and firm characteristics

$Y = RES_{t+1}$	M1	M2	M3	M4	M5	M6	M7
TURN	0.008***					0.007***	0.006***
	[6.47]					[5.69]	[4.85]
LNME		0.010***				0.009***	0.008***
		[10.68]				[6.67]	[5.91]
SPR			-0.160***			-0.057**	
			[-4.29]			[-2.13]	
ILLIQ				-555.606***			-287.741**
				[-3.29]			[-2.03]
REV					-0.000	-0.000*	-0.000
					[-0.81]	[-1.86]	[-1.51]
Constant	-0.032***	-0.112***	-0.012*	-0.022***	-0.029***	-0.102***	-0.096***
	[-7.20]	[-13.38]	[-1.87]	[-4.57]	[-6.90]	[-6.72]	[-6.81]
N	15,708	15,312	15,708	15,708	15,708	15,312	15,312
R-sq	0.010	0.031	0.030	0.037	0.010	0.068	0.083

These results were obtained by applying the Fama & Macbeth (1973) methodology. The table presents the coefficients obtained from the time-series average of cross-sectional coefficients for some firm characteristics. *N* is the number of observations for each regression, and *R*-sq denotes the average *R*-squared of the cross-sectional regressions. Newey-West *t*-statistics reported in parentheses with a lag of 4. *** p<0.01, ** p<0.05, *p<0.1

4.1. Univariate Portfolio Analysis

One of the main approaches in empirical asset pricing is the univariate portfolio analysis, where one pretends to assess the cross-sectional relation between *RES* and the outcome variable, *RET*. The procedure is as follows: first, it is necessary to calculate the periodic breakpoints that will be used to group the companies into portfolios based on *RES*, the sort variable; then, the portfolios are formed for each time period and the average value of *RET* within each portfolio for each time period is determined. Both the equally-weighted and value-weighted average were calculated, being the market capitalization used as the weight of value[11]. The primary value used to detect a cross-sectional relation between *RES* and *RET* is the difference in averages between the highest and lowest portfolio for each time period.

[11] The value-weighted approach reflects the importance of a stock relative to the rest of the market, as well as the perspective of the investor in terms of liquidity and value. However, the equally-weighted one forces both liquid and illiquid stocks to have the same weights, and the average *RET* may not be realized due to the high transaction costs suffered by low market cap firms.

Table 3 presents the time-series averages of monthly holding returns, considering equally-weighted and value-weighted portfolios. Panel A refers to the entire sample considered since the beginning of this analysis, while Panel B refers only to the 100 most liquid stocks (that is, excluding the lower-cap firms)[12]. The average returns do not provide evidence of an illiquidity premium, as some conditions are not met. First, in most cases, the *t*-statistics calculated based on Newey & West (1987) are not strong enough to reject the hypothesis of zero mean[13]. Also, the average values of *RET* across the deciles do not present a monotonic or near monotonic pattern[14]. Therefore, there is an indication that the results of the difference portfolios are spurious, not allowing us to infer if investors demand a premium for illiquidity or not.[15]

However, if the results were significant, one could argue that resiliency is important to large-cap stocks, given that the value-weighted difference portfolios yield a higher average return than the equally-weighted counterparty. The lack of significance can be justified by *RES* being a noisy measure of resiliency in general, and specifically to low-cap stocks with low trading activity and higher error in measurement. Also, other effects that are correlated and not related to liquidity can possibly be captured by our resiliency measure, affecting its accuracy.

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[12] The entire sample contains all stocks composing the FTSE All-Share Index. The 100 most liquid stocks were considered those composing the FTSE 100 Index.

[13] For the Newey & West (1987) t-statistics, the number of lags is an arbitrary decision. However, it was decided to use the following rule from T. Bali, Engle, & Murray (2017): the number of lags is the result of $4\left(\frac{T}{100}\right)^{2/9}$, where T is the number of periods in the time series. Therefore, with $T = 132$, it was assumed a lag of 4 for the entire paper.

[14] Patton & Timmermann (2010) developed a statistical test of monotonicity that could be applied. However, as it seems obvious that there is no monotonic pattern, the test was not performed. No conclusions about *RES* can be inferred with this condition not holding.

[15] Even if the results were near to monotonicity and conclusions could be inferred, the difference portfolios “2-10” and “1-9” would not be significant, neither in Panel A nor Panel B.

Table 3 Univariate Portfolio Analysis

A. *Full sample*

RES decile	Average *RET*		Avg *RES*	Mkt Share
	Equal Weighted	*Value Weighted*		
1 (low)	0.66 [1.83]	0.56 [1.42]	-0.26	10.95
2	0.97 [2.31]	0.75 [1.89]	-0.14	15.07
3	0.99 [2.75]	0.37 [0.93]	-0.09	15.55
4	0.91 [2.24]	0.57 [1.55]	-0.06	16.08
5	0.58 [1.61]	0.13 [0.32]	-0.03	15.77
6	0.82 [2.15]	0.40 [1.0]	-0.01	15.91
7	0.73 [1.87]	0.48 [1.11]	0.01	14.56
8	0.83 [2.24]	0.59 [1.40]	0.04	15.63
9	0.50 [1.15]	0.20 [0.39]	0.08	18.29
10 (high)	0.44 [1.08]	0.09 [0.20]	0.16	16.57
1 – 10 (low-high)	0.22 [0.92]	0.47 [1.13]		

(*Continued*)

4.2. Bivariate Dependent Portfolio Analysis

In the previous section, only the relationship between *RES* and average *RET* was studied. However, other effects not related to liquidity can interfere with our results, making *RES* to capture them. Therefore, it is worth performing bivariate analysis and Fama-MacBeth regression analysis.

Bivariate analysis aims to understand the relation between *RES* and *RET*, conditional on other variables. These other variables are used as control variables, and can be separated in liquidity and firm characteristics. The procedure applied in Table 4 is as follows: for each control variable, the stocks are separated in tercile portfolios; then, we form *RES* decile portfolios based on each tercile.[16] The average return is then computed in percentage terms for the following month. Panel A presents the results for the liquidity variables, and Panel B for the remaining firm characteristics. As in the previous section, neither the results are monotonic or near monotonic, nor significant. Moreover, in some situations, the difference portfolios yield a negative value, contradicting the hypothesis.

B. *FTSE 100 sample*

	Average *RET*		Avg *RES*	Mkt Share
RES decile	*Equal Weighted*	*Value Weighted*		
1 (low)	0.93 [2.22]	0.66 [1.73]	-0.23	15.12
2	0.92 [2.08]	0.65 [1.58]	-0.13	18.52
3	0.91 [2.35]	0.53 [1.39]	-0.08	19.80
4	0.67 [1.52]	0.41 [1.06]	-0.05	19.24
5	0.58 [1.6]	0.27 [0.65]	-0.03	18.77
6	0.89 [2.51]	0.27 [0.57]	-0.01	18.54
7	0.82 [2.16]	0.56 [1.31]	0.02	17.81
8	0.64 [1.61]	0.60 [1.43]	0.04	19.26
9	0.44 [1.02]	0.21 [0.45]	0.08	20.69
10 (high)	0.35 [0.86]	0.06 [0.12]	0.15	19.67
1 – 10 (low-high)	0.58 [2.15]	0.59 [1.49]		

For each month, the breakpoints are calculated according to *RES*, and used to form portfolios for each time period. In these cases, the sort variable was divided into decile portfolios. The results presented are the average monthly holding period returns. Panel A refers to the full sample, while Panel B refers to the sample of the FTSE 100 components (generally assumed to be the 100 most liquid stocks traded in the United Kingdom). The column "Avg *RES*" reports the average *RES* values corresponding to each decile portfolio. The columns "Mkt Share" reports the average market share for each portfolio, assuming the last value of the month. The row "1 – 10" corresponds to the differences in monthly returns between decile 1 and decile 10 portfolios. Average returns are in percentage terms, and market share in billion pounds. Newey-West *t*-statistics reported in parentheses, assuming a lag of 4.

[16] The tercile portfolios were constructed based on the lowest 30%, medium 40%, and highest 30%.

Table 4 Bivariate Dependent Portfolio Analysis

A. Controlling for liquidity variables

RES decile	ILLIQ	SPR	PS	HLSPR	ROLL
1 (low)	0.49	0.69	0.58	0.71	0.73
2	0.97	0.96	0.84	0.93	1.00
3	1.02	0.87	0.96	0.97	0.91
4	0.43	0.71	0.76	0.79	0.89
5	0.85	0.83	1.02	0.70	0.57
6	0.92	0.75	0.69	0.81	0.87
7	0.69	0.70	0.76	0.75	0.69
8	0.95	0.83	0.83	0.84	0.79
9	0.58	0.66	0.39	0.54	0.51
10 (high)	0.54	0.42	0.47	0.48	0.50
1 - 10 (low-high)	-0.05	0.27	0.11	0.24	0.23
	[-0.17]	[1.10]	[0.51]	[0.97]	[1.04]

B. Controlling for firm characteristics

RES decile	BETA	LNME	LNBM	MOM	REV	IVOL	MAX	TURN	RET5VOL
1 (low)	0.79	0.80	0.80	0.80	0.93	0.69	0.66	0.87	0.70
2	0.97	1.06	1.11	0.77	0.82	0.87	0.93	0.94	1.08
3	0.88	0.95	0.97	0.90	0.92	0.99	1.08	0.69	0.86
4	0.86	0.74	0.77	0.91	0.84	0.86	0.60	0.72	0.70
5	0.81	0.76	0.46	0.57	0.86	0.82	0.94	0.85	0.92
6	0.57	0.70	0.90	0.83	0.80	0.75	0.77	0.87	0.87
7	0.75	0.99	0.75	0.91	0.68	0.66	0.91	0.70	0.64
8	0.84	0.67	0.69	0.96	0.72	0.76	0.76	0.70	0.84
9	0.54	0.56	0.67	0.40	0.57	0.67	0.31	0.77	0.36
10 (high)	0.48	0.46	0.47	0.42	0.45	0.32	0.47	0.37	0.51
1 - 10 (low-high)	0.32	0.34	0.33	0.38	0.49	0.38	0.19	0.50	0.19
	[1.42]	[1.34]	[1.36]	[1.45]	[2.14]	[1.39]	[0.80]	[2.15]	[0.83]

The equally-weighted average monthly returns are reported in these tables after sorting by a control variable, followed by *RES*. Breakpoints are first calculated for the terciles, and then, within each tercile, the decile portfolios are formed. The *RES* decile portfolios result from the merge between the corresponding deciles from each tercile. Panel A refers to liquidity variables (Amihud's illiquidity ratio, bid-ask spread, Pastor-Stambaugh sensitivities to innovations, high-low spread, and Roll's measure, respectively). Panel B refers to other variables not related to liquidity (market beta, size, book-to-market ratio, momentum, return reversal, idiosyncratic volatility, maximum daily return, share turnover, and long-term volatility). Newey-West *t*-statistics are reported in parentheses, with a lag of 4.

4.3. Fama-MacBeth Regressions

Finally, in order to test the effect of *RES* on expected returns controlling for several control variables, the following monthly cross-sectional regression was obtained:

$$R_{i,t+1} = \alpha_{t+1} + \gamma_{t+1} RES_{i,t} + \varphi_{t+1} X_{i,t} + \varepsilon_{i,t+1} \tag{7}$$

where $R_{i,t+1}$ represents the excess return on stock i in month $t + 1$, and $X_{i,t}$ a vector of control variables for stock i in month t.

Table 5 reports the results of the Fama-MacBeth regressions above. The first model includes the market beta, the log of market capitalization, and log of book-to-market ratio. Then, some more control variables related to the return prediction have been included, namely, the momentum, the monthly return reversal, the idiosyncratic volatility, the maximum daily return, the share turnover, and the long-term monthly volatility. At last, the model was tested, including liquidity-related variables, namely, Amihud's illiquidity ratio, the bid-ask spread, the high-low spread estimates, Pastor-Stambaugh sensitivities to innovations in liquidity, and Roll's measure. In all models, *RES* presents negative slopes as expected, even though they are not significant, with the exception of model 1 with 5% and model 2 with 10% level. Therefore, once again, there is no statistical evidence that, with our *RES* measure, stocks with lower resiliency yield higher returns. However, the average slope coefficients that are significant are in line with previous studies: *LNME* (stock size) is significant at 1% with negative coefficients, consistent with (Fama & French, 1992); *MOM* (momentum) is positive and significant at 10% and lower values, consistent with (Jegadeesh & Titman, 1993); *REV* is negative as in (Jegadeesh, 1990), although not significant. Among the liquidity-related variables, only *ILLIQ* and *PS* are significant at 10% and 1% level, respectively. However, one would expect *ILLIQ* to be negative, which is not the case. The remaining variables do not add value to our model.

Table 5 Fama-MacBeth regressions

$Y = RET_{t+1}$	M1	M2	M3	M4	M5	M6
RES	-1.060**	-0.933*	-0.695	-0.751	-0.652	-0.645
	[-2.10]	[-1.71]	[-1.26]	[-1.36]	[-1.21]	[-1.16]
BETA	0.467**	0.239	0.304*	0.285	0.265	0.207
	[2.47]	[1.25]	[1.70]	[1.66]	[1.55]	[1.18]
LNME	-0.285***	-0.286***	-0.213***	-0.268***	-0.267***	-0.267***
	[-3.27]	[-3.86]	[-2.87]	[-3.61]	[-3.65]	[-3.49]
LNBM	-0.251**	-0.182**	-0.182**	-0.177**	-0.169**	-0.148*
	[-2.33]	[-2.14]	[-2.22]	[-2.25]	[-2.16]	[-1.89]
MOM		0.837*	0.908**	0.936**	0.919**	0.885**
		[1.87]	[2.08]	[2.19]	[2.26]	[2.07]
REV		-0.011	-0.007	-0.008	-0.009	-0.009
		[-0.81]	[-0.50]	[-0.56]	[-0.67]	[-0.65]
IVOL		-0.577**	-0.622**	-0.561**	-0.547**	-0.508**
		[-2.33]	[-2.54]	[-2.26]	[-2.26]	[-2.05]
MAX		0.012	0.016	-0.000	0.010	0.016
		[0.21]	[0.28]	[-0.00]	[0.19]	[0.27]
TURN		-0.033	0.010	-0.011	-0.001	-0.015
		[-0.34]	[0.11]	[-0.11]	[-0.02]	[-0.16]
RET5VOL		0.818***	0.644**	0.647**	0.641**	0.653**
		[2.93]	[2.19]	[2.14]	[2.13]	[2.23]
ILLIQ			14,644.826*	17,850.051*	16,894.891*	17,588.461*
			[1.75]	[1.84]	[1.80]	[1.80]
SPR				-2.795*	-2.609	-3.141*
				[-1.67]	[-1.57]	[-1.85]
HLSPR					-0.063	-0.117
					[-0.20]	[-0.38]
PS						-0.010***
						[-4.46]
ROLL						-0.049
						[-0.44]
Constant	2.428**	2.036**	1.227	1.925**	2.020**	2.120**
	[2.45]	[2.39]	[1.41]	[2.19]	[2.52]	[2.58]
N	14,916	14,916	14,916	14,916	14,916	14,916
R-sq	0.093	0.215	0.239	0.253	0.262	0.283

The table presents the results of Fama & Macbeth (1973) methodology, namely the average slope coefficients from the regression of monthly excess returns on *RES* and control variables. *N* stands for the number of observations, and *R*-sq for the average *R*-squared of the monthly cross-sectional regressions. Newey-West *t*-statistics are reported in parentheses, with a lag of 4. For details about the lagged variables, see Table 1. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

5. Conclusions

More recently, resiliency has been presented as the time dimension of liquidity. Hua et al., (2018) presented a resiliency measure as the standardized return covariance between the first thirty minutes and the rest of the trading day, and that captures both the price impact of a liquidity shock and its persistence. They find that there is a demand for illiquidity premia as *RES* is negatively related to returns. Given that they only provide evidence for the US market, one cannot use this measure outside the US without proving its effectiveness in capturing resiliency.

As intraday data are not widely accessible for long time periods and there is no CRSP-like database for other markets than the US, it was tested how effective was a similar measure using the opening and closing prices in capturing the resiliency of stocks in the UK. During the trading day, all liquidity shocks would occur, and the transitory component would still be present, while after the closing of the market and the next opening, the shocks would have time to completely repair from the transitory impact to the new fundamental value. The correction from the price dislocation translates into a negative *RES*. These new time periods do not contradict the conditions set by the authors of the model; however, it is obvious that it introduces more noise into the measure, as well as it can capture other effects that can be related to aspects other than liquidity.

Sorting stocks according to their *RES* levels, forming portfolios, and calculating their average returns did not yield the required monotonic pattern as well as the significance required for the difference portfolios. Both the equally-weighted and value-weighted portfolios reflect the lack of monotonicity and significance. When performing double sorting in dependent way, the results are even more inconclusive: for some control variables, besides the lack of monotonic pattern and significance, the results of the difference portfolios are negative. Finally, the Fama-MacBeth regressions, that allow for jointly control firm characteristics and liquidity variables, show *RES* to be insignificant, even though other variables are consistent with the literature. The results are very similar for both the full and small samples.

Some explanations can be provided to justify the disastrous results obtained: first, the chosen time periods may not be the best as it is possible that the transitory component has vanished before time *t* and, therefore, it already reflects the new equilibrium price, as well as the results may be biased due to time *T* not being the closing of the market, as referred by (Hua et al., 2018); second, the quality of data is not guaranteed as it was not produced for scientific work like CRSP database; and at last, the type of analyses performed may lead to wrong conclusions as it makes some strong assumptions that do not reflect the reality of the data.

About the last explanation, the main issues are the failure of the assumption of linearity for some entities with specific variables being considered (especially in the Fama-MacBeth methodology), and the lack of joint assessment of the relation between *RES* and *RET* in the portfolio analyses. However, it is also important to consider that there is evidence that the Fama-French model appears to work worse for the UK than the US (see Gregory et al., (2013)), which can explain the insignificance of the market beta in the Fama-MacBeth regressions performed in the last section (even though the idiosyncratic volatility has significance). Also, the power of the Fama-MacBeth methodology has been questioned by some researchers, as they argue that explanation power is low for small time periods, which is the case in this paper (see Bradfield (1993)). Periods exceeding 30 years have provided more significant results. At last, and what can be the biggest failure, is the noisy *RES* measure. For future research, one can try to produce a measure that can be applied using widely accessible data.

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Appendix

Table 6 Bivariate Dependent Portfolio Analysis (FTSE 100 sample)

A. Controlling for liquidity variables

RES decile	ILLIQ	SPR	PS	HLSPR	ROLL
1 (low)	0.76	0.89	0.81	0.84	0.63
2	0.79	0.70	0.96	0.86	0.99
3	0.74	0.86	0.72	0.99	0.81
4	0.64	0.68	0.90	0.64	0.89
5	0.62	0.52	0.98	0.71	0.85
6	0.96	1.04	0.57	0.83	0.51
7	0.94	1.00	0.80	0.87	0.81
8	0.75	0.51	0.93	0.42	0.65
9	0.59	0.66	0.27	0.23	0.41
10 (high)	0.31	0.41	0.37	0.52	0.47
1 -10 (Low-High)	0.45	0.48	0.44	0.32	0.16
	[2.16]	[1.97]	[1.81]	[1.18]	[0.56]

B. Controlling for firm characteristics

RES decile	BETA	LNME	LNBM	MOM	REV	IVOL	MAX	TURN	RET5VOL
1 (low)	0.97	0.82	0.98	0.90	0.99	0.88	0.99	0.77	0.93
2	0.95	0.75	0.77	0.86	0.99	0.78	0.90	1.11	1.01
3	0.88	0.91	0.74	0.90	0.81	1.00	0.72	0.81	0.82
4	0.86	0.81	0.77	0.67	0.62	0.83	1.00	0.75	0.54
5	0.73	0.66	0.44	0.64	1.00	0.59	0.81	0.86	0.82
6	0.50	0.90	0.63	0.72	0.46	1.00	0.77	0.71	0.77
7	0.80	0.78	1.04	1.02	0.73	0.85	0.88	0.82	0.85
8	0.82	0.91	0.69	0.66	0.79	0.64	0.31	0.38	0.67
9	0.33	0.28	0.20	0.52	0.41	0.27	0.45	0.56	0.31
10 (high)	0.39	0.30	0.49	0.42	0.45	0.49	0.39	0.20	0.43
1 -10 (Low-High)	0.58	0.52	0.49	0.48	0.54	0.39	0.60	0.57	0.50
	[2.11]	[2.00]	[1.77]	[1.61]	[2.01]	[1.40]	[2.07]	[2.22]	[1.85]

The equally-weighted average monthly returns are reported in these tables after sorting by a control variable, followed by *RES*. Breakpoints are first calculated for the terciles, and then, within each tercile, the decile portfolios are formed. The *RES* decile portfolios result from the merge between the corresponding deciles from each tercile. Panel A refers to liquidity variables (Amihud's illiquidity ratio, bid-ask spread, Pastor-Stambaugh sensitivities to innovations, high-low spread, and Roll's measure, respectively). Panel B refers to other variables not related to liquidity (market beta, size, book-to-market ratio, momentum, return reversal, idiosyncratic volatility, maximum daily return, share turnover, and long-term volatility). Newey-West *t*-statistics are reported in parentheses, with a lag of 4.

Table 7 Fama-MacBeth regressions (FTSE 100 sample)

$Y = RET_{t+1}$	M1	M2	M3	M4	M5	M6
RES	-1.183**	-0.725	-0.542	-0.470	-0.319	-0.410
	[-2.09]	[-1.12]	[-0.81]	[-0.70]	[-0.49]	[-0.62]
BETA	0.632***	0.380*	0.460**	0.425**	0.407**	0.421**
	[3.05]	[1.77]	[2.26]	[2.14]	[2.05]	[2.27]
LNME	-0.257***	-0.292***	-0.212***	-0.212**	-0.205**	-0.214**
	[-2.62]	[-4.03]	[-2.67]	[-2.34]	[-2.36]	[-2.44]
LNBM	-0.308***	-0.191**	-0.177**	-0.182**	-0.176**	-0.176**
	[-2.65]	[-2.30]	[-2.16]	[-2.26]	[-2.25]	[-2.29]
MOM		0.989*	0.904*	0.909*	0.831	0.712
		[1.92]	[1.74]	[1.76]	[1.62]	[1.43]
REV		-0.012	-0.010	-0.013	-0.015	-0.013
		[-0.77]	[-0.68]	[-0.88]	[-0.99]	[-0.87]
IVOL		-0.487*	-0.510*	-0.480*	-0.441	-0.427
		[-1.78]	[-1.86]	[-1.75]	[-1.65]	[-1.64]
MAX		-0.001	0.006	-0.010	0.002	0.013
		[-0.02]	[0.08]	[-0.14]	[0.03]	[0.17]
TURN		-0.010	0.021	0.015	0.027	0.021
		[-0.11]	[0.23]	[0.17]	[0.30]	[0.22]
RET5VOL		0.608*	0.412	0.385	0.403	0.415
		[1.75]	[1.12]	[1.05]	[1.08]	[1.14]
ILLIQ			19,269.752	23,156.539	22,639.912	23,039.529
			[1.19]	[1.16]	[1.16]	[1.18]
SPR				-1.639	-1.344	-2.167
				[-0.70]	[-0.57]	[-0.94]
HLSPR					-0.272	-0.322
					[-0.69]	[-0.81]
PS						-0.018***
						[-2.99]
ROLL						-0.073
						[-0.55]
Constant	1.991*	1.866*	1.101	1.237	1.367	1.622
	[1.75]	[1.96]	[1.04]	[1.06]	[1.26]	[1.47]
N	12,012	12,012	12,012	12,012	12,012	12,012
R-sq	0.108	0.252	0.271	0.284	0.296	0.317

The table presents the results of Fama & Macbeth (1973) methodology, namely the average slope coefficients from the regression of monthly excess returns on *RES* and control variables. *N* stands for the number of observations, and *R*-sq for the average *R*-squared of the monthly cross-sectional regressions. Newey-West *t*-statistics are reported in parentheses, with a lag of 4. For details about the lagged variables, see Table 1. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$